Energy Research and Development Division

FINAL PROJECT REPORT

Do Energy Efficiency Investments Deliver at the Right Time?

Evaluating Energy Savings from Residential Air Conditioning Upgrades

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 that promote greater reliability, lower costs, and increase safety for the California electric ratepayer and include:

- Providing societal benefits.
- Reducing greenhouse gas emission 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.

Do Energy Efficiency Investments Deliver at the Right Time? is the final report for the Examining the Heterogeneity of Energy Efficiency Take-up and Savings Across Socio-Economic and Ethnic Groups Using a Large Scale Quasi-Experiment project (agreement number EPC-14-026) conducted by the Energy Institute at Haas at the University of California, Berkeley. 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

This project uses cutting-edge econometrics to evaluate three primary research questions regarding energy efficiency programs: (1) How is participation in energy efficiency programs affected by increases in customer incentives? (2) What is the value of the energy saved when taking into account the timing of savings? and (3) How does participation and savings vary among locations of different levels of household income, education, racial makeup, and household size? The project research focused on Southern California Edison's (SCE's) *Quality Installation Program*, a rebate program for energy-efficient residential air conditioners, including hourly smart meter data and other program data from almost 9,000 program participants. In addition, it incorporates demographic data from the U.S. Census Bureau. The study finds no evidence that higher incentives increase program participation. The project also estimates electricity savings using hourly smart meter data and shows that savings tend to occur during hours when the value of electricity is high, significantly increasing the overall value of the program. The study then compares this estimated savings profile with engineering-based estimates for this program and a variety of alternative energy efficiency investments. The results illustrate a surprisingly large variation in economic value across investments. The study tests for variation in savings between locations with different climates, levels of household income, education, racial makeup, and household size. The project finds that energy savings are larger in hot climate zones than in warm or mild zones. Participation is strongly influenced by demographic factors. The study recommends changes to program design and targeting based on these findings.

Keywords: energy efficiency, air conditioning, peak demand, smart meters, rebate, incentives, climate, reliability, capacity, DEER database, wholesale, data, duck curve, residential, income, education, race

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EXECUTIVE SUMMARY

Introduction

Energy efficiency is receiving attention from policymakers as a lever to reduce carbon dioxide emissions and other negative impacts from energy use. Electric utilities in the United States spent $34 billion on energy-efficiency programs between 1994 and 2012. These policies are considered a "win-win," reducing private energy expenditures and the impacts associated with energy use.

Energy efficiency measures like building shell retrofits, appliance replacement, and industrial process changes can reduce energy consumption; however, despite decades of evaluating energy efficiency programs, there are still important knowledge gaps.

Project Purpose and Process

California's investor-owned utilities (IOUs) have devoted significant resources to programs aimed at reducing heating, ventilation and air conditioning (HVAC) energy use. This project looked at energy efficiency and energy savings focusing on differences among social, cultural and socioeconomic groups, using data from the Southern California Edison's (SCE) Quality Installation Program, a rebate program for energy-efficient residential air conditioners.

SCE's Quality Installation Program can have a large potential impact on energy use and savings. Statewide, air conditioning is responsible for 10 percent of average residential energy use, 15 percent of average commercial energy use, and 30 percent of peak power demand. This project used cutting-edge econometrics to evaluate three primary research questions: (1) How is participation in energy efficiency programs affected by increases in customer incentives?, (2) What is the value of the energy saved when taking into account the timing of savings?, and (3) How does participation and savings vary between locations with different levels of household income, education, racial makeup, and household size?

The study uses hourly smart meter data and other program data from almost 9,000 participants in the SCE program. In addition, demographic data from the U.S. Census Bureau was incorporated and merged with these data using 9-digit zip codes.

The project goals looked at:

- Optimizing rebates to increase energy efficiency adoption among residential customers.
- Increasing cost-effective energy efficiency adoption and energy savings within particular subpopulations by customizing programs to better target them.
- Improving electricity demand forecasting.

The team:

- Applied big data and cutting-edge econometrics to identify new ways to increase the adoption of, energy savings from, and value of energy efficiency programs.

- Performed a regression-discontinuity analysis (a method that can be used to estimate impacts of programs that use cutoff criteria) to study how participation in the energy efficiency program varies with the subsidy amount. The estimated demand curve was used to evaluate the potential cost-effectiveness of alternative program designs.
- Used regressions and propensity score matching (a statistical matching technique) to quantify the energy savings by hour-of-day and month-of-year for participants based on energy usage before, and after participating in the *Quality Installation Program*. These estimates were then combined with estimates of energy and capacity prices to calculate the value of the energy saved.
- Examined the diverse nature (heterogeneity) of energy efficiency adoption and energy savings across household incomes, education, racial makeup, and household size. These estimates were then used to recommend specific opportunities for improved program targeting that could increase electricity savings and decrease program costs.

Project Results

No Evidence that Higher Incentives Increase Program Participation

In 2014, SCE's Quality Installation Program offered three subsidy amounts for central air conditioners: $550, $850, and $1,100, depending on the climate zone. Households in warm and hot zones qualified for larger subsidy amounts than in cooler zones.

Geographic differences in programs like those used in the Quality Installation Program can shed light on how households respond to changes in subsidy offers. Similar households can be treated differently, even within close geographic boundaries. The Quality Installation Program has a low participation rate, with only about one-fifth of 1 percent of SCE residential customers participating in the program during the study period. Consequently, the analysis found there are relatively few participants living close to these climate zone boundaries and, using Regression Discontinuity Analysis, it was difficult to draw conclusions about how participation in the program varied for households located in similar geographic locations with different rebate amounts. In future studies, the decision to use Regression Discontinuity should be based on a prior review of the data set to ensure that the participation rate is high enough to obtain statistically significant results. Alternatively, for a low participation energy efficiency program, the program could be piloted and analyzed using a randomized controlled trial or other experimental approach.

The results showed no evidence of more customer participation in warm-hot zones (larger subsidy) than in the cooler zones (less subsidy). If the $250 or more increases are not resulting in a higher participation rate then it would be less costly and just as effective to use lower subsidy amounts.

Electricity Savings Peak Later in the Day than Is Generally Assumed

The study uses hourly smart meter data to estimate the change in electricity consumption after installing an energy-efficient air conditioner. These savings tend to occur disproportionately during July and August and during 3 p.m. to 9 p.m. With hourly data from more than 9,000 participants, the team could precisely characterize the savings profile across seasons and hours of the day. The econometric estimates indicate peak savings at 7 p.m., compared to 5 p.m. in the engineering estimates. This small difference has important implications for electricity markets given growing concern in meeting steeply increasing evening demand.

Electricity Savings Are Greatest When the Value of Electricity Is High

The study uses price data from wholesale energy and forward capacity markets to quantify the economic value of these estimated savings. The energy savings are correlated with periods of high prices and the periods that drive resource adequacy requirements. This results in a "timing premium" relative to a calculation that uses an average energy price that ignores timing.

Savings from the Quality Installation Program are strongly correlated with the value of electricity, making the SCE program 53 percent more valuable than an estimate of value that ignores the value of energy savings in the wholesale market at the specific times when the energy is saved. In particular, the average annual value of the savings per megawatt hour is $33 when taking into account the value of energy at the time it is saved, compared to $21 in a simple analysis that assumes the value of energy does not vary at different times. As the analysis demonstrates, including capacity prices is important in this calculation. Most of the value of electricity in ultra-peak (very expensive) hours is captured by forward capacity payments to generators to guarantee availability.

Accounting for Timing, Air Conditioning Investments Are 53 Percent More Valuable

Air conditioning was compared to a larger set of residential and non-residential energy efficiency investments. Overall, there is a remarkably wide range of value across investments. In California, when calculating savings resulting from residential air conditioning investments, savings were 53 percent higher when considering varying energy prices hour-to-hour versus treating the price of energy to be the same for all hours of the day. Across four major U.S. markets, the average "timing premium" is 35 percent.

Timing Premiums Vary for Other Energy Efficient Investments

For commercial and industrial heat pumps and chillers the timing premiums in California are 37 percent and 32 percent, respectively. They tend to save energy at times when energy is valuable, but the savings are not as valuable as for residential air conditioning. Other investments, like refrigerators and freezers have timing premiums of only 6 percent because savings are weakly correlated with system load. Lighting also does poorly, reflecting that savings occur disproportionately during the winter when electricity tends to be less valuable.

Energy Savings Is Strongly Influenced by Climate, but Not Demographic Factors

Climate is found to be the most significant indicator of energy savings in the Quality Installation Program. On average, program participants in hot areas save 1,100 or more kilowatt-hours annually, compared to 300 kilowatt-hours annually in warm areas, and approximately zero average savings in mild areas. The analysis did not find that differences in household income, education, racial makeup, and household size had much effect on the savings. However, participation varies significantly based on demographic factors. Zip codes with higher incomes, higher percentage of white residents, and a higher prevalence of college degrees participate at higher rates.

These results imply that the Quality Installation Program is likely to be most cost-effective in the hot areas of SCE's territory. Eliminating the program in mild climate zones may be appropriate because of the small savings, spending limited resources in the high opportunity hot areas targeted at underserved households, which are participating at a very low rate and where there is the biggest possible return on investment. In addition, it would make sense to perform additional analyses of the program in warm climate zones. Savings are modest enough in these areas to merit a full-scale cost-benefit analysis.

Demographic Factors Strongly Influence Participation, but Not Energy Savings

The study finds that high-income households (defined as households living in zip codes with median income higher than $75,000) participate in the program at approximately twice the rate as low-income households. However, it does not appear that income causes differences in energy savings. Therefore, a particularly cost-effective strategy would be to focus on increasing the participation of low-income households in hot areas. There is also a strong equity argument for targeting these programs to underserved groups.

Project Benefits

Demonstrating How Smart Meter Data Can Be Used for Precise Energy Efficiency Estimates to Improve Power Plant and Transmission Planning

This project is one the first to successfully demonstrate how customer-specific, interval electricity use data generated by utility smart meters can be used to more precisely estimate the energy savings that result from the adoption of a more efficient technology. Understanding the impact of energy efficiency at this granular level will be more and more important for forecasting and planning purposes as energy efficiency programs expand and intermittent renewables continue to create new electricity supply patterns in the state. If similar analysis is performed in the future on additional programs then energy forecasting models and energy efficiency potential studies can be made more precise. More precise forecasts can improve power plant and transmission planning and help to pinpoint what types of investments are needed, when and where. This could lower ratepayer costs over time.

Improving Valuation of Energy Efficiency Upgrades to Better Target Energy Efficiency Spending

The project matched the timing of energy saved by energy efficiency upgrades with California wholesale energy and capacity prices. For some energy efficiency upgrades, such as air conditioning, incorporating the value of energy savings in the wholesale market at the specific times when the energy is saved significantly increases the value of the upgrade. For other upgrades, such as refrigerators and lighting, the timing is less valuable. Incorporating the value of energy savings at the specific time saved would change the results of cost-effectiveness calculations and could lead to putting more resources into some energy efficiency programs and fewer resources into others. This could increase the amount energy saved and decreasing costs. Quantifying the benefits would involve an analytical effort that is beyond the scope of this project, but could involve applying the approach used in this project.

Improving Targeting of Energy Efficiency Programs to Specific Demographic Groups to Increase Energy Savings

The project found that since energy savings from this program are influenced by climate (1,100 or more kilowatt hours annually in hot areas, compared to 300 kilowatt hours annually in warm areas and zero savings in mild area), the SCE program should be eliminated in mild areas, evaluated more rigorously in warm areas, and potentially be eliminated in those areas. These changes would free up more resources for targeting the program in the most cost-effective, hot parts of the state. If the customer incentives used in the mild and warm areas were redeployed to hot areas, the program's energy savings could be more than doubled using the same amount of total incentives.

Additionally, energy savings could be increased if the program were able to increase participation of households in low income zip codes. If the low income take-up rate in hot zones were increased to the level of higher income zip codes then the program's energy savings could increase by over 20 percent.

CHAPTER 1: Introduction

The vast majority of anthropogenic (human caused) carbon dioxide emissions come from the production and consumption of energy. Economists agree the best policy to reduce carbon dioxide emissions and other negative externalities from energy use would be to use a Pigouvian tax, named after the British economist A.C. Pigou who advocated them. Although California has a cap-and-trade market, utilities are given free permits to cover most of their emissions and the California Public Utilities Commission (CPUC) has said that it will not allow greenhouse gas costs to raise rates. Moreover, current prices in the cap-and-trade market are only $12 per ton, much smaller than most estimates of the true externality cost.

If externalities will not be addressed directly, then there is an important potential role for alternative policies. Among these alternatives, one of the policy levers receiving the most attention is energy efficiency. Electric utilities in the United States, for example, spent $34 billion on energy efficiency programs between 1994 and 2012. Energy efficiency measures like building shell retrofits, appliance replacement, and industrial process changes have the potential to enormously reduce energy consumption. Energy efficiency policies are promoted as a "win-win", that can reduce both private energy expenditures and the externalities associated with energy use.

Despite decades of evaluating energy efficiency programs, there are still important gaps in this knowledge. For example, a recent Energy Institute working paper argues there is a great potential for a new body of credible empirical work in this area, both because the questions are so important and because there are significant unexploited opportunities for randomized control trials and quasi-experimental designs that have advanced knowledge in other domains. (Allcott and Greenstone, 2012).

This project uses cutting-edge econometrics to evaluate three primary research questions: (1) How is participation in energy efficiency programs affected by increases in customer incentives?, (2) What is the value of the energy saved when considering the timing of savings?, and (3) How do participation and savings vary among locations of different levels of household income, education, racial makeup, and household size?

The project answers these questions based on Southern California Edison's (SCE) Quality Installation Program, a rebate program for energy-efficient residential air conditioners.

The Quality Installation Program is particularly interesting because of its large potential impact. Statewide, air conditioning is responsible for 10% of average residential energy use, 15% of average commercial energy use (California Energy Commission, 2012), and 30% of peak power demand (California Public Utilities Commission, 2011). California's investor-owned utilities (IOU), under the regulation of the CPUC, have devoted significant resources to programs aimed at reducing heating, ventilation, and air conditioning (HVAC) energy use.

The study uses hourly smart meter data and other program data from almost 9,000 participants in the program. In addition, demographic data from the U.S. Census Bureau was merged with these data using 9-digit zip codes.

CHAPTER 2: Estimating the Effect of Subsidies

2.1 Introduction

This chapter describes project findings which use a regression discontinuity (RD) research design to understand how program participation varies with the subsidy amount. Understanding the demand curve for participation is crucial for efficient program design, and this approach mitigates selection bias and other challenges that have thwarted previous attempts to understand this relationship. This report describes the empirical strategy in detail, discusses the work done to construct the datasets, and presents results.

2.2 Background

This application is Southern California Edison's Quality Installation Program, which provides rebates to households that install an energy-efficient central air conditioner according to ENERGY STAR® guidelines. This is an important incentive program because it addresses adoption and installation issues that are barriers to achieving energy efficiency potential. As Figure 1 shows, the program offered customers the opportunity to receive up to $1,100 in rebates while reducing electricity consumption.

The Quality Installation Program is particularly interesting because of its large potential impact. Statewide, air conditioning is responsible for 10% of average residential energy use, 15% of average commercial energy use (California Energy Commission, 2012), and 30% of peak power demand (California Public Utilities Commission, 2011). California's investor-owned utilities (IOUs), under the regulation of the CPUC, have devoted significant resources to programs aimed at reducing HVAC energy use. For example, during 2010 and 2011 the California IOUs spent $86 million collected from ratepayers on programs aimed at HVAC.

Despite these substantial efforts and ongoing technological improvements, efforts to reduce energy use from air conditioning have faced numerous hurdles. It is estimated that 30% to 50% of new residential central air conditioning systems in California are not properly installed, resulting in reduced energy savings and 30% more greenhouse gas emissions (California Public Utilities Commission, 2011). Figure 2 shows that these large potential savings were prominently emphasized in the marketing around the program, for example, showing that low airflow, improper charge, and duct leakage can lead to more than 25% reductions in delivered cooling.

Figure 1: Quality Installation Program, Screen Shot


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Homeowners > Quality Installation Program (QI)

Quality Installation Program (QI)

Get up to $1,100* in rebates
Read More >

More efficiency means more savings. With our Quality Installation Program, you can lower your electric bill, improve the air quality in your home, and make sure your A/C is in top working order.

Did you know that 70% of air-conditioned homes have A/C units that exceed the home's cooling needs? A unit too large for your home costs more to run and uses more electricity. Plus, incorrect sizing or installation puts undue stress on components and shortens equipment life.

