# Appendix K:

2018 Low Income Electric Heating and Cooling Analysis

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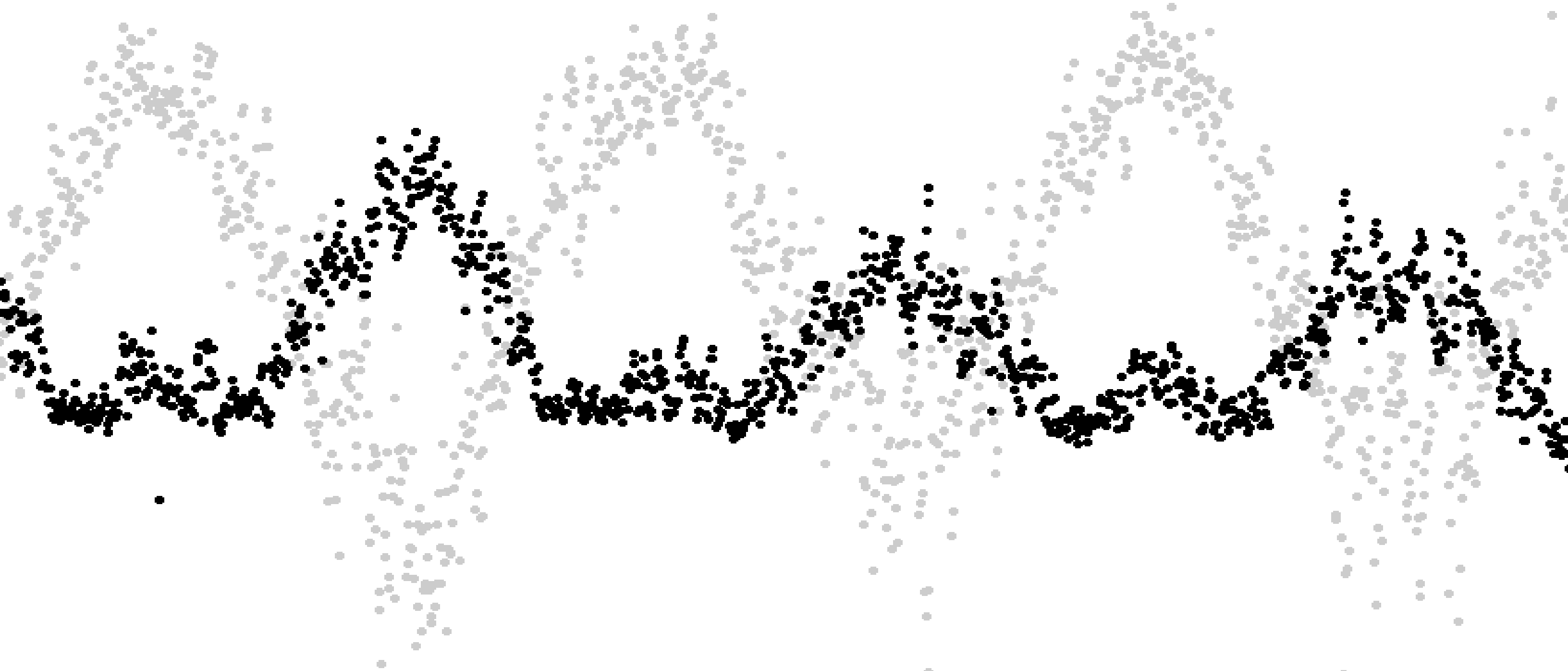

Convergence Data Analytics

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For Efficiency Maine
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# Contents



Cover image: three years' worth of daily electric consumption (black) and outside temperature (gray), averaged across all studied customers.

# Introduction

The purpose of this memo is to provide estimates of the amount of electric heating and cooling found in the Maine homes of low-income customers using data from the Arrearage Management Program (AMP). The memo also provides the background needed to understand the derivation of those estimates.

Electric heating sensitivity estimates are derived from the extent to which meter data documents high consumption during colder weather. Annual estimates of low-temperature-correlated loads (believed to be a combination of space heating and other seasonally varying loads) are derived by combining sensitivity estimates with standardized TMY3[1] weather data. Annual space heating estimates are disaggregated from low-temperature-correlated loads by computing the increase in loads associated with the presence of electric hot water heaters and subtracting that value from all relevant customer totals. Annual estimates of high-temperature-correlated loads (AKA cooling loads) are computed using similar methods.

## Summary of findings

**Tables 7 and 8 summarize the key findings of this analysis.** Normalized annual electric space heating loads are found to be 2876 kilowatt hours (kWh) per year for Maine homes that do not report electricity as their primary heating fuel and 7609 kWh per year for those that report electricity as their primary heating fuel. The average of electric space heating across the set of customers studied was 3527 kWh/year. Normalized annual space cooling loads are found to be 462 kWh per year on average, up to 628 kWh per year in households reporting both central and window AC units.

