Energy Research and Development Division

FINAL PROJECT REPORT

Cultural Factors in Energy Use Patterns of Multifamily Tenants

California Energy Commission

Edmund G. Brown Jr., Governor

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PREFACE

The California Energy Commission's Energy Research and Development Division supports energy research and development programs to spur innovation in energy efficiency, renewable energy and advanced clean generation, energy-related environmental protection, energy transmission and distribution and transportation.

In 2012, the Electric Program Investment Charge (EPIC) was established by the California Public Utilities Commission to fund public investments in research to create and advance new energy solution, foster regional innovation and bring ideas from the lab to the marketplace. The California Energy Commission and the state's three largest investor-owned utilities – Pacific Gas and Electric Company, San Diego Gas & Electric Company and Southern California Edison Company – were selected to administer the EPIC funds and advance novel technologies, tools and strategies that provide benefits to their electric ratepayers.

The Energy Commission is committed to ensuring public participation in its research and development programs which promote greater reliability, lower costs and increase safety for the California electric ratepayer and include:

- Providing societal benefits.
- Reducing greenhouse gas emissions in the electricity sector at the lowest possible cost.
- Supporting California's loading order to meet energy needs first with energy efficiency and demand response, next with renewable energy (distributed generation and utility scale), and finally with clean conventional electricity supply.
- Supporting low-emission vehicles and transportation.
- Providing economic development.
- Using ratepayer funds efficiently.

This is the final report for the *Cultural Factors in Energy Use Patterns of Multifamily Tenants* project (Contract Number EPC-14-039) conducted by TRC Engineers, Inc. The information from this project contributes to Energy Research and Development Division's EPIC Program.

All figures and tables are the work of the author(s) for this project unless otherwise cited or credited.

For more information about the Energy Research and Development Division, please visit the Energy Commission's website at www.energy.ca.gov/research/ or contact the Energy Commission at 916-327-1551.

ABSTRACT

One-third of Californians live in multifamily housing, and that percentage is on an upward trend. Little research, however, on energy patterns and cultural factors in multifamily housing exists. With changing demographics in the state there is a new focus on understanding how the cultural and demographic characteristics of Californians may influence energy use and preferences for energy efficiency and how that may affect energy efficiency programs.

Funded by the Electric Program Investment Charge Program and in partnership with Pacific Gas and Electric Company, TRC Engineers, Inc. studied how cultural and demographic factors correlate with multifamily tenants' electric energy use patterns, before and after building retrofits and tenant engagement activities. Through tenant surveys and interval meter data analytics, this study investigated the variations in multifamily energy use patterns.

Better understanding of energy use patterns in multifamily settings provide important insight into the future of energy use as this housing type becomes a more common and essential component of any zero-net-energy strategy for the state and the dynamic changes to the United States population. This paper presents findings from this study and recommendations for future programmatic efforts to better target customers and for energy load forecasting to consider cultural and demographic factors. This report discusses how "behavior" used in programs may not be the same as inherent cultural and demographic preferences for certain energy-using patterns that may be adopted for energy efficiency efforts.

Keywords: Multifamily, energy, demographics, cultural, patterns

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EXECUTIVE SUMMARY

Introduction

California is thought of as a sprawling, suburban state, with vast tracts of single-family homes. Just as many multifamily homes, however, are being built as single-family, and the proportion is likely to continue to increase as land costs rise, cities look for ways to reduce infrastructure costs, and younger and older people seek out walkable lifestyles.

Efforts to reduce residential energy use have focused on improvements to the building structure and major energy-using equipment, which seem to be the most reliable and persistent efficiency measures. Actual energy use in homes, however, varies widely and relates only partially to the efficiency of the building and related permanent equipment. The building occupant presents a huge variable, especially as the biggest use of electricity in multifamily homes is usually lights, appliances, and electronic devices (plug loads) rather than cooling, heating, or ventilation.

To improve the ability to predict statewide energy use and develop successful policies and programs to reduce energy use, it is essential to have a deeper understanding of the diversity of use patterns and the consumer's motivations for selecting and using these plug loads. Energy use varies widely different types of people make different lifestyle decisions that impact energy use. It is not known, however, how to predict who will make what decisions, or how all those decisions are likely to impact future energy use.

Project Purpose

This study provided greater insight into the energy use patterns of multifamily residents. In California, almost 30 percent of occupied housing units are in multifamily buildings of five or more units. According to the United States Bureau of the Census for 2017, this is 30 percent higher than the multifamily buildings for the United States as whole of 17.5 percent. The study explored the connection between the California multifamily population's cultural and demographic characteristics and different use patterns, especially after completing building owner-initiated retrofits. In addition, the study examined how cultural factors influence tenant interest in technologies that can reduce electricity use, especially for lighting and plug loads.

The findings of this study will guide future program design, targeting and marketing, and inform the accuracy of statewide energy use forecasts and savings potential studies. This study provides quantitative results with measured changes in energy use using sociological and ethnographic research methods of a subset of the study population.

Project Process

This research project collaborated with Pacific Gas and Electric (PG&E) to study tenants in multifamily homes undergoing building upgrades as part of the utility's Multifamily Upgrade Program. The project team recruited a subset of the building owners participating in the program for deeper research into their tenants' energy use patterns. The project used the communication between building owners and managers and their tenants to identify study subjects, collect survey data, and conduct interventions testing research hypotheses about cultural factors in energy use patterns.

As a partner in this study, PG&E provided demographic data about study subjects and interval electric meter data. As part of the co-funding of the project, PG&E provided a subcontractor to conduct interval data analysis and participated in project planning, review and dissemination to ensure that the project findings are directly useful to program marketing, planning, and evaluation.

The project recruited study participants during the 2015 2016 Multifamily Upgrade Program cycle and analyzed energy use patterns from data a year before and after retrofits. The research team combined information about these energy use patterns with information about the cultural and demographic characteristics, attitudes and behaviors of the participants. Information from existing PG&E data sets and other public studies was collected and used.

The team also developed tenant education and activities used to explain the benefits of energy efficiency and encourage the consumers to adopt efficiency devices that can reduce plug and lighting loads.

Project Results

The research team considered two major dimensions of energy savings potential in this analysis. The energy efficiency retrofit projects administered by PG&E's Multifamily Upgrade Program were designed to provide savings across a range of multifamily properties. The team examined these savings through the Advanced Metering Infrastructure Customer Segment model method. It was also imperative to understand how to identify and capture the energy savings potential efficiently when exploring technical or behavioral changes in the market. The team explored promising niches of technical potential and developed reasonable strategies that might exploit these niches.

- The analysis of retrofit savings in the Multifamily Upgrade Program projects found 2.7 percent savings overall, based on the Advanced Metering Infrastructure Customer Segment method. These savings are adjusted for weather differences.

- Separate from the Multifamily Upgrade Program retrofits, the team found households with more miscelleneous plug loads have, on average, higher energy use than those with fewer such plug loads. The amount of plug loads is also correlated with other household factors, such as the number of people, income, the amount of time at home, or various other lifestyle elements.

- For this portion of the analysis, sample size was small and limited to the survey data sample. The team was not able to make precise statistical claims about these relationships; however, it is a promising result especially for multifamily homes, and where plugged equipment is generally purchased by occupants and plug load electricity use may often be a higher proportion of total building energy use than for single-family homes. Nevertheless these results suggest that improved plug load power management could make a noticeable difference to overall energy use.

- The multivariate analysis shows no single demographic or cultural factor (not interactions with others) by themselves explain the differences more than or as much as the effects of location and climate. While none of these factors alone tells the story of why energy use varies, it does indicate these factors should be considered when planning for the state's energy future. This study provides a starting point to understand how cultural and demographic factor in multifamily energy use.

- In addition, surveyed households expressed a high level of interest in testing a "smart" power strip that could control some of these plug loads. A smart power strip resuces the power use by shutting down power to products that go into standby mode. As noted, a next research step could link household *interest* in plug load management, household *behaviors* with respect to plug load uses, *technical data* on plug load energy use patterns in multifamily homes, and smart power strip *design*, toward a more comprehensive perspective on energy savings potential through plug load management.

Benefits to California

The multifamily residential population represents an essential component of California's goals to create a low-carbon, sustainable future as outlined in Assembly Bill 32 (Núñez, Chapter 488, Statues of 2006), the Global Warming Solutions Act of 2006, and Assembly Bill 758 (Skinner, Chapter 470, Statutes of 2009), Building Efficiency. Multifamily units are a steadily increasing percentage of California homes, currently housing about 13 million of the population. With substantially lower environmental impacts, multifamily buildings represent an important pathway to achieve zero-net-energy homes.

CHAPTER 1: Introduction

Residential energy use in California is complex. Efforts to reduce residential energy use have focused on improvements to the building structure and major energy-using equipment, which seem to be the most reliable and persistent efficiency measures. Actual energy use in homes varies widely, however, and relates only partially to the efficiency of the building and associated permanent equipment. The role of the building resident is a huge variable, especially in the selection and operation of appliances and electronic devices in the home. To improve predictions for statewide energy use and develop successful policies and programs to reduce energy use, it is essential to have a better understanding of the building residents' role.

California has always been thought of as a sprawling suburban state, with vast tracts of single-family homes. However, that trend changed in 2008. The state is building just as many multifamily homes as single-family, and the proportion is likely to continue to increase as multifamily units have represented 50 percent of all new housing starts in the state since 2009[1]. Historically, energy patterns and cultural factors in multifamily settings have been understudied. The impact of changing demographics and shifts in housing type on the state's future energy use as well as the impacts of retrofits, products, and behavioral strategies with respect to these demographic and housing factors, is unknown.

The research team also investigated specific loads within multifamily homes. The biggest use of electricity in multifamily homes is not for cooling, heating, or ventilation. Rather it is the unregulated loads, such as lights[2], appliances, electronic devices, and miscellaneous electric loads (MELs), collectively known as *plug loads*. To meet the state's zero-net-energy goals, it is imperative to have a deeper understanding of the diversity of use patterns and the consumer's motivations for selection and using these plug loads. Energy use varies and different types of people make very different lifestyle decisions that impact energy use. It is not known, however, how to predict who will make what decisions, or how the sum of all those decisions is likely to impact aggregate, or collective, stateside energy use in the future, or the extent to which program interventions or strategies might be customized to best address these loads.

With substantially lower energy use per inhabitant on average than in single-family homes, multifamily buildings represent an important pathway to achieve zero-net-energy homes. This study builds on Pacific gas and Electric Company's (PG&E) Multifamily Upgrade Program (MUP) to help the state meet these goals by providing deeper understanding of the multifamily population, its diversity in energy use patterns, and motivations for adoption of efficiency measures.

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[1] California Building Industry Association.

[2] Lighting does have minimum efficiency requirements; however, no energy performance requirements in residential spaces.

Research Objectives

This study aimed to improve knowledge of how residents in multifamily dwellings use electric energy in their homes and how energy use patterns vary according to cultural and demographic factors, especially before and after whole-building retrofits. The project combined survey results and interval meter data analysis to delve into the *who*, *what*, and *why* of variations in multifamily energy use patterns.

There are five primary research objectives for this study:

1. Investigate if there are statistical (and underlying “lifestyle”) relationships between electric energy use and demographic characteristics of a multifamily household.
2. Study if resident use varies following a whole-building retrofit.
3. Investigate if communications to residents touting the benefits of a whole-building retrofit and providing education about related resident actions result in a reduction of resident electric energy use.
4. Investigate if providing residents with energy reduction devices designed to influence plug load energy use results in an overall reduction of resident electric energy use.
5. Determine if future modeling of statewide electric energy use patterns should include more detailed information about multifamily resident demographics.

Futhermore, this study addressed numerous “observational opportunities” and qualitative questions, such as:

- What are the various modes of communication favored by building owners to their residents? Can the research team detect any difference in receptivity to different mode types according to resident demographic characteristics?
- Can any differences be observed in residents’ attitudes towards energy efficiency based on their demographic characteristics?
- Do residents have different levels of interest in energy reduction devices based on their demographic characteristics?
- Does hands-on experience with energy reduction devices affect resident attitudes toward energy use and energy efficiency?
- How do residents react to energy reduction devices and how do they suggest improving the device’s user experience?
- How can findings from this study affect future energy efficiency programs and efforts?

Study Team and Partners

The project was led by TRC Engineers, Inc. with Mithra Moezzi of Ghoulem Research providing statistical analysis and project technical support.

As a partner in this study, PG&E provided substantial customer data about study subjects and interval electric meter data. As part of its cofunding of the project, PG&E also provided a subcontractor, Evergreen Economics, to conduct interval data analysis. PG&E actively participated in project planning, review and dissemination activities, to ensure that the project findings are directly useful to program marketing, planning, and evaluation.

Study Population

The research team used participants in the PG&E MUP as the study population and TRC engineers have implemented MUP since 2014. The program serves market rate and affordable multifamily properties (defined as five or more attached units) undergoing energy efficiency retrofits within PG&E's electric or natural gas service territories.

Projects participating in MUP must complete a minimum of two energy efficiency upgrades spanning two of the following categories: heating, ventilation, and air-conditioning (HVAC); envelope; domestic hot water (DHW); and lighting and appliances. The measures completed by the projects were intended to reduce either owner-paid or resident-paid energy use, or both. Some of the changes such as HVAC and DHW upgrades may not have any direct visibility to the residents whereas measures such as efficient appliances may be visible and under direct day-to-day control of the residents. This mix of measures offers this study the opportunity to test whether visibility of the whole building retrofits has any effects on energy use actions taken by the residents.

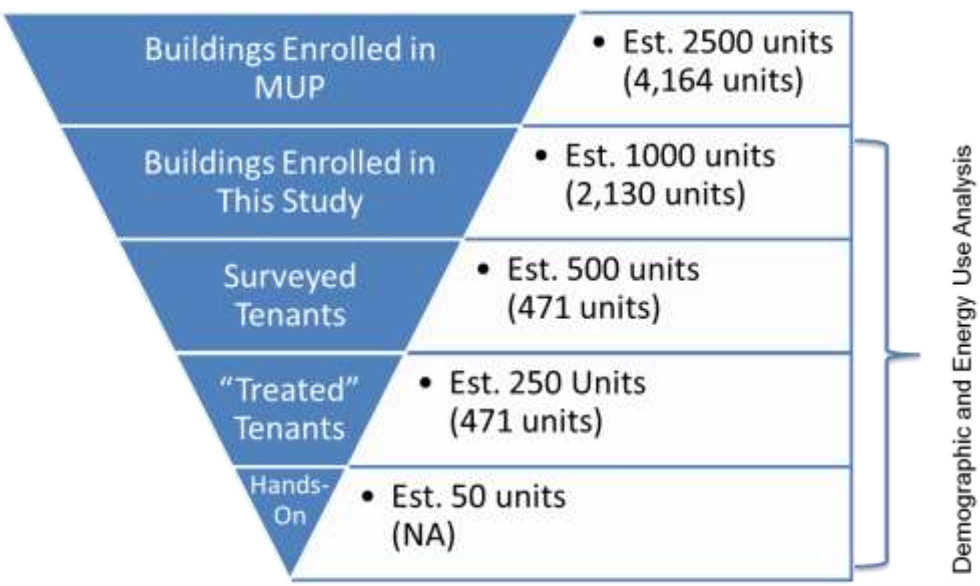
Eligible projects[3] for this study are located throughout PG&E territory (representing inland and coastal regions). Figure 1 shows the location of 42 completed projects in the MUP program (as of fourth quarter 2016).

Using participating MUP projects, TRC implemented a nested study approach (Figure 2). Anticipated number of units and actual (in parenthesis) units are reported below. This approach makes use of preexisting program completions to identify further subgroups for more detailed study.

[3] Buildings that receive electric service from municipal utilities, such as the Sacramento Municipal Utility District, were not eligible for this study.

Figure 1: Completed MUP Project Locations

Figure 2: Nested Study Approach: Estimated Number of Units and Actual Study Participation



During this study, 4,641 units participated in the PG&E MUP (increased from an estimated 2,500 units). From these, TRC anticipated up to 40% of units would participate in this study, whereas at final count, TRC saw a higher percentage of units enrolled in the study at 51% (2,130 of 4,641 units). By "enrolled in the study," means the energy use of these units was analyzed for the study and building owners and managers at these properties allowed TRC to collect demographic and other data from tenants through surveys. Tenants in 471 of these enrolled units completed a detailed survey of the resident demographics and energy consumption practices. Originally, the research plan called for a subset of these surveyed tenants ("treated" tenants) to receive energy use information and education as tenant communication pieces. In the end, TRC included all 471 units that provided surveys as "treated" tenants. Finally, a limited subset of tenants (50 units) was anticipated to participate in hands-on experimentation and use of energy reduction devices that control plug loads and appliances within the units. This portion of the study was removed from the project scope through a contract modification to dedicate additional resources to site and tenant recruitment for surveys. This was necessary due to most sites eligible for this study completing construction in third and fourth quarters 2016, which affected the timeline to adequately implement the "hands-on" portion of the study.

Expected Analysis Outcomes

This project improves knowledge of how residents in multifamily dwellings use electric energy in their homes and how patterns of energy use vary according to cultural factors. Analysis of historical and concurrent interval meter data provided by PG&E gave the research team specific energy outcomes to compare with information collected about the demographic characteristics of the resident population.

TRC anticipated the following outcomes for the study based on the activities outlined in the Method chapter:

- Conduct quantitative analysis to correlate cultural and demographic factors of the study population to energy usage patterns and changes in energy use patterns due to the study interventions.
  - Look for factors that may predict differential savings due to retrofit efficiency measures, rebound effects, or propensity to adopt consumer efficiency products
- Summarize qualitative observations and insights gained during the various interventions conducted during the project, including
  - Building owner and manager interest in promoting additional tenant savings
  - Tenant interest in adoption and use of consumer efficiency products
- Provide feedback and recommendations on how future utility programs might
  - Better target multifamily retrofit programs to accrue the highest savings
  - Encourage greater engagement from multifamily tenants in reducing personal energy use
- Report on factors that could be useful in future forecast and potential studies in predicting energy use and savings by
  - Multifamily tenants, according to their cultural and demographic characteristics, and
  - Examining to what extent this information might also be useful for other residential populations

The quantitative outcomes were driven by the data collection activities detailed Chapter 2: Method, but, in summary, consisted of two processes:

1. Data aggregation of interval meter data of participating MUP buildings to develop energy use profiles. The outcome of this analysis will be energy use data, by unit, including:
    - Weather-normalized electricity use load profiles.
    - Estimates of plug loads and lighting electricity use.
2. Regression analysis of the energy use profiles to investigate correlation of energy use with demographic factors.

The teams' analysis sought to determine the effect of enhanced communications or resident engagement or both.

The qualitative outcomes were based upon analysis of observations of building owner and tenant communication preferences, tenant willingness to participate in the study, and tenant willingness and response rates to the communications.

Finally, TRC combined the quantitative and qualitative analyses to draw conclusions to help guide future energy efficiency efforts. While the study focuses on multifamily dwellings, many of the study techniques and findings may also speak to broader residential energy use behavior, since multifamily residents are not a distinct demographic group in California but rather part of a statewide continuum. The results are structured to explain how changing demographics may impact future energy efficiency potential studies and demand forecasting models.

Study Challenges

This study used real customer account data with buildings that underwent retrofits. As a result, there are many factors outside the control of TRC that affected final results.

Sample Size: The study sample is a subset of the units enrolled in MUP. Even with a high resident participant rate, this sample is small relative to the complexity of energy use, the many dimensions of change, and the size of statistical effects anticipated. In addition, it is a sample of convenience. The TRC team did not know the demographic balance of the MUP population ahead of time as the program does not collect any information on residents and cannot predetermine sampling goals. The primary criterion for being accepted into the study was willingness to participate, by the owners and the building residents, and therefore the study has a certain self-selection bias inherent in this approach. Though statistically sensible methods were used to properly analyze the data, the statistical results cannot fairly be claimed to represent MUP participants or multifamily households overall[4].

Demographic Data: The team designed the demographic questions in the survey to synchronize with the definitions used in Census Bureau products, with attention paid to keeping the survey reasonably easy and appealing and balance acquiring detail with assumptions about the statistical viability of this detail in the final sample. The team assumed

[4] Statistically representative samples are rare in energy efficiency fieldwork.

at the very least it would be able to distinguish multifamily residents by basic age and economic brackets with a reasonable sample size. Given the recruitment success the team could also differentiate residents by more than one ethnic, language, educational status, family status, lifestyle or attitudinal group. Small sample sizes for various demographic categories did not support definitive statistical analysis but instead supported more qualitative observations about attitudes and behaviors.

Time Frame and Budget: This study was designed to leverage information about and access to MUP participants, requiring tight coordination between two programs with different time frames and budget constraints -MUP and EPIC. To complete the study within project time frame, and to have at least a year of interval data to analyze before and after building retrofit and behavioral "treatment" of residents, the time to recruit and interact with those residents was limited to 14 months with most projects completing retrofits the third and fourth quarters of 2016.

Confidentiality: Since PG&E was a key partner with TRC on this study, the study complied with PG&E's customer confidentiality and information security protocols. This included protecting all customer data from public release and having the management of data handling and analysis pre-approved by a PG&E Data Governance Committee. TRC worked with PG&E to obtain Data Governance Committee approval where necessary. The team maintained the confidentiality of customers by limiting the processing of electric meter data to a third-party interval data analyst, Evergreen Economics, hired directly by PG&E. This analysis was guided by TRC, and its output became input to the regression models of this study.

CHAPTER 2: Method

This section outlines the methodology, data sources, and collaboration among multiple project team members.

TRC used a multistep data collection and analysis plan including;

1. Multifamily Upgrade Program Participant recruitment, and tenant engagement to complete surveys and advance tenant communication pieces.
2. PG&E interval data for 12 months preretrofit and postretrofit for all buildings that enroll in the research project.
3. Multivariate statistical techniques to jointly analyze energy-use data in combination with information about the cultural and demographic characteristics of the tenants.

Prior to any interaction with building owners, managers, or tenants, TRC reviewed available demographic and marketing information, including data from PG&E and other sources such as the United States Census and California Residential Appliance Saturation Surveys. In addition, TRC reviewed current CPUC potential study models and the California Energy Commission demand forecast models. These data points were reviewed and used to develop a research plan documenting agreed-upon research objectives, data collection method, analysis methods, and key decision points for the study.

TRC used a nested study approach (discussed in the Study Population section) which used preexisting Multifamily Upgrade Program (MUP) enrollments to identify further subgroups for more detailed study.

As the implementer for PG&E's MUP, TRC recruited and enrolled owners of multifamily buildings that would undergo whole-building retrofits during 2015. The MUP staff would ask building owners and managers if they would like to participate in this research study, and explained likely benefits to the building owner, with emphasis on and public relations and goodwill with tenants. This approach leveraged two key benefits of multifamily buildings: the density of the buildings and a preexisting communication channel. Another advantage of MUP collaboration was that every unit is part of a building undergoing a large-scale energy retrofit. As screening criteria to participate in this research study, buildings must already have interval electric meters for all units.

The team worked with the building owners and managers to identify the best approach to contact their tenants. Following initial contact, TRC worked with the building owner or manager to survey tenants through electronic surveys, paper surveys, and/or interviews, or a combination thereof. The survey objective was to gain a better understanding of tenant demographic information, energy use habits, attitudes, and preferences. To allow easier comparison, the structure of survey questions correlated as much as possible with other relevant studies, such as the *California Residential Appliance Saturation Survey* (RASS) or the Opinion Dynamics Segmentation Study for the California Public Utilities Commission (CPUC).

TRC also worked MUP staff and building owners and managers to craft tenant engagement (survey form and tenant communication mailers) activities best suited to their facilities and tenant culture. The team provided information including targeted tenant communications that explain the benefits of the building retrofit underway, the role of the building owner in undertaking these upgrades, and opportunities for tenants to join in with their own energy saving efforts.

PG&E then provided interval data for 12 months pre- and postretrofit for all buildings enrolled in the research project. One of PG&E's contractors, Evergreen Economics, analyzed the interval meter data funded by PG&E. Electricity use data were provided in 15-minute intervals for one year pre-retrofit and post-retrofit. The period for interval analysis spanned from 24 to 30 months, encompassed a matched set of seasons for pre- and poststudy periods, and excluded the time of retrofit installations. This interval meter data analysis is a cornerstone of the study's findings, assisting in understanding energy use patterns among various cultural and demographic groups and how they varied before and after the whole-building retrofit.

After completing the interval data analysis, multivariate statistical techniques were used to analyze energy use data in combination with information about the tenants' cultural and demographic characteristics. The analysis techniques included such methods such as general linear models (including multivariate regression models), clustering analysis, and other exploratory data analysis methods.[5]

The following sections discuss the methods used for data sources and uses, participant outreach and recruitment, participant engagement, survey analysis, and utility data analysis.

Data Sources and Uses

A variety of data from multiple sources feed the two-part analysis for this study – qualitative analysis and quantitative analysis.

Qualitative Analysis

The qualitative analysis used existing data sources (listed below) as well as primary data collected by TRC. The following sections describe in detail each data source, use in this study, which project team member handled and analyzed the data.

Publicly Available Data Sets

Publicly available data sets related to demographics or energy use or both, including the California RASS for 2009 and the U.S. Census.

RASS was a survey funded by the Energy Commission in 2009 that analyzed the energy-using devices in single-family and multifamily households. The aggregate RASS data weres available

[5] For more information, see: Mardia, K. V., Kent, J. T., and Bibby, J. M. (1979). *Multivariate Analysis.* Academic Press.

online[6] through a KEMA-hosted data server linked to the Energy Commission website. Detailed (household-level) microdata were available only with Energy Commission consent. To the extent appropriate, the TRC survey instrument was designed to parallel survey questions and response categories from RASS and the as U. S. Census Bureau categories, where relevant, to simplify comparisons between the two data sets.

The U.S. Census provided aggregate data on household demographics used to consider and make inferences about data collected in the study. Where appropriate, study categories were replicated from those used in the Census to assist this comparison and to otherwise standardize basic categorical data. Census data were obtained online.

Both data sets were obtained by TRC and the survey analyst to help inform the tenant survey instrument.

CPUC's Energy Efficiency Potential Study and Demand Forecast

This study intended to provide insight into whether there is the potential for demographics to be factored into developing the CPUC's Demand Forecast and Energy Commission's Energy Efficiency Potential Study. TRC conducted an analysis determining how the models are developed and how outputs from this study could in theory be incorporated into the Forecast and Potential Study.

The *2013 California Energy Efficiency Potential and Goals Study* by Navigant Consulting, Inc. for the CPUC used a bass diffusion theory (Bass 1969)-based model to forecast potential adoption of energy efficiency program measures offered by the investor owned utilities (IOUs). The predicted annual adoption rates over time are multiplied by the energy savings per unit of the efficiency measure to produce the annual market potential of the corresponding efficiency measure.

The *2018 California Energy Efficiency Potential Study* was released in September 2017 (Navigant, Inc. 2017). As did the 2013 potential study, the 2018 study used a Bass diffusion model to simulate adoption of energy efficiency measures. The 2018 study included a refreshed list of residential (and commercial) measures, as well as the potential of behavioral, retrocommissioning, and operational (BRO) efficiency measures including some for the residential sector. For the residential sector, the study considered 18 appliance and plug-load measures and 29 lighting measures out of 68 measures as the those most relevant to the occupant-controlled portion of multifamily housing units. Residential BROs considered were home energy reports, Web-based real-time feedback, in-home display real-time feedback, small residential competitions, and large residential competitions (Navigant, Inc. 2017, p. 72).

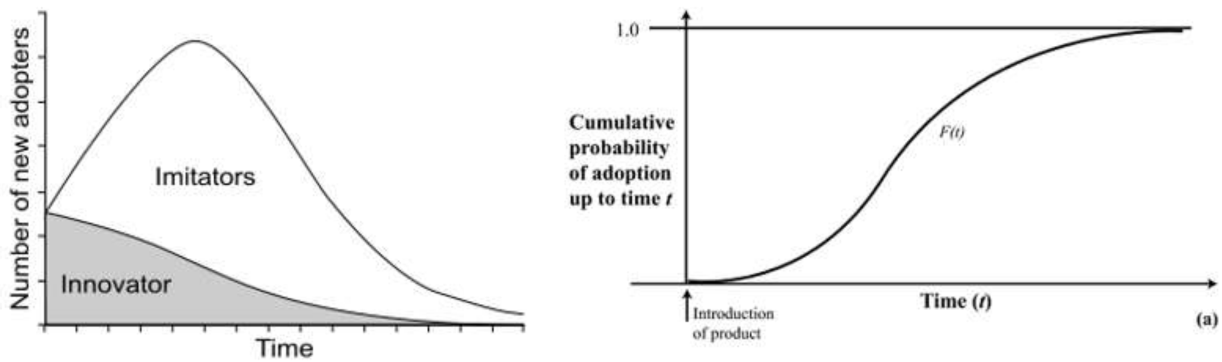
The Bass Diffusion Theory

The Bass diffusion theory developed by Dr. Frank Bass has been widely used to model the market adoption of new products. According to this theory, there are types of adopters, innovators and imitators, who reflect two market adoption mechanisms. Innovators make

[6] www.energy.ca.gov/appliances/rass/

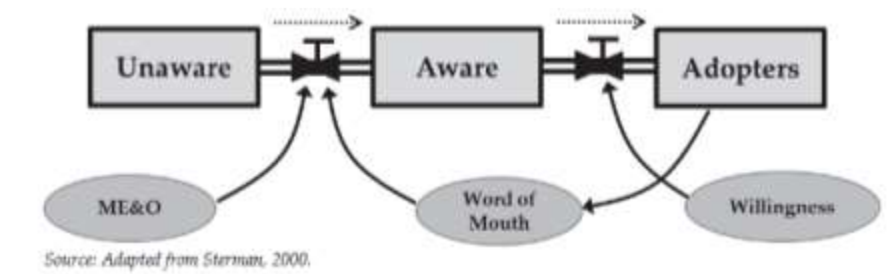
adoption decisions based on their own evaluation of the product, while imitators are influenced by existing adopters. Innovators generate the initial adoption, while the imitators produce faster growth of adoption as they are produced through the multiplying effect of existing adopters. Figure 3 illustrates how the two adopter groups grow over time (left) and the right diagram shows the cumulative adoption rate over time, which is characterized as a S-curve.

Figure 3: Adopter Groups



The model approach used by the CPUC/Navigant potential study to implement the Bass diffusion theory is illustrated in Figure 4. The population of potential adopters was separated into two, those who were unaware of the efficiency measure and those who were aware. Only the aware population became adopters and the rate of transition as determined by the willingness factor. Conversion from unaware population to aware population was through a factor reflecting marketing, education, and outreach (ME&O) effects and the influence of adopter through the word-of-mouth (WoM) effect. The latter reflected the adoption mechanism for imitators.

Figure 4: PG Model



Adoption Model

The CPUC/Navigant potential study report did not provide a detailed explanation of how the three adoption effects (ME&O, WoM, and willingness factor) were modeled to predict adopter rates. A further investigation of the software used to develop the model[7]reveals complicated calculation steps (Figure 5 and 6) and the adoption model includes multiple inputs (Figure 7).

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[7] The CPUC/Navigant potential model was developed using the Analytica® software (http://www.lumina.com)

Figure 5: Awareness Model Used in the CPUC Potential Study

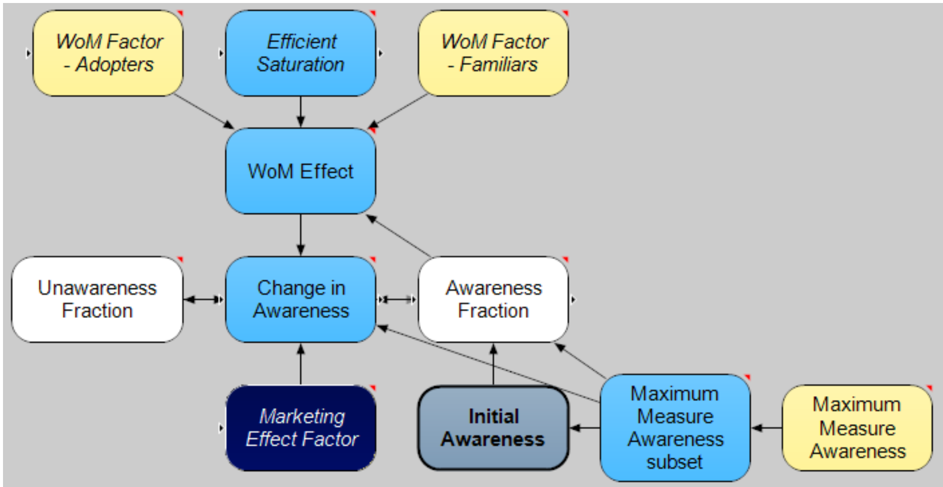


Figure 6: Details of the Awareness Model Used in the CPUC Potential Study

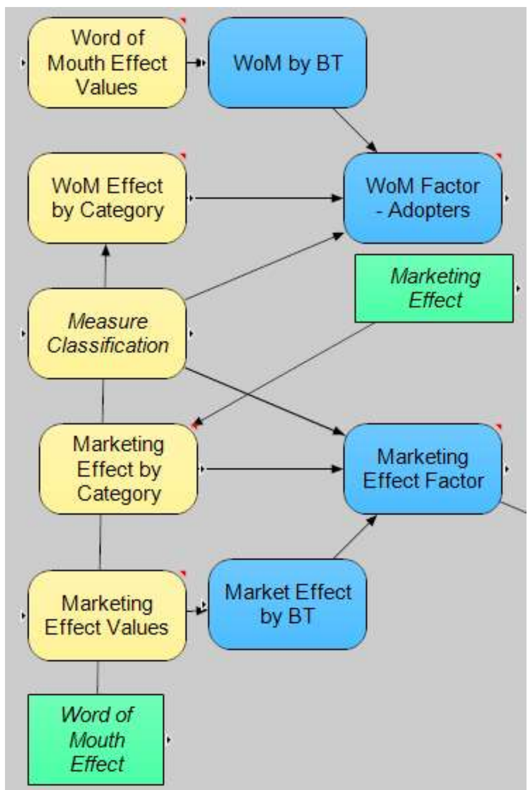
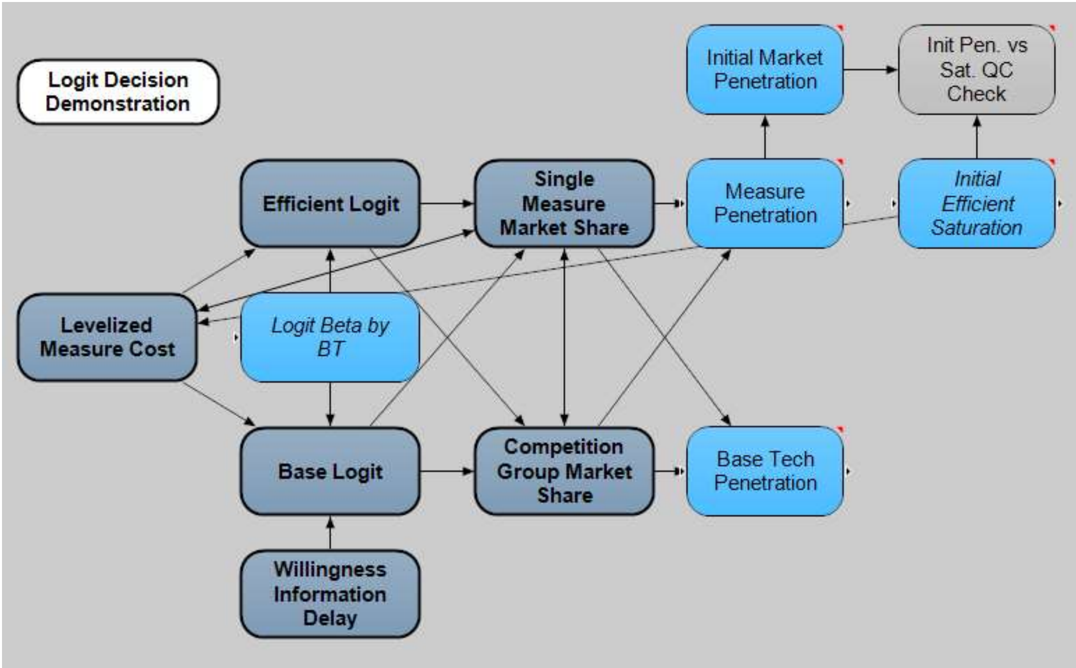


Figure 7: Willingness Model Used in the CPUC Potential Study



The adoption model was applied to each efficiency measure to be installed in different buildings types (labeled BT) and market sectors (residential, commercial, industrial, agriculture, mining, and street lighting). The model data structure was designed to use adoption parameters that are specific to each measure, building type, and market sector. The model contained detailed assumptions of each input parameters related to the three adoption effects.

In theory, these model parameters depended on the characteristics of efficiency technology, program implementation, and market actors. However, the CPUC/Navigant potential model used constant values for many efficiency measures. For example, the marketing effect factor was assumed to be 0.024 for commercial lighting measures, 0.015 for most commercial nonlighting measures, and 0.05 for most residential measures. The parameter of the WoM Factor – the fraction of the potential adopter population exposed per year because of contact with those who are familiar but haven't adopted the product was assumed 0.1 for all measures. These simple assumptions may reflect the modeler's assessment that these market effects are not measure sensitive or the fact that detailed market effect information is not available. The potential study report also explained that adoption forecasts were calibrated to past program achievements but did not reveal which modeling parameters were adjusted during the calibration to align the forecast with past program achievement.

Cultural and demographic differences will influence all three adoption effects (ME&O, WoM, and willingness). To incorporate this influence into the potential study model, the existing model was expanded so that values are developed for different cultural and demographic groups. This expansion allowed the different adoption model parameters to be used for different cultural and demographic groups, if there were substantial variations among these groups. To support this modeling approach, this study surveyed study participants to gauge their responses to marketing efforts and reported how different groups were affected. The collected data could be used as the basis for any future effort to develop adoption model parameters. If different adoption effects are quantified for different cultural and demographic groups, then future demand forecast and energy efficiency potential studies will more accurately reflect the impact that these populations have on the state's energy use.

PG&E Customer and Electric Interval Data

To assess changes to electric energy use, this study analyzed detailed electric use data of MUP tenants. PG&E provided the most vital pieces of data for this study for 12 months pre- and postretrofit for all buildings identified as eligible by the TRC team. Before providing any data to the TRC team, PG&E went through its data governance review process for approval. The TRC team at no point possessed the raw electric interval meter data, and PG&E and its interval data analyst used PG&E's secure transfer procedures to ensure data was always privileged and secure. PG&E's interval data analyst examined the raw interval meter data to generate typical energy-use load profiles that were shared with the TRC team.