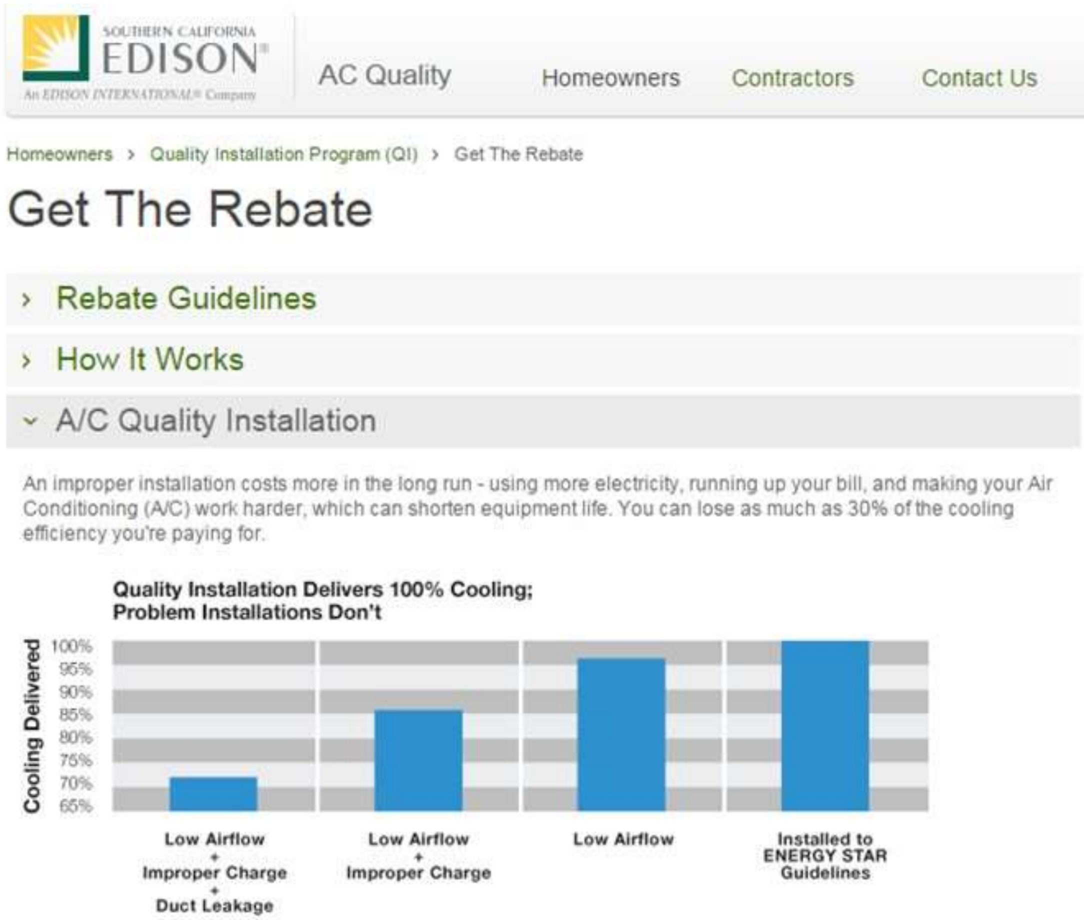
Simply replacing your old system may not save as much energy as you expected. That's why SCE offers our Quality Installation Program. When it's time for a new A/C system, this program makes sure your new air conditioner is sized properly for your home, and ensures its installation follows guidelines set by ENERGY STAR®—saving you the most energy and money. **Plus you get a rebate of up to $1,100*. >**

SCE's Quality Installation Program eliminates common problems that can reduce the efficiency of your new A/C system:

- Low airflow
- Improper refrigerant charge
- Duct leakage

SOURCE: Southern California Edison program website: www.ac-quality.com.

Figure 2: Quality Installation Program, Screen Shots



SOURCE: Southern California Edison program website: www.ac-quality.com

2.3 Empirical Challenge

In the first phase of the project, several related questions were of interest. Most importantly, how does participation in the Quality Installation Program vary with the magnitude of the subsidy? Understanding the demand curve for participation is crucial for program design because the research team was interested in assessing whether the program is structured to get the most possible benefits at least cost. For example, the analysis could show if participation could be increased substantially by modestly restructuring the structure for subsidies.

In general, it is very difficult to know how program participation varies with subsidy amounts. With typical program data one observes the participation rate under the current subsidy structure, but not what the participation rate would have been under an alternative subsidy, or with no subsidy at all. It is hard to construct this type of counterfactual. How many more California households would buy energy-efficient air conditioners were rebates increased from $1100 to $1200? How many fewer California households would buy energy-efficient air conditioners were rebates decreased from $1100 to $1000?

These are deceptively difficult questions because they depend on changes in behavior, which are typically not observed. In this first-phase of the project an RD analysis was used to construct these "what if" counterfactuals. These kind of quasi-experimental techniques have been widely used in other areas of human inquiry, but are just beginning to catch on in energy efficiency (Boomhower and Davis, 2014). This RD approach addresses selection bias and other challenges that have thwarted previous attempts to understand the relationship between subsidy amount and participation.

2.4 Climate Zones

The research team's empirical strategy exploits that in 2014, Southern California Edison offered three different subsidy amounts for central air conditioners: $550, $850, and $1,100. Figure 3 shows how these subsidy amounts varied by climate zone. Households in hot zones (that is, Climate Zones 13 and 15) qualified for larger subsidy amounts than in mild zones (Climate Zone. 6).

Figure 3: Subsidy Amounts Varied by Climate Zone

Climate Zone	Major Cities	SEER 16 or higher Split Gas/Electric	SEER 14 & 15 Heat pump & Packaged AC/Gas	SEER 16 or higher Heat Pump & Packaged AC/Gas
06	Torrance	550	500	550
	Huntington Beach	550	500	550
08	Downey	850	600	850
	Irvine	850	600	850
09	Walnut	850	600	850
	Covina	850	600	850
10	Chino	850	600	850
	Redlands	850	600	850
13	Bakersfield	1100	900	1100
	Visalia	1100	900	1100
14	Searles	850	600	850
	Yuca Valley	850	600	850
15	Palm Springs	1100	900	1100
	Palm Desert	1100	900	1100
16	Tehachapi	850	600	850
	Pacoima	850	600	850

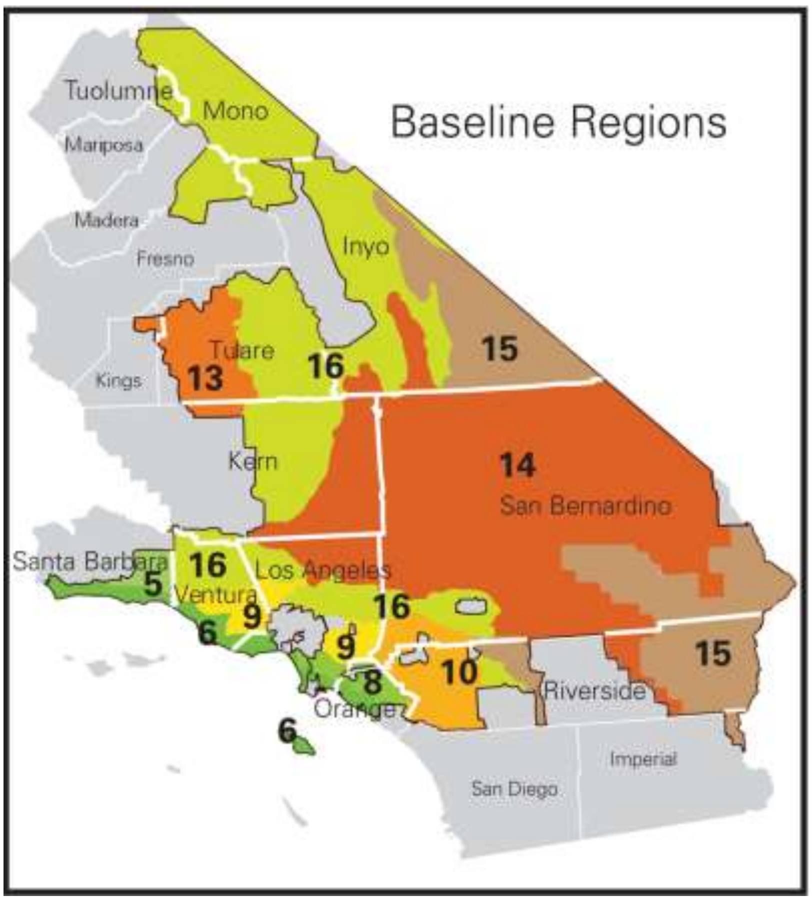
SOURCE: Southern California Edison program website: www.ac-quality.com

This variation by climate zone is an important feature of the program and an opportunity for better understanding household behavior. While it is tempting to compare participation among these climate zones, this type of "cross-sectional" comparison is highly problematic. Households living in different climate zones are inherently different. Most obviously, they face different climates and thus will already have made different choices particularly with regard to investments in air conditioning. Households in hot climate zones are more likely to have air conditioning, for example. But more broadly, households are simply different, with different average levels of household income, different sized homes, different demographic characteristics, and so forth. Consequently, it is hard to learn from cross-sectional comparison.

The researchers' method for addressing this omitted variables problem is to use an RD analysis. The researchers regress an indicator variable for participation on a flexible polynomial in distance to the climate zone boundary. The polynomial captures all climate and other unobserved factors that vary by distance, allowing the researchers to interpret any observed discontinuous change in participation at the boundary as the causal impact of the difference in subsidy amounts. This will allow the researchers to measure the increased participation associated with increasing the subsidy from $550 to $850 and then, again, from $850 to $1,100.

Several features of this application make it a particularly good candidate for a regression discontinuity analysis. First, climate zones were established by California law in 1978 and are immutable, thus reducing potential concerns about threshold manipulation. Figure 4 shows Southern California's climate zones. There is rich variation in climate from mild coastal regions, to warm in-between areas, to the hot central valley.

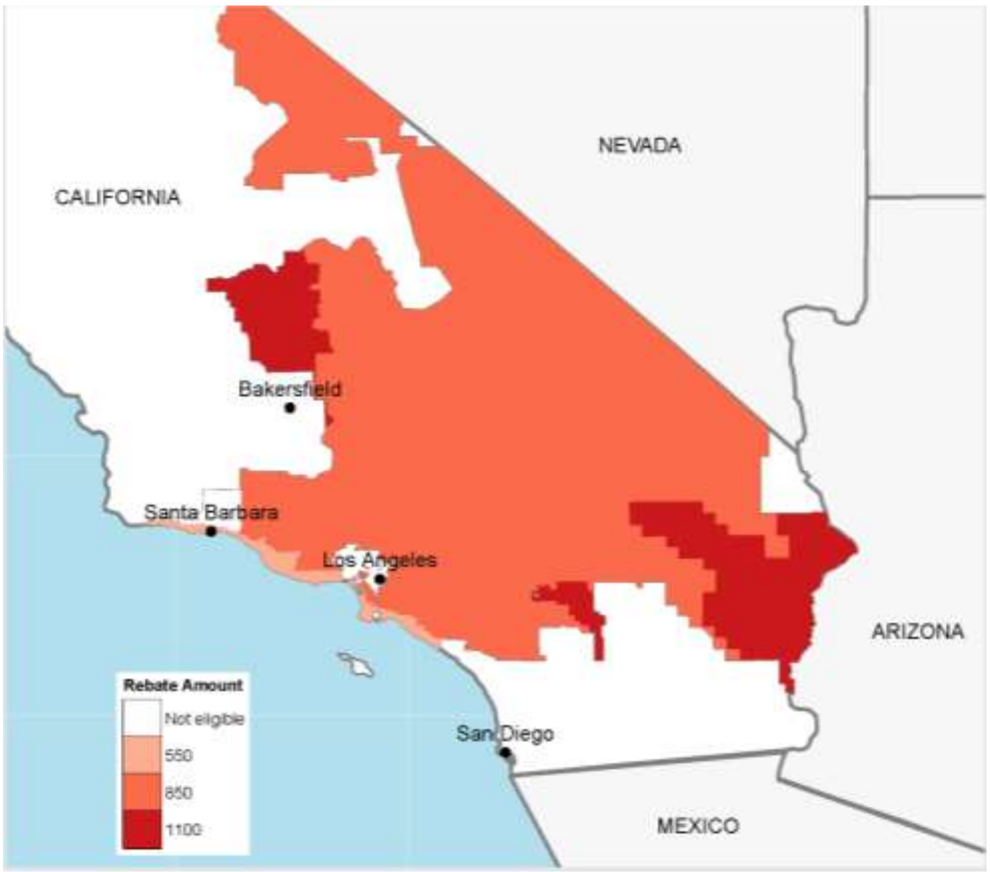
Figure 4: Southern California Climate Zones



SOURCE: https://www.sce.com/wps/wcm/connect/f08b847c-4d53-4a5b-9612-b1678187ba0c/Baseline_Region_Map.pdf?MOD=AJPERES

In the Quality Installation Program not every climate zone received a different subsidy amount. Figure 5 shows the relevant variation for the researchers' purposes. The $550 subsidy was available only along the narrow coastal region. The $850 subsidy applied for most of Southern California Edison's territory, including most of greater Los Angeles as well as the entire central area. Finally, the $1100 subsidy applied only in two smaller very hot areas including the Bakersfield area in the North, and a mixed area in the South.

Figure 5: Geographic Distribution of Rebate Amounts



SOURCE: Energy Institute at Haas

RD uses highly-localized comparisons right along these geographic boundaries. There are two main discontinuities. First is the discontinuity between $550 and $850, that is, between "mild" and "warm" areas. Second is the discontinuity between $850 and $1100, that is, between "warm" and "hot" areas. Close to these geographic boundaries households should be very similar on both sides of the boundary, so any observed differenced in behavior can be attributed to differences in the subsidy amount.

2.5 Data

2.5.1 Descriptive Statistics

Before proceeding to the main analysis, descriptive statistics are presented. These data consist of program data, describing participants in the Quality Installation Program and billing data, describing electricity consumption for participating customers. These data were compiled generously by Southern California Edison and shared early in fall 2015. In addition to these data from Southern California Edison, demographic data from the U.S. Census Bureau was incorporated and merged with these data using 9-digit zip codes.

Table 1 shows descriptive statistics for the zip codes where the program participants live. During the period for which data is available (January 2010 - March 2015), there were almost 9,000 participants in Southern California Edison's *Quality Installation Program*. Median household income in these zip codes was $78,000 annually, 47% of household heads were non-white, and 69% of households owned their home.

Table 1: Descriptive Statistics for Program Participants

	count	mean	sd	min	max
Median Household Income	8910	78380	29934	15875	250001
Average Household Size	8910	3.0	0.7	1.3	6.2
Number of Housholds Zip9 Level	8910	5.1	2.3	0.3	77.2
Proportion Non-White	8910	0.47	0.24	0.01	1.00
Proportion Completed High School	8910	0.88	0.11	0.24	1.00
Proportion Completed College	8910	0.31	0.17	0.00	0.94
Median Housing Value	8905	362101	181693	9999	1000001
Median Gross Rent	8271	1489	427	184	2001
Proportion Owner-Occupied	8910	0.69	0.19	0.00	1.00
Proportion Multi-Unit	8910	0.14	0.18	0.00	1.00

Notes:
85 participants don't have zip+4.
961 participants have no matching zip9 level demogrpahic data.
Education level is measured for population 25 or older.

SOURCE: Energy Institute at Haas

Table 2 shows statistics for all zip codes in Southern California Edison's territory. Median household income is somewhat lower at $66,000 annually, though, interestingly, the median housing value is actually higher than for program participants. Southern California Edison's territory overall has a higher fraction non-white (60%), and a lower proportion owner-occupied homes (51%). Overall, the impression from Tables 1 and 2 is that participants tend to be richer, whiter, and more educated than in Southern California Edison's territory overall.