# Data

The data available for this project includes account details, customer characteristics derived from survey responses, and associated hourly meter data from customers participating in AMP in Maine. In addition to the provided data, zip codes were used to download hourly local temperature data that could be assigned to each customer.[2]

For any meter data project there are some key concepts that should be made clear. First is the relationship between people, accounts, premises, and meters. We typically talk about analysis in terms of “customers” and it is important to work with a specific and consistent definition for what that means. In the case of Maine’s AMP, the recipients of program resources are people. However, the focus of the potential for energy efficiency (EE) interventions, especially insulation, sealing, and HVAC work, tends to be the premises themselves. For program purposes, much of the potential for improvement lies in understanding the state of the premises.

For this analysis we have performed a unique assessment of the meter data for **each “customer”, which we define as the data from one person at one premise, as codified in a single account identifier**. If the

[1] TMY stands for Typical Meteorological Year. TMY files provide a full year of weather data, compiled month by month by selecting historical data from months that are typical of weather at a given location to support simulation and weather normalization. The TMY3 set of files are the third and latest release of TMY data and are documented in this publication: https://www.nrel.gov/docs/fy08osti/43156.pdf

[2] NOAA weather station data was obtained using the Python scripts of https://github.com/sborgeson/local-weather

person moves, they get a second analysis at their new premise and if they hold more than one account, they get more than one analysis. If there are cases where multiple meters are associated with the same account, we total their readings into a single virtual meter (but we note that there are meter configurations possible that are not simply additive). Most premises have a single meter and a single occupying account holder. Most account holders are only on a single account a single premise at a time and did not move for the duration of our study. However, there are exceptions to all of these conditions.

Table 1 summarizes the counts of data categories available for this analysis. This work required both meter and account data for all analyzed customers (816 of these) and further required the enforcement of data quality validation that required all accounts to have more than 50% of their readings non-zero, average demand over 180 Watts (W) (or 0.18 kWh/hour), more than 60 days' worth of data, and sufficient weather data to calculate temperature sensitivities, leading to a total of 792 accounts included in this analysis.

*Table 1: Count of meters, accounts, and customers available for various parts of the data sample studied.*

| | count |
|---|---|
| **unique meters** | 1088 |
| **unique accounts (in the meta data)** | 838 |
| **unique accounts (meter/meta match)** | 816 |
| **feature validation failures** | 24 |
| **accounts with estimates** | **792** |

We can also classify customers by the heating fuel choices revealed by their survey responses to see the extent to which those survey responses impact our results. Table 2 provides a summary of data on primary heating fuel as reported by each customer. These boil down to 96 who reported electricity as their primary space heating fuel, 601 who reported a different fuel, and 95 who did not respond.

*Table 2: Customer counts for each space heating fuel type found in survey responses.*

| primary space heating fuel | count |
|---|---|
| **electric** | 82 |
| **gas** | 46 |
| **oil** | 473 |
| **partial electric** | 14 |
| **propane** | 44 |
| **unknown** | 8 |
| **wood** | 30 |
| **NA** | 95 |

Similar data is available for hot water heating and summarized in Table 3. The counts boil down to 519 who reported electric hot water, 157 who reported other fuels, and 116 who didn't know or didn't respond.

*Table 3: Primary water heating fuels reported by surveyed customers.*

| Primary water heating fuel | count |
|---|---|
| **electric** | 518 |
| **gas** | 11 |
| **oil** | 125 |
| **partial electric** | 1 |
| **propane** | 21 |
| **unknown** | 12 |
| **NA** | 104 |

# Methods

## Estimating temperature sensitivities

To isolate cooling energy from total customer load, a prerequisite for weather normalization and estimating weather sensitive loads, we run a **weather sensitivity regression model** for every customer that explains total daily kWh ($KWH_d$) as a function of daily heating degree hours ($HDH_d$) and cooling degree hours ($CDH_d$) and an indicator for weekend ($WKND_d$) or weekday.[3] A day's HDH is the sum of the degrees the hourly outside temperature (Tout) is below 65°F (or 0 if warmer than 65°F) across all hours (h) in each day (d). A day's CDH is the sum of the degrees the hourly outside temperature (Tout) is above 65°F (or 0 if cooler than 65°F) across all hours in each day.

$$HDH_d = \sum_{h=1}^{24} max\big(0, (65 - Tout_{h,d})\big)$$

$$CDH_d = \sum_{h=1}^{24} max\big(0, (Tout_{h,d} - 65)\big)$$

$$KWH_d = c + \beta_1 \cdot HDH_d + \beta_2 \cdot CDH_d + \beta_3 \cdot WKND_d + \varepsilon$$

The regression coefficient *c* is the expected daily energy consumption for weekdays with zero CDH and zero HDH (i.e. constant 65F). The coefficient $\beta_1$ quantifies the heating sensitivity of each customer and can be used to predict daily heating energy given a computed HDH for day d. The coefficient $\beta_2$ quantifies the cooling sensitivity of each customer and can be used to predict daily cooling energy given a computed CDH for day d.

