AMI Billing Regression Study Appendices

Final Report

February 23, 2016

Appendix A Alternative Models Methodology And Results

This appendix provides details on the other models that were explored as part of this research. The alternative models include:

- Fixed effects billing regression model
- Princeton Scorekeeping Method (PRISM)
- Energy Charting and Metrics (ECAM)

A summary of the models and results for each of these methods is provided below, with additional detail included in the following appendices.

A.1 Fixed Effects Billing Regression Model

This section summarizes the results of using a traditional fixed effects billing regression to estimate program-level savings for the SCE Quality Installation and PG&E Quality Maintenance Programs. In order to demonstrate the usefulness of hourly interval consumption data, we estimated the same fixed effects billing regression models with the same data aggregated into monthly, daily, and hourly consumption intervals. In addition to comparing the resulting estimates of program savings, we also assess the improvement in model fit and precision for key variables based on the shift from monthly to hourly data.

A.1.1 Fixed Effects Model Specification

The fixed effects regression model is one of the most common billing analysis approaches to evaluate savings for energy efficiency programs. The fixed effects regression model controls for unique customer-specific characteristics that may influence energy use, beyond controlling for weather variables. This is accomplished by including a customer-specific constant term in the model to control for factors such as home size, occupancy, vintage and other household characteristics that affect electricity use and are not otherwise represented in the model. Ultimately, this constant serves as a proxy for possible omitted variables that might bias the estimation results.

To ensure a direct comparison between the fixed effects model approach and the annual random coefficients model, each model uses the exact same set of homes and observations. The SCE QI data include 2,038 homes dispersed across nine different climate zones. The PG&E data include 1,216 homes dispersed across four different climate zones. For the purposes of this research, we relaxed a common criterion in fixed effects models for impact evaluation, which is to limit homes in the analysis to those with at least a full year of pre- and post- installation data. Rather, to ensure a direct comparison in the results, we included all homes and all observations used in the random coefficients model. The resulting sites had pre-period data ranging from one month to thirteen months with an average of 12 months of billing data, and post period data ranging from one month to thirteen months with and average of 8 months of post-period billing data.

We estimated a fixed effects model with the same billing data at three levels of aggregation: hourly, daily, and monthly. The model specification is kept consistent across each aggregation level in order to isolate the impact of the interval size and determine its effect on the savings estimate, model fit, and precision. Due to the differing levels of aggregation, however, some of the specific variables are altered for each level of aggregation to account for the different time dimensions (hourly, daily, etc.). The installation date was provided as part of the program data and is used to determine the pre- and post-periods; periods during which the installation occurred (i.e. the month or day of installation) were flagged as blackout periods and not included in the analysis. To calculate degree days, we retrieved average hourly temperature NOAA and appended to the hourly AMI data. We selected weather station data based on proximity to each observation home's zip code, matching climate zone, and availability of complete hourly data. We computed degree days by summing each days cooling degree hours derived by taking the difference between the average hourly temperature and a base temperature of 65˚F and dividing by 24.

The model is specified as follows:

$$kWh_{i,t} = \alpha_i + \beta_1(Post_{i,t}) + \beta_2(C_{i,t}) + \beta_3(H_{i,t}) + \beta_4(C_{i,t} * Post_{i,t}) + \beta_5(H_{i,t} * Post_{i,t}) + \sum_{j=6}^{16} \beta_j(M_t) + \varepsilon_{i,t}$$

$Where:$

Monthly Model:

$kWh_{i,t}$ = Average daily kWh consumption during month t for customer i

$Post_{i,t}$ = Dummy variable indicating post-participation during month t* for customer i, (value of 0 if pre-participation and 1 if post)

$C_{i,t}$ = Sum of Cooling degree days (CDD) during month t for customer i

$H_{i,t}$ = Sum of Heating degree days (HDD) during month t for customer i

Daily Model:

$kWh_{i,t}$ = Actual daily kWh consumption during day t for customer i

$Post_{i,t}$ = Dummy variable indicating post-participation during day t** for customer i, (value of 0 if pre-participation and 1 if post)

$C_{i,t}$ = Cooling degree days (CDD) during day t for customer i

$H_{i,t}$ = Heating degree days (HDD) during day t for customer i

Hourly Model:

$kWh_{i,t}$ = Actual hourly kW consumption during hour t for customer i

$Post_{i,t}$ = Dummy variable indicating post-participation during hour t** for customer i , (value of 0 if pre-participation and 1 if post)

$C_{i,t}$ = Cooling degree hours (CDH) during hour t for customer i

$H_{i,t}$ = Heating degree hours (HDH) during hour t for customer i

All Models:

$C_{i,t} * Post_{i,t}$ = Interaction between the cooling degrees and post-period indicator variable

$H_{i,t} * Post_{i,t}$ = Interaction between the heating degrees and post-period indicator variable

M_t = Series of dummy variables for each month, excluding January

$\beta_1 \ldots \beta_j \ldots$ = Coefficients to be estimated in the regression model

α_i = Customer specific constant

$\varepsilon_{i,t}$ = Random error term, assumed to be normally distributed

* Month of installation treated as a blackout period.

** Day of installation treated as blackout period.

The variables that capture the savings attributable to the program (at each aggregation level) are those terms including the *Post* variable: $Post_{i,t}$, $C_{i,t}*Post_{i,t}$ and $H_{i,t}*Post_{i,t}$. The coefficient on the $Post_{i,t}$ variable can be interpreted as the average change in consumption attributable to a household in the post-intervention period (i.e. the change in consumption resulting from the Quality Installation or Quality Maintenance of HVAC equipment). The coefficient on the $C_{i,t}*Post_{i,t}$ variable can be interpreted as the average change in consumption attributable to a household in the post-intervention period due to an increase of one cooling degree-day (or cooling degree-hour) in that period. Likewise, the coefficient on the $H_{i,t}*Post_{i,t}$ variable can be interpreted as the average change in consumption attributable to a household in the post-intervention period due to an increase of one heating degree-day (or heating degree-hour) in that period.

To calculate the average household energy savings based on the regression results, the following equation is used that incorporates the coefficient estimates from the model and the average actual weather values across all sites in the post period for cooling degrees and heating degrees:

$$Avg\Delta kWh_{i,t} = \beta_1 + \beta_4(\overline{C}) + \beta_5(\overline{H})$$

Estimates of the standard error of this transformation were calculated using the delta method.[1] The detailed coefficient estimates for each model are included in Appendix D. The results from each time dimension (hourly, daily, etc.),

A.1.2 Fixed Effects Model Results

SCE QI Program Results

Figure 1 presents a graphical representation of the savings estimates for each model for the SCE QI program, with savings expressed as a percentage of energy consumption. Each point estimates also includes a 95 percent confidence intervals shown as vertical bars.[2]

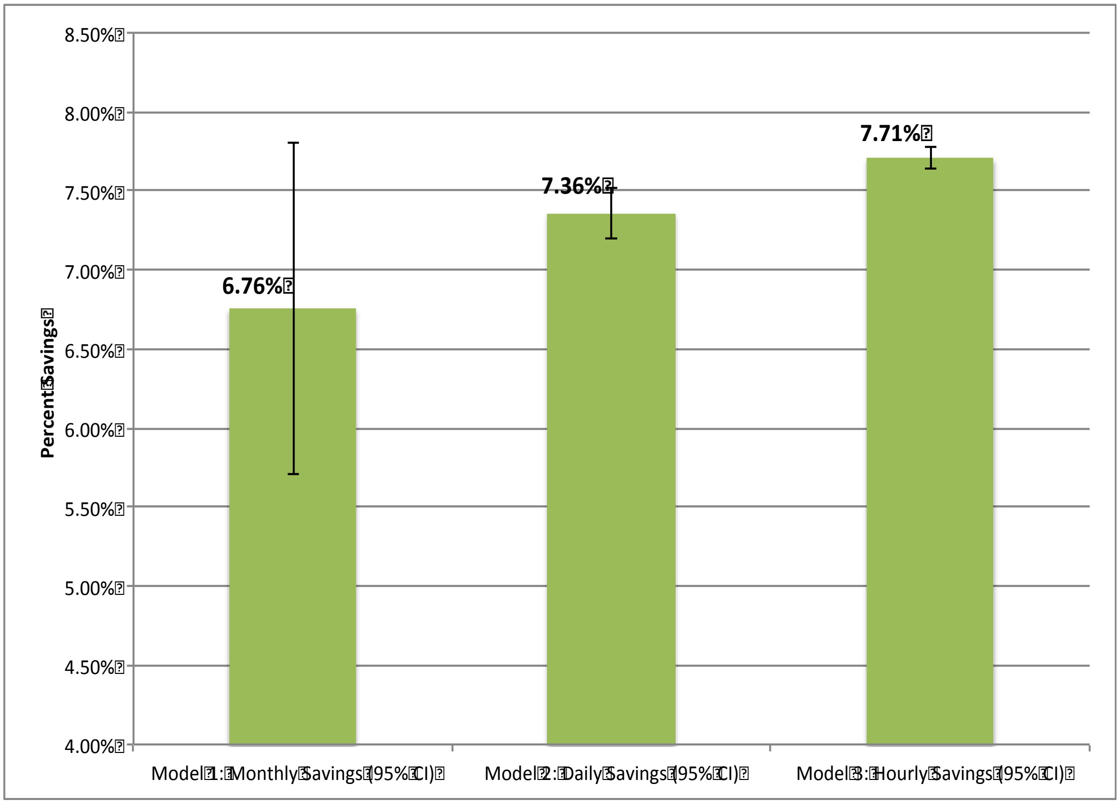
There are two important trends from these models as we move from the monthly to the hourly data. The first is that the impact estimates increase as the data become more granular, ranging from 6.76 percent in the annual model to 7.36 percent in the daily model and 7.71 percent in the hourly model. Overall, the shift from monthly to daily data results in a 14 percent increase in the savings estimates. While we expect that this increase is likely to be a general trend resulting from the model incorporating the actual variation in daily energy consumption that is masked in the monthly data, we cannot be certain that this is not specific to these two programs without testing it on data from a variety of programs.

[1] The delta method allows calculation of standard errors of associated with each estimate (when the estimate is a transformation of coefficient estimates) based on the variance-covariance matrix estimated in the billing regression. An explanation of the delta method is available at http://www.math.montana.edu/~parker/PattersonStats/Delta.pdf.

[2] Complete estimation results for the SCE QI model are provided in Appendix D.

The second important trend is that the 95 percent confidence interval becomes much smaller as the granularity of the data increases, allowing for a much more precise estimate with the hourly data. As shown on the graph, the 7.71 percent estimate from the daily model is statistically different than the 6.76 percent point estimate from the monthly model. Note that the reverse is not true, the estimate from the monthly model is not statistically different from the hourly model, due to the wide confidence band around the estimate from the monthly model.

Figure 1: Fixed Effects Savings Estimates for SCE QI Program



PG&E QM Program Results

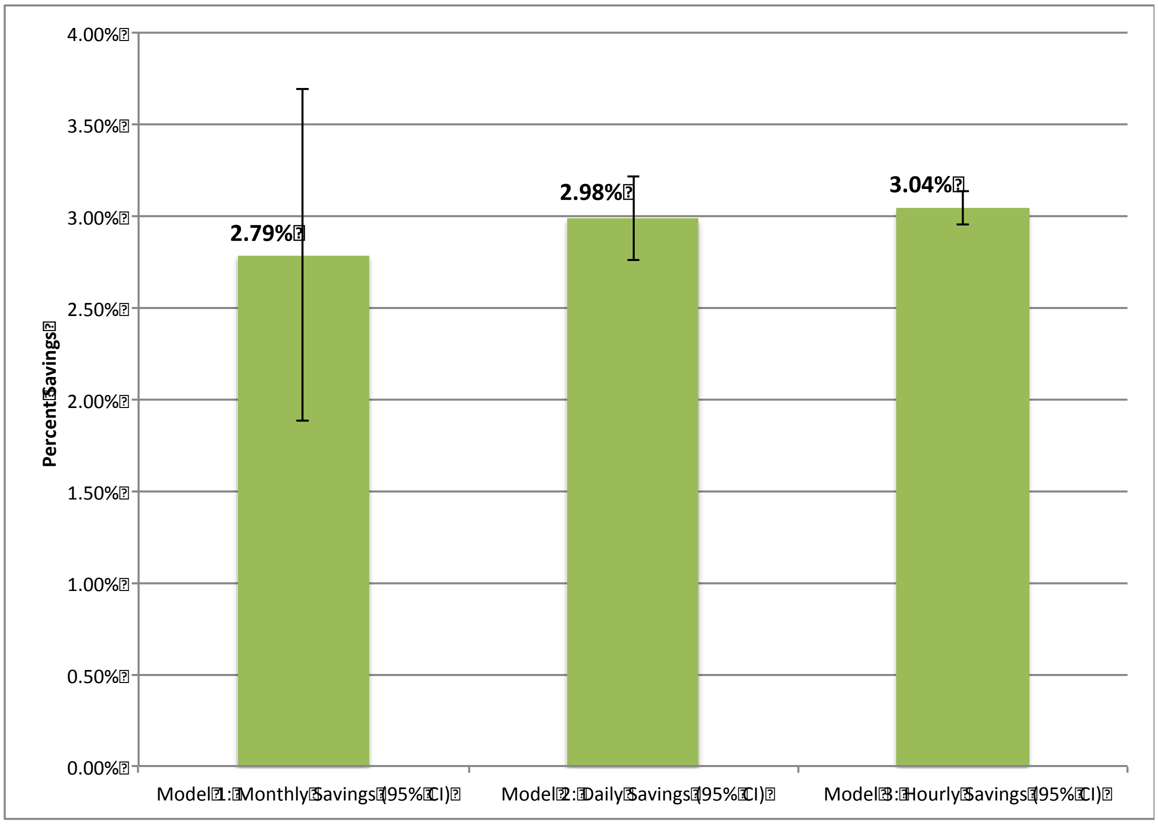
The same fixed effects model specifications were used with the PG&E QM customer data, and these results are displayed graphically in Figure 2.[3] From the QM model, the same basic trends are observed as with the QI results, although savings are lower overall due to the fact that the QM program involves conducting maintenance rather than replacing the entire HVAC system.

From the QM models, the savings range from 2.79 percent with the annual model to 2.98 with the daily model and 3.04 with the hourly model – an overall increase of 9 percent from the annual to the daily model. The 95 percent confidence bands also decrease significantly when

[3] Complete estimation results for the PG&E QM model are provided in Appendix D.

moving from the annual to the hourly models. The monthly savings point estimate of 2.79 percent does not fall within the bounds of the 95 percent confidence interval around the hourly savings estimate of 3.04 percent. Neither the daily nor hourly savings estimate is significantly different from the monthly savings estimate.

Figure 2: Fixed Effects Savings Estimates for PG&E QM Program



Our simple exploration of using AMI data with the traditional fixed effects model has already yielded some positive results, in that the move from annual to hourly data resulted in higher savings estimates and much tighter confidence bands for both the QI and QM impact estimates. The fixed effects model form, however, is somewhat rigid and is not easily adapted to take full advantage of the hourly data.

As this example demonstrates, the typical fixed effects model will produce a single savings estimate that is then applied to all customers participating in the program. With AMI and its variation across customers and day types, there is the opportunity to consider models that can produce a variety of savings values that are more closely tailored to specific conditions. To investigate this, the Evergreen team developed a random coefficients model for use with the hourly AMI data, and this model and estimation results are presented in the following chapter.

A.2 Princeton Scorekeeping Method (PRISM)

In addition to the billing regression models, we also wanted to explore how well AMI could be used with other software tools to estimate program impacts. The first of these we examined was PRISM (PRInceton Scorekeeping Method) software[4]. Our interest in PRISM was two-fold. First, we wanted to compare PRISM's estimates of each home's heating and cooling base temperatures to the commonly used static baseline of 65˚ Fahrenheit. Second, we wanted to determine whether PRISM was able to extract HVAC load estimates from total household consumption data and compare the performance of PRISM in estimating HVAC load to the random coefficients model. In order to accomplish this second task, we relied on the RBSA data that had submetered HVAC consumption data in 15-minute intervals. Since the HVAC submetered data were not available for the QI and QM participants, we did not attempt to use PRISM to estimate impacts for these programs

A.2.1 PRISM Methods

PRISM uses a variable base degree-day (VBDD) approach to perform regression analysis with billing data. The VBDD approach uses regression analysis to determine an appropriate base temperature for each home's heating and cooling, and then specifies a separate regression to model each home's energy consumption. The alternative approach, often used for fixed effects models, assumes a fixed base temperature, typically 65˚F for heating and cooling in all homes.[5]

The PRISM models span the period from April 2012 through September 2014, including data from year two of the RBSA published in May 2015. These models were built from whole home kWh and weather station temperatures provided in the RBSA data; all other detailed metering and temperature variables were disregarded for this first stage of analysis.

PRISM is not designed to handle hourly interval data (for metering or weather), so we aggregated the RBSA data, from 15-minute intervals to daily intervals.[6] We excluded four homes from the full sample of 103 homes due to missing 15-minute interval observations, which prevented us from calculating reliable sums of their daily usage. The RBSA dataset includes information about the types of HVAC equipment used in each home, and the fuel they use. We ran PRISM's heating and cooling (HC) models for homes known to have both heating and cooling equipment, and heating only (HO) models for the remaining homes.

The preferred approach for PRISM is to use many years of weather data before and after the study period to generate an estimate of household consumption that is truly "normalized". In our current application, however, we are only interested in how well the model performs at

[4] Fels, M., et al. 1995. PRISM (Advanced Version 1.0)

[5] It is common practice to test multiple base temperatures models that use a fixed base temperature. In some cases different base temperature are used for heating and cooling, for example, 60˚F for heating, and 70˚F for cooling.

[6] For some regions, the daily metering files were too large for PRISM to process so we had to roll up the observations into sets of two or three days to be able to proceed.

predicting consumption during the study period, and consequently we used only the study period for weather normalization.

The RBSA database has the advantage of having both whole house and HVAC metering data. This allowed us to estimate a billing regression model and then validate the model's ability to isolate the HVAC consumption with the actual HVAC metering data for that same time period. We assumed that all predicted weather-dependent consumption (i.e., any consumption over the weather normalized baseline) predicted by the model was caused by operation of HVAC equipment. We extracted this estimated HVAC consumption from the total energy consumption predictions generated by PRISM, then compared these to the actual HVAC consumption, as measured by the RBSA submeters.

A.2.2 PRISM Residential Building Stock Assessment Results

Figure 3 is a scatterplot with bars indicating a 95 percent confidence interval around PRISM's estimates for the heating baseline temperature among RBSA homes with electric heating equipment. Similarly, Figure 4 is a scatterplot with bars indicating a 95 percent confidence interval around the cooling baseline temperature among RBSA homes with cooling equipment. The commonly used baseline temperature of 65˚F appears to be a reasonable, though slightly high, estimate for both the heating baseline and cooling baseline temperatures for the majority of these homes.

Figure 3: Estimated Heating Baseline Temperature

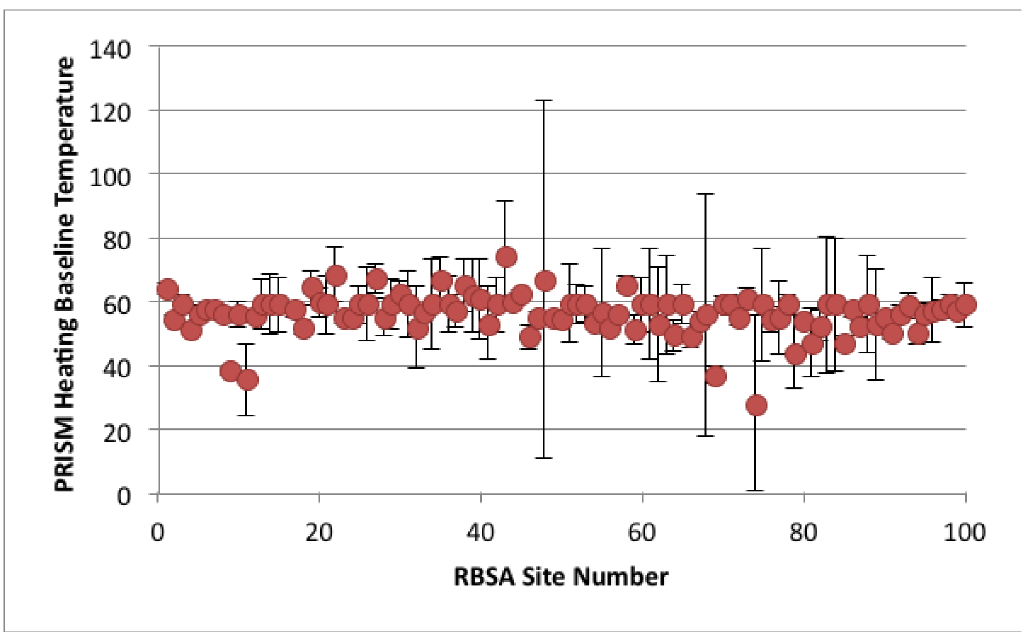


Figure 4: Estimated Cooling Baseline Temperature

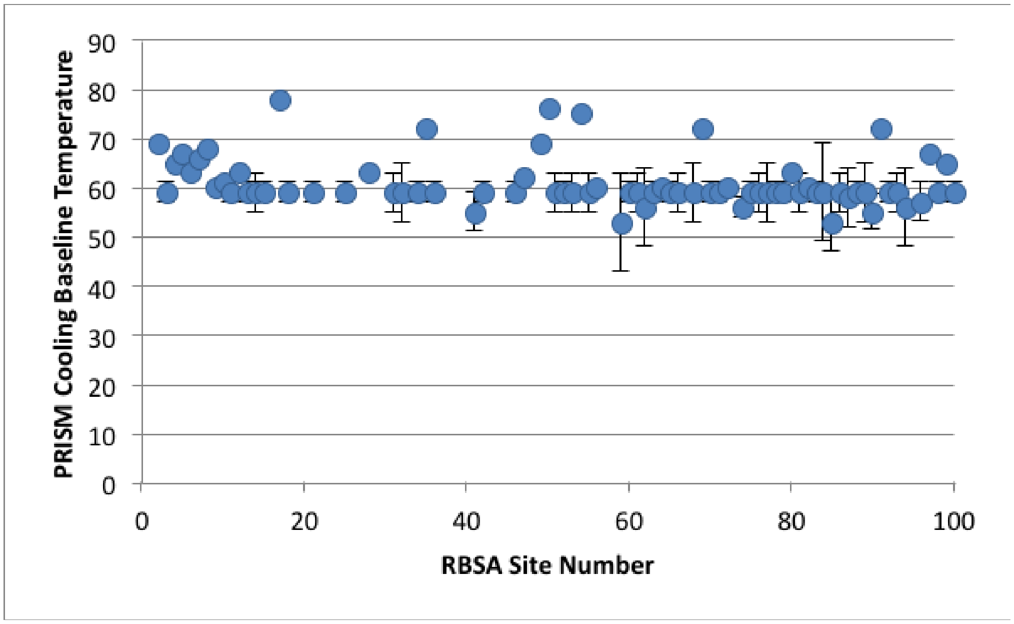


Figure 5 shows the actual average daily total kWh consumption (purple) and PRISM's prediction of the average daily total kWh (yellow) for each month during the test period of April 2012-September 2014. The PRISM models were able to predict consumption reasonably well throughout the study period. The RMSE of the PRISM model is 3.02 kWh, which is about 8 percent of the average daily electricity usage. PRISM's predictions of household consumption during winter months more accurate than during summer months

Figure 5: Actual versus PRISM's Predicted Daily Total Consumption

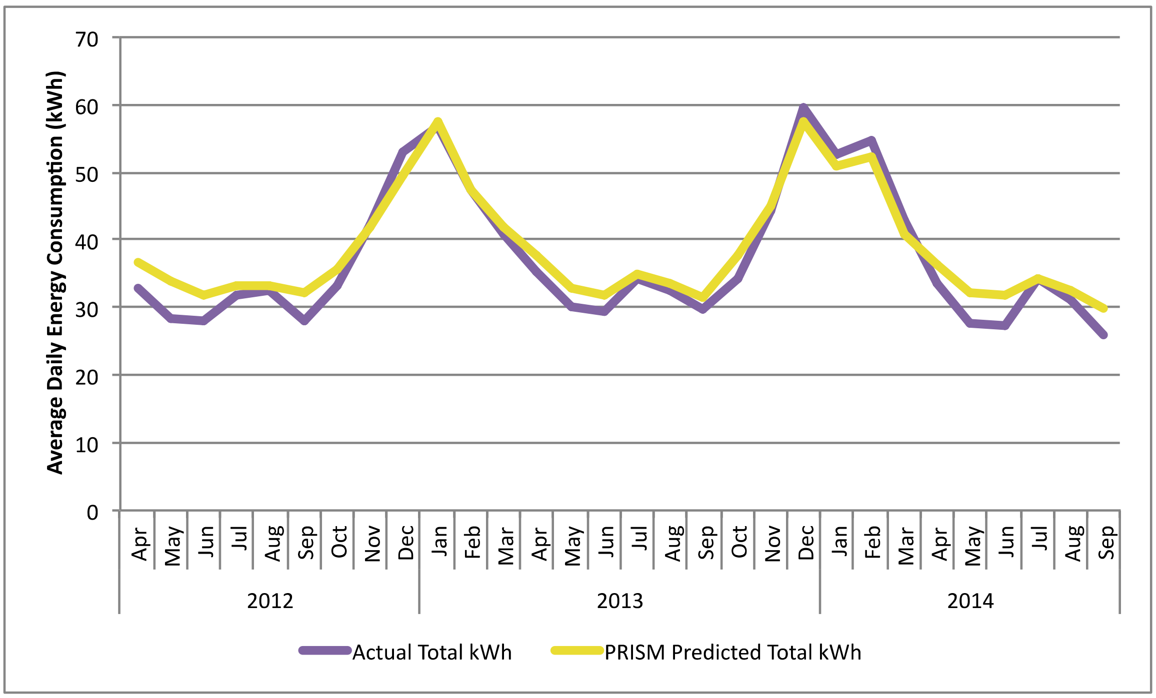
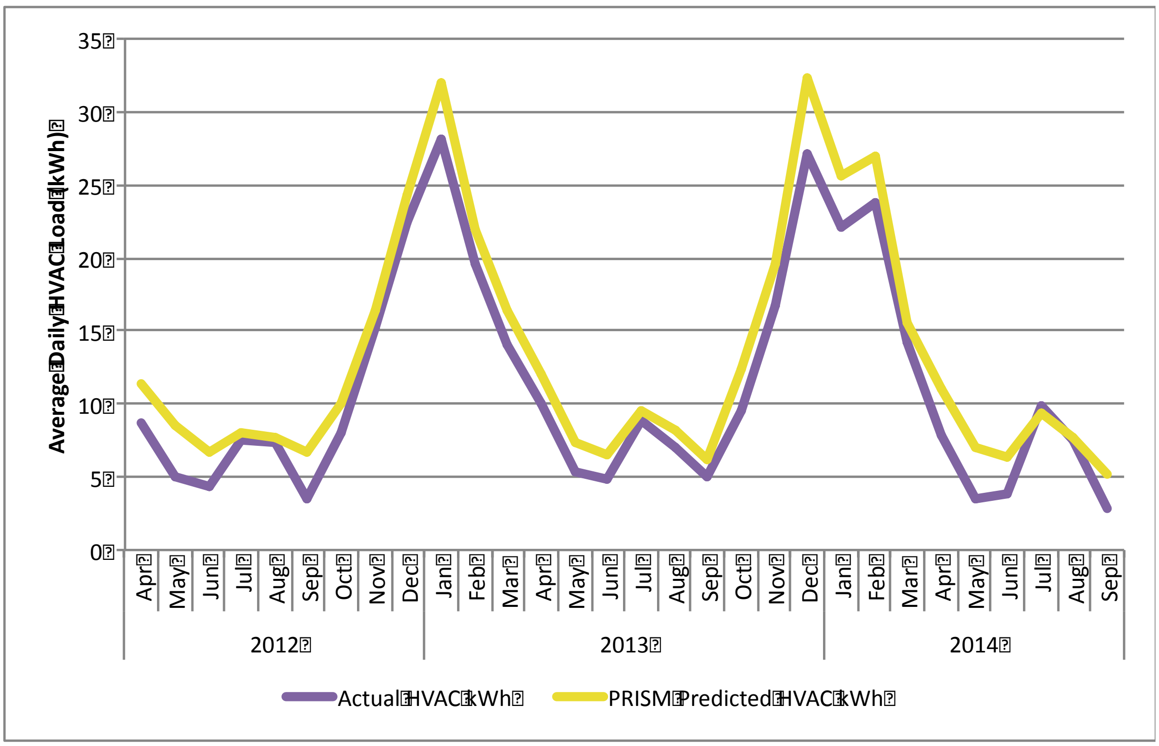


Figure 6 shows the actual average daily HVAC kWh consumption (purple) and PRISM's prediction of the average daily HVAC kWh consumption (yellow) for each month during the test period of April 2012-September 2014. The RMSE of the PRISM model for HVAC is 2.77 kWh, which is almost 12 percent of average daily electricity usage for HVAC equipment by the homes in the RBSA study. The PRISM model overestimated HVAC consumption during most months. However, we assumed that all of PRISM's predicted weather-dependent consumption could be attributed to HVAC equipment, but it is possible that other end uses or consumption behaviors (e.g., increased lighting of water heating in winter months, for example) that are correlated with weather or season are being attributed to HVAC use in the PRISM model.