Table 2: Descriptive Statistics for All Edison Customers

	count	mean	sd	min	max
Median Household Income	1132135	66051	32024	2499	250001
Average Household Size	1132402	3.0	0.9	1.2	8.5
Number of Housholds Zip9 Level	1136286	4.1	3.3	0.0	1315.0
Proportion Non-White	1133761	0.60	0.28	0.00	1.00
Proportion Completed High School	1133761	0.80	0.17	0.08	1.00
Proportion Completed College	1133761	0.28	0.20	0.00	1.00
Median Housing Value	1093822	401849	237752	9999	1000001
Median Gross Rent	1088078	1353	411	99	2001
Proportion Owner-Occupied	1132797	0.51	0.27	0.00	1.00
Proportion Multi-Unit	1132797	0.36	0.31	0.00	1.00

Notes:

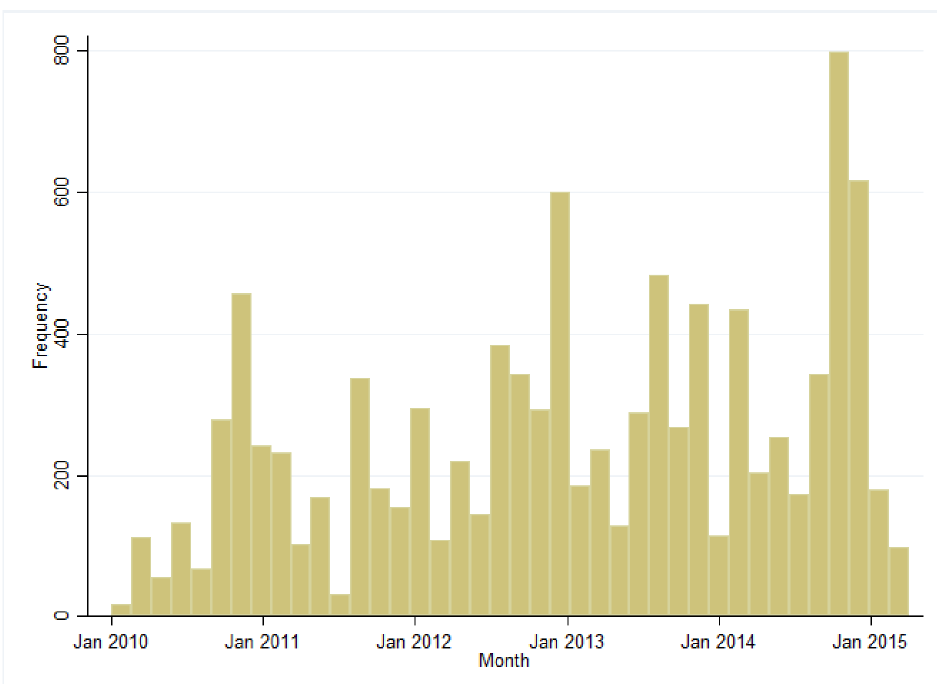
Count is number of zip9s

Education level is measured for population 25 or older.

SOURCE: Energy Institute at Haas

Figure 6 shows the pattern of participation between 2010 and 2015. There has been steady participation in the program throughout this period. Oddly, there appears to be more installations late in the year. More participation in the summer was expected when air conditioning is used most heavily. The team speculated that some of the end-of-year installations might be projects from earlier in the year, for which the paperwork for the rebate was processed before the year's end; however, there is no evidence to evaluate that possibility.

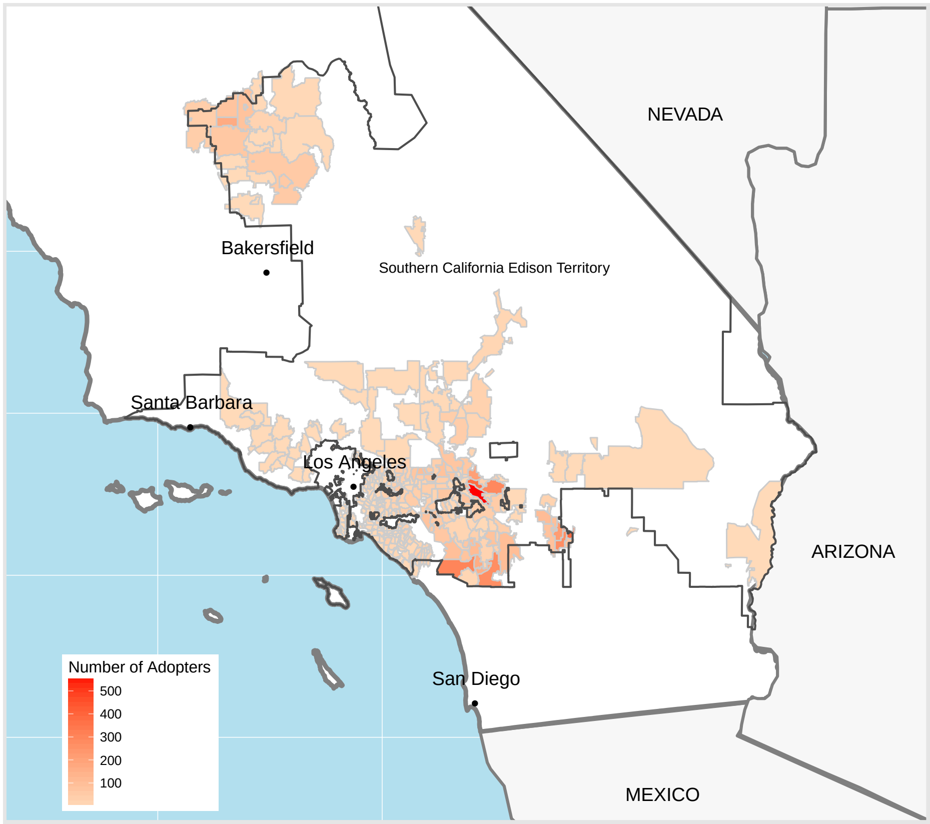
Figure 6: Histogram of Installation Dates



SOURCE: Energy Institute at Haas

Finally, Figure 7 shows where program participants live.

Figure 7: Number of Participants, By Zip Code

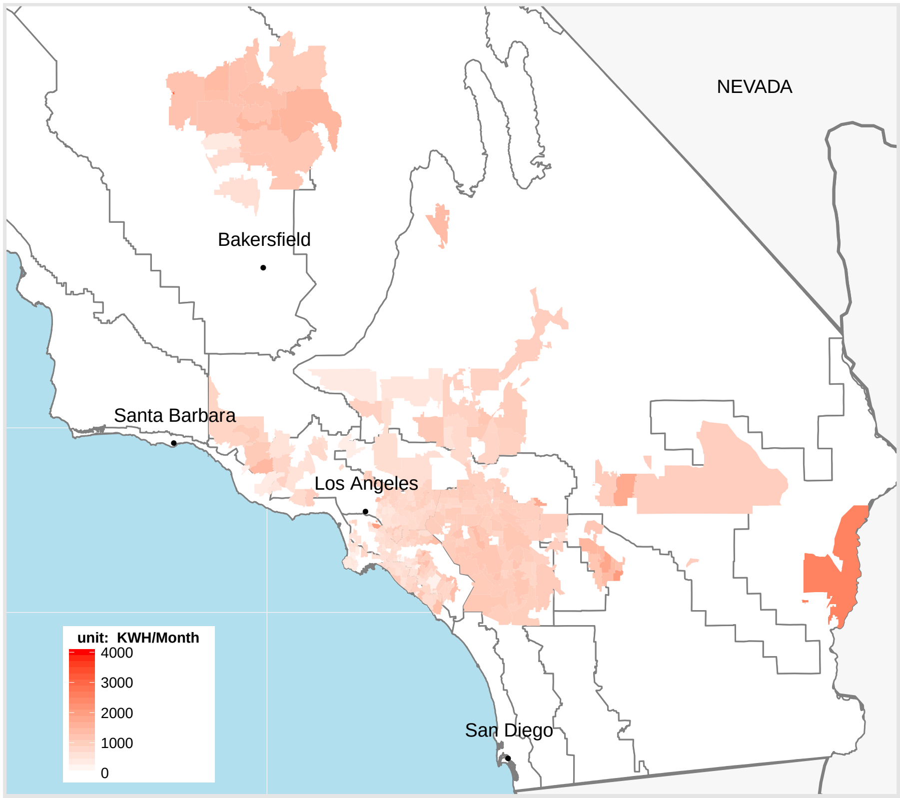


SOURCE: Energy Institute at Haas

2.5.2 Electricity Consumption

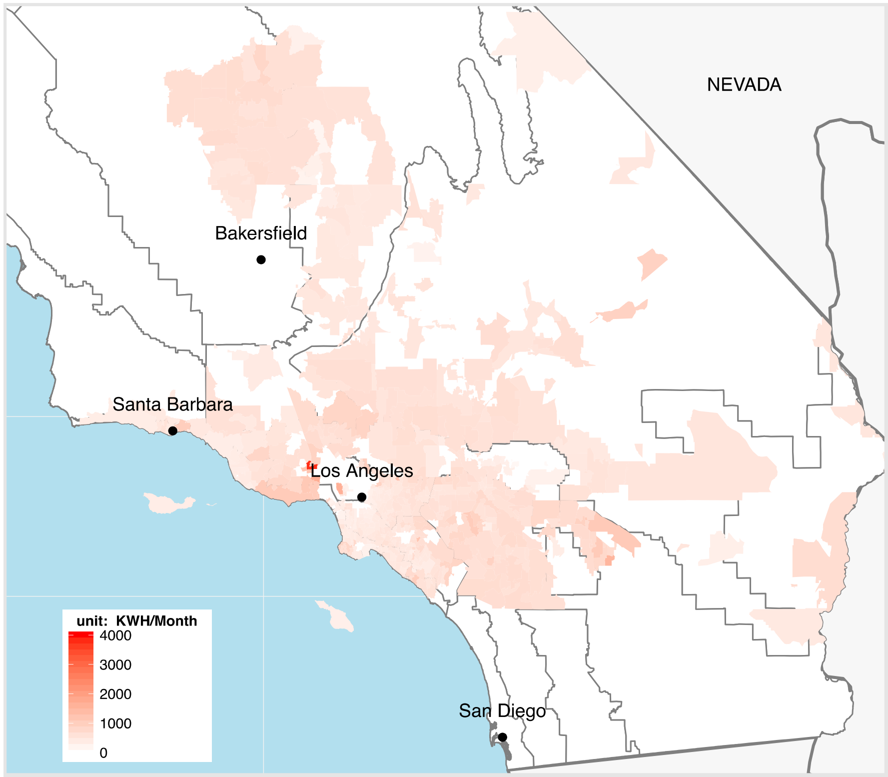
Figures 8 and 9 show average monthly electricity consumption for Quality Installation Program participants and for all Southern California Edison customers, respectively.

Figure 8: Average Summer Electricity Consumption in 2014 for Program Participants



SOURCE: Energy Institute at Haas

Figure 9: Average Summer Electricity Consumption in 2014 for All Southern California Edison Customers



SOURCE: Energy Institute at Haas

The important take-home message from Figures 8 and 9 is that participants tend to have higher electricity consumption during the summer than Southern California Edison customers as a whole. This bodes well for potential energy savings from an air conditioner replacement program because it means there is more scope for electricity demand reductions. Even relative to other SCE customers in the same locations, these are households that tend to use more summer electricity, consistent with having larger homes and/or keeping their homes cooler during the summer. Energy-efficient air conditioners use less electricity per unit of cooling, so will have the largest impact on carbon dioxide emissions when deployed in homes with high levels of baseline usage.

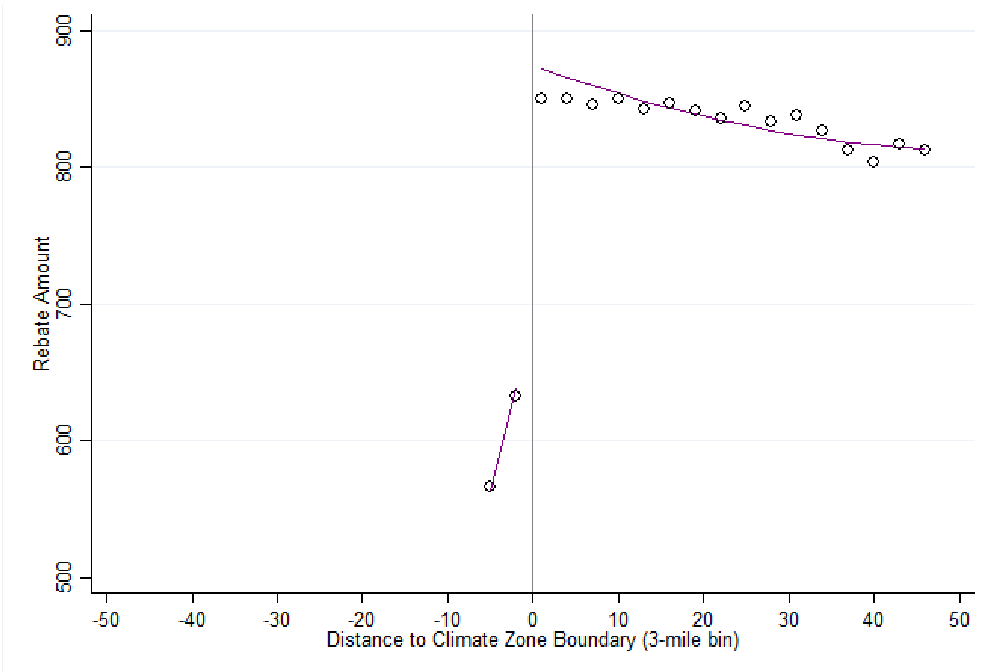
2.6 Regression Discontinuity Analysis

2.6.1 Confirming the Discontinuities

Before proceeding to the main RD analysis, the rebate amounts were confirmed to differ at the climate zone boundaries as prescribed under the program. For this exercise and the RD analysis that follows the data was restricted to include only participants from 2014. The climate zone discontinuities were not used in other years so the RD approach cannot be applied.

Figure 10 confirms the discontinuity between mild and warm zones. The x-axis in the figure is the distance to the climate zone boundary, measured in miles, with the same distance measured for each participant using standard GIS techniques. The vertical line indicates the climate zone boundary. All observations to the left of the boundary are in the mild zone, and all observations to the right are in the warm zone. Because the mild zone is the narrow strip along the coast, there are no participants more than about 5 miles away from the boundary on the mild side.

Figure 10: Confirming the Discontinuities in Rebate Amount, Between Mild and Warm Zones – Rebate Amount

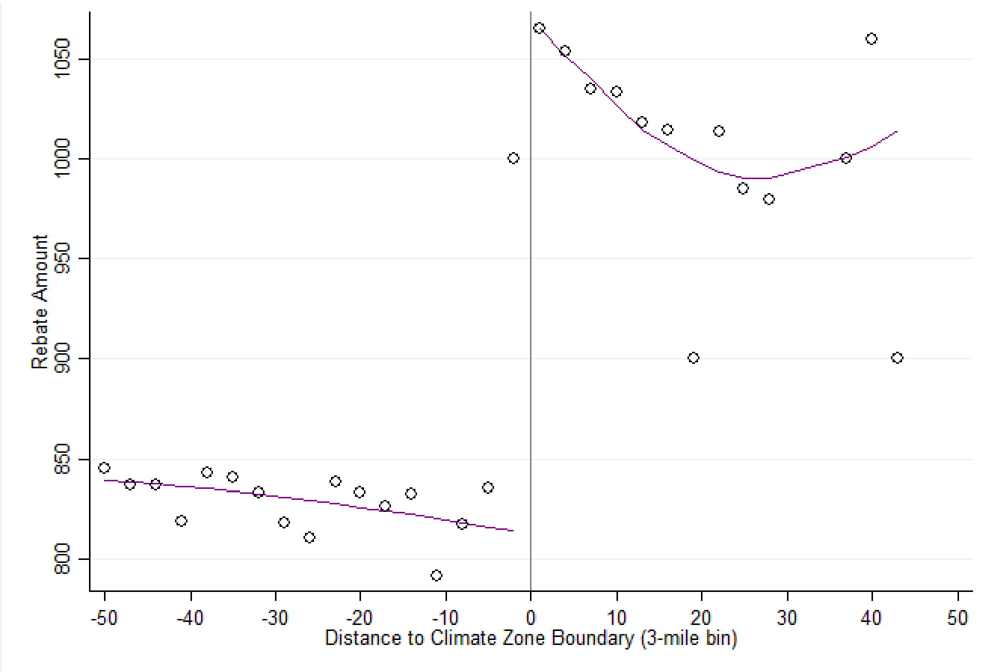


SOURCE: Energy Institute at Haas

The figure confirms that the program rules were followed closely. The y-axis plots the average rebate amount for all participants within 3-mile distance bins. There is a clear discontinuous change in the rebate amount at the climate zone boundary, roughly increasing from about $550 per rebate to about $850 per rebate. There is some variation in rebate amounts within the mild and warm zones, but it is small relative to the change at the discontinuity and likely due to households purchasing slightly different air conditioner systems which qualified for different subsidy amounts.

Figure 11 repeats the same exercise for the discontinuity between the warm and hot zones.