To illustrate this process, Figure 1 visualizes daily consumption data (in kWh/day) for two representative customers, "a" and "b", as a time series in the left column and scattered against heating degree hours in the right column. The time series plot shows daily average outside temperature in gray (scaled to be visible in the plot) for visual reference. The HDH scatter plots show the same daily kWh as the corresponding time series plot on the y-axis, but the x-axis is daily heating degree hours (HDH). The blue

[3] This model is consistent with the venerable PriSM piecewise regression methodology, which has updated manifestations in IPMVP Option C, VISDOM, and CalTRACK/OpenEE Meter.

points are the regression model fits for the same days. From these plots, we can see that the electric consumption of customer “a” is highly responsive to cold weather (black and blue points angling toward the upper left of the plot) and that customer “b” is not (blue points essentially flat towards the left of the plot). However, “b” is responsive to hot weather (right most points past zero heating degree hours), indicating the presence of air conditioning loads.

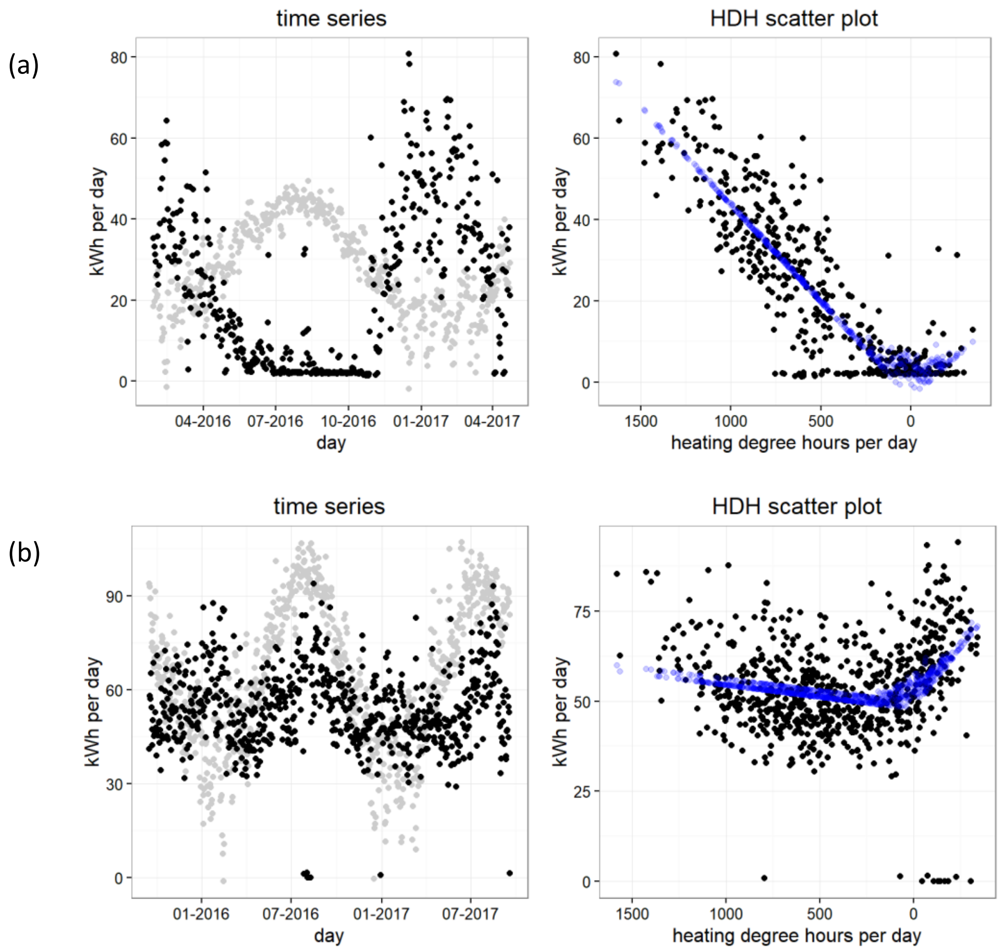


*Figure 1: Time series and heating degree day scatter plots for (a) a representative customer highly responsive to heating degree hours and (b) a representative customer not very responsive to heating degree hours, but who is responsive to cooling degree hours. Each row of plots is for the same customer.*

The weather sensitivity regression model is run for each customer, with the results used to disaggregate heating and cooling consumption from the daily totals. Figure 2 and Figure 3 provide histograms of the daily kWh associated with the model estimated low and high temperature correlated loads, respectively. These are computed as $\beta_1$*mean($HDH_d$) and $\beta_2$*mean($CDH_d$), respectively per customer. The values vary widely within the population but in both cases, the mean values are significantly above zero. Note that the x-axes have different scales and that the cooling loads are significantly smaller than the heating loads.