The TRC team made it a priority to ensure that PG&E interval meter data reliably linked to the correct physical location and customer. This was challenging because of the complexity of multifamily buildings and tenants, where not only do tenants move frequently, but even building addresses and unit numbers are often revised. To address these issues, the TRC team and PG&E developed a multistep process to map MUP building addresses and number of units on each site to PG&E service agreements for each customer. After several rounds of address mapping this resulted in most units matching to a PG&E service agreement.

Once unit addresses were mapped to a PG&E service agreement, PG&E provided to the appropriate parties for analysis. Customer information used to analyze electric energy use and demographic data are in Tables 1-3:

Table 1: Customer Characteristics for Population of Residential Electric Accounts

Anonymized Account ID	Anonymized Premise ID	Person ID
Service account ID	Service point ID	Service account status
Service account start date	Service account stop date	Service account Customer Name
Service account Customer Name2	Date on premise	CARE indicator
Full service address	Service address city	Service address zip code
CEC zone	Climate	Weather station
Net metering status	Meter configuration	Rate schedule
Service account type code	Residential dwelling type	Premise type
Medical baseline	Vulnerable or disabled status with corresponding dates	Energy Savings Assistance (ESA) indicator
Energy Savings Assistance (ESA) participation dates		

Provided to TRC and interval data analyst

Table 2: Account-Level Customer Attribute Data

Acxiom Data Elements		
Anonymized Account ID	Anonymized Premise ID	Service account ID
Service point ID	Age	Country of origin
Education	Estimated household income	Owner or Renter
Property type	Square footage	Year built
Household Size	Length of residence	Number of adults
Occupation	Presence of children	Ethnicity
Language preference		

Provided to TRC and interval data analyst

Experian Data Elements (continued)		
Date of Birth/Combined adult age	Homeowner	Combined homeowner
Homeowner/Renter indicator	Number of children (Maximum Of 8 Children Per Household)	Number of adults in household
Additional adult household members	Presence of children age ranges	Presence of children 0-18
Swimming pool indicator	Estimated household income	Average Scores Plus score
Base square footage in hundreds	Home stories	Dwelling type
Length of residence	Language spoken in home – Ethnicity	

Previously purchased by PG&E from third party providers and provided to TRC and interval data analyst

Table 3: Interval Electric Meter Data in 15-Minute Intervals

Service account ID	Service point ID	Account ID
Premise ID	Date	Hour
kWh	UOM	DIR

For one-year pre-retrofit and post-retrofit (Provided to PG&E interval data analyst only)

Furthermore, PG&E provided weather data for all PG&E weather stations to the PG&E interval data analyst.

Multifamily Upgrade Program Data

As part of implementing MUP, TRC collected a large amount of data on the buildings and related retrofits. Some of these retrofits, such as exact details of architectural plan sets, were not recorded in a rectangular database that can be sorted. A great deal of data, however, was tracked in a database that can be coordinated with the other data sources and includes this information on the building:

- Age
- Number of units
- Number of bedrooms
- Square footage
- Retrofit measures being adopted
- Types of mechanical systems
- Energy savings estimated (modeled)
- Dates of retrofit beginning and completion

These data were mined from the database TRC manages on behalf of MUP and provided to the survey analyst in an anonymized format.

Multifamily Tenant Energy Habits and Attitudes

The TRC team developed a survey to administer to tenants in participating MUP sites. The survey was designed to collect data on household demographic and cultural characteristics, energy-use practices and experiences, and some of the occupant-installed energy using equipment. The intent was to create a compact instrument that captured behavioral, social, demographic, and technical information that could support the advanced metering infrastructure (AMI) data analysis in exploring relationships between household characteristics and electricity-use diversity, support plug-load and related household interventions, and make progress in painting a more general picture of energy use in these homes. Questions and response categories for demographic and house characteristics data were modeled after the California RASS, the U.S. Department of Energy's Residential Energy Consumption Survey (RECS), and U.S. Census questions to the extent reasonable. The survey questions were written to ask about **all individuals in the household, not just the head of household** (as the U.S. Census is written). Surveys were provided in English and Spanish and were fielded by a variety of methods (paper or internet) based on the recommendations of the property manager. Survey topics included (full survey is in the attachment):

- Household information and demographics such as number of residents, age, gender, ethnicity, employment, and occupancy
- Energy use technologies and practices such as appliances, heating, cooling, cooking, and water heating
- Thoughts and opinions on energy use and energy costs such as energy upgrades and comfort

These data were collected, stored, and anonymized by TRC and provided to the interval data analyst and the survey analyst for analysis.

Quantitative Analysis

A variety of data feed into the analysis. Table 4 provides a list of the data used for each of the quantitative analysis steps. Depending on the source, different subsets (and thus sample sizes) were available for the various analyses.

Table 4: Data Needs by Analysis Task

Analysis Process	Data Required	Source
Data aggregation of interval meter data of participating MUP buildings to develop energy use profiles	Demographic information of household members	Survey, Acxiom, Experian
	Changes to household preceding, during, and after retrofit	MUP
	Electric use 12 months prior to retrofit Electric use 12 month following retrofit	PG&E
	Building information	MUP
	Type of retrofit	MUP
	Weather data	PG&E
	Electricity consuming devices in household	Survey
	Changes to household preceding, during, and after retrofit	Survey
Regression analysis of the energy use profiles	Energy use profiles	Interval Data Analyst (PG&E)
	Demographic information of household members	Survey, Acxiom, Experian
	Changes to household preceding, during, and after retrofit	Survey
	Building information	MUP
	Type of retrofit	MUP
	Electricity consuming devices in household	Survey

Participant Outreach and Recruitment

TRC used a multistep process for participant outreach and tenant recruitment. The first step was to identify projects from within the population of MUP-participating buildings undergoing building retrofits efforts in 2015 and early 2016 eligible for the study. Since TRC has been implementing MUP since 2014, regular meetings between MUP staff and the TRC team conducting this research identified ongoing project completions eligible for study recruitment. The TRC team conducted ongoing outreach to fulfill study participation goals and coordinated closely with MUP staff to receive regular updates on MUP project completion to add projects into the outreach pipeline.

The first phase of outreach focused on recruiting MUP participant property owners and managers (owners). Participating owners served as a connection to multifamily tenants and allowed TRC to verify retrofit project and tenant information (including any changes in unit occupancy). The owners also supported TRC's efforts to recruit tenant participation.

TRC sent an initial email to all building owners who participated in MUP and who receive electric service from PG&E to inform them of the study. The intent was to inform the building owners of the potential benefits of this study and alert the owners that TRC would contact them in the future for study participation. Next, TRC advanced this initial email communication by contacting building owners to persuade them to participate in this study. To do so, TRC assigned appropriate MUP staff member(s) to either call or email each owner individually to recruit for this study.

As part of agreeing to participate in the study, the building owners reviewed and approved TRC's outreach to residents. Owners were requested to provide TRC with information about the number of residents, languages spoken, and preferred means of communication among other known demographic characteristics of their residents. TRC realized that this level of information might not always be available for each building or unit but would collect this information where available. TRC used the surveys to collect this information directly from the residents, but having some of this information early in the recruitment process helped TRC determine the most effective formats for messaging and tenant enrollment in the study.

TRC worked with the sites to provide study announcement flyers to post on site before issuing surveys. This was not always possible due to site policies regarding solicitation.

TRC kept systematic records of all owner enrollment activities including the effectiveness of various forms of owner outreach. TRC developed a project database that recorded all interactions with building owners and kept track of participation decisions. This database contains the following pieces of information (parentheses indicate source of information):

- Age of the building (MUP program data)
- Appliances built into unit (MUP program data)
- Breakdown of affordable vs. market-rate units (MUP program data)
- Condo or rental (MUP program data)
- Condo price or monthly rent (building owner outreach)
- Fuel type for cooking (MUP program data)
- History of retrofits (MUP program data)
- Languages spoken by residents (building owner outreach)
- Primary method of resident communications (building owner outreach)
- Turnover rate (building owner outreach)

Phase 2 of outreach targeted tenants of participating sites to engage with the study activities (survey, communications, etc.).

TRC developed the following outreach materials to recruit projects and tenants (Table 5).

Table 5: Participant Outreach Materials

Collateral Piece	Purpose
MUP Email Announcements	Stand-alone announcement that provides study overview/introduction to MUP property owners and managers. Distributed through MUP email channels Targeted email announcement to property owners sent upon completion of MUP participation
Study prospectus: owner/manager and tenant versions	One-page prospectus that outlines study details, including benefits and participation timelines; two versions to appeal to owners and tenants
Tenant door hangers	Direct communication to tenant units introducing the study requesting their participation

Outreach materials are in Attachment A: Outreach Materials.

Participant Engagement

This section outlines participant engagement activities including tenant survey and tenant communication pieces.

Surveys

TRC administered all tenant surveys through a hard copy door hanger placed on each tenant's door. The door hanger included a paper survey and Web link to an electronic version (administered through Survey Monkey). Surveys were provided in Spanish and English via hard copy and electronically. In consultation with the building owner or manager, preset incentives for all were used to encourage greater participation.

Questions in the surveys focused on (1) household characteristics and demographic information (2) energy-use behaviors, attitudes, and knowledge; and (3) technical characteristics of the house. Resident survey questions and possible responses were modeled after the survey forms used for the RASS and U.S. Census surveys to ensure that results from this project are comparable to those of these broader and ongoing survey efforts.

Tenant Communications

Tenants who completed a survey received further study engagement via tenant communication pieces. Information provided to residents emphasize the social value, energy savings, and improved comfort of the building retrofit underway and the residents' ability/options to contribute to the energy goals of the building retrofit via participation in this study.

A series of six tenant communication pieces were delivered by U.S. Postal Service on oversized postcards. The communication pieces focused on the following topics and translated in English and Spanish.

1. Energy Use Awareness: Save on your utility bill
2. Lighting: Tips for Saving

3. Heating and Cooling: Tips for Saving
4. Appliances: Tips for Saving
5. Water and Energy: Tips for Saving
6. Plug-in Devices: Tips for Saving

The tenant communication pieces are in ATTACHMENT III: TENANT COMMUNICATION MAILERS.

Data Management

To determine how best to manage the data in this study, TRC reviewed the data management requirements as part of the grant agreement between TRC and the California Energy Commission, identified all the data sources that the study used, and determined the best process for storing and combining the data.

Data Management Requirements

TRC incorporated and treated all data in accordance with the EPIC Standard Grant Terms and Conditions and the EPIC Special Terms and Conditions. These included the following provisions:

- TRC will maintain a record of the source of an individual's personal information.
- TRC will only keep personal information as long as necessary to comply with the terms of this agreement and then will destroy it.
- TRC will employ appropriate and reasonable safeguards to ensure the security and confidentiality of personal information and to protect against anticipated threats or hazards to the personal information's security or integrity, which could result in any injury.
- TRC has no ownership or other rights to the personal information.
- Upon the request of the Energy Commission, or upon termination of this agreement, whichever is earlier, TRC and any subcontractor or partner who will collect or otherwise have access to personal information, shall promptly deliver to the Energy Commission or destroy all personal information existing in written or electronic form or recorded in any other tangible medium (and all copies, abstracts, media, and backups thereof, however stored) in TRC's, and all of its subcontractors' and partners', possession. No personal information shall remain with TRC, nor its subcontractors, after the termination of this agreement.

Data Sources and Formats

TRC used the following data sources to process this study:

- **PG&E Account Data**: PG&E provided TRC with data for the accounts of those residents that participated in the study. These includes information on how the accounts have interacted with PG&E in the past, including service start/stop dates, and information purchased from third-party providers. PG&E provided this information for the roughly 4,100 units in Multifamily Upgrade Program (MUP)-participating buildings. PG&E

provided TRC with a data dictionary for the third-party purchased data and TRC received these data in comma-separated values (CSV) format.

- **MUP Program Data**: As part of its activities as the MUP implementer, TRC collected information about participants in MUP, including building size, location, and retrofit measures. TRC was required through its contract with PG&E to keep project specific information private and maintains this information in a Microsoft Dynamics database. PG&E gave TRC approval to use MUP data for this EPIC study. MUP data were maintained separately from any EPIC study data, eliminating the possibility of accidental data contamination.
- **TRC Data Collection:** TRC collected two types of data throughout this study.
  - **Owner Questionnaire:** To recruit owners, TRC used a standard questionnaire that confirmed study eligibility, and solicited information about residents and how to best engage them in the study. TRC administered this questionnaire to 42 owners. Following the interviews, TRC manually recorded their answers in an electronic database.
  - **Resident Survey:** Upon securing building owner agreement to participate in and promote communication regarding the study, TRC administered a survey to residents of such buildings (nearly 2,100 units). TRC received 471 surveys from participating sites. Residents completed surveys in either electronic or paper format; the paper format was scanned using optical recognition software and input into an electronic format that is compatible with outputs from the electronic surveys.

PG&E Electric Energy Use Data: PG&E provided interval electric meter data to an interval data analyst (IDA), who produced energy use load profiles to TRC. TRC did not have access to the original interval electric meter data that PG&E provided to the IDA. The IDA generated energy use load profiles for both the approximately 4,100 units in MUP-participating buildings. The IDA provided these data in Microsoft Excel format through a secure File Transfer Protocol (SFTP). These data were stored on a restricted server accessible only by select TRC employees. The server backups are stored separately from other TRC server backups so that sensitive data can be destroyed at the appropriate time.

TRC also consulted publicly available data sources, including the *2009 California Residential Appliance Saturation Survey* (RASS) and the U.S. Census. Since these data sets are not specific to the study residences, TRC did not include them in the database or processes and instead used them as a comparison for macrolevel findings, such as between income groups, housing types, or regions.

Data Management: In determining a data management approach, TRC identified three priorities: (1) linking data sources to enable analysis, (2) ensuring the security and confidentiality of all resident and building owner data, and (3) transmitting information between TRC and Ghoulem Research.

To track units across all the different data sets and reduce the effect of differing building or unit nomenclature, TRC worked with PG&E to develop a unique identifier for each unit in the study. PG&E provide these identifiers to the IDA. Moreover, TRC maintains all data in Structured Query Language (SQL), which is the standard language for relational database management systems according to the American National Standards Institute. To view all the data concurrently, TRC used Microsoft's SQL Server Reporting Services, which enables the integration of data from a variety of sources, such as Excel spreadsheets and Dynamics databases.

To ensure the security and confidentiality of data, TRC:

- Stored all the resident and building information collected on a secure server that was accessible only by TRC employees designated to view this data. This allowed TRC to keep MUP data separate from resident and building-specific study data (that TRC collected).
- Transmitted any private resident or building data through a SFTP.
- Required Ghoulem Research to adhere to the data security protocols described here for these data files. This enabled TRC to share data with Ghoulem Research without compromising the data.
- Assigned a unique identifier to each unit (as discussed above) to reduce the need to store account usage information and account identifier information together.

Data Analysis

Surveys

The surveys were designed to provide basic characterizations of household demographics, equipment, energy-related practices, and related perspectives, in addition to supporting load shape comparisons across demographic and other group definitions. The survey data were cleaned and recoded where warranted. All valid records were matched to PG&E account information based on tenant address. To protect respondent privacy and comply with data security agreements, each record was henceforth identified by a unique ID composed of PG&E account ID, premise ID, and meter number, with the address and all other personally-identifiable information suppressed.[8]

The survey data were then merged with basic PG&E account information (e.g., account start date, rate class, and climate zone), information on the MUP upgrades completed, and with consumer data from Experian and Acxiom.[9] Thus the master household characterization data base consisted of a combination of survey data, PG&E account information, MUP retrofit information (including property identifier), Acxiom data and Experian data, with varying degrees of record completeness. The interval meter data, as noted above, were stored and analyzed independently of the master household characterization data set.

[8] That is, the survey data analyst had access to this ID and premise ZIP code but no personally identifiable information and no electricity usage data.

[9] In addition, where available, the team drew on supplemental information from the property (e.g. unit square footage) to fill in data for incomplete surveys when possible.

The surveys were designed to provide data of interest in addition to coordinating with load data. There were two main phases of survey data analysis. First, survey data were used to produce basic descriptions of the households and what respondents said about their energy use and energy equipment (e.g., how they heated and cooled their home, satisfaction with indoor temperature in summer and winter, the presence of a variety of plug loads).

Load Shape Analysis

Second, a set of grouping variables was developed for use in the load-shape analysis. This grouping analysis used available data to find a small set of variables (grouping variable), each of which consisted of several categories across which household load data could be differentiated (variable categories) (Table 6). For example, one grouping variable pertained to a hybrid of ethnicity, race, and language, and another grouping variable pertained to income. This suite of grouping variables was developed to meet several criteria: (a) to cover the most basic demographic characteristics known to be related to energy use patterns and levels; (b) to include variables of specific interest to the research project (e.g., ethnicity, plug loads) that were likely to yield differences across groups or for which it would be useful to know if there were no such differences; (c) to produce adequate group sizes as required for the statistical procedures in the interval data analysis and to avoid groups that were too small with respect to customer data protection; and (d) to bring into play as many of the available customer records as possible.

Achieving grouping variable definitions that met these criteria was an iterative process that sometimes required coordinating across variable definitions that were inconsistent across data sources (e.g., income categories). Since the load data analysis was designed to be conducted separately from the survey data analysis, the survey data analyst used the fixed effects coefficients provided by the interval data analyst to help develop an early set of grouping variables. Candidate groupings were examined graphically and with analysis of variance modeling. These grouping variables were later refined based on usage bin (average energy use across all hours) and normalized load bin derived from k-means clustering of customer load shapes. Table 6 summarizes the grouping variables used in the final load shape analysis.

Table 6: Grouping Variables Used in Demographic Load Shape Analyses

Grouping Variable/Dimension	Records Group	Variable Categories
AC-Related Upgrade Project	All records	Direct, indirect, non-AC, incomplete projects
County Group	All records	Alameda, Contra Costa, Fresno, Kern, Placer, San Benito, San Francisco, San Joaquin/Yolo/Tehama, San Mateo, Santa Clara, Sonoma/Napa/Marin

Tenure	All records	1 year or less; from 1 to 2 years; from 2 to 4 years; from 4 to 10 years; from 10 to 20 years; 20 or more years
Household Income	All records	Under \$10K-\$15K; \$11-\$25K; \$15K-\$30K; \$26K-\$40K; \$30K-\$40K; \$41K-\$70K; \$71K-\$100K; Over \$100K
Household Composition	All records	1 person 19-35; 1 person 36-65; 1 person 66 or older; 2 more people with kids; 2 people 1 over 65; 2 people under 65; 3 or more people, no kids
Ethnicity, Race, Language, Foreign-Born	All records	African-American, European, English-speaking Hispanic not born in US, English-speaking Hispanic born in in US, Spanish-speaking Hispanic not born in US, Spanish-speaking Hispanic born in US, English-speaking non-European; Non-European non-English speaking; other English speaking
Number of small electronics	Surveyed units only	Few, low-middle, high-middle, lots

Utility Interval Data by Evergreen Economics Through PG&E Match Funds

PG&E provided AMI whole-home consumption data and weather station data for 8,675 customers residing in 42 buildings that participated in the Multifamily Upgrade Program. For consistency across customers in the study, all 15-minute interval consumption data were aggregated to the hourly level.

The AMI data for this study contained nearly 111 million hourly observations from January 2014 to mid-June 2017; the intent was to capture at least one year of preretrofit and one year of postretrofit data. However, only 31 percent of customers in the sample had at least one full year of preretrofit AMI data. This is to be expected, given the high tenant turnover rates in multifamily buildings and the long building retrofit periods of 3 to 30 months. Rather than base program-level savings estimate on this small subset of customers with sufficient preretrofit data (and unusually long tenure), the pre-retrofit data requirements were relaxed. For this analysis, customers were excluded with:

- Net energy meters.
- Less than two weeks of pre-retrofit AMI data.
- Average daily kilowatt-hours (kWh) of less than 0.1 in the pre- or postretrofit.
- Extreme changes in average daily kWh from the pre- to postretrofit of more than 150 percent or less than -67 percent

The billing analysis conducted in this study uses the interval data analyst's AMI Customer Segmentation (AMICS) model; this approach was tested extensively on residential HVAC programs in Phase I of the AMI Billing Analysis Study conducted by Evergreen Economics for PG&E through a separate contract. The ongoing Phase II study (also between PG&E and Evergreen Economics through a separate contract) has expanded this research to include a variety of commercial programs and PG&E's residential Home Energy Reports.

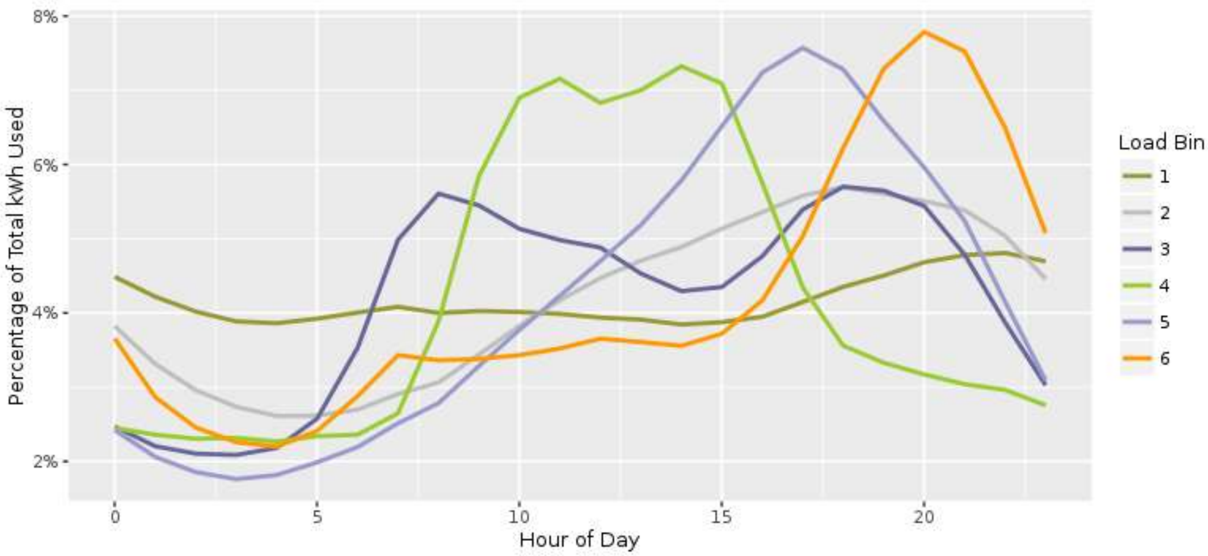
A unique step in the AMICS approach is segmenting the data into thousands of distinct bins. Each bin contains customers with similar energy usage patterns on days with similar characteristics. By binning the data before modeling, Evergreen Economics limited the amount of variation (across customers and days) that the model must account for.

For this study, Evergreen Economics segmented customers by two key characteristics: their daily energy use (magnitude) and their load shape (hours of use) during the preretrofit period.

For the daily energy use, customers were ranked in ascending order by this statistic and then assigned to one of 10 usage bins, such that each bin represents about 10 percent of total daily electricity usage for the sample. The number of customers in each bin varied but the kWh represented by each bin was approximately the same.

The load-shape bins are groups of customers with similar hours of use (i.e. load shapes), identified through *k*-means clustering. Cluster analysis is an unsupervised machine-learning algorithm designed to detect patterns in the data. The *k*- means clustering algorithm randomly assigns each customer's load shape to one of *k* clusters and then calculates the sum of the distance between each load shape and the centroid (i.e. average load) of the cluster to which it was assigned. Load shapes are then reassigned to the nearest cluster centroid, and the process is repeated until the variation within each cluster cannot be improved. Evergreen Economics used *k*-means clustering to identify the six unique clusters shown in Figure 8, each containing a subset of customers with similar load shapes (hours of use) throughout the preretrofit. The benefit of using cluster analysis is that similar customer groups can be created automatically from the AMI data, rather than relying on customer characteristics that are often not tracked (or not regularly updated) by the utility. For this study the TRC team had access to these load-shape clusters and used them to validate and further analyze the AMICS approach to evaluate the effect of customer demographic and cultural factors.

Figure 8: Load Shape k-Means Clusters



Next, every day of the study period is binned with weather and day type. The weather bins are created by calculating cooling degree hours (CDH) for each hourly observation using a base temperature of 65 degrees Fahrenheit and then taking the average of these hourly values to create a single cooling degree-day (CDD) value for each customer on each day (i.e., each "customer-day") in the study period. These customer-days are assigned to a series of bins, each containing a range of three CDDs. This process is repeated to assign days to heating degree-day (HDD) bins, again using a base temperature of 65 degrees Fahrenheit. Segmenting days by their CDDs and HDDs in this manner explicitly incorporates temperature into the research team's model.

To help control for the differences in energy usage across days with the same weather conditions, Evergreen Economics also binned by day type and season. Weekends were assigned to day type 1, and weekdays were assigned to day type 0. The four seasonal bins are defined as winter (December-February), spring (March-May), summer (June-August), and fall (September-November).

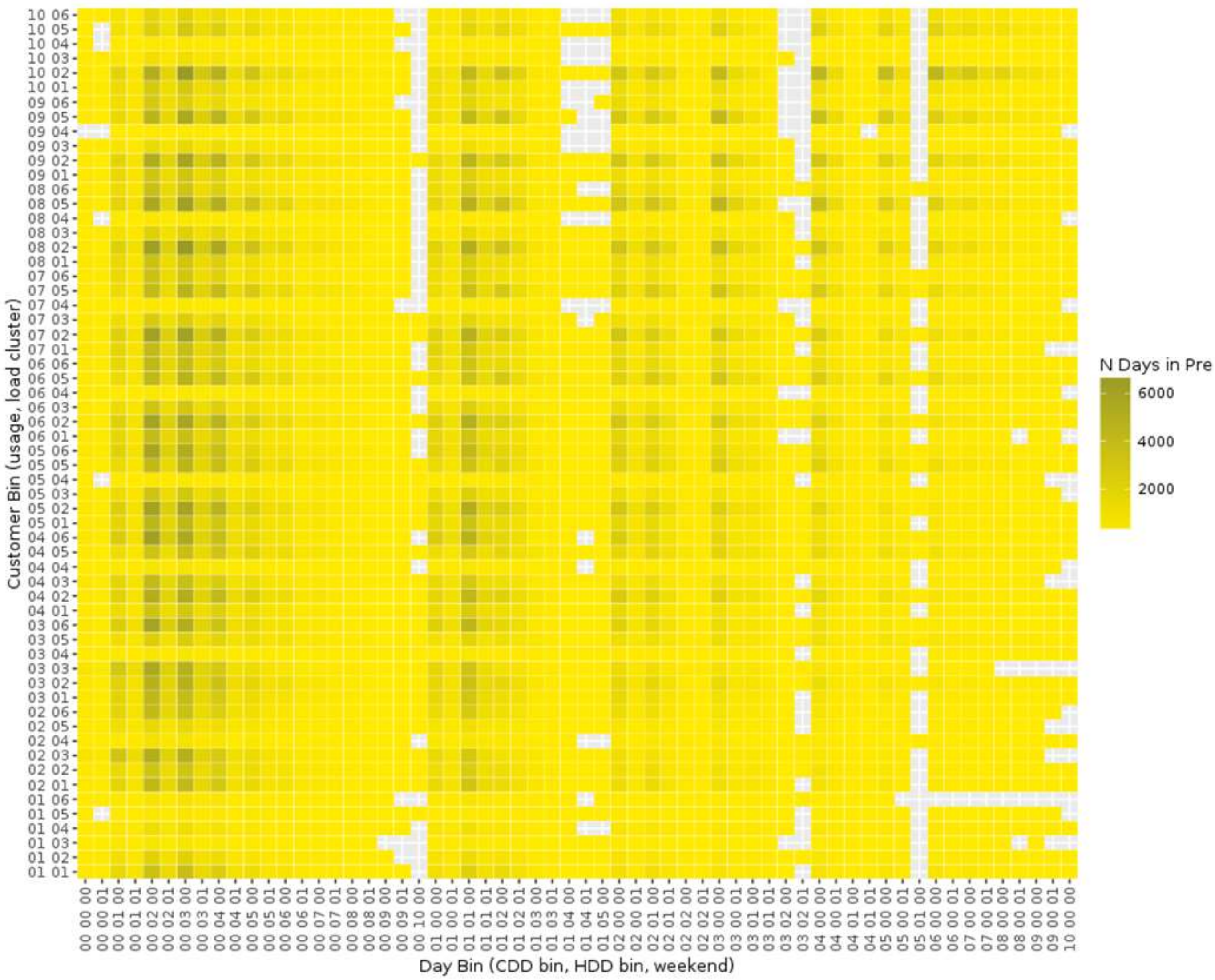
Figure 9 provides an example of a single customer and day being binned. Each customer was assigned to just one customer bin, but because temperature and day type change throughout the year, each customer had customer-days that were assigned to different bins.

Figure 9: Customer-Day Segmentation Example

This segmentation approach created 60 customer bins and 180 day bins, for a total of 9,960 distinct customer-day bins.[10] Figure 10 is a heat table showing the number of customer-days observed during the preretrofit by bin. The rows show customers grouped by their average energy use (highest users at the top) and then their load shape cluster. The columns show days grouped by the cooling degree-days (CDD), heating degree-days (HDD), and day type (weekday versus weekend); season has been omitted from this figure. Each cell shows the number of days observed in the preretrofit for a specific customer-day bin. Evergreen Economics automatically color-coded the cells with the highest number of observations in dark green and the lowest in yellow; grey cells have no observations. Within each customer bin, there are customer-days from a wide range of temperatures. Similarly, each set of days with similar conditions (e.g. CDD) includes customer-days from a wide range of households (e.g. high users with midday peak load). This table shows the actual distribution of customers and days experienced in the preretrofit period. There are thousands of distinct bins, and each type of customer-day (bin) is not equally represented in the data.

[10] The 60 customer bins are composed of 10 use and 6 load clusters. The 180 day bins consist of 4 seasons, 11 CDD bins, 11 HDD bins, and 2 day types – not all 968 possible combinations of these day characteristics were observed in the data.

Figure 10: Pre-Period Customer-Day Observations by Bin



Once the data were segmented, Evergreen Economics estimated a linear regression model with a simple specification of dummy variables for each hour of the day:

$$kWh_{i,t} = \beta_{0i}H00_{i,t} + \beta_{1i}H01_{i,t} + \beta_{2i}H02_{i,t} + \cdots + \beta_{23i}H23_{i,t} + \varepsilon_{i,t}$$

Where:

$kWh_{i,t}$ = Energy consumption, for customer in bin i during hour t

$H00, H01, \ldots$ = Array of dummy variables (0,1) representing the hour of the day

$\beta_{0i}, \beta_{1i}, \ldots$ = Coefficients estimated by the model, for customers in bin i

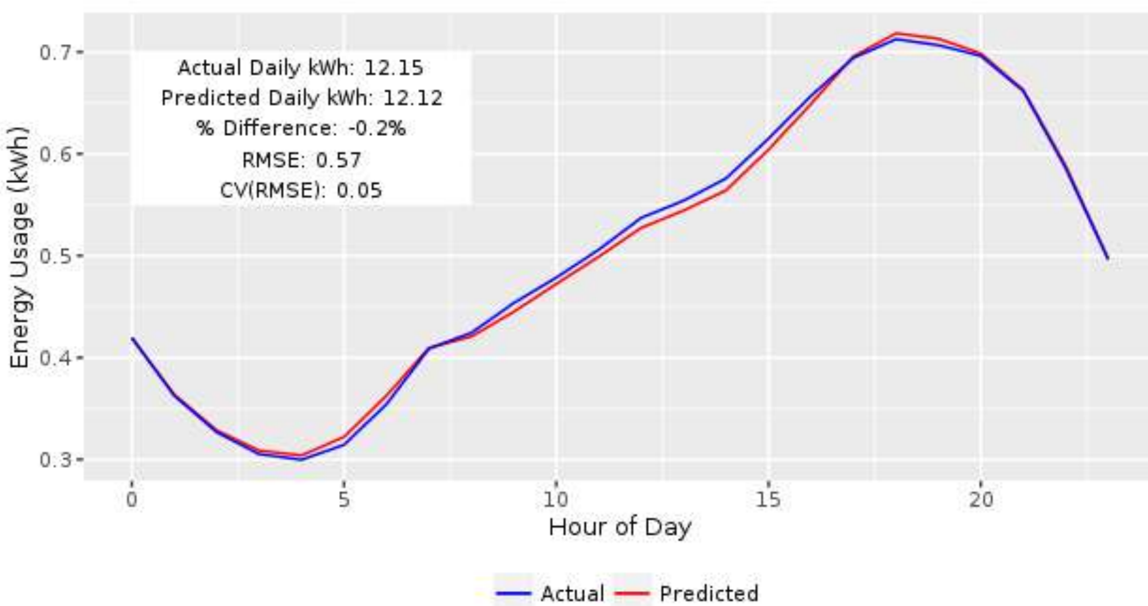
ε = Random error, assumed normally distributed

Unlike a traditional fixed effects regression, which produces a single set of coefficients and customer-specific constants, this regression model produces thousands of separate coefficient estimates, one for each customer segment and day type (i.e. bin).

To validate the ability of the model to make reasonable predictions, Evergreen Economics conducted a holdout test using only pre-retrofit data. This involved randomly selecting 30 percent of the customers in the team's data as a holdout sample; the remaining 70 percent of the customers are used to define the bins and estimate the model. These model results were used to predict energy use for the holdout customers that were not used to develop the model. When the model is performing well, the actual usage of the holdout customers will line up with the predictions of the model. This testing allowed Evergreen Economics to compare a variety of customer-day segmentation techniques and regression specifications, to select the approach that minimizes model error.

The results of this holdout test are shown in Figures 11-13, comparing the predicted pre-retrofit load shape from the model (red) to the actual pre-retrofit load shape for the holdout group (blue). As demonstrated in these graphs, the AMICS model did a good job of predicting energy use for customers that were not included in the model (i.e. the holdout), across all seasons and day types. This is in line with past studies[11, 12, 13] done using the AMICS model as documented in this ACEEE paper[14].

Figure 11: Model Predictions vs. Actual Load of Holdout Customers in Preretrofit



[11] Grover, S., J. Cornwell, S. Monohon, and T. Helvoigt. 2017. *Take it From the Top! An Innovative Approach to Residential and Commercial Program Savings Estimation Using AMI Data,* Presented at the International Energy Program Evaluation Conference (IEPEC), Baltimore, MD.

[12] Evergreen Economics. 2016.*AMI Billing Regression Study Final Report*. Prepared for Southern California Edison.

[13] Grover, S., T. Helvoigt, S. Monohon, and J. Cornwell. 2015.*Random Walk to Savings: A New Modeling Approach Using a Random Coefficients Model and AMI Data.* Presented at the International Energy Policy & Programme Evaluation Conference (IEPPEC) in Amsterdam, Netherlands.

[14] Helvoigt, Ted, Steve Grover, John Cornwell, and Sarah Monohon, *A Smart Approach to Analyzing Smart Meter Data*, ACEEE 2016 Summer Study on Energy Efficiency in Buildings.

Figure 12: Model Predictions vs. Actual Load of Holdout Customers in Preretrofit, by Season

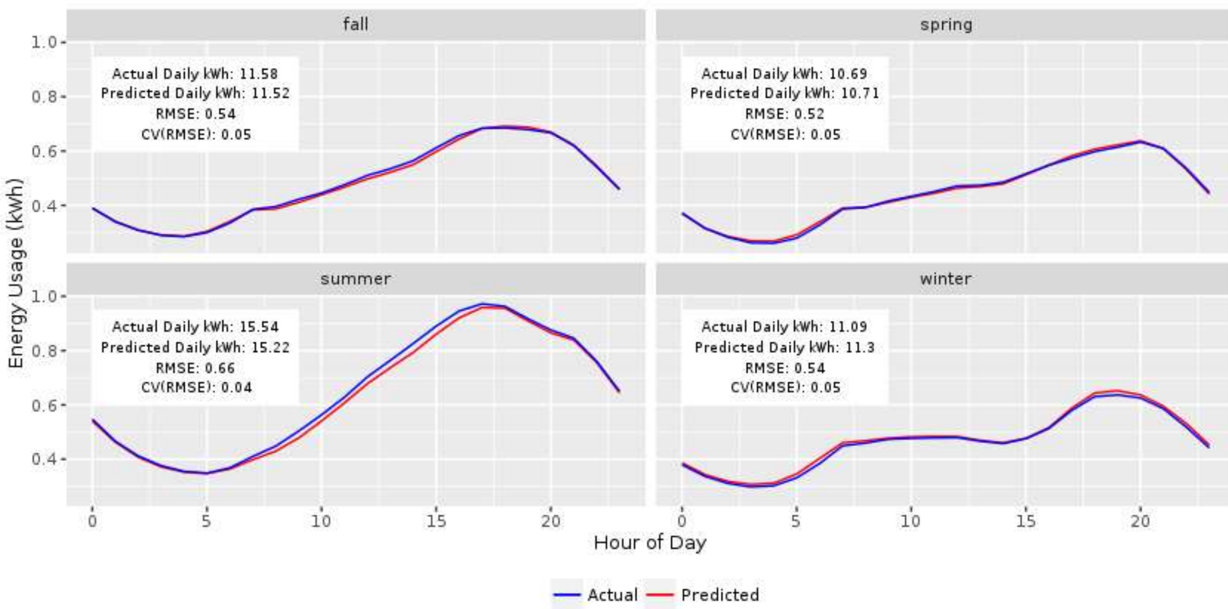
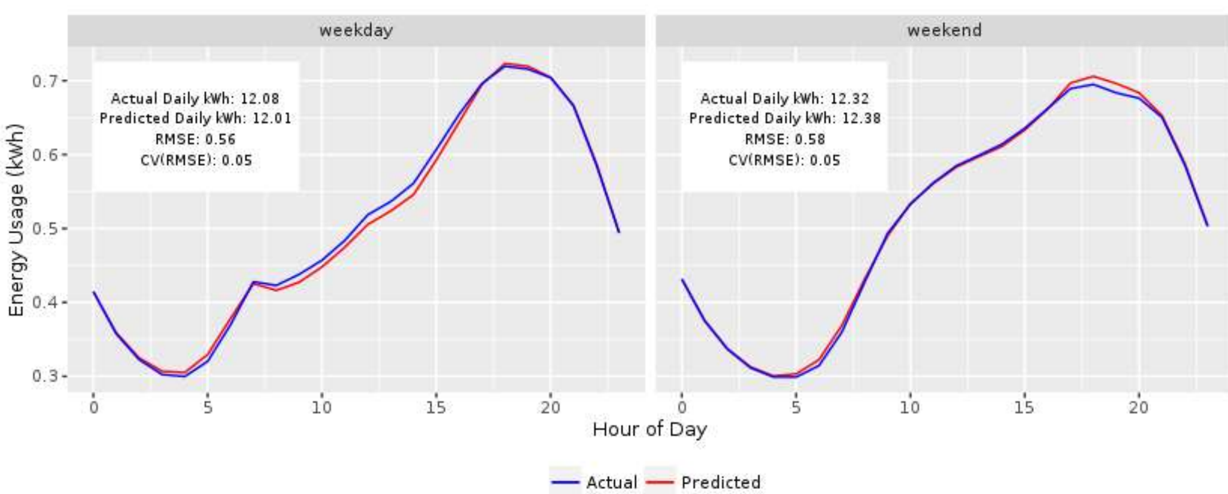


Figure 13: Model Predictions vs. Actual Load of Holdout Customers in Preretrofit, by Day Type



Once Evergreen Economics was confident the AMICS model accurately predicted preretrofit consumption for the customers in the holdout sample, it reestimated the model using the full sample (no holdout) to take advantage of all available data. Evergreen Economics then used this model to predict load shapes for the postretrofit, estimating each tenant's energy consumption in the postretrofit as if the program had not existed. These predicted load shapes were then compared to actual energy consumption over the same period to determine the total change from the pre- to postretrofit, controlling for any differences in weather and day type.