Figure 11: Confirming the Discontinuities in Rebate Amount, Between Warm and Hot Zones – Rebate Amount



SOURCE: Energy Institute at Haas

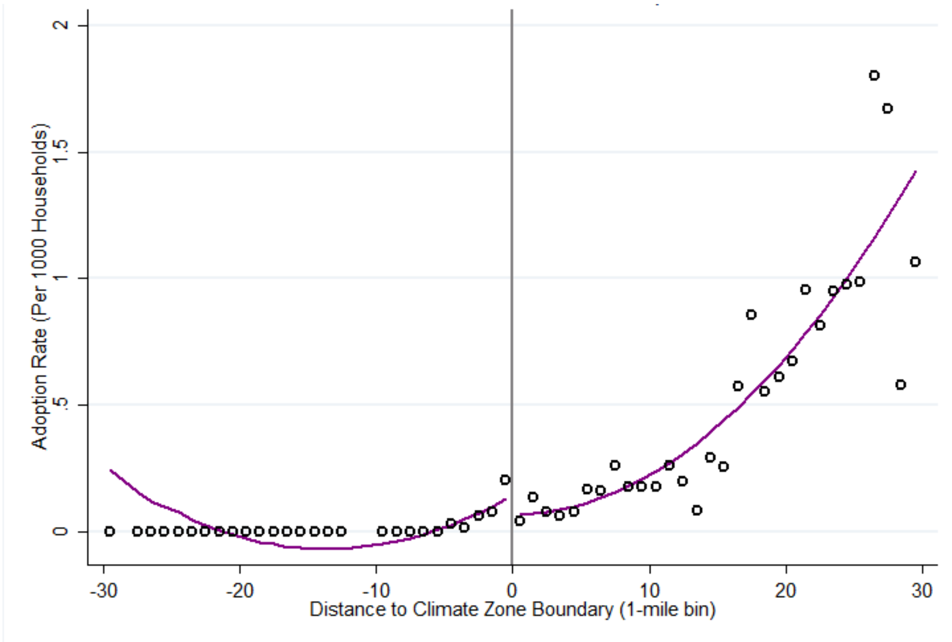
Again, there is a clear discontinuous change in the rebate amount at the climate zone boundary. Just on the warm side of the boundary, participants receive an average subsidy close to $850, while just on the hot side of the boundary participants receive an average subsidy between $1000 and $1100. As with the other figure there is some variation across bins, again likely due to slight differences in the type of air conditioning system purchased, but these differences are small compared to the discrete $250 or more change at the climate zone boundary.

2.6.2 Participation Rates

Confident that the rebate amounts indeed change discontinuously at the climate zone boundaries, the effect of rebate amounts on program participation were examined, looking at the fraction of households that participated in the *Quality Installation Program*. If households are sensitive to the amount of the subsidy, then a sharp increase in participation at these boundaries is expected.

Figure 12 plots the participation rates for the mild-warm boundary. For this boundary there is a relatively high population density - "zooming in" to the area within 30 miles on either side. The y-axis is the participation rate during 2014 per 1000 households. Raw data (in bins) are included, as well as quadratic polynomials (that is, second-order) in distance on each side of the climate zone boundary.

Figure 12: Testing for Change in Participation Rate at Discontinuities, Between Mild and Warm Zones – Adoption Rate



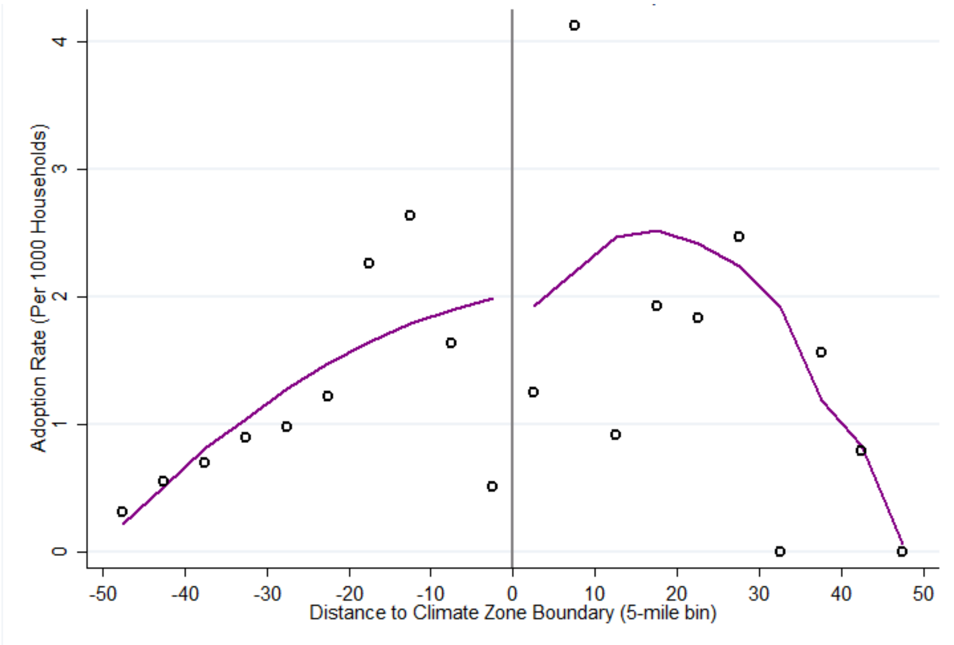
SOURCE: Energy Institute at Haas

Overall, there is little difference in the participation rate at the climate zone boundary. The subsidy is more generous on the right side of the boundary, so if participation rate were sensitive to the subsidy amount, one would expect to see a significant increase in participation at the boundary. There is no evidence of such an increase. The participation rate is very low near the boundary, with only about 1 in 10,000 households participating, and this is true on both sides of the climate zone boundary.

The results from the warm-hot boundary, shown in Figure 13, are similar.

Again, there is no evidence of an increase in the participation rate at the climate zone boundary despite the large change in generosity of the subsidy. This is a much warmer part of Southern California Edison territory where air conditioning is more prevalent, and on both sides of the climate zone boundary the participation rate is much higher that at the mild-warm boundary. The population density is also considerably lower at this boundary so the bin averages are noisy, but there does not appear to be any discontinuous increase in participation as the subsidy goes from $850 to $1100.

Figure 13: Testing for Change in Participation Rate at Discontinuities, Between Warm and Hot Zones – Adoption Rate



SOURCE: Energy Institute at Haas

2.6.3 Regression Estimates

Table 3 reports regression point estimates and standard errors from six separate regressions. Analogous to the previous graphical evidence estimates are reported separately for the mild-warm and warm-hot boundaries. In all regressions, the regressor of interest is an indicator variable corresponding to the generous side of the climate zone boundary. All specifications, in addition, control for quadratic polynomials in distance on each side of the climate zone boundary. Finally, the research team reports estimates corresponding to three different data "windows," ranging from 10, 30, and 50 miles on either side of the thresholds.

Overall, the regression estimates corroborate the graphical evidence. Across specifications there is no evidence of increased participation rates on the generous side of the climate zone boundaries. For the mild-warm boundary, all estimates are actually negative, implying lower participation, but the estimates are not statistically significant. For the warm-hot boundary the estimates vary with the width of the window, but in no case are positive and statistically significant. At this second boundary, the estimates are imprecise, so it is impossible to rule out economically significant changes in the adoption rate in either direction.

Table 3: The Effect of Rebate Generosity on Program Participation

	(1) 10-Mile Range	(2) 30-Mile Range	(3) 50-Mile Range
	Panel A. Mild-Warm Boundary		
1(Warm)	-0.147	-0.0763	-0.165
	(0.0766)	(0.0735)	(0.0865)
	Panel B. Warm-Hot Boundary		
1(Hot)	-0.401	1.313	-0.368
	(0.830)	(1.201)	(1.205)

Standard errors clustered by zip code are in parenthesis;
The dependent variable in all regressions is the adoption rate per 1000 households;
All specifications include quadratic polynomials in distance on each side of climate zone boundary;

SOURCE: Energy Institute at Haas

2.7 Conclusion

Geographic differences in program generosity like those used in Southern California Edison's Quality Installation Program are interesting because they can shed light on how households respond to changes in program generosity. Close to geographic boundaries, very similar households are treated differently, almost like having a randomized controlled trial in which the subsidy amount is randomly assigned.

Although this general approach continues to hold great promise, with this particular application there were a couple of challenges. Southern California Edison's Quality Installation Program has a very low participation rate. Consequently, there are relatively few participants living close to these climate zone boundaries and it becomes difficult to make strong statements about how participation is affected by differences in rebate amount. This is particularly true at the mild-warm boundary where the participation rate in 2014 is only about 1 in 10,000 households. At the warm-hot boundary there was an additional challenge; the participation rate is considerably higher but the population density is much lower so the estimates are imprecise.

That said, the results are nonetheless interesting. At neither threshold is evidence found of an increased participation rate on the generous side of the border. This is striking. If these $250 or more increases are not resulting in a higher participation rate then it would be cheaper and just as effective to use lower subsidy amounts. It is emphasized, however, that these estimates are imprecise so it makes it impossible to make definitive statements on the basis of the RD analysis.

CHAPTER 3: Estimating the Timing and Value of Energy Savings

3.1 Introduction

Unlike most other goods, electricity cannot be cost-effectively stored even for short periods. Supply must meet demand at all times, or the frequency in the grid will fall outside of a narrow tolerance band, causing blackouts. In addition, electricity demand is highly variable and inelastic. As a result, electricity markets clear mostly on the supply side, with production ramping up and down to meet demand. During off-peak hours electricity prices in U.S. markets tend to be below $30 per megawatt-hour. However, during peak hours prices rise substantially, frequently to more than $50 per megawatt-hour. Moreover, there are a small number of peak hours during the year when prices increase much more, to $200 or more per megawatt-hour. During these ultra-peak hours generation is operating at full capacity and there is little ability to increase supply so demand reductions are extremely valuable.

These features of electricity markets are well known, yet most analyses of energy efficiency policies ignore this variation. When the U.S. Department of Energy (DOE) considers new energy efficiency standards, they focus on total energy savings without regard to when they occur.[1] When state utility commissions evaluate energy efficiency programs, they focus on total energy savings, typically with little regard to timing.[2] Also, most large-scale energy models including the DOE's National Energy Modeling System lack temporal granularity altogether and instead model energy demand at the monthly or even annual level. With a few notable exceptions discussed later in the chapter, there is surprisingly little attention by policymakers and in academic literature to how the value of energy efficiency depends on when savings occur.

In part, these limitations reflect historical technological constraints. Before smart meters and other advanced metering infrastructure, it was impossible to measure policy effects at the hourly level. The necessary high frequency data simply did not exist, since meters were read

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1 DOE Energy Efficiency and Renewable Energy Office, Energy Conservation Standards for Single Package Vertical Air Conditioners and Single Package Vertical Heat Pumps, Final Rule, Federal Register, Vol. 80, No. 184, September 2015.

2 See, for example, California Public Utilities Commission, 2015; Public Service Commission of Maryland, "The EmPOWER Maryland Energy Efficiency Act Standard Report of 2015", April 2015; Massachusetts Energy Efficiency Advisory Council, "2013 Annual Report: Energy Efficiency Sets the Stage for Sustainable, Long-Term Savings", 2014; Northwest Power and Conservation Council, "2014 Achievements: Progress Toward the Sixth Plan's Regional Conservation Goals", November 2015; Consortium for Energy Efficiency, "2015 State of the Efficiency Program Industry", March 2016.

only once per billing cycle. This situation is rapidly changing. Today in the United States more than 40% of residential electricity customers have smart meters, up from less than 2% in 2007.[3]

In this chapter, the importance of accounting is demonstrated for the timing of energy savings using novel evidence from Southern California Edison's (SCE) *Quality Installation Program*, a rebate program for energy-efficient air conditioners described in Chapter 2. Hourly smart-meter data is used to estimate the change in electricity consumption after installation of an energy-efficient air conditioner, and show that savings tend to occur disproportionately during July and August, and during 3 p.m. to 9 p.m. With hourly data from more than 9,000 participants, the team can precisely characterize the savings profile across seasons and hours of the day.

The estimated time profile of energy savings is similar to ex ante engineering estimates, but there are several interesting differences. Most importantly, the econometric estimates indicate peak savings at 7 p.m., compared to 5 p.m. in the engineering estimates. This seemingly small difference has important implications for electricity markets given growing concern about meeting the steep evening ramp emphasized in the much-discussed "duck" chart (see, for example, CAISO, 2013).

Price data from wholesale energy and forward capacity markets is used to quantify the economic value of these estimated savings. Savings are strongly correlated with the value of electricity, making the program 53% more valuable than under a naive calculation ignoring timing. As demonstrated, including capacity prices is important in this calculation. Most of the value of electricity in ultra-peak hours is captured by forward capacity payments to generators to guarantee their availability.

Air conditioning is compared to a larger set of energy efficiency investments - residential and non-residential. Overall, there is a remarkably wide range of value across investments. Across four major U.S. markets, air conditioning investments are found on average 35% more valuable than under a naive calculation ignoring timing. For commercial and industrial heat pumps and chillers the "timing premium" is 28% and 24%, respectively. Other investments, like refrigerators and freezers have timing premiums below 5% because savings are only weakly correlated with system load. Lighting also does surprisingly poorly, reflecting that savings occur disproportionately during the winter when electricity tends to be less valuable.

These findings have important policy implications. Energy efficiency is a primary focus of energy policy in the United States and other countries. Electric utilities in the United States, for example, spent $32 billion on energy efficiency programs between 2005 and 2014, leading to more than 1.2 million gigawatt hours in reported total electricity savings.[4] In addition, the U.S. Federal government has spent $12 billion since 2009 on income tax credits for residential energy

[3] U.S. Department of Energy, "Electric Power Annual 2014", Tables 2.1 and 10.10.

[4] Tabulations by the authors based on data from U.S. Department of Energy, Energy Information Administration, "Electric Power Annual", 2012 (Tables 10.2 and 10.5) and 2014 (Table 10.6). Expenditures are reported in year 2015 dollars.

efficiency investments (Borenstein and Davis, 2015). Virtually all analyses of these programs have ignored the timing of energy savings.

This chapter proceeds as follows. Section 3.2 provides background about electricity markets and energy efficiency. Section 3.3 describes this empirical application, estimating framework, and savings estimates. Section 3.4 then examines the correlation between savings and the value of electricity, incorporating engineering-based estimated savings profiles from alternative energy efficiency investments. Section 3.5 concludes.

3.2 Background

3.2.1 Electricity Markets

Electricity is supplied in most markets by a mix of different generating technologies. Wind, solar, and other renewables are at the bottom of the supply curve with near-zero marginal cost. Nuclear, coal, and natural gas combined-cycle plants come next, all with low marginal cost. Higher up the supply curve come less efficient generating units like natural gas combustion turbines and even oil-burning "peaker" plants. Beyond that the supply curve for electricity is perfectly vertical, reflecting the maximum total generating capacity.

This mix is necessary because electricity cannot be stored cost-effectively. Demand for electricity is price inelastic and varies widely across hours. Consequently, electricity markets clear primarily on the supply side, with generation ramping up and down to meet demand. During off-peak hours, the marginal generator typically has a relatively low or even zero marginal cost. But during peak-hours the marginal generator has a much higher marginal cost. Even within natural gas plants, for example, marginal costs can vary by a factor of 2 or more. There are also typically a small number of ultra peak-hours each year in which demand outstrips the maximum capacity of generation, leading the market to clear on the demand side and resulting in prices that can spike to many times the marginal cost of any plant.

This ramping up and down occurs in all electricity markets, regardless of market structure and type of regulation. Where electricity is sold through centralized organized markets, wholesale prices provide a highly visible measure. But ramping up and down occurs in the exact same way where centralized markets are not used and electricity is instead dispatched by a vertically-integrated utility or publicly-owned company. There is some evidence that regulated markets are less efficient at dispatch (Cicala, 2015), but all electricity markets are characterized by large swings in marginal cost across hours.

An immediate implication of these features of electricity markets is that the value of demand reductions varies widely across hours. During off-peak hours the marginal cost of electricity is very low, typically less than a couple of cents per kilowatt hour. During peak-hours, however, the value of demand reductions is much higher. And during a small number of ultra-peak hours each year, the value of demand reductions can be extremely high as the system operator scrambles to avoid blackout. Most electricity buyers do not see these real-time prices, however, so many electric utilities instead have implemented demand response programs, optional critical peak pricing tariffs, and other policies aimed at curbing electricity demand during ultra-peak periods.

Where available, wholesale prices provide a measure of how the value of electricity varies across hours. In an idealized "energy-only" market, this would be the complete measure of value and the only signal power plant owners would need when deciding whether to enter or exit. In a competitive market in long-run equilibrium, the number of power plants would be determined by price competition and free entry. Additional plants would be built until the average price across all hours just equaled average cost. In such a market, the hourly wholesale electricity price represents the full value of avoided electricity consumption in any given hour.

The reality of electricity markets, even "deregulated" ones, is more complex. Price signals for new investment are partially communicated through separate capacity markets where generators commit to offer power for sale during future periods. Capacity payments lead to positive "reserve margins" (generation capacity in excess of expected peak demand). Large reserve margins are a response to the inability of most electricity consumers to adjust their consumption in real time. Because price cannot instantaneously clear the market, there is a risk of excess demand in peak periods, potentially leading to blackouts or costly equipment damage.[5] In many markets regulators enforce minimum required reserve margins, for example, requiring utilities to procure sufficient capacity to reduce the risk of electricity shortages below one event every 10 years.[6] The equilibrium capacity price just covers the shortfall between expected energy market revenues and total cost for the marginal new power plant at the desired reserve margin.