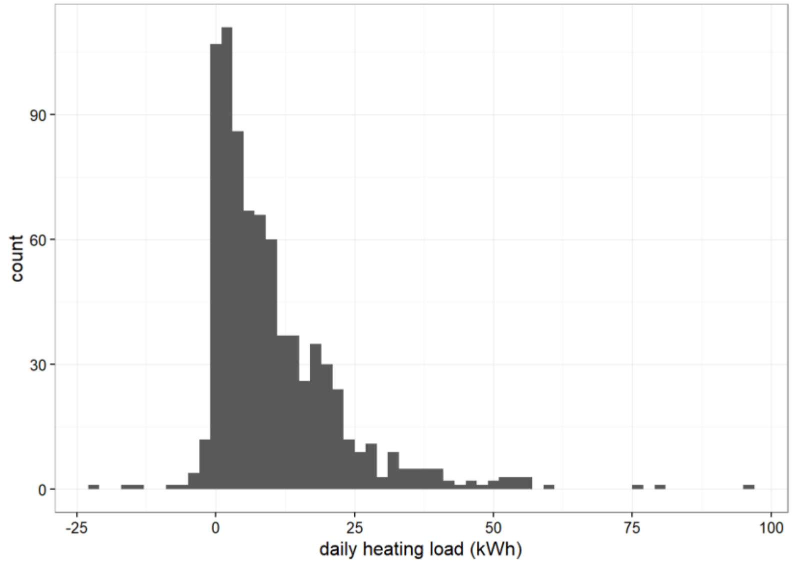


*Figure 2: Histogram of daily heating loads (Heating-Degree-Hour correlated) across all customers. N=792.*

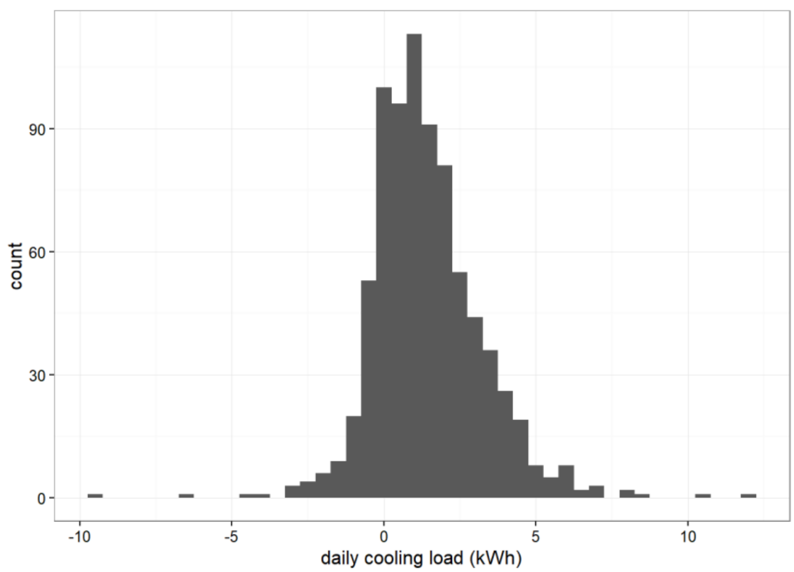


*Figure 3: Histogram of daily cooling loads (Cooling-Degree-Hour correlated) across all customers. N=792.*

## Normalizing heating and cooling results to TMY3 conditions

The values for low-temperature- and high-temperature-responsive loads presented so far were calculated using the regression model CDH and HDH temperature sensitivities to predict disaggregated heating and cooling consumption **given the observed weather data for each customer**. To address what should be expected in the future under typical conditions across the state, it is necessary to weather normalize the results.

Weather data that summarizes typically expected meteorological conditions is referred to as Typical Meteorological Year, or TMY, data. The latest versions of TMY data are known as TMY3. For this study, we calculated normalized low and high temperature responsive loads per customer using each customer's HDH and CDH regression model coefficients and HDH and CDH values computed from TMY3 data. The data used was a population weighted average of TMY3 data from Portland (71.2%), Bangor (23.4%) and Caribou (5.4%). The results of the weather normalization averaged 3779 kWh per year using customer local weather and 4153 kWh per year using TMY3 data. This means that the observed temperature data corresponding to each meter reading tends to be higher than TMY3 data. This is likely due to some combination of long term warming not accounted for in TMY3 historical data, unusually warm weather during the period for which we have data, and the possibility that the population weights used with the TMY3 data don't accurately reflect the geography of our sample.[4]

## Disaggregating space heating from water heating

There can be several temperature responsive loads in every home and each contributes to the whole home temperature sensitivities that we estimated. We can typically assume that space heating and cooling will be dominant loads, but we know that water heaters in particular often use more energy in the cool weather and less in hot weather.[5] The study team verified that both electric space heat and electric hot water survey responses correlate with increased cold weather correlated consumption. Table 4 provides a cross tabulation of mean annual cold temperature responsive loads for all permutations of space and hot water fuel types.