Figure 6: Actual versus PRISM's Predicted Daily HVAC Consumption

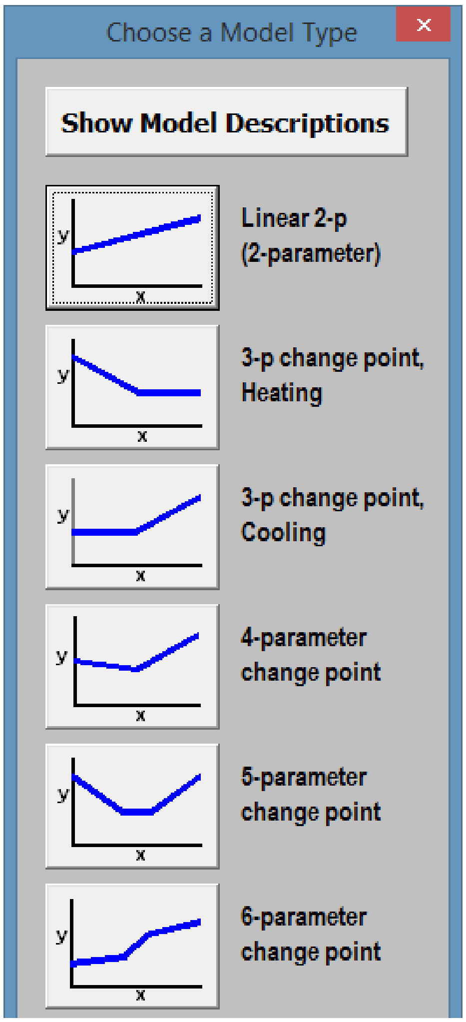


As the preceding results show, PRISM provides an accurate estimate of daily energy consumption, but a less accurate forecast of HVAC use. The inability to process hourly AMI data makes (it needs to be aggregated to daily levels at a minimum) makes PRISM a less attractive option. A comparison of the PRISM results with the other analytical approaches is provided at the end of this report.

A.3 Energy Charting and Metrics (ECAM)

A.3.1 ECAM Overview

An additional tool we examined for use with AMI data is Energy Charting and Metrics (ECAM), which is an Excel add-in that uses energy consumption data to estimate impacts. ECAM creates various types of linear and change-point linear regression models and uses these models for measurement and verification (M&V) of energy savings (an image capture demonstrating model selection capability is shown). The ECAM models are based on ASHRAE approaches developed and documented through ASHRAE research project 1050-RP, *Development of a Toolkit for Calculating Linear, Change-point Linear and Multiple-Linear Inverse Building Energy Analysis Models.*[7] The default model types available in ECAM without customization are shown below. For further information on the models used in ECAM, refer also to the Bonneville Power Administration (BPA) *Verification by Energy Modeling Protocol* and the BPA *Regression for Measurement and Verification Reference Guide*.[8]



ECAM M&V models can be multivariate, and most models characterize energy use as a function of ambient (outdoor) temperature, but ECAM is not limited to just ambient temperature as an independent variable. ECAM models typically include one continuous variable and one or more categorical or indicator variables. The categorical variables are typically one or more of the following:

- Day type
- Occupancy period
- Hour of day or hour of week

The baseline and post time periods can be input, specifying the data to be used in the model(s).

[7] Disclosure: An SBW staff member is the author of the referenced BPA protocol documents.
[8] These guides are available at the BPA Implementation Manual document library at http://www.bpa.gov/EE/Policy/IManual/Pages/IM-Document-Library.aspx

IPMVP and ECAM

The International Performance Measurement and Verification Protocol (IPMVP) describes two types of savings: avoided energy use and normalized savings. Most of this analysis estimates avoided energy use, although an estimate of normalized savings was also developed for a few data sets.

The general steps used in ECAM to estimate savings are similar to those used with the random coefficients model. To estimate avoided energy use, the post-period energy consumption is subtracted from the estimated energy use in absence of any installed efficiency measures. The baseline model is adjusted to the same conditions as actually existed during the post-period. In other words, the actual post conditions are used as inputs to the baseline model, and are part of the set of independent variables. “Same conditions” may refer to, as relevant:

- Weather
- Occupancy
- Production rate
- Other variables

Since avoided energy use savings utilizes the actual post-project energy consumption, it requires just one model—a model of the baseline energy use. Normalized savings is estimated by subtracting the post-project energy use estimated for a set of “normal” conditions from an estimate of energy use under the same normal conditions without the project. The equation for normalized savings is: adjusted baseline minus adjusted post, where the adjusted baseline and adjusted post are each from separate data-driven models.

Therefore, normalized savings requires two models—a model of the baseline energy use and a model of the post-period energy use. Both models are adjusted to a set of normal or typical conditions, which may refer to, as relevant, a typical set of weather, occupancy, production rate, and other variables. The most common normalization for this type of analysis is for weather, using typical meteorological year data.[9]

ECAM can estimate both types of savings in a manner adherent to the IPMVP. Adjusting a model to another set of conditions, whether they are post or normal conditions, requires that the data used in creating the model cover a sufficient range of the independent variables to be credible when applied to alternate conditions. For example, in an ideal scenario, the ambient temperature data used in developing a model would cover the full range of temperatures that occurs in post or normal conditions.

9 Typical meteorological year (TMY) data are collations for a particular location over several years that form a representative typical year of weather data, rather than a specific year with extreme weather events. The TMY3 data are derived from the 1961-1990 and 1991-2005 National Solar Radiation Data Base (NSRDB) archives.

A.3.2 ECAM Analysis Methods

This section describes how ECAM was used for each dataset, including method benefits and shortcomings. We created site-level ECAM models with the RBSA and SCE QI data and group-level ECAM models with the PG&E QM data. Based on these models, we generated savings estimates for both the QI and QM program participants.

Many of the ECAM models we constructed use the hourly data after the data were aggregated to the daily level. According to ASHRAE research, modeling daily energy usage is usually the best approach for M&V despite the inherent limitation that analysis conducted at the daily level may require a longer time period to cover the full range of weather that homes experience in a typical year. However, one of the primary goals of this research is to explore approaches for determining the timing of the energy savings. For this reason, we explored the use of ECAM for both daily and hourly models.

When comparing the results of the ECAM model with the random coefficients model, note that the times in the ECAM model are offset by one hour. This is due to a difference in modeling approaches where ECAM assumes the measurements occur at the start of each hour, rather than at the end of each hour. This does not affect the savings estimate (it may have a very small effect on regression uncertainty), but it will prevent the load profiles from lining up perfectly.[10]

As part of the model development, ECAM creates scatter charts of power versus ambient temperature. For hourly models, there is a separate chart for each hour of the day. If multiple day types were needed, then there would be separate charts for each day type in the daily models, and for each day type/hour of day combination for these hourly models. However, we found that there was little difference in the scatter charts for each day type, so day types were not used in the final analyses.

ECAM also provides four types of charts of residuals to help with evaluation of autocorrelation, heteroscedasticity, and changes of energy use over time. Hourly energy models typically have significant autocorrelation, and daily models have some autocorrelation, which ECAM incorporates in estimating the uncertainty of savings. ECAM uses classical regression statistics to estimate uncertainty. However, the data sets used in these models are an average of all of the homes included in the data set, and the uncertainties of these averages were not calculated. Therefore, the savings uncertainty would be slightly underestimated and hence is not included in this report. This additional uncertainty should be very minor, so if desired, the uncertainty from the regression could be used as a close estimate of the overall savings uncertainty.

The chart showing the relationship of residuals versus time is important when conducting billing analysis for M&V. This chart provides evidence as to whether energy use was changing

[10] We corrected for this difference later in this report where we directly compared the predicted load shapes and savings from ECAM to the random coefficients model for the same set of homes.

over time outside of the impact of the project. In all cases, there was little change in energy use looking only at the pre-period or only at the post-period. Comparison of data before and after the project indicated the greatest change, suggesting that most change in energy use was due to program participation.

The following sections describe the specific analysis conducted with each dataset, followed by a results section. This includes examples of the scatter plots and charts of residuals versus time for the baseline period for specific homes and groups. Additional charts are provided in the Appendix D.

Residential Building Stock Assessment Methods

ECAM was first tested using data from five homes from the NEEA RBSA. We developed models using interval meter data for the homes and compared these with models developed using data from submeters on the air conditioning equipment. In this case, air conditioning equipment refers to all equipment that provides space cooling (we have included some homes that have heat pumps, which provide both heating and cooling). All the analyses are for individual RBSA homes; no grouped ECAM analysis was conducted with these data.

All of these analyses were conducted using daily energy consumption data. Since there is a limited amount of cooling in many Pacific Northwest climates, the observations of cooling equipment usage is limited. This makes it difficult to establish the increase in energy use with cooling, especially using daily observations. Based on this conclusion, we constructed the remaining ECAM models for SCE and PG&E using hourly whole building data to increase the total number of observations available.

Some initial day typing was done, a process that involves identifying and grouping days with unique schedules or loads. However, there may be additional day types we did not explore that would improve the likelihood of matching models developed from total household-level interval data and submeters on the cooling equipment from the NEEA RBSA sites. Our analyses in SCE and PG&E service territories did not find significant differences between day types.

SCE Quality Installation Program Methods

The SCE QI program analyses using ECAM were site-specific estimations of savings for ten homes. The savings are IPMVP “avoided energy use” with the reporting period including all of the available post data. Savings have not been normalized to a typical year and therefore are comparable to savings estimates derived from the random coefficients model. The savings reported are for all ambient temperatures and are based on total metered electricity use.

PG&E Quality Maintenance Program Methods

Most of the ECAM analysis was performed using the PG&E QM data. These data had a longer period of data available than the SCE QI program data covering both the period before and after each home participated in the program.

Table 1 presents savings estimates for all 689 homes with complete baseline and post data. Homes with partial data were excluded from the analysis. In this case, partial data include all homes with one or more missing hourly consumption observations from 2012-2014. The elimination of homes with partial data was done to reduce the possibility of bias caused by including a different group of homes in one hour than the next hour, or a different group of homes from one season to the next. Binning homes by energy use would allow these homes with partial data to be included with minimal bias, similar to the approach used in the random coefficients model. However, the simplest approach to control for this bias is to eliminate all homes with partial data.

There were four climate zones in the dataset. However, the data for a single climate zone often include temperature data from multiple stations, with different temperature readings for each hour and day. The data were divided into sub-climate zones to limit the variation in temperatures experienced by each home in each group. The sub-climate zones were as follows:

Table 1: Homes in ECAM Analysis by Sub-Climate Zone

CZ	CsubZ	Homes	Homes with Complete Data	Analysis Performed?	Homes Analyzed
CZ4	CZ4a	1	1	N	
	CZ4b	2	0	N	
CZ11	CZ11a	52	26	N	
	CZ11b	5	2	N	
	CZ11c	28	13	**Y**	13
CZ12	CZ12a	1	0	N	
	CZ12b	25	19	**Y**	19
	CZ12c	37	21	**Y**	21
	CZ12d	6	5	N	
	CZ12e	17	11	**Y**	11
	CZ12f	361	193	**Y**	193
	CZ12g	1	1	N	
CZ13	CZ13a	166	102	**Y**	102
	CZ13b	4	3	N	
	CZ13c	1	0	N	
	CZ13d	6	3	N	
	CZ13e	517	289	**Y**	289
	Totals	**1230**	**689**		**648**

Grouping homes by climate sub-zone adds some control for weather conditions, theoretically similar to what could be achieved by grouping homes by the CDD and HDD of days they experienced. In an ideal model, these groups will also control for the change point temperature for each home and the temperatures they experienced. This would be equivalent to grouping homes by CDD and HDD if these values were calculated using a variable base temperature approach. However, that approach would require us to model each home individually, instead of as a group. Due to time limitations for this project, we chose to group homes by the sub-climate zones described above. Most likely, grouping homes by the weather they experienced, but ignoring their individual change point temperatures, has caused the bottom of the scatterplot of kW versus outside air temperature (OAT) at mid-ranges of OAT to flatten out. If the model correctly estimates the shape of the consumption curve in the pre-period, then we are confident that the savings estimate has not been affected. However, the regression uncertainty could be lower if homes were grouped by change point temperature(s).

All of the climate sub-zones with more than 10 homes with complete data were included in the ECAM models, except for CZ11a. There were some issues with the weather observed in CZ11a—some significant and unreasonable spikes in outside air temperature.

We also analyzed subsets of the 193 homes in climate zone CZ12f, to see the effect of sampling. Models were created and savings estimated for the following random subsets of CZ12f: 10 homes, 25 homes, 50 homes, and 100 homes. Finally, for climate zone 12f, savings were estimated for the full data set of 193 homes using both actual 2013 weather data and TMY3 weather data from the same weather station.

A.3.3 ECAM Analysis Results

Residential Building Stock Assessment Results

Graphical and tabular results for the model of a single RBSA home are presented below, with the remaining four home results included in Appendix E. Models developed using interval meter data are compared with models developed using data from submeters on the air conditioning equipment. Since the models are to be visually compared, the charts should be viewed as pairs, with each chart pair having the same axes minimums and maximums.

The following three figures show the results for Home #1, which is one of the sites for which the home model and the air conditioning model matched closely. The data series for "Min Modeled" and "Max Modeled" are the regression prediction intervals at the 95 percent confidence level. Note that there is a negative slope below the change point temperature of 58.4˚F, indicating some electrical heating. This is shown in Figure 41.

In these three figures, and other scatter charts with models, the data series for "Min Modeled" and "Max Modeled" bound the regression prediction intervals at the 95 percent confidence level.

Figure 7: Model for Air Conditioning Unit Energy Usage, Home #1

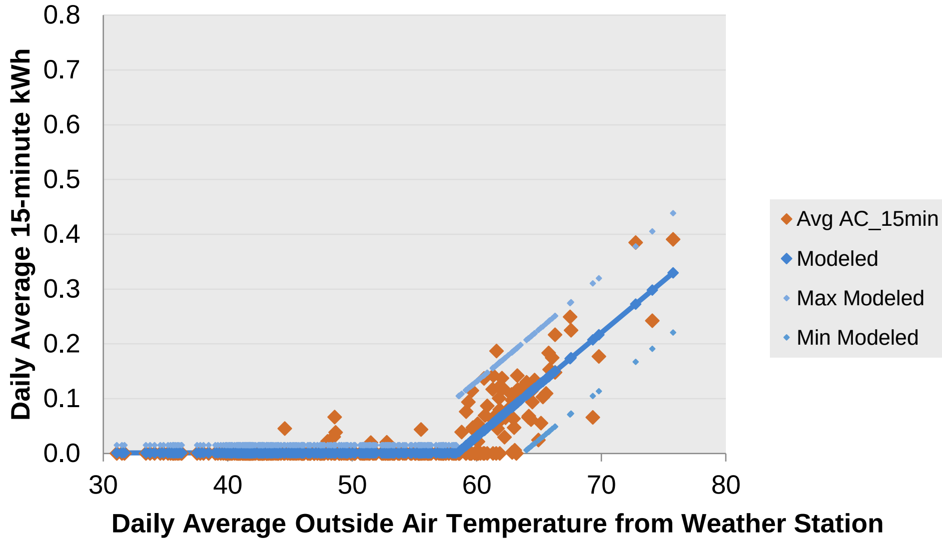
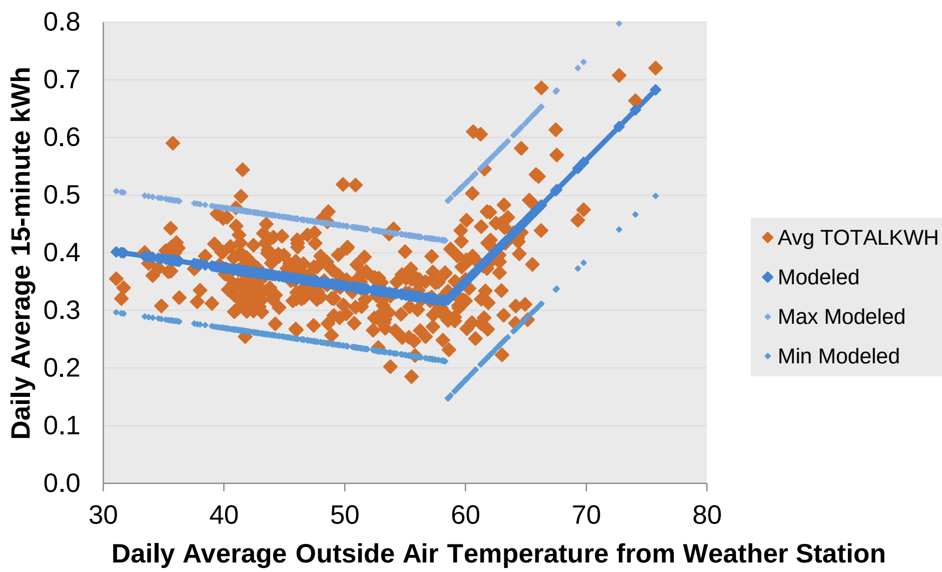
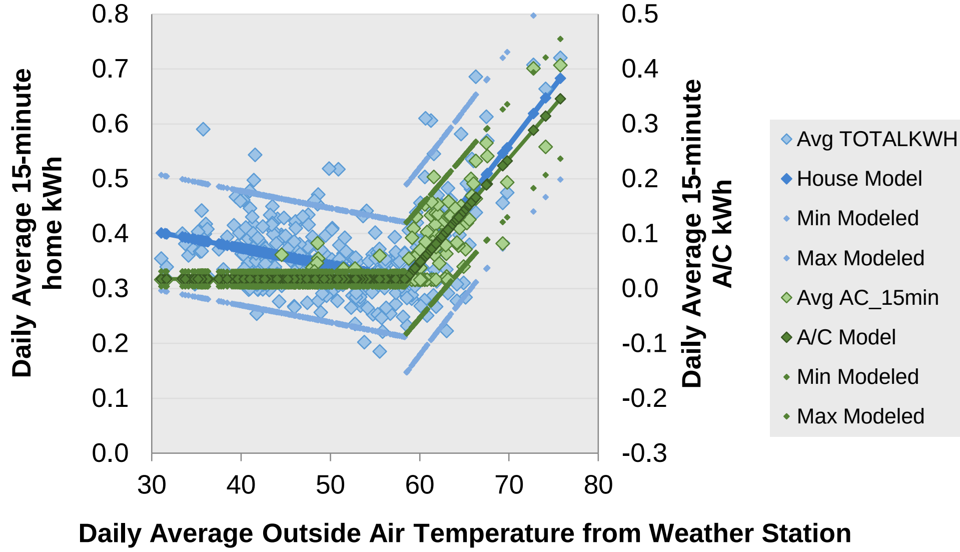


Figure 8: Model for Whole Home Interval Energy Usage, Home #1



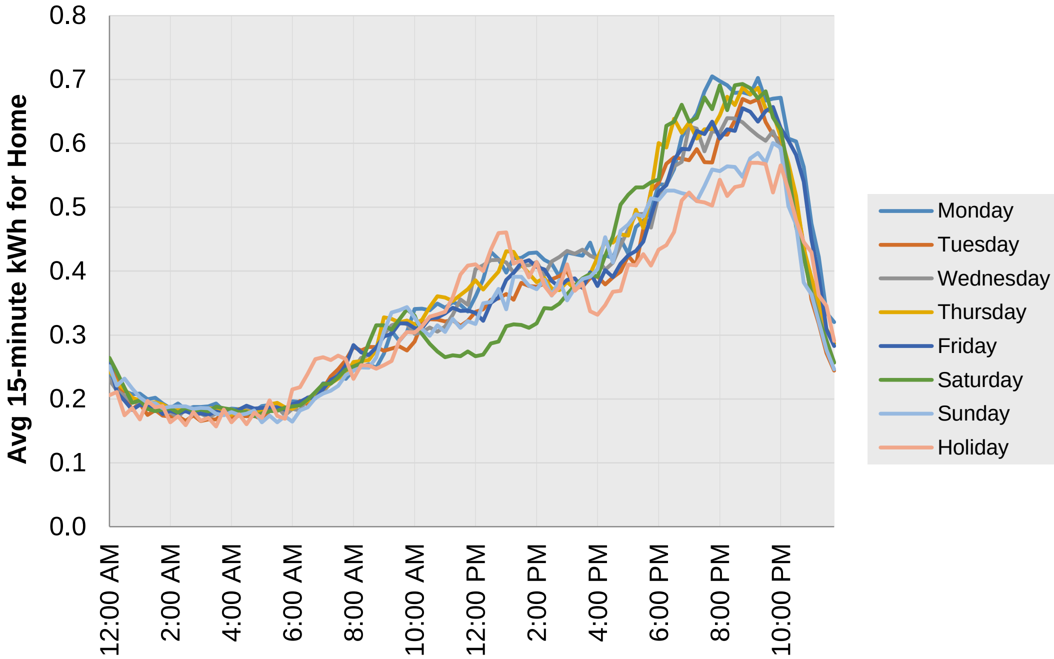
The next chart puts both of these models—the model of the air conditioning unit energy use and the model of whole home energy use— on the same chart, and adjusts the axis for the air conditioning to better facilitate model comparison. Note that the models have about the same change point at which cooling is needed, and predict almost the same increase in cooling energy as the outside air temperature increases.

Figure 9: Models of Air Conditioning Unit and Whole Home Energy Usage, Home #1



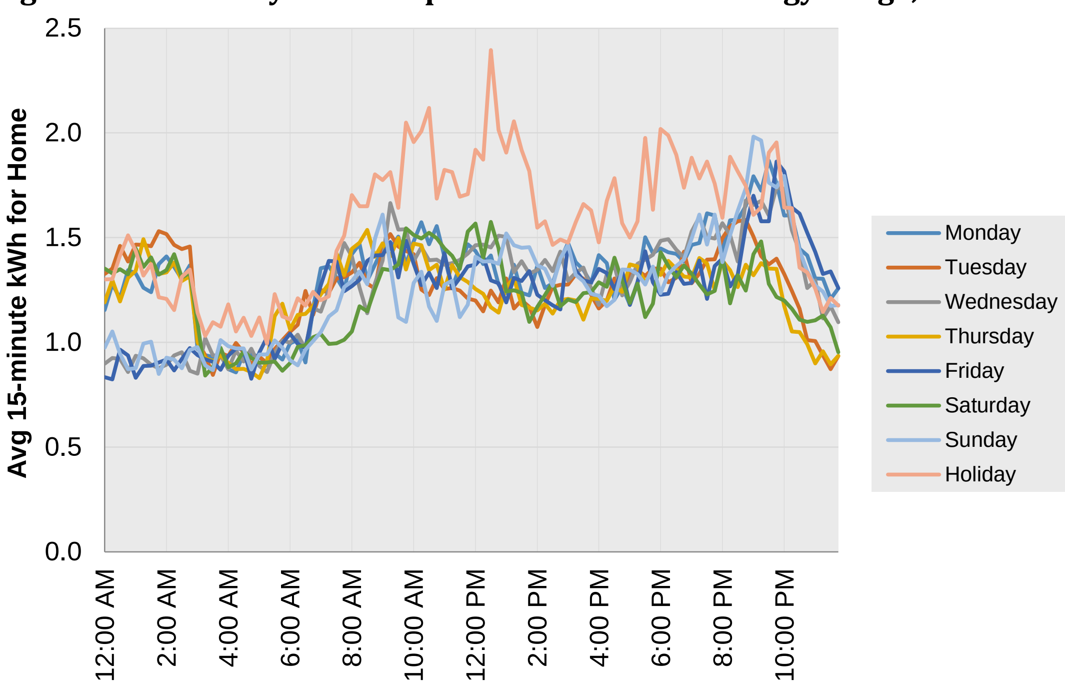
In preparing the models, the data for each home were reviewed and similar days were combined into a day type. The evaluation of day types was done visually using the load shapes for each day of the week, with similar days of the week being grouped together depending on the energy consumption characteristics of the individual homes. These load shapes are shown in the following four graphs. Holidays were combined with another day type since we used a generic list of holidays and did not evaluate which holidays affected home energy use.

Figure 10: Weekday Load Shapes of Whole Home Energy Usage, Home #1



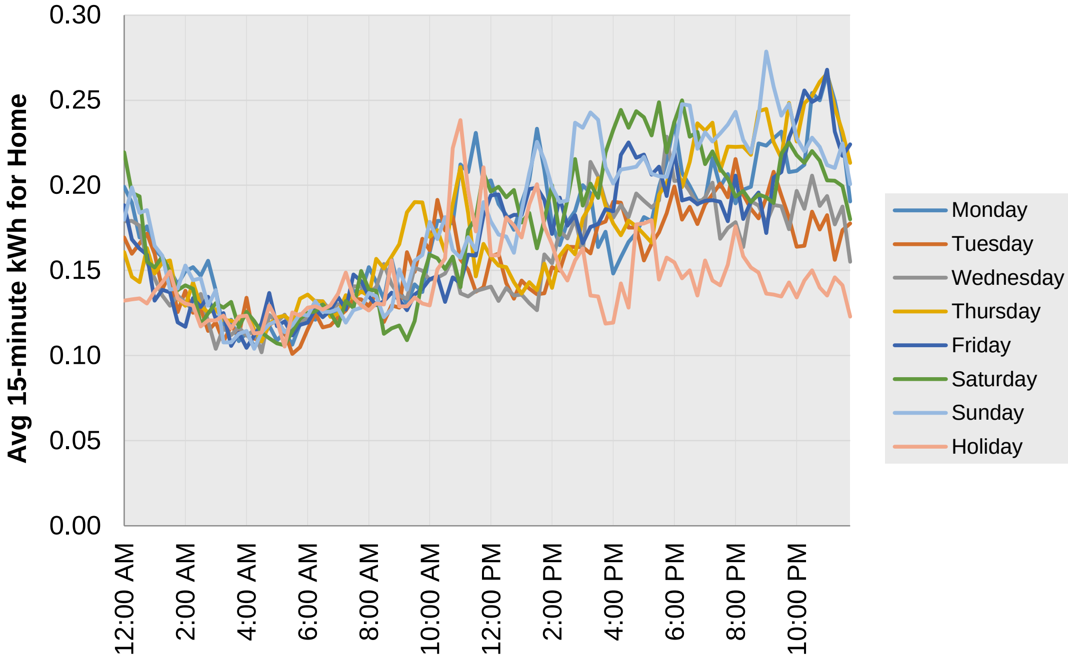
For home number 1, all days of the week were combined into a single day-type.

Figure 11: Weekday Load Shapes of Whole Home Energy Usage, Home #2



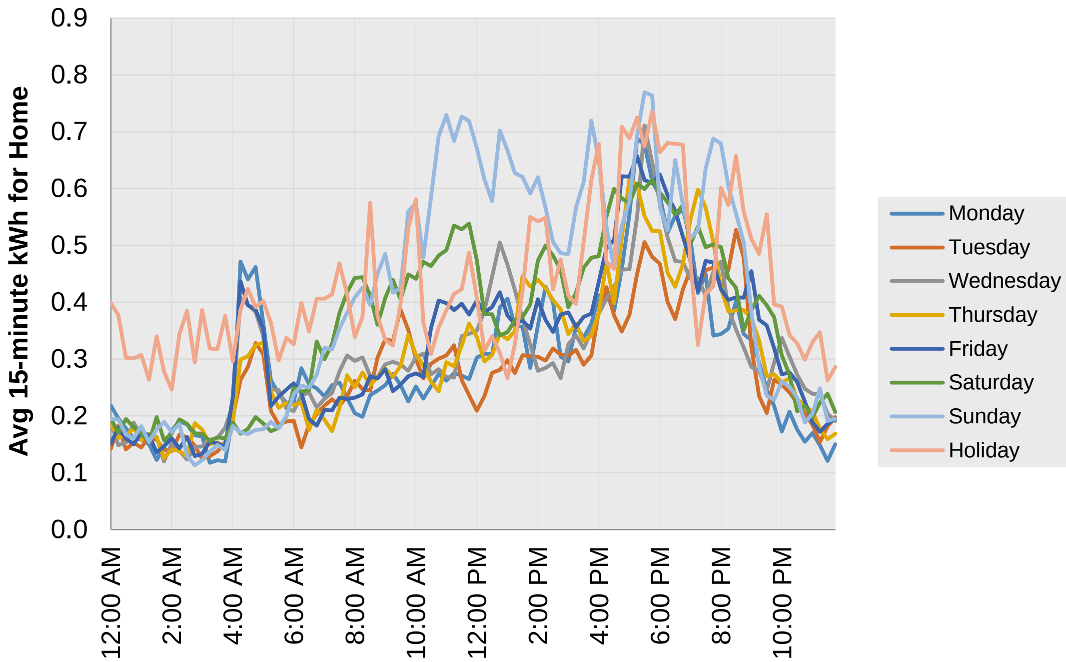
For home number 2, there were three day types used: Tuesdays, Thursdays and Saturdays; Wednesdays, Fridays, and Sundays; and Mondays and Holidays.

Figure 12: Weekday Load Shapes of Whole Home Energy Usage, Home #3



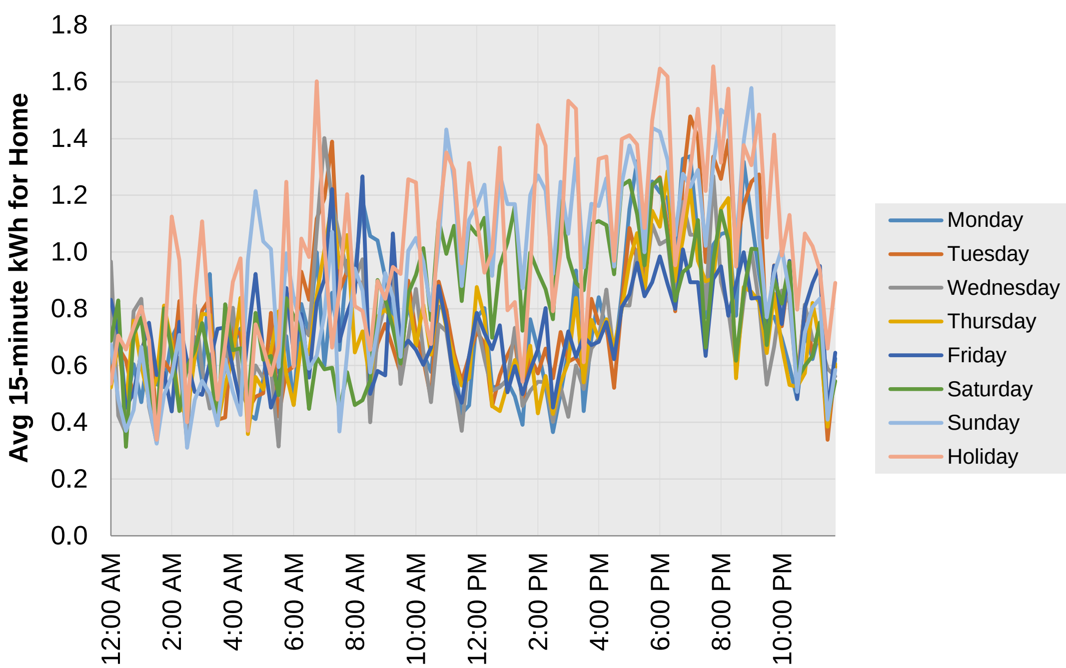
For Home number 3, all days of the week were combined into a single day-type.