It is important to take these capacity markets into account when measuring how the value of electricity varies across hours. As shown later, considering only wholesale electricity prices ("energy prices") tends to systematically understate the degree to which the value of electricity varies across hours. Although the total size of capacity markets tends to be much smaller than the electricity markets themselves, the amounts of these payments depend only on the highest few demand hours each year. In the extreme, consider a "peaker" plant that receives a significant capacity payment for being available to be used only a very small number of hours each year. The implicit "price" of generation during those hours is therefore extremely high, potentially more than 100 times the short-run marginal cost of the plant.

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[5] Household-level interruptible tariffs are infeasible because it is not possible to remotely shut off individual consumers, except for the very largest. Some electricity markets also include price caps, which can depress energy market revenues and create an additional rationale for capacity markets. For more discussion of capacity markets see Bushnell (2005); Cramton and Stoft (2005); Joskow (2006); Joskow and Tirole (2007); Alcott (2013).

[6] For example, the California Public Utilities Commission adopts a forecast of peak demand for each month and requires utilities to enter into "resource adequacy" contracts to ensure that they can meet 115% of this demand. The payments in these contracts are very high in months when peak electricity demand is expected to be near total system capacity. As later shown, reducing forecast peak demand in August by one megawatt-hour avoids thousands of dollars in resource adequacy payments, which is many times the energy market price in those hours.

Another important feature of real-world electricity markets is the presence of large externalities. Like electricity prices, the external costs of energy production also vary across hours. Callaway et al. (2015) use site-level data on electricity generation from renewables and engineering estimates of the hourly load profile for residential and commercial lighting, to show how the total social value of those resources varies across U.S. markets. External damages are large, accounting for between one-quarter and one-half of total value, and there are large regional differences with particularly large external damages in the Midwest. However, the hourly variation in external costs is small relative to the hourly variation in electricity prices and capacity values. The private value of energy savings in the most valuable hours can be 20 or more times the average value, while emission rates vary only by about a factor of 2 among fossil-fuel plants. The following analyses focuses exclusively on private costs.

3.2.2 Energy Efficiency

Electricity is a widely-used input. Firms use electricity in producing goods and households use electricity in producing cooling, lighting, refrigeration, and other services. Energy efficiency is the rate at which energy inputs are converted into these various outputs. Investments in energy efficiency are usually capital-intensive, but can increase the amount of output per unit of energy. How much households and firms invest in energy efficiency depends on capital costs, energy prices, discount rates, and other factors.

Governments intervene in energy efficiency to reduce externalities from energy consumption and to reduce peak demand. Most economists argue for better-targeted policies, such as emissions taxes and real-time pricing of electricity, but these are politically unpopular. Instead, there are a growing number of policies aimed at increasing energy efficiency. This report fits into a recent literature that emphasizes the importance of rigorous ex post analyses of these programs using actual market data (Davis et al., 2014; Fowlie et al., 2014; Allcott and Greenstone, 2015). This chapter includes the hourly shape of demand reductions.

The majority of existing economic analyses of energy efficiency have focused on total savings, rather than on when these savings occur (see, for example, Dubin et al. [1986]; Metcalf and Hassett [1999]; Davis [2008]; Arimura et al. [2012]; Barbose et al. [2013]; Davis et al. [2014]; Fowlie et al. [2014]). An important exception is Novan and Smith (2016) which uses hourly data from a similar energy efficiency program to illustrate important inefficiencies with current retail rate designs for electricity. This analysis in contrast is more focused on the timing of energy savings and how this affects the total value of energy efficiency investments.

Energy efficiency policy and related analyses have tended to focus overwhelmingly on total energy savings, without regard to when those savings occur. Standards are probably the most pervasive form of government intervention in energy efficiency. In the United States there are minimum energy efficiency standards for more than 40 categories of residential and commercial technologies. Most analyses of energy efficiency standards focus on total energy savings, ignoring timing. Meyers et al. (2015), for example, calculate energy costs savings for U.S. federal energy efficiency standards using average annual energy prices, thus ignoring any potential correlation between savings and the value of electricity.[7]

Another major category of policies are subsidies for energy-efficient technologies. This category includes federal and state income tax credits for energy efficiency investments, sales tax holidays, and, at the state level, utility-sponsored rebates and upstream manufacturer incentives. Most state utility commissions require these programs to be evaluated by third-party analysts. Although thousands of studies have been performed looking at subsidy programs, the vast majority focus on total energy savings (for example, see references cited in Footnote 2).[8]

There are exceptions. California requires that proposed utility-sponsored energy efficiency programs be evaluated against engineering models of hourly electricity values before programs are implemented. California's Title 24 building efficiency standards also explicitly consider time value. In addition, while the vast majority of third-party analyses of energy efficiency programs ignore the timing of savings, an important exception is Evergreen Economics (2016), which compares random coefficients versus alternative models for estimating hourly savings.

3.3 Empirical Application

The empirical application focuses on a residential air conditioner program in Southern California. Section 3.3.1 briefly describes the key features of the program, Section 3.3.2 provides graphical evidence on average electricity savings, Section 3.3.3 plots savings estimates by season and hour-of-day, and then Section 3.3.4 reports regression estimates.

3.3.1 Program Background

The project's empirical application is an energy efficiency rebate program offered by SCE, a major investor-owned utility. SCE is one of the largest electric utilities in the United States, providing electricity service to 14 million people. SCE purchases power in California's wholesale electricity market operated by the California Independent System Operator and sells it to residential, commercial, and industrial customers.

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[7] Meyers et al. (2015) find that U.S. energy efficiency standards saved households and firms $60 billion in 2014. Economic analyses are performed every time a new U.S. energy efficiency standard is implemented, but again, the emphasis is on total energy savings without regard to when these savings occur (see references in Footnote 1). Interestingly, DOE explored incorporating hourly price variation into the planning process for its 2011 central air conditioner standards. The agency ultimately decided, surprisingly, to ignore time variation because it was thought to have little effect on the value of the standard. See, U.S. Department of Energy, Energy Efficiency and Renewable Energy Office, "Technical Support Document: Energy Efficiency Program for Consumer Products: Residential Central Air Conditioners, Heat Pumps, and Furnaces", 2011, Appendix 8-G.

[8] Some evaluations acknowledge timing in a very coarse way by reporting the effect of programs on annual peak demand. This recognizes the importance of physical generation constraints, but ignores the large hour-to-hour variation in the value of electricity in all other hours. This approach also does not assign an economic value to peak load reductions.

The rebate program provides incentives of up to $1,100 for households that install an energy-efficient central air conditioner. The new air conditioner is installed by an accredited third-party contractor and then the household applies for the rebate and receives a check in the mail from SCE. As is the case with most utility-sponsored energy efficiency programs, the utility commission compensates SCE for running the program by allowing the utility to pass on costs to ratepayers in the form of higher electricity prices.

The program is known as the Quality Installation Program and part of the objective of the program is to encourage better installation of air conditioners. It is estimated that 30% to 50% of new residential central air conditioning systems are not properly installed, resulting in increased energy consumption and greenhouse gas emissions (California Public Utilities Commission, 2011, p. 54). These installation issues were prominently emphasized in the marketing around the program, which showed, for example, that improper air conditioning installation can lead to more than a 25% reductions in delivered cooling.

This program is particularly interesting because of the large potential impact. Air conditioning is responsible for 10% of average residential electricity use and 15% of average commercial electricity use in California (California Energy Commission, 2012, p. 22–23). California's investor-owned utilities, under the direction of the California Public Utilities Commission, have devoted significant resources to programs aimed at reducing energy use from air conditioning. More broadly, air conditioning is widely perceived to be one of the fastest growing sources of electricity consumption worldwide (see, for example, Davis and Gertler, 2015).

The data consist of detailed information about program participants and hourly electricity consumption records. The main empirical analyses are based on 8,431 households that participated in the program between January 2010 and April 2015.

3.3.2 Event Study

Graphical evidence on average energy savings is presented as an event study figure. This evidence motivates the more detailed analyses that follow and confirms that the observed changes in electricity consumption coincide closely with the timing of new air conditioner installation. In constructing these figures, the natural variation in the timing of program participation is exploited to control for trends in electricity consumption, weather, and other time-varying factors.

Figure 14 describes the effect of new air conditioner installation on electricity consumption during the summer and winter, respectively. The x-axis is the time in years before and after installation, normalized so that the year of installation is equal to zero. The figure plots estimated coefficients and ninety-fifth percentile confidence intervals corresponding to event time indicator variables from the following regression,

$$y_{it} = \sum_{k=-4}^{4} \alpha_k 1[\tau_{it} = k]_{it} + \omega_{ct} + \epsilon_{it}. \qquad (1)$$

The dependent variable y_{it} is average hourly electricity consumption for household i in year t and τ denotes the event year defined so that $\tau = 0$ is the exact year in which the new air conditioner was installed, $\tau = -4$ for four years before, $\tau = 4$ for four years after, and so on. An indicator variable for the year before installation ($\tau = -1$) is not included, so the other coefficients are measured relative to that year. A year by climate zone fixed effects, ω_{ct}, is included to remove the effect of annual changes in average electricity consumption in each climate zone due to weather and other time-varying factors.

For summer, this regression is estimated using July and August data from 2010 to 2015 collapsed to the year-by-household level. The sample includes households that installed new air conditioners between January 2010 and April 2015. Data from installations that occurred during August, September, and October are dropped to ensure that participants did not have new air conditioners during the zero-year summer. This exclusion is for the event study figure only and these installations are included in all subsequent analyses.

The event study figure for summer shows a sharp decrease in electricity consumption in the year in which the new air conditioner is installed. The magnitude of the decrease is about 0.2 kilowatt hours per hour. Electricity consumption is otherwise approximately flat, both during the four years before and during the four years after.

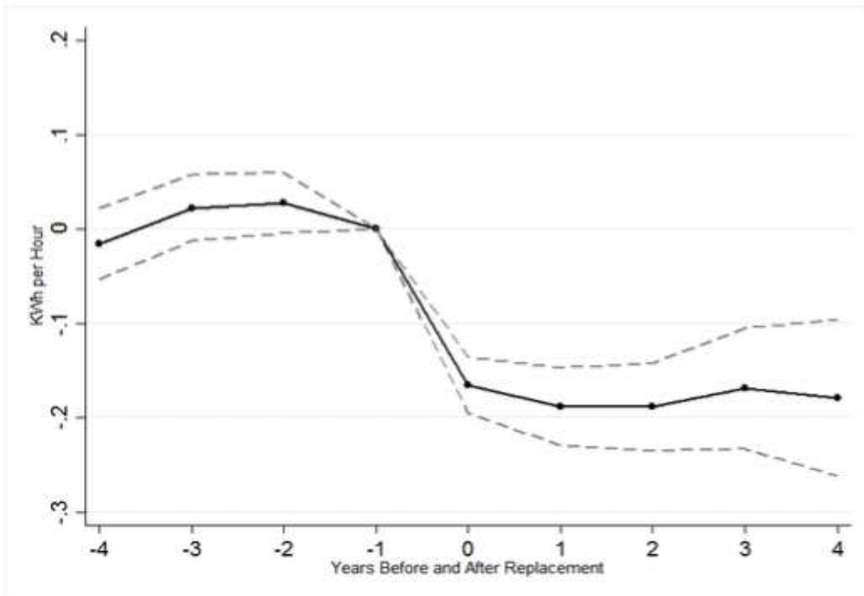
The event study figure for winter was constructed in exactly the same way but using data from January and February, and excluding data from installations that occurred during February, March, or April. As expected, winter consumption is essentially unchanged after the new air conditioner is installed. This is reassuring because it suggests that the sharp drop in electricity consumption during summer is indeed due to the new air conditioner and not some other unrelated change in household appliances or behavior.[9]

The project team could have alternatively constructed these event study figures using monthly or even weekly time indicators. However, air conditioner investments are not well suited for higher-frequency event studies because the treatment effect varies widely across months-of-the-year. In addition, air conditioner investments do not occur uniformly throughout the calendar year, introducing subtle differences in the composition of participants throughout the year that are difficult to control for in an event study. For these reasons focus on annual time indicators is preferred.

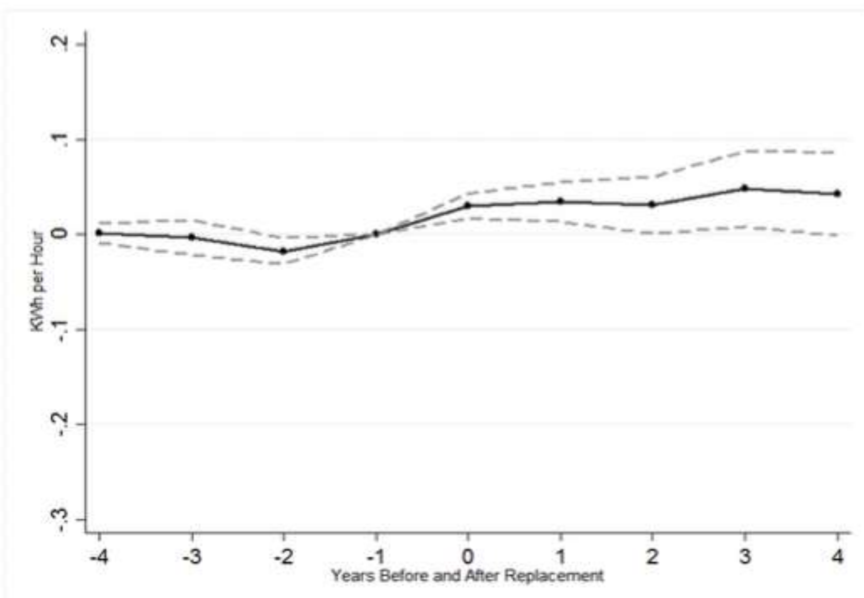
[9] These estimates of aggregate program impact are quantitatively similar to estimates in SCE-sponsored Evergreen Economics (2016) based on a random coefficients model. The Evergreen study estimates program impacts for this program using a smaller number of homes, and also for two other energy efficiency programs.

Figure 14: The Effect of New Air Conditioner Installation on Electricity Consumption

Summer



Winter



Notes: These event study figures plot estimated coefficients and ninety-fifth percentile confidence intervals describing average hourly electricity consumption during July and August and January and February, respectively, before and after a new energy-efficient air conditioner is installed. Time is normalized relative to the year of installation (t = 0) and the excluded category is $t = -1$. The regression includes year by climate zone fixed effects. Standard errors are clustered by zip code.

SOURCE: Energy Institute at Haas

These event study figures and estimates in later sections measure the electricity savings from a new air conditioner installation. This is different, however, from the causal effect of the rebate program. Many participants in energy efficiency programs are inframarginal, getting paid to do what they would have done otherwise (Joskow and Marron, 1992). Measuring the causal impact also requires figuring out how the program changed the type of appliances that were purchased. In the extreme case in which all participants are inframarginal, a program may have no causal impact whatsoever, even while the savings from an investment are large. Recent studies have used regression discontinuity and other quasi-experimental techniques to attempt to tease out these causal effects and perform cost-benefit analysis (Boomhower and Davis, 2014; Houde and Aldy, 2014).