Evergreen repeated this analysis using variations in the holdout group assignments and customer binning criteria to confirm that the estimated energy savings were consistent. This model was selected for low prediction error, ease of interpretation, and usefulness for the preretrofit demographic analysis.

In general, Evergreen found that the customer segmentation process was simpler for the MUP tenants, relative to previous applications of the AMICS approach to HVAC programs for single-family customers. This is likely due to the increased homogeneity of MUP participants; customers from the same apartment complex are more likely to have the same building characteristics (e.g. insulation, vintage) and major appliances (e.g. HVAC, refrigerator).

Tenant Mailers – Enhanced Communications

In addition to the whole building retrofits, a subset of these tenants received a series of six mailers between April 17 and June 19, 2017. The tenants who were chosen to receive these mailers were those who responded to TRC's tenant survey. Of the 457 tenants who completed the survey and received the mailers, around half (n=239) were linked to AMI whole-home consumption data during the preretrofit period (before the MUP projects began) and met the filter criteria for inclusion in the AMICS model.

To estimate the effect of these mailers, PG&E provided Evergreen Economics with additional whole-home AMI data through October 10, 2017 for the remaining tenants. Because the last mailer was sent on June 19, 2017, the data included up to four months of postperiod for each tenant. While this short time period is not ideal, this analysis was limited by the overall project timeline and reporting deadlines.

The mailer recipients were a relatively small subset of all MUP tenants, and they were not selected randomly from the population of MUP tenants. For this reason, the AMICS model's predictions for the mailer recipients were effected by sampling error and survey response bias. To determine the extent of this bias, Evergreen Economics compared the predictions of the AMICS model with the full sample (i.e. no holdout) to the actual energy usage in the pre-retrofit period for the survey respondents. Figure 14 shows the predicted preretrofit period load shape (red) from the AMICS model of all MUP tenants in relation to the actual preretrofit period load shape for the subset of tenants who received the mailers (blue).

The AMICS model predictions controlled for any differences in customer use (magnitude) and load shape (hours of use), as well as weather. Despite these controls, the mailer recipients (i.e. survey respondents) deviated from the predicted energy use of the model. In other words, the AMICS model was unable to account for all differences in customer characteristics between the mailer recipients and the broader population of MUP tenants. An adjustment was necessary to offset this bias and improve the AMICS model when making predictions for the recipient group.

**Figure 14: Full Sample Model Predictions vs.
Actual Load of Mailer Recipients in Preretrofit Period**

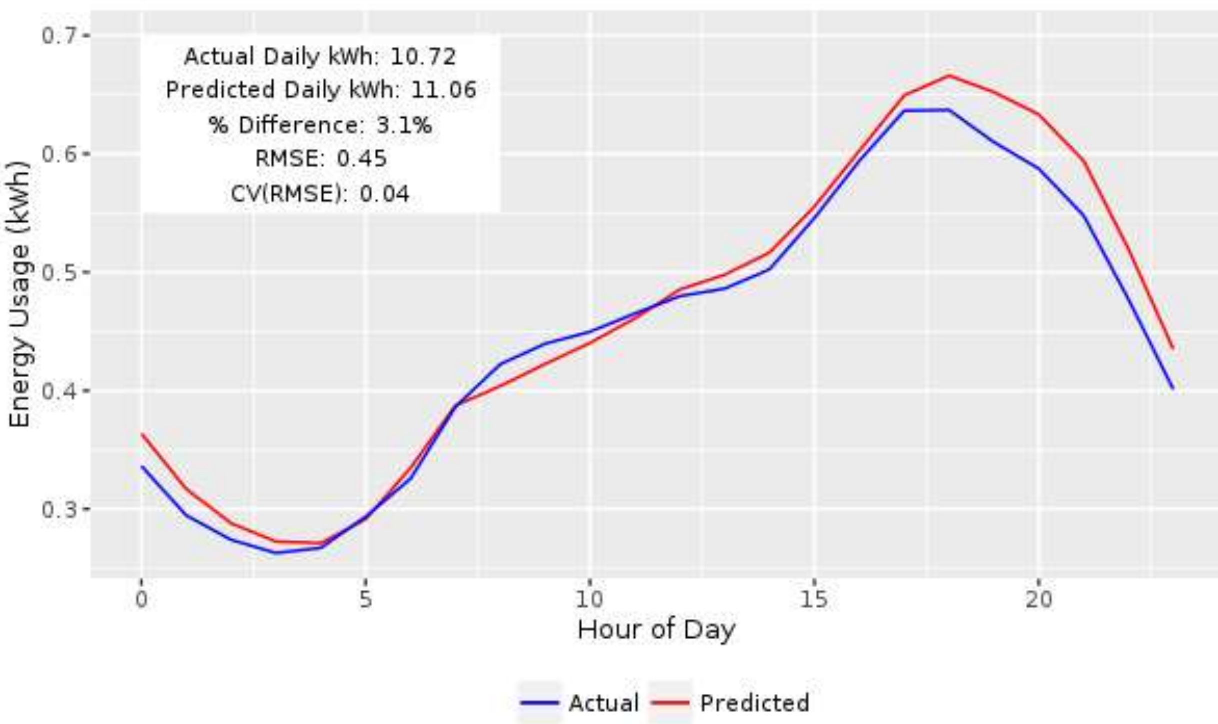
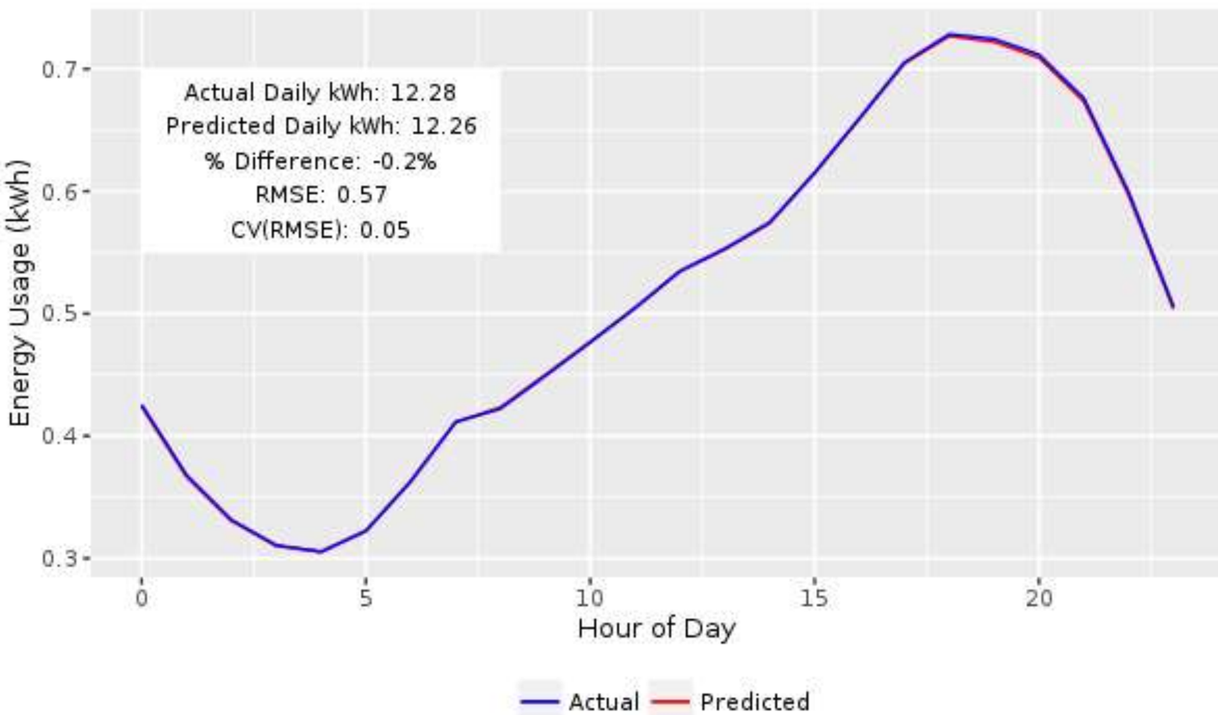


Figure 15 shows the results of the same test, when performed for the population of MUP tenants who did *not* receive mailers (i.e. survey nonrespondents). For this group, the AMICS model predictions lined up very closely with the average actual use. This is not surprising, as the clear majority of MUP tenants did not respond to the survey. No adjustment was necessary when the AMICS model was used to make predictions for tenants who did not receive the mailers.

Figure 15: Full Sample Model Predictions vs. Actual Load of Non-Recipients in Pre-Retrofit Period



To improve the AMICS model predictions for the mailer recipient group, Evergreen Economics created a bias adjustment factor based on the difference between the original model predictions and actual usage in the pre-retrofit period. This was done for each customer-day bin by hour, to capture any variation in estimated model bias across bins.

To validate the ability of the adjusted model to make reasonable predictions for the recipient group, Evergreen Economics repeated the holdout test using only preperiod data of mailer recipients and the bias adjustment. The results of this holdout test are shown in Figure 16-18. Each figure compares the actual pre-retrofit load shape for the holdout customers (blue solid line) to the predicted preretrofit load shape of the model for all MUP tenants (red dotted line) and the adjusted prediction for the mailer recipients (red solid line). As demonstrated in these graphs, the AMICS model with a bias adjustment did a very good job of predicting energy use for customers that were not included in the model (i.e., the holdout), across all seasons and day types.

Figure 16: Adjusted Model Predictions vs. Actual Load of Holdout Recipient Customers in Preretrofit Period

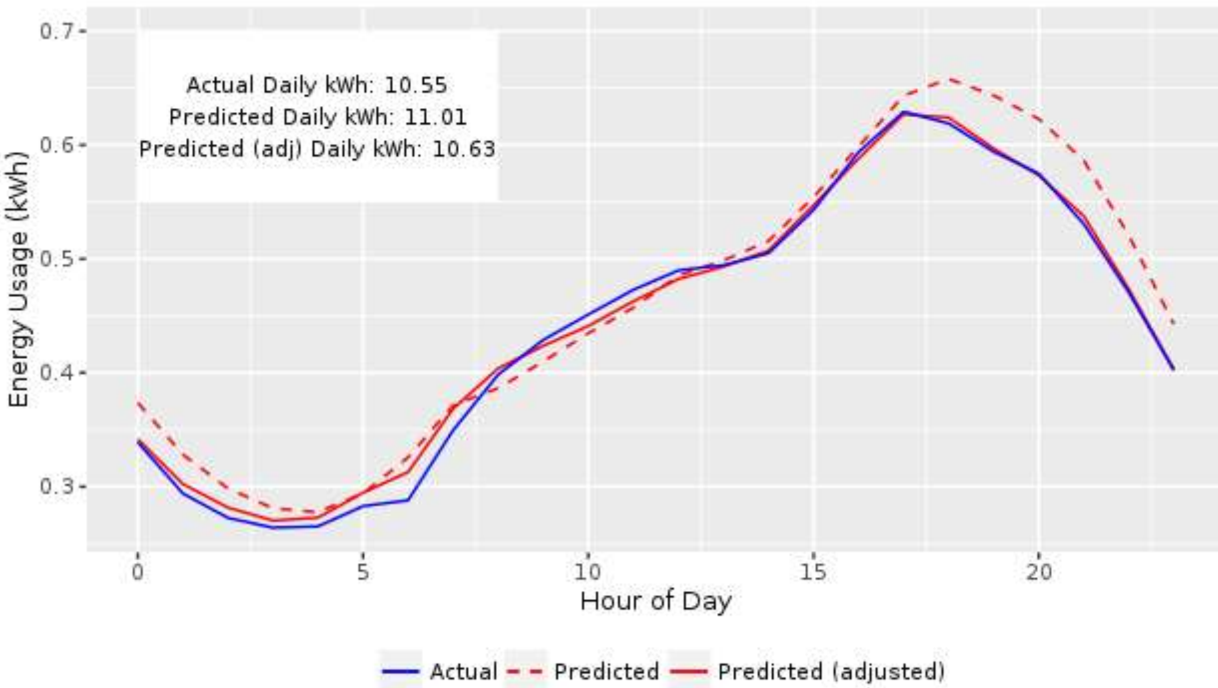


Figure 17: Adjusted Model Predictions vs. Actual Load of Holdout Recipient Customers in Preretrofit Period, by Season

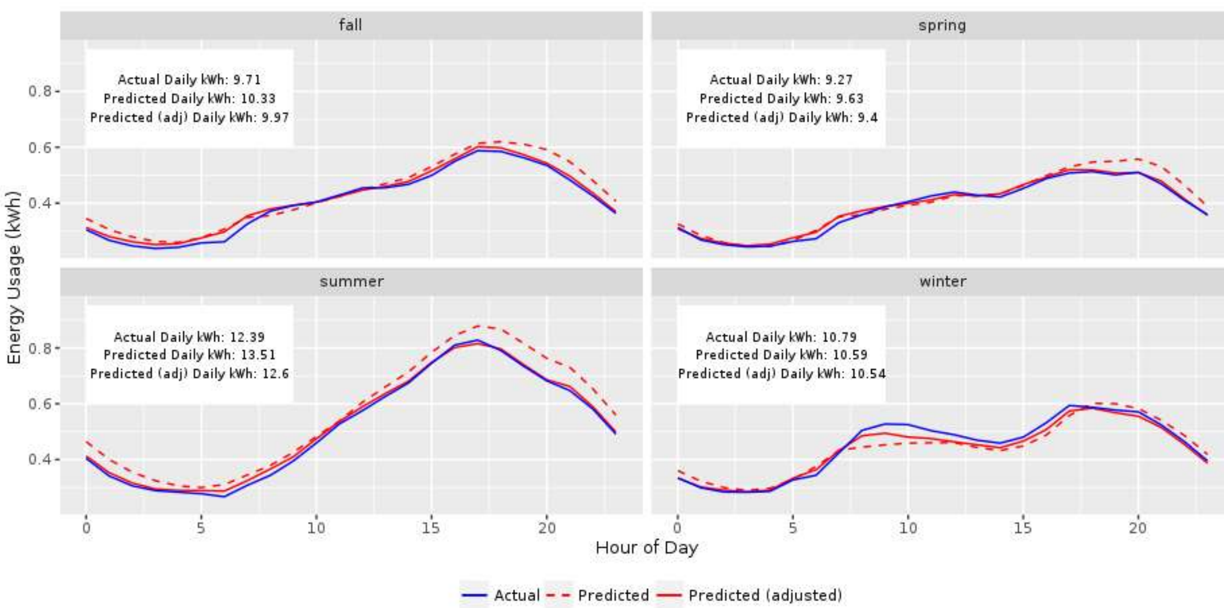
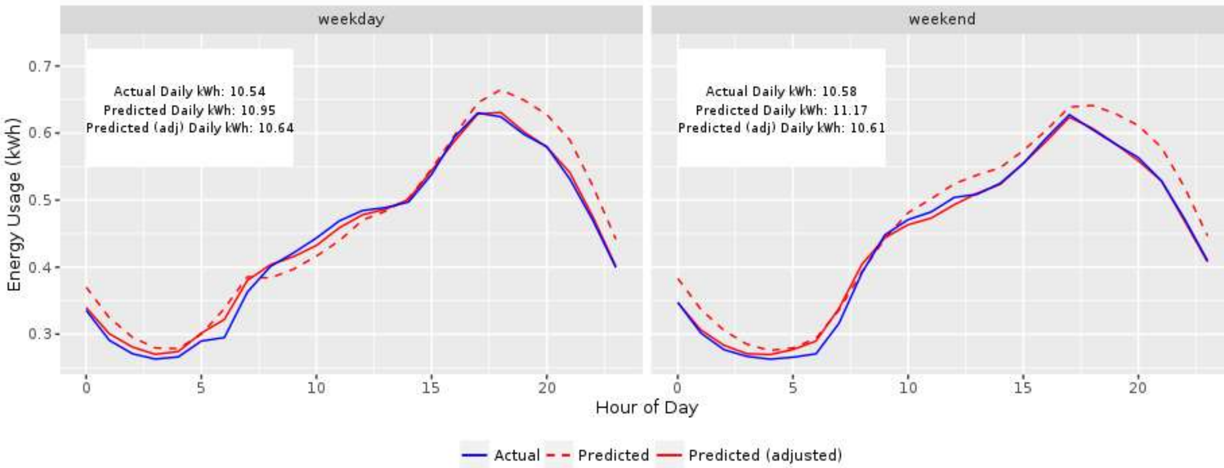


Figure 18: Adjusted Model Predictions vs. Actual Load of Holdout Recipient Customers in Preretrofit Period, by Day Type



These adjusted model predictions can be used to estimate load shapes for the mailer recipients in the postretrofit period before and after the mailers, predicting their energy consumption if the MUP program had not existed. To determine how much of the energy savings are attributable to each of the program interventions (the MUP retrofits and mailers) Evergreen calculated the difference-of-differences between the adjusted predictions of the AMICS model recipients' actual use before the mailers, and actual use after the mailers all during the postretrofit period. This comparison was done within each customer-day bin to control for any differences in weather and day type.

PG&E Demographic Databases

PG&E provided selected fields for units located in MUP project properties from Acxiom and Experian household-level consumer databases. These fields included, for example, information on the number and ages of adults in the household, the presence of children, length of residence, household income, birthplace, and ethnicity (Acxiom), as well as more detailed household demographic composition data, language preferences, and housing unit characteristics (Experian).[15] These fields were used to supplement the survey responses provided by respondents as well as to provide basic data for households who did not respond to the survey.

These consumer market data were not always complete, nor, in cases where survey data were available, did they necessarily match the data provided in the survey. There are various possibilities to explain these mismatches, ranging from "incorrect" information, to nonsynchronized data (e.g., changes in the household), to differences in how things are said (e.g., who is counted as an occupant, what is counted as income). For developing the grouping variables described above, the research team prioritized survey information where it was

[15] This amounted to a total of 2027 household-level records from each database for units where retrofits were completed.

available, supplementing it with Experian and Acxiom data. In cases where survey data was not available, classification data were drawn from the Acxiom and Experian data.

For the demographic load analysis, the survey analyst provided the interval data analyst (Evergreen Economics) with seven demographics/characteristics for each customer in the sample. The interval data analyst used the AMI data provided by PG&E to calculate an average load shape for each demographic group in the preretrofit period.[16] The AMICS model was used to estimate the load shape of the general population of MUP tenants under the same conditions (i.e. controlling for weather and day type). The difference between these two load shapes provides an estimate for the impact each demographic has on energy usage.

Comparing the actual pre-retrofit period energy usage of each demographic group provided an initial insight into the total differences between groups. If the predicted pre-retrofit use of the model was also varied across the demographic groups, it would be concluded that the differences are due (at least in part) to differences in the weather conditions rather than the demographic itself. The model allowed the researchers to see which demographic differences were driven more by geographic differences than solely the demographic.

There are two important caveats to this analysis:

1. Response bias – there may be unobserved differences between the survey respondents (with reported demographics) and the general population of MUP tenants.
2. Limited control – this comparison controls for difference weather and day type, but not any correlated demographics or internal factors that may be contributing to these trends[17].

[16] The demographic analysis was limited to the preretrofit because statistically significant differences were found between customers' load shapes in the pre- and postretrofit periods. If this type of comparison were made in the postretrofit, the differences could to be attributed to demographic factors but also the varied MUP retrofits and program spillover effects (e.g. customer installed measures, behavioral changes).

[17] For example, some properties and regions are highly related to household ethnicity. These correlations can be partially parsed by statistical analysis post-AMICS analysis.

CHAPTER 3:
Results

Recruitment and Participation

TRC contacted 49 sites (4,164 units) to participate and more than half enrolled in the study. The 28 participating sites provided a pool of 2,130 units. Figure 19 shows the location of the eligible projects (red) that were contacted and the project sites that participated (blue) in the study. Of those units at participating sites, more than 20% completed surveys. TRC received 471 completed submissions (online and paper), nearly achieving the project goal of 500 completed surveys.

Figure 19: Eligible (orange) and Participating (blue) Sites

To maximize participation TRC worked directly with management staff at each participating site to develop an outreach approach using familiar communication methods. For most sites TRC developed a study introduction flyer to prepare tenants for the upcoming survey. The flyer was written in English and Spanish. Depending on the location preference, TRC staff or property management posted flyers in common areas such as mail rooms, laundry rooms, leasing office, and door hangers on each residential unit. Typically, one week after the introduction flyer was posted surveys were delivered as a door hanger to each residential unit. Additional surveys were left in the leasing office or site manager's office or unit. Distributing the materials was timed near the first of the month to coincide with the due dates of the monthly rent. This allowed property management staff to remind residents to take the survey. Two weeks following the surveys TRC staff or property management posted a reminder flyer to encourage residents who had not filled out the survey to do so.

Table 7 summarizes the number of submission per site by surveys completed and returned in hardcopy or filled out online. An additional four surveys were submitted without sufficient address information, whereby they were omitted from AMI data analysis since their accounts could not be identified. There were 13 surveys submitted by the same tenant via a hardcopy and online. Those submissions were evaluated and if answers were similar (indicating that it was basically the same household) the surveys were kept. If responses did not match, the survey were removed from the number of completed surveys.

Table 7: Completed Tenant Surveys by Site

Site ID	Paper	Online	Premises With Duplicate Submissions	Total Premises
2	7			7
3	9			9
5	37	15	1	51
6	27			27
7	5	3		8
9	10	1		11
10	8	1		9
11	19	2	1	20
12	5	1		6
15	10	2		12
16	11	1		12
18	14	1		15
19	25	1	2	24
20	8	3		11
21	20			20
22	8			8
24	4			4
27	4	2		6
29	28	23		51
30	35	9	2	42
31	26	2	1	27
34	27	2	2	27
37	7			7

Site ID	Paper	Online	Premises With Duplicate Submissions	Total Premises
40	11	2	1	12
42	30			30
Unknown Address*	2	2		4
Subtotal	*397*	*73*	*10*	*460*
Omissions				
Could Not Match to PG&E Data	-	-	-	8
Master Metered	-	-	-	7
Total Usable for Energy Analysis				**446**

For four surveys, no address was provided in survey response; these have no Project ID and are listed in this row. For an additional four surveys (one each at four different project sites), the unit address could not be located in the PG&E data; these are included in the rows above but were not usable for energy analysis.

TRC processed the completed surveys into a database for the survey analyst to evaluate usability and compare against the PG&E Acxiom and Experian database sets, and determine number of survey respondents living in their unit before and after the retrofit. Table 8 summarizes of data completeness. Of the 446 usable surveys with unique addresses, 54% of tenants lived in their unit before and after the retrofit. Furthermore, there was a high match of tenants who took the survey and PG&E had information on the customer in the Experian and Acxiom databases. This was higher than expected and offered a means to compare the survey responses to PG&E's demographic information.

Table 8: Summary of Data Matching and Status With Respect to Retrofit Activity

	Total	Before & After Retrofit	Other
Number of survey records	460	246 (44%)	211 (52%)
Number with match in Experian Data	279 (61%)	210 (75%)	69 (25%)
Number with match in Acxiom Data	279 (61%)	210 (75%)	69 (25%)
Number with match in PG&E Data	446 (97%)	--	--

Analysis

Demographics of the Sample

This section outlines basic demographic information on the sample with energy use data. For some of these households, survey information was collected for some of these households ("survey population") and used consumer market information to obtain demographic information for many others ("nonsurveyed population").[18]

The general research population was households in properties that participated in the MUP program. The research team used Census Bureau data to illustrate differences relative to the general population of California, toward characterizing the MUP household population. Overall, these households had lower income and lower education than Californians in general. The team also found the survey population had lower income and lower levels of non-English speaking households than did the general research population, as represented by the market data sets and Census data.

Income

Most of the households in the sample were low-income, with the households who responded to the survey overall having lower income than those who did not. The median annual household income in California (2011-2015, in 2015 dollars), was $61,818 (U.S. Bureau of the Census 2017).[19] Less than one-third (31%) of the homes included in the sample population (and for which income data was available) had annual incomes more than $40,000. These sampled households were markedly poorer than those in California overall. Lower income levels are to be expected, since the sample households all occupy multifamily units and are almost exclusively renters. What was particularly notable was the number of households with very low income, especially among survey respondents: 71% of the surveyed households with income data reported annual income of **under $30,000**. In comparison, only a quarter of California households had income at that level (U.S. Bureau of the Census 2017, in 2015 USD). In 2016, poverty level for a family of four was defined as income below $24,000.[20]

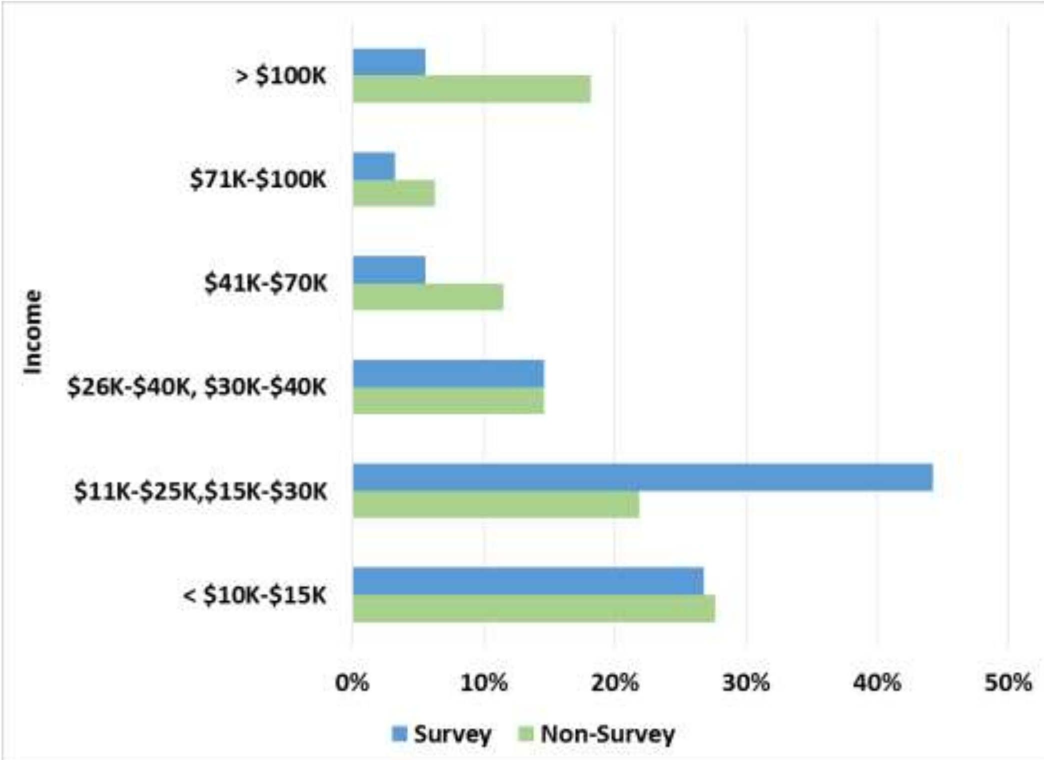
As shown in the nonsurveyed households in the sample had higher incomes. About half of these non-surveyed households had incomes of less than $30,000. Still nearly one-fifth (18%) of these nonsurveyed households had annual income of $100,000 or more, higher than the 6% of surveyed households. Of California households overall, 43% have income more than $100,000 (U.S. Bureau of the Census 2017).

[18] In some cases, demographic information for the surveyed households was derived from the market data sets. For a few analyses, a fuller set of energy data for households in MUP projects was available.

[19] U.S. Bureau of the Census "Quick Facts", September 25, 2017

[20] Public Policy Institute of California (http://www.ppic.org/publication/poverty-in-california/).

Figure 20: Income Categories for Surveyed and Nonsurveyed Households

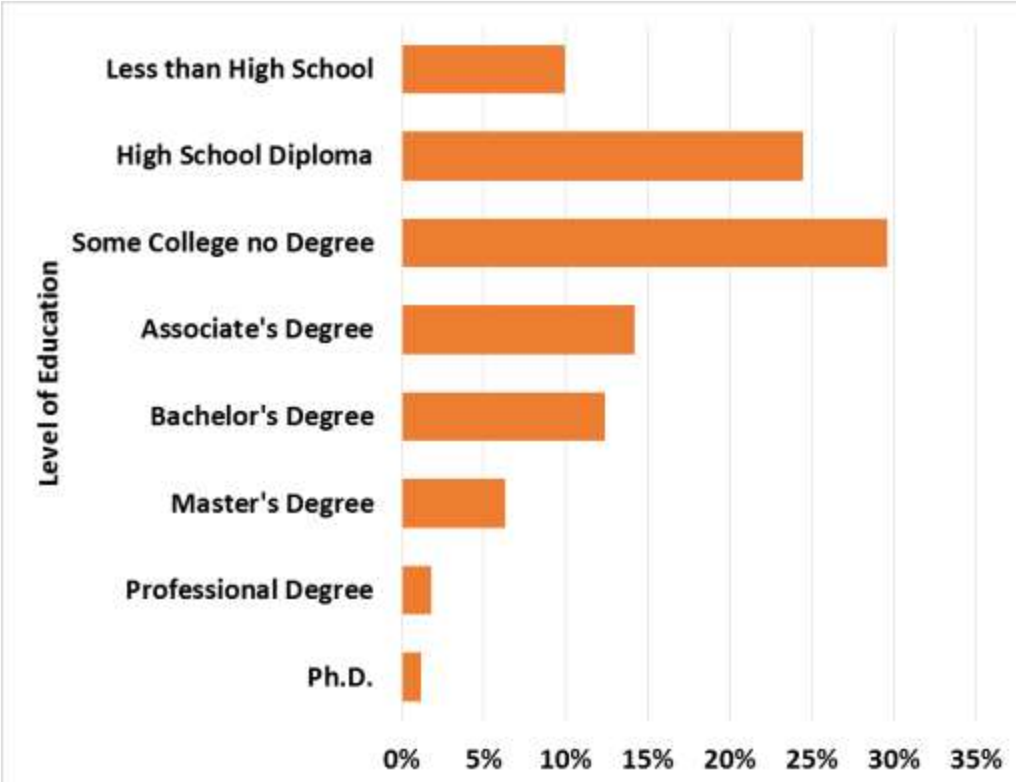


Education

One-third of the surveyed households reported that the highest level of education in their households was a high school diploma (24%) or less than a High School diploma (10%), while 21% had a bachelor's degree or higher (Figure 21). In comparison, 18% of Californians 25 or older have less than a high school diploma and 31% have a Bachelor's Degree or higher (U.S. Bureau of the Census 2017).[21] Education levels for the nonsurveyed households were not determined because the data were too incomplete.

[21] The Census Bureau statistics and the survey statistics are not completely comparable, both because our survey asked for highest education within a household versus the Census Bureau's population-based definition, and because the Census Bureau restricts the statistic to adults 25 years or older.

Figure 21: Highest Reported Educational Attainment for Surveyed Population



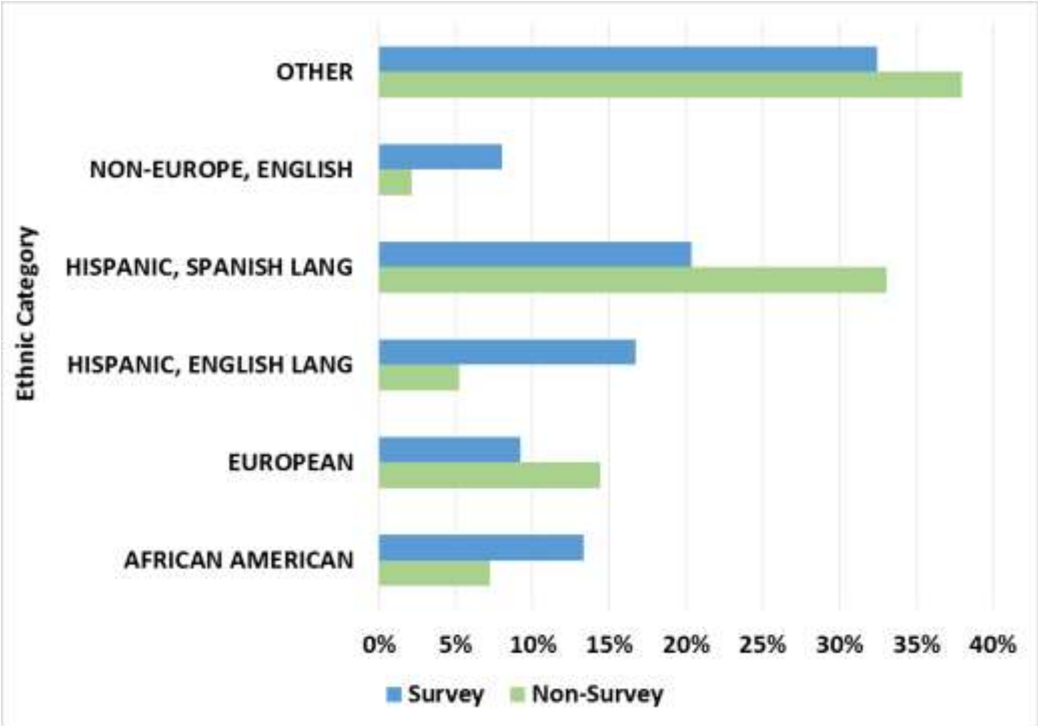
Ethnicity and Racial Origin

One of the guiding questions in the research was the extent to which households who identify as being of particular ethnic or racial origins differ in their energy use, and similarly whether primary language (as a cultural indicator) makes a difference to energy use. The team classified households into several broad "General Ethnic" categories, according to the information collected on ethnicity, race, and language[22]. Figure 22 summarizes membership for these categories by whether the household was in the surveyed or nonsurveyed population.[23] Households where the respondent identified as Hispanic made up 38% of the sample almost exactly the overall representation as in the state (39% in 2016; US Bureau of the Census 2017). African Americans made up 7% of the total sample population, again matching the overall representation of African Americans in California (6.5% in 2016, U.S. Bureau of the Census 2017). Hispanic or Latino-identifying persons who spoke English as the primary language in the home were more likely to answer the survey even though the survey was provided in English and Spanish.

[22] Ideally, even more detailed categories could be developed, drawing both from the information collected in the surveys and the consumer market data. However, because the research team planned to use these categories in combination with other demographic/classification factors in the load analysis, and because of the unevenness and complexity of the data, the team proceeded with these rather large groups.

[23] The large "Other" category included households where data were incomplete (e.g., no ethnicity identified) as well as those that did not fall into the remaining five categories.

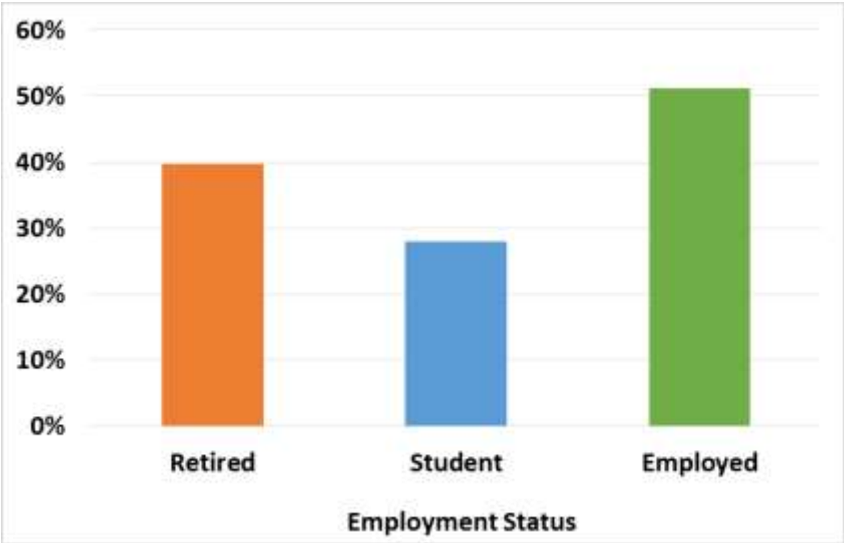
Figure 22: General Ethnic Categories Used in the Load Analysis



Status: Students, Employed, Retired

Surveyed households were asked whether anyone in the household was retired, a student, or employed (Figure 23). Only half of the households replied that somebody in the household was employed. In California, 63% of the population 16 or older is in the labor force, according to the American Community Survey (U.S. Bureau of the Census 2017, 2011-2015).[24]

Figure 23: Activity Status of Surveyed Households



[24] These data were not completely comparable to the survey figure, since the Census Bureau data refers to individuals rather than households, and being in the labor force is not the same as being employed.