Figure 13: Weekday Load Shapes of Whole Home Energy Usage, Home #4



For Home number 4, three day-types were used: Weekdays and holidays, Saturdays, and Sundays.

Figure 14: Weekday Load Shapes of Whole Home Energy Usage, Home #5



For Home number 5, two day-types were used: Weekdays were one day type, and weekends and holidays were the other.

Table 2 summarizes the models for each site. In reviewing the data in the table and the model graphs, the key items to note are the slope and intercept for the portion of the table on the right, which represents the air conditioning. In many cases, these match very well, indicating that whole home interval meter data can be used for estimating cooling energy use and savings, albeit with somewhat higher uncertainty than with sub-metering of the cooling equipment.

Table 2: Summary of ECAM Model Results of RBSA Sites

	Site	#1		#2		#3		#4		#5	
	Model	**Total**	**AC Only**	**Total**	**AC Only**	**Total**	**AC Only**	**Total**	**AC Only**	**Total**	**AC Only**
Daytype 1	Days in Daytype	MoTuWeThFr SaSuHo		TuThSa		MoTuWeThFr SaSuHo		MoTuWeThFr Ho		MoTuWeThFr	
	Cooling Change Point Temperature, F	58.4	58.5	55.7	55.6	63.6	63.7	69.0	67.6	62.1	58.1
	Cooling Slope, (Daily Average) 15-minute kWh per F	0.021	0.019	0.016	0.008	0.021	0.015	0.018	0.017	0.021	0.021
	Correlation Coefficient R-squared	0.416	0.622	0.183	0.372	0.531	0.569	0.453	0.779	0.624	0.866
Daytype 2	Days in Daytype			WeFrSu				Saturday		SaSuHo	
	Cooling Change Point Temperature, F			73.6	57.5			73.8	65.8	59.2	55.8
	Cooling Slope, (Daily Average) 15-minute kWh per F			0.058	0.007			0.039	0.016	0.018	0.019
	Correlation Coefficient R-squared			0.168	0.333			0.613	0.663	0.359	0.817
Daytype 3	Days in Daytype			MoHo				Sunday			
	Cooling Change Point Temperature, F			68.2	61.8			57.6	68.6		
	Cooling Slope, (Daily Average) 15-minute kWh per F			0.035	0.011			0.007	0.018		
	Correlation Coefficient R-squared			0.498	0.548			0.306	0.792		

Notes: #2 has wood use, PTAC as well as HP. Data indicates that not all HVAC equipment was monitored, or a scale factor issue
#5 has propane use as well as HP.

SCE Quality Installation Results

The SCE QI program analyses using ECAM were site-specific estimations of savings for 10 homes. This section presents savings estimates and charts of the baseline and post models. Table 3 is a summary of the results. If more than one change point temperature is shown in a cell, it is for a second day type. The change point for the most common day type is shown first.

Table 3: Summary of ECAM Analysis for SCE QI Homes

Site	Savings, kWh	Savings Uncertainty*, kWh	Percent Savings**, ±%	Percent Savings Uncertainty*, ±%	Heating Change Point Temperature, ºF	Cooling Change Point Temperature, ºF
QI-01	1,850	260	17.5%	2.5%	N/A	70, 66
QI-02	-1,498	101	-46.7%	3.2%	N/A	68
QI-03	1,767	277	14.3%	2.2%	N/A	67, 70
QI-04	1,113	134	17.2%	2.1%	N/A	63
QI-05	413	232	4.7%	2.7%	N/A	68, 69
QI-06	-104	550	-1.0%	5.4%	54	74
QI-07	3,801	312	23.0%	1.9%	63, 66	63, 66
QI-08	-706	457	-10.1%	6.6%	N/A	70, 68
QI-09	6,790	1,158	33.6%	5.7%	N/A	72
QI-10	-1,692	420	-32.2%	8.0%	69, 64	69, 64

* This is the standard error of the savings estimate, not a confidence interval.
** Percent savings are based on total household consumption

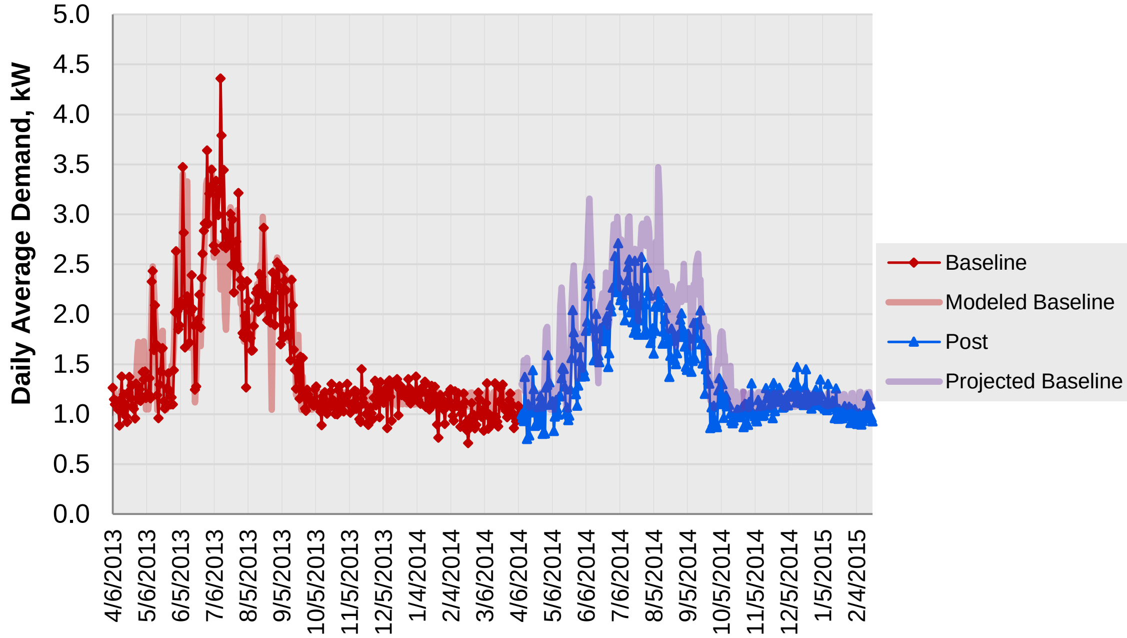
Results for one of these sites, QI-03 is provided Table 4. As shown, site QI-03 experienced statistically significant savings of approximately 14 percent savings, or 1,767 kWh.

Table 4: Savings Summary for Sites QI-03

Site ID	QI-03
Projected Baseline Energy	12,364
Measured Energy	10,598
Energy Savings	1,767
Energy Savings and Uncertainty @ 95% Confidence Level	1,767 ±427
Energy Savings and Uncertainty @ 95% Confidence Level	14.3% ±3.5%

Figure 15 presents ECAM's predicted consumption (modeled) and the actual observed consumption for site QI-03. The modeled baseline in the pre-period (red) aligns quite well with the actual baseline consumption. This suggests that the model is able to predict consumption with sufficient accuracy. The projected baseline, which uses the pre-period model to estimate consumption in the post-period, is consistently higher than the actual observed post-period consumption from May to October of 2014; this indicates that this home realized substantial savings.

Figure 15: Modeled vs. Actual Consumption for Site QI-03



PG&E Quality Maintenance Results

The baseline and post period were each a full calendar year. The baseline year was 2012, the install year was 2013, and the post year was 2014. The savings reported are for all ambient temperatures and are based on total metered electricity use.

The savings estimates for the various climate sub-zones ranged from a low of 5.0 percent to a high of 8.0 percent for the daily models, and a low of 4.8 percent to a high of 7.4 percent for the hourly models. The average estimate of savings was 4.9 percent for the hourly models and 5.4 percent for the daily models. The results in the following tables are presented on a per-home basis.

Table 5: ECAM Savings Estimates by Sub-Climate Zone Group

Climate Zone	Number of Homes	Model Time Aggregation	Projected Baseline Energy	Measured Energy	Energy Savings	Energy Savings
CZ11c	13	Daily	7,640	7,185	455	6.0%
		Hourly	7,595	7,184	411	5.4%
CZ12b	19	Daily	8,379	7,809	570	6.8%
		Hourly	8,265	7,808	457	5.5%
CZ12c	21	Daily	9,823	9,121	702	7.1%
		Hourly	9,746	9,120	626	6.4%
CZ12e	11	Daily	8,360	7,688	671	8.0%
		Hourly	8,306	7,688	618	7.4%
CZ12f	193	Daily	9,405	8,879	526	5.6%
		Hourly	9,324	8,878	445	4.8%
CZ13a	102	Daily	10,988	10,428	560	5.1%
		Hourly	10,958	10,427	531	4.8%
CZ13e	289	Daily	11,272	10,710	562	5.0%
		Hourly	11,253	10,709	544	4.8%
All	648	Daily	10,417	9,862	555	5.4%
		Hourly	10,372	9,861	511	4.9%

A series of charts are provided for each of these sub-climate zone groups in Appendix E. As an example, we have provided the post-period model of daily consumption versus outside air temperature and a comparison of the baseline and actual hourly load in the post-period for group CZ12f.

Figure 16: Group CZ12f Model of Average Hourly Consumption in 2014, post-period

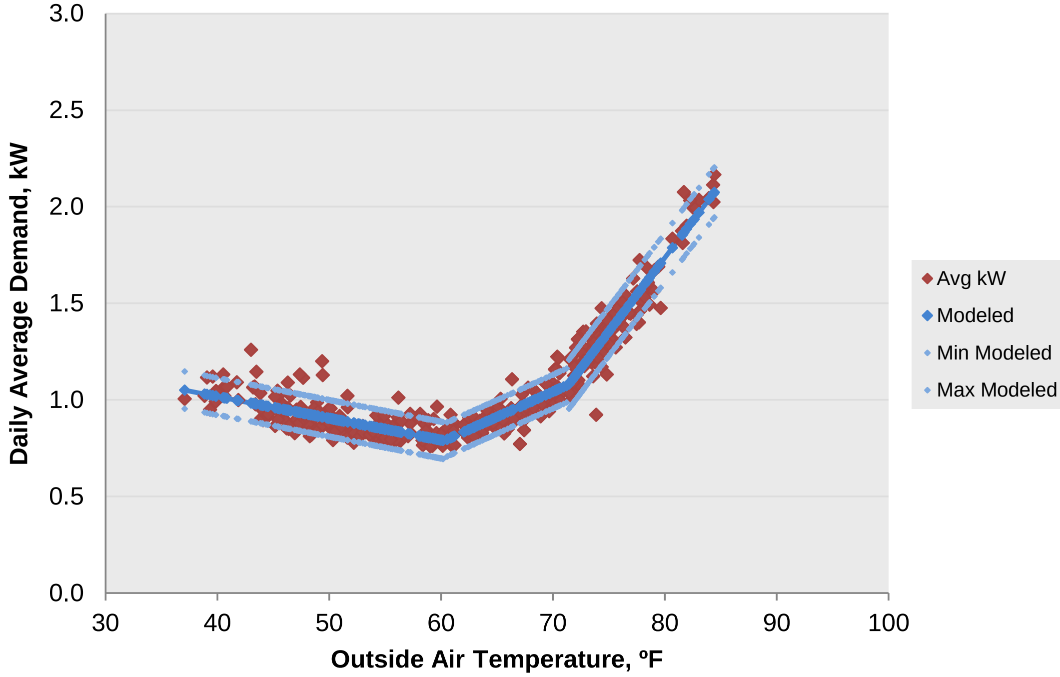
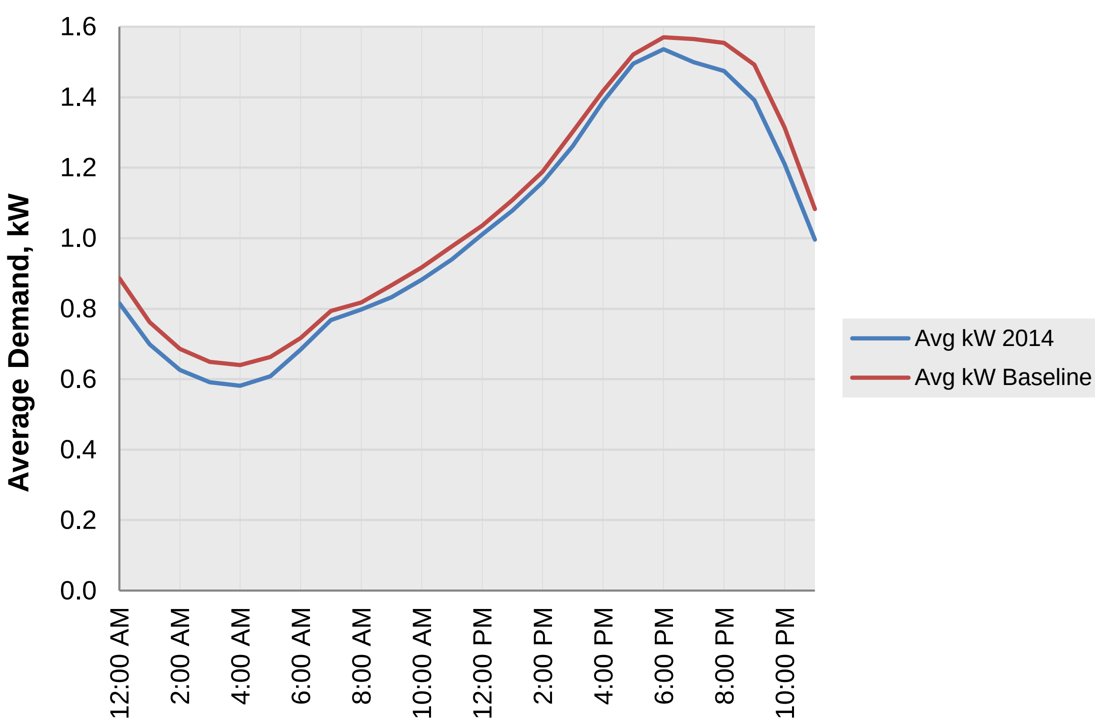


Figure 17: Group CZ12f Predicted Baseline vs. Actual Average Load Profile in 2014



A.4 *Alternative Models and Samples – Climate Zone Subgroup 12f*

Additional analyses were performed for homes in climate zone CZ12f to see the effect of different models and sample sizes. The models differ in the number of parameters used (e.g., 4p, 5p, 6p) and the level of aggregation (daily vs. hourly).[11] For the full dataset of 193 homes, note that there was not a significant difference between the 4p, 5p, and 6p hourly models. There was significant variation in the savings estimated using the random samples from the data for CZ12f, until the sample sized reached 100 homes.

Table 6: ECAM Savings Estimates for CZ12f with Alternative Models and Samples

Climate Zone	Number of Homes	Model Time Aggregation	Projected Baseline Energy	Measured Energy	Energy Savings	Energy Savings
CZ12f	193	Daily	9,405	8,879	526	5.6%
Stockton TMY3	193	Daily	9,170	8,674	496	5.4%
CZ12f	193	Hourly 4p	9,324	8,878	445	4.8%
	193	Hourly 5p	9,300	8,878	422	4.5%
	193	Hourly 6p	9,317	8,878	438	4.7%
	100	Hourly 4p	9,284	8,829	455	4.9%
	50	Hourly 4p	9,194	8,873	321	3.5%
	25	Hourly 4p	9,546	8,853	693	7.3%
	10	Hourly 4p	9,504	8,835	669	7.0%

These homes had an average hourly savings of 0.16 kW per home, which is a reasonable aggregate for all the homes analyzed. However, this savings estimate is somewhat uncertain as can be seen by the hot day load profiles for each climate subzone. In many cases, the baseline has lower hourly kW than the post case. Therefore, it should be reiterated that this is an *average* hourly reduction of 0.16 kW; the hourly reduction on any individual hot day is less certain, and there may even be increased demand. This is possible if the quality maintenance results in increased capacity for some cooling units, allowing them to be more fully loaded.

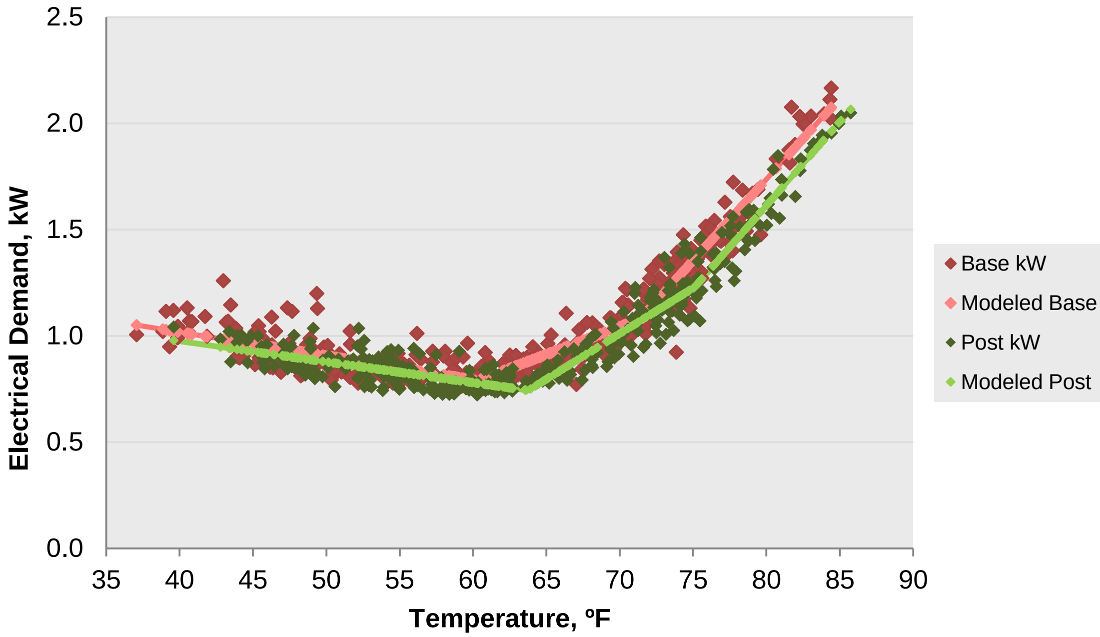
Overall, however, with a sufficient number of sites, there appears to be reliable hourly reduction on hot days of 0.10 to 0.20 kW per home. The hot day load profile for the sub-climate zone with the most homes, CZ13e, showed a clear reduction during peak hours. For the 648 homes analyzed, between 12:00 p.m. to 6:00 p.m. when outside air temperatures were between 90˚F and 105˚F, there was a consistent reduction in hourly usage of about 5 percent of baseline usage.

The savings for the TMY3 and actual 2014 weather were similar. Although 2014 had about 14 percent more cooling degree-days than the TMY3 data, the savings estimates were close because the savings occur at all temperatures, not just during cooling. This is shown in the

[11] A 2p model is a simple linear regression with two parameters – a slope and an intercept. A 4p model could be specified in various ways, but one option is three slopes and an intercept. These daily models are based on the hourly data after they are aggregated to the daily level .The hourly models use 24 regressions, one for every hour.

following two figures, which use daily average data for climate zone 12f. When looking at the results for the individual climate zones like the one below, note that the scatter chart of daily average power versus outside air temperature shows a minor but clear reduction in average power from before to after implementation.

Figure 18: Daily Average Energy Usage versus Outside Air Temperature, for Base and Post



There is a time-series behavior that is not accounted for solely by outside air temperature, evidenced by a seasonal shape to the model residuals. Specifically, energy consumption is increasing relative to the model's predictions, resulting in a downward slope of the trend line shown in Figure 19. Since electricity use is slightly higher in mid-summer than predicted, we theorize that occupants avoid turning on the cooling equipment early in the summer season, maintain comfort levels through the summer, and again turn the cooling off in the fall even on warm days. This theory could be verified if data become available for indoor temperatures in homes with air conditioning equipment over time.

Other possible reasons for seasonal changes unrelated to temperature include school schedules—which may be partly responsible for the changed cooling behavior—and holiday lighting. The analyses herein do not account for these seasonal effects. This should not impact the magnitude of savings estimates, but it could affect the uncertainty.

The charts below show the residuals, relative to the baseline model estimate, for all three years of the data; including the baseline year, the year of implementation, and the post year.

The seasonal adjustment shown in the second chart used a 30-day rolling average of the residuals for the baseline model.

Figure 19: Residuals versus Time without Seasonal Adjustment

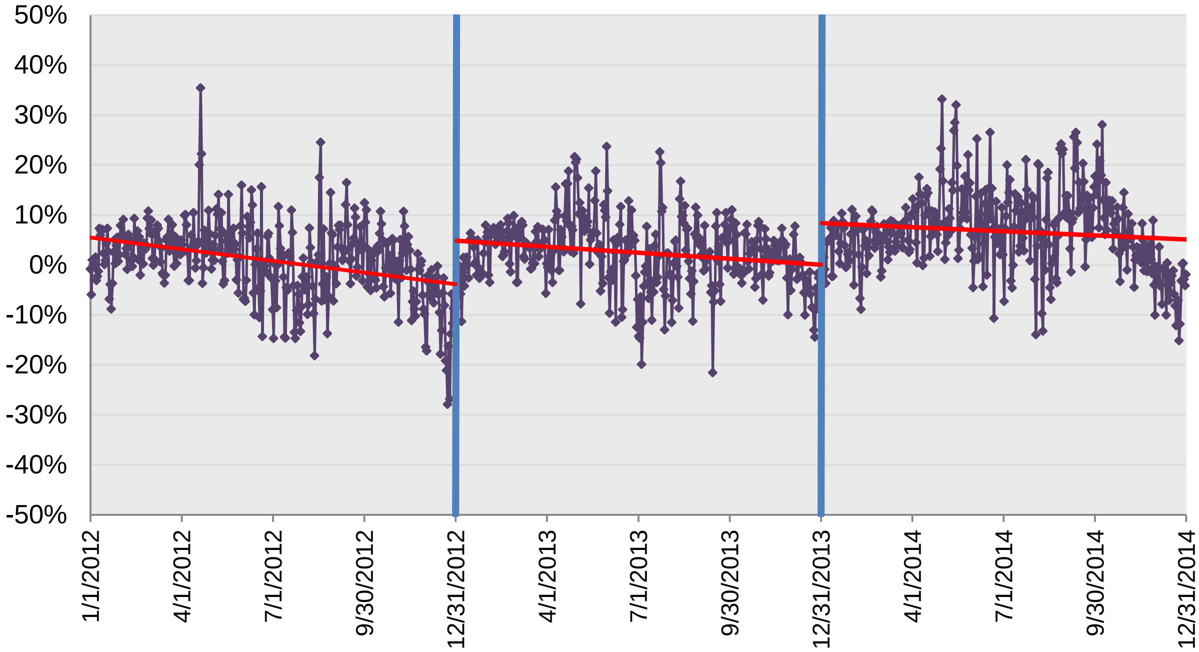
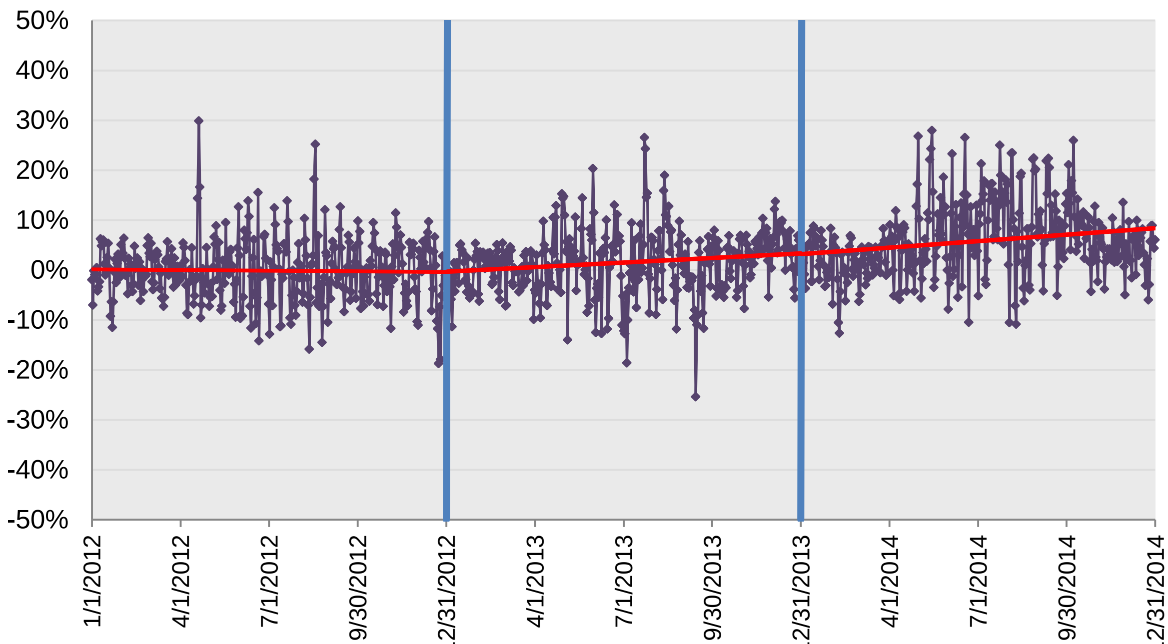


Figure 20: Residuals versus Time with Seasonal Adjustment, Based on 2013 Residuals



Appendix B Summary of Household Characteristics

The following sections provide a brief summary of the characteristics of each data source.

B.1 NEEA Residential Building Stock Assessment

The RBSA study metered 103 homes in the Pacific Northwest. Table 7 below presents the geographical dispersion of these sites across the Northwest region. The majority (65 percent) of sites are located west of the Cascades with the remaining sites east of the Cascades in Eastern Washington, Idaho and Montana. Among the 103 homes, 78 homes had electric cooling and/or heating, with approximately 58 percent of these homes located west if the Cascades.

Table 7: Regional Distribution of RBSA Metering Study Sites

	All Homes		HVAC Homes	
Region	**Frequency (n)**	**Percent**	**Frequency (n)**	**Percent**
Eastern Washington	16	16%	15	19%
Idaho	15	15%	15	19%
Montana	5	5%	3	4%
Puget Sound	37	36%	23	29%
Western Oregon	30	29%	22	28%
Total	**103**	**100%**	**78**	**100%**

Figure 21, below presents the distribution of average daily electricity consumption across the metered homes.

Figure 21: Distribution of Average Daily Consumption (kWh)

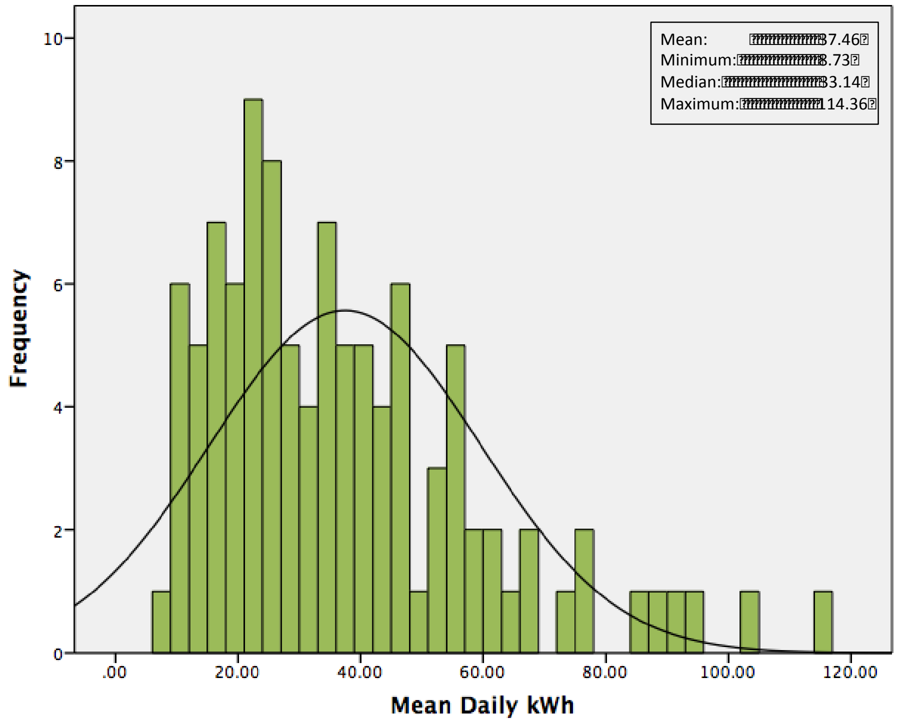


Figure 22 presents average daily consumption across all RBSA metered homes by month. Electricity consumption among RBSA homes is highest in the winter months and lowest in the shoulder and summer seasons. This pattern is driven by cooler temperatures in the Northwest in winter requiring heating, combined with approximately 34 percent of homes in the Northwest heating with electricity. Lower summer consumption is a reflection of the temperate summer weather and consequently fewer homes with central air conditioning.