[4] Because the program will be run statewide, these weights can be understood as correcting the weather experience by the studied customers to be more representative of the weather experienced by all customers.
[5] The basements and garages they sit in are colder, incoming water is often colder, and the pipes that carry the water to its end use are often colder, each contributing to more energy input to achieve the same tap/shower temperatures.

*Table 4: Cross tabulation of customer count, mean annual cold temperature responsive load, with standard deviation and median for all permutations of space heating (SH) and hot water (DHW) fuel types.*

| electric SH | electric DHW | count | annual mean kWh | sd | median |
|---|---|---|---|---|---|
| No | no | 164 | 2937 | 4052 | 1592 |
| No | yes | 424 | 4087 | 3970 | 3181 |
| No | NA | 13 | 2798 | 1878 | 2962 |
| Yes | no | 5 | 5584 | 8696 | 3809 |
| Yes | yes | 91 | 8955 | 7117 | 7239 |
| NA | yes | 4 | 738 | 907 | 594 |
| NA | NA | 91 | 2113 | 3368 | 828 |
| Either | either | 792 | 4153 | 4780 | 2841 |

As a final step, the TMY3 normalized values for *all cold and hot weather correlated* loads need to be adjusted to isolate the just the space heating and cooling loads. To provide estimates for electric space heating and cooling in isolation, we need to subtract the temperature sensitive electric usage for water heating. The survey data on end use fuels can be used to formulate a regression model for this purpose. The studied customers' indication of primary space and water heating fuels summarized in Table 5.

*Table 5: Count of customers indicating the presence or absence of electric space heat, electric domestic hot water, and the count of those who didn't answer (NA)*

| end use | "no" count | "yes" count | N/A count |
|---|---|---|---|
| electric space heat | 601 | 96 | 95 |
| electric hot water | 169 | 519 | 104 |

To separate the cold temperature responsive loads into space heating and hot water components, the TMY3 normalized annual totals of the daily heating degree hour responses are regressed against 1/0 indicators for space heating ($E_{SH}$) and hot water ($E_{DHW}$) that is primarily electric for each customer with survey data available. The regression equation is as follows:

$$annual\ cold\ temp\ responsive\ kWh = \alpha_{SH} + \beta_{E\_SH}E_{SH} + \beta_{E\_DHW}E_{DHW} + \epsilon$$

Similar to the heating analysis, survey data provided information, summarized in Table 6, about cooling technology ownership at a customer level.

*Table 6: Count of customers indicating the presence or absence of central AC, window AC, any type of AC, electric domestic hot water, and the count of those who didn't answer (NA)*

| | "no" count | "yes" count | N/A count |
|---|---|---|---|
| **central AC** | 634 | 158 | 0 |
| **window AC** | 470 | 322 | 0 |
| **any AC** | 391 | 401 | 0 |
| **electric DHW** | 169 | 519 | 104 |

To separate the hot temperature responsive loads into space cooling and hot water components, the TMY3 normalized annual totals of the daily cooling degree hour responses are regressed against 1/0 indicators for air conditioning type ($E_{central}$ and $E_{window}$) and hot water ($E_{DHW}$) that is primarily electric for each customer with survey data available. The regression equation is as follows:

$$annual\ hot\ temp\ responsive\ kWh = \alpha_{AC} + \beta_{E\_central}E_{central} + \beta_{E\_window}E_{window} + \beta_{E\_DHW}E_{DHW} + \epsilon$$

# Results

## Space heating estimates

Table 7 summarizes the coefficients from the above space heating model and Figure 4 visualizes the values, with error bars plus and minus one standard error from each coefficient value. In words, it shows that independent of primary space heating fuel customers consume an average of 2876 kWh per year in base electric heating. Customers who report their primary space heating fuel as electric consume an additional 4733 kWh per year heating, for a total of 7609 kWh/year of space heating. Customers who reported electric hot water heating additionally consume an estimated average of 1236 kWh **of cold weather responsive load** per year (*i.e.*, above and beyond the year-round baseline hot water heating loads[6]). According to this model, a customer reporting non-electric space heating and electric hot water would be expected to have 2876 + 1236 = 4112 kWh/year of cold weather responsive loads on average, but only the 2876 kWh attributable to space heating, on average, could be impacted by building envelope improvements.

*Table 7: Regression model disaggregation of estimated TMY normalized annual heating loads conditional on customer characteristics.*

| | annual mean kWh | std. err |
|---|---|---|
| **base heating** | 2876 | 352 |
| **additional if electric SH** | 4733 | 512 |
| **additional If electric DHW** | 1236 | 412 |

[6] Efficiency Maine calculates that electric resistance tanks consume an average of 3,386 kWh/year total.