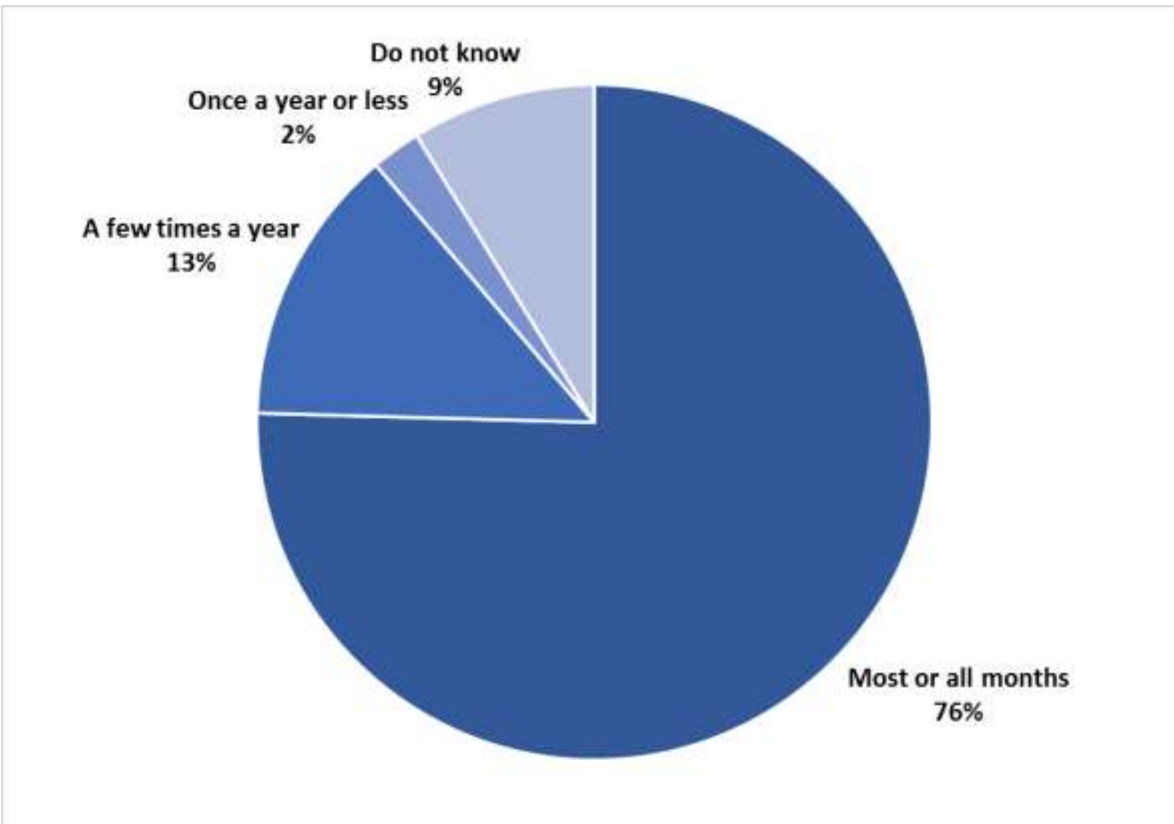
Household Perceptions of Energy Bills and of Renovation

The survey posed households a series of questions about their energy bills and about the renovations in general. These answers give a basic background on the level of concern and engagement with respect to energy and particularly the costs.

How Often Does the Household Check the Energy Information?

Survey respondents were asked how often anybody in the household looked at energy bills or other information on energy use for their home. Three-fourths said that they looked at it every month, or nearly so, while 15% rarely looked (no more than a few times per year). So, most respondents, but not all, are regularly attentive to energy costs (Figure 24).

Figure 24: How Often Survey Respondents Look at Energy Bills or Other Household Energy Use Information



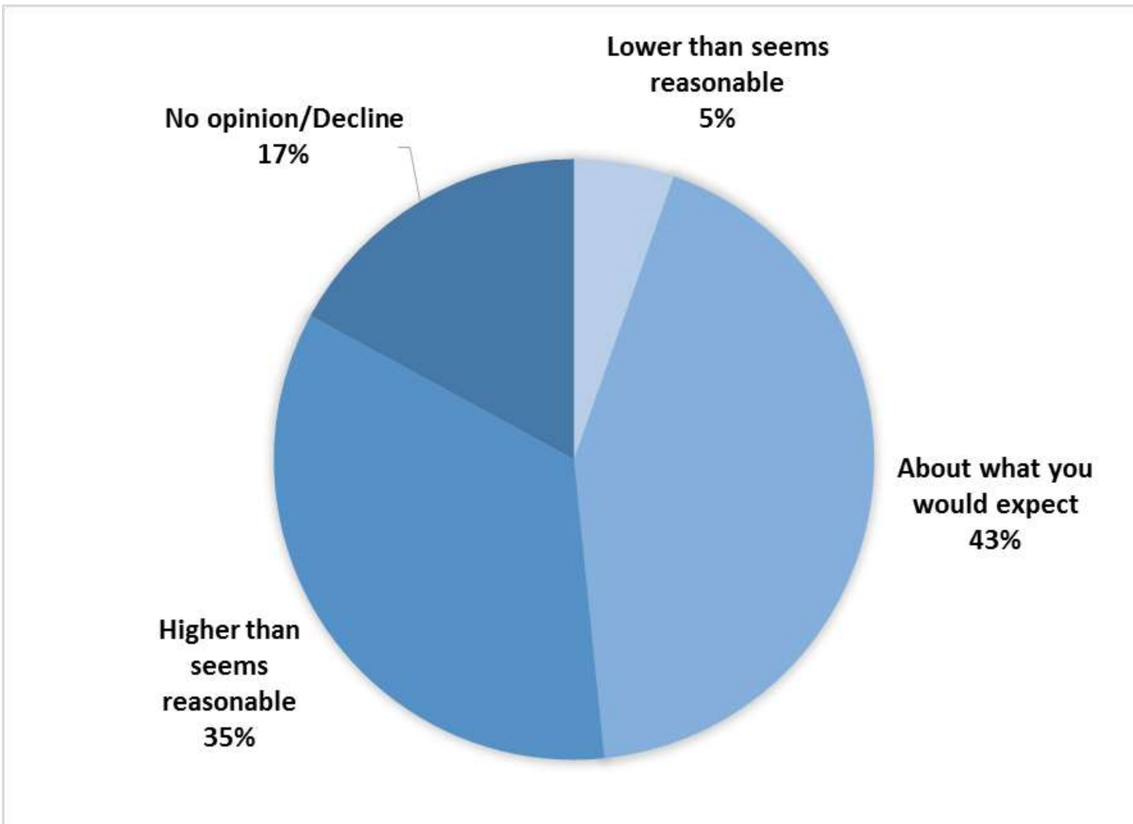
(n=448)

Perception of Bill Level

As a way of examining household concern for energy costs without asking directly, households were asked to what degree they considered their household energy costs reasonable. As shown in Figure 25, just over one-third said that they found their energy costs higher than seems reasonable, while nearly half said either that their bills were about what they would expect (43%), or even, in some cases, lower than seems reasonable (5%). Households that felt their bills were as expected or lower were less likely to say that they were interested in receiving a smart power strip.

The team also examined at rate classifications based on PG&E account information for these households. Of all study participants, 26% were on California Alternate Rates for Energy (CARE) rates. Being on a CARE rate was far more prevalent for households who had been residents before and after the retrofits (58%); this difference likely has something to do with subscribing to the CARE rates. Four percent of the study population and 14% of those who were residents before and after the retrofit were on PG&E's Energy Savings Assistance Program.

Figure 25: What Survey Respondents Say About How Reasonable Their Household Energy Bills Are



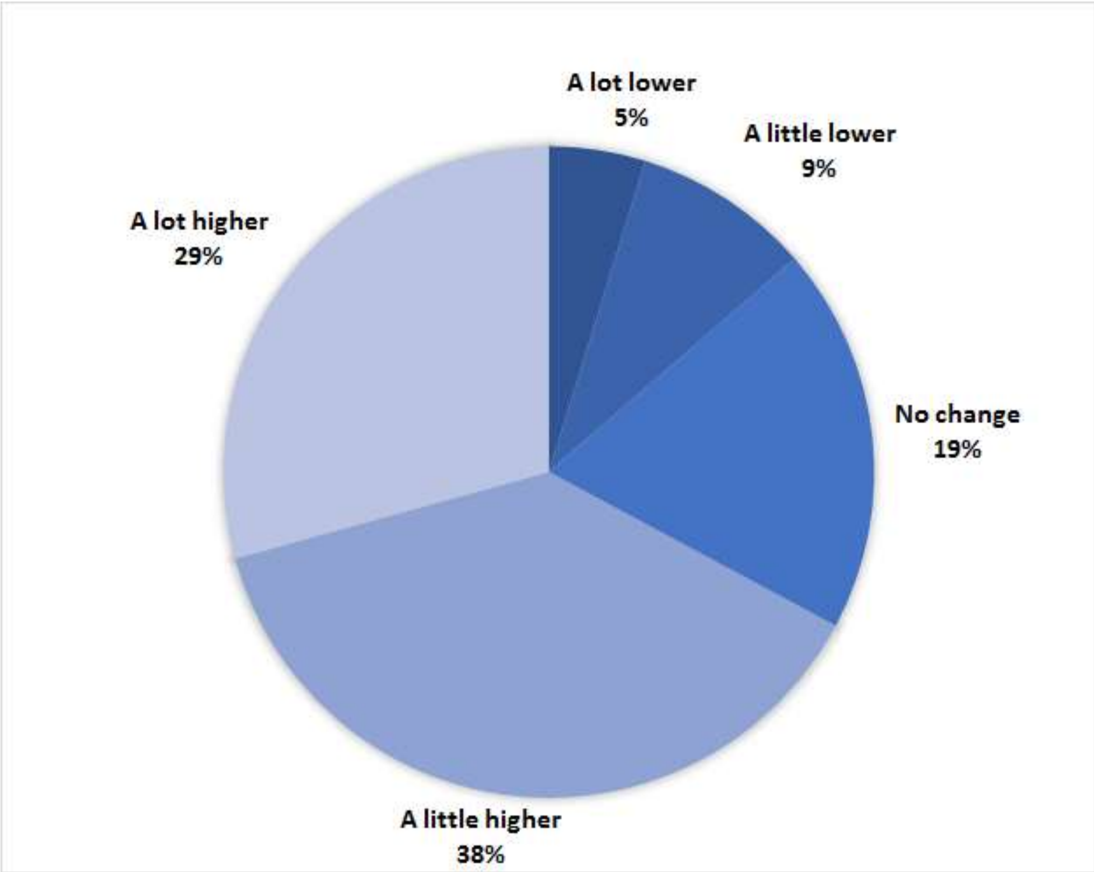
(n=384)

Changes in Energy Costs

Asked whether their energy costs had changed much over the past year, two-thirds said that they were higher, whether "a little higher" (38%) or "a lot higher" (38%). On the other hand, 14% said that their energy costs were lower over the past year, sometimes "a lot lower" (5%) (Figure

26). The team did not access the accuracy of these judgements. Rate changes during the past few years could affect some multifamily household energy bills substantially.[25]

Figure 26: What Survey Respondents Say About Any Recent Changes in Energy Bills



(n=396)

Renovation

Survey respondents were asked if before participating in the study, they had been aware of the renovation activity in their complex. Seventy percent said that they were aware of this activity. Of the remaining 30%, some had moved in after the renovations were complete. Asked what they perceived the purpose of the renovation to be, more than one-third (39%) though energy efficiency was among the reasons. The most common response, however, was the renovation was to improve appearance (57%) (Table 9).

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[25] See PG&E's Residential Rate Changes discussion (https://www.pge.com/en_US/residential/rate-plans/how-rates-work/rate-changes/residential-rate-changes/residential-rate-changes.page), which describes changes in tiered rates (including at lower tiers) and modest increases in minimum bills.

Table 9: Survey Respondents' Perceptions of the Purpose of Retrofit Activity

Perceived Purpose of Renovation (multiple responses allowed)	Percentage of Respondents
Improve appearance	57%
Improve energy efficiency	39%
Fix structural issues/improve safety	38%
Add amenities	18%
Other	8%

(n=407)

Energy Savings

MUP Retrofits

This section provides estimates for the energy savings realized by customers (i.e. tenants) in buildings that completed a whole building retrofit through MUP, based on the Evergreen Economics AMICS model and post-retrofit AMI data through mid-June 2017.

Figure 27 compares the postretrofit predicted load shape (red) without the retrofits with the actual postretrofit load shape (blue) across all customers in the data set. This prediction is based on the **preretrofit** consumption model and **postretrofit** weather data; it represents the expected load shape for these customers in absence of the PG&E MUP program participation. The error of each hourly prediction is depicted as a 95 percent confidence interval in the shaded area around each estimate. Whenever the actual **postretrofit** load shape falls below the predicted **postretrofit** load shape, this indicates that savings were realized during that hour. The AMICS model finds 0.31 kWh savings per day, or 2.7 percent.[26] Most savings were realized during the latter part of the day, from 6 p.m. to 9 p.m., which is also when the highest electricity use levels occur.

Figure 28 shows the hourly kWh savings estimates with error bars depicting 95 percent confidence intervals around each estimate. The AMICS model found statistically significant savings from 6 p.m. to 2 a.m. Two of the morning hours had small increases in use (i.e. negative savings), but these increases were not statistically significant.

The model results can also be viewed by the individual binning criteria, including the four seasons. Figure 29 shows the actual average load shape for each season (blue) and the prediction of the model (red) with 95 percent confidence intervals (shaded area). Figure 30 shows the corresponding hourly savings estimates by season. Most of the program savings occurred in the summer, with an average daily savings of 1.66 kWh, or 11.3 percent. Spring and fall had more modest savings of 0.43 kWh and 0.52 kWh, respectively. However, these savings

[26] It is not possible to separate the estimated savings impacts for PG&E's MUP whole-building retrofits from any spillover (customer-installed measures or behavioral changes) that occurred during the retrofit period without a control group.

were offset slightly by an increase in usage (i.e. negative savings) in the winter months of 0.71 kWh.

Figure 27: Model Predictions vs. Actual Load of Customers in Postretrofit

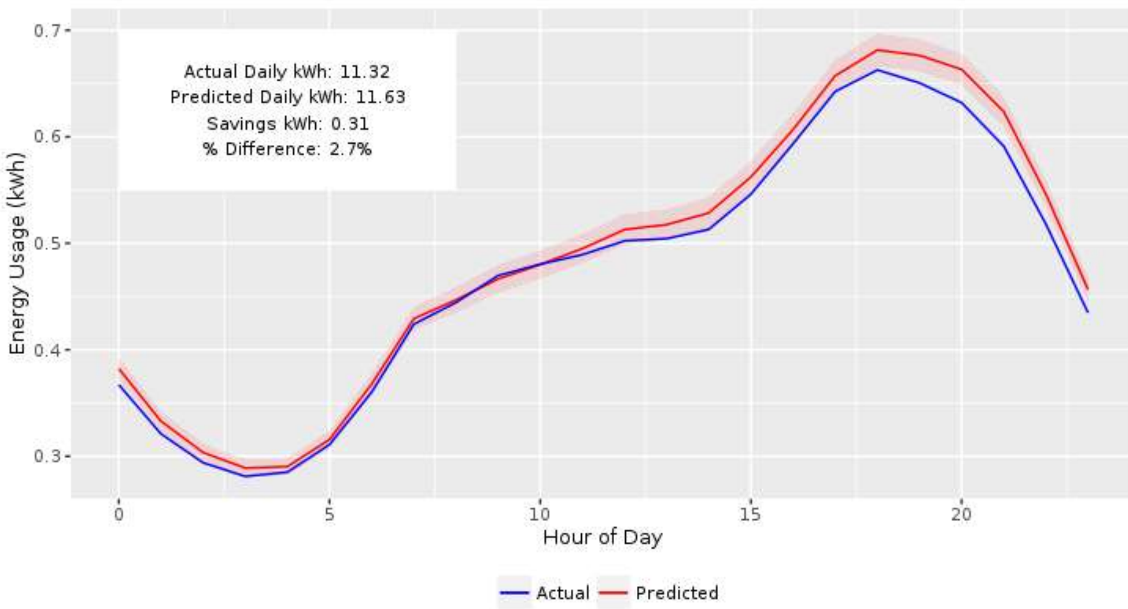


Figure 28: Estimated Retrofit Energy Savings

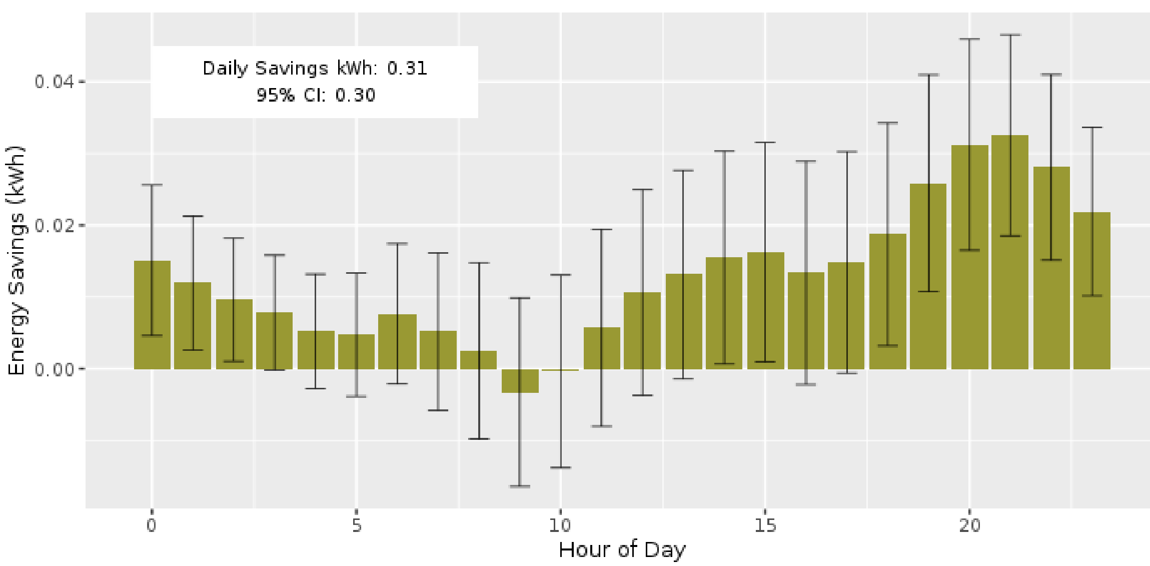


Figure 29: Model Predictions vs. Actual Load of Customers in Postretrofit, by Season

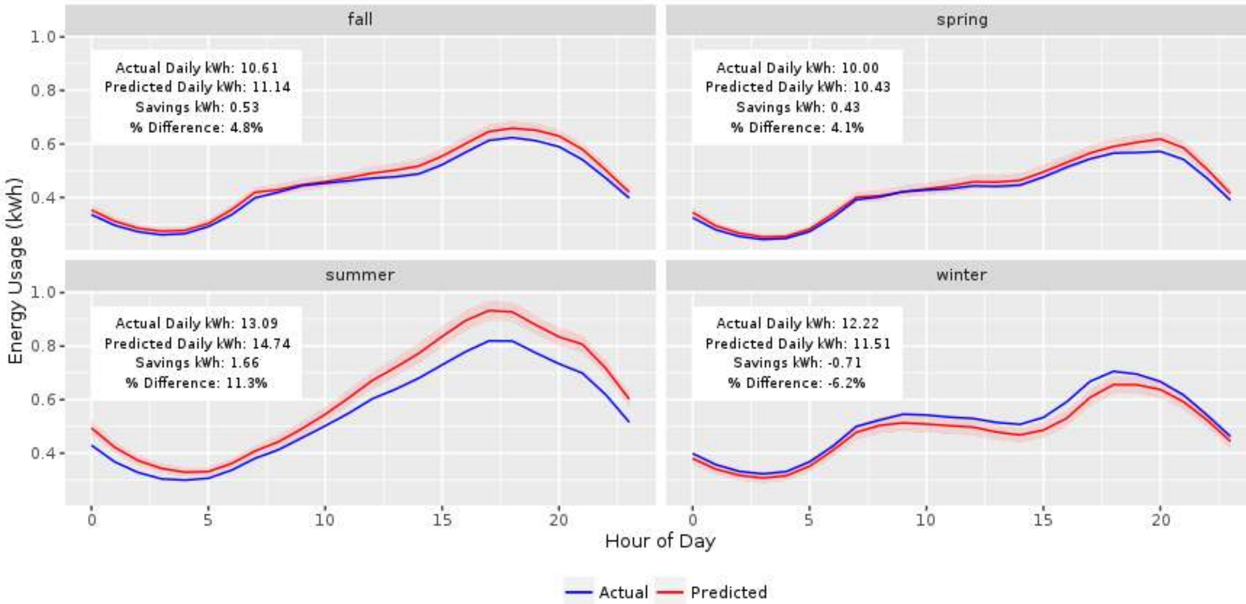


Figure 30: Estimated Retrofit Energy Savings, by Season

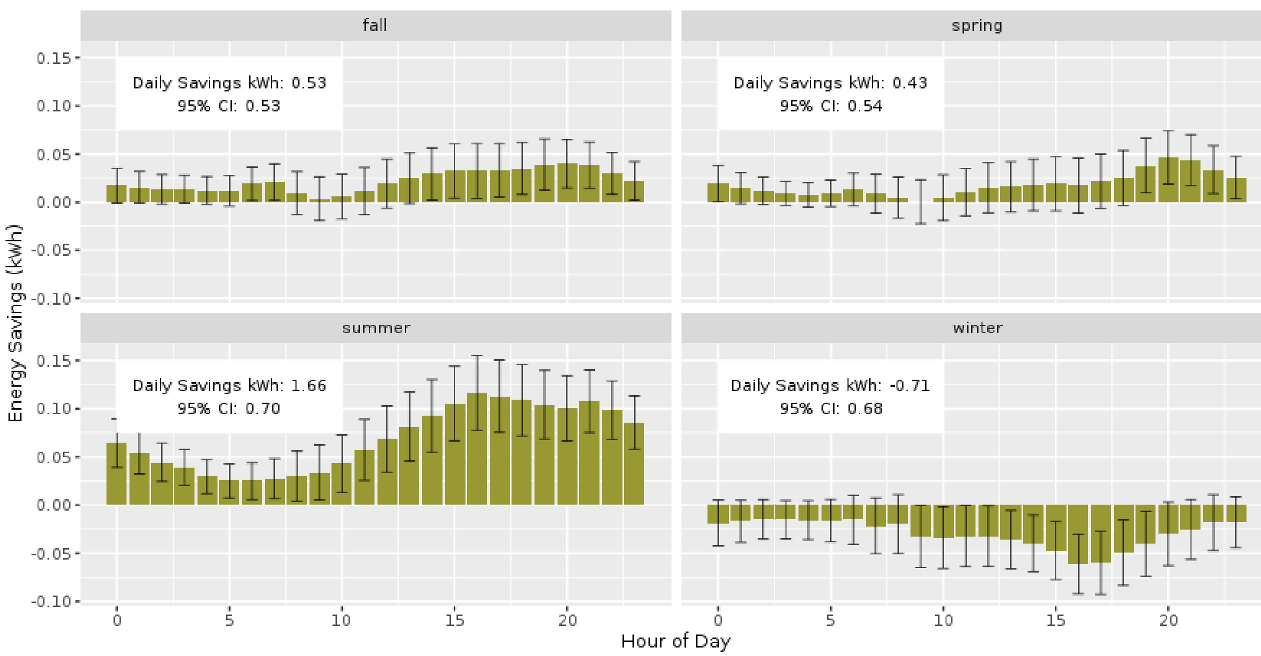


Figure 30 shows the average daily savings estimated by the AMICS model by customer usage bin and heating load. The columns show the cooling load by HDD, with the coldest days on the right. In all but one of the customer groups, program savings occurred during days with limited heating load. Consistent with the trends, the lowest energy users (Bin 1) had negative savings (i.e. increased their use) across all levels of heating load.

Figure 31 and Figure 32 show the average daily savings estimated by the AMICS model by customer use bin and cooling load. The rows show customers grouped by their average energy usage in the preperiod (highest users at the top), while the columns show the cooling load by CDD (hottest days on the right). Each cell shows the estimated program savings (kWh per day) for one customer group on days with the same cooling load. The team color-coded the cells with the highest kWh savings in dark green, the lowest in dark red (negative savings = increased usage); yellow cells fall in the middle of this spectrum. As this heat table shows, most program savings are coming from the mid- to high-energy users on days with at least moderate cooling load. The lowest energy users (Bin 1) had negative savings (i.e. increased their use) across all levels of cooling load.

Figure 31: Retrofit Energy Savings by Customer Use and CDD

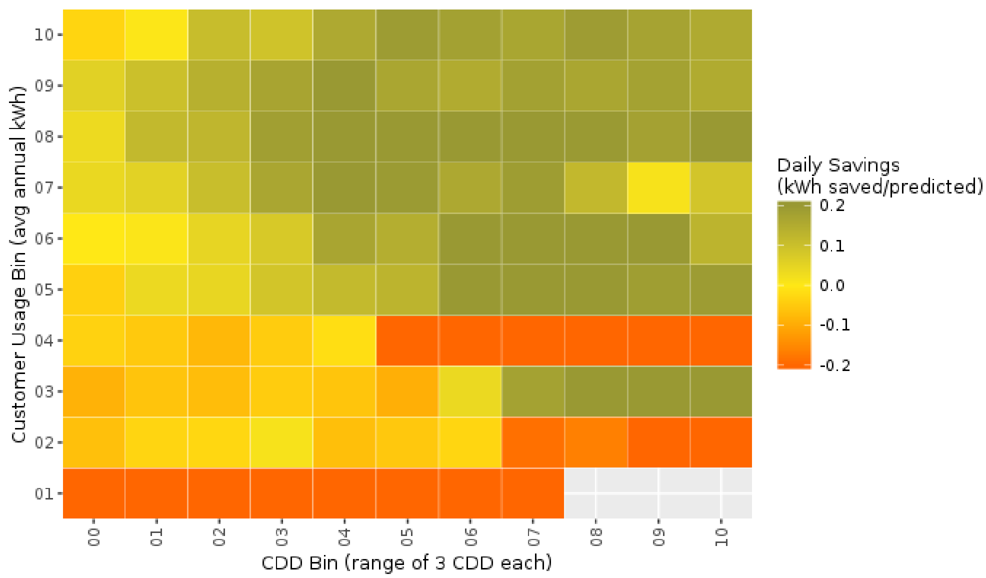
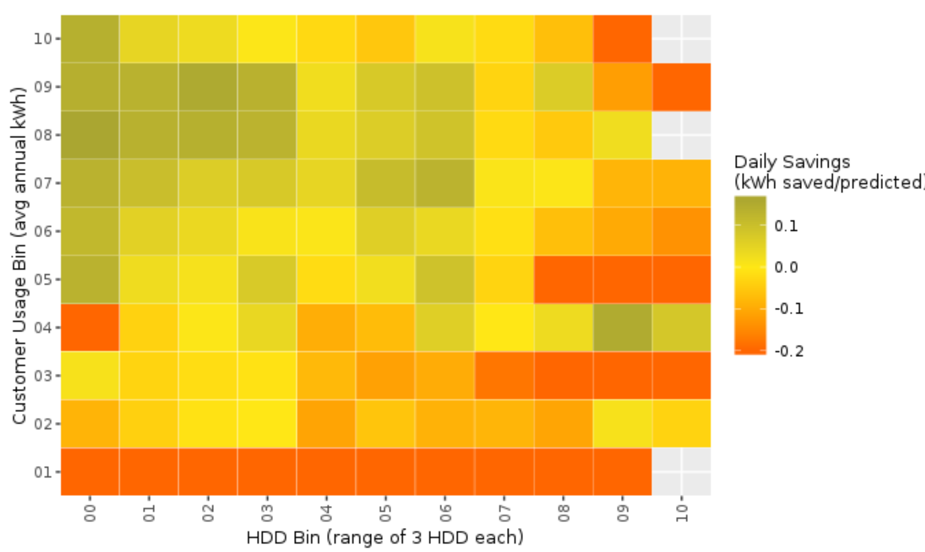


Figure 32: Energy Retrofit Savings by Customer Use and HDD



In addition to their average energy usage (kWh), customers were segmented by their load shapes (hours of use) in the preperiod. Figure 33 shows the six load shapes that were identified in the methods section. They are ordered from flattest (Bin 1) to steepest (Bin 6).

Figure 33: Load Shape k-Means Clusters

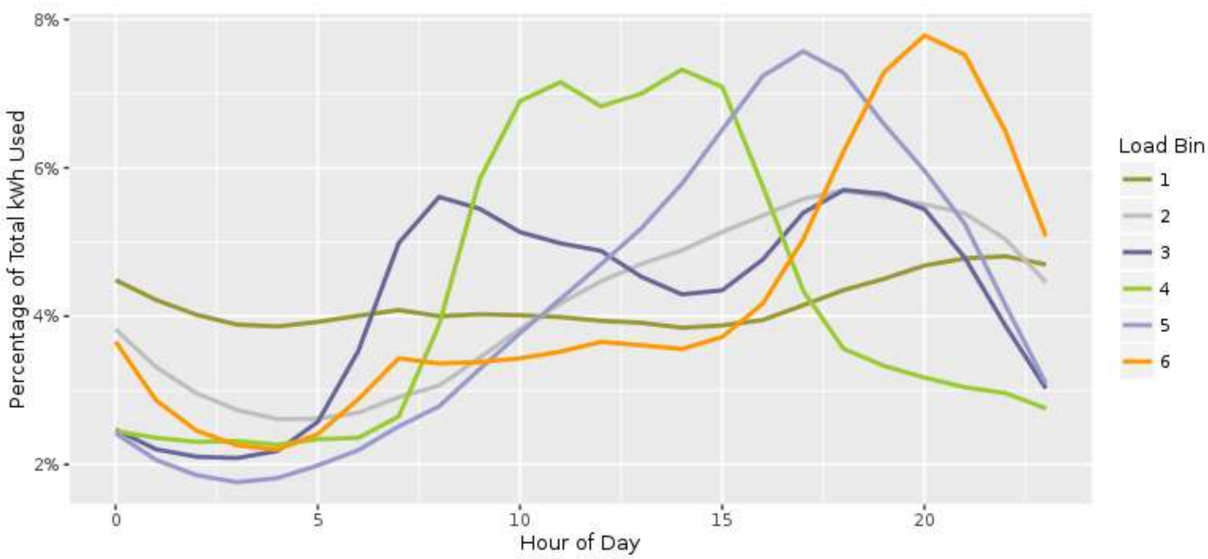


Figure 34 shows the average daily savings estimated by the AMICS model by customer load shape bin and cooling load, with the hottest days on the right. The rows show customers grouped by their load shape cluster from Figure 33. The load shape bins with the highest energy savings on hot days (high CDD) are customers with evening or night peak use (Bins 2, 5, and 6).

Figure 34: Retrofit Energy Savings by Customer Load Bin and CDD

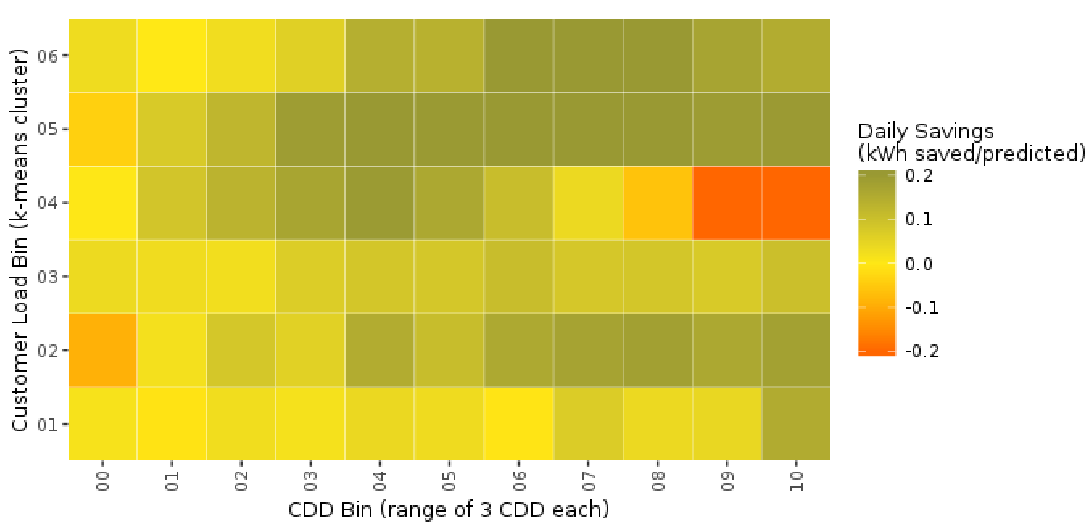
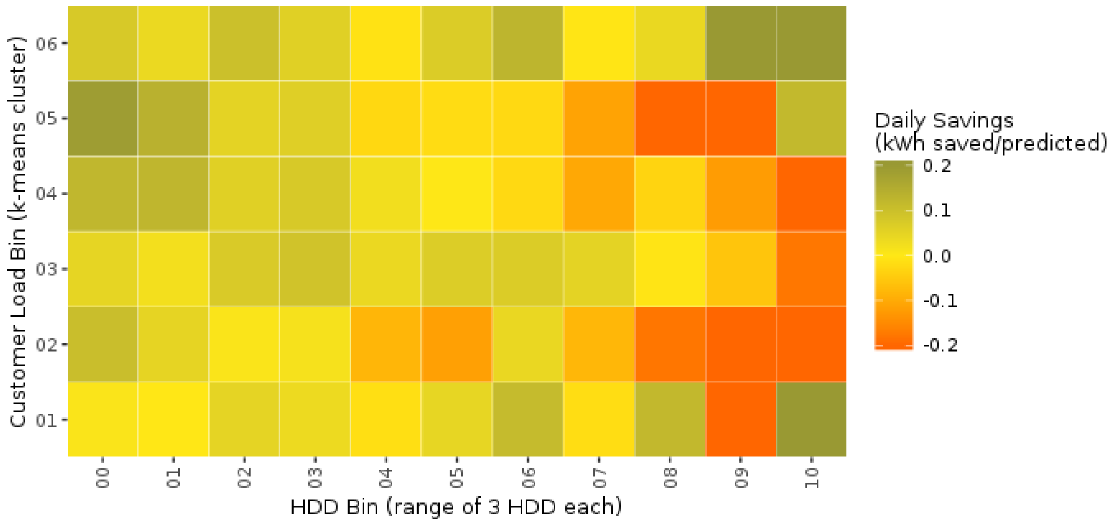


Figure 35 shows the average daily savings estimated by the AMICS model by customer load shape bin and heating load, with the coldest days on the right. Customers with night peak usage (Bin 6) had the most consistent energy savings on cold days (high HDD).

Figure 35: Retrofit Energy Savings by Customer Load Bin and HDD



Overall, tenants residing in the 42 buildings that participated in the Multifamily Upgrade Program saved an average of 0.31 kWh per day, or 2.7 percent. These energy savings varied substantially across seasons and customer segments. The next few sections will rely on the same AMICS preretrofit regression model to estimate savings for tenant mailers and then investigate demographic factors that contribute to customers' energy use.

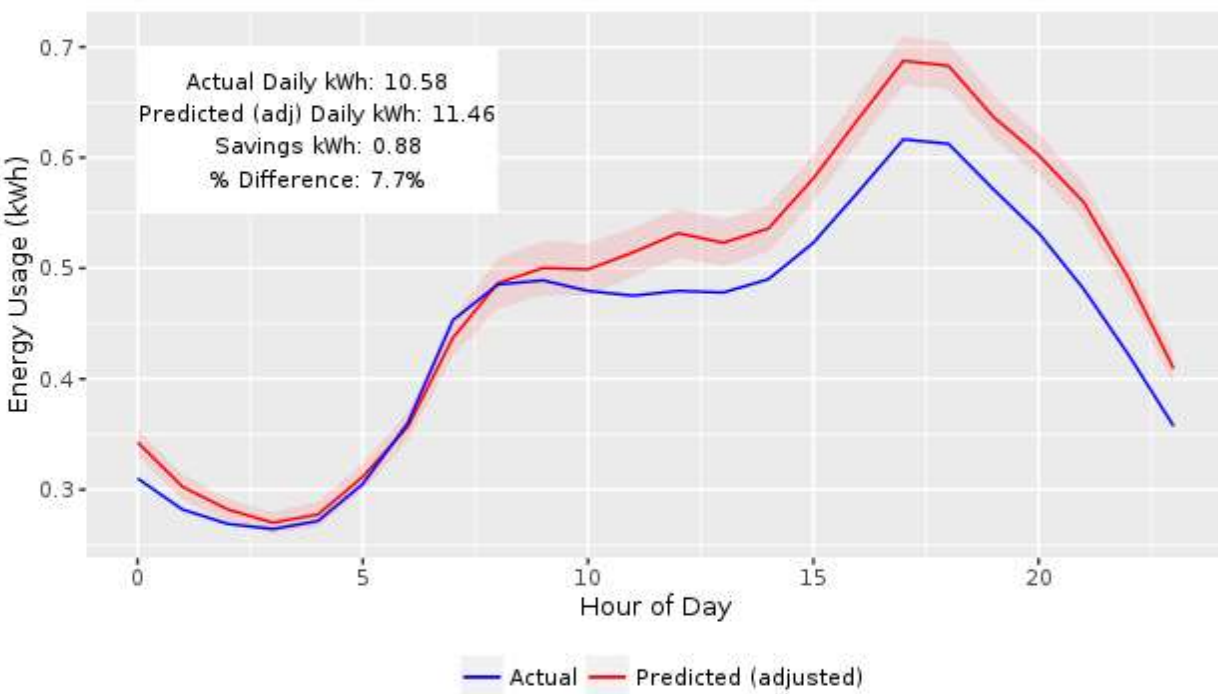
Tenant Mailers–Enhanced Communications

This section provides estimates for the energy savings realized by customers (i.e. tenants) that received six program mailers, based on Evergreen Economics' AMICS model and postretrofit AMI data through early October 2017. These customers reside in buildings that completed MUP retrofits and each opted to complete TRC's tenant survey.

Figure 36 and Figure **37** compare the post-retrofit predicted load shape (red) with the actual postretrofit load shape (blue) from the time that each retrofit was completed until the first mailer was sent (April 17, 2017). These predictions are based on the preretrofit period consumption AMICS model and postretrofit period weather data; they represent the expected load shape for these customers in absence of the PG&E MUP program retrofits. The timeline depicted in these charts is before the first mailer, so both charts reflect changes in energy use that are attributable to the MUP retrofits.

Before the mailers, the AMICS model estimates that the mailer recipients saved 0.88 kWh per day (7.7%) from the MUP retrofits, while the non-recipients saved 0.19 kWh per day (1.6%). This comparison is over a consistent period but does not control for any differences in weather conditions or customer type. It is provided only to emphasize that the mailer recipients have a different average load shape and realized greater MUP retrofit savings than the nonrecipients, even before the mailers began.[27]

Figure 36: Model Predictions vs. Actual Load of Mailer Recipients in Postretrofit Period, Before the First Mailer



[27] There are many possible reasons why these differences were observed. For instance, tenants who experienced drastic bill reductions from the MUP retrofits may have become more interested and willing to participate in the study. Alternately, tenants who were naturally interested in energy efficiency may have been more likely to respond to the survey but also may have been more likely to act and reduce their usage during the MUP retrofit period.