Figure 22: Average Daily Consumption (kWh) by Month

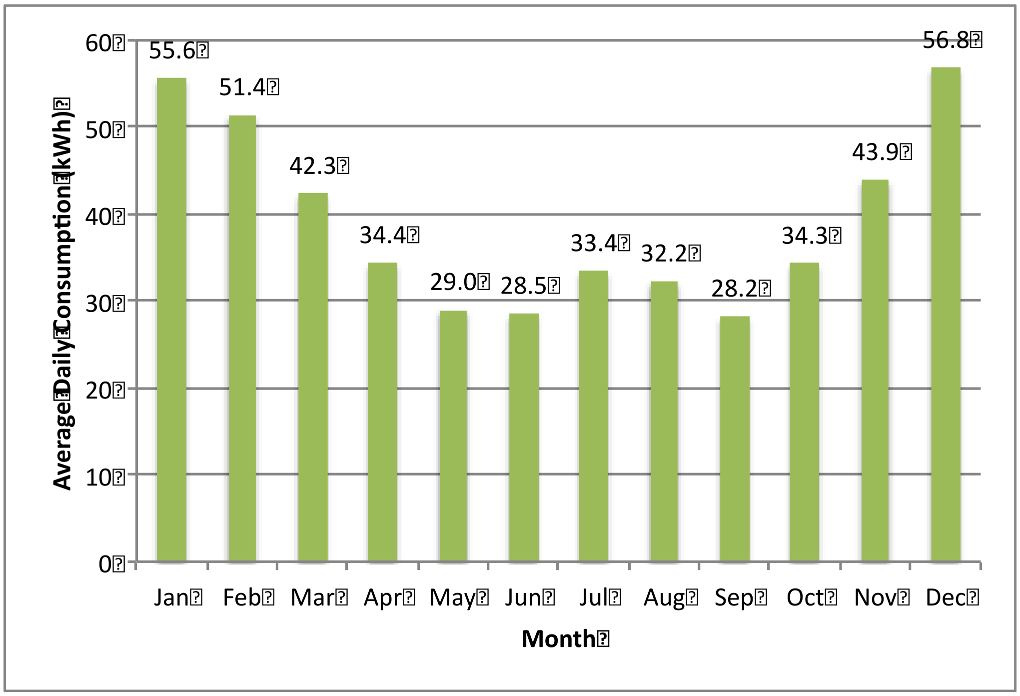
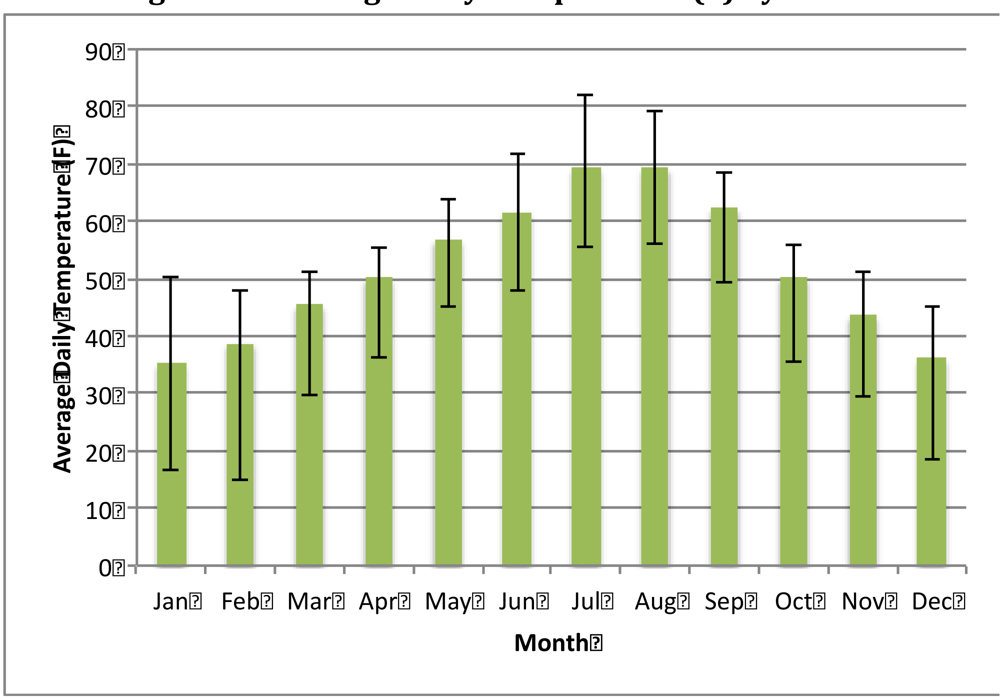


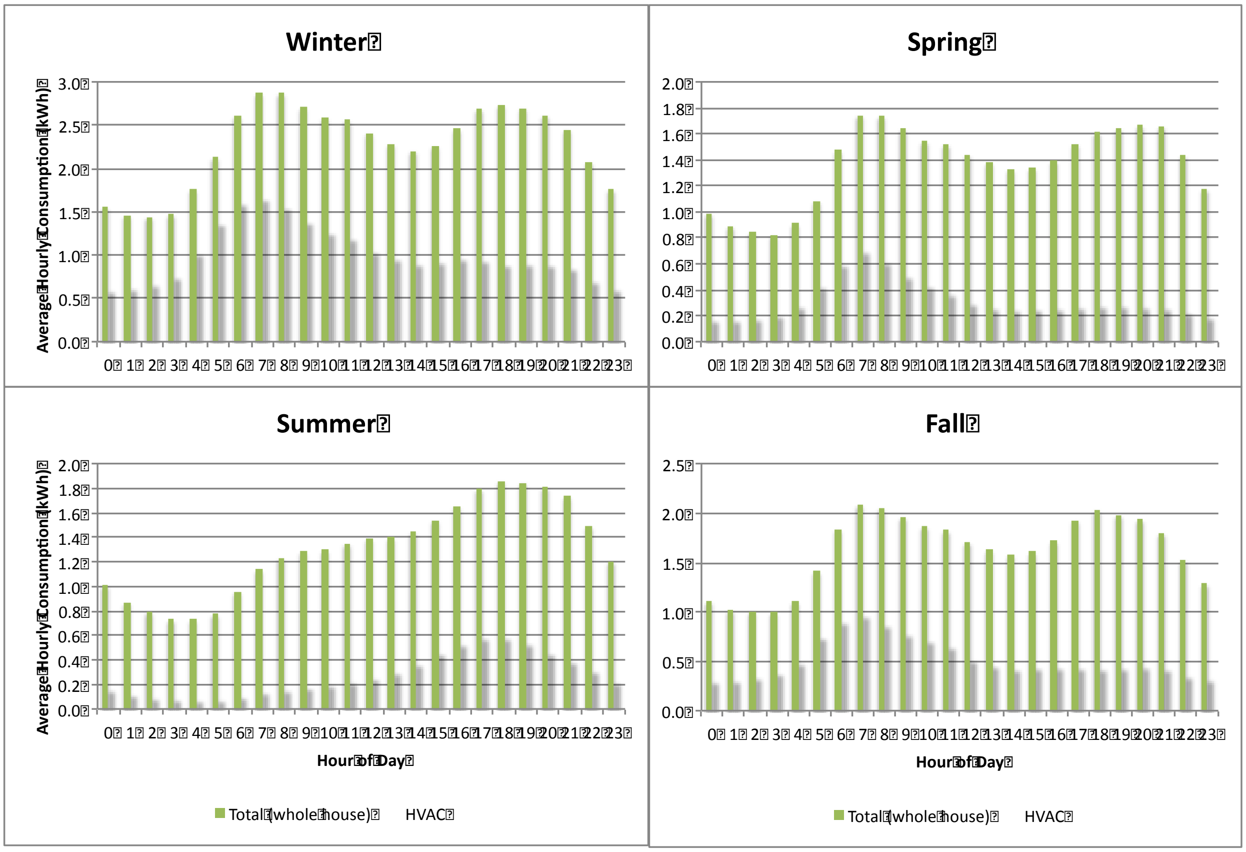
Figure 23 below presents a summary of the weather experienced by the RBSA metered homes, with monthly average highs and lows represented by the bars.

Figure 23: Average Daily Temperature (F) by Month



Household hourly load shapes vary across seasons for both total whole house load and HVAC only load as shown in Figure 24, below.

Figure 24: Seasonal Hourly Whole House and HVAC Load Shapes (RBSA Metered Homes)



B.2 SCE Quality Installation

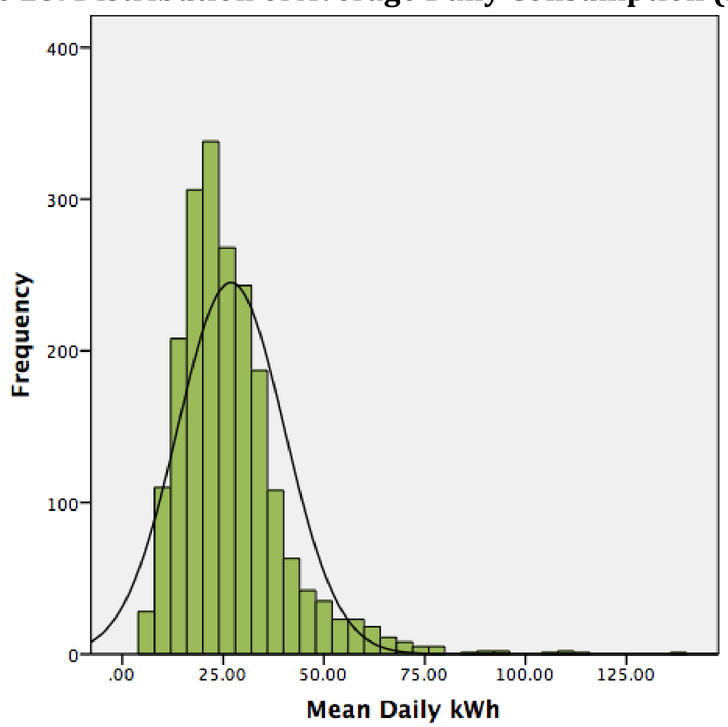
The SCE Residential QI participant dataset contains AMI interval data and program participation data between January 2012 and December 2014 for 2,039 homes dispersed across nine climate zones in SCE service territory. The distribution of homes by climate zone is presented in Table 8, below. Over half of these homes (57%) are located in climate zone 10.

Table 8: Distribution of Climate Zones for SCE QI Homes

	All Homes	
Region	**Frequency (n)**	**Percent**
6	28	1%
7	1	<1%
8	108	5%
9	191	9%
10	1,168	57%
13	247	12%
14	52	3%
15	203	10%
16	41	2%
Total	**2,039**	**100%**

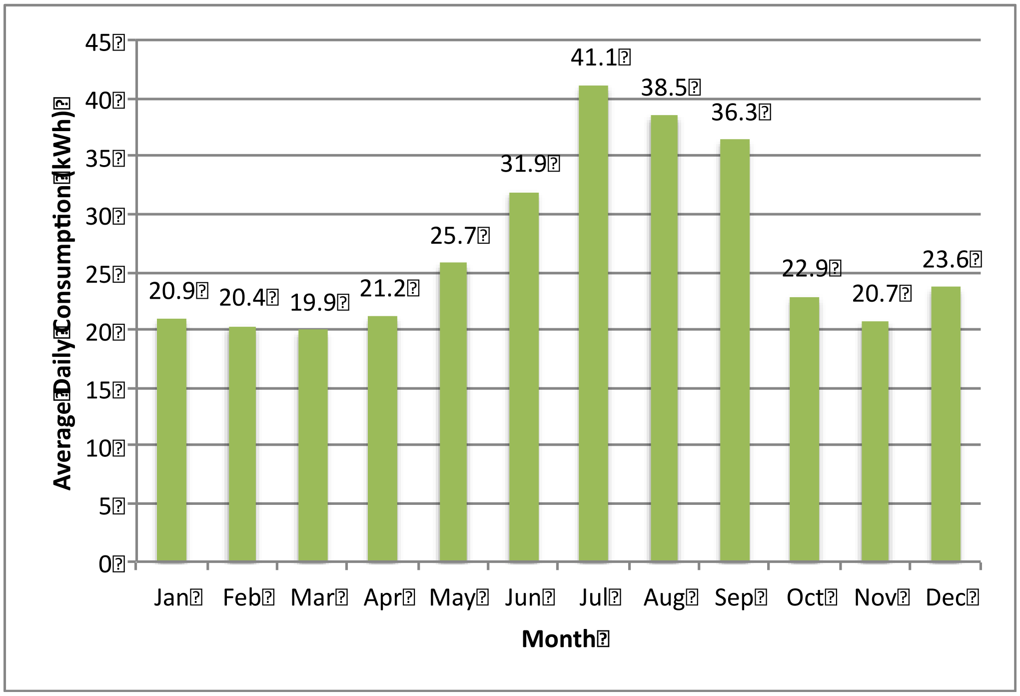
The figure below presents the distribution of average daily electricity consumption across the metered homes.

Figure 25: Distribution of Average Daily Consumption (kWh)



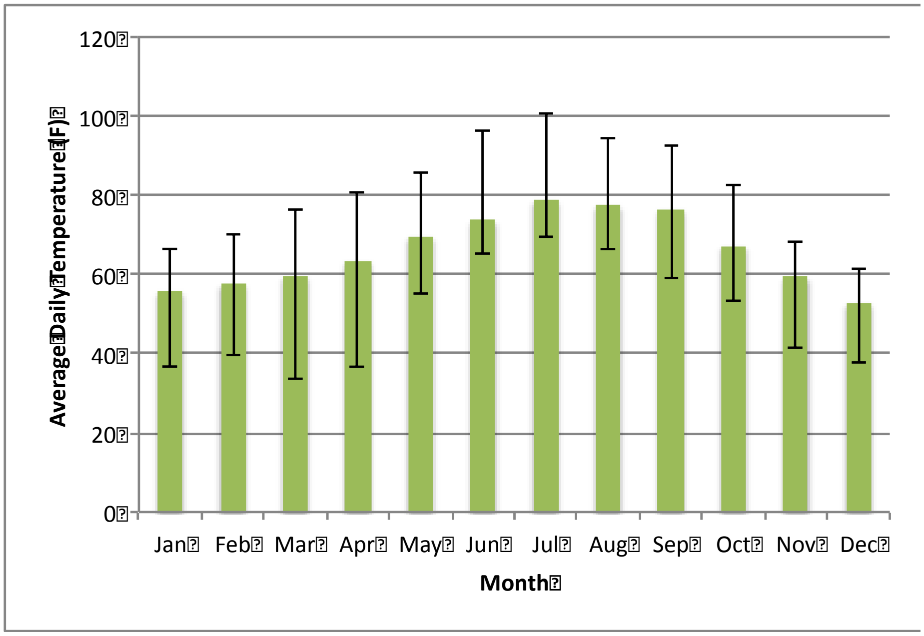
The figure below presents the average daily consumption across all SCE QI metered homes by month. Electricity consumption among the QI homes is highest in the summer months and lowest in the shoulder and winter months. California's hot temperatures drive this pattern during the summer, with most homes requiring some form of cooling. Lower winter consumption is a reflection of the temperate winter weather and consequently fewer homes with electric heating (primary and/or back-up systems).

Figure 26: Average Daily Consumption (kWh), by Month



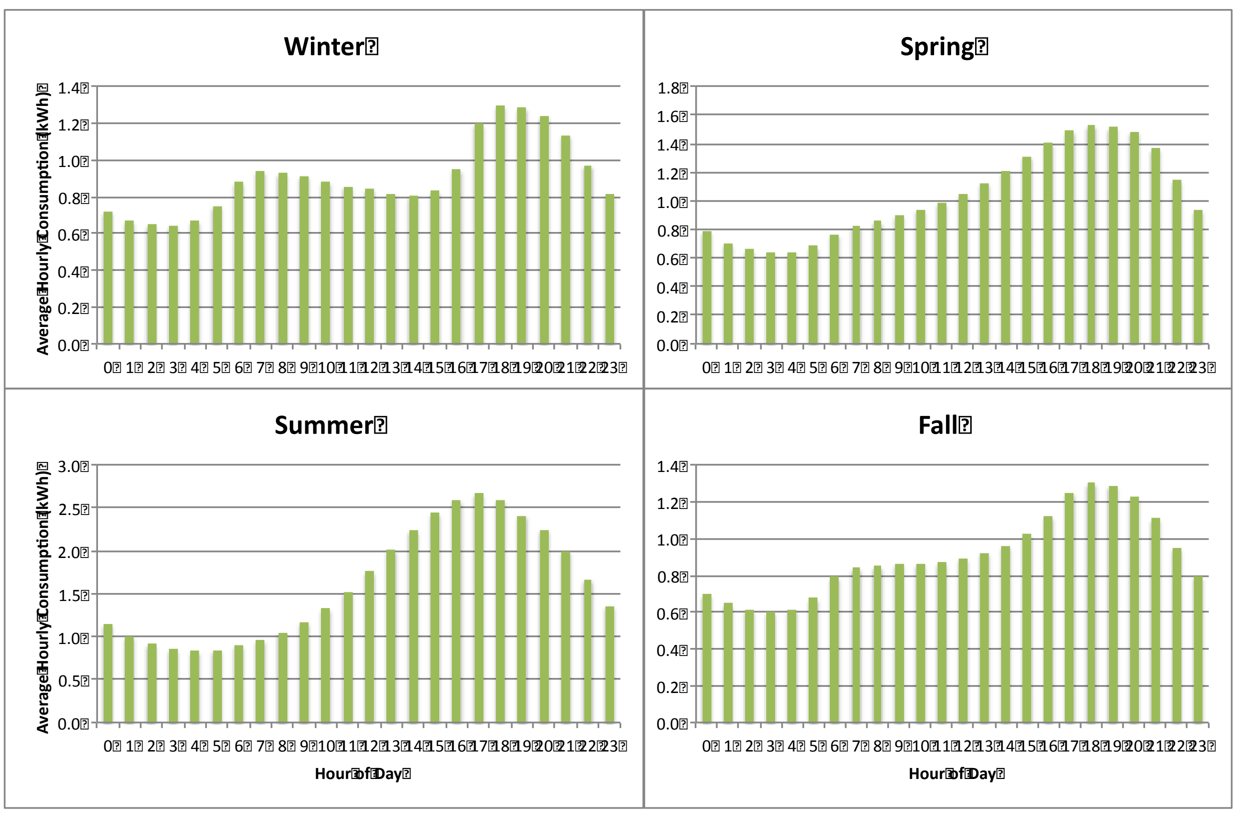
The figure below presents a summary of the weather experienced by these homes, with monthly average highs and lows represented by the bars. As you can see, winter temperatures are still quite warm, averaging above 50 degrees Fahrenheit in all winter months.

Figure 27: Average, High and Low Daily Temperature (F°), by Month



Household hourly load shapes vary across seasons as shown in the figure below.

Figure 28: Seasonal Hourly Whole House Load Shapes (SCE QI Metered Homes)



B.3 PG&E Quality Maintenance

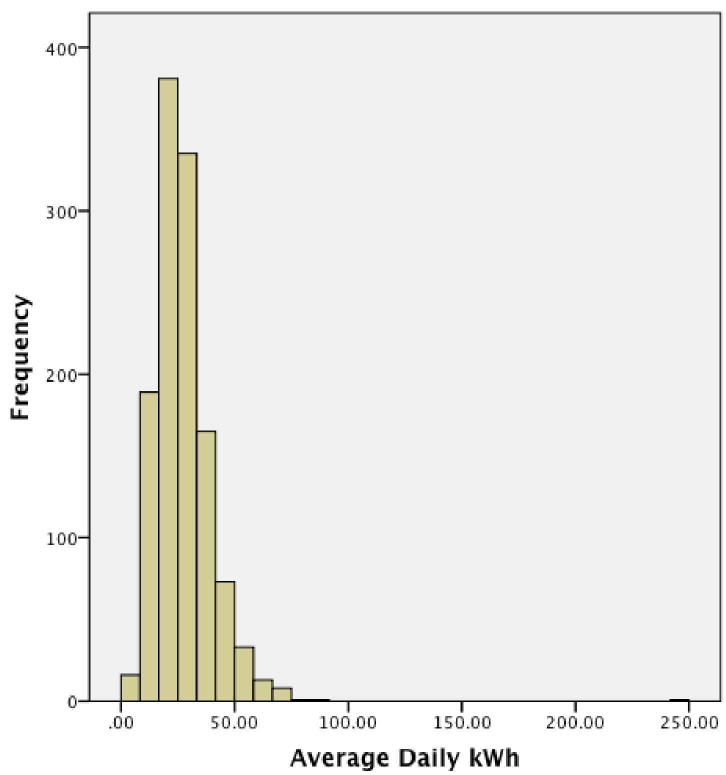
The PG&E Residential QM participant dataset contains AMI interval data and program participation data between January 2012 and December 2014 for 1,230 homes dispersed across four climate zones in the PG&E service territory. The distribution of homes by climate zone is presented in Table 9, below.

Table 9: Distribution of Climate Zones for PG&E QM Homes

	All Homes	
Region	**Frequency (n)**	**Percent**
4	3	<1%
11	85	7%
12	448	36%
13	694	56%
Total	**1,230**	**100%**

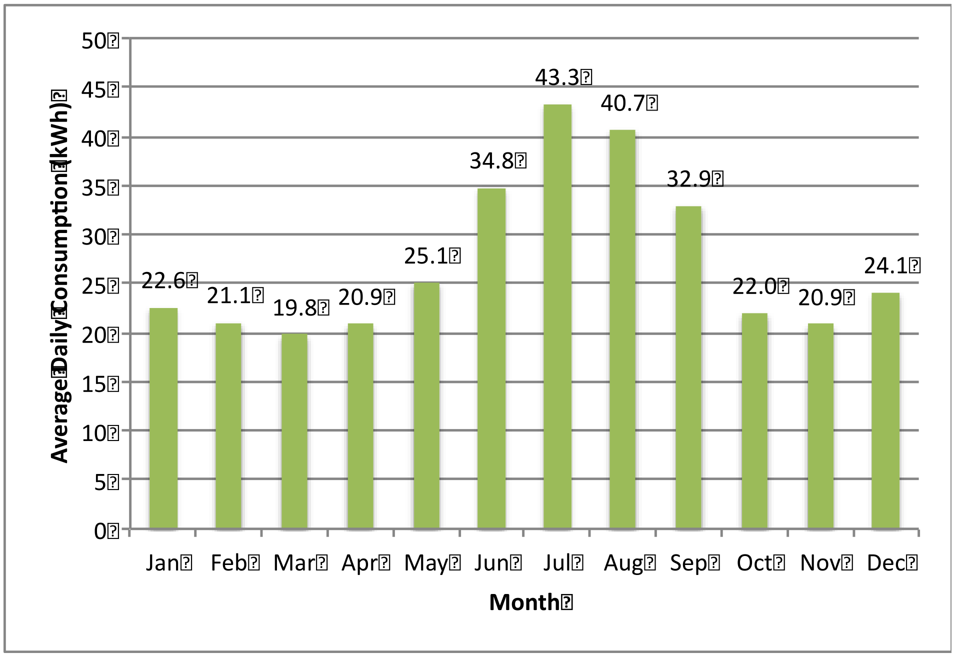
The figure below presents the distribution of average daily electricity consumption across the metered homes.

Figure 29: Average Daily Consumption (kWh)



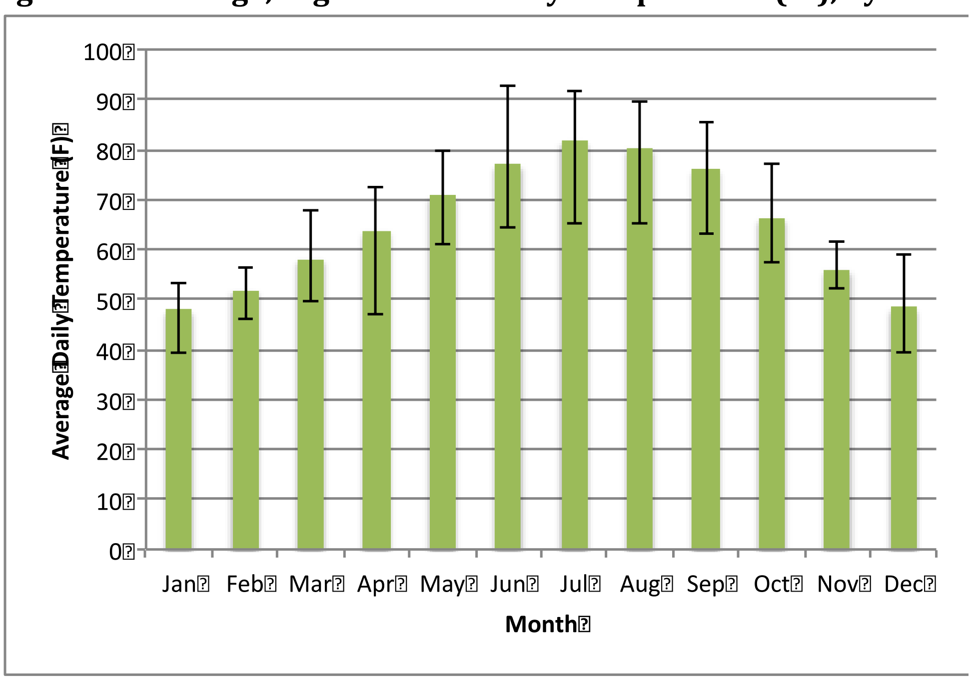
The figure below shows average daily consumption across all SCE QI metered homes by month. As with the QI homes, electricity consumption among the QM homes is highest in the summer months and lowest in the shoulder and winter months.

Figure 30: Average Daily Consumption (kWh), by Month



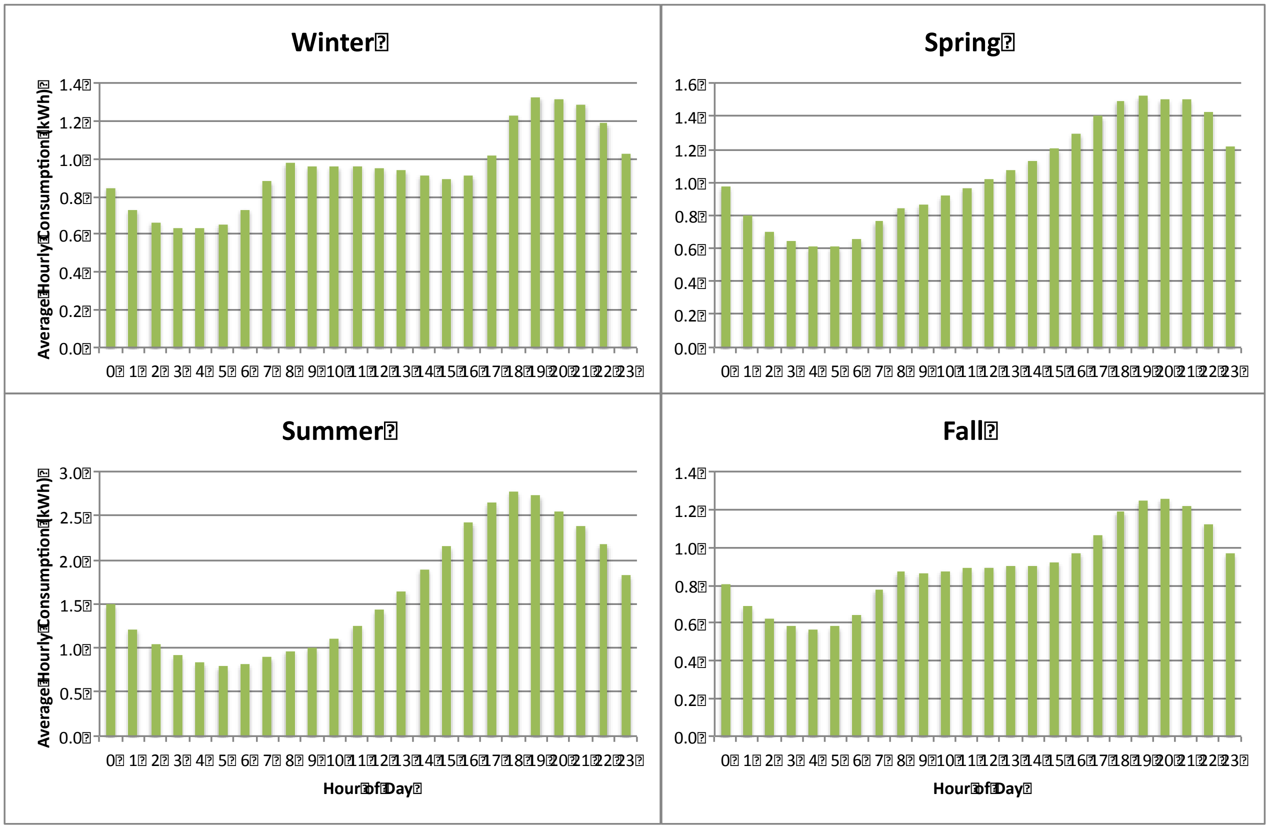
The figure below presents a summary of the average daily weather experienced by these homes in each month, with the monthly average highs and lows represented by the bars.

Figure 31: Average, High and Low Daily Temperature (F°), by Month



Household hourly load shapes vary across seasons as shown in the figure below.

Figure 32: Seasonal Hourly Whole House Load Shapes (PG&E QM Metered Homes)



Appendix C Random Coefficients Model Additional Results

C.1 Alternative Specifications and Filters

We ran a series of alternate random coefficient models for both the QI and QM programs to confirm that the results would not change substantially and look for differences in savings across smaller groups of households. Each variation involves changing one of four key aspects of the model:

1. Specification – for example, using a different temperature metric for weather normalization in the fixed effects model or different change points in the random coefficients model;
2. Bins – uses a different number of bins for a specific group;
3. Holdout sample – selects the holdout using a stratified random approach instead of a completely random approach;
4. Filter – modeling a subset of homes (e.g. from climate zone 10) or days (e.g. summer days).

For each of these variations, the following tables provide the number of households in the model, the difference between the actual hourly kWh of the holdout sample versus the model's prediction (as a percent), the adjusted model prediction of the post-period daily kWh, and the resulting savings estimate as a percent of the daily consumption in absence of the program (i.e. the adjusted post-period model prediction).