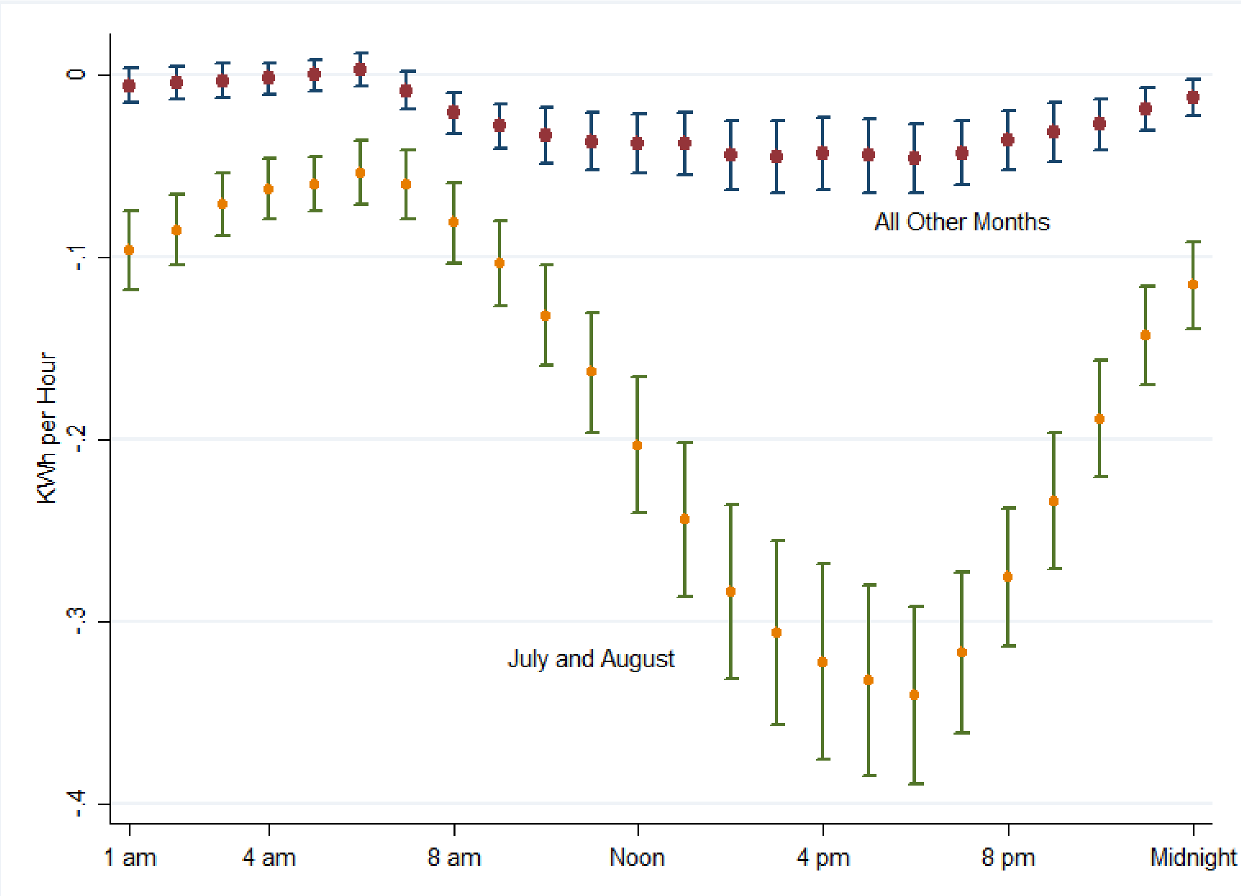
3.3.3 Hourly Impacts by Season

Figure 15 plots estimated electricity savings by hour with separate estimates for summer and non-summer months. The coefficients and standard errors for this figure are estimated using 48 separate least squares regressions. Each regression includes electricity consumption for a single hour-of-the-day and either summer- or non-summer months. For example, for the top left coefficient the dependent variable is average electricity consumption between midnight and 1 a.m. during non-summer months. All regressions are estimated at the household-by-week level and control for week-of-sample and household by month-of-year fixed effects.

The figure reveals large differences in savings across seasons and hours. During July and August there are large energy savings, particularly between noon and 10 p.m. Savings reach their nadir in the summer at 6 a.m. which is typically the coolest time of the day. During non-summer months savings are much smaller, less than 0.05 kilowatt hours saved on average per hour, compared to 0.2 to 0.3 kilowatt hours saved on average per hour during July and August.

This temporal pattern provides some reassurance that savings estimates are not biased by omitted variables. A potential concern for this type of observational study is that participating households might have experienced other changes at the same time they installed a new air conditioner. Program take-up might coincide with, for example, a major home remodel or the arrival of a new baby. Although it is impossible to rule out this concern completely, air conditioning has a particular pattern of usage that makes it different from most other energy-using durable goods. In particular, the near zero estimates during winter months imply that participants are not systematically investing in refrigerators, lighting, or other appliances which are used all year.

Figure 15: Electricity Savings by Hour-of-Day



Notes: This figure plots estimated coefficients and ninety-fifth percentile confidence intervals from 48 separate least squares regressions. For each regression, the dependent variable is average electricity consumption during the hour-of-the-day indicated along the x-axis. All regressions are estimated with household-by-week observations and control for week-of-sample and household by month-of-year fixed effects. The sample for all regressions includes all households that installed a new air conditioner between January 2010 and March 2015, and all summer- or non-summer months, as indicated. Standard errors are clustered by zip code.

SOURCE: Energy Institute at Haas

3.3.4 Regression Evidence

A regression framework for estimating average savings and for characterizing the distribution of savings across hours of the day and months of the year is described as:

$$y_{ith} = \beta_{hm} 1[New\ Air\ Conditioner]_{it} 1[hour/month]_{hm} + \gamma_{ihm} + \omega_{th} + \epsilon_{ith}. \qquad (2)$$

Here y_{ith} is electricity consumption by household i during week-of-sample t and hour-of-day h, measured in kilowatt hours. The model in levels is estimated because the primary interest is the number and timing of kilowatt hours saved. The indicator variable $1[New\ Air\ Conditioner]_{it}$, is equal to one for participating households after they have installed a new air conditioner through the *Quality Installation Program*. Installation dates vary, allowing comparisons of households that have already installed a new air conditioner to those that have not. The main covariates of interest are a set of interaction terms between this indicator variable and a vector of indicator variables 1[*hour/month*] for each hour-of-day (h) by month-of-year (m) pair. For example, one pair is 1:00-2:00 p.m. during November. The team estimates 288 separate β coefficients, each equal to the average change in hourly electricity consumption for a particular hour-of-day and month-of-year.

All specifications include household by hour-of-day by month-of-year fixed effects, γ_{ihm}. That is, for each household 288 separate fixed effects were included that allow for different household-level average consumption over the day and the year. This allows for rich heterogeneity across households in typical seasonal electricity usage. This is important because electricity usage by air conditioned homes varies widely across the months of the year. In addition to controlling for time-invariant seasonal patterns for each household, these household fixed effects control for other time-invariant characteristics such as the size of the home, number of household members, and number and type of appliances.

All specifications also include week-of-sample by hour-of-day fixed effects ω_{th}. This controls flexibly for territory-wide trends in electricity consumption. These fixed effects absorb average trends caused by weather variation or secular trends in household electricity consumption. Some specifications include, instead, separate week-of-sample by hour-of-day fixed effects for each of 8 climate zones. This richer specification controls for climate-zone specific variation in weather, as well as differential trends across climate zones. This is potentially important because there are large climatological and demographic differences between California's coastal and inland areas. Finally, the error term ε_{ith} captures unobserved determinants of consumption across periods.

Table 4 reports estimates from four different specifications which include different combinations of fixed effects and sample exclusions. For each specification average annual energy savings per household in kilowatt hours per year are reported. For computational reasons, equation (2) is estimated using separate regressions for each hour-of-day by month-of-year pair and then calculated using annual average savings as the weighted sum of the 288 β coefficients. This yields identical point estimates but requires use of the bootstrap standard errors. A block bootstrap by household is used to account for dependent observations within household.

Table 4: Average Energy Savings from a New Central Air Conditioner

	(1)	(2)	(3)	(4)
Energy Savings Per Household (kWh/year)	368.5	353.1	414.4	310.8
Household by hour-of-day by month-of-year fixed effects	Y	Y	Y	Y
Week-of-sample by hour-of-day fixed effects	Y			
Week-of-sample by hour-of-day by climate zone fixed effects		Y	Y	Y
Drop 8 weeks pre-installation			Y	
Drop observations before July 2012				Y
Number of observations	35.7 M	35.7 M	35.7 M	19.3 M
Number of households	8,431	8,431	8,431	5,548

Notes: This table reports results from four separate regressions. The dependent variable in all regressions is average hourly electricity consumption measured at the household by week-of-sample by hour-of-day level. The main variables of interest in these regressions are 288 month-of-year by hour-of-day indicators interacted with an indicator for observations after a new air conditioner installation. Annual average energy savings is calculated as the weighted sum of these 288 estimates. Standard errors are calculated using block bootstrap by household with 25 replications. The regressions are estimated using 2010 to 2015 data from all participating households. Column (4) limits the sample to observations after July 2012 by which time 90% of participants had smart meters.

SOURCE: Energy Institute at Haas

In columns (1) and (2) the implied annual savings per household are 369 and 353 kilowatt hours per year, respectively. The difference between these two specifications is that the latter adds the richer set of time fixed effects. In columns (3) and (4) the estimation sample is varied, dropping for each household the eight weeks before installation. This might make a difference if an old air conditioner was not working or if the installation date was recorded incorrectly. The sample to observations is limited to after July 2012, by which time 90% of households had smart meters. Relatively few households had smart meters when the data begins in 2010 so one might have been concerned about bias arising from this being an unbalanced panel. The estimates are somewhat larger in column (3) and somewhat smaller in column (4) but overall the average savings are similar across the four columns.

3.4 The Value of Energy Efficiency

In this section the value of electricity varies substantially across hours discussed. It's important to account for this variation when valuing energy efficiency investments. Data on wholesale energy prices and capacity values in several U.S. electricity markets (Section 3.4.1) are shown. With the empirical application from the previous section, the correlation between electricity savings and the value of electricity (Section 3.4.2) is measured, quantifying the average value of savings (Section 3.4.3). With this proof of concept completed, the engineering estimates from a broader set of energy efficiency investments are reviewed. The time profile differs significantly between investments (Section 3.4.4) and these different profiles imply large differences in value (Section 3.4.5).

3.4.1 The Value of Electricity in U.S. Markets

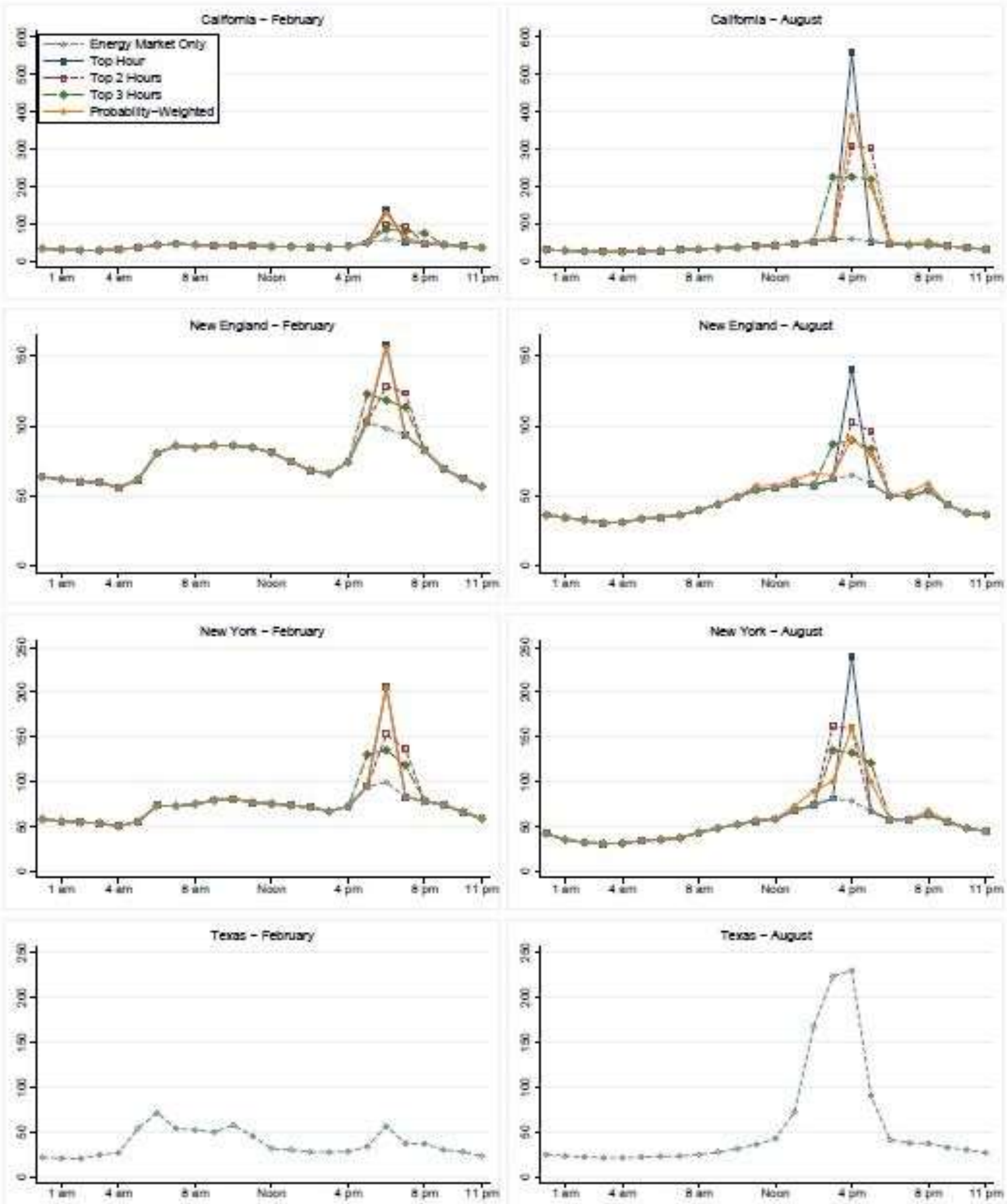
Figure 16 plots hourly wholesale electricity prices and capacity values for two months-of-year (February and August) and for four U.S. electricity markets (California/CAISO, New England/ISONE, New York/NYISO, and Texas/ERCOT). February and August were selected because they tend to be relatively low- and high-demand months but adjacent months look similar. For each market average prices by hour-of-day for several years during 2010 to 2015 are reported. The energy and capacity price data used come from SNL Financial.

The figures plot average wholesale prices as well as four alternative measures of capacity value. As discussed in Section 3.2.1, capacity markets pay electricity generators to remain open and available, thereby avoiding electricity shortages. Capacity costs are zero or close to it during off-peak hours because electricity demand can be easily met by existing inframarginal generators (plants that are not close to the margin between staying in the market and exiting). However, during peak hours large capacity payments are required to ensure desired reserve margins. In the extreme, think of a plant which receives a significant capacity payment for being available to be used only a very small number of hours each year.

ERCOT has no capacity market and, not coincidentally, has some of the highest energy market prices, particularly during summer. In the three other markets, generation capacity is procured at the monthly level. To value energy savings in a given hour, these monthly prices must be allocated across individual hours. This is done in several different ways and the results of each are reported. In the first approach, an hourly load data is used to calculate the hour-of-the-day with the highest average load each month. The capacity contract value for that month is then assigned entirely to that hour-of-the-day. This means dividing the monthly contract value by the number of days in the month, and assigning that amount to the peak hour. In other specifications, the capacity contract value is evenly divided between the top two or three hours-of-the-day with the highest load each month. The final approach treats each day of load data as a single observation of daily load shape in a given month. The historical likelihood that each hour-of-the-day was the daily peak hour is calculated, and monthly capacity prices are allocated to hours of the day proportionally according to these probabilities.[10] This allocation method is referred to as the "probabilistic allocation."

[10] For example, during February in the CAISO market, 6:00 p.m. was the highest-demand hour on 87% of days from 2013–2015. On 13% of days, 7:00 p.m. was the daily peak. So, the capacity value associated with 6:00 p.m. in February would be 87% of the February average contract price, divided by the number of days in the month.

Figure 16: Wholesale Electricity Prices and Capacity Values



Notes: This figure shows the average hourly opportunity cost of electricity consumption in February and August in four major U.S. markets, under various assumptions about capacity value. The vertical axis units in each figure are dollars per megawatt-hour. The hour labels on the x-axis refer to the beginning time of each one-hour interval (e.g., "3 - 4 p.m."). See text for details.

SOURCE: Energy Institute at Haas

Incorporating capacity values substantially increases the value of electricity during peak periods. In California during August, for example, capacity values increase the value of electricity during peak evening hours to between $200 and $600 per megawatt hour. Peak electricity values tend to be somewhat lower in the other regions, but with a similar overall pattern. The value of electricity in ERCOT surges in August to more than $200 during evening hours, considerably higher than the marginal cost of any generator. And, overall, the pattern is very similar across the four approaches for allocating capacity value across hours. As expected, allocating the entire capacity value to the single highest-load hour results in the highest peak, though the other approaches have similar shapes.

An alternative approach to valuing capacity would be to use engineering estimates for the cost of new electricity generating equipment like a natural gas combustion turbine plant. This would address the concern that capacity markets may not be in long-run equilibrium, and thus may not reflect the true long-run cost of capacity. Some market participants have argued, for example, that the recent influx of renewables into U.S. electricity markets has pushed capacity market prices down below long-run equilibrium levels. If this is the case then over time entry and exit decisions should lead to increased capacity prices and it would be straightforward to repeat these calculations with updated data. Larger capacity prices would lead to larger variation in economic value between off-peak and peak, thus strengthening the central findings.