Figure 37: Model Predictions vs. Actual Load of Nonrecipients in Postretrofit Period Before the First Mailer

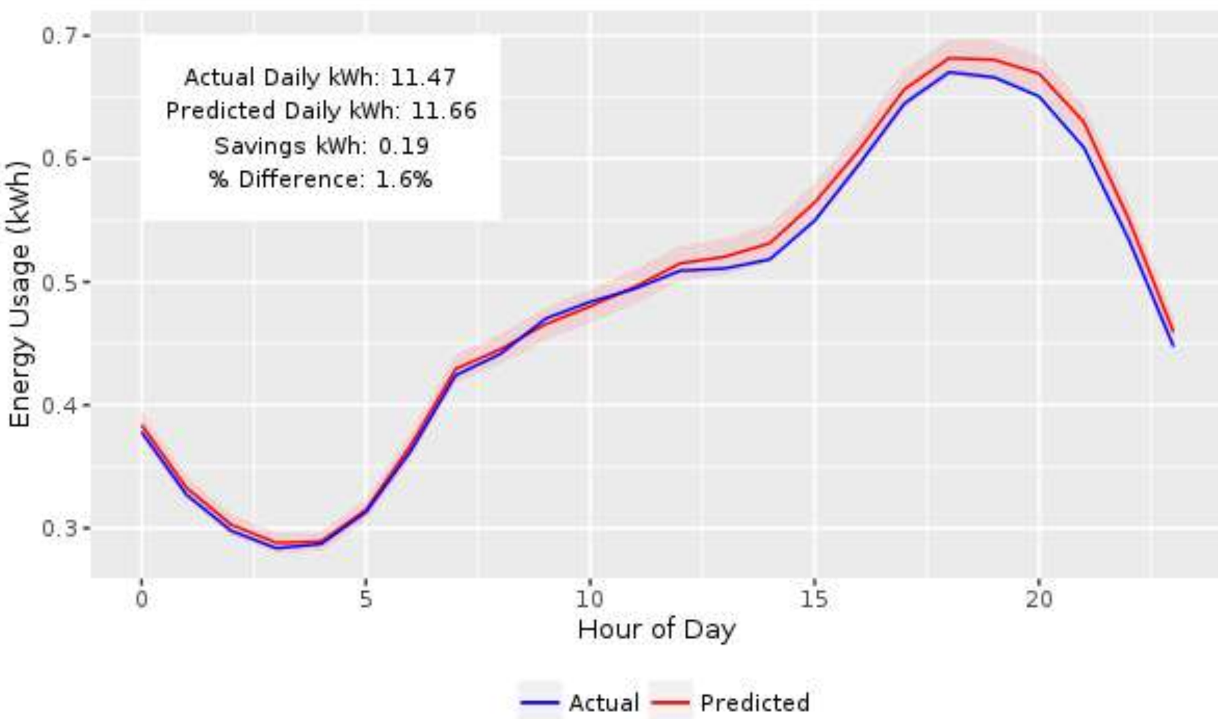


Figure 38 shows the average load shapes of the mailer recipients during the conditions (i.e. weather and day types) that they experienced from June 20-October 10, 2017, after all the MUP retrofits and mailers were complete. These three load shapes include:

- **Predicted load (red line)** – Represents the expected load shape without any program intervention (i.e. no retrofits or mailers), with a 95 percent confidence interval in the shaded area around each estimate. This is based on the adjusted AMICS model of preretrofit consumption and post-period weather data.
- **Average actual use, after mailers (solid blue line)** – Displays the true average load shape, after both the MUP retrofits and the mailers were complete.
- **Average actual use, before mailers (dotted blue line)** – Represents what these customers actually used on comparable days, after the MUP retrofits but before the mailers. [28]

The two actual load shapes help distinguish any changes attributable to the mailers from those changes attributable to the MUP retrofits, using the difference-of-differences method. Whenever the actual use before mailers (blue dotted line) falls below the predicted postperiod load shape (red line), this indicates that MUP retrofit savings were realized during that hour. This figure shows statistically significant MUP retrofit savings during all 24 hours of the day, for a daily

[28] This load shape is an aggregation the average actual load shapes of each customer-day bin during the postretrofit period *before* the mailers were sent, weighted by the number of days when each customer-day bin was observed in the postretrofit period *after* the last mailer was sent.

total of 2.54 kWh per day, or 19.4 percent. Whenever the actual use before the mailers (blue dotted line) also falls above the actual use after the mailers (blue solid line), this indicates that mailer savings were realized during that hour (in excess of any MUP retrofit savings). This analysis finds there are only a few hours in the morning with energy savings that can be attributed to the mailers.

Figure 39 shows the hourly kWh savings estimates for the postretrofit periods before the mailers to after the mailers, under the conditions that these customers experienced from June 20 – October 10, 2017. Error bars depicting 95 percent confidence intervals are provided around each estimate. There are a few hours with statistically significant decreases in savings; however, the magnitude of the difference in savings during these hours is too small (<0.05 kWh) to hold any practical significance.

Figure 38: Model Predictions vs. Actual Loads of Mailer Recipients in the Postretrofit Period, After the Last Mailer

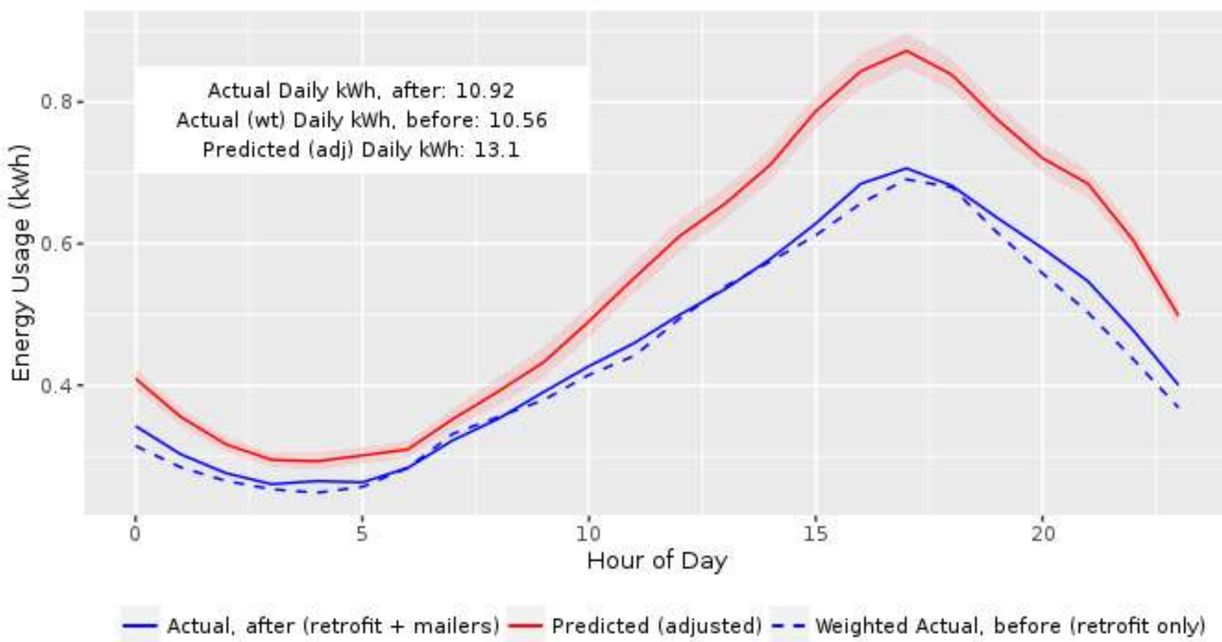
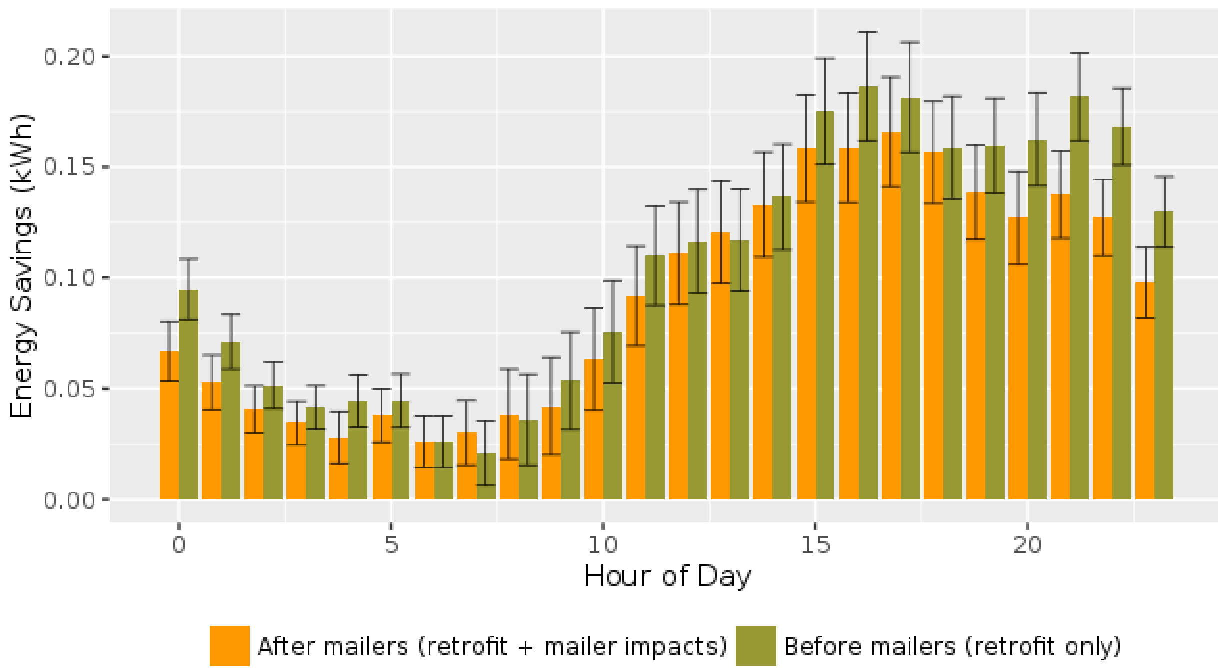


Figure 39: Estimated Energy Savings for Mailer Recipients



Evergreen also estimated the difference-of-differences for the postretrofit periods before the mailers to during the mailers. This analysis confirmed no statistically significant energy savings were realized from the mailers, even with short-term behavioral changes while the mailers were being received. Overall, the 239 tenants who received the six program mailers did not experience any statistically significant energy savings from these mailers. While the savings did vary substantially across days and customer segments, there were few patterns to explain why overall savings were not found. This analysis was limited by a small sample size and short analysis period after both interventions were complete (June 20-October 10, 2017). It is possible that the true energy savings from the mailers are simply too small to be detectable without a larger sample and/or additional post-period energy use data. Evergreen's analysis did confirm that the mailer recipients have continued to experience large and statistically significant energy savings from the MUP building retrofits.

Relating Energy Use to Demographic Factors

This section focuses on the diversity of energy use across the households in the sample, and on the degree to which available information on demographic and other household characterizations seem to explain some of this diversity.

Load Shape Diversity

Within the realm of social sciences, there has been little opportunity to combine detailed house-level energy use data with these household-level characterizations. Most work relating consumption to social and behavioral data has been confined to using aggregated energy use such as annual electricity and natural gas consumption, as in household energy survey microdata like California's *Residential Appliance Saturation Survey* (RASS) or the U.S. Department of Energy's Residential Energy Consumption Survey (RECS).[29] Good examples of such analyses include Sanquist et al. (2012) and Estiri (2015) for the United States and Belaïd (2016) for France. These recent studies have emphasized the task of disentangling threads in the multiple spheres of influence between individuals and energy use, including both direct effects (energy use "behaviors") and indirect effects (where inhabitants live, i.e., dwelling choice). This study advances this stream of inquiry by integrating hourly load shape data, statistically analyzing these data so they can be used to provide a new dimension for expressing energy use patterns. That is, being able to see **load shapes** with respect to demographic and other household-level data is new.

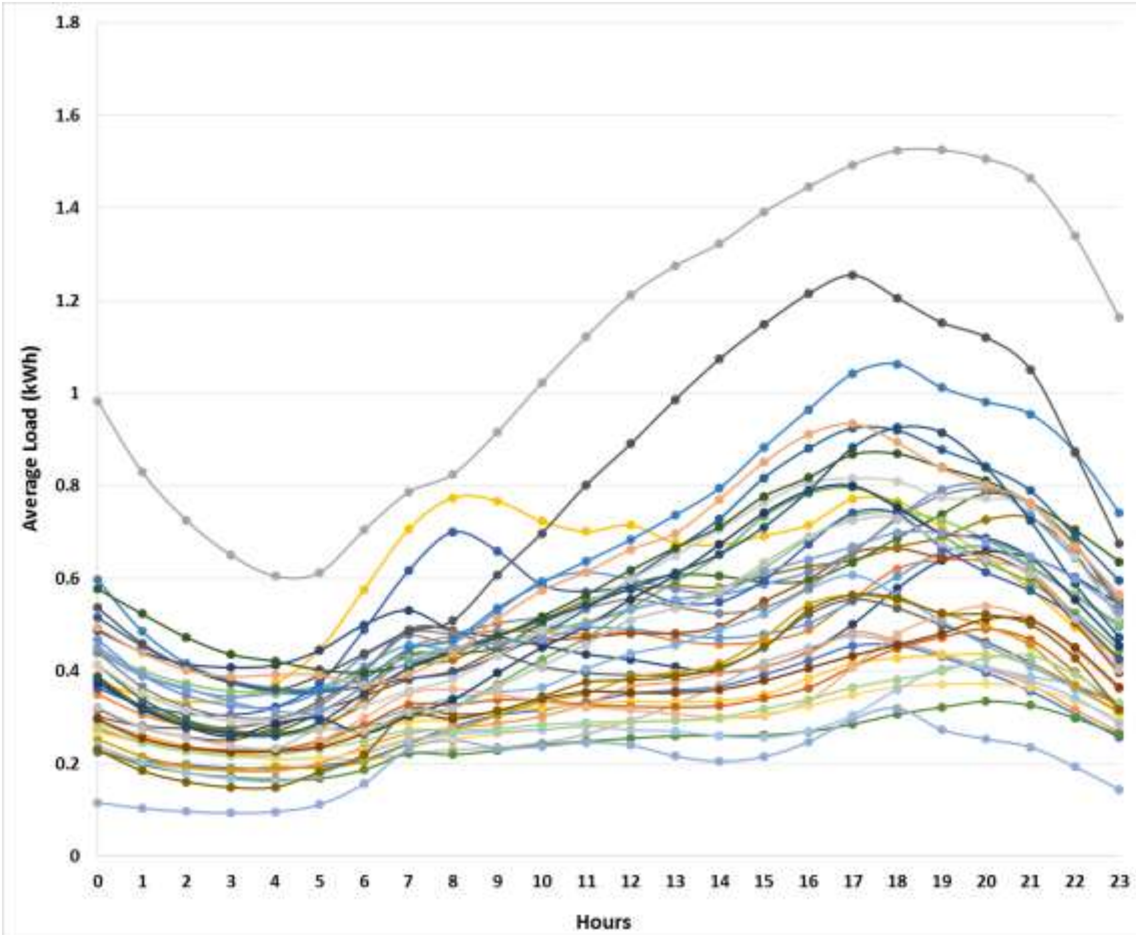
From the standpoint of estimating and capturing energy savings potential, recognizing this complexity may create a different view from the more standard "average" savings approach based on technology characteristics and framed around technical potential (see Moezzi et al. 2009). Recent work, however, has added innovations that better speak to this complexity. In particular, Jaske (2016) examined energy savings potential with respect to hourly electricity system impacts versus earlier studies that focused on aggregate energy savings and peak load impacts. Not only do load shape data help speak to the integration of demand and supply, which is becoming increasingly important in a more renewables-based future, they can guide efforts to more promising strategies to capture potential via helping focus measures on the hours of the day where they matter most.

What is clear from the data is that average load shapes differ remarkably across the different project sites. Each project can cover multiple buildings. The variety in load shapes is already clear from the cluster analysis presented above which group individual household load shapes across all properties into six very different shapes.

Figure 40 illustrates this variety using the **preretrofit period load data** by project. This depiction is based in simple averages of kWh, in contrast to separating load shape and load level.

[29] Both survey series have been collecting monthly billing data and relying on these files to create end-use estimates, but the monthly energy use data are generally not available to the public. Upcoming versions of these data sets may use AMI data to create end-use estimates.

Figure 40: Diversity of Load Shapes Across Participating Projects.



For example, the highest load shape (in gray) shows average hourly loads that are usually **at least five times higher** than those for the lowest load shape (in light blue). That difference holds even in the early morning hours, which are often a proxy for baseload at least when they are relatively flat as in that lowest load shape. Within these project-level average load shapes, households may often have a great variety of load shapes, as addressed in more detail in the demographic analyses.[30]

Taking a factor-oriented perspective on energy use, a basic set of questions inherent in the project scope asks what contributes to this variety, and how much in each case, among various physical characteristics of the buildings and housing units, equipment efficiency, weather and

[30] As noted above, within the negotiated data privacy agreements, these individual-level load shapes cannot be paired with full household information data for joint analysis, except as in the AMICS analysis, which starts with demographic factors.

other environmental factors, and household use patterns.[31] It also explores methods to investigate these in a pragmatic manner.

The team examined the extent to which the 10 load categories and the 6 different load shapes were correlated with MUP project properties, i.e. precise location. There were some clear tendencies showing load bin by weather city and Figure 41 and Figure 42 show load bin by weather city.[32] Weather city usually corresponds to a single project. For example, about 40% of the study households in the Fresno, Gilroy and Shafter weather cities (all of which are hot) and a few other cities were assigned to Load Shape 2, but so too were 16% of the households assigned to the much more temperate San Francisco area. In short, household-level load shapes comprising any average representation, even in a single multifamily property, may show great variety when considered individually.

Load Concentration

While electricity use does not translate precisely to electricity savings potential, in general potential savings will be higher for the highest-using households as compared to the very lowest users. The uneven distribution of electricity consumption across households is well-illustrated by the empirical cumulative distribution function of the sample households (Figure 43).[33] The highest-using 20% of the units (the 80% percentile along the y-axis) account for 43% of the total electricity use in the sample.[34] So from an aggregate perspective, this top 20% of multifamily residents might provide close to half of the electricity savings potential. More accurately, as argued by Lutzenhiser et al. (2017), if the top quartile of electricity users in this group used electricity in the same way as the third quartile, this could provide enormous savings. From a broader societal perspective, there are other considerations for pursuing policy strategy that focuses on the highest users (e.g., equity and household well-being), as well as logistical challenges. Still it provides a useful unflattening.

[31] The availability of multiple sites in varied locations and the controls that each site offers in terms of similarities of physical structure characteristics, environmental conditions, and major equipment (e.g., heating, air conditioning, fixed lighting, and possibly appliances) within the site provide an excellent opportunity to look at the influence of cultural or other demographic factors. This study was not designed to dissect at this level of detail, but doing so may be possible, pending consideration of sample restrictions that limit the use of energy data for individual units.

[32] Weather cities are provided in the PG&E account information records. Researchers use them in preference to other geographic definitions here because are the most obvious proxy for weather.

[33] The distribution was computed based on the midpoints of the ranges of the assigned bins for the lowest nine bins and the mean of the load within the highest (tenth) bin, thus giving the appearance of a step function.

[34] This is the level below the curve right of the 80th percentile.

Figure 41: Load Levels by City Identifier

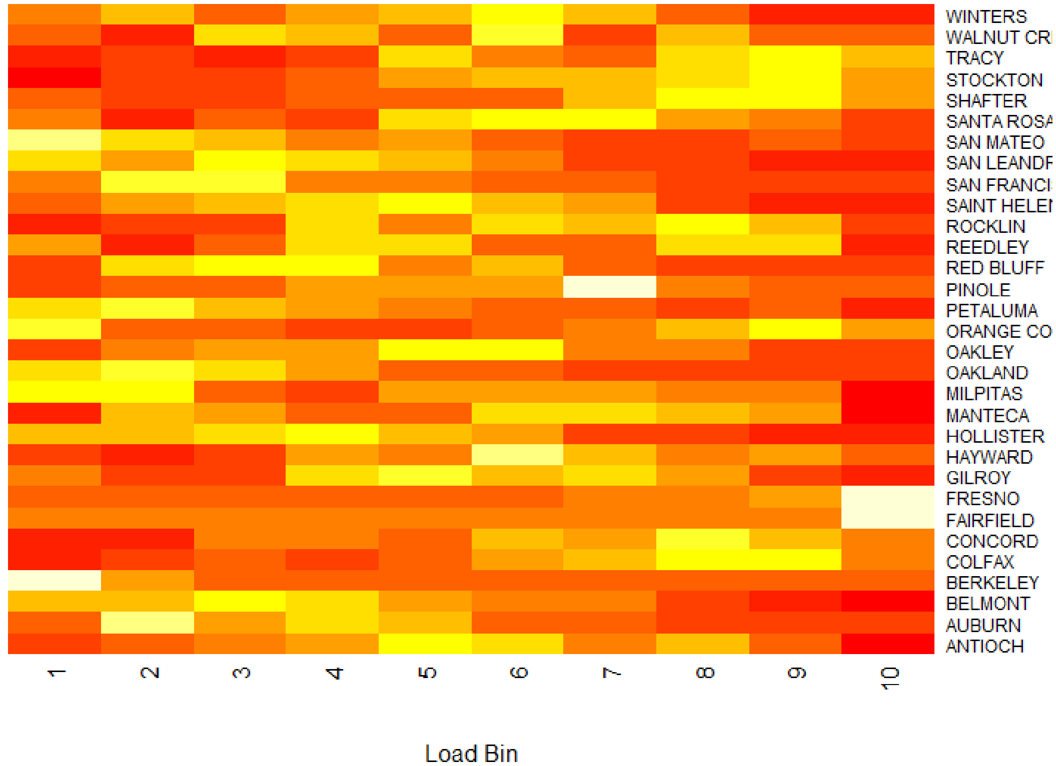


Figure 42: Normalized Load Bin by City Identifier

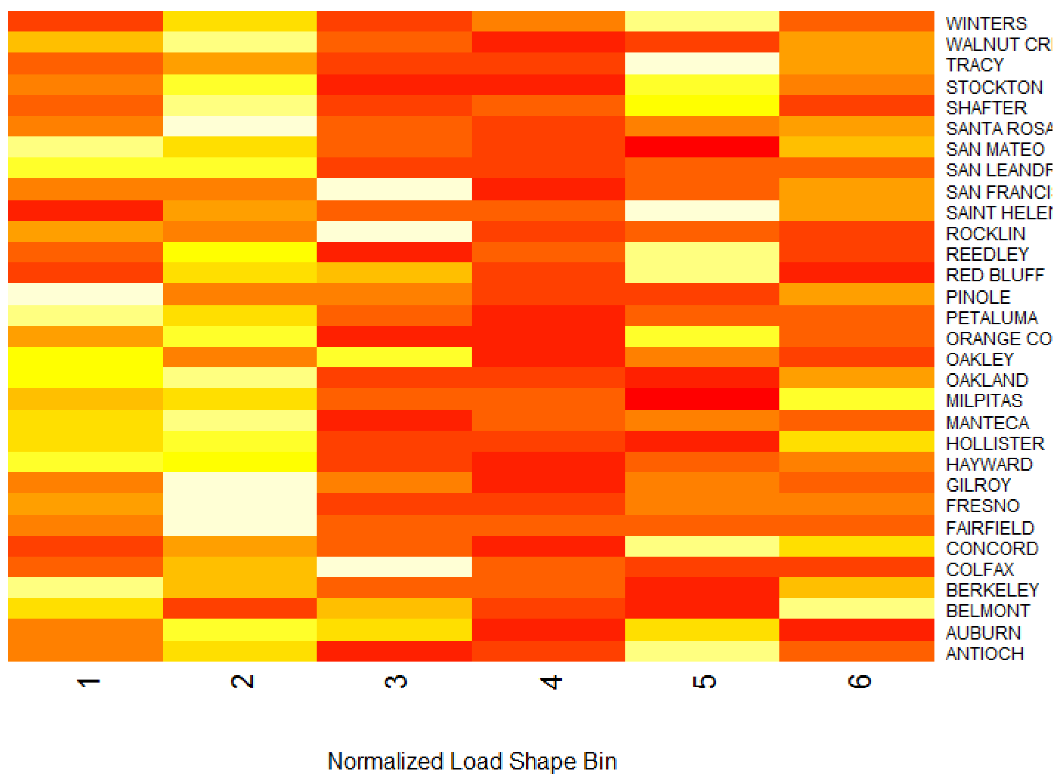
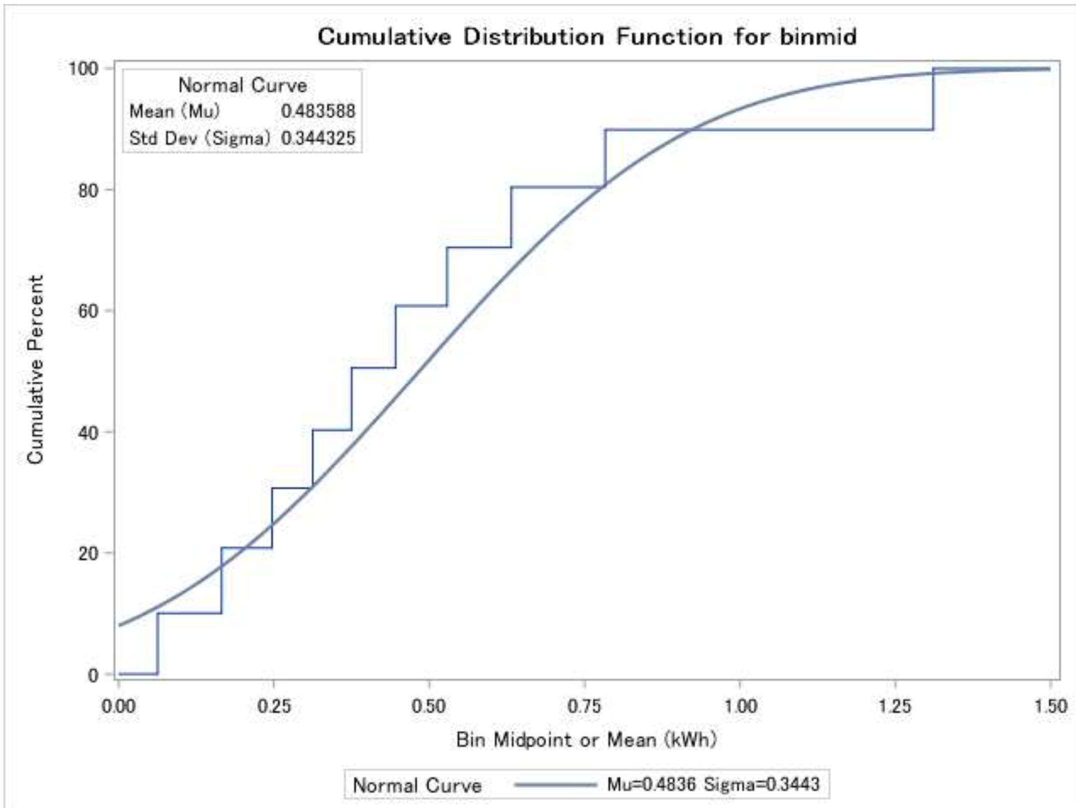


Figure 43: Empirical Cumulative Distribution Function for Household Average Hourly Load



Load Analysis by Demographic Factors

Energy efficiency analyses in general have focused on physical factors rather than those of the occupants. When occupant factors have been considered, the explanations have usually focused on number of people in the household and their income. This research project was designed to venture into advancing these explanations by collecting and analyzing far more detailed information on the characteristics, practices, and "stuff" of the occupants. These are related to each other, however, as well as to the physical characteristics of the homes and property. For example, new immigrant Latino households are more likely to have lower incomes and live in hotter areas than nth generation European-origin Americans. These numerous interacting and related factors make statistical analysis challenging. Dissecting the influence of these factors, to the extent appropriate, generally requires very large samples and is sensitive to sampling biases, which are difficult to avoid. However, because physical, cultural, and behavioral influences are interdependent—and any intervention operates on "packages" of influences—there are limits to the value of trying to distill energy use into independent components. The comparisons in this section are deliberately simple and descriptive, as befits a univariate depiction of load shapes. Future analyses could combine multiple demographic factors, particularly pairing geographic or property-level classification with other demographics.

One of the central arguments of a people-centered view of home energy use is that different households have different lifestyles, and that these lifestyles have substantial consequences for energy use (Lutzenhiser et al. 2017). While on the one hand this should be obvious, it also contrasts with the conventional focus on technology and physical factors, wherein people are seen mostly through the lenses of economics and "behavioral" choices. Until recently it has been difficult to find cultural- or lifestyle-related patterns because the data have been too crude. The combination of AMI data and detailed demographic information collected and analyzed in this project, however, provided a strong basis to help better understand some of these patterns.

As a reminder of the process described, the research team used the survey and consumer market data to define a variety of demographic and related dimensions (Table 6) to examine how differences within these dimensions mapped to differences in energy use patterns. Evergreen Economics used these data to develop pre-period load shapes for each of the seven dimensions. The report discusses the results below. In each case there are two sets of graphs: one showing the actual versus weather-adjusted load shapes for each category within the dimension, and the other comparing the actual load shapes across the categories in a single graphic. The team also draws in results from the survey and consumer market data to help translate these quantitative results to the household level.

Plug Loads

One of the underlying questions for this research was the opportunity to investigate the contribution of plug loads and miscellaneous electrical equipment in multifamily household energy use and conservation actions. While the major end-use - equipment central heating, cooling, water heating, refrigerators, cooking equipment, etc. - and envelope conditions in rented multifamily homes are not within the purview of the occupant, plug loads are general selected by the renters themselves. The way that inhabitants use the home (e.g., thermostat settings, amount of cooking, management of window coverings, etc.) has consequences for energy use, but the "owner-added" plug-load equipment is the most easily accountable. Thus, the survey was designed to capture a detailed set of questions about the entertainment, electronic, lighting, and other plug-load equipment in the household. These may also be the questions that occupants can answer most easily, e.g. versus the details of use or technical description of their other equipment. Table 10 summarizes the survey responses for the presence of this plug-in equipment. More than half (52%) of the surveyed households have two or more televisions, very close the 2015 national estimate of 51% for multifamily housing units in five-plus-unit buildings (EIA 2017). Nearly one-half of the surveyed households report gaming consoles. These electronic end uses can vary widely in consumption, depending on the exact equipment present and how much they are used. Ten hours of use or more per day for the most-used television is not uncommon; 12% of multifamily homes nationally report this level of usage (EIA 2017). Almost one-third of the multifamily household units surveyed report having a portable heater, perhaps making up for inadequacies or perceived inadequacies in built-in heating equipment. A nonnegligible minority (12%) reported having electric medical equipment (e.g. CPAP machine).

Table 10: Summary of Miscellaneous Plug-Load Equipment Reported by Survey Respondents.

Equipment	Presence (n=444)
Televisions (number)	3% have none (n=14) 44% have 1 (n=197) 38% have 2 (n=169) 14% have 3 or more (n=64)
Television/Cable Equipment	62% (n=275)
Computing Devices (number)	30% have none (n=133) 37% have 1 (n=164) 19% have 2 or 3 (n=85) 12% have 3 or 4 (n=53) 2% have 5 or more (n=9)
Gaming Equipment	48% (n=214)
Aquarium	5% (n=23)
Medical Equipment	12% (n=54)
Entertainment/Audio Systems	33% (n=147)
Plug-In Lamps (number)	13% have none (n=58) 69% have 1 to 3 (n=307) 16% have 4 to 6 (n=70) 2% have 7 or more (n=9)
Portable Heater	31% (n=138)
Dehumidifier	5% (n=23)
Other Devices Mentioned by Respondents	Pet monitoring camera, golf cart charger, fountain, train set, air cleaner, etc.

To use these data in the load shape analysis, a simple accounting of the number of devices reported for each surveyed housheold was done, without trying to account for expected energy consumption in detail. Households were then categorized by the number of plug load devices reported, in four tiers, from “Few” to “Lots” (Table 11), with half reporting only three-five plug loads.

Table 11: Categories Used for Defining Level of Plug-In Devices for Surveyed Households.

Reported Plug Loads	Percentage (n=444)
Few (0-2)	21% (n=92)
Lower Middle (3-5)	51% (n=225)
Upper Middle 6-7)	16% (n=70)
Lots (8-14)	13% (n=57)

Figure 44 shows the actual and weather-adjusted load shapes for each of these four categories of miscellaneous plug loads. The relationship between the weather-adjusted load shape (red) and the actual load shape (blue) changes gradually over the four levels of plug loads. Homes with the fewest plug loads use less than would be expected relative to the weather-adjusted estimates (top left graph). Those with high levels of plug loads use markedly more (lower right graph) than the weather-adjusted estimates.

Figure 45 depicts the average pre-retrofit load shapes for households in each of these four categories. The graphs showing satisfying distinctions. Households with lots of plug loads show substantially higher loads throughout the day, with a higher base load (as judged from the earliest hours of the day) as well as a higher peak than the other categories — 47% higher than the “Few” category.

In short, households with more miscelleneous plug loads have higher energy use on average than those with fewer such plug loads. It cannot be assumed that this difference is due to the plug loads themselves, rather than related to correlated differences such as bigger spaces, higher income, or more stuff. However the energy use of plug loads themselvesis likely part of the explanation, especially in the case where there are suites of related high-energy use equipment such as for medical needs. Nevertheless these results suggest that improved plug-load power management could make a noticeable difference to overall energy use.

The number of plug loads and level of plug load use are likely also correlated with other household factors, such as the number of people, income, the amount of time at home, or various other lifestyle elements. Some of these correlations were evident in the survey data though the sample is generally not suitable to draw broader conclusions about the strength of these correlations.

Survey data results on number of small loads had evident correspondence to both the load shape assignment as well as the load bin assignments. That is, the level of small loads (categorized into four bins, as noted above) was positively correlated with load (as is clear from the picture), but also possibly with load shape.

Figure 44: Actual and Weather-Adjusted Load Shapes by Level of Number of Small Plug-In Devices.

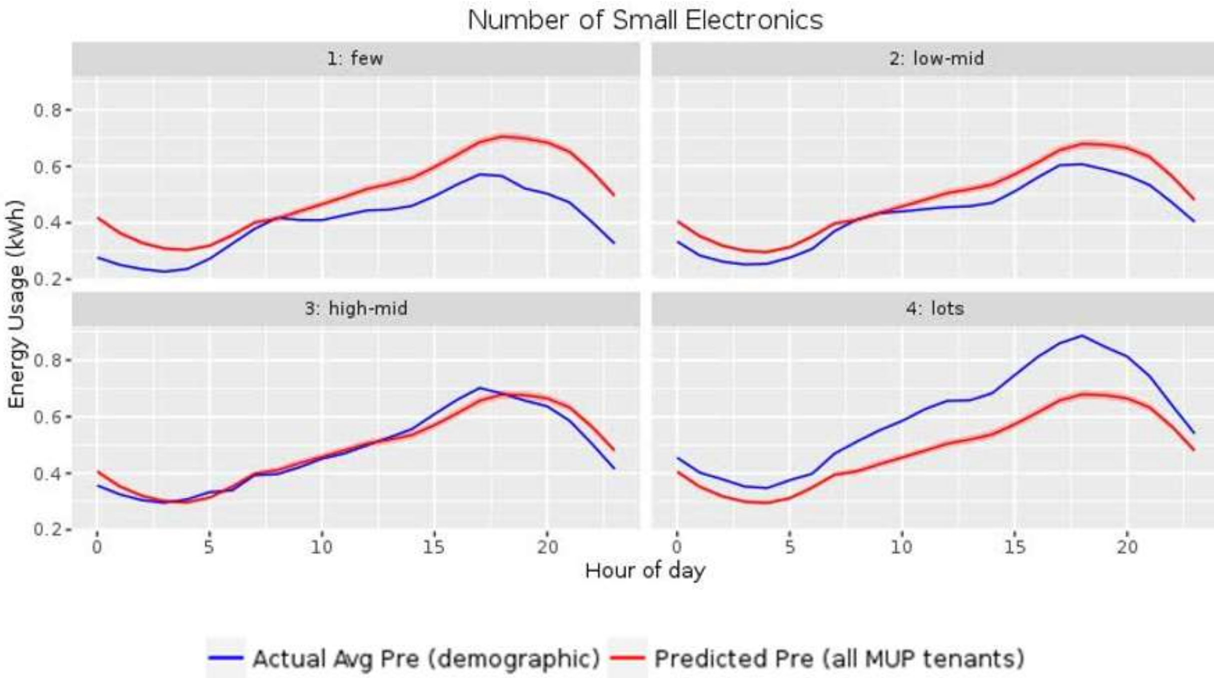
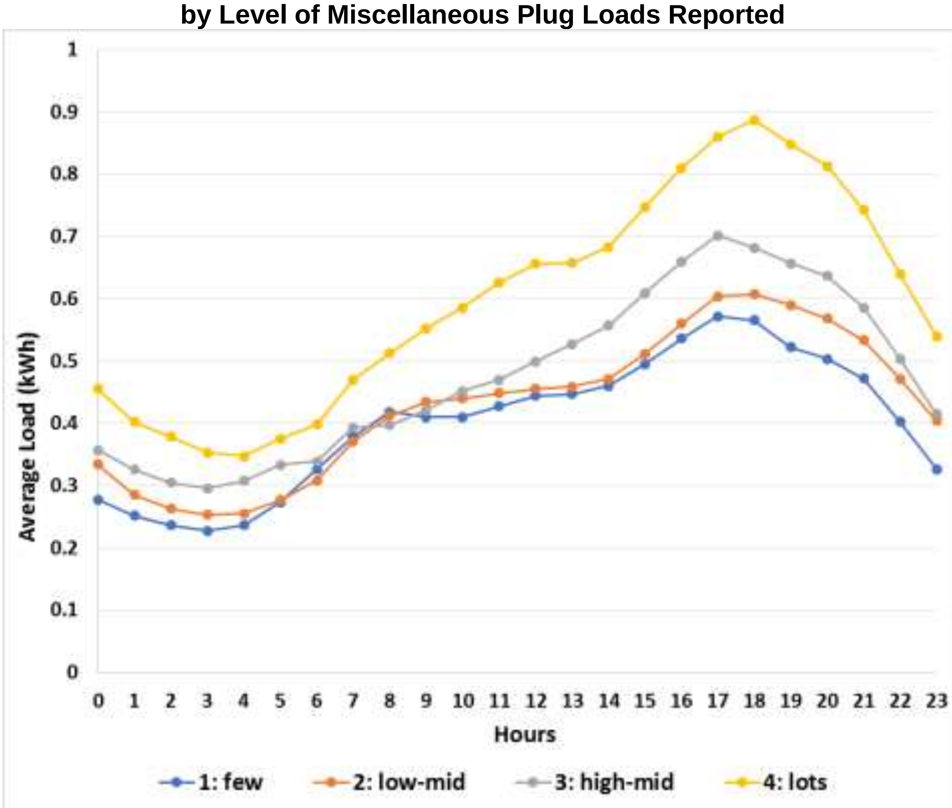


Figure 45: Comparison of Preretrofit Load Shapes by Level of Miscellaneous Plug Loads Reported



Surveyed households only

Managing Plug Loads

As part of the survey, households were asked if they would be interested in receiving a smart power strip. Few (5%) said “no,” most (73%) said “yes,” and the remaining 23% said “maybe.” Though the statistical and comparative bases are shaky, some research suggests that lower-income households are often very attentive to energy conservation — i.e., monitoring, turning off, unplugging and other behaviors (Dillahunt et al. 2009, Lamadrid et al. 2017). While perhaps anybody offered the chance for a free smart strip might be interested in receiving one in the expectation that it will save energy, effort, or both, certainly many of these largely low-income households in the sample were interested in such a device.