Table 10: Alternative Model Specifications and Filters with SCE QI Summer Data

	Description of Model	Variation	N Households	Holdout Difference (%)	Adj Predicted Post Daily kWh	Savings (%)
1	Final summer weekday model	-	1,379	-1.2%	40.89	14.6%
2a	Only homes without NEMs	Filter	1,371	-0.2%	41.37	15.5%
2b	Only homes with NEMs	Filter	8	-23.5%	33.47	16.7%
3	Different temp metric, CDD calculated from average temp (instead of sum CDH)	Specification	1,377	1.3%	35.06	17.7%
4	CDD bins with 2 CDD in each, up to the true maximum	Bins	1,379	-1.1%	40.99	14.9%
5	CDD binned by percentile of total CDD, resulting in 25 CDD bins	Bins				
6	CDD bins with 1 CDD in each, up to the true maximum	Bins	1,379	-1.0%	40.57	13.8%
7	Model with different change points (at hour 6, 9, 11, 17, 21)	Specification	1,379	0.6%	41.68	16.2%
8a	Homes in climate zone 10	Filter	820	0.5%	39.80	16.3%
8b	Homes in climate zone 13	Filter	162	1.1%	50.49	21.0%
8c	Homes in climate zone 15	Filter	140	-6.1%	57.85	20.2%
8d	Homes in climate zone 8	Filter	64	-1.4%	31.26	4.7%
8e	Homes in climate zone 14	Filter	33	-0.9%	36.77	5.4%
9	Weekend days only	Filter	1,379	-1.2%	42.85	16.1%
10a	Using 10 household bins	Bins	1,379	-1.1%	40.94	14.6%
10b	Using 25 household bins	Bins	1,379	-1.4%	40.82	14.4%
11	Holdout 30% from each household bin instead of overall	Holdout	1,379	-1.1%	40.93	14.6%
12a	Early QI homes - 2013 installations only	Filter	1,379	-4.6%	44.62	12.8%
12b	Middle QI homes - 2014 installations before summer only	Filter	1,379	-0.5%	40.70	15.5%
12c	Late QI homes – 2014 installations during summer only	Filter	1,379	-1.3%	40.89	13.1%
13	Including 2014 pre-period in full modeling sample	Filter	2,002	0.4%	41.78	16.5%
14	Adding lagged temperatures to fixed effects model for normalization and bins	Specification & Bins	1,379	0.5%	41.64	16.3%
15	Model with hourly dummies instead of change points and interactions in RC model	Specification	1,379	-0.9%	41.04	14.9%

Table 11: Alternative Specifications and Filters using PG&E QM Summer Data

	Description of Model	Variation	N Households	Holdout Difference (%)	Adj Predicted Post Daily kWh	Savings (%)
1	Final summer weekday model	-	1,166	-0.1%	37.93	1.1%
2a	Without NEMs	Filter	1,112	0.4%	37.47	0.5%
2b	Only NEMs	Filter	54	-0.7%	52.69	4.7%
3a	Climate Zone 13	Filter	663	0.0%	44.44	1.4%
3b	Climate Zone 12	Filter	424	-0.9%	31.25	1.9%
4a	Measure specific – airflow correction	Filter	1,065	-0.1%	38.44	0.9%
4b	Measure specific – blower motor retrofit	Filter	99	4.7%	28.96	-2.4%
4c	Measure specific – refrigerant system assessment with savings	Filter	15	1.4%	43.52	4.1%
5	Opposite day type - Weekends	Filter	1,165	0.9%	39.68	1.5%
6a	Early QI – before summer	Filter	647	-0.7%	36.64	0.7%
6b	Middle QI – during summer	Filter	231	1.4%	39.87	1.8%
6c	Late QI – after summer	Filter	288	-0.9%	42.82	4.0%
7	CDD bins up to true maximum	Bins	1,166	0.7%	37.58	0.2%
8	CDD bins with 2 in each, up to true maximum	Bins	1,166	0.3%	37.71	0.5%
9	Different change points (at hour 4, 8, 11, 17, 20)	Specification	1,166	0.2%	37.93	1.1%
10a	Holdout 30% from each kWh-CDD bin	Holdout	1,166	0.1%	37.88	0.9%
10b	Holdout 30% from each household bin	Holdout	1,166	0.1%	37.86	0.9%
12	Adding lagged temperatures to fixed effects model for normalization and bins	Specification & Bins	1,166	-0.2%	37.96	1.1%
13	Model with hourly dummies instead of change points and interactions in RC model	Specification	1,166	-0.1%	37.92	1.0%

Table 12: Alternative Specifications and Filters using SCE QI Annual Data

	Description of Model	Variation	N Households	Holdout Difference (%)	Adj Predicted Post Daily kWh	Savings (%)
1	Final annual model (modeled post, calculates impacts from one full year of 2014 weather)	-	2,038	-0.5%	28.34	7.5%
2	Actual post (i.e. not modeled), calculates impacts from all post-period observations (actual 2013-2014 post weather)	Bins	1,861	-0.4%	28.09	10.1%
3	Modeled post, calculates impacts from one full year of TMY3 weather	Filter	2,039	-0.5%	27.29	6.6%

Table 13: Alternative Specifications and Filters using PG&E QM Annual Data

	Description of Model	Variation	N Households	Holdout Difference (%)	Adj Predicted Post Daily kWh	Savings (%)
1	Final annual model (actual 2014 post)	-	1,085	0.1%	27.89	3.5%
2	Calculates impacts from all post-period observations (actual 2013-2014 post)	Filter	1,216	0.1%	27.81	1.9%
3	Modeled post, calculates impacts from one full year of TMY3 weather	Filter	1,084	-0.1%	26.39	1.5%
4	Modeled post, calculates impacts from one full year of 2014 weather	Filter	1,084	-0.1%	27.91	1.9%
5	Does not bin by day type	Bins	1,216	0.2%	27.23	1.6%
6	Does not bin by day type, calculates HDD and CDD from base of 75 degrees	Specification	1,216	0.1%	27.29	1.9%
7	Does not bin by day type, bins by average temperature instead of CDD and HDD	Bins	1,216	0.4%	27.26	1.7%

C.2 Annual Model Detailed Results

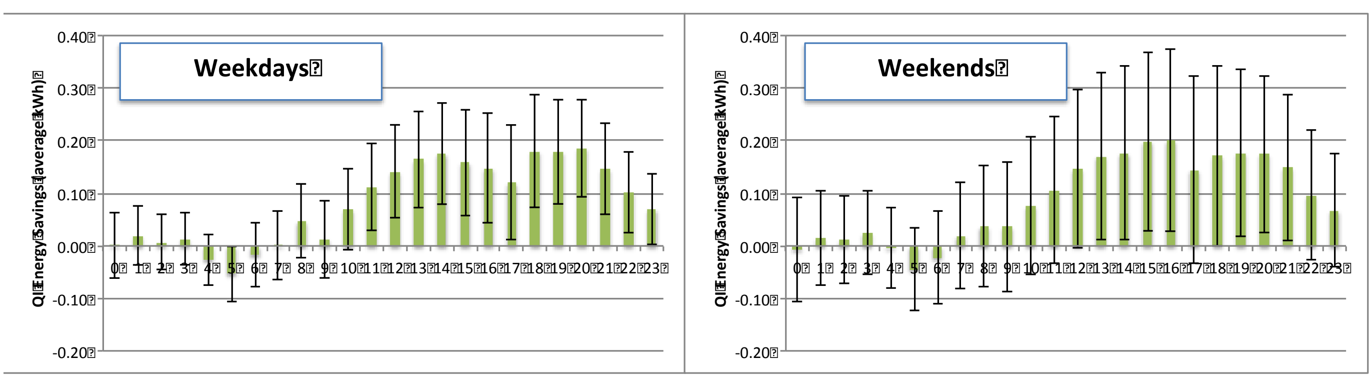
This section provides tables with the holdout sample error and final savings estimates from a variety of seasons and day types, all based on the output of our final annual model for each program (i.e. not separate models). The bar charts show hourly kWh savings estimates in green with bars depicting 95 percent confidence intervals around each estimate.

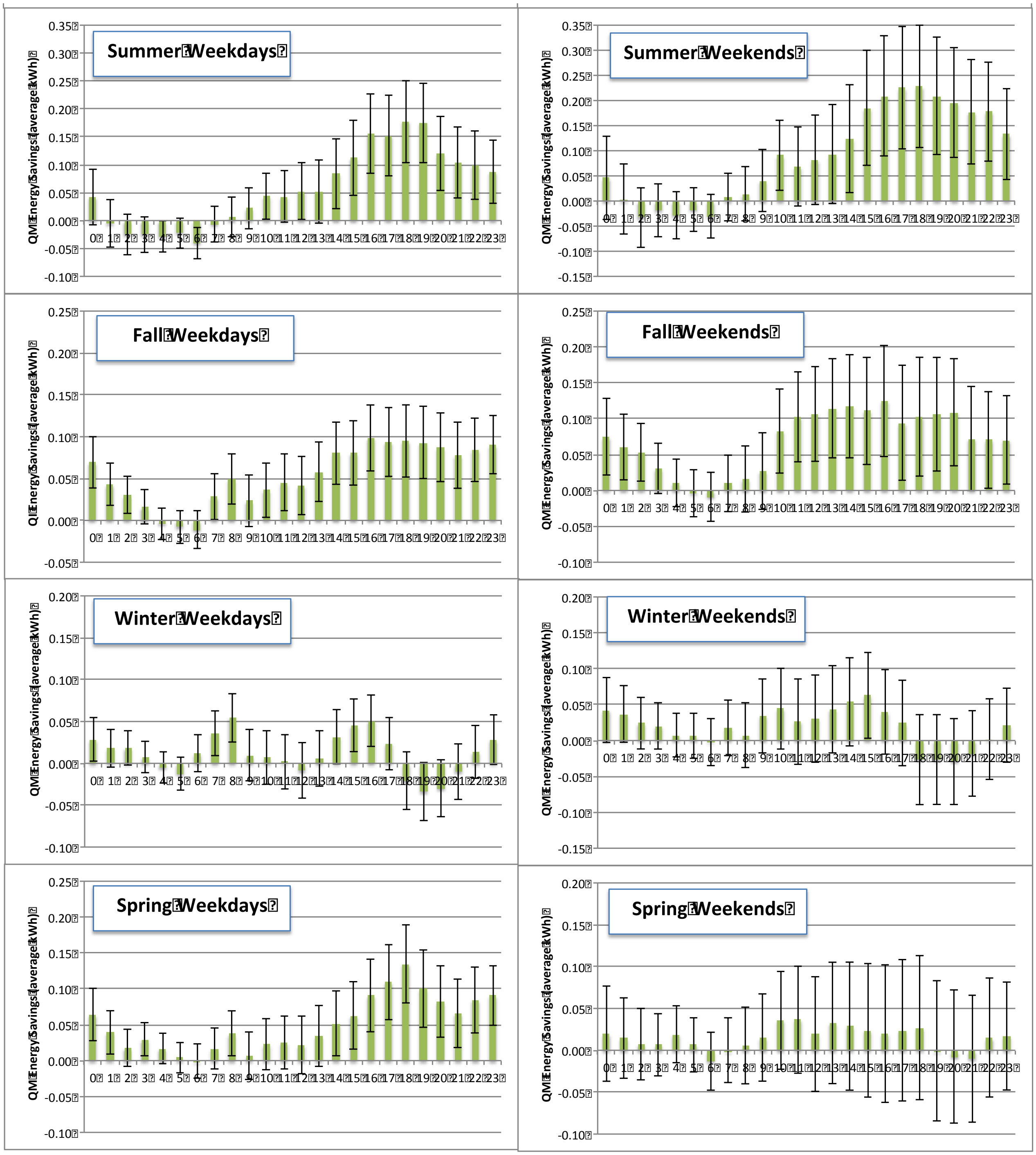
C.2.1 SCE Quality Installation

Table 14: Savings Estimates from Annual Model of SCE QI Data

Description of Data		Holdout Sample Models		Final Model and Savings Estimates		
		Difference Holdout Pre (%)	Difference Holdout Post (%)	Adj Predicted Post (kWh)	Adj Actual Post (kWh)	Savings (%)
Total	Annual	-0.5%	-0.2%	28.35	26.38	6.96%
Day Type	Annual Weekday	-0.2%	-0.2%	28.08	26.12	6.98%
	Annual Weekend	-0.7%	0.1%	29.20	27.08	7.26%
Season	Fall	-6.8%	-5.9%	23.40	21.59	7.74%
	Spring	-7.4%	-4.5%	25.31	24.12	4.70%
	Summer	5.9%	4.2%	41.62	36.27	12.84%
	Winter	2.4%	0.7%	22.25	22.17	0.33%
Season and Day Type	Fall Weekday	-6.2%	-6.9%	23.26	21.07	9.41%
	Fall Weekend	-7.9%	-4.0%	23.81	22.73	4.55%
	Spring Weekday	-8.1%	-5.4%	24.97	23.71	5.06%
	Spring Weekend	-5.7%	-2.8%	26.10	25.00	4.24%
	Summer Weekday	6.4%	4.4%	41.15	36.01	12.51%
	Summer Weekend	4.6%	3.6%	42.78	36.92	13.69%
	Winter Weekday	2.3%	0.9%	21.97	22.07	-0.44%
	Winter Weekend	2.1%	0.1%	22.90	22.44	2.03%

Figure 33: SCE QI Hourly Savings Estimates on Weekdays vs. Weekends, Annually and by Season





These four seasons are made up of days with unique distributions of temperatures. A household's total kWh consumption and load shape typically changes as the need for heating and cooling changes. The random coefficients model generates separate load shapes and savings estimates for each type of temperature day, based on their CDD and HDD groups. The following charts show the results of our model on four of these groups: CDD group 5, CDD group 20, HDD group 5, and HDD group 20. These include a comparison of the hourly predictions vs. actual pre-period consumption of homes in the holdout sample, a comparison of the hourly predictions vs. actual post-period consumption of all homes, and hourly savings estimates derived from these models. As with the seasonal and day types, these results are not from separate models but were generated within the annual model.

Figure 34: SCE QI Hourly Annual Predicted vs. Actual Pre-Period Consumption of Holdout Group, by CDD and HDD Group

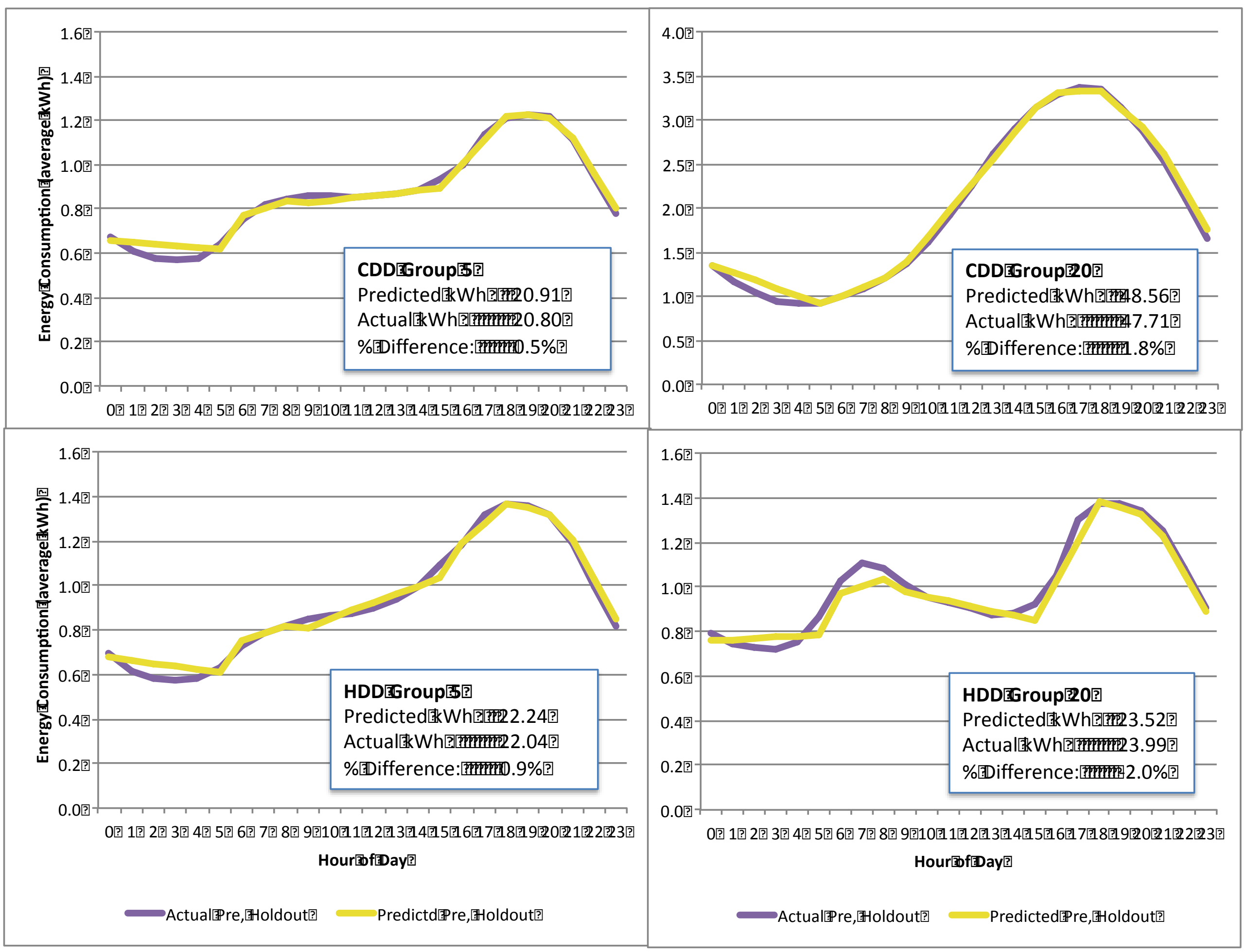


Figure 35: SCE QI Hourly Annual Predicted vs. Actual Post-Period Consumption, by CDD and HDD Group

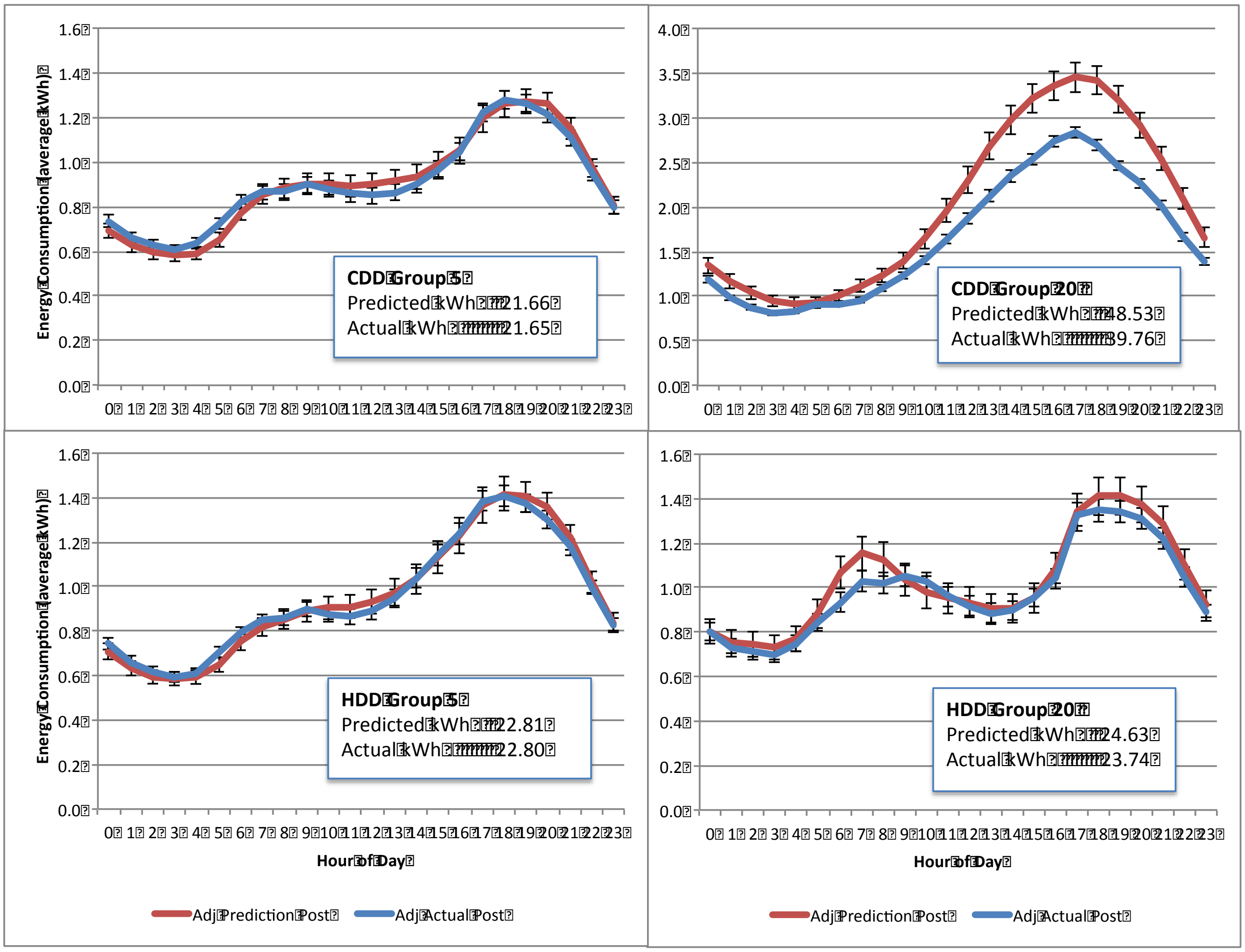
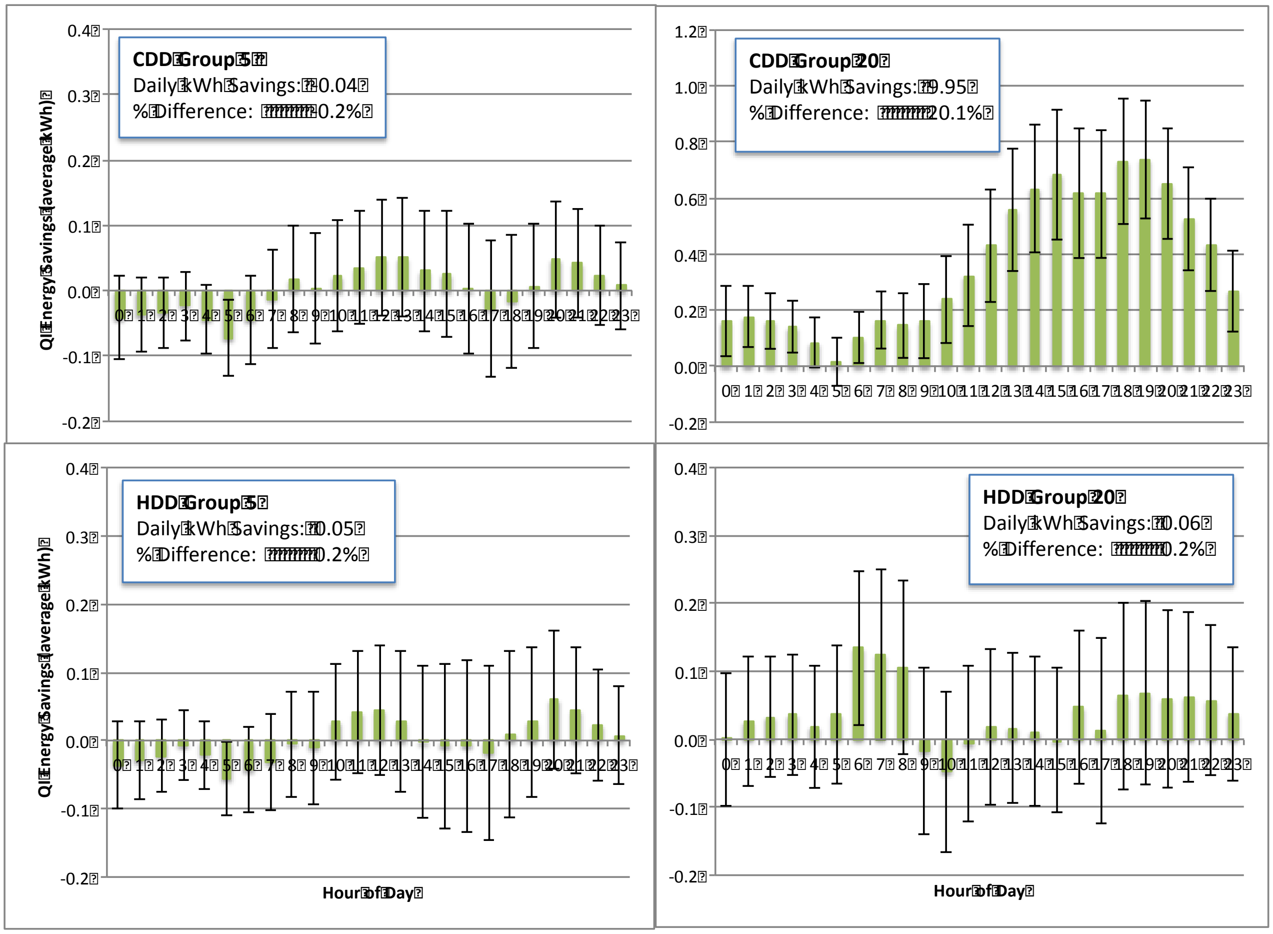


Figure 36: SCE QI Hourly Annual Savings Estimates, by CDD and HDD Group



A household's total kWh consumption and load shape is partially dependent on factors unrelated to weather. The random coefficients model generates separate load shapes and savings estimates for each home type, based on their weather-normalized baseline usage groups. The following charts show the results of our model on four of these groups: household group 2, group 10, group 15, and group 19. These include a comparison of the hourly predictions vs. actual pre-period consumption of homes in the holdout sample, a comparison of the hourly predictions vs. actual post-period consumption of all homes, and hourly savings estimates derived from these models. As with the temperature groups, these results are not from separate models but were generated within the annual model.

Figure 37: SCE QI Hourly Annual Predicted vs. Actual Pre-Period Consumption of Holdout Group, by Household Usage Group

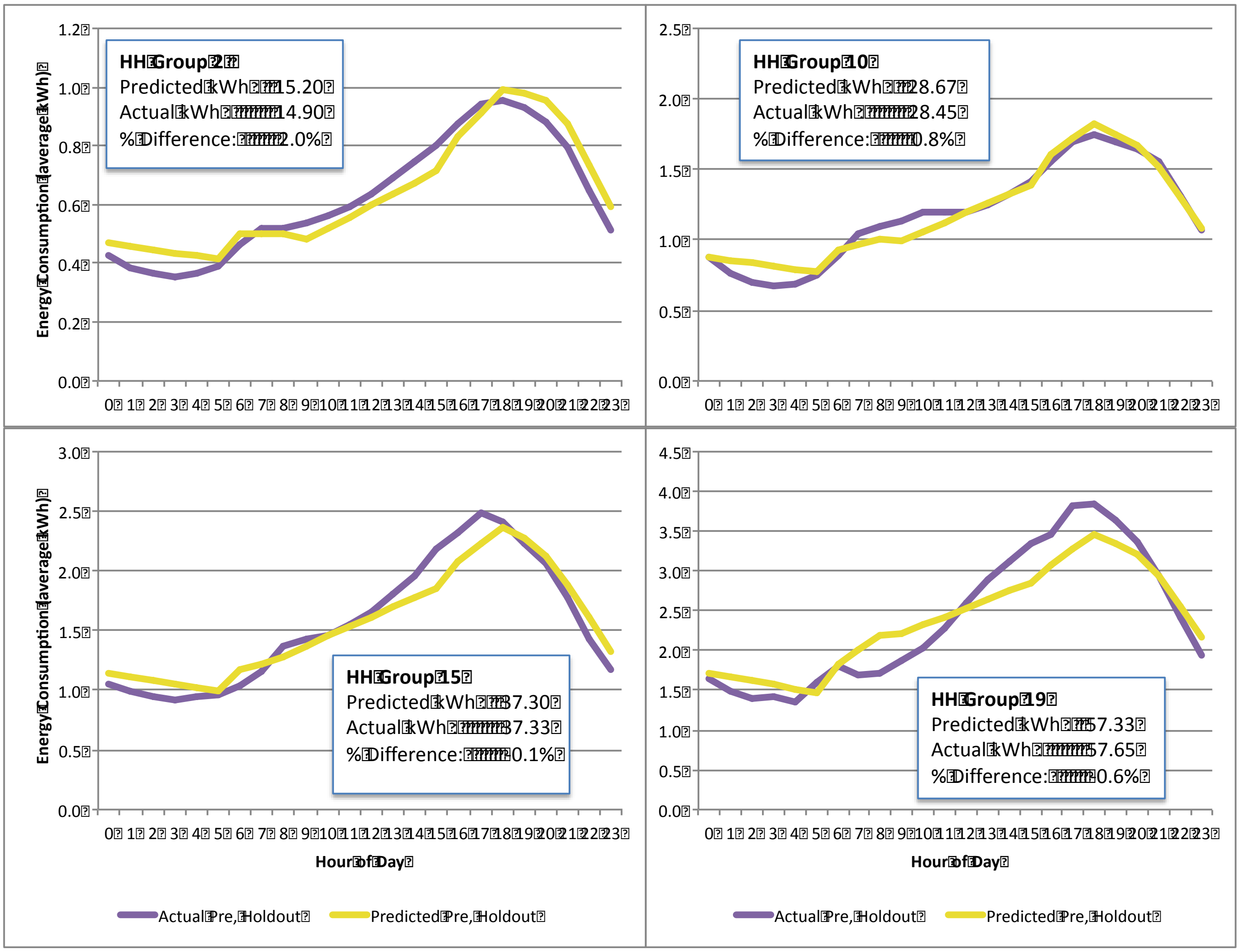


Figure 38: SCE QI Hourly Annual Predicted vs. Actual Post-Period Consumption, by Household Usage Group