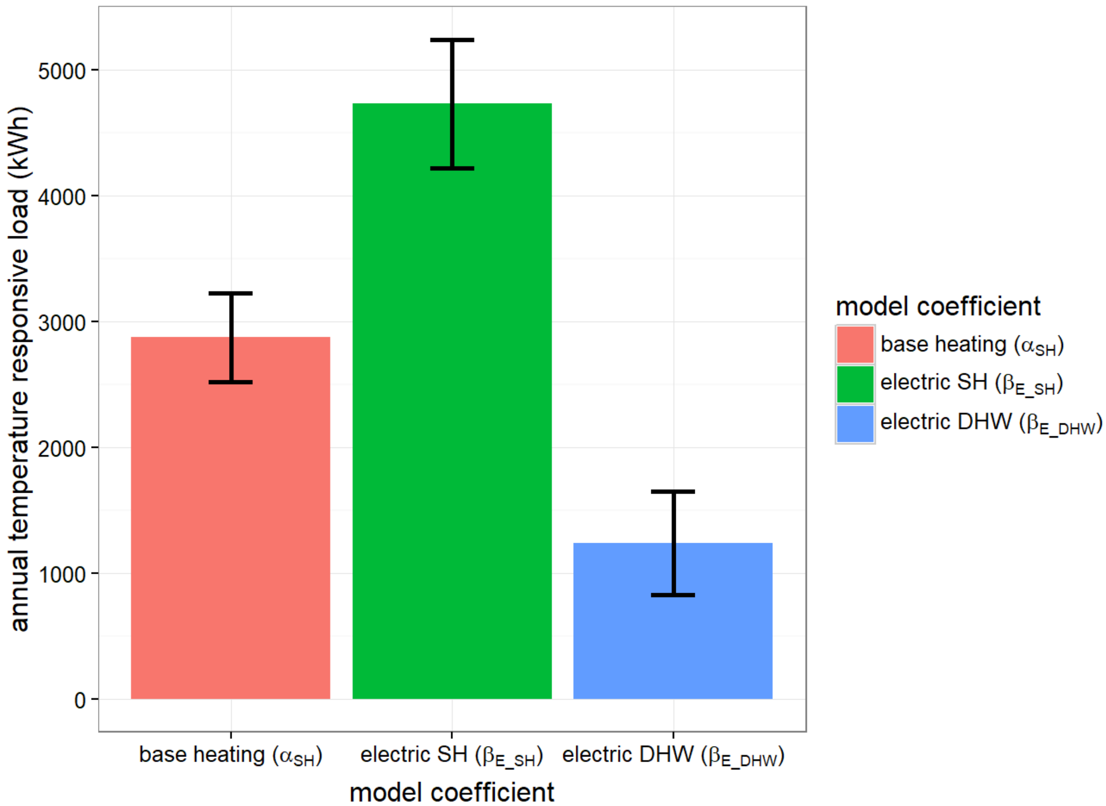


*Figure 4: Annual electric load impact estimates for base space heating (SH), with adjustment terms for reported electric primary and domestic hot water (DHW) with error bars corresponding to one standard deviation in either direction.*

It can be easily verified that customers reporting electric space heating (red + green) have significantly higher observed disaggregated space heating loads than those that report space heating using other fuels (red). It is also evident that customers who do not report electricity as their primary fuel nevertheless have significant electric heating loads.

The coefficients displayed in Figure 4 can be used to predict loads for individual customers. To calculate population wide averages, we predict the loads for each individual and then aggregate across all individuals. Table 8 tabulates the results by primary space heating fuel. Customers who have electric heat are in the minority, so the consumption for everyone together is closer to the consumption for customers who do not report electricity as their primary heating fuel.

*Table 8: TMY3 weather normalized annual electric heating consumption estimates (kWh/year) by primary space heating fuel*

| Primary space heating fuel | count | annual mean kWh |
|---|---|---|
| **electric** | 96 | 7609 |
| **non-electric** | 601 | 2876 |
| **either** | 697 | 3527 |

## Space cooling estimates

Table 9 summarizes the coefficients from the above space cooling model and Figure 5 visualizes the values, with error bars plus and minus one standard error from each coefficient value. In words, it shows that independent of air conditioning technology customers consume an average of 393 kWh per year in base electric cooling. Customers who report central and window AC units consume an additional 129 and 107 kWh per year cooling, respectively. This results in a grand total of 628 kWh/year of consumption, on average, for customers reporting both central and window AC units. Notably, the negative coefficient associated with electric hot water means that the presence of electric hot water systematically lowers hot weather correlated loads (they do not work as hard in hot weather) compared to customers without electric hot water. Including this effect raises estimates of space cooling loads.