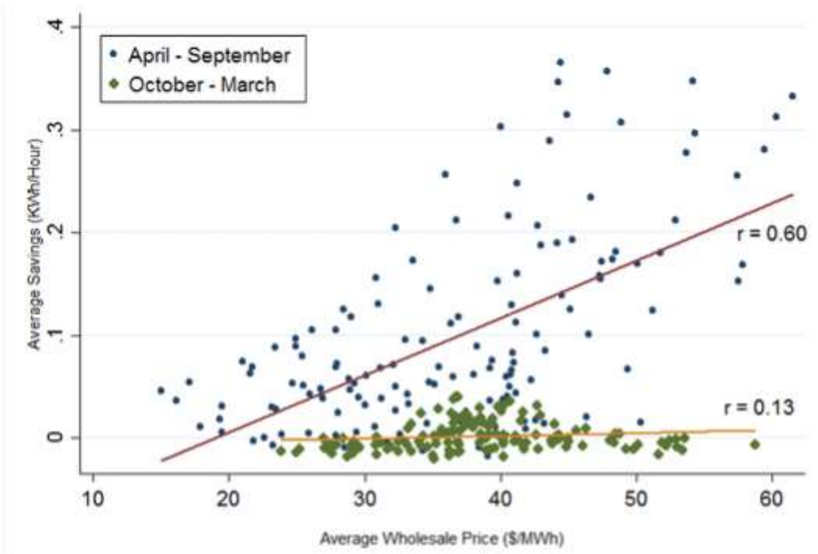
The calculations which follow also account for line losses in electricity transmission and distribution. In the United States, an average of 6% of electricity is lost between the point of generation and the point of consumption (DOE, 2016, Table 7.1), so 1.0 kilowatt hour in energy savings reduces generation requirements by 1.06 kilowatt hours. Line losses vary over time by an amount approximately proportional to the square of total generation. These losses are incorporated explicitly following Borenstein (2008) and range from 2% during off-peak periods to 12% during ultra-peak periods. Incorporating line losses further increases the variation in economic value between off-peak and peak.

3.4.2 Correlation between Savings and Value

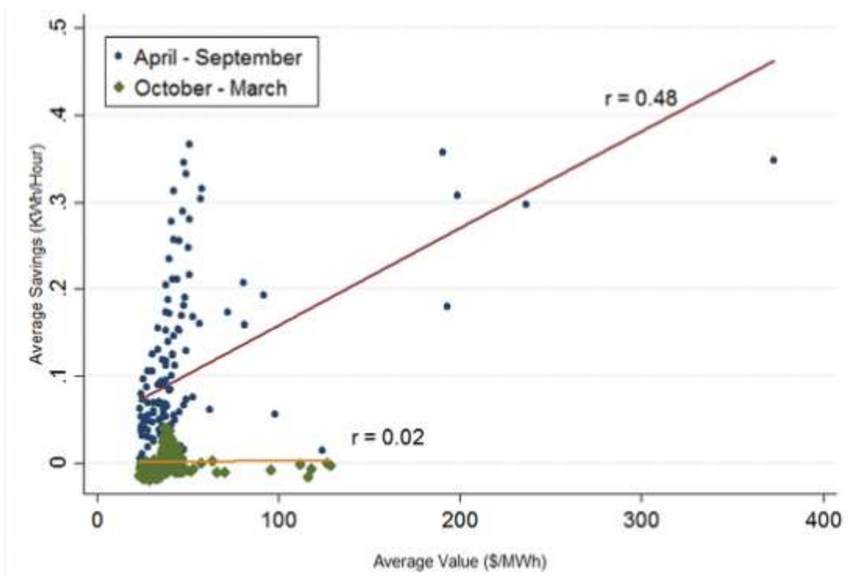
Figure 17 shows the correlation between energy savings and the value of energy. Panel A compares hourly average energy savings to energy prices only. Panel B compares the same savings estimates to the sum of energy and capacity values. Each marker in each plot corresponds to an hour-of-day by month-of-year pair (for example, 1:00–2:00 p.m. during November). The vertical axes show average hourly energy savings. These are the 288 β coefficients from estimating Equation 2. In Panel A, the horizontal axis shows average wholesale energy prices from California for 2010–2014. In Panel B, the horizontal axis shows energy and capacity values, using the probabilistic allocation method for capacity prices described in Section 3.4.1.

Figure 17: Correlation Between Savings and Prices, By Season

Panel A. Energy Prices Only



Panel B. Energy and Capacity Prices



Notes: These scatterplots show the correlation between electricity savings and the value of electricity. Each observation is an hour-of-day by month-of-year pair (for example, 1–2 p.m. during November). Electricity savings are estimated with 288 separate regressions (12*24), each using observations from a single hour-of-day and month-of-year. All regressions control for household and week-of-sample by climate zone fixed effects. Electricity savings are identical in Panels A and B. Panel A uses wholesale electricity prices only, while Panel B also includes hourly capacity values. Energy and capacity price data are from the California electricity market during 2010–2014. See text for details. The figure also includes least squares fitted lines for April-September and October-March observations with the correlation indicated in text above.

SOURCE: Energy Institute at Haas

Several facts are apparent in Panel A. First, the summer months include many more high-price realizations than the winter months. Blue markers are used to indicate April through September, and the number of intervals with energy prices above $40 per MWh is clearly higher during these summer months. Second, this energy efficiency investment delivers larger savings in the summer, with average savings in excess of 0.1 kilowatt-hours per hour in many summer hours.

The figure also includes least-squares fitted lines for April–September (in red) and October–March (in yellow). The fitted line for summer slopes steeply upward. In the top panel, predicted savings when energy prices are $55/MWh are twice as large as predicted savings at $35/MWh. The fitted line for winter, however, is essentially flat. This energy efficiency investment delivers essentially zero electricity savings in all hours during the winter, so there is little correlation between savings and prices.

The same patterns are apparent in Panel B. However, this panel emphasizes the importance of accounting for hourly capacity values. There are a few ultra-peak hours in the summer when generation capacity is extremely valuable. The air conditioner program delivers above-average savings in all of these hours.

3.4.3 Quantifying the Value of Energy Savings

This positive correlation during the summer increases the value of this investment. In this section the value of these energy savings are quantified under several alternative assumptions. The total value differs across approaches, but in all cases the savings from this investment are considerably more valuable than under a naive calculation ignoring timing.

Total electricity savings are calculated by multiplying each coefficient in β_{mh} by the number of days in the month φ_m, and then take the sum of these products to yield total annual savings in kilowatt hours,

$$\sum_{m=1}^{12}\sum_{h=1}^{24}\beta_{mh}\phi_m. \tag{3}$$

The total value of electricity savings are then calculated. Let p_{mh} denote the average value of electricity per kilowatt hour in month-of-year (m) and hour-of-day (h). The total annual value of savings is,

$$\sum_{m=1}^{12}\sum_{h=1}^{24}\beta_{mh}\phi_m p_{mh}. \tag{4}$$

The average value of savings are calculated as the total value of savings (equation 4), divided by total savings (equation 3).

Table 5 reports estimates of the average value of savings under five alternative approaches for valuing electricity. In column (1) the capacity values are ignored and wholesale energy prices are used from the California electricity market (SP-15, Day Ahead) between 2010 and 2014.

Specifically, the vector p_{mh} is calculated as the average wholesale price during this five-year period in each month-of-year (m) and hour-of-day (h). There is a 4:1 ratio in prices within this vector between the highest-price period (August 6-7 p.m.) to the lowest-price period (June 5-6 a.m.). Using these prices the value of the program is 14% higher than originally calculated with the program's value using average energy prices and ignoring timing.

Table 5: Does Energy Efficiency Deliver at the Right Time?

	Energy Prices Only	Energy Plus Capacity Prices, Various Assumptions			
		Capacity Value in Top 4% of Hours	Capacity Value in Top 8% of Hours	Capacity Value in Top 12% of Hours	Capacity Value Allocated Probabilistically
	(1)	(2)	(3)	(4)	(5)
Average Value of Savings ($/MWh)					
(A) Accounting for Timing	$20.69	$32.78	$32.75	$32.75	$32.69
(B) Not Accounting for Timing	$18.16	$21.39	$21.39	$21.39	$21.39
Timing Premium ($\frac{A-B}{A}$)	14%	53%	53%	53%	53%

Notes: These calculations were made using estimated energy savings for each hour-of-day by month-of-year from the full regression specification as in Column (3) in Table 4. See Equations 3 and 4 in the text for details. Energy prices are wholesale electricity prices from the California electricity market (CAISO-SP15-Day Ahead Market) between January 2010 and December 2014. Capacity prices are based on Resource Adequacy contract prices reported in California Public Utilities Commission, "2013-2014 Resource Adequacy Report". In Columns (2), (3), and (4), monthly capacity prices are allocated evenly across the one, two, and three (respectively) hours of the day with the highest average load each month. In Column (5), monthly capacity prices are allocated to hours of the day based on their historical probability of containing the monthly peak-load event. Hourly load data are from SNL Financial.

SOURCE: Energy Institute at Haas

Columns (2) through (5) incorporate capacity values. Each column takes a different approach to allocating monthly capacity payments across hours of the day, as described in Section 3.4.1 and Figure 16. Incorporating capacity values significantly increases the value of air conditioning investments. This is not so much the case when one doesn't account for timing; the value of savings increases only modestly from $18 per MWh to $21 per MWh. However, when one accounts for timing the value almost doubles to $33 per MWh. This reflects the positive correlation observed earlier. Air conditioning investments save electricity during the months-of-the-year and hours-of-the-day when large capacity payments are needed to ensure that there is sufficient generation to meet demand.

Exactly how capacity values are accounted for has little impact, changing the estimated timing premium only slightly across Columns (2) through (5). This reflects the fact that the estimated savings are similar during adjacent peak hours, so assigning capacity value to, for example, 6 p.m. vs. 7 p.m. does not significantly impact the estimated value of savings. The probabilistic allocation is used as the preferred measure; however, results are qualitatively similar using the other allocation methods.

3.4.4 Savings Profiles for Selected Energy Efficiency Investments

Engineering estimates of hourly savings profiles for air conditioning and for a much larger set of energy efficiency investments are considered. This information is valuable as a point of comparison to the econometric estimates and because these engineering estimates form the basis of this broader analysis of whether energy efficiency investments deliver at the right time.

The total annual consumption decreases measured in the econometric analysis are broadly similar to engineering predictions of total savings from air conditioner replacement, allowing for small differences due to rebound and other factors. For example, a "savings calculator" from the Energy Star program says that a typical central air conditioner upgrade in Los Angeles would save about 550 kWh/year.[11] While the total annual savings measured generally agree with engineering predictions, the timing of these savings might be quite different.

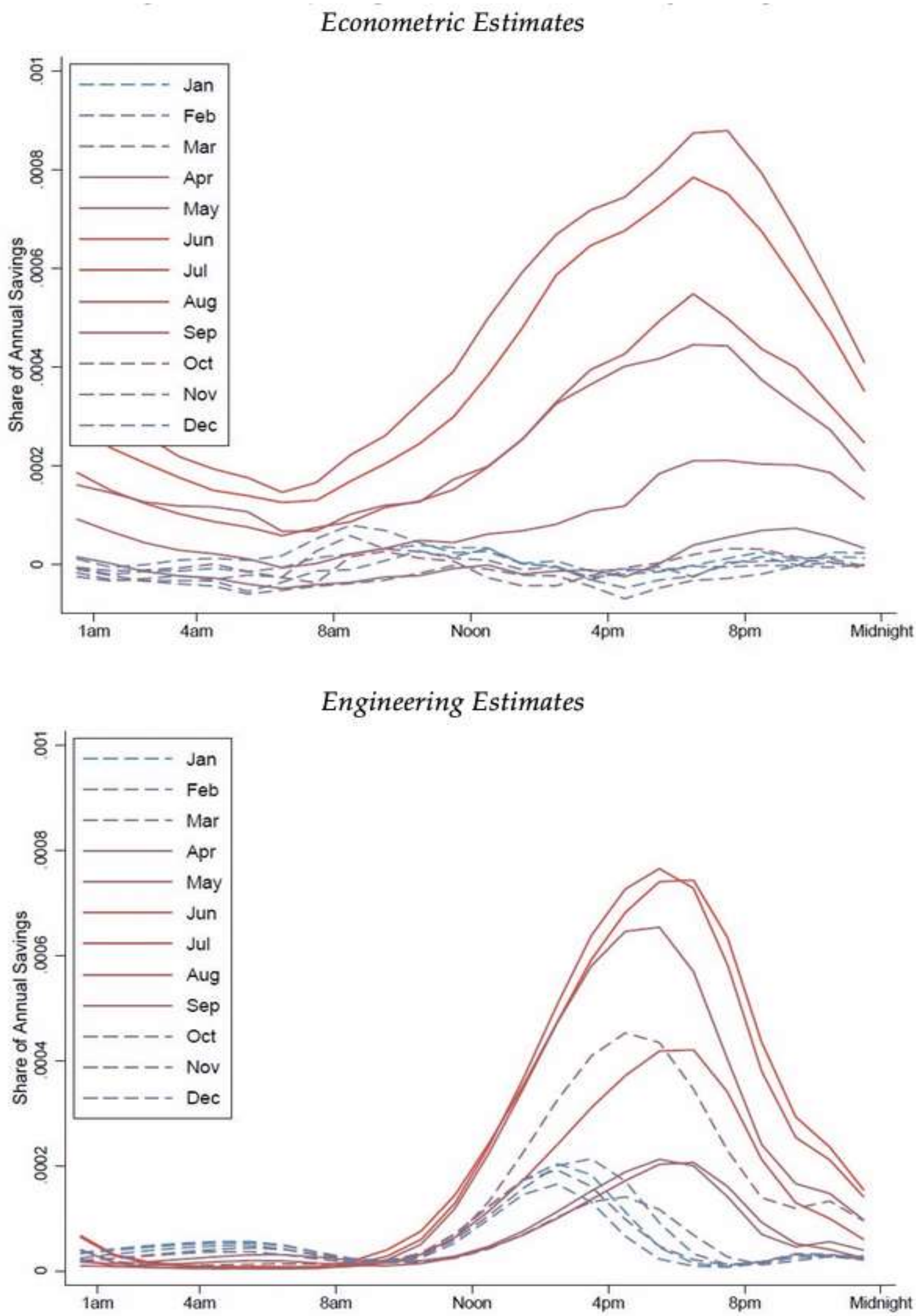
An hourly savings profiles is used from the *E3 Calculator*, a publicly-available software tool developed for the California Public Utilities Commission by Energy and Environmental Economics, Inc., a San Francisco-based energy consulting company.[12] These are ex ante engineering estimates of energy savings, constructed using weather data and other inputs.

Figure 18 compares the econometric estimates from Section 3.4.2 with engineering estimates. The engineering estimates are energy savings for residential air conditioning investments in this same geographic area. The savings profiles are similar, but there are several interesting differences. Probably most importantly, the econometric estimates indicate peak savings later in the evening. Whereas with the engineering estimates peak energy savings occur between 4 - 5 p.m. the econometric estimates peak between 6 - 7 p.m. This timing is particularly interesting and policy-relevant given all of the discussion about the "duck chart" and related trends in U.S. electricity markets.

[11] Replacement of a 3-ton 13 SEER unit with 3-ton 15 SEER without programmable thermostat before or after. See Energy Star Program, "Life Cycle Cost Estimate for 1 ENERGY STAR Qualified Central Air Conditioner(s)", 2013. https://www.energystar.gov/.

[12] The *E3 Calculator* is used by the California Public Utilities Commission (CPUC) to track and evaluate energy efficiency programs administered by California investor-owned utilities. See https://ethree.com/public_projects/energy_planning_tools.php. The most recent hourly savings estimates are used from a file called DEER2011-HrlyProfiles-SCE-v2-Shifted. The *E3 Calculator* is closely related to the CPUC-sponsored *Database for Energy Efficient Resources (DEER)*. For each energy efficiency investment, the *E3 Calculator* reports 8,760 numbers, one for each hour of the year. For these figures the data are collapsed and report average hourly profiles by month. These savings profiles are intended to reflect average impacts across all applicable building types in Southern California Edison territory.