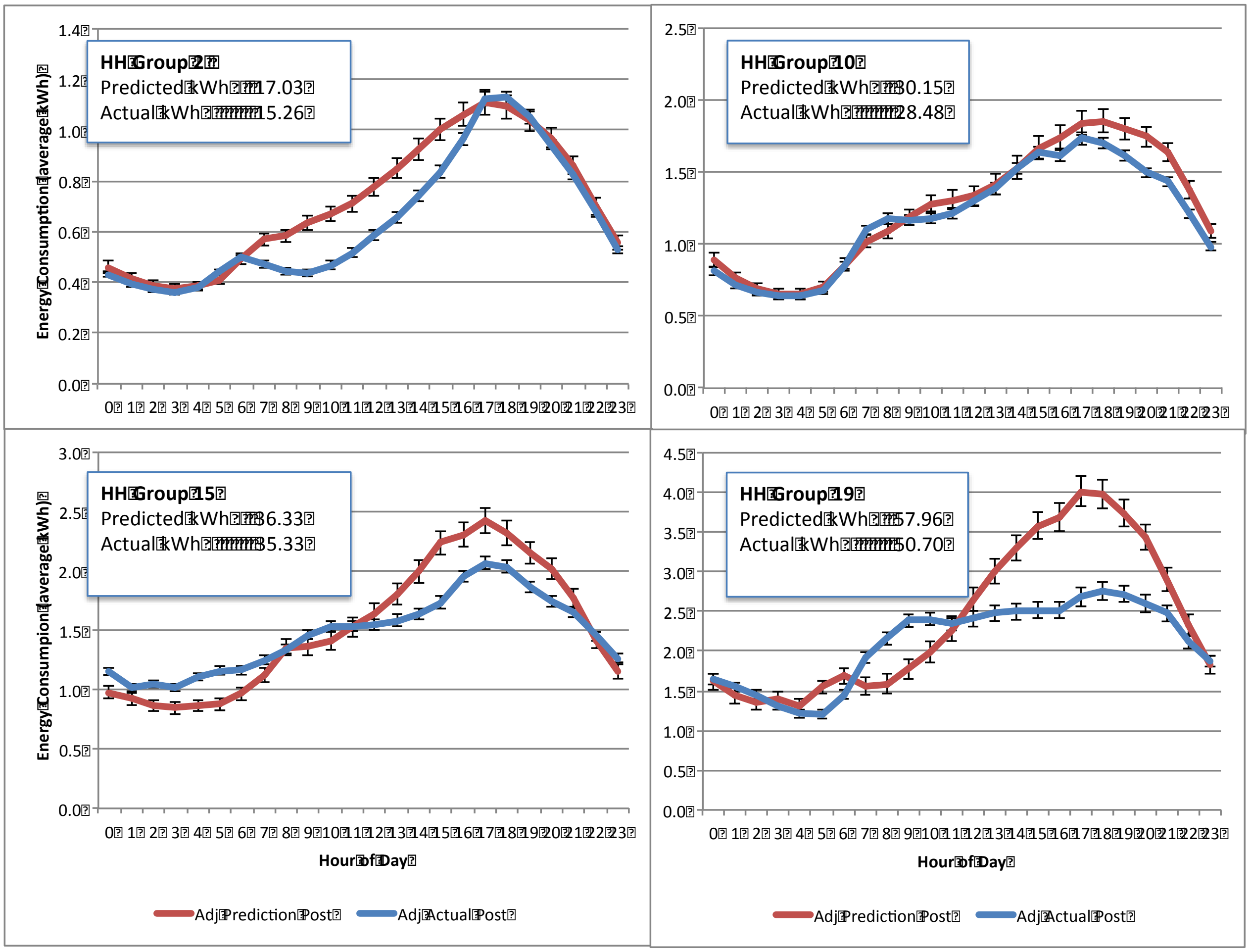
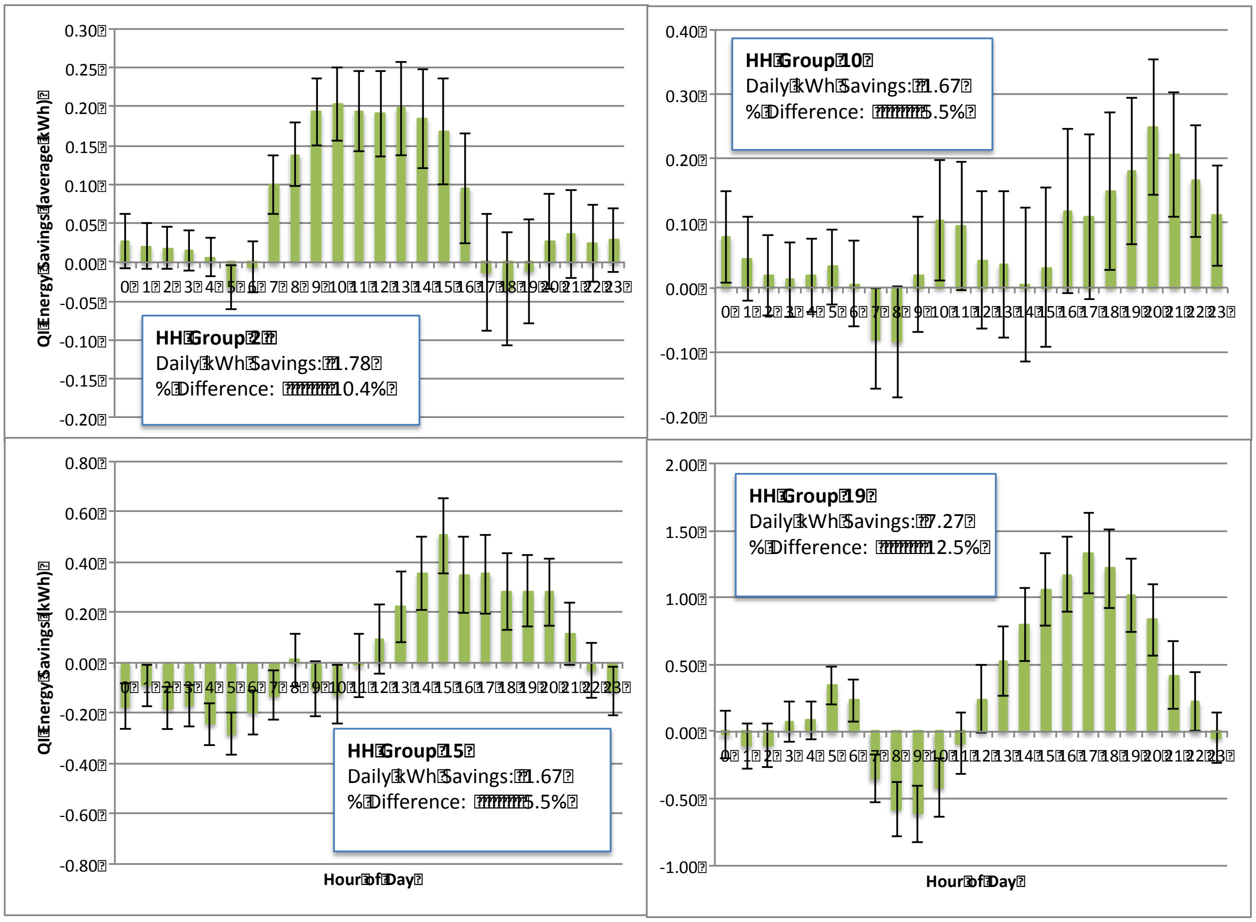


Figure 39: SCE QI Hourly Annual Savings Estimates, by Household Usage Group



The following two tables show the average daily savings estimate for each bin in the annual QI model. The top table has results for weekdays and the bottom table has results for weekends. The columns show households, grouped by their weather normalized energy usage in the pre-period (highest users on the right). The rows show the days these homes experienced, grouped by their temperatures via cooling degree-days (hottest days on the bottom) and heating-degree days (within each CDD group). Each cell shows the estimated program savings (kWh per day) for a specific home-day bin. We automatically color-coded the cells with the highest kWh savings in dark blue and the lowest kWh savings in dark red; colorless cells fall in the middle of this spectrum. Within each household group, there are home-days from a wide range of temperatures, each with their own savings estimate. Similarly, each group of days with similar temperatures (i.e. CDD and HDD) includes home-days from a range of households (i.e. high, mid, and low users), which experience a wide range of daily kWh savings. In general, this shows that savings are higher on hotter days (i.e. higher CDD) except for the highest users (i.e. highest household group). QI savings were higher during days with higher temperatures except in the case of CDD 26, HDD 2, and household group 20.

Table 15: Daily QI Savings Estimates, by Home-Day Bin

Day Type		Weekdays																			
Household Group		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
CDD	HDD																				
2	2	0.9	0.9	-0.4	1.8	-1.1	-1.3	-2.2	-0.8	3.9	1.5	-2.8	-0.2	-0.3	-0.2	-7.0	-4.3	-7.9	-1.4	6.0	-12.5
	5	0.3	0.8	-0.1	0.4	-0.7	0.2	-0.9	0.0	0.4	0.2	-0.3	0.4	0.0	-0.2	-1.9	-4.2	-2.1	-1.7	0.7	-5.6
	8	1.1	1.1	0.7	0.4	-0.7	0.0	-1.2	-0.2	-0.2	-0.6	-0.6	-0.9	0.4	-0.4	-0.9	-3.6	-1.4	-1.8	-1.7	-7.7
	11	1.0	1.1	0.6	0.4	-0.7	-0.1	-0.8	-0.5	-0.5	-0.3	-0.3	-1.2	0.2	-0.2	-0.6	-2.7	-1.4	-1.5	-0.4	-4.8
	14	1.2	0.8	0.8	0.1	-0.1	-0.3	-1.5	-1.2	-0.9	-0.6	-0.3	-1.1	0.0	-1.3	-0.4	-3.6	-0.7	-1.2	0.3	-6.0
	17	1.5	2.3	1.5	1.1	1.1	0.9	0.0	-0.9	0.1	1.7	0.2	-0.2	1.1	-0.8	2.5	-1.9	0.0	1.3	1.1	-2.5
	20	1.1	2.0	3.1	0.8	0.2	-0.1	-0.3	-1.5	0.3	0.7	0.2	0.5	2.1	-0.4	1.7	-3.8	0.1	-2.2	3.8	-14.6
	23	1.7	1.1	1.2	1.0	0.6	0.0	-1.3	-1.6	-0.9	1.6	-0.2	-0.9	1.5	-0.6	1.5	-3.7	1.0	-0.7	-3.7	-11.4
	26	1.2	0.9	1.1	-0.1	-1.5	0.8	-0.6	-2.7	-2.0	1.7	-0.4	-0.3	0.1	-2.3	0.8	-6.3	2.5	3.9	3.5	-6.2
5	2	1.0	1.4	1.0	1.3	0.4	0.8	0.3	0.4	1.2	0.4	1.1	1.0	1.5	1.6	-3.0	-0.9	-1.1	1.3	-4.0	-2.6
	5	0.8	1.3	1.0	0.7	0.1	0.4	-0.4	0.0	0.7	0.1	1.0	0.1	1.9	0.6	-1.3	-0.7	-1.1	1.7	0.2	-1.6
	8	0.8	1.6	1.4	0.9	0.2	0.8	-0.5	0.5	0.3	-0.4	0.3	-0.3	-0.1	0.5	0.1	-0.9	-1.2	-1.1	2.4	-6.0
	11	0.1	0.0	1.1	0.0	0.6	0.6	-1.0	0.3	-0.7	-0.7	-1.4	-1.6	-1.5	-0.6	-0.2	-3.6	-1.9	-3.2	1.5	-13.4
	14	2.1	1.8	3.4	1.1	2.7	2.8	0.4	1.2	-0.2	0.7	0.9	0.7	1.5	2.4	1.4	-1.2	-2.0	2.0	4.1	2.4
	17	0.0	0.0	7.5	0.0	0.0	0.0	-0.5	0.0	0.0	0.0	-4.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
8	2	1.0	1.1	1.5	1.5	0.7	0.9	-0.1	-0.1	0.7	0.6	2.1	2.0	2.6	2.1	-1.6	0.8	0.0	4.5	-1.8	3.5
	5	0.8	1.5	1.2	0.1	-1.0	0.6	-0.8	0.1	1.3	-0.3	0.7	-0.4	1.2	0.6	-1.4	0.6	0.4	1.0	2.3	5.2
	8	0.6	0.5	1.5	-0.1	-0.6	-0.6	-1.4	-0.1	0.1	-0.2	-0.4	-1.0	-1.2	-0.6	-0.6	-2.9	-0.3	0.2	1.0	-4.3
	11	0.0	-0.9	0.4	-2.6	-1.6	-2.1	-4.9	-2.7	-5.9	-2.2	-2.5	-11.6	-8.3	0.6	-4.0	-10.1	-7.6	-9.7	1.1	-9.6
11	2	0.9	2.1	2.5	2.1	1.4	2.7	1.8	3.0	2.8	3.4	4.0	3.3	3.7	3.3	2.5	4.6	4.6	6.8	3.1	9.1
	5	1.0	1.5	1.5	1.5	0.7	1.5	0.5	0.7	1.4	2.1	1.5	0.3	1.6	2.9	0.9	3.8	3.7	1.1	5.0	8.8
	8	-1.0	-1.3	2.1	-0.4	-1.2	-1.3	-3.2	-0.6	1.1	-3.5	-6.2	-1.1	-7.3	-1.7	-6.2	-5.7	-3.7	0.5	0.0	-10.7
14	2	1.3	2.4	2.8	3.6	3.0	3.0	2.8	4.4	5.2	5.3	6.0	6.2	6.3	5.6	4.6	7.7	8.3	10.0	8.6	16.7
	5	1.0	0.6	0.8	-1.3	-2.1	-2.4	0.3	0.6	3.9	0.2	-2.1	0.8	1.5	-0.3	-4.7	4.3	3.7	0.5	5.8	2.9
17	2	1.8	3.8	3.4	4.9	4.9	4.5	4.1	6.1	7.2	7.7	7.7	8.0	7.6	7.8	7.5	10.4	11.7	12.8	14.0	24.4
	5	-13.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
20	2	3.2	5.8	4.2	7.4	7.6	7.4	6.5	9.5	11.8	10.9	11.0	10.1	11.3	11.8	13.9	14.6	14.8	17.0	20.7	34.1
23	2	4.7	7.1	6.4	8.8	8.1	7.0	7.0	8.9	10.3	11.7	16.4	8.6	11.2	12.9	10.7	17.6	18.0	19.3	24.0	31.6
26	2	7.3	5.4	5.9	14.5	1.9	14.6	14.6	3.5	8.2	10.2	17.8	7.7	14.1	5.4	2.8	14.7	18.1	33.6	12.7	-23.7

Day Type		Weekends																			
Household Group		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
CDD	HDD																				
2	2	1.6	0.6	-1.5	0.2	-1.3	-0.5	-1.9	2.0	4.7	0.7	-1.0	2.7	0.9	-0.2	-2.0	-0.2	0.4	15.2	12.9	-12.6
	5	0.8	1.2	0.5	0.4	-0.8	0.5	-0.4	0.2	0.2	0.6	0.3	-0.8	0.2	-0.6	-0.9	-4.2	-2.4	1.6	5.0	-6.2
	8	1.2	1.8	0.6	0.9	-0.3	0.8	-0.4	0.0	0.1	0.3	0.2	-0.9	1.5	-0.1	-0.3	-3.5	-0.4	-0.9	0.4	-6.7
	11	1.2	0.9	0.4	-0.2	-0.2	0.8	-1.4	-0.5	-1.0	0.4	-0.1	-1.4	-0.3	-0.4	0.4	-2.4	-0.4	-2.8	0.2	-2.3
	14	1.6	0.8	0.4	0.5	-0.2	0.9	-1.0	-1.6	-0.6	0.2	-0.7	-1.7	0.4	-0.3	0.6	-2.6	0.5	-2.1	1.9	-1.3
	17	1.6	2.3	1.8	1.5	0.1	1.2	0.3	-0.3	-0.3	0.6	-0.2	-0.7	0.5	-1.1	2.3	-3.7	-0.8	0.9	1.8	-8.0
	20	1.2	2.4	1.5	2.0	0.0	0.8	-0.5	0.5	0.6	1.1	1.2	0.2	2.2	0.0	2.2	-4.1	0.2	0.4	8.1	-8.8
	23	2.5	2.5	4.0	1.7	0.3	2.5	1.0	-0.9	1.0	3.8	0.7	1.6	1.8	-2.9	2.0	-0.3	6.9	6.8	-5.1	-6.4
	26	2.3	3.4	3.0	3.1	2.9	4.5	1.8	1.5	1.7	4.4	0.2	1.8	4.2	1.5	1.7	-1.3	2.9	3.9	7.8	1.1
5	2	1.5	1.2	1.6	1.9	1.4	2.9	1.8	2.2	2.0	2.7	1.5	1.5	4.4	3.0	-0.6	0.5	2.1	1.8	1.8	0.4
	5	1.3	1.6	0.6	1.1	0.1	1.0	-0.5	0.3	-0.2	-0.2	0.5	-0.8	1.8	0.3	-2.7	-1.6	-1.0	0.1	-1.0	-2.9
	8	0.9	1.6	0.8	0.3	-0.8	1.1	-0.9	0.1	1.9	-0.3	-0.3	-1.0	0.9	0.9	0.4	-0.8	-1.8	-0.4	3.0	-6.7
	11	1.4	2.0	2.6	0.4	1.7	0.7	-1.1	-0.5	-1.4	-0.7	-0.7	-0.3	0.5	-0.7	0.4	-1.4	-1.9	-1.5	2.9	-11.5
	14	1.3	0.7	1.7	-0.5	1.4	1.1	-0.2	0.0	-0.3	-0.6	-0.8	-0.9	-1.1	0.9	1.3	-4.2	-2.5	0.8	3.9	9.9
	17	1.7	0.0	7.7	-0.4	0.0	0.0	0.0	0.0	0.2	-0.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
8	2	1.2	1.9	2.7	2.9	1.4	2.9	1.9	2.0	2.9	2.3	3.2	3.3	4.0	3.2	2.6	2.1	2.7	4.7	3.4	4.1
	5	1.1	2.0	1.9	0.6	-0.5	1.6	0.1	-0.5	0.8	0.4	0.8	-1.1	1.0	-0.8	-1.1	0.3	0.5	1.1	2.9	-1.7
	8	0.5	0.0	0.8	-1.0	-0.3	0.7	-1.5	1.5	0.0	-0.3	-1.2	-2.8	-1.2	-0.7	-1.7	-0.8	2.6	1.9	-1.1	-9.5
	11	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
11	2	1.2	1.8	2.2	2.1	1.5	2.0	0.1	2.1	0.8	2.4	3.3	1.6	3.4	3.8	1.1	2.2	3.9	8.2	1.6	11.3
	5	0.4	0.7	2.8	1.3	-1.3	-1.7	-2.3	0.5	0.3	-0.7	-0.5	-1.8	0.8	3.0	-2.4	4.4	2.8	2.7	3.2	8.5
	8	0.0	0.0	3.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
14	2	1.3	2.7	3.4	3.4	2.8	3.8	4.3	4.9	2.9	5.9	7.2	4.2	4.4	4.9	6.7	7.9	8.5	8.8	8.0	19.0
	5	-0.8	-2.8	0.2	-3.5	-4.2	-2.5	1.9	0.2	4.3	2.8	-2.5	-0.6	1.7	-3.3	-5.5	5.9	10.3	-1.3	11.1	4.7
17	2	2.6	5.0	6.3	6.3	6.8	9.0	6.2	8.6	9.8	10.7	11.2	10.1	12.0	10.8	9.3	10.3	14.2	14.0	19.0	25.3
	5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
20	2	3.4	5.9	5.5	8.8	9.1	9.0	7.1	9.6	10.3	11.0	11.6	11.6	10.8	10.9	11.5	15.2	15.1	14.1	27.1	38.9
23	2	4.5	9.1	4.2	9.6	4.9	11.0	6.9	6.6	9.9	11.5	12.5	10.2	10.1	6.7	5.1	14.7	15.2	23.3	16.8	10.6
26	2	9.7	8.5	6.8	12.5	2.4	18.1	7.2	-1.0	9.6	10.9	20.1	5.7	13.0	12.7	3.3	18.3	17.1	34.4	16.3	-24.0

The next two tables show the count of home-days in the post-period that was assigned to each bin. As with the previous tables, we automatically color-coded the cells with the highest count in dark blue and the lowest count in dark red, white cells fall somewhere in the middle of this spectrum. Hence, this table shows the actual distribution of participant households and the weather they experienced in 2014 (i.e. the post-period for this model).

As we would expect, in this model, there are more home-days in the lower household bins than the higher bins and more weekdays than weekends. There are very few home-days with no need for heating or cooling, as shown by the low counts in CDD 2 & HDD 2. There are also few home-days with low temperatures that could require heating, shown by the small HDD groups with high values (CDD 2 & HDD 20-26). There are some home-day bins with no observations. For example, the row for CDD group 5 and HDD group 17 in the weekday table has only three observations, one each in household groups 3, 7, and 11.

Table 16: Number of QI Home-Days in the Post-Period, by Home-Day Bin

Day Type		Weekdays																				
	Household Group	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	Total
CDD	HDD																					
2	2	154	130	175	170	130	143	86	160	99	89	142	68	48	77	57	105	25	83	84	54	2,079
	5	1,663	1,552	1,461	1,283	1,200	1,241	1,118	1,197	1,077	954	1,074	919	790	722	738	758	497	721	561	412	19,938
	8	3,117	3,003	2,624	2,585	2,357	2,373	2,299	2,287	2,120	1,808	1,884	1,901	1,759	1,596	1,618	1,487	1,170	1,271	1,097	784	39,140
	11	3,548	3,167	2,783	2,694	2,551	2,434	2,226	2,246	2,119	1,915	1,835	1,893	1,912	1,692	1,680	1,600	1,402	1,330	1,124	868	41,019
	14	2,048	2,058	1,812	1,784	1,708	1,601	1,570	1,486	1,376	1,242	1,143	1,316	1,322	1,199	1,145	1,048	929	823	704	545	26,859
	17	1,483	1,374	1,259	1,213	1,224	1,119	995	958	921	844	724	864	949	851	778	737	696	558	476	411	18,434
	20	778	655	614	534	610	541	506	398	429	424	384	418	471	400	341	348	352	275	203	197	8,878
	23	330	336	265	244	264	204	256	179	197	165	141	224	210	168	150	149	140	108	90	81	3,901
	26	554	611	472	505	453	299	458	413	339	290	246	394	337	309	283	254	230	177	160	88	6,882
5	2	1,344	1,302	1,179	1,116	959	966	974	1,024	925	767	818	795	693	641	676	647	427	541	496	333	16,623
	5	3,566	3,167	2,504	2,605	2,350	2,188	2,389	2,235	2,201	1,736	1,828	1,932	1,729	1,523	1,583	1,463	1,191	1,197	1,169	740	39,296
	8	2,105	1,836	1,724	1,591	1,535	1,542	1,365	1,379	1,252	1,222	1,252	1,153	1,071	1,012	1,033	916	813	865	698	542	24,906
	11	943	693	892	920	787	702	520	739	463	634	557	476	461	587	503	464	462	365	288	230	11,686
	14	227	147	203	208	178	157	133	170	97	143	125	105	97	137	114	102	105	72	79	51	2,650
	17	-	-	1	-	-	-	1	-	-	-	1	-	-	-	-	-	-	-	-	-	3
8	2	3,615	3,083	2,641	2,620	2,332	2,229	2,300	2,299	2,108	1,848	1,977	1,868	1,570	1,470	1,509	1,440	1,109	1,291	1,137	760	39,206
	5	2,175	1,672	1,597	1,544	1,485	1,424	1,281	1,288	1,144	1,164	1,144	1,077	1,017	1,022	970	812	818	758	676	500	23,668
	8	473	364	441	471	418	369	325	388	260	303	306	273	219	287	246	227	209	185	176	121	6,061
	11	121	85	107	119	89	82	62	83	56	75	60	57	54	73	60	56	56	37	35	23	1,400
11	2	4,198	3,760	3,337	3,146	2,777	2,846	2,681	2,681	2,541	2,223	2,336	2,233	2,064	1,849	1,821	1,756	1,415	1,655	1,355	907	47,581
	5	922	735	818	828	717	716	559	666	525	573	528	500	490	532	497	454	406	381	314	247	11,408
	8	88	58	92	85	83	69	58	74	59	61	62	48	48	58	50	44	44	38	27	22	1,138
14	2	3,369	2,914	2,693	2,573	2,462	2,422	2,245	2,095	2,037	1,848	1,887	1,871	1,838	1,651	1,588	1,474	1,301	1,324	1,143	825	39,560
	5	200	150	209	203	188	157	131	174	101	152	148	116	102	134	126	107	108	94	71	62	2,733
17	2	3,090	2,470	2,272	2,071	1,997	2,034	1,796	1,673	1,673	1,574	1,540	1,468	1,521	1,354	1,253	1,238	1,139	1,089	918	681	32,851
	5	3	3	2	2	-	3	5	-	-	-	2	-	-	-	3	-	-	-	[illegible]	3	30
20	2	1,642	1,130	1,034	841	919	947	809	656	738	742	690	652	695	602	518	536	552	483	415	333	14,934
23	2	1,076	509	486	414	520	479	372	299	344	394	378	271	330	311	261	294	334	236	261	208	7,777
26	2	4,839	1,456	1,078	814	1,013	833	738	525	634	1,184	991	384	306	527	409	555	954	505	908	517	19,170
Total		47,671	38,417	34,775	33,181	31,306	30,120	28,258	27,782	25,815	24,374	24,203	23,276	22,093	20,784	20,010	19,171	16,884	16,462	14,674	10,555	509,811

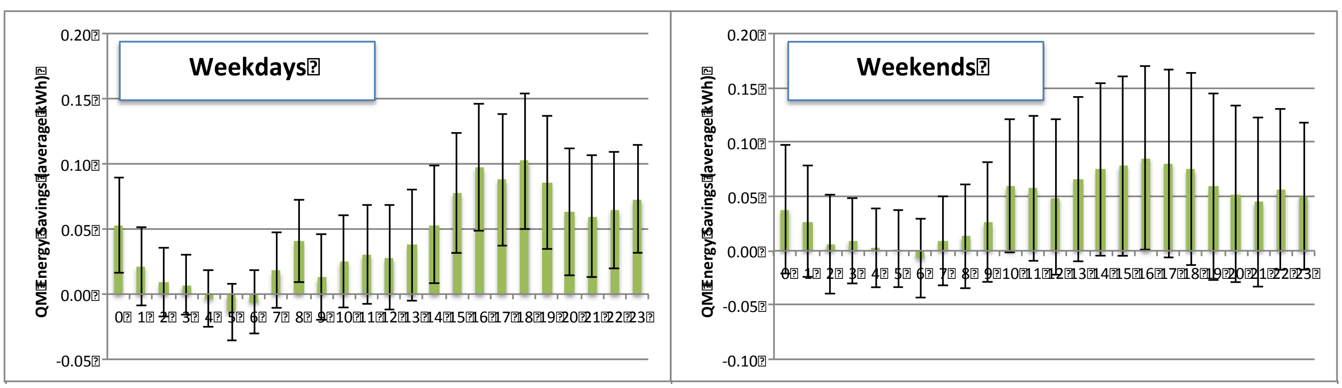
Day Type		Weekends																				
	Household Group	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	Total
CDD	HDD																					
2	2	77	33	44	28	27	31	17	29	19	28	33	12	9	16	12	22	13	17	28	13	508
	5	508	495	496	434	387	407	358	406	336	297	345	289	247	239	229	252	148	232	178	127	6,410
	8	1,688	1,340	1,190	1,171	1,072	1,064	988	1,021	937	855	881	805	752	714	702	678	570	572	522	366	17,888
	11	1,161	1,188	1,062	985	945	966	841	820	808	729	702	726	739	626	646	595	496	536	406	351	15,328
	14	1,213	1,171	1,026	1,016	966	894	876	855	777	700	647	729	730	673	640	573	523	457	401	295	15,162
	17	473	483	411	424	411	329	363	358	313	265	248	315	296	267	262	241	215	182	156	119	6,131
	20	400	323	317	310	301	257	238	238	202	225	186	207	215	212	176	172	172	131	105	82	4,469
	23	196	222	170	167	155	135	143	123	132	106	91	130	139	107	107	100	86	77	67	53	2,506
	26	210	196	171	174	178	114	160	134	111	109	91	139	116	117	87	94	89	61	50	35	2,436
5	2	553	521	483	442	393	406	380	414	369	330	355	318	266	251	264	262	160	224	198	143	6,732
	5	1,452	1,263	992	1,044	964	929	931	875	913	697	749	761	724	618	677	618	512	503	503	350	16,075
	8	775	659	597	523	547	562	504	446	468	417	437	408	424	362	357	327	303	303	253	197	8,869
	11	223	196	231	212	196	183	166	187	125	161	160	136	108	131	126	115	103	104	77	61	3,001
	14	160	114	147	160	125	109	84	128	74	103	84	76	71	99	81	77	76	51	49	32	1,900
	17	40	28	35	39	29	26	19	31	18	25	18	17	17	24	19	19	18	11	10	7	450
8	2	1,131	1,093	1,008	969	847	851	834	865	771	647	737	678	588	543	546	512	368	511	414	263	14,176
	5	783	690	666	687	609	600	548	592	504	467	478	460	423	433	422	386	321	318	278	197	9,862
	8	211	170	202	202	167	156	136	173	109	143	134	124	104	129	112	95	96	84	63	44	2,654
	11	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
11	2	1,766	1,429	1,225	1,186	1,083	1,016	1,053	987	931	865	859	875	761	711	682	654	561	573	507	339	18,063
	5	284	212	272	268	238	213	188	225	146	188	169	160	132	174	148	137	128	113	80	66	3,541
	8	1	2	7	4	6	4	4	6	1	4	9	5	1	2	5	2	3	6	2	3	75
14	2	1,124	974	869	806	765	795	696	651	668	590	595	586	592	504	510	497	427	440	387	293	12,769
	5	120	89	109	125	99	77	68	101	57	80	69	64	54	77	62	63	59	39	34	23	1,469
17	2	1,116	869	812	762	719	742	622	597	592	571	549	518	554	502	469	452	415	397	347	264	11,869
	5	-	-	1	-	-	-	1	-	-	-	1	-	-	-	-	-	-	-	-	-	3
20	2	726	654	595	505	545	564	505	399	451	397	399	412	455	358	324	307	300	287	225	178	8,586
23	2	764	282	269	206	265	206	192	154	150	232	200	128	113	146	103	129	189	109	137	89	4,063
26	2	1,714	498	362	279	352	287	260	176	225	409	351	127	102	180	141	189	328	173	329	185	6,667
Total		18,869	15,194	13,769	13,128	12,391	11,923	11,175	10,991	10,207	9,640	9,577	9,203	8,732	8,215	7,909	7,568	6,679	6,511	5,806	4,175	201,662