This interest suggests that providing an easy way to get the right smart power strips, free or at an attractive price, along with advice on where in the home these power strips might best be used, has promise as an energy savings measure in multifamily homes. Those with a moderate or high number of plug loads were slightly more interested in receiving a smart power strip (81%) than those with fewer plug loads (67%).

Cultural, Ethnic, Racial and Language Grouping

Using survey data and consumer market data, the research team devised a “General Ethnicity/Cultural/Origin” grouping that consisted of a set of nine categories based on ethnicity, race, language, and birthplace (US vs. non-US), as outlined above. These data were available for 1182 households.

Figure 46 shows the series of load shapes for each of these categories, with the blue lines indicating observed load shapes and the red lines indicating the weather-adjusted load shapes.

Figure 47 shows average preretrofit load shapes for six of the categories on one graph, to ease cross-category comparisons. The sample sizes in some of the categories are small, so the differences offered are suggestive rather than statistically definitive. The figure shows some striking differences among these categories. First, those with a European origin (as well as "Other" English-speaking) have substantially higher loads throughout the day versus the other categories, while the "Non-European, Non-English" group has clearly lower loads at almost every hour. The African-American group is in the middle.

These differences are not simple to interpret, because the distribution of ethnic and cultural identities is different across the various properties. Location (property) and General Ethnic/Cultural Group are strongly correlated (Table 12). For example, 56% of the African American group is in Alameda and Contra Costa Counties, whereas only 24% of the Spanish-speaking Hispanic households in the participating MUP properties are in these counties. Ideally, generating bi-variate load shapes that combine locational information with other demographic information could help tease out some of these differences. The researchers concluded, however, there are considerable differences across the categories in this General Ethnicity/Cultural/Origin group.

Figure 46: Actual and Weather-Adjusted Load Shapes by General Ethnicity/Cultural/Origin Category

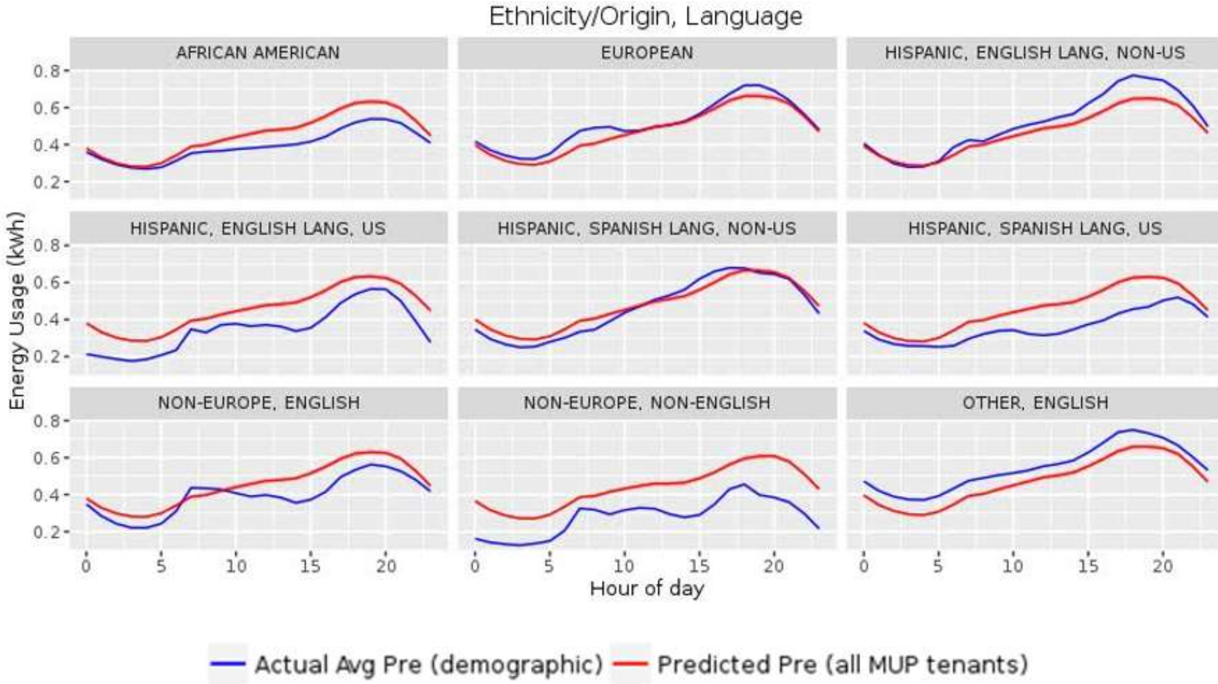


Figure 47: Comparison of Preretrofit Average Load Shapes Across Selected Ethnic and Cultural Groups

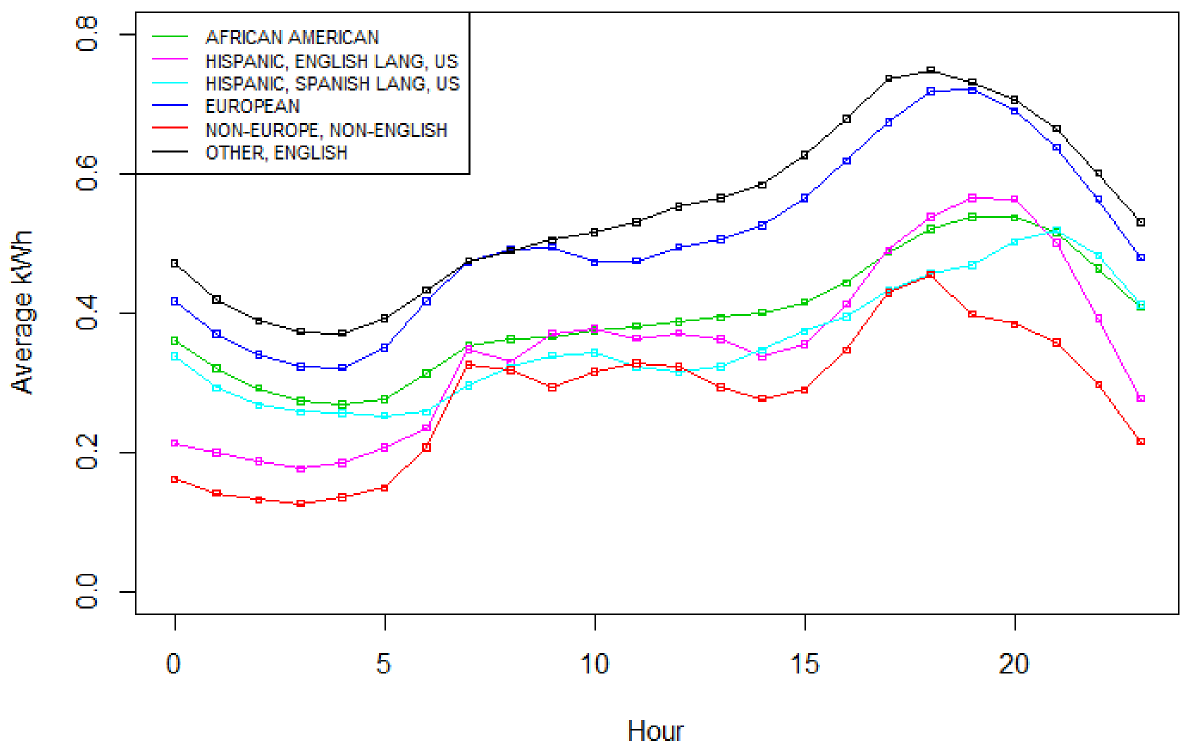


Table 12: Distribution of General Ethnicity/Race/Cultural Category by County Group

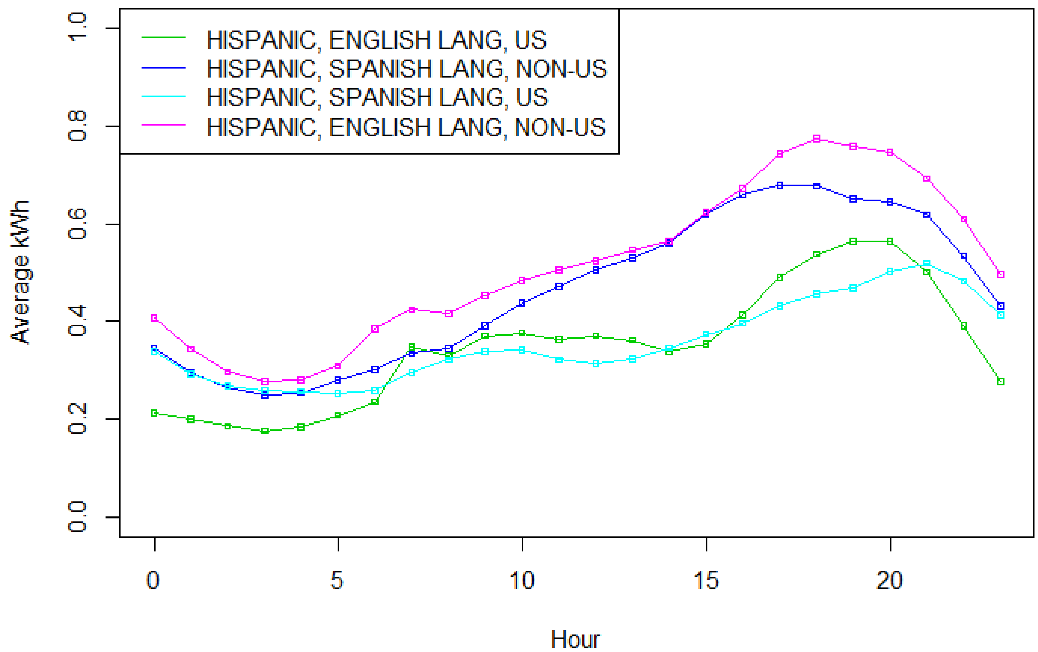
	African American	European	Hispanic, English Language, Born Outside of US	Hispanic, English Language, US	Hispanic, Spanish Language Outside of US	Hispanic, Spanish Language, US	Non-European Origin, English Language	Other, English Language
Alameda	54	3	3	8	8	0	5	21
Contra Costa, Santa Clara	25	2	2	9	13	4	7	38
Fresno	14	2	0	38	28	6	2	10
Placer	0	24	4	0	0	0	7	65
San Joaquin, Yolo, Tehama	4	14	2	6	33	0	1	40
San Mateo	4	16	4	4	0	0	37	35
Sonoma, Napa, Solano	8	6	2	10	18	2	4	50
Column Percent	13	9	2	15	18	2	7	34

Percentage of row; n=455 survey respondents

Figure 48 compares average preretrofit load shapes for households of Hispanic origin, classified by whether the heads of household were US-born, and whether the primarily language in the household is Spanish or English.[35]

[35] These categories are analyzed separately to ease visual analysis.

Figure 48: Comparison of Preretrofit Average Load Shapes for Hispanic-Respondent Households by Language and Birthplace.



The most striking pattern is that the two load shapes for the U.S.-born households (green and turquoise) look different– and are substantially lower than - the two load shapes for the households born outside the United States (blue and pink). The load shapes for the Spanish-language households are, in both the US and non-US cases, somewhat lower than for the English-speaking counterparts. These distinctions, again, can have a variety of origins, including location, income, and number of occupants, as well as those having to do with activities such as amount of time in the home, cooking, temperature preferences, etc. These differences are further explored below. But it remains clear that the average load shapes are distinct, particularly between US-born and non-U.S.-born Hispanic households.

Location

In lieu of producing property-specific load shapes for every participating MUP property, loads shapes were sometimes combined across properties to permit sufficient sample sizes. These aggregations were defined by counties and groupings of neighboring counties, as shown in ad shapes among those compared.in Table 13.

Table 13: Number of Projects, Total Candidate Households and Households Qualifying for Retrofit Analysis

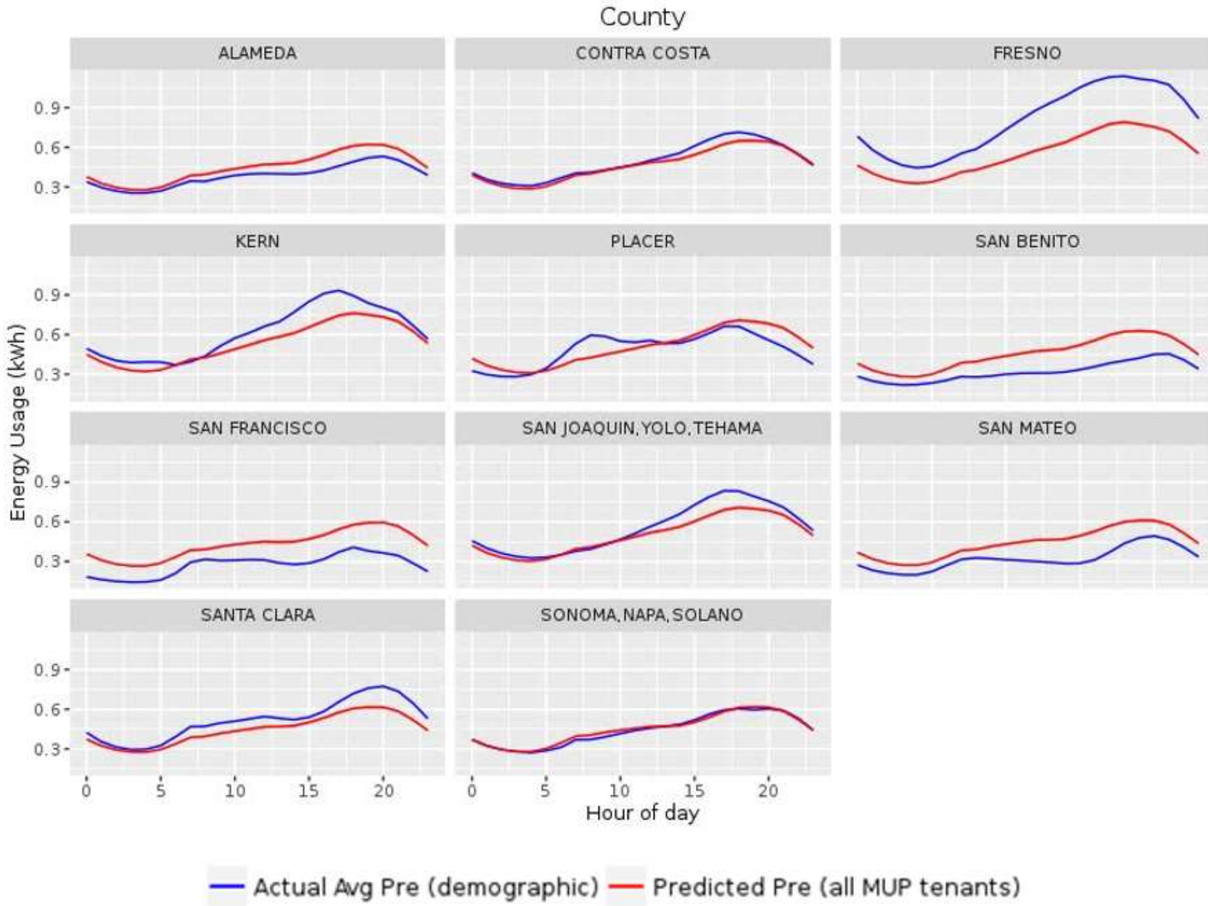
County Grouping	Number of Projects	Number of Households[36]
Alameda	7	572

[36] This is the total number of households, rather than the number of households included in the postretrofit analysis.

County Grouping	Number of Projects	Number of Households[36]
Contra Costa	5	1254
Fresno	4	2424
Kern	1	112
Placer	3	280
San Benito	2	108
San Francisco	2	239
San Joaquin, Yolo, Tehama	9	1887
San Mateo	2	844
Santa Clara	2	2773
Sonoma, Napa, Solano	5	524
All	42	11,017

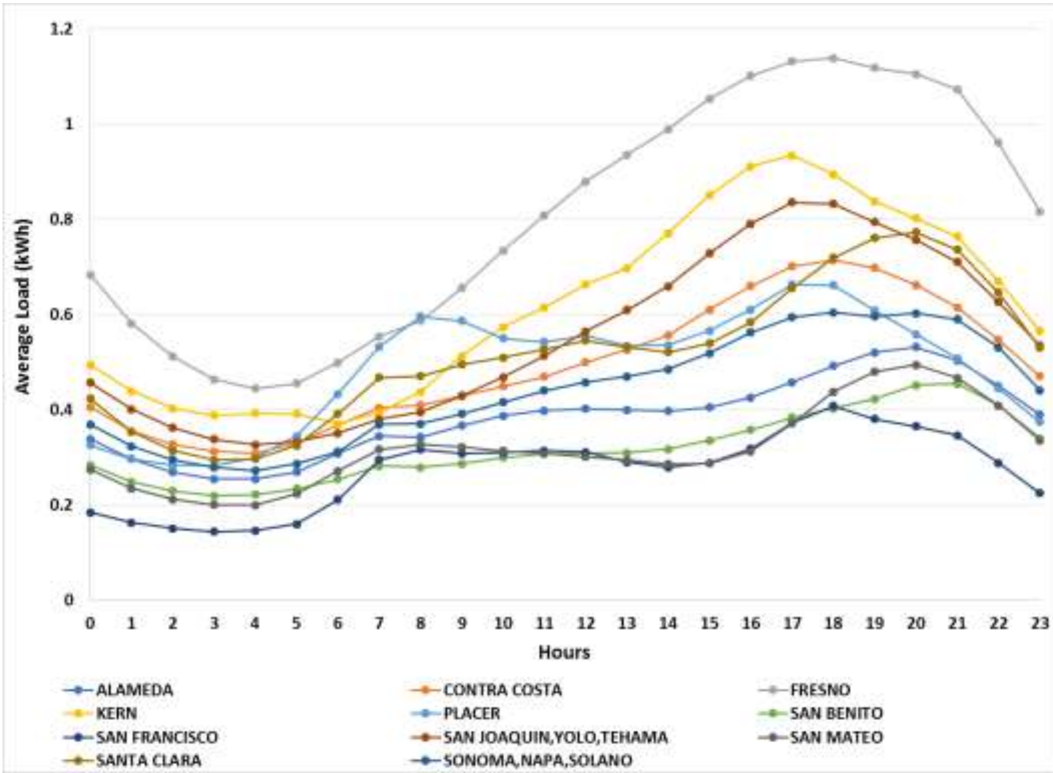
Figure 49 shows, by the county groupings, the average preretrofit load shapes across all housing units located in MUP properties. This comparison clearly shows the effects of cooling, with roughly similar load shapes among the hotter areas (Fresno, Kern, and San Joaquin/Yolo/Tehama) and, similarly, flatter load shapes across the milder areas (Alameda, San Francisco, San Mateo, and Sonoma/Napa/Solano). The actual load shape is clearly higher than the weather-adjusted load shape for Fresno and Kern Counties, again indicating the effect of cooling. For the other county groupings, the weather-adjusted load shapes are similar or higher than the actual load shapes.

Figure 49: Actual and Weather-Adjusted Load Shapes by County Grouping



shows the county group load shapes on one graph, to facilitate cross-county comparison. The figure echoes the load shapes in the project-level analyses above, though the aggregation below makes the effects of weather clearer. Households in the valley—Fresno (light green), to a lesser extent Kern (purple) and San Joaquin/Yolo/Tehama—show the highest loads and peakiest load shapes. Projects in the Coastal Bay Area counties (San Francisco, Alameda, and San Mateo), as well as the San Benito project, have the lowest energy use and least peaky load shapes among those compared.

Figure 50: Comparison of Preretrofit Average Load Shapes by Project Location



Income Groupings

Figure 51 shows actual and weather-adjusted load shapes by income category with weather-adjustments making little difference.

Figure 51: Actual and Weather-Adjusted Load Shapes by Income Grouping

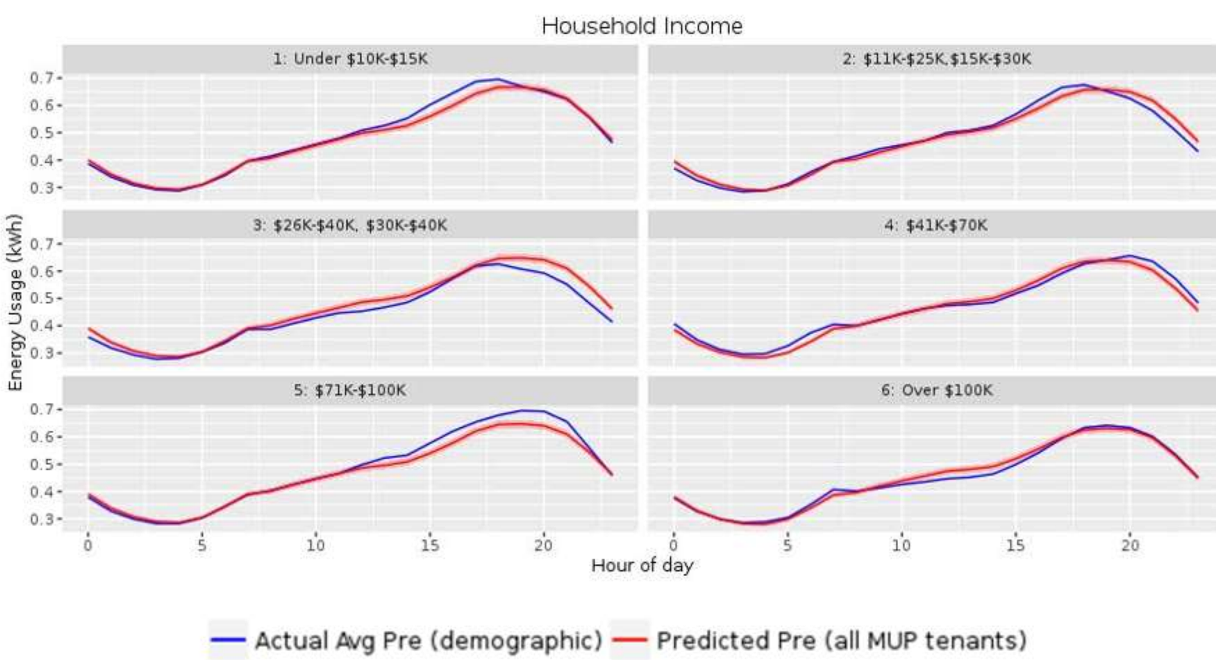
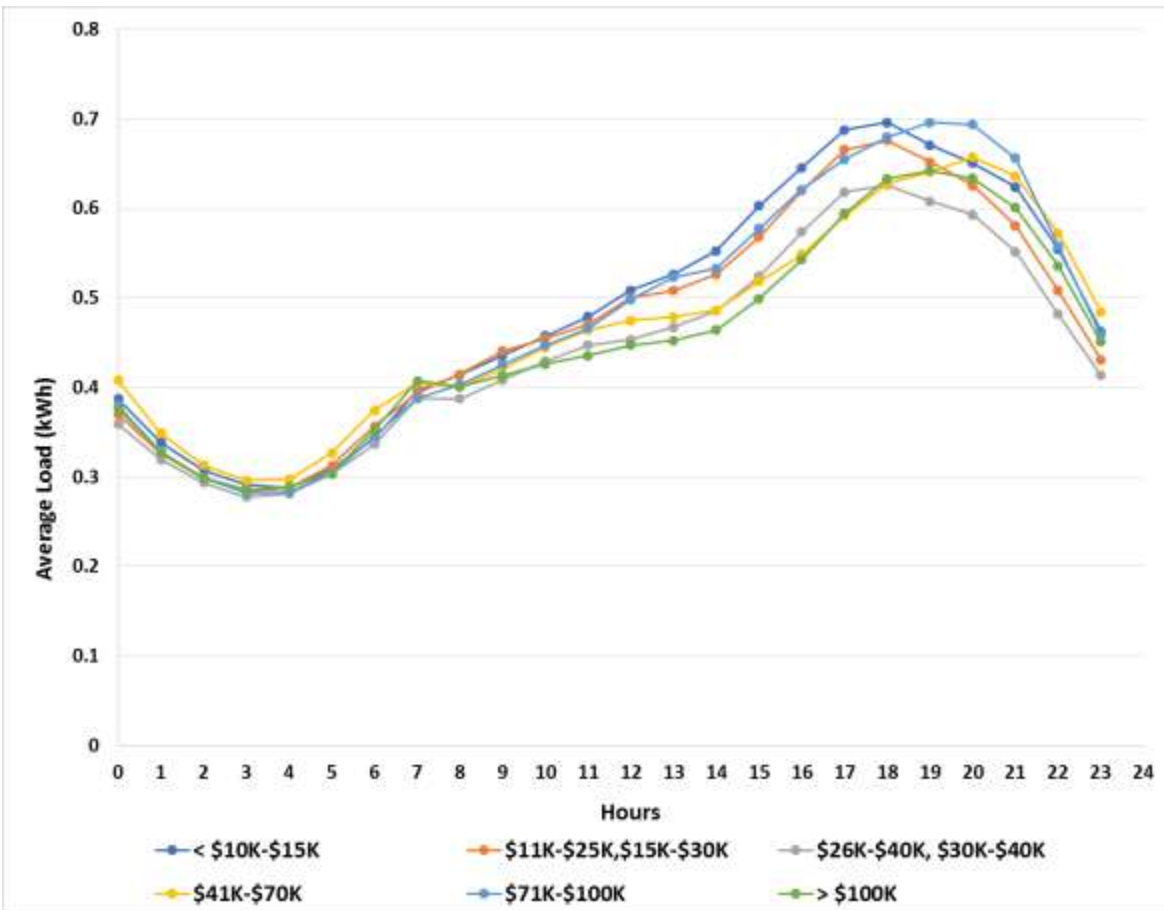


Figure 52 compares average preretrofit load shapes across income categories. Of all the demographic category comparisons, this plot shows the smallest differences across the categories compared. The two lowest-income categories have among the highest loads (deep blue and deep orange lines) but are similar to those of the “Upper Middle” group (light blue), which has a somewhat later peak.

This result contrasts with the generic assumption that energy use increases with income. There are various possible explanations for these patterns, ranging from demographic and related factors associated with lower income (time spent at home, health conditions) that tend to correlate with higher energy consumption, as well as physical, environmental, and economic aspects such as location, housing quality, medical equipment, and tariff differences that influence use. Also, the two highest-income groups are quite small, given the generally low-income distribution of the sample population.

Figure 52: Comparison of Preretrofit Average Load Shapes by Income Category



Household Type

The number and ages of people within a household unit provide a simple way to consider household type as a rough lifestyle grouping, particularly since the necessary data to assign households to such types are widely available. The team developed seven Household Type group categories based on the number of people in the home and their ages.

Figure 53: Actual and Weather-Adjusted Load Shapes by Household Composition

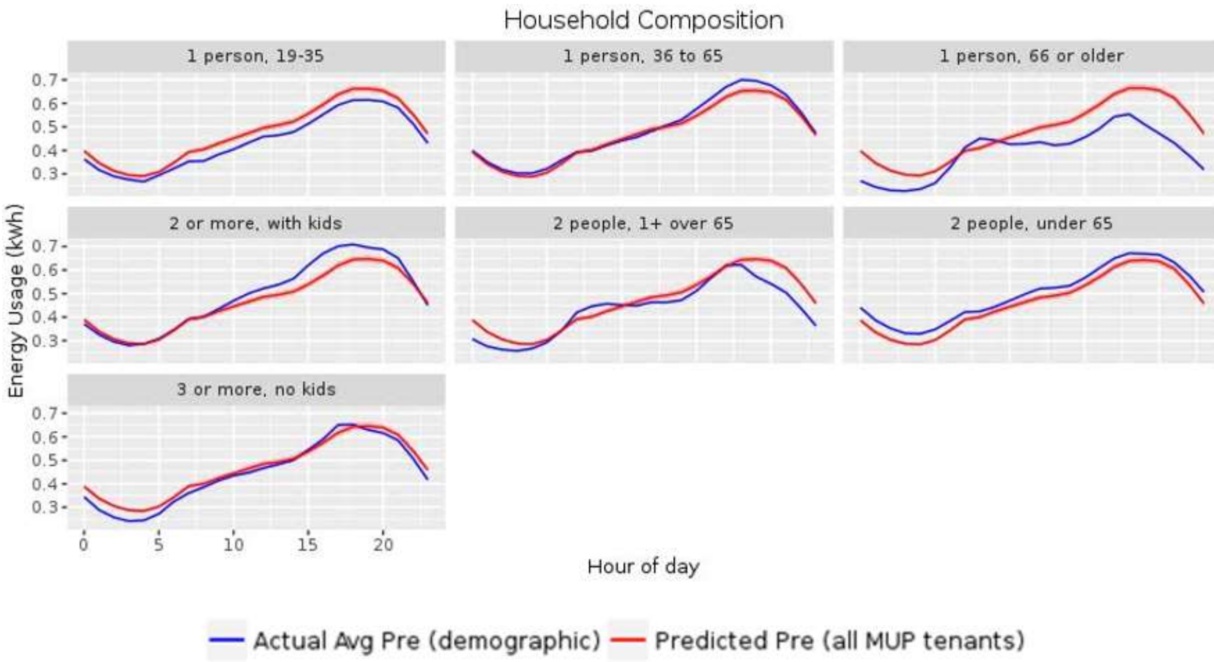


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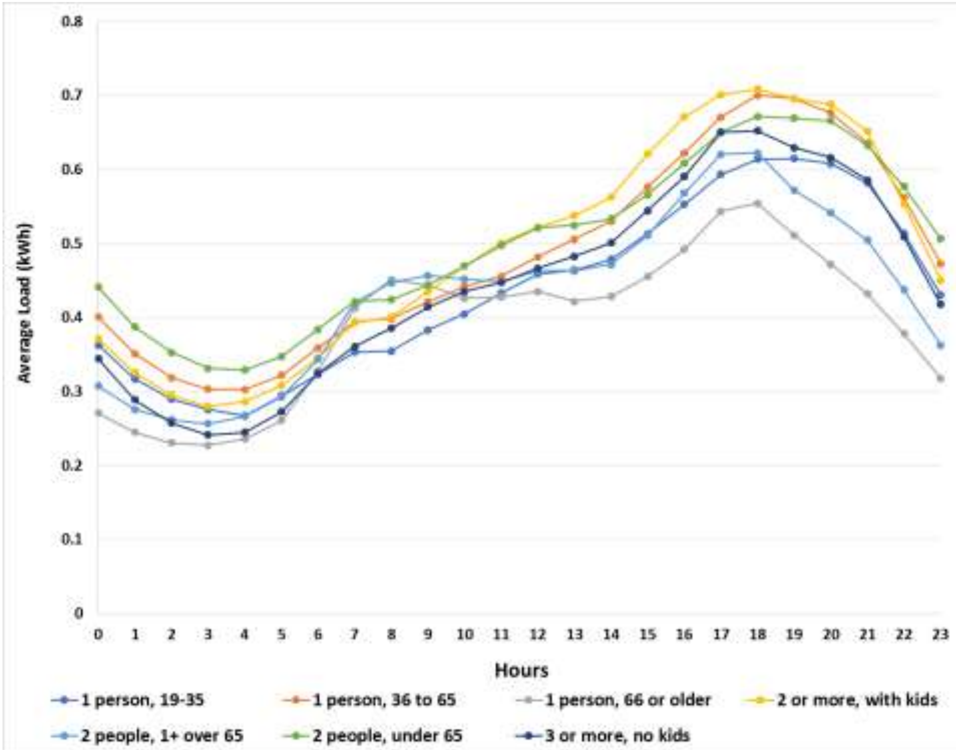
Figure 53shows the actual and weather-adjusted loads shapes for the seven categories of Household Type. Figure 54 shows the load shapes on one graph, comparing across the seven groups. While most of the load shapes are not dramatically different, there are some clear distinctions. Single-person households with the occupant aged 66 or older have the lowest shape overall, showing a relative sharp morning local peak and a steep decline in load after the evening peak at 6pm. Households with two or more persons, at least one of which is a child under 18 (light orange), show the highest energy use. In terms of load shape versus level, these households are similar to middle-aged adult single-person households.

Figure 54: Comparison of Preretrofit Average Load Shapes by Household Type



Tenure

Anecdotally, statistical analyses of energy use in single-family homes have found evidence that energy use increases the longer occupants have lived within a home, consistent with an accumulation of "stuff," though housing age and occupant age are also correlated with length of time in a home. To investigate this, the team examined the estimated length of time that occupants had lived in the home and used these distinctions to compare preretrofit load shapes.[37]

Figure 56 shows actual and weather-adjusted load shapes by tenure. The relatively large difference between actual and weather-adjusted load shape in the longest-tenured category (20 years or more, lower right) echoes the difference seen for older single-person households just above.

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[37] Additional data on length of time in the household were available for most survey respondents and, for many of the nonsurveyed sample, from the consumer market data bases. For this analysis, however, the team used utility account data to estimate tenure. In some cases, account information may have changed without a change in occupancy, and occupancy may have changed without a change in account information.

Figure 55: Actual and Weather-Adjusted Load Shape by Tenure Category

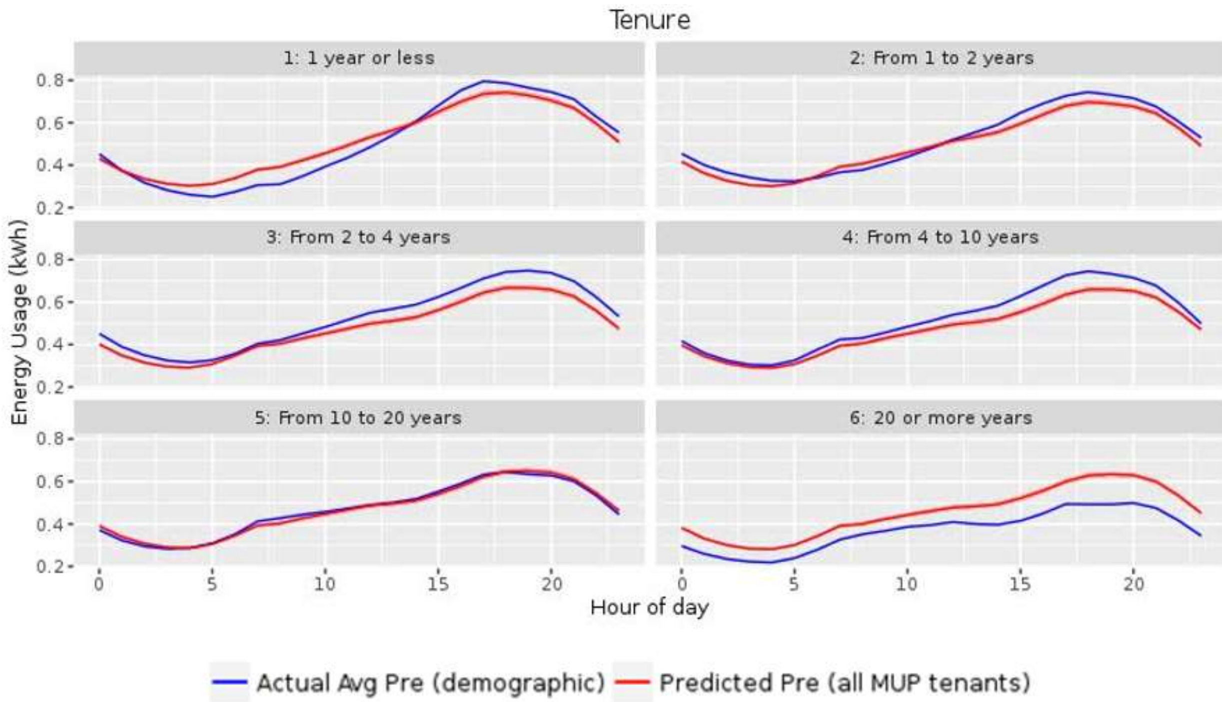
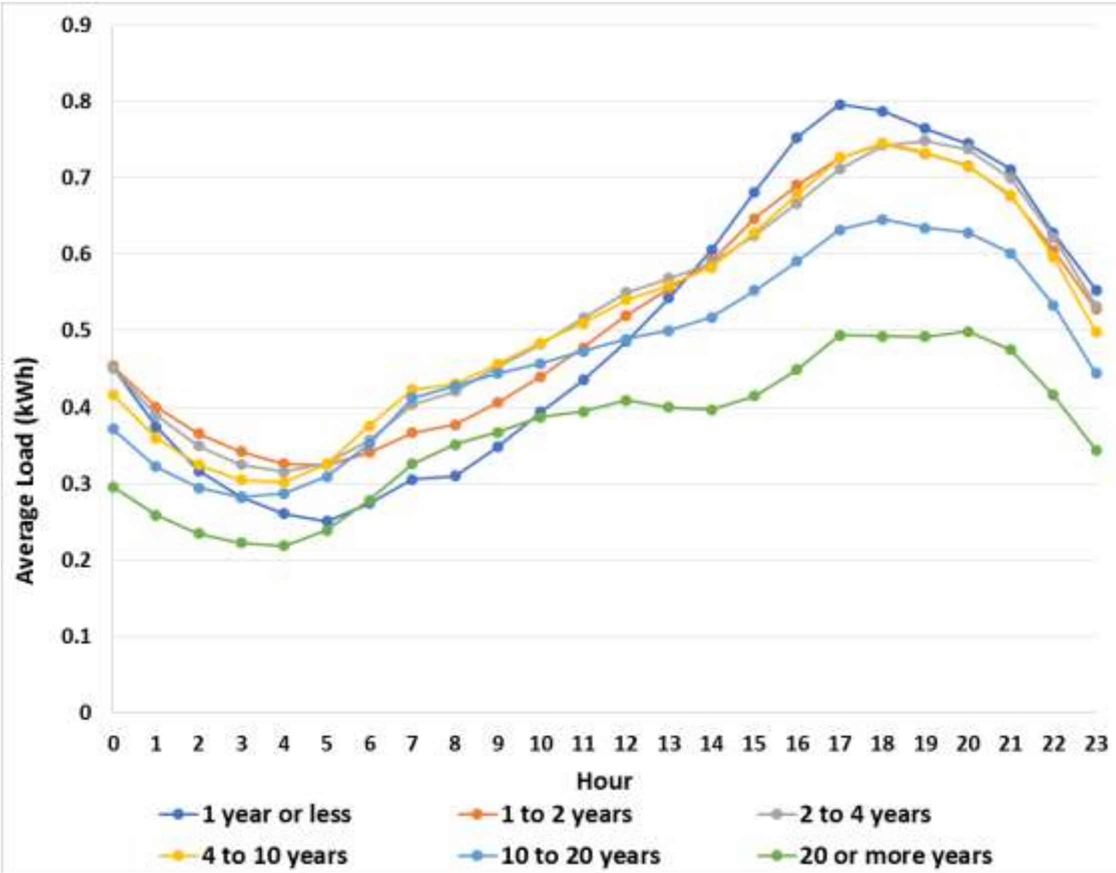


Figure 56 compares actual load shapes across all six categories of tenure. There is a striking difference between those who have been in the home for more than 20 years and those who have been in the home for one year or less. The occupants with the longest tenure are generally older than those with shorter tenure. For example, 16% of households who have lived in the same home for 20 or more years have at least one occupant aged 66 or older, while only 1% of those who have lived in the home for one year or less have an occupant 66 or older. The longer-tenure households may also be living in older properties.