*Table 9: Regression model disaggregation of estimated TMY normalized annual cooling loads conditional on customer characteristics.*

| | annual mean kWh | std.err. |
|---|---|---|
| **base cooling** | 393 | 42 |
| **additional if central AC** | 129 | 46 |
| **additional if window AC** | 107 | 37 |
| **additional if DHW** | -114 | 43 |

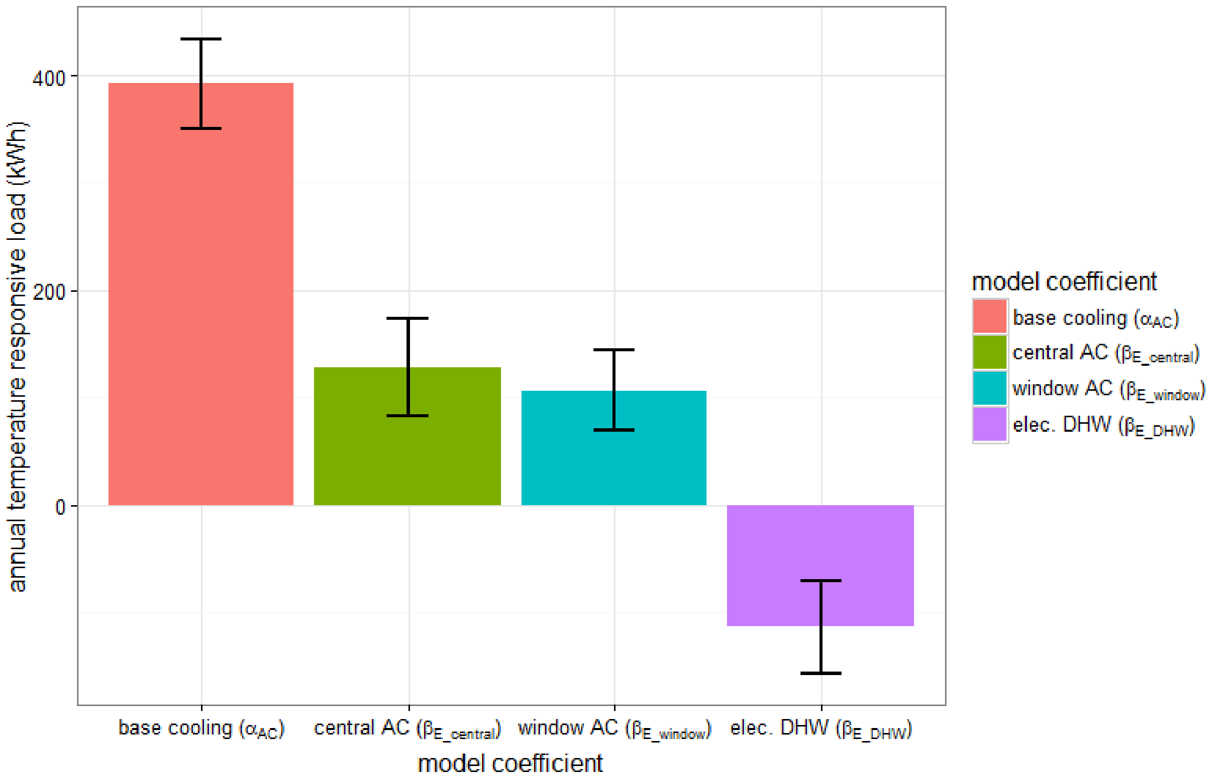


*Figure 5: Annual electric load impact estimates for base cooling (AC), with adjustment terms for central and window air conditioning, and electric domestic hot water (DHW) with error bars corresponding to one standard deviation in either direction.*

Table 10 tabulates the weather normalized electric consumption for air conditioning. As one would expect for a northern climate, these loads are significantly smaller than the heating loads. However, they are significant enough to constitute roughly 13% of the heating loads and could therefore represent an increase in overall electric benefits from building envelope retrofits.

*Table 10: TMY3 weather normalized annual electric cooling consumption estimate (kWh/year)*

| central AC | window AC | count | annual mean kWh |
|---|---|---|---|
| no | no | 391 | 393 |
| no | yes | 243 | 499 |
| yes | no | 79 | 521 |
| yes | yes | 79 | 628 |
| either | either | 792 | 462 |

# Discussion

## Arrearage vs. general population low-income customers

Due to the ready availability of their data, this project relied primarily on data from customers in Maine's AMP. Those customers are the subset of low-income customers that have fallen behind on their bills and have agreed to participate in a program that forgives their arrearages as they get current on their payments. A logical question to ask is to what extent do the energy consumption patterns of arrearage customers match the consumption of the broader set of customers eligible for low-income program interventions.

To begin to address this question, we were provided a second data set from a sample of customers drawn at random from the broader low-income population. A comparison of results from each data set could, in principle, help to quantify any differences between the two. However, the second sample included just 42 customers and these customers did not provide space and water heating fuel information. As a result, there are too few customers to establish statistically significant estimates of the differences between arrearage and general low-income customers and there is no ability to differentiate space and water heat for the second group.