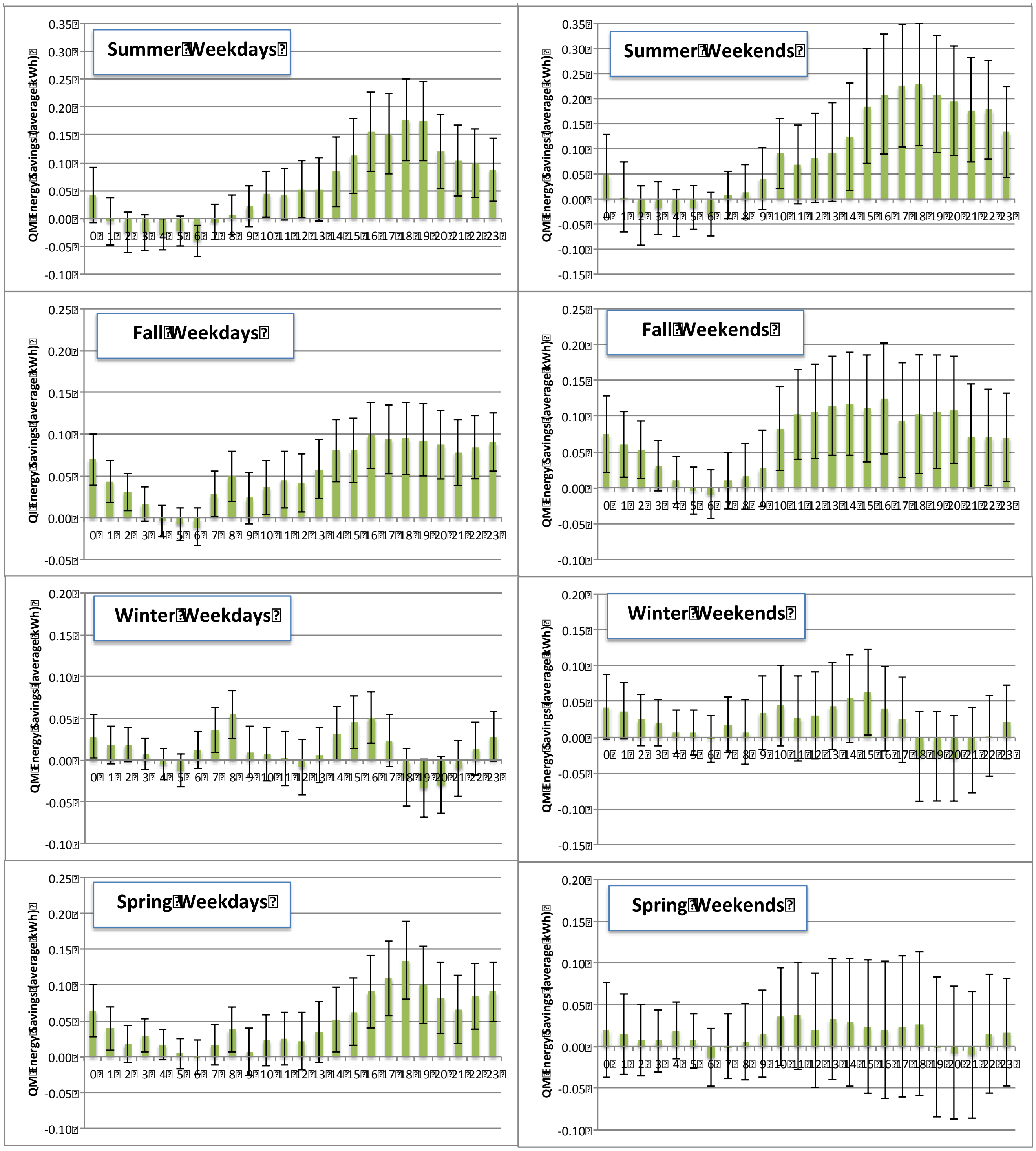
C.2.2 PG&E Quality Maintenance

Table 17: Savings Estimates from Annual Model of PG&E QM Data

Description of Data		Holdout Sample Model			Final Model and Savings Estimates		
		Actual Holdout Pre (kWh)	Predicted Holdout Pre (kWh)	Difference (%)	Adj Predicted Post (kWh)	Actual Post (kWh)	Savings (%)
Total	Annual	26.23	26.26	-0.1%	27.91	26.90	3.60%
Day Type	Annual Weekday	25.72	25.73	0.0%	27.53	26.51	3.72%
	Annual Weekend	27.52	27.55	-0.1%	28.93	27.91	3.50%
Season	Fall	21.01	21.34	-1.6%	22.74	21.35	6.11%
	Spring	23.75	24.74	-4.2%	25.82	24.86	3.74%
	Summer	38.31	36.77	4.0%	40.64	39.04	3.95%
	Winter	21.90	21.84	0.3%	21.67	21.37	1.39%
Season and Day Type	Fall Weekday	20.97	21.38	-2.0%	22.27	20.98	5.83%
	Fall Weekend	21.13	21.24	-0.5%	23.90	22.25	6.91%
	Spring Weekday	22.90	23.83	-4.1%	25.66	24.45	4.71%
	Spring Weekend	25.90	27.07	-4.5%	26.21	25.87	1.31%
	Summer Weekday	37.98	36.42	4.1%	39.95	38.57	3.44%
	Summer Weekend	39.10	37.62	3.8%	42.41	40.22	5.15%
	Winter Weekday	21.61	21.54	0.3%	21.35	21.08	1.26%
	Winter Weekend	22.66	22.55	0.5%	22.62	22.18	1.95%

Figure 40: PG&E QM Hourly Savings Estimates on Weekdays vs. Weekends, Annually and by Season




Summer Weekdays
Summer Weekends
Fall Weekdays
Fall Weekends
Winter Weekdays
Winter Weekends
Spring Weekdays
Spring Weekends

Appendix D Additional Fixed Effects Model Detail

The following section provides additional detail on the fixed effects regression model approach and results. Specifically we provide a summary of the aggregation approach for each dataset by which the hourly datasets were aggregated to the daily and monthly level, and detailed regression results.

D.1 Data Aggregation

Following the hourly AMI data cleaning for each utility dataset, we created datasets at the three aggregation levels of interest, hourly, daily and monthly.

Hourly Dataset*:* The original hourly AMI data for each utility was manipulated to form a panel dataset suitable for analysis with each observation representing a single hour, day, home-record. Program data containing the HVAC equipment installation date was then appended and the pre- and post- installation periods defined for each household. Periods during which the installation occurred were flagged as blackout periods and not included in the analysis. At the hourly aggregation level, the day of installation was flagged as a blackout period. Hourly weather station data including actual average hourly temperature were retrieved from NOAA and appended to the hourly AMI data. We selected weather station data based on proximity to each observation home's zip code, matching climate zone, and availability of complete hourly data. The selection process resulted in hourly data for 95.5 percent of hourly observations; the remaining hourly weather data were interpolated by taking the mean of the preceding and following temperature reads. Accurate mean hourly temperature data allowed us to create heating and cooling degree variables at the hourly level. We computed hourly degree days by taking the difference between the average hourly temperature and a base temperature of 65^0 F and dividing by 24, with hourly temperature less than 65^0 F being heating hour and greater than 65^0 F being cooling hours:

$$DD_{hourly} = \frac{1}{24} * (basetemp(65) - \overline{Temp}_{hour})$$

Daily Dataset*:* To aggregate to the daily level we simply take the daily sum of hourly kWh consumption, hourly HDD and hourly CDD, to get daily kWh consumption and daily HDD and CDD. The dataset is then limited to one row representing a single day, home record.

Monthly Dataset*:* Similarly, aggregation to the monthly level involves taking the sum of daily HDD and CDD for each month. For ease of comparability, rather than taking the sum of daily kWh, we calculate the average daily consumption (ADC) for each month. ADC is an equivalent variable to normalized monthly kWh and is the recommended consumption variable according to the UMP. The resulting dataset is limited to one observation representing a single month, home record.

Table 18: Dataset Summary by Aggregation Level

	SCE			PG&E		
	Hourly	**Daily**	**Monthly**	**Hourly**	**Daily**	**Monthly**
Observations	28.263,264	1,177,636	40,299	27,400,008	1,141,667	37,950
Households	2,038	2,038	2,038	1,216	1,216	1,216
Average kWh*	1.12	26.91	786.35	1.14	27.42	824.99
Average CDD*	0.26	6.18	180.71	0.27	6.57	197.57
Average HDD*	0.23	5.64	164.67	0.27	6.59	198.24

* Average kWh, CDD and HDD values are given at each aggregation level, hourly degree-days, daily degree-days and monthly degree-days.

The following tables present the full regression results for each of the six models, three models for SCE at the hourly, daily and monthly aggregation level and six models for PG&E and the hourly, daily and monthly aggregation level

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D.2 SCE Quality Installation Results

Table 19: SCE QI Program Monthly Aggregation Results

Model Summary	
Daily kWh Mean	27.85
Number of Households	2,038
Number of Observations	40,299
Adjusted R-Squared	.474
Estimated Savings (95% CI)	1.88 $\pm$ 0.293 kWh (6.76% $\pm$ 1.05%)

Variable	Coefficient ($\boldsymbol{\beta}$)	Standard Error	t-statistic	Sig. (p-value)
Post (Month)	3.076	0.250	12.307	< 1%
CDD	0.038	0.001	64.520	< 1%
HDD	0.007	0.001	8.783	< 1%
Post*C	-0.020	0.001	-29.117	< 1%
Post*H	-0.007	0.001	-9.211	< 1%
Feb	-0.414	0.192	-2.159	3.1%
Mar	-0.752	0.221	-3.399	< 1%
Apr	-1.819	0.245	-7.424	< 1%
May	-0.211	0.285	-0.739	45.9%
Jun	4.205	0.315	13.362	< 1%
Jul	9.740	0.360	27.049	< 1%
Aug	7.938	0.346	22.918	< 1%
Sep	7.101	0.330	21.496	< 1%
Oct	-0.934	0.250	-3.733	< 1%
Nov	-0.121	0.199	-0.611	54.1%
Dec	3.546	0.190	18.651	< 1%

Table 20: SCE QI Program Daily Aggregation Results

Model Summary	
Daily kWh Mean	27.95
Number of Households	2,038
Number of Observations	1,177,636
Adjusted R-Squared	.385
Estimated Savings (95% CI)	2.05 $\pm$ 0.046 kWh (7.36% $\pm$ 0.16%)

Variable	Coefficient (β)	Standard Error	t-statistic	Sig. (p-value)
Post (Day)	2.245	0.053	42.014	< 1%
CDD	1.367	0.003	443.942	< 1%
HDD	0.354	0.004	99.721	< 1%
Post*C	-0.535	0.004	-126.840	< 1%
Post*H	-0.150	0.005	-32.066	< 1%
Feb	-0.528	0.047	-11.141	< 1%
Mar	-1.006	0.054	-18.700	< 1%
Apr	-1.909	0.055	-34.402	< 1%
May	-0.284	0.057	-4.962	< 1%
Jun	3.451	0.060	57.961	< 1%
Jul	8.486	0.063	134.250	< 1%
Aug	7.205	0.061	118.501	< 1%
Sep	6.082	0.060	101.986	< 1%
Oct	-0.686	0.051	-13.348	< 1%
Nov	0.107	0.047	2.262	< 1%
Dec	3.333	0.046	72.440	< 1%

Table 21: SCE QI Program Hourly Aggregation Results

Model Summary	
Daily kWh Mean	27.95
Number of Households	2,038
Number of Observations	28,263,264
Adjusted R-Squared	.203
Estimated Savings (95% CI)	2.15 $\pm$ 0.009 kWh (7.71% $\pm$ 0.07%)

Variable	**Coefficient (β)**	**Standard Error**	**t-statistic**	**Sig. (p-value)**
Post (Hour)	0.019	0.001	28.788	< 1%
CDD	1.321	0.001	1820.253	< 1%
HDD	0.173	0.001	194.043	< 1%
Post*C	-0.358	0.001	-320.933	< 1%
Post*H	-0.044	0.001	-33.829	< 1%
Feb	-0.030	0.001	-36.615	< 1%
Mar	-0.068	0.001	-74.088	< 1%
Apr	-0.116	0.001	-123.855	< 1%
May	-0.066	0.001	-71.569	< 1%
Jun	0.081	0.001	86.717	< 1%
Jul	0.280	0.001	299.545	< 1%
Aug	0.229	0.001	252.189	< 1%
Sep	0.183	0.001	203.157	< 1%
Oct	-0.077	0.001	-91.368	< 1%
Nov	-0.013	0.001	-15.779	< 1%
Dec	0.154	0.001	194.905	< 1%

D.3 PG&E Quality Maintenance Program Results

Table 22: PG&E QM Program Monthly Aggregation Results

Model Summary	
Daily kWh Mean	27.30
Number of Households	1,216
Number of Observations	37,950
Adjusted R-Squared	.497
Estimated Savings (95% CI)	.761 $\pm$ 0.081 kWh (2.79% $\pm$ 0.58%)

Variable	**Coefficient (β)**	**Standard Error**	**t-statistic**	**Sig. (p-value)**
Post (Month)	-0.172	0.294	-0.585	55.9%
CDD	0.048	0.002	26.480	< 1%
HDD	0.015	0.001	17.410	< 1%
Post*C	-0.002	0.001	-1.696	8%
Post*H	-0.002	0.001	-2.381	2%
Feb	0.444	0.129	3.434	< 1%
Mar	-0.659	0.212	-3.103	< 1%
Apr	-2.068	0.290	-7.139	< 1%
May	-2.262	0.438	-5.167	< 1%
Jun	1.501	0.609	2.464	< 1%
Jul	3.637	0.803	4.527	< 1%
Aug	2.926	0.739	3.960	< 1%
Sep	1.146	0.559	2.051	4%
Oct	-1.635	0.331	-4.944	< 1%
Nov	1.046	0.219	4.781	< 1%
Dec	2.344	0.120	19.587	< 1%

Table 23: PG&E QM Program Daily Aggregation Results

Model Summary	
Daily kWh Mean	27.48
Number of Households	1,216
Number of Observations	1,141,667
Adjusted R-Squared	.397
Estimated Savings (95% CI)	0.82 $\pm$ 0.062 kWh (2.98% $\pm$ 0.23%)

Variable	Coefficient (β)	Standard Error	t-statistic	Sig. (p-value)
Post (Day)	-0.331	0.192	-1.726	8.4%
CDD	1.430	0.025	56.385	< 1%
HDD	0.393	0.012	31.899	< 1%
Post*C	-0.043	0.021	-2.047	4.1%
Post*H	-0.035	0.012	-2.883	< 1%
Feb	-0.277	0.066	-4.201	< 1%
Mar	-1.272	0.098	-12.947	< 1%
Apr	-2.828	0.112	-25.316	< 1%
May	-2.728	0.139	-19.639	< 1%
Jun	0.521	0.165	3.160	< 1%
Jul	3.477	0.208	16.680	< 1%
Aug	2.699	0.193	13.973	< 1%
Sep	0.192	0.161	1.188	23.5%
Oct	-2.158	0.127	-17.059	< 1%
Nov	0.531	0.150	3.529	< 1%
Dec	2.346	0.114	20.656	< 1%

Table 24: PG&E QM Program Hourly Aggregation Results

Model Summary	
Daily kWh Mean	27.49
Number of Households	1,216
Number of Observations	27,400,008
Adjusted R-Squared	.189
Estimated Savings (95% CI)	0.836 $\pm$ 0.009 kWh (3.04% $\pm$ 0.07%)

Variable	Coefficient ($\boldsymbol{\beta}$)	Standard Error	t-statistic	Sig. (p-value)
Post (Hour)	-0.034	0.001	-52.270	< 1%
CDD	1.288	0.001	1628.102	< 1%
HDD	0.046	0.001	50.753	< 1%
Post*C	-0.024	0.001	-23.231	< 1%
Post*H	-0.027	0.001	-22.853	< 1%
Feb	-0.066	0.001	-74.311	< 1%
Mar	-0.172	0.001	-188.637	< 1%
Apr	-0.264	0.001	-279.858	< 1%
May	-0.283	0.001	-288.498	< 1%
Jun	-0.138	0.001	-135.174	< 1%
Jul	0.000	0.001	-0.174	86%
Aug	-0.039	0.001	-37.219	< 1%
Sep	-0.157	0.001	-154.500	< 1%
Oct	-0.251	0.001	-262.503	< 1%
Nov	-0.077	0.001	-84.929	< 1%
Dec	0.093	0.001	104.030	< 1%

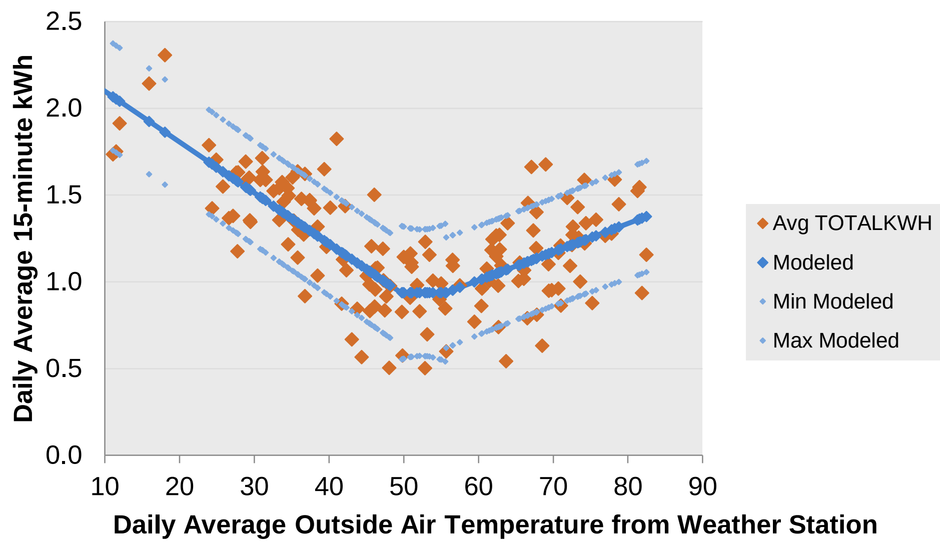
Appendix E ECAM Analysis Results – Additional Detail

E.1 NEEA RBSA Site-Level Results

Models for the remaining four of the five homes analyzed are shown in the following pages. For each site and day type, the home-level model is shown first, and then the model using only the air conditioning unit(s) data.

E.1.1 RBSA Home #2

Figure 41: Models of Home #2 on Tuesdays, Thursdays, and Saturdays



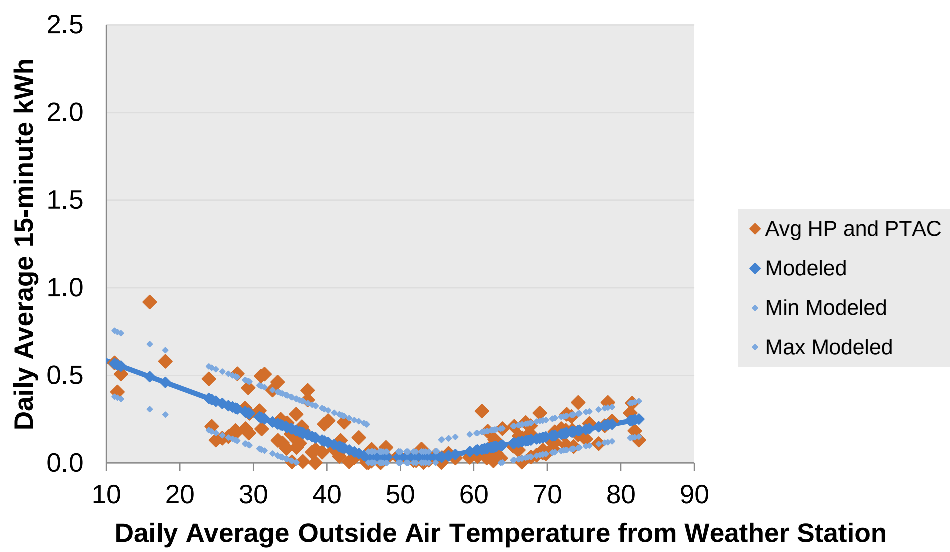
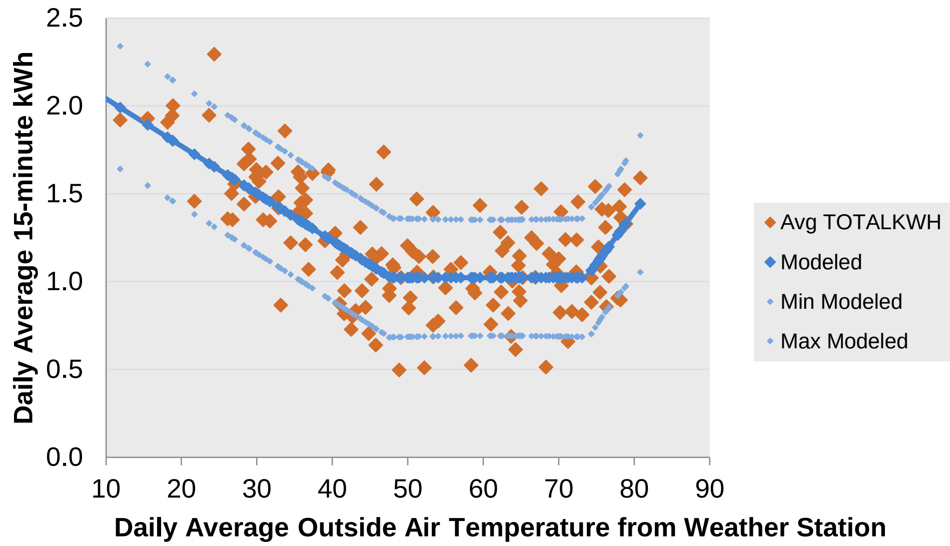


Figure 42: Models of Home #2 on Wednesdays, Fridays, and Sundays



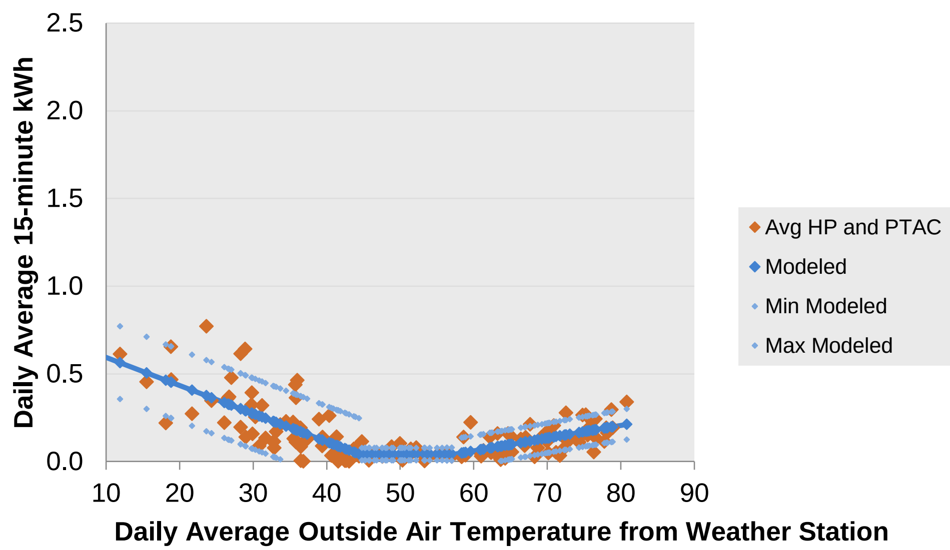
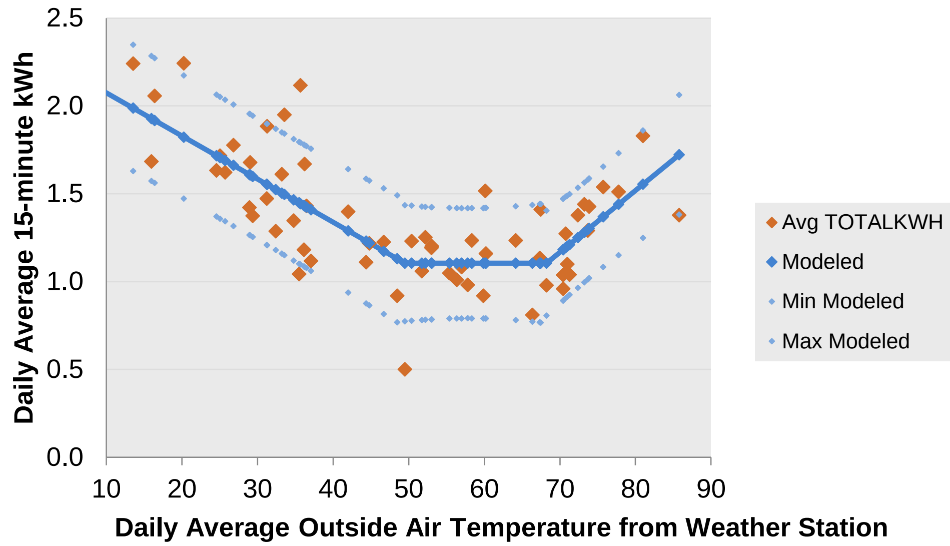
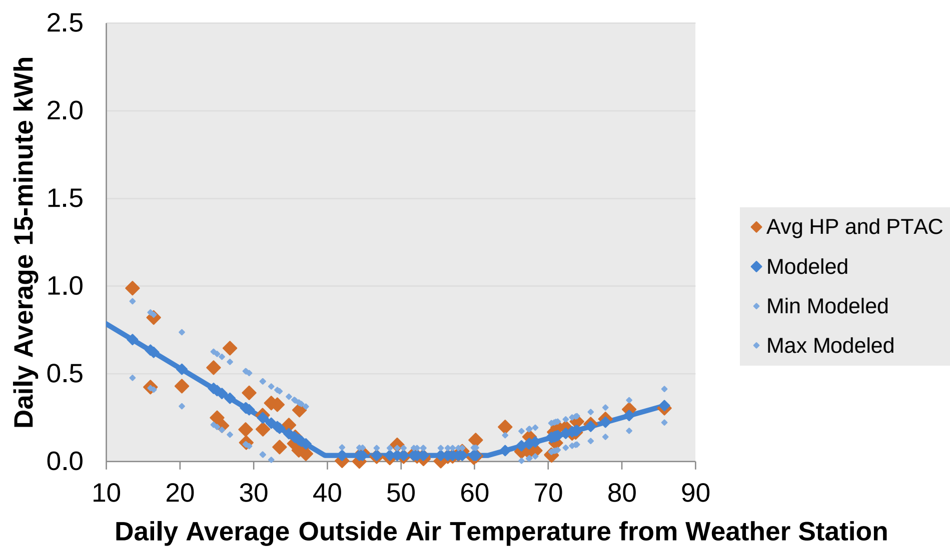


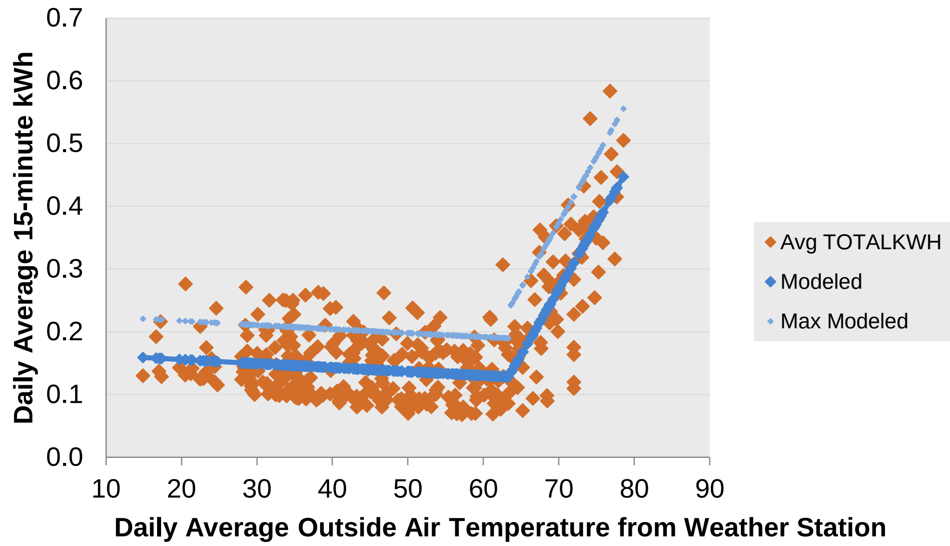
Figure 43: Models of Home #2 on Mondays and Holidays

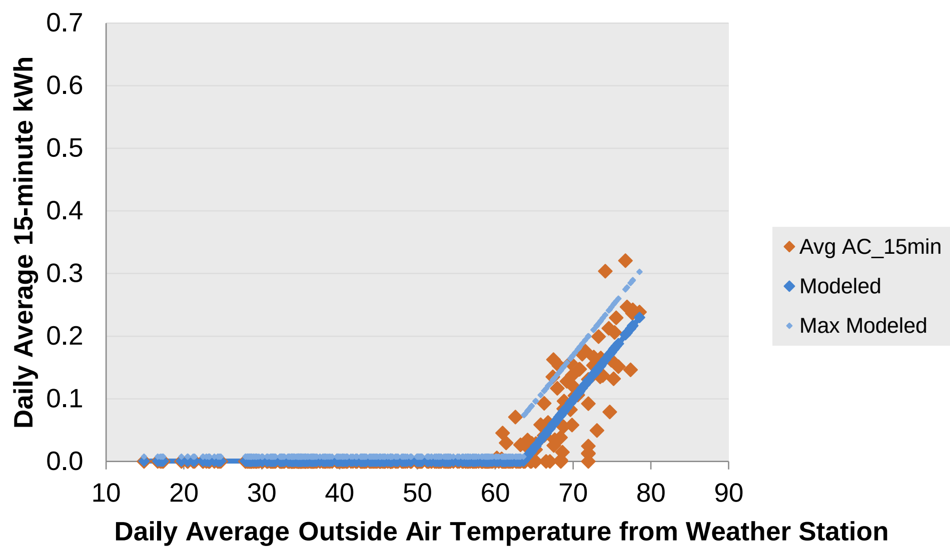




E.2 RBSA Home #3

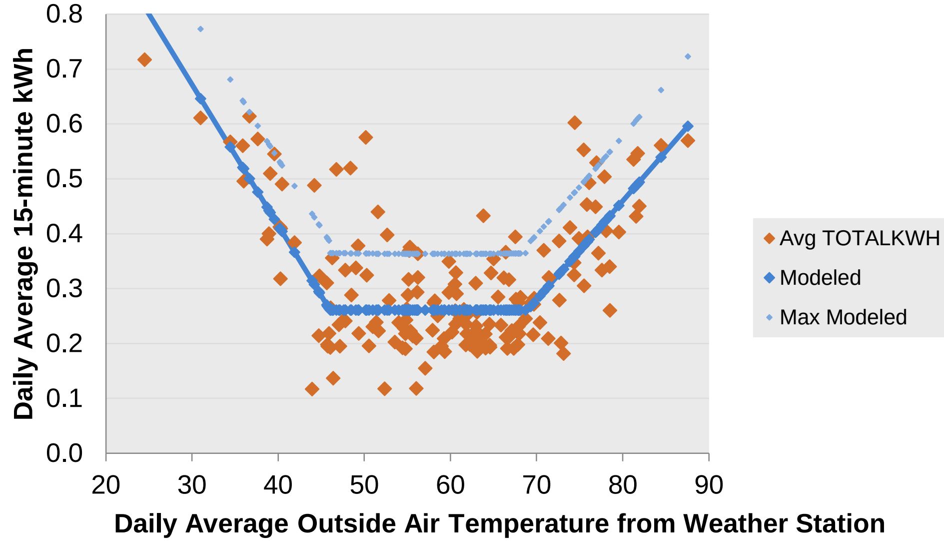
Figure 44: Models of Home #3 on all Weekdays and Holidays