Figure 56: Comparison of Preretrofit Average Load Shapes by Tenure



AC-Related Project

Preretrofit load shapes were also examined to whether the planned retrofit involved direct improvements to air conditioning (17 projects), indirect improvements (e.g., such as window measures 19 projects), or no improvements (one project) related to air conditioning. One of these projects *added* air conditioning. The team included a category for "all other" projects, which are those for which retrofits were incomplete and the survey was not distributed.

Figure 57 shows the actual and weather-adjusted load shapes for each of these four categories. Households in properties where air conditioning was directly affected by the retrofit clearly use the most electricity on average, as expected; it is here that weather-adjustment makes the most difference.

Figure 58 compares the actual load shapes on one graph.

Figure 57: Actual and Weather-Adjusted Load Shape by Category of Air-Conditioning Upgrade

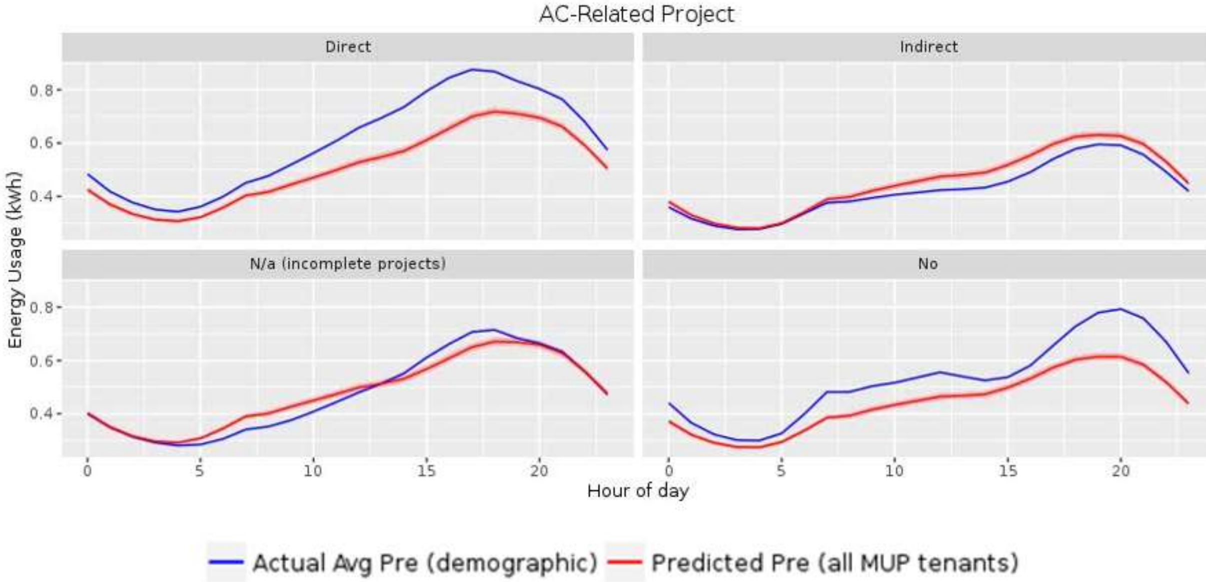
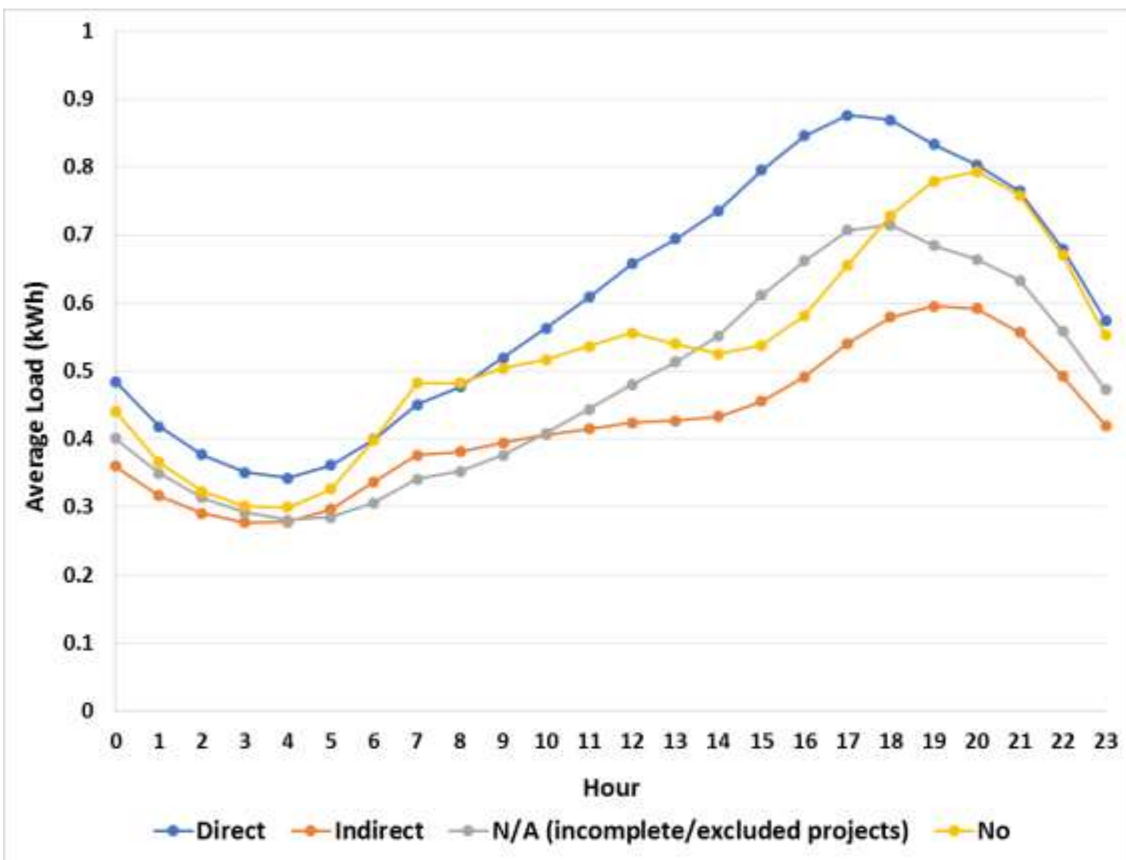


Figure 58: Comparison of Average Pre-Retrofit Load Shapes by Retrofit With Respect to Air Conditioning

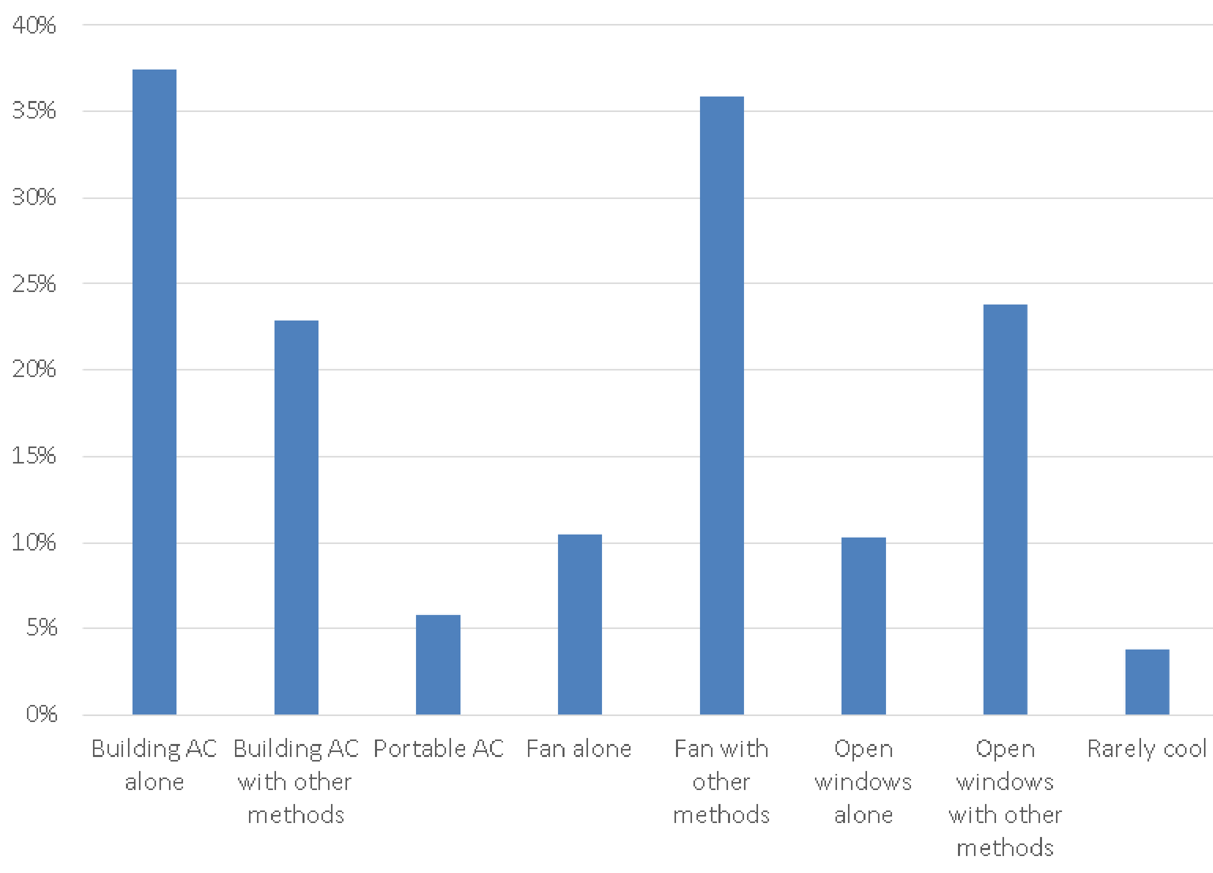


Cooling and Heating: A World of Dissatisfaction

In the survey, respondents were asked a short series of questions about their use of and satisfaction with the cooling and heating equipment in their home. These results underscore the nonuniformity of use behaviors and experiences across the households in the sample, even within properties. In most cases this question was asked after the retrofits had taken place, though the questions were not geared to evaluating specific satisfaction with any related measures.

Figure 59 summarizes the cooling methods reported by survey respondents. Sixty percent reported using the building air-conditioning system, whether exclusively (37%) or in combination with other methods (23%). Fan use, often forgotten in analyses of comfort-centered energy use, was common with nearly half reporting either using fans alone (10%) or fans with other methods (36%).

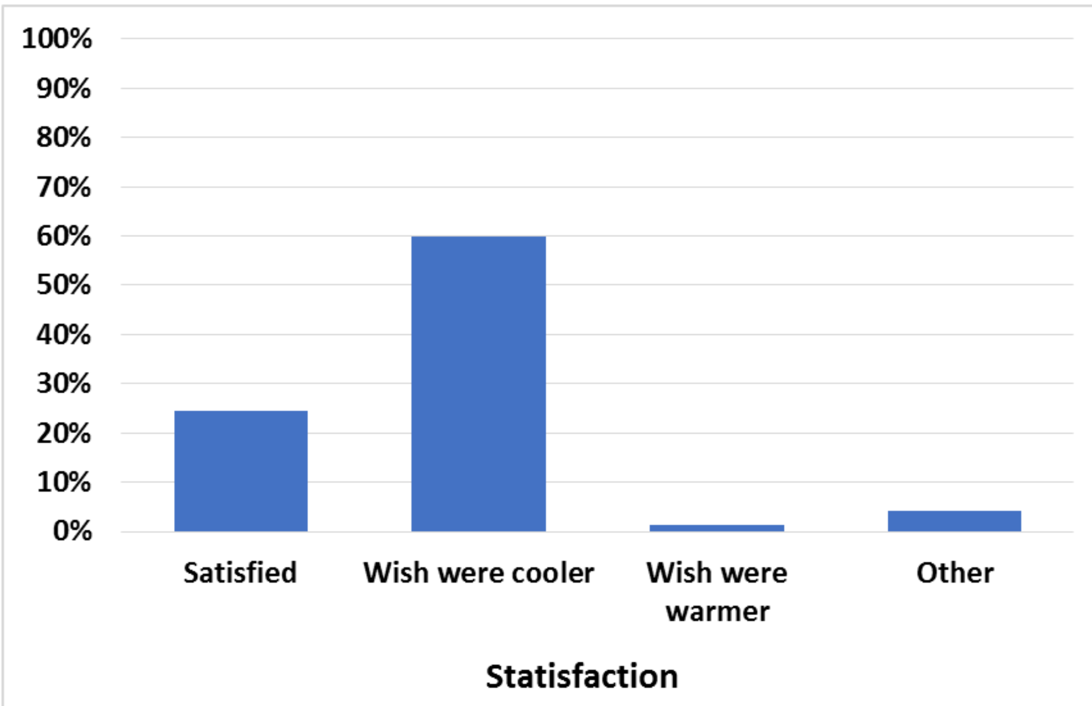
Figure 59: Cooling Methods Reported by Survey Respondents



n=449 responses

The team asked about household satisfaction with cooling: "During the summers, do you wish that" with four fixed response options (as well as an open-ended option) (Figure 60). These results were particularly interesting. Two-thirds (67%) of those who gave a definitive response (n=401) said that they wished it were cooler in the summer. Only27% said that they were satisfied with summer temperatures. This high level of dissatisfaction has implications for the future. First, renovations that improve air conditioning or reduce the costs *may* save less than predicted, if residents take back these improvements to improve their satisfaction with indoor coolth. Second, if temperatures become hotter in general, or in cases of heat waves, a high proportion of households in the study population may experience more periods of uncomfortably high indoor temperatures. This survey was not designed to determine the detailed reasons for dissatisfaction with summer temperatures, in particular, whether the constraints were more technological or more behavioral (including economic concerns). This may be a valuable topic for future research, especially in the relatively forgotten realm of multifamily energy conditions.

Figure 60: Survey Respondent Satisfaction With Home Cooling (n=401).



For heating, two-thirds of the households surveyed said that they used central or building heating alone, as shown in Figure 61.[38] But 18% used portable heaters and sometimes (10%) only portable heaters. This can be an expensive method of heating, even if it may often be used by inhabitants under the assumption that using portable resistance heaters rather than the central heating saves money. Reducing the use of portable heaters in lieu of central heating in multifamily homes may be a promising savings measure that otherwise falls between the cracks of "heating" and "plug loads." There may be safety benefits as well. Further research on the possibility of educational measures on portable heating seems warranted.

Survey respondents were asked about their satisfaction with winter temperatures in their homes. Levels of dissatisfaction were high, with 59% saying that they wished it were warmer in

[38] This proportion cannot directly be compared to the use of central cooling, since fewer properties have central cooling than have central heating systems.

the winter. Most of the rest (38%) said that they were satisfied with winter indoor temperatures (Figure 62).

This type of question has rarely been asked for California homes, so it is not possible to put it the results for these surveyed units in perspective to conditions and perceptions in other housing units. On the surface, at least, the occupants of these units show high levels of "unfulfilled" desires for more cooling and more heating, respectively, with most respondents wanting "more."

Figure 61: Heating Methods Reported by Survey Respondents (n=447).

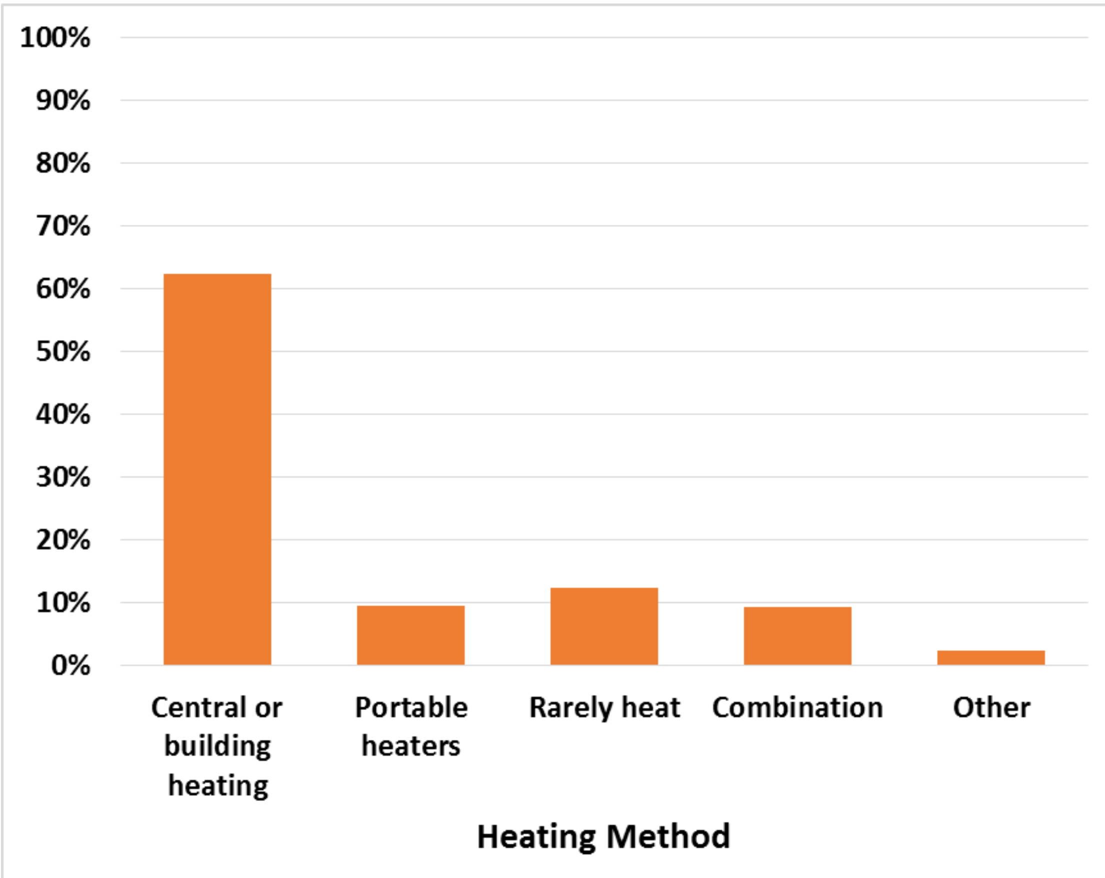
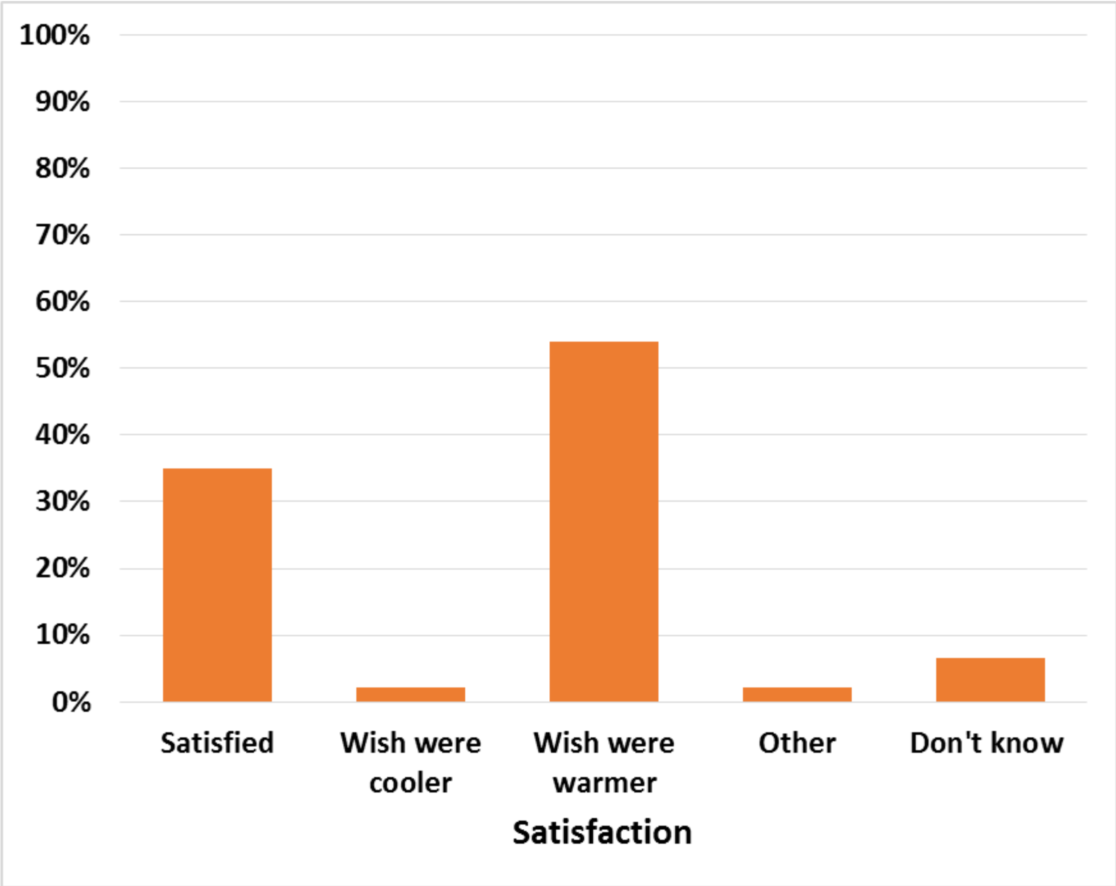


Figure 62: Survey Respondents Satisfaction With Winter Temperatures (n=407).



Multivariate Regression

The Statistical Context

A central motivation for this research was to better understand the diversity of energy-use levels and patterns with respect to a wide range of household characteristics, and to develop and assess methods to pursue these lines of inquiry. For the most part, in the past this sort of analysis has been performed with only total electricity use (e.g., monthly or annual usage) and with the limited household-level data available through existing household energy-use surveys. This research overcame these past data limitations by accessing the much richer energy use data available through AMI streams and by collecting and assembling a richer, more multidimensional set of household characteristics. The ability to collect multiple observations within properties provides an excellent statistical context, in that it helps isolate or control for some elements of variation when comparing households within any complex.[39]

[39] As to past work using similar controls, Hackett and Lutzenhiser (1991) examined changes in electricity use with respect to household characteristics within a large apartment complex. The classic Twin Rivers study used a related design to look at variation in heating use a New Jersey housing development, focusing particularly on changes in tenancy (Socolow 1978, Sonderegger 1978).

This provides a strong basis for analysis. There remain important statistical and administrative limitations. First, to the extent that electricity-use patterns are a product of a combination of social, behavioral, environmental, and technical "factors" understanding this complexity requires parsing multiple correlated variables that interact in nonlinear ways. So statistically, distinguishing energy-use signals and relating them to these factors requires a large data set for sufficient sample. Second, administrative requirements limit the ability to combine detailed unit-level energy-use information with household characteristics; in general, these can be accessed only in aggregate (e.g. combining across multiple housing units). Third, while it is easy to generate multiple sets of effects from statistical regressions, this does not necessarily provide insight on its own.

To investigate relationships between energy use (load level and load shape), the team ran a series of multivariate regressions in a generalized linear model context, particularly testing the effect of the demographic classification variables used for the load shape comparison. This modeling provided a more statistical view than the graphical comparisons of load shapes offered above, and allowed

Analyses and Results

Load Levels and Load Shapes

All households (with sufficient preperiod data) were binned into 10 different use bins and six different load shapes across all seasons based on preretrofit data,[40] creating the basic electricity use characterization for individual households. That classification can be used to examine relationships between household characteristics (e.g., income) and load profile.

As previously shown, these bins represent considerable electricity use diversity. Multivariate regressions were used to explore relationships between household characteristics and corresponding binned usage (as daily sum) and bin load shape. As can be expected, the property had the greatest explained power for use. This is in part because of the geographic distribution of properties and the importance of cooling for some properties. A series of property-specific models were run, testing for differences across the main demographic classification variables (general ethnic group, income, household type, reported presence of plug loads, and tenure) and other household-level data. This series of tests found little in the way of large statistical effects for interactions – as opposed to the general single-variable effects evidenced above. The influence of the property itself (which is highly related to some of the demographic variables) takes most of the explanatory power. There were, however, several statistically significant effects indicating differences for various combinations. The team also looked at the relationships between household characteristics and normalized load shape, with effects again dominated by the property.

These regressions successfully identified promising directions and clues, without overstating the statistical basis. There is plenty of room for further analyses, in refining the statistical modeling process, and developing a more refined set of demographic classifications

[40] The criteria of sufficient post period data were instated to assess retrofit savings.

(particularly combining multiple dimensions, such as geographic and ethnicity variables) to be analyzed with respect to actual and weather-adjusted load shape.

Understanding Differences Between Actual and Predicted Baseline Load

The AMICS analysis described earlier in the report generated predicted the energy-use baseline for the preretrofit condition, and compares this to actual energy use. The multivariate analysis described just above focused on relating household characteristics to the differences in the actual (and weather-adjusted) baseline (preretrofit) hourly load for each of the household classifications. This analysis showed some weak patterns of interactions across variables however, the property location or other single-variable factors dominated the effects.

CHAPTER 4: DISCUSSION AND RECOMMENDATIONS

This study was designed to improve knowledge of how residents in multifamily dwellings use electric energy in their homes and how energy-use patterns vary according to cultural and demographic factors. In the U.S. energy literature, this topic has been given little attention. First, there has been a relative disinterest in energy use in multifamily households since occupants in multifamily homes have less control over energy efficiency than do the inhabitants of owner-occupied homes and may often be presumed to be too transient or inaccessible. They also seem to provide less energy savings potential since energy use per customer is lower. Second, detailed energy use data have rarely been available outside program evaluation contexts. Much of the attention to multifamily energy use has been within the low-income framing, as in programming designed to reduce energy bills.

In California, 22.9% of occupied housing units are in multifamily buildings of five or more units. This is 30% higher than the prevalence of housing multifamily buildings of five or more units for the United States as whole (17.5%) (U.S. Bureau of the Census 2017). Multifamily housing also offers promising future opportunities to meet California's housing needs with lower energy-related emissions and lower resource and land use than required for single-family homes. So, they are well-worth examining for a variety of reasons, including greenhouse gas emissions reductions (Assembly Bill 32), building efficiency (Assembly Bill 758), the CPUC's *Energy Efficiency Strategic Plan* including the zero net energy goals, and energy efficiency potential, as in CPUC rulemaking.

Because of its close familiarity with the MUP retrofit program, the project team saw the possibility of access to a very large and diverse population of multifamily homes, along with knowledge about the properties and PG&E's willingness to grant access to the AMI data and certain account data for many of the homes on these properties. This data forum was used to pursue two main topic areas. Though most of the participating households are low-income (71% under $30K), this project did not focus explicitly on low-income aspects, other than a general acknowledgment that energy costs and energy investments may be a struggle for many participants.

The first topic was an exploration of relationships between demographic factors and energy use patterns in the multifamily sector, as well as of methods and data considerations for conducting such explorations. In the context of increasing attention, the diversity of energy-use across households, and how this diversity (or heterogeneity) is related to program design and to assessing the future, particularly energy potential studies. These findings could inform potential estimates of energy savings, strategies, programs and process designs for efficiently capturing this potential; broader agendas relating to poverty, health, and well-being in multifamily homes in the context of climate change; and multifamily energy-use research in more general.

The second topic related to the MUP retrofits that had recently been completed for the participating properties: how much electricity, if anything, did the retrofits save, and how did these savings vary by season and weekday versus weekend.

One of the advantages of working with multifamily complexes is the physical and geographic similarity of the units help control any differences in what individuals in the households buy and do. The project results show that there is value in considering demographic and cultural variables when analyzing customer energy use. Through an intricate data collection and analysis strategy, together with a partnership with PG&E, this research project successfully combined detailed multiyear AMI and account data with consumer market data and a customized survey. In ensemble, the data collection covers a fair sample of multifamily households, though not statistically significant for the statewide multifamily tenant population. Using sophisticated load classification and analysis techniques, the research team examined load shapes in combination with demographic and other household characteristics, including in the context of "before and after" retrofit energy consumption.

Impact of Demographic and Cultural Factors

The AMICS analysis showed that there are differences in the projected energy use versus actual energy use based on time of day, season and weekday versus weekend. Further, the analysis shows that the differences between load profiles are also correlated with demographic and cultural factors such as race/ethnicity of the occupants as well as the amount of plug loads they use. These are second-order effects though to the weather-dependent energy use such as use of cooling energy in the hot Central Valley versus relatively mild coastal areas. The multivariate analysis shows that no single demographic or cultural factor (nor interactions with others) alone explains the differences more than or as much as the effects of location and climate.

Some of the graphics shown in the analysis emphasize the dramatic differences in electricity load shapes due to cultural and demographic factors. These range from negligible (i.e. income) differences to noticeable (i.e. ethnic/cultural/ language) effects on energy use. While none of these factors alone tells the story of why energy use varies it does indicate these factors should be considered when planning for the state's energy future. This study provides a starting point to understanding how cultural and demographic factor into multifamily energy use.

Electricity-Use Diversity

This research underscored the importance of social, cultural, and behavioral diversity in residential energy use. This people-based diversity interacts with, complements, and is bundled with the physical side of energy efficiency and energy use. While to some this may seem obvious, that perspective contrasts with the practice of "average" and "typical" energy use and energy users that form the basis of the statistical representation of energy use in most energy modeling, and contrasts as well with treating people as "behavior" and behavior as a modifier to technology.

The data and statistical analyses conducted used data for thousands of homes in the PG&E service territory and helped clarify this diversity in the arena of multifamily homes. The key general points can be easily summarized as the following:

1. Household-level energy use among these multifamily households is diverse. This can be seen even in the statistially reduced form represented by the combination of the six normalized load shapes and 10 load levels developed in this report.
2. There are clear and often very strong central tendencies in load shapes that distinguish customers in one apartment complex or region from another, e.g., hot Fresno versus generally milder coastal areas. However household energy use is diverse even within a property.
3. Electricity use is highly unevenly distributed across households. In the team's sample, the highest-using 20% of households accounted for 43% of the total electricity used.

These findings all have implications for identifying and capturing energy savings potential.

Energy Savings Potential

Two major dimensions of energy savings potential were considered in this analysis. First, the energy efficiency retrofit projects administered by PG&E's MUP over the past few years were designed to provide savings across a wide range of multifamily properties. The research team looked this savings through the AMICS method described. Second, from the point of view of market facilitation for energy efficiency measures, the questions immediately following from foregrounding diversity is how it reflects with respect to identifying and capturing energy savings potential efficiently, whether through technical or behavioral changes. This is a matter of finding promising niches of technical potential and developing reasonable strategies that might exploit these niches.

1. The analysis of retrofit savings in the MUP projects considered found 2.7% savings overall, based on the AMICS methodology. These savings are adjusted for weather differences.
2. Apart from the MUP retrofits themselves, investigation of the load-shape data found that households with more miscelleneous plug loads have higher energy use on average, than those with fewer such plug loads. The level of plug loads is also correlated with other household factors, such as the number of people, income, the amount of time at home, or various other lifestyle elements. For this portion of the analysis, sample size was small and limited to the survey data sample. While precise statistical claims about these relationships could not be made, this is a promising result, especially for multifamily homes where plugged equipment is generally purchased by occupants and where plug load electricity use may often be a higher proportion of total premise energy use than for single-family dwellings. Nevertheless these results suggest that improved plug-load power management could make a noticeable difference to overall energy use.
3. In addition, surveyed households expressed a high level of interest in testing a smart power strip that could control some of these plug loads. A next research step could involve linking household *interest* in plug-load management, household *behaviors* with

respect to plug-load uses, *technical data* on plug load energy-use patterns in multifamily homes, and smart power strip *design*, toward a more comprehenisve perspective on energy savings potential through plug-load management.

Energy savings potential in households is not only about technical opportunities in isolation. To realize savings, technical potential needs to be put in the context of the energy users themselves. The completed survey-based analyses provided insights that help make this connection.

Survey Respondent Views on Energy Use

Surveys that are designed to help assess energy savings potential often ask respondents to directly describe their attitudes, beliefs, and concerns with respect to energy use, energy bills, and the environment (see Moezzi et al. 2009). The research team took a different approach, asking respondents what they thought about the level of their energy bills and their satisfaction with the levels of heat and cooling in their homes in the winter and summer, respectively. The results have important implications for thinking about the future savings potential of physical and behavioral measures. A series of tenant communications were used describing energy savings measures to test whether there was a noticeable effect of these treatments on energy use.

1. For heating and cooling, survey respondents reported high levels of dissatisfaction with comfort levels in their homes. More than half said that they wished their homes were warmer in the winter and cooler in the summer.
2. These high levels of dissatisfaction have implications for energy savings measures intended to reduce heating and cooling load. For example, if HVAC efficiency upgrades make heating or cooling less expensive, higher performing, or both, occupants may choose to use more heating and cooling toward reducing their current discomfort. Or they may be using substantially less heating and cooling than assumed, via a conservation effect. More in-depth investigation of heating and cooling usage practices in multifamily dwellings could shed light on these possibilities.
3. The information treatments administered did not result in a statistically significant reduction in energy use among tenants. The sample size, however, was quite small relative to the expected level of effects, so there was limited statistical power to detect such an effect, even if there is one.

Research Recommendations

From a statistical and data analytical point of view, this research was exploratory. It broke new ground in terms of methods for combining hourly load data with household-level demographic and cultural information. There was no attempt to draw a statistically valid sample, and the detailed demographic data were available for only the relatively small number of households that completed surveys. This research, however, provides better insights into how demographics play a role in multifamily tenant energy use and how these findings can be applied to future energy planning in the following ways:

- The research team believes the available data could be further exploited, especially instituting a more iterative process in combining demographic data with load data, and in testing additional statistical techniques. These could further isolate the effects of weather/location versus demographics.
- The analysis also uncovered many questions concerning linking occupant practices and attitudes with energy savings potential. A more ethnographic focus on how multifamily occupants use and manage plug loads, heating, and cooling could be combined with technical information on these end uses toward a more sophisticated view of energy savings potential in multifamily homes.

GLOSSARY

Term	Definition
AMI	Advanced Metering Infrastructure
AMICS	AMI Customer Segmentation Model, created by Evergreen Economics
BRO	Behavioral, retro commissioning, and operational measures for energy savings potential
CPUC	California Public Utilities Commission
EPIC	Electric Program Investment Charge
MUP	PG&E's Multifamily Upgrade Program
RASS	California's Residential Appliance Saturation Survey. The most recent edition in 2009.
RECS	Residential Energy Consumption Survey, a series of surveys on household use nationwide, produced by the Energy Information Administration at the U.S. Department of Energy.

REFERENCES

Bass, F. 1969. A New Product Growth Model for Consumer Durables." *Management Science* 15 (5): 215–227.

Belaïd, F., 2017, Untangling the Complexity of the Direct and Indirect Determinants of the Residential Energy Consumption in France: Quantitative Analysis Using a Structural Equation Modeling Approach." *Energy Policy* 110: 246–56.

Evergreen Economics. 2016. *AMI Billing Regression Study Final Report*. Prepared for Southern California Edison.

Grover, S., J. Cornwell, S. Monohon, and T. Helvoigt. 2017. *"Take it From the Top! An Innovative Approach to Residential and Commercial Program Savings Estimation Using AMI Data."* Presented at the International Energy Program Evaluation Conference (IEPEC), Baltimore, MD.

Grover, S., T. Helvoigt, S. Monohon, and J. Cornwell. 2015. *"Random Walk to Savings: A New Modeling Approach Using a Random Coefficients Model and AMI Data".* Presented at the International Energy Policy & Programme Evaluation Conference (IEPPEC) in Amsterdam, Netherlands

Helvoigt, T., S. Grover, J. Cornwell, and S. Monohon. 2016. *"A Smart Approach to Analyzing Smart Meter Data."* Presented at the American Council for an Energy-Efficient Economy (ACEEE) Summer Study, Asilomar, California.

Jaske, M., 2016, *Translating Aggregate Energy Efficiency Savings Projections Into Hourly System Impacts*. California Energy Commission Staff Report. Publication Number CEC-200-2016-007.

Dillahunt, T., Mankoff, J., Paulos, E. and Fussell, S., 2009, September. *It's Not All About Green: Energy Use in Low-Income Communities*. In *Proceedings of the 11th international Conference on Ubiquitous Computing* (pp. 255-264). ACM.

Estiri, H., 2015, The Indirect Role of Households in Shaping U.S. Residential Energy Demand Patterns." *Energy Policy* 86: 585–94.

Hackett, B. and L. Lutzenhiser. 1991. Social structures and economic conduct: interpreting variations in household energy consumption. In *Sociological forum* (Vol. 6, No. 3, pp. 449-470). Springer Netherlands.

Helvoigt, T., S. Grover, J. Cornwell, and S. Monohon, 2016, "A Smart Approach to Analyzing Smart Meter Data." *ACEEE 2016 Summer Study on Energy Efficiency in Buildings*. American Council for an Energy Efficient Economy.

King, J. and C. Perry. 2017. *Smart Buildings: Using Smart Technology to Save Energy in Existing Buildings*. Report A1701. American Council for an Energy Efficient Economy.

Lutzenhiser, L., . Moezzi,. Ingle, and .Woods. 2017. *Final Project Report: Advanced Residential Energy and Behavior Analysis Project.* Prepared for the California Energy Commission. Publication Number: CEC-500-2017-029.

Moezzi, M., M. Iyer, L. Lutzenhiser, and J. Woods, 2009, Behavioral assumptions in energy efficiency potential studies. May. Prepared for CIEE. Berkeley, California.

Navigant Consulting, Inc., 2017, *Energy Efficiency Potential and Goals Study for 2018 and Beyond.* Final public report. Prepared for the California Public Utilities Commission. Reference No: 174655.

Sanquist, T. F., H. Orr, B. Shui, and A.C. Bittner. 2012. "Lifestyle Factors in U.S. Residential Electricity Consumption." *Energy Policy* 42:354–64.