With those caveats, we were able to replicate most of the analysis performed on the arrearage customers on the random low-income sample as well. Figure 6 presents the average annual cold weather responsive loads (left) and average annual total consumption (right) for the arrearage sample and random draw low-income sample. The right panel suggests that arrearage customers consume more electricity than low-income customers in general and the left panel suggests that arrearage customers have larger cold temperature responsive loads than low-income customers in general and that the magnitude of their cold temperature responsive loads exceeds what would be expected if they were merely proportional to annual total consumption. A larger random sample of low-income customers would need to be analyzed to determine whether these differences are statistically significant.

All else being equal, we might hypothesize that arrearage customers fall behind because their bills are higher than typical of their peers or their incomes are lower than typical of the broader community of low income customers. The former is consistent with the results presented in the figure. Regardless of cause, if the pattern observed holds with a larger sample drawn from the general population of low income customers, arrearage customers would be expected to have larger program savings opportunities than the rest of the low-income population.

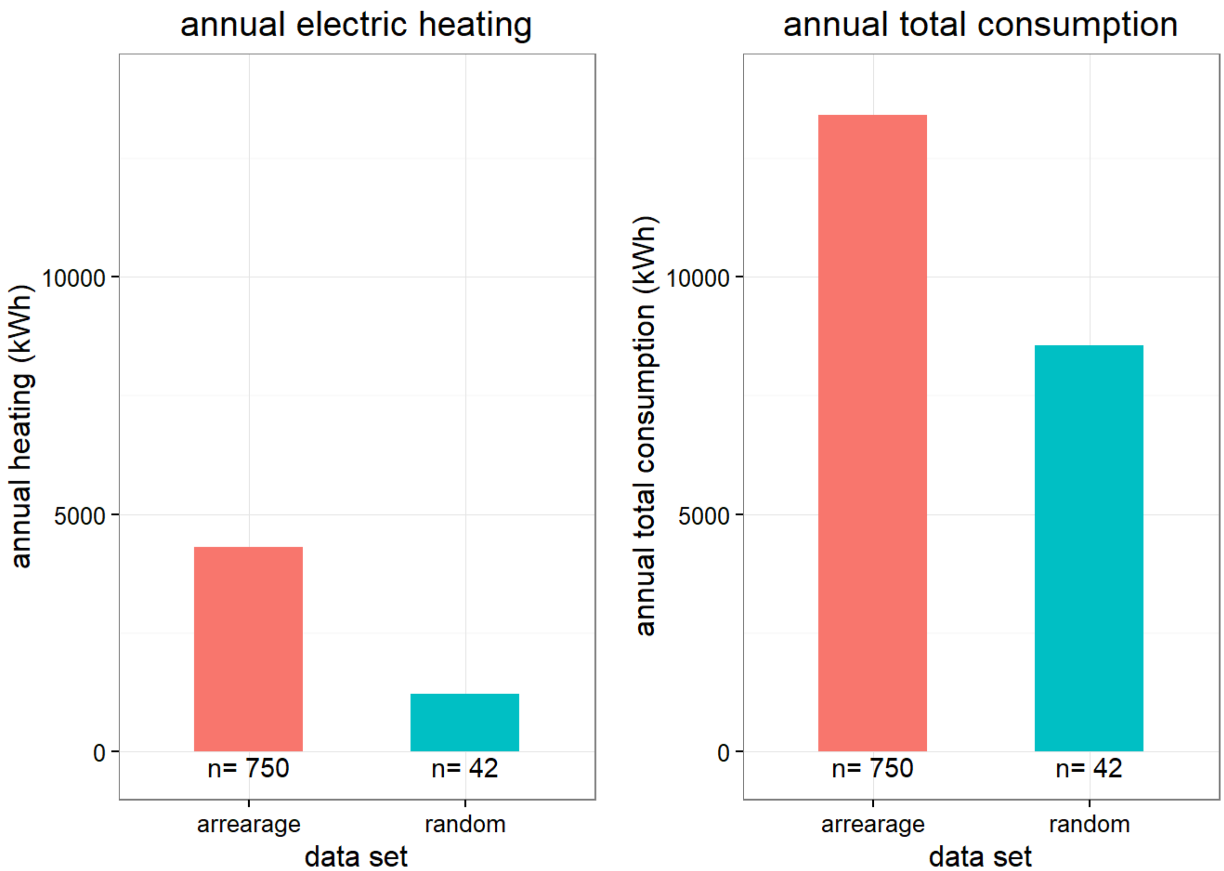


*Figure 6: Annual total electric energy use (right) and estimated cold weather responsive electric energy use (left) for arrearage customers (red) and a random sample of low-income customers (blue).*