E.2.1 RBSA Home #4

Figure 45: Models of Home #4 on all Weekdays and Holidays



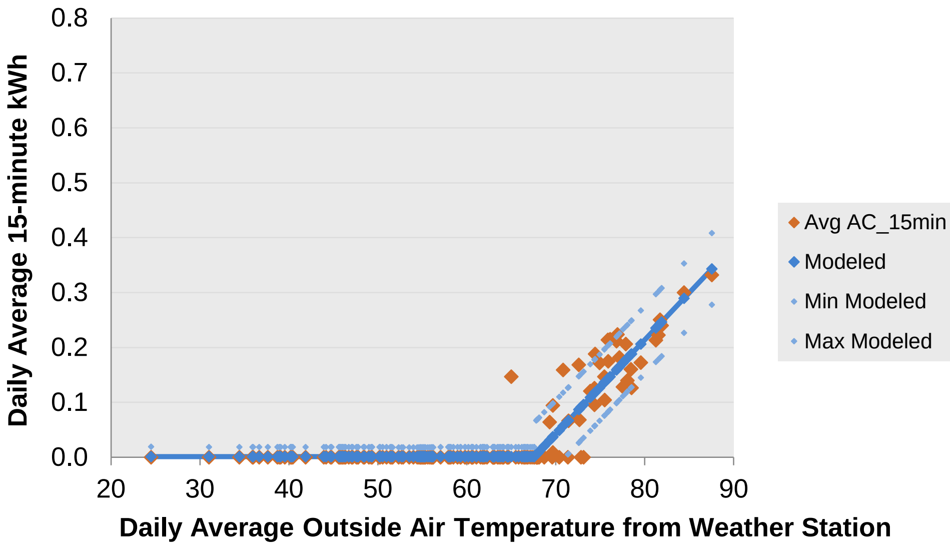
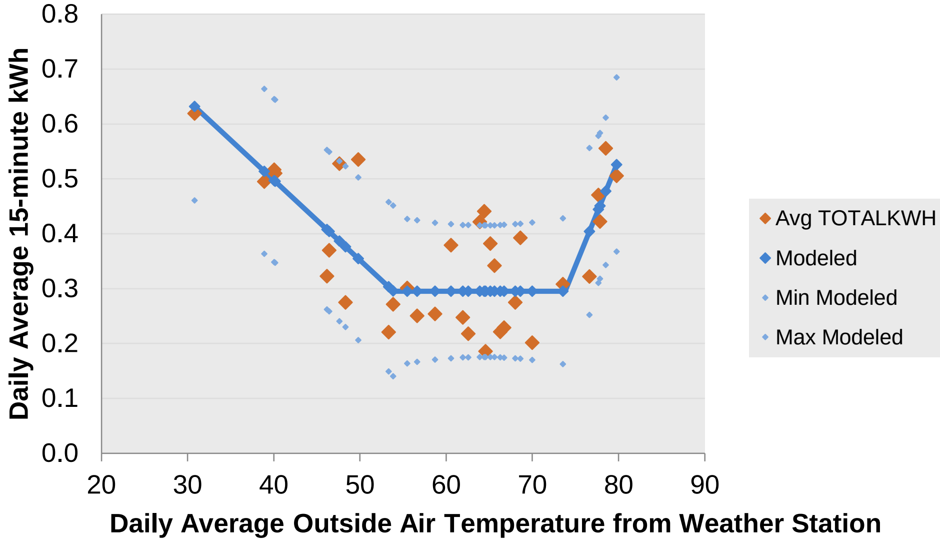


Figure 46: Models of Home #4 on Saturdays



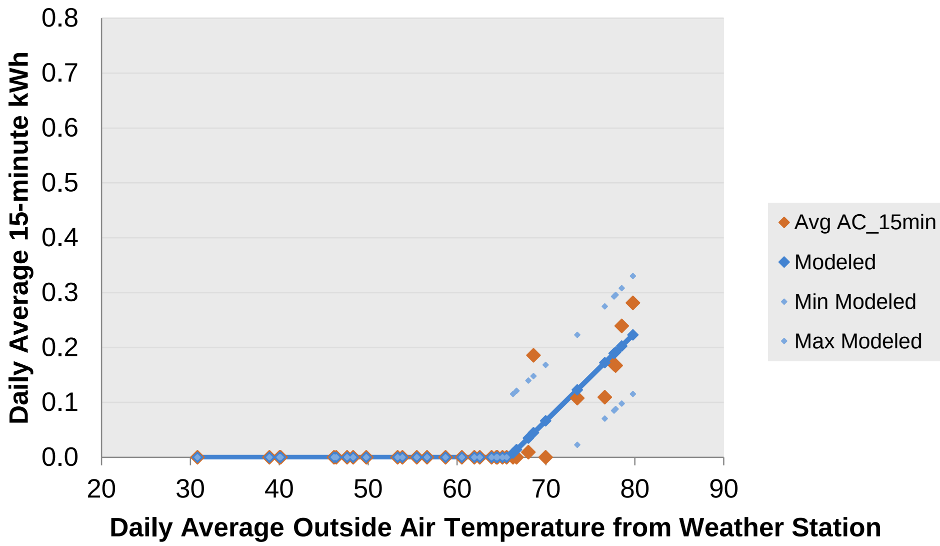
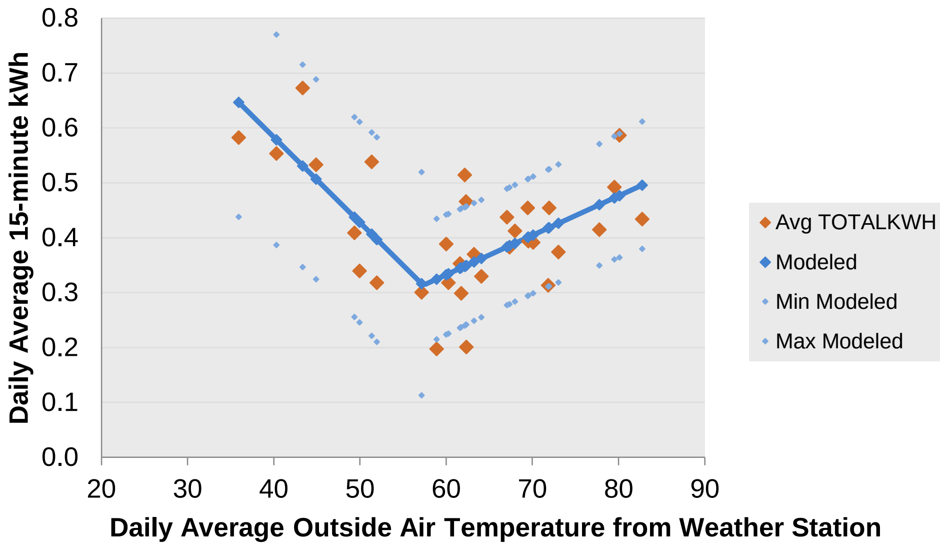
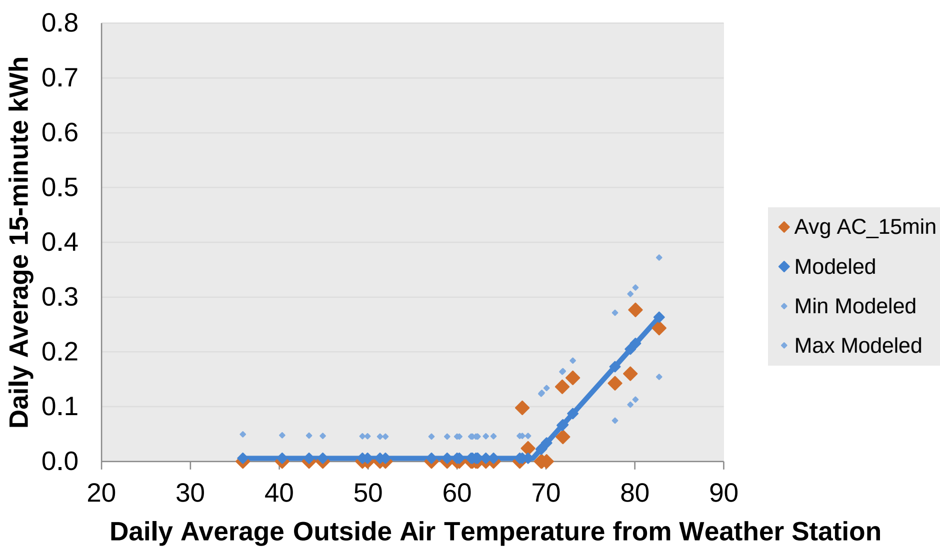


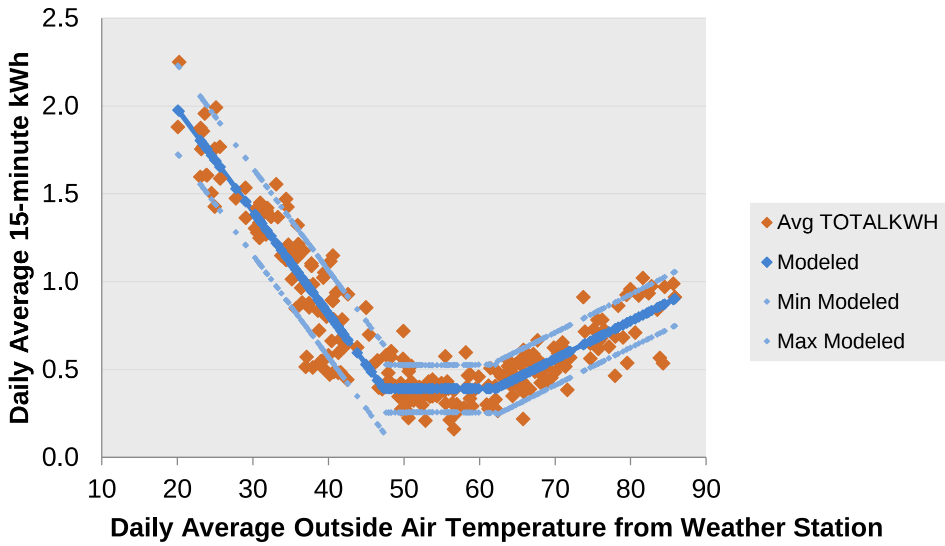
Figure 47: Models of Home #4 on Sundays





E.2.2 RBSA Home #5

Figure 48: Models of Home #5 on Weekdays



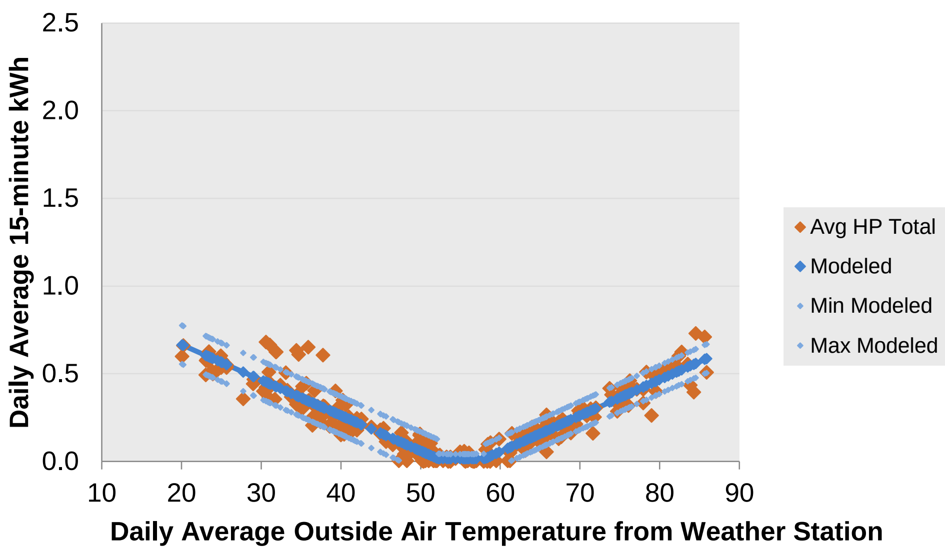
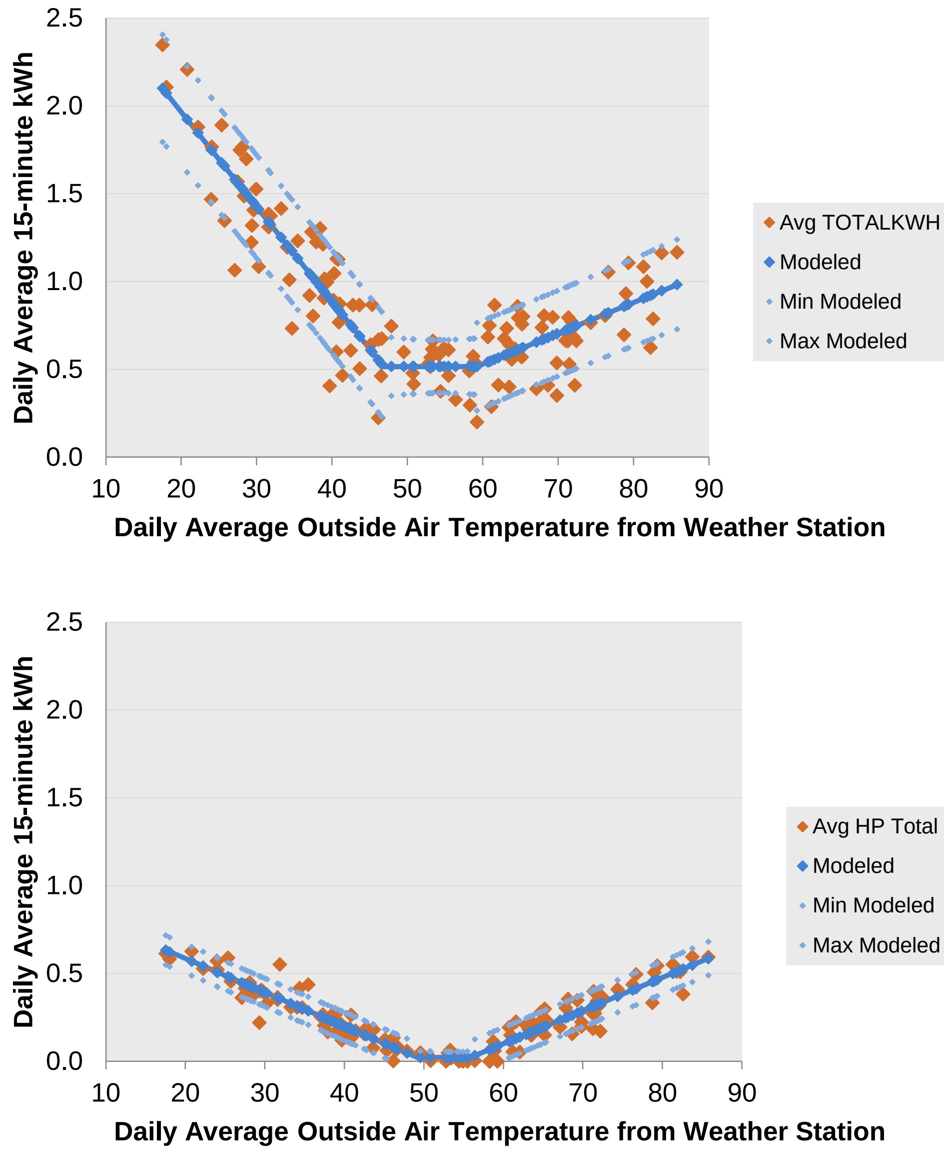


Figure 49: Models of Home #5 on Weekdays and Holidays

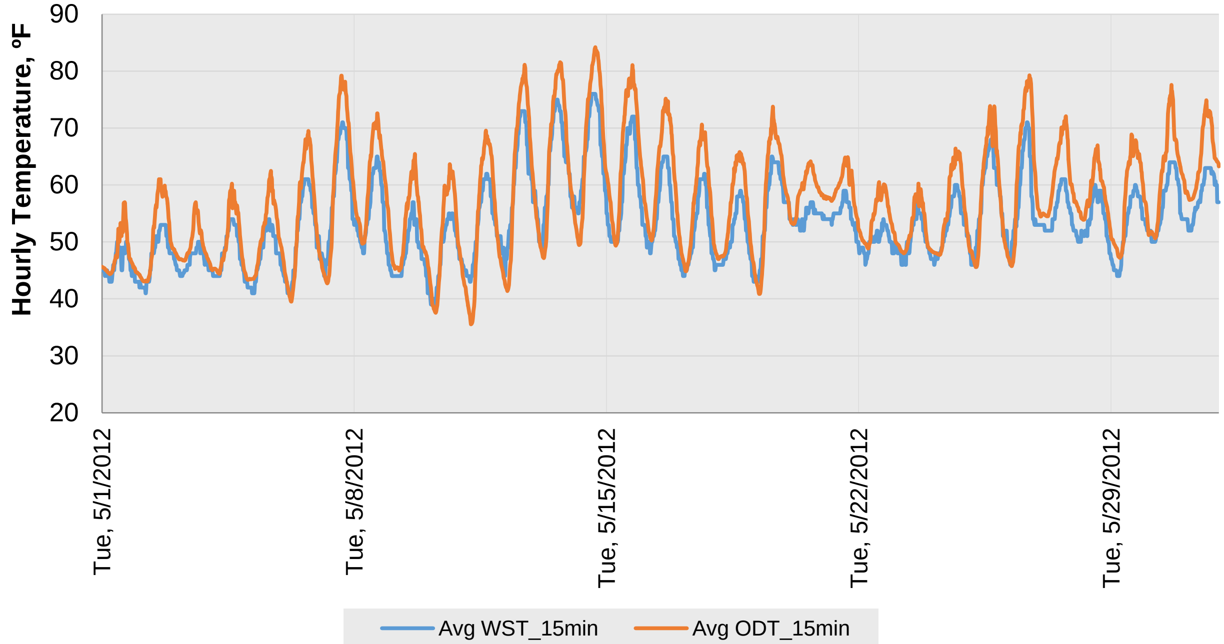


E.2.3 Outside Air Temperature Comparisons

To appraise the quality of weather data available, for each house we compared the site-based outdoor air temperature (ODT) with the temperature from the nearest weather station (WST), both of which are provided in the RBSA data. In all cases, the site-measured temperatures averaged higher than the temperatures from the nearest airport. Most of the difference in the daily average is due to the site sensor measuring much higher daytime temperatures than at the weather stations, as shown in Figure 50 Home #1 in May 2012. There were some hours and days when the weather station measured lower than the site, but these times were relatively few.

Because there are often issues with site-based outside air temperature measurements, and the main goal of this project was to use only meter data from the site for modeling and savings estimation, the RBSA analyses relied on weather station temperature data instead of the site-specific outdoor temperature.

Figure 50: Comparison of Weather Station Temperature (WST) and Outdoor Temperature (ODT), Home #1 in May 2012



The rest of these temperature comparisons show daily average temperatures for each site based on the outdoor temperature (ODT), indoor temperature (IDT), and the weather station (WST).

Figure 51: Comparison of Weather Station (WST), Outdoor (ODT), and Indoor Temperatures for Home #1

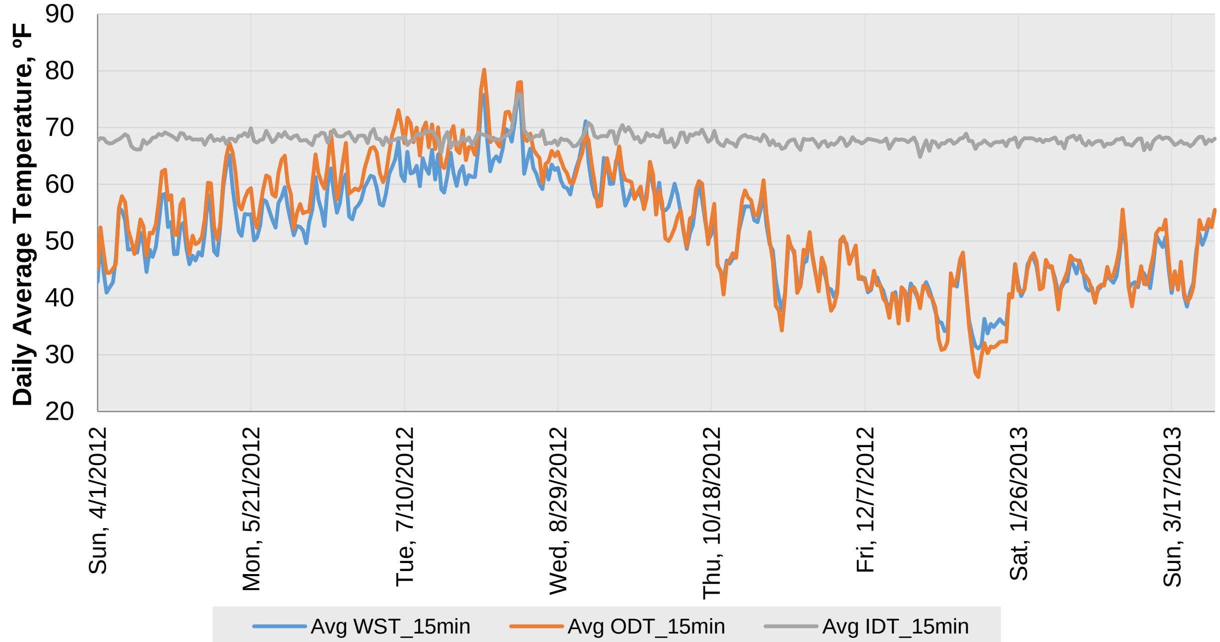


Figure 52: Comparison of Weather Station (WST), Outdoor (ODT), and Indoor Temperatures for Home #2

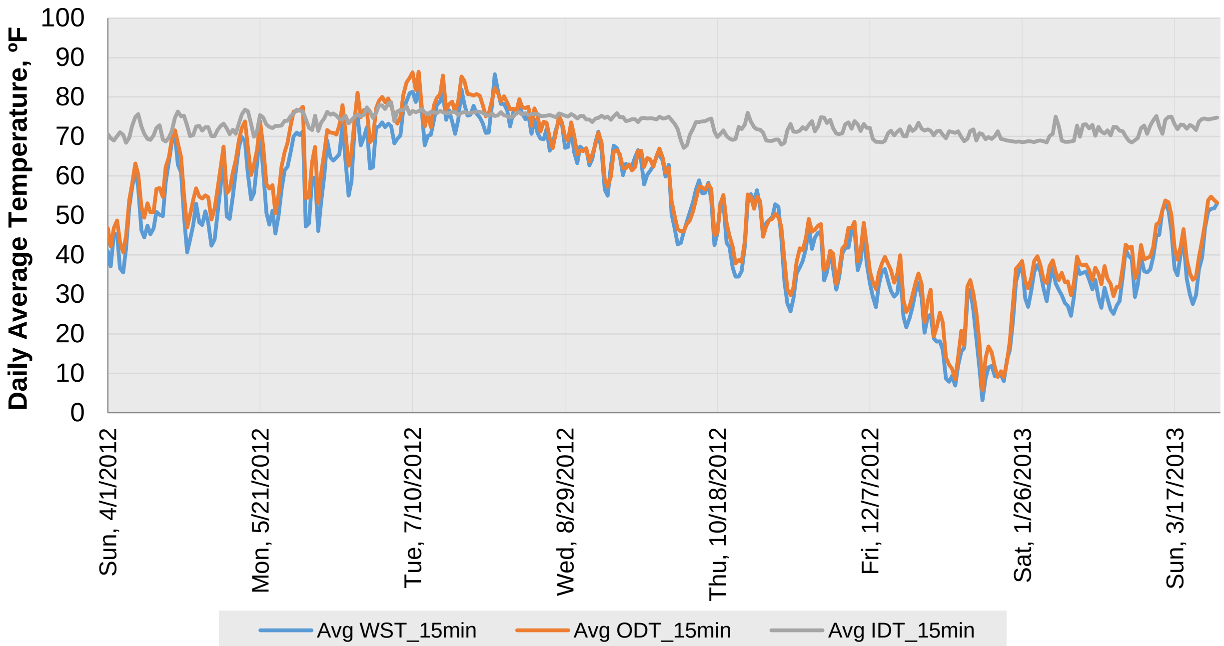


Figure 53: Comparison of Weather Station (WST), Outdoor (ODT), and Indoor Temperatures for Home #3

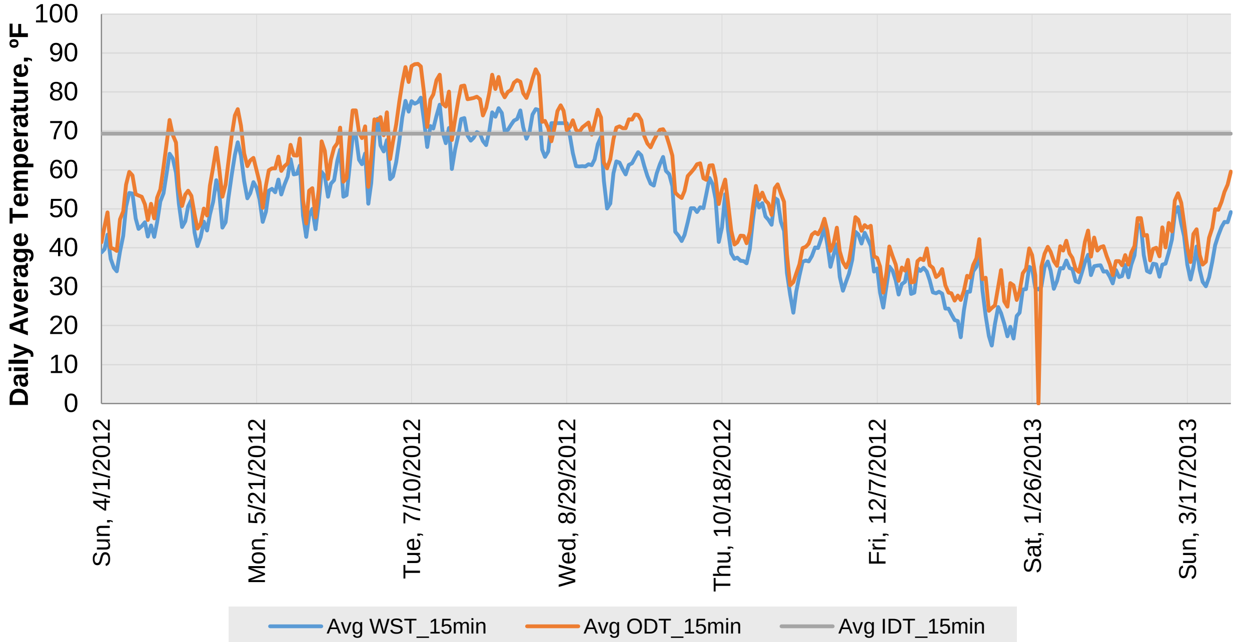


Figure 54: Comparison of Weather Station (WST), Outdoor (ODT), and Indoor Temperatures for Home #4

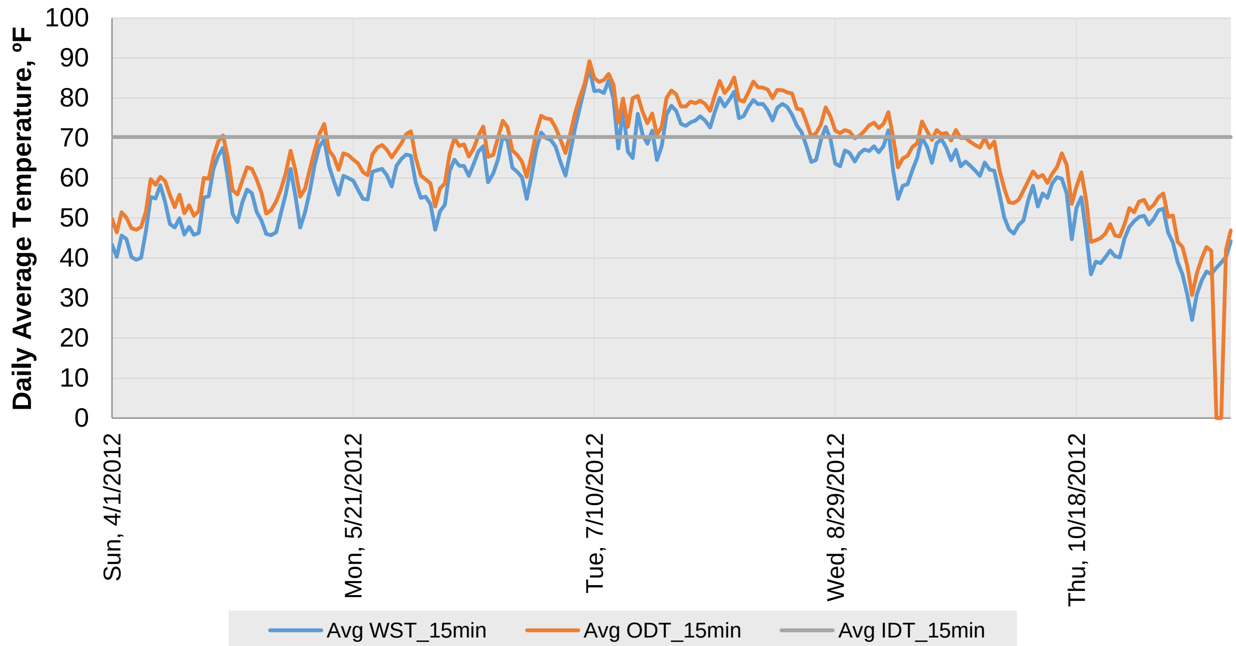


Figure 55: Comparison of Weather Station (WST), Outdoor (ODT), and Indoor Temperatures for Home #5