Figure 18: Comparing Estimates of Electricity Savings

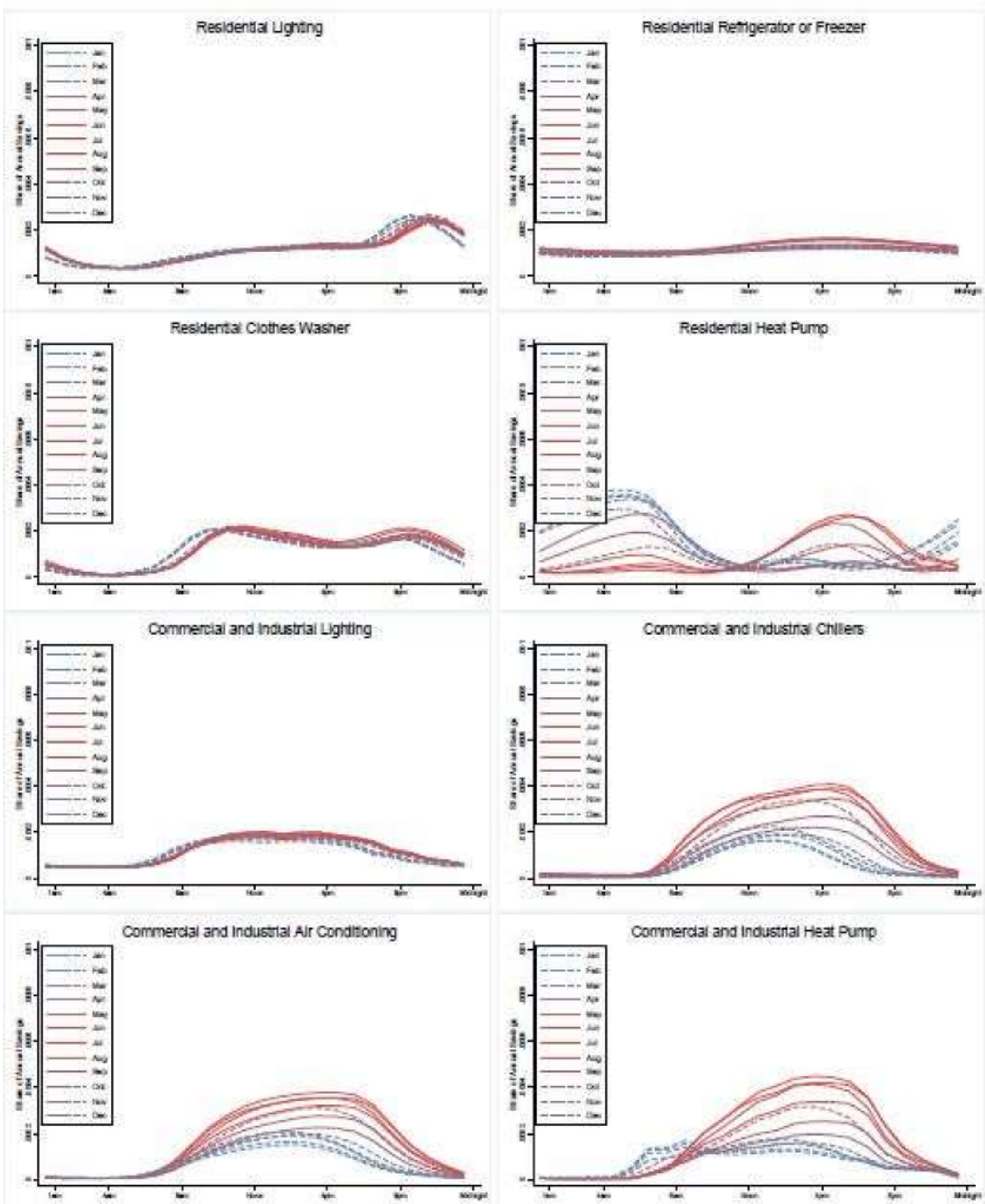


SOURCE: Energy Institute at Haas

There are other differences as well. The econometric estimates show a significant share of savings during summer nights and even early mornings, whereas the engineering estimates show savings quickly tapering off at night during the summer, reaching zero at midnight. It could be that the engineering estimates are insufficiently accounting for the thermal mass of California homes and how long it takes them to cool off after a warm summer day. The econometric estimates also show greater concentration of savings during the warmest months. Both sets of estimates indicate July and August as the two most important months for energy savings. But the engineering estimates indicate a significant share of savings in all five summer months, and a non-negligible share of savings during winter months. In contrast, the econometric estimates show a much more modest share of savings in May, and essentially zero savings in other months.

Figure 19 plots hourly savings profiles for a broader set of energy efficiency investments. Eight different investments with four residential and four non-residential are included. Savings profiles for additional energy-efficient investments are available in the appendix. The savings profiles are remarkably diverse. The flattest profile is residential refrigeration, but even this profile is not perfectly flat. Residential lighting peaks between 8 - 9 p.m. all months of the year, and residential heat pumps peak at night during the winter and in the afternoon during the summer.

Figure 19: Savings Profiles for Selected Energy Efficiency Investments



SOURCE: Energy Institute at Haas

The non-residential profiles are also interesting, and quite different from the residential profiles. Whereas residential lighting peaks at night, commercial and industrial lighting is used steadily throughout the business day. Commercial and industrial chillers and air conditioning follow a similar pattern but are much more concentrated during summer months. Finally, commercial and industrial heat pumps are assumed to peak only in the summer, unlike the residential heat pumps for which the engineering estimates assume both summer- and winter-peaks.

3.4.5 Comparing the Value of Alternative Energy Efficiency Investments

Finally, the timing premiums are calculated for this wider set of energy efficiency investments. Just as previously done, the timing premiums are calculated as the additional value of each investment in percentage terms relative to a naive calculation that ignores timing,

$$\frac{\sum_{m=1}^{12}\sum_{h=1}^{24}\alpha_{mh}p_{mh}-\overline{p_{mh}}}{\overline{p_{mh}}} \tag{5}$$

Here α_{mh} is the share of savings which accrue during a particular month-of-year (m) and hour-of-day (h). Additional subscripts are omitted for clarity, but these shares α_{mh} differ across energy-efficient investments as shown in Figure 19. By definition, the sum of these α_{mh} shares is equal to one. Consequently, if savings are uniform across all hours of the year then the summation is equal to average system cost p_{mh} and the relative value is equal to zero. As before, p_{mh} is the value of electricity during month-of-year (m) and hour-of-day (h). If savings are positively correlated with p_{mh} then the relative value is greater than zero, and if savings are negatively correlated with p_{mh} then the relative value is less than zero. For p_{mh}, wholesale energy prices are used plus capacity values allocated probabilistically, as in column (5) in Table 5. Results are qualitatively similar with the other allocation methods.

Table 6 presents results. Each column is a different U.S. electricity market. Each row is a different energy efficiency investment. The first row uses the econometric estimates, and all other rows use the engineering savings profiles described in Section 3.4.4. Estimates for California (California ISO), Texas (ERCOT), New England (NE-ISO), and New York (NYISO) are provided. Comparable seasonal capacity market data are not available for Pennsylvania/New Jersey/Maryland (PJM) or Midwest (MISO).

Table 6: Timing Premiums for Selected Energy Efficiency Investments

	California (CAISO)	Texas (ERCOT)	New England (NE-ISO)	New York (NYISO)	Average
		A. Residential			
Air Conditioning (Econometric Estimates)	53%	52%	7%	27%	35%
Air Conditioning	61%	49%	12%	30%	38%
Clothes Washers	11%	12%	10%	14%	12%
Lighting	11%	5%	5%	8%	7%
Heat Pump	7%	8%	2%	0%	4%
Refrigerator or Freezer	6%	5%	1%	4%	4%
		B. Commercial and Industrial			
Heat Pump	37%	37%	13%	25%	28%
Chillers	32%	32%	9%	22%	24%
Air Conditioners	31%	30%	11%	22%	24%
Lighting	11%	11%	7%	10%	10%

Notes: This table reports the estimated timing premiums for nine energy efficiency investments. As in the final row of Table 5, the statistics in each cell of this table represent the additional value (in percentage terms) compared to an investment with a completely flat savings profile. Except for the first row (econometric estimates for air conditioning), all estimates are based on engineering estimates of savings profiles prepared for the California Public Utilities Commission by Energy and Environmental Economics, Inc. Values are estimated using wholesale energy prices and capacity prices from four major U.S. markets as indicated in row headings. See text for details. The last column is the simple average of the other columns.

SOURCE: Energy Institute at Haas

Air conditioning investments in California have the highest timing premium. This is true regardless of whether the econometric or engineering estimates are used, and reflects the relatively high value of electricity in CAISO during summer afternoons and evenings. Air conditioning has a large timing premium in ERCOT as well, either 52% or 49% depending on whether the econometric or engineering estimates are used. In other U.S. markets air conditioning has a timing premium greater than zero, but nowhere else is the value as high as in California and Texas.

Other investments also have large timing premiums. Commercial and industrial heating and cooling investments, for example, all return a 20% premium, reflecting relatively high value of electricity during the day. This is particularly true in CAISO (30%), but also true in ERCOT and NYISO.

The timing premiums of other investments, like refrigerators and freezers are much lower. This makes sense because savings from these investments are only very weakly correlated with system load. Lighting, as well, does surprisingly poorly as the savings occur somewhat after the system peak in all U.S. markets and disproportionately during the winter, when electricity tends to be less valuable. This could change in the future as increased solar generation moves net system peak later in the evening, but for the moment both residential and non-residential lighting have timing premiums of 11% or below in all markets. There are no investments with negative timing premiums, reflecting the fact that all of these investments are at least weakly positively correlated with demand (no investment disproportionately saves energy in the middle of the night, for example).

3.5 Conclusion

Airline seats, restaurant meals, movie tickets, and many other goods are more valuable during certain times of the year and hours of the day. The same goes for electricity. If anything, electricity prices are even more volatile, often varying by a factor of ten or more within a single day. Moreover, as a greater fraction of electricity comes from intermittent renewables, there are also a growing number of hours with negative prices. These features of electricity markets are widely understood yet they tend to be completely ignored in analyses of energy efficiency policy. Much attention is paid to quantifying energy savings, but not to when those savings occur.

Accounting for timing matters. The empirical application comes from air conditioning, one of the fastest growing categories of energy consumption and one with a unique temporal “signature” that makes it a particularly lucid example. New air conditioners lead to a sharp reduction in electricity consumption in summer months during the afternoon and evening. Electricity market data was used to document a strong positive correlation between energy savings and the value of energy.

Overall, accounting for timing increases the value of this investment by 50% relative to a naïve calculation which values electricity savings using average prices. Especially important in this calculation was accounting for the large capacity payments received by electricity generators. Most electricity markets in the U.S. and elsewhere now have capacity markets which compensate generators in addition to revenue generated through electricity sales. These payments are concentrated in the highest demand hours of the year, making electricity in these periods even more valuable than is implied by wholesale prices alone.

The analysis was broadened to incorporate a wide range of different energy efficiency investments. The timing of all of these end uses is weakly positively correlated with energy value. Ignoring timing understates the value of every electricity energy efficiency investment, though to widely varying degrees. Residential air conditioning has an average timing premium of more than 35% across markets. Commercial and industrial heat pumps, chillers, and air conditioners have 20-30% average premiums. Lighting, in contrast, does considerably worse with a 7-10% average premium reflecting that these investments save electricity mostly during the winter and at night, when electricity tends to be less valuable. And refrigerators and freezers have average premiums below 5%, as would be expected for an investment that saves approximately the same amount at all hours of the day.

These results have immediate policy relevance. For example, energy efficiency programs around the world have tended to place a large emphasis on lighting.[13] These programs may well save large numbers of kilowatt hours, but they do not necessarily do so during time periods when electricity is the most valuable so rebalancing policy portfolios toward different investments could improve the social value of energy efficiency programs.

This chapter also highlights the enormous potential of smart meter data. This econometric analysis would have been impossible just a few years ago with traditional monthly billing data, but today more than 50 million smart meters have deployed in the United States, including over 12 million in California alone. This flood of high-frequency data can facilitate smarter, more evidence-based energy efficiency policies that are better integrated with market priorities.

[13] For example, In California, 81% of estimated savings from residential energy efficiency programs come from lighting. Indoor lighting accounted for 2.2 million kilowatt-hours of residential net energy savings during 2010–2012. Total residential net savings were 2.7 million kilowatt-hours. (California Public Utilities Commission, 2015).

CHAPTER 4:
How Take-Up and Savings Vary Across Customers

4.1 Introduction

This chapter describes estimates from the third phase of the project aimed at describing how take-up and energy savings vary across customers. The empirical strategy is briefly described which closely follows from Chapter 3. Using the same empirical difference-in-differences framework used in the second phase of the project (Chapter 3), the analysis in this phase is expanded to examine heterogeneity. This is done first with a series of "paired" regressions, and then with a single regression which pits the different types of heterogeneity against each other in an attempt to disentangle which factor is most important.

Most significantly, the results show large variation in energy savings between mild, warm, and hot areas of Southern California Edison territory. On average, program participants in hot areas (Climate Zones 13, 14, and 15) save more than 1,100 kilowatt hours annually, compared to 300 kilowatt hours annually in warm areas (Climate Zones 9 and 10), and approximately zero average savings in mild areas (Climate Zones 6, 8, and 16). This central finding comes through in both the "paired" and single regression approaches.

Variations in savings between locations are tested with different levels of household income, education, racial makeup, and household size. These factors prove to be much less significant than climate, however. In particular, once climate is included, none of these factors prove to have a large effect on energy savings. The coefficient estimates for these non-climate factors also don't have any consistent pattern, further underscoring the main finding that climate seems to be the most important form of heterogeneity.

The potential implications of these results are discussed for the cost-effectiveness of the program as well as for the potential for better targeting of the program to increase benefits. Even though energy savings vary relatively little with demographics, these demographic factors do strongly influence take-up. For example, it is found that higher-income households are approximately twice as likely to participate in the program as lower-income households. Underserved groups in hot climate areas would thus appear to be a particularly valuable potential target for future programs.

4.2 Empirical Strategy

The estimating equation is essentially identical to the equation used in Chapter 3. The response variable is electricity consumption measured in kilowatt hours. The explanatory variable of interest is 1[*New Air Conditioner*] an indicator variable equal to one for participating households after they have replaced their air conditioner through the *Quality Installation Program*. All regressions include the complete set of fixed effects including household by hour-of-day by month-of-year, and week-of-sample by hour-of-day fixed effects, and thus identify savings via difference-in-differences.

The innovation in this third phase of the project is to look not only at average electricity savings, but also at how savings vary across participants. This is first done with a series of paired regressions in which the sample is divided into different subsets, for example, participants for which annual household income in that zip code are above or below median annual household income.

In addition to these paired regressions a single regression is also estimated which pits the different types of heterogeneity against each other in attempt to disentangle which factor is most important. In particular it is estimated a model with 1[*New Air Conditioner*] interacted with household income, educational attainment, climate, and the other factors.

Household-level demographic information is not available, instead, census data from a private vendor called Geolytics is used that has household income, educational attainment, race, and household size available at the 9-digit zip code level. This data was imputed for each household demographic variable, equal to the average characteristics for their 9 digit zip code.

4.3 Results

4.3.1 Paired Regressions

Table 7 reports estimates from the paired regressions. In addition to reporting estimates for energy savings, this table reports the take-up rate for each group. These take-up rates are of significant independent interest because they can indicate how successful the program has been on reaching different categories of households.

Table 7: Take-Up and Energy Savings, Paired Regressions

	(1) Number of Households	(2) Takeup Rate (%)	(3) Average Savings per Replacement (kWh/year)
A. Baseline Specificiation			
All Households	7,284	0.13	398.6 (34.2)
B. By Annual Household Income in Zip Code			
Below $75,000 Median	3,786	0.11	508.9 (48.2)
$75,000+ Median	3,498	0.19	284.8 (48.8)
C. By Educational Attainment in Zip Code			
Less than 30% with College Degree	3,724	0.12	324.1 (45.1)
More than 30% with College Degree	3,560	0.16	488.1 (51.8)
D. By Climate Zone			
Mild Areas (Zones 6, 8, & 16)	829	0.03	-29.1 (82.9)
Warm Areas (Zones 9 & 10)	4,954	0.23	267.4 (38.1)
Hot Areas (Zones 13, 14, & 15)	1,501	0.23	1,199.0 (103.6)
E. By Racial Makeup of Zip Code			
Less than 50% Non-White	4,077	0.20	542.8 (47.8)
More than 50% Non-White	3,207	0.09	228.5 (48.5)
F. By Average Household Size in Zip Code			
Less than 3 People per Household	3,697	0.14	593.9 (52.2)
More than 3 People per Household	3,587	0.13	222.2 (44.5)

This table describes take-up and energy savings by zip code-level demographics. Take up rates in Column (2) is percentages of SCE residential customers. Energy savings estimates and standard errors in Column (3) are estimated with separate regressions in each row. The dependent variable is average hourly electricity consumption at the household by week-of-sample by hour-of-day level. Average savings is the weighted sum of the coefficients on 288 indicator variables measuring the effects of replacement by month-of-year and hour-of-day. The weights are the number of days in the month. All regressions include household by hour-of-day by month-of-year, and week-of-sample by climate zone fixed effects. The 8 weeks prior to the replacement date are excluded. Standard errors are clustered at the household level.

SOURCE: Energy Institute at Haas