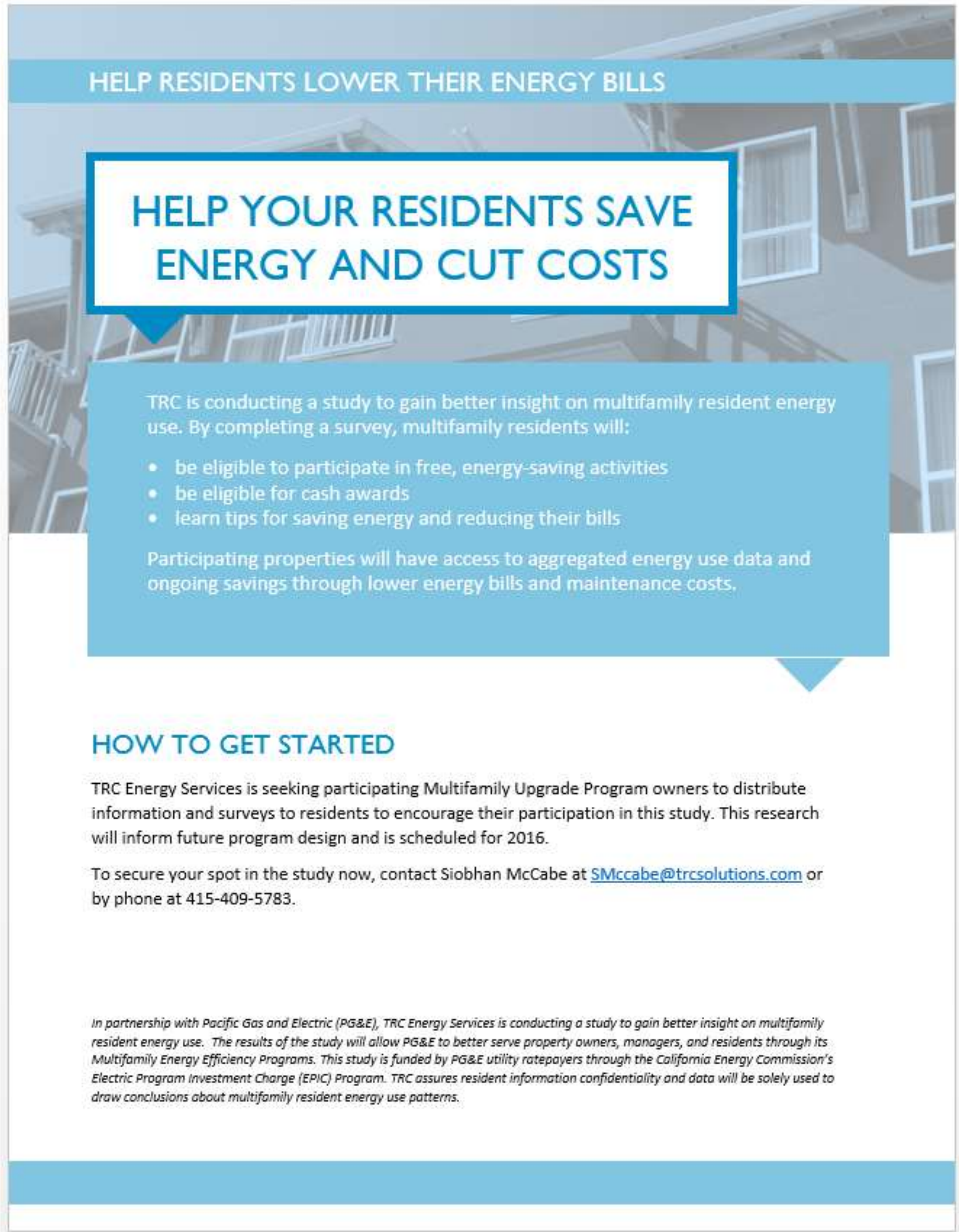
Socolow, R.H., 1978. The Twin Rivers program on energy conservation in housing: Highlights and conclusions. *Energy and Buildings*, *1*(3), pp.207-242.

Sonderegger, R.C., 1978. Movers and stayers: The resident's contribution to variation across houses in energy consumption for space heating. *Energy and Buildings*, *1*(3), pp.313-324.

U.S. Bureau of the Census. 2017. American Community Survey Five-Year Estimates (2011-2015).

ATTACHMENT I: OUTREACH MATERIALS

Owner Flyer



HELP RESIDENTS LOWER THEIR ENERGY BILLS

HELP YOUR RESIDENTS SAVE ENERGY AND CUT COSTS

TRC is conducting a study to gain better insight on multifamily resident energy use. By completing a survey, multifamily residents will:

- be eligible to participate in free, energy-saving activities
- be eligible for cash awards
- learn tips for saving energy and reducing their bills

Participating properties will have access to aggregated energy use data and ongoing savings through lower energy bills and maintenance costs.

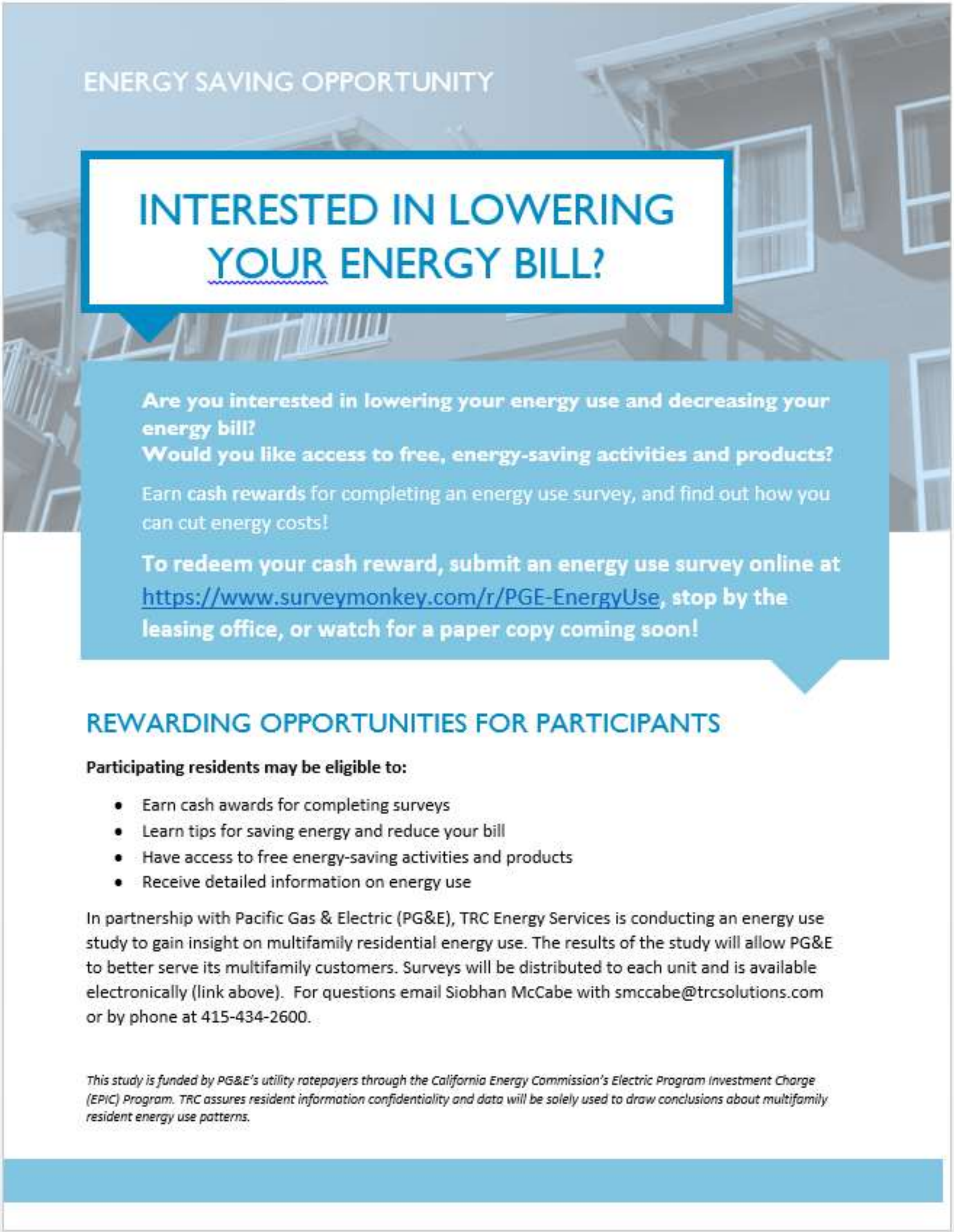
HOW TO GET STARTED

TRC Energy Services is seeking participating Multifamily Upgrade Program owners to distribute information and surveys to residents to encourage their participation in this study. This research will inform future program design and is scheduled for 2016.

To secure your spot in the study now, contact Siobhan McCabe at SMccabe@trcsolutions.com or by phone at 415-409-5783.

In partnership with Pacific Gas and Electric (PG&E), TRC Energy Services is conducting a study to gain better insight on multifamily resident energy use. The results of the study will allow PG&E to better serve property owners, managers, and residents through its Multifamily Energy Efficiency Programs. This study is funded by PG&E utility ratepayers through the California Energy Commission's Electric Program Investment Charge (EPIC) Program. TRC assures resident information confidentiality and data will be solely used to draw conclusions about multifamily resident energy use patterns.

Tenant Flyer



ENERGY SAVING OPPORTUNITY

INTERESTED IN LOWERING YOUR ENERGY BILL?

Are you interested in lowering your energy use and decreasing your energy bill?
Would you like access to free, energy-saving activities and products?

Earn **cash rewards** for completing an energy use survey, and find out how you can cut energy costs!

To redeem your cash reward, submit an energy use survey online at https://www.surveymonkey.com/r/PGE-EnergyUse**, stop by the leasing office, or watch for a paper copy coming soon!**

REWARDING OPPORTUNITIES FOR PARTICIPANTS

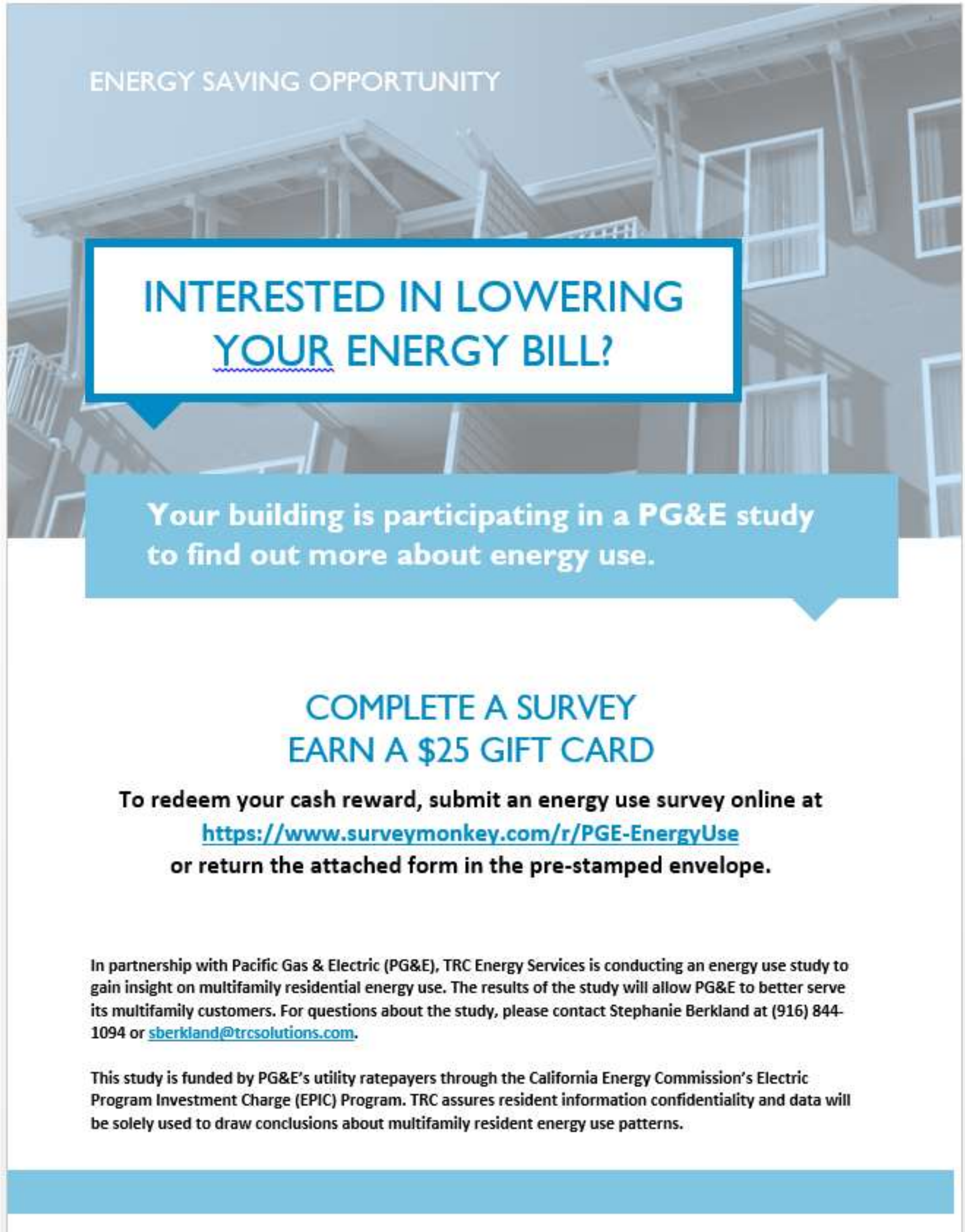
Participating residents may be eligible to:

- Earn cash awards for completing surveys
- Learn tips for saving energy and reduce your bill
- Have access to free energy-saving activities and products
- Receive detailed information on energy use

In partnership with Pacific Gas & Electric (PG&E), TRC Energy Services is conducting an energy use study to gain insight on multifamily residential energy use. The results of the study will allow PG&E to better serve its multifamily customers. Surveys will be distributed to each unit and is available electronically (link above). For questions email Siobhan McCabe with smccabe@trcsolutions.com or by phone at 415-434-2600.

This study is funded by PG&E's utility ratepayers through the California Energy Commission's Electric Program Investment Charge (EPIC) Program. TRC assures resident information confidentiality and data will be solely used to draw conclusions about multifamily resident energy use patterns.

Door Hanger


ENERGY SAVING OPPORTUNITY

INTERESTED IN LOWERING YOUR ENERGY BILL?

Your building is participating in a PG&E study to find out more about energy use.

COMPLETE A SURVEY
EARN A $25 GIFT CARD

To redeem your cash reward, submit an energy use survey online at
https://www.surveymonkey.com/r/PGE-EnergyUse
or return the attached form in the pre-stamped envelope.

In partnership with Pacific Gas & Electric (PG&E), TRC Energy Services is conducting an energy use study to gain insight on multifamily residential energy use. The results of the study will allow PG&E to better serve its multifamily customers. For questions about the study, please contact Stephanie Berkland at (916) 844-1094 or sberkland@trcsolutions.com.

This study is funded by PG&E's utility ratepayers through the California Energy Commission's Electric Program Investment Charge (EPIC) Program. TRC assures resident information confidentiality and data will be solely used to draw conclusions about multifamily resident energy use patterns.

ATTACHMENT II: SURVEY

MULTIFAMILY RESIDENT ENERGY USE STUDY

ABOUT THIS SURVEY

Dear Resident,

Multifamily buildings (apartments) are a growing share of California's residential buildings. TRC Engineers Inc. (TRC) is conducting this survey funded by the California Energy Commission*[1] in partnership with your electric utility, Pacific Gas and Electric. Our goal is to better understand the diversity of ways that people use energy in apartments, and to use this information to help improve energy policy, programs, financial support, and products to better meet the needs of people living in apartments. Your experiences and opinions are very important to this effort.

CONFIDENTIALITY STATEMENT

TRC assures confidentiality of all the information provided through this survey. Our method anonymizes collected data, which we use to draw conclusions about resident's energy use patterns. Any of the data collected within this survey will not be made public, except as part of statistical summaries such as averages. Your personal information will remain anonymous, and TRC will not use any information collected for this study for any other purposes beyond this study. For more information, please see *Attachment A – Notice to Individuals* at the end of this survey.

SURVEY COMPLETION

This survey will take approximately 10-15 minutes to complete. You may complete either the online survey, or the following paper version and return it in the enclosed addressed, postage-paid envelope.

As a token of our appreciation, individuals who complete the survey and provide their street or email addresses will receive a $25 American Express® gift card. Limit one gift card per dwelling unit.

Completing the survey now also qualifies you to be eligible for free energy-saving devices, which will be provided to some of the households that complete this survey.

In order to deliver the $25 American Express® gift card that you will receive for completing this survey, please provide the address for the home *where you received this survey* and your email (if possible).

Street Address: ______________________

Unit Number: ______________________

City: ______________________

ZIP: ______________________

Email: ______________________

For information or comments, please write to multifamilysurvey@trcsolutions.com *or* Multifamily Survey, 11211 Gold Country Blvd, Suite 103, Gold River, CA 95670

[1] This study is funded by utility ratepayers through the California Energy Commission's Electric Program Investment Charge (EPIC) Program.

HOUSEHOLD INFORMATION AND DEMOGRAPHICS (1 of 3)

For the remainder of the survey, please give responses **only for this address**, even if you live elsewhere.

ABOUT YOURSELF:

First, tell us a little about you.

Are you:

- ☐ A head of household
- ☐ The spouse or partner of the head of household
- ☐ Somebody else who lives at the above address
- ☐ I don't live at the above address

What is your age?

- ☐ Under 18
- ☐ 18-35
- ☐ Over 35
- ☐ 36-65
- ☐ 66 and over

Are you:

- ☐ Male
- ☐ Female
- ☐ Other/Decline to State

ABOUT YOUR HOUSEHOLD:

Next, tell us a little about the people who live at this address.

How many people live here in total?

Please include anybody who lives here six months a year or more.

☐ 1 ☐ 2 ☐ 3 ☐ 4

☐ Other: _________

Of the adults (18 or older) in the household, how many are male?

☐ 1 ☐ 2 ☐ 3 ☐ 4

☐ Other: _________

Of the adults (18 or older) in the household, how many are female?

☐ 1 ☐ 2 ☐ 3 ☐ 4

☐ Other: _________

Age of Occupants

How many people living in this household are in each of the following age groups?

Include yourself.

Age	None	1	2	3	4	5 or more
2 and under	○	○	○	○	○	○
3-5	○	○	○	○	○	○
6 – 18	○	○	○	○	○	○
19-35	○	○	○	○	○	○
36-65	○	○	○	○	○	○
66 and over	○	○	○	○	○	○

Unit Size

What is the size of *this* home, in square feet?

Please make your best guess.

- ☐ Less than 500
- ☐ 501-1000
- ☐ 1001-1500
- ☐ 1501-2000
- ☐ More than 2000
- ☐ Do not know

How many bedrooms are in your home?

Count the number of rooms your building manager would list if this apartment were for rent/sale.

0 (Studio)	1	2	3	4 or more
○	○	○	○	○

HOUSEHOLD INFORMATION AND DEMOGRAPHICS (2 of 3)

Household Language

What is the primary language spoken in this home?

- ☐ English
- ☐ Spanish
- ☐ Chinese
- ☐ Tagalog
- ☐ Vietnamese
- ☐ Korean
- ☐ Farsi/Persian
- ☐ Armenian
- ☐ Russian
- ☐ Arabic
- ☐ Hmong, Laotian, Khmer, or Cambodian
- ☐ Hindi/Other Indic Language
- ☐ Other European Language
- ☐ Other Asian Language
- ☐ Other. What language? ______________

What other languages, if any, are regularly spoken in the home?

- ☐ No other languages – only the language marked in the previous question
- ☐ English
- ☐ Spanish
- ☐ Chinese
- ☐ Tagalog
- ☐ Vietnamese
- ☐ Korean
- ☐ Farsi/Persian
- ☐ Armenian
- ☐ Russian
- ☐ Arabic
- ☐ Hmong, Laotian, Khmer, or Cambodian
- ☐ Hindi/Other Indic Language
- ☐ Other European Language
- ☐ Other Asian Language
- ☐ Other. What language?

How many adults in this home are comfortable communicating in English?

- ☐ None
- ☐ 1 adult
- ☐ 2 or more adults
- ☐ All adults in this home are comfortable communicating in English

Hispanic Origin

Are any household members Hispanic or Latino?

- ☐ Yes
- ☐ No
- ☐ Do not know
- ☐ Decline to answer

If yes, are all household members Hispanic or Latino?

- ☐ Yes
- ☐ No

Race

Do any household members consider themselves to be the following race(s)?
Please check all that apply.

- ☐ White
- ☐ Black or African American
- ☐ American Indian or Alaska Native
- ☐ Asian Indian
- ☐ Japanese
- ☐ Native Hawaiian or Other Pacific Islander
- ☐ Chinese
- ☐ Korean
- ☐ Filipino
- ☐ Vietnamese
- ☐ Samoan
- ☐ Middle Eastern or North African
- ☐ Other Asian
- ☐ Other Pacific Islander

Birthplace

Where did the adults in the household spend most of their childhood?
Please check (or fill in) all that apply.

- ☐ In California
- ☐ In other U.S. state
- ☐ Outside the United States. If so, where? ______________________________

HOUSEHOLD INFORMATION AND DEMOGRAPHICS (3 OF 3)

Years in Residence

How long has the household been living at this address?

- ☐ Less than 1 year
- ☐ Between 1 and 2 years
- ☐ Between 2 and 3 years
- ☐ Between 3 and 5 years
- ☐ Between 5 and 10 years
- ☐ Between 11 and 20 years
- ☐ More than 20 years

Over the *last year*, have there been any changes in who lives here?

- ☐ No
- ☐ Yes, there are 1-2 more members than a year ago.
- ☐ Yes, there are 3 or more members than a year ago.
- ☐ Yes, there are 1-2 fewer members than a year ago.
- ☐ Yes, there are 3 or fewer members than a year ago.
- ☐ Yes, but the total number of people is the same as a year ago.

Occupation Frequency

How often is somebody home during each of the following time periods?

Time Period	Never or Rarely (0-2 days per week)	Frequently (3-5 days per week)	Usually or Always (6-7 days per week)	Decline to State
Day (9am-5pm)	○	○	○	○
Evening (5pm-9pm)	○	○	○	○
Night (9pm-6am)	○	○	○	○

Activity

Of the adults (18 or older) in this household,

...how many are employed?

☐ None	☐ 4
☐ 1	☐ 5
☐ 2	☐ 6
☐ 3	☐ 7 or more

...how many are retired?

☐ None	☐ 4
☐ 1	☐ 5
☐ 2	☐ 6
☐ 3	☐ 7 or more

...how many are students?

☐ None	☐ 4
☐ 1	☐ 5
☐ 2	☐ 6
☐ 3	☐ 7 or more

ENERGY USE TECHNOLOGIES AND PRACTICES (1 of 2)

How many refrigerator/freezers do you have in your home?
Please count only those that were plugged in at least three months over the last year.

- ☐ None
- ☐ 1
- ☐ 2
- ☐ 3 or more

During the summer months, how do you *usually* cool your home?
Please choose as many as applicable.

- ☐ With an air conditioner provided by building management or owner
- ☐ With portable or ceiling fans
- ☐ With a portable air conditioner
- ☐ We rarely cool our home
- ☐ We open our windows
- ☐ Don't know

Which of the following best describes how the household uses the cooling strategy selected above?

- ☐ It's always or usually on during the hot parts of year, at least when somebody is home
- ☐ We use it a few times per week during the hot parts of the year
- ☐ We only use it when it is especially hot, when we have company, or other special occasions
- ☐ We use it throughout the year
- ☐ We rarely use it
- ☐ We never use it
- ☐ Something else. Please describe: ____________________

During the summers, do you wish that:

- ☐ Your home were cooler
- ☐ Your home were warmer
- ☐ Neither, the summer temperature is fine
- ☐ Don't know
- ☐ Something else. Please describe: ____________________

During the winter months, how do you *usually* heat your home?
Please choose as many as applicable.

- ☐ With the central/main heating system provided by the building manager or owner
- ☐ With portable heaters
- ☐ We rarely heat
- ☐ Other
- ☐ Don't know

How do you usually use heating equipment?

- ☐ It's often on during the colder parts of year, at least when somebody is home
- ☐ We use it a few hours per day
- ☐ We only use it a few days per week
- ☐ We use it throughout the year
- ☐ We rarely use it
- ☐ We never use it
- ☐ Something else. Please describe: ____________________

During the winters, do you wish that:

- ☐ Your home were warmer
- ☐ Your home were cooler
- ☐ Neither, the winter temperature is fine
- ☐ Do not know
- ☐ Something else. Please describe: ____________________

How often is the oven or stove used for preparing meals or baking?

- ☐ Very often: 2-3 times per day on most days
- ☐ Frequently: about once per day on most days
- ☐ Sometimes: a few times per week
- ☐ Rarely: less than a few times per week
- ☐ Don't know

ENERGY USE TECHNOLOGIES AND PRACTICES (2 of 2)

How many showers or baths per day are taken in your home, counting all members of the household?

- ☐ Less than one shower or bath per day
- ☐ 1-3 per day
- ☐ 4-8 per day
- ☐ More than 8 showers or baths per day
- ☐ Do not know
- ☐ Decline to answer

When it comes to lighting your home, which of these comes closest to what you do:

- ☐ We often have lights on throughout the home
- ☐ We usually have lights on only when somebody is in the room
- ☐ We do not use lights very much, even when we are home
- ☐ Something else. What? ________________

What kind of light bulbs do you usually buy?
Check all that apply

- ☐ Incandescent (normal bulb-shaped lights)
- ☐ Compact Fluorescent Light (CFL) bulbs (usually "curly")
- ☐ LEDs
- ☐ Other
- ☐ Don't know

How many plug-in lamps do you tend to use in your household?
Do not count overhead lights, bathroom vanities, or other built-in lights.

- ☐ None
- ☐ 1-3
- ☐ 4-6
- ☐ 7-9
- ☐ 10+

How many televisions are there in your home?

- ☐ None
- ☐ 1
- ☐ 2
- ☐ 3 or more

How many computers, laptops, or tablets are there in your home?

- ☐ None
- ☐ 1
- ☐ 2
- ☐ 3-4
- ☐ 5-6
- ☐ 7 or more

Does your household have any of the following electrical devices?

	Yes	No
Portable heaters?	☐	☐
Aquarium?	☐	☐
Medical equipment that is plugged-in, such as an oxygen tank?	☐	☐
Dehumidifier?	☐	☐
Set-top box for cable or other service, such as Xfinity/Comcast, DISH, DIRECTV, etc.?	☐	☐
Gaming console such as Xbox, PlayStation, or Wii?	☐	☐
Entertainment or audio system?	☐	☐

Other. Specify ________________

Do you have an in unit clothes washer and dryer?

- ☐ Yes, both
- ☐ Yes, clothes washer only
- ☐ Yes, clothes dryer only
- ☐ No

Does your home have a dishwasher?

- ☐ Yes
- ☐ No

Later in the study, we will give some households devices that can help save energy. Would you be interested in receiving one of these free devices?

- ☐ Yes
- ☐ Maybe
- ☐ No

THOUGHTS AND OPINIONS ON ENERGY USE AND ENERGY COSTS (1 of 1)

Almost done! This section asks about how you think about your energy use and energy costs.

How often do you or somebody in your household look at the energy bill or information on energy use for your home?

- ☐ Most or all months
- ☐ A few times per year
- ☐ Once a year or less
- ☐ Do not know

Do you consider your household energy costs to be:

- ☐ Higher than seems reasonable
- ☐ About what you would expect
- ☐ Lower than seems reasonable
- ☐ Do not know
- ☐ No Opinion / Decline to Answer

Have your energy costs changed much over the past year?

- ☐ Yes, they are a LOT higher
- ☐ Yes, they are a LITTLE higher
- ☐ Yes, they are a LITTLE lower
- ☐ Yes, they are a LOT lower
- ☐ No, they have not changed
- ☐ Do not know / Decline to Answer

Before participating in this study, were you aware of the recent renovation activity in your apartment complex?

- ☐ No
- ☐ Yes

If you answered YES:

What do you think the main purpose of the renovation was?
Please choose as many as applicable.

- ☐ Improve appearance
- ☐ Add amenities
- ☐ Fix structural issues or improve safety
- ☐ Improve energy efficiency
- ☐ Other: please describe

____

DEMOGRAPHICS (1 of 1)

For classification purposes, we need a little more information about your household.

Household Education

What is the highest level of education that anyone in the household has completed?

- ☐ Less than 9th grade
- ☐ 9th-12th grade, no diploma
- ☐ High school diploma
- ☐ Some college, no degree
- ☐ Associate's degree
- ☐ Professional Degree
- ☐ Technical degree (e.g., health care, auto mechanics, etc.)
- ☐ Bachelor's degree
- ☐ Master's Degree
- ☐ Ph.D

Income

Please check the range that best describes your household's total annual income (before taxes) for 2015.

Please include income for all occupants living at this address

☐ Less than $10,000	☐ $70,000 - $84,999
☐ $10,000 - $24,999	☐ $85,000 - $99,999
☐ $25,000 - $39,999	☐ $100,000 - $149,999
☐ $40,000 - $54,999	☐ $150,000 or more
☐ $55,000 - $69,999	☐ Decline to answer

On behalf of the research team, thank you very much for your time. If you have completed the survey, the gift card will be delivered to you at the address you provided above. If you prefer to receive the gift card by email, please provide your name and email address:

Name ______________________________

Email address: ______________________________

May we contact you for a follow up survey in a few months?

- ☐ Yes
- ☐ No

Attachment A – Notice to Individuals

TRC Engineers, Inc. ("TRC") [insert subcontractor, if applicable] is [are] under agreement with the California Energy Commission (Agreement # EPC-14-039) to assist with research to improve understanding of the social; cultural; and behavioral aspects which shape household energy use in California, and in particular to research the adoption of energy efficiency measures by multifamily tenants in California before and after energy efficiency upgrades. As part of this work, TRC [or subcontractor] is conducting surveys and interviews, and otherwise collecting information, in order to assess and report on energy usage and energy efficiency measure adoption. When a state agency or its contractor collects information, California law protects information that is personal under the California Information Practices Act of 1977 ("Information Practices Act") (Civil Code, sections 1798 et seq.). Personal information includes, but is not limited to, your name, home address, home telephone number, family size, and your education and employment history.

As required in Section 1798.17 of the Information Practices Act, you are hereby provided the following notice regarding information collected:

a. TRC requests this information as part of its activities under a grant from the California state agency the State Energy Resources Conservation and Development Commission (California Energy Commission or Energy Commission), Energy Research and Development Division.
b. TRC Project Manager, Stephanie Berkland, and the Energy Commission's Commission Agreement Manager (CAM) are responsible for the system of records and shall, upon your request, inform you regarding the location of your records and the categories of any persons who use the information in those records. The Energy Commission's CAM can be reached at 1516 9th Street MS 51, Sacramento, CA 95814 or (916) 445-5310. You have a right to access records with your personal information maintained by TRC under its agreement with the Energy Commission.
c. The Energy Commission is authorized to maintain your information by Public Resources Code, section 25218(e) and its authority to conduct the Electric Program Investment Charge (EPIC) Program, Public Resources Code 25710 et seq.
d. Each item of information you submit is entirely voluntary and optional. Information sought by TRC may include but not be limited to: your name, address, building unit or apartment physical characteristics, ethnicity, household language(s) spoken, household income, household size, household age(s), home ownership status, energy efficiency program participation status, utility account number, electricity usage data including hourly electricity usage history before and after participation in energy efficiency upgrade program(s) and hourly electricity usage history before and after participation in the study conducted by TRC.
e. Although provision of the information requested is voluntary, refusal to provide all or part of the requested information may result in your not being eligible to be a participant in any studies conducted under TRC's agreement with the Energy Commission, and consequentially not receiving compensation, if any, for study participation.
f. The purposes for collecting this information ("Principal Purposes") and sharing it between TRC, its subcontractors assisting in this work (if any), and the Energy Commission are to:
    1. Analyze and report on activities funded under the Electric Program Investment Charge;
    2. Share data collected with PG&E;
    3. Conduct a study, with published results, to determine whether social and cultural factors influence multifamily tenants' uptake and adoption of energy efficiency technologies;
    4. Present aggregated results of the study at academic and industry conferences and events and in Energy Commission reports and on the Energy Commission's website.

ANY PERSONAL INFORMATION YOU PROVIDE WILL NOT BE USED FOR ANY OTHER PURPOSE. IT WILL NOT BE SOLD OR OTHERWISE TRANSFERRED TO OTHER ENTITIES, NOR WILL THE ENTITIES INVOLVED IN COLLECING AND USING IT FOR THE PUROSES DESCRIBED HEREIN USE IT TO CONTACT YOU FOR THE MARKETING OF ANY PRODUCT OR SERVICE.

g. TRC plans to publish a report which will use aggregated statistics from information collected from you. The information, as published, will be anonymized and will not be linked to you as an individual. The final report resulting from this study may be referenced and cited in future studies of similar subject matter. The results of this study may also be presented at academic and industry conferences and events, or on the Energy Commission's website or in its publications, again with all personally identifying information removed.
h. The Energy Commission does not plan to share the information you provide with parties other than TRC and its subcontractors, if any; you if you request it; and internally within the Energy Commission. In the event a request for information is received under the Public Records Act, and the information collected from you would be responsive to such a Request, the Energy Commission may refuse to disclose the personal information pursuant to Government Code § 6254 (c).

Pursuant to Civil Code § 1798.34, you have a right of access to personal information that concerns you.

ATTACHMENT III:
TENANT COMMUNICATION MAILERS

Save on your utility bill

¡Español!

Where are the savings opportunities in your apartment?

Do you know which areas of your apartment use the most energy? The graphic at the right shows a California home's average energy use by area. Most often, high-energy-use areas are a great place to start when looking for savings.

Choices matter.

Simple, everyday decisions can help lower your utility bill. We all know to save by turning off unused devices, however, smart purchasing decisions can also help.

The cost savings provided by LED bulbs and low-flow faucet aerators can help pay for the item in as little as one year. Likewise, using devices such as timers or smart power strips can further reduce energy use and lower your utility bill.

Conserve, while being more comfortable!

In the coming weeks, look for more tips in postcards like this one that can help you lower your utility bill and keep your apartment comfortable.

TRC

Results you can rely on

Typical home energy costs *

Appliances Accesorios	$$$$
Lighting Iluminación	$$$
Electronics & Plug-Ins Electrónica y Enchufares	$$$
Heating & Cooling Calefacción y Enfriamiento	$$
Miscellaneous Diverso	$$
Pools Piscinas	$

* Statewide average, actual costs vary by household.

ONLINE SURVEY REWARDS

Earn cash rewards for completing our online survey, and find out how you can cut energy costs!

https://www.surveymonkey.com/r/PGE-EnergyUse

Lighting: Tips for Savings

¡Español!

Simple steps to save!

Improving your apartment's lighting not only helps lift your mood and increases productivity – better lighting can help lower your utility bill!

Lighting is up to 22% of an average utility bill, and you don't have to sacrifice to save.

Take control of your apartment's lighting by following these simple tips.

Buy LED bulbs

A $4 LED lightbulb can lower your utility bill $5 every year – the cost savings pay for the bulb. LEDs can last up to 20 years, giving you $100 in lifetime savings for each bulb.

Install timers and sensors

Timers and motion sensors turn your lights on only when needed, great for areas like bathrooms and living rooms.

Window shades

If you need some privacy, light-filtering shades fill your apartment with sunlight while filtering out glare and harmful UV rays.

TRC

REGISTER TO WIN

For a smart strip to help you save energy from your plug-in devices, email: **multifamilysurvey@trcsolutions.com!**

Heating & Cooling: Tips for Savings

¡Español!

Simple steps to save!

Keeping comfortable during summer and winter usually means lots of air conditioning and heating, which can make up as much as 12% of your utility bill.

Fortunately, you don't have to sacrifice comfort to save! Take control of your apartment's heating and cooling by following these simple tips.

For assistance with setting your thermostat or ceiling fan, contact your maintenance staff for assistance.

Program your thermostat

In *summer*, set your thermostat to 78 F°. In *winter*, set your thermostat to 68 F° during the day and 60° at night.

Use fans

If you use air conditioning during the summer, use floor and ceiling fans *with* air conditioning to keep cool and reduce use.

Peak periods

To discourage overuse, electricity is 25% more expensive during the hours of 3 P.M. to 8 P.M. Run your clothes or dishwasher during off-peak times and save 25%!

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Appliances: Tips for Savings

¡Español!

Simple steps to save!

You use appliances around your apartment every day to make your life easier and more enjoyable!

While the energy used by appliances, like refrigerators or washers may seem small, it can add up. Appliances typically account for 11% of a household's total energy use.

But there are many quick and easy steps you can take to save energy and money, without replacing or even turning off your appliances!

Refrigerator & freezer temperature

Set fridge temperature to 40°F and freezer to 0°F. Check temperatures with a $5 appliance thermometer, which can pay for itself in 1 month with the energy savings.

Clothes washer

Use cold water to save on water heating costs and reduce wear on clothes. Most modern detergents work as well with cold water as they do with warm and hot.

Dishwasher

Use water-saving mode, if available. Run the dishwasher when full, but not over-filled, as this can inhibit the washer and force you to re-run it.

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For a smart strip to help you save energy from your plug-in devices, email: **multifamilysurvey@trcsolutions.com!**

Water Heating: Tips for Savings

¡Español!

Simple steps to save!

We often don't think about it, but using hot water raises your utility bill.

Either electricity or natural gas are used to heat water, so by conserving when cooking, cleaning, and bathing, you save energy as well.

Heating water makes up 15% of an average household's total energy use. Follow these simple tips to save money, help conserve water, and alleviate future droughts!

Low-flow fixtures

Installing a $10 low-flow showerhead saves up to $40 each year. A $5 faucet aerator saves up to $20 each year.

If available, use a dishwasher

Dishwashers use less water than hand-washing. Use energy and water-saving cycles if possible, and only run when full.

Fix leaks

A leak of one drip per second can cost $35 dollars a year, plus potential property damage. Contact your maintenance staff immediately to fix leaks.

TRC

REGISTER TO WIN
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Plug-in Devices: Tips for Savings

¡Español!

Simple steps to save!

Plugged-in devices such as televisions, computers, lamps, and countertop appliances continue to use energy when they are not in use.

Plug-in devices can make up to 20% of your utility bill, and reducing their idle energy use can help you save.

Follow these simple tips to lower plug-in devices' energy use and save on your utility bill.

Plug-ins continually use electricity

A device plugged into an outlet *never stops using electricity*. An idle PC, monitor, and printer can cost $50 per year to power!

Countertop appliances

Unplug countertop appliances, especially those only used occasionally like a mixer or coffee maker, to save.

Smart power strips

Smart power strips detect when devices are not in use and cut their power. A $40 smart strip can save $200 in annual energy costs.

TRC

REGISTER TO WIN

For a smart strip to help you save energy from your plug-in devices, email: **multifamilysurvey@trcsolutions.com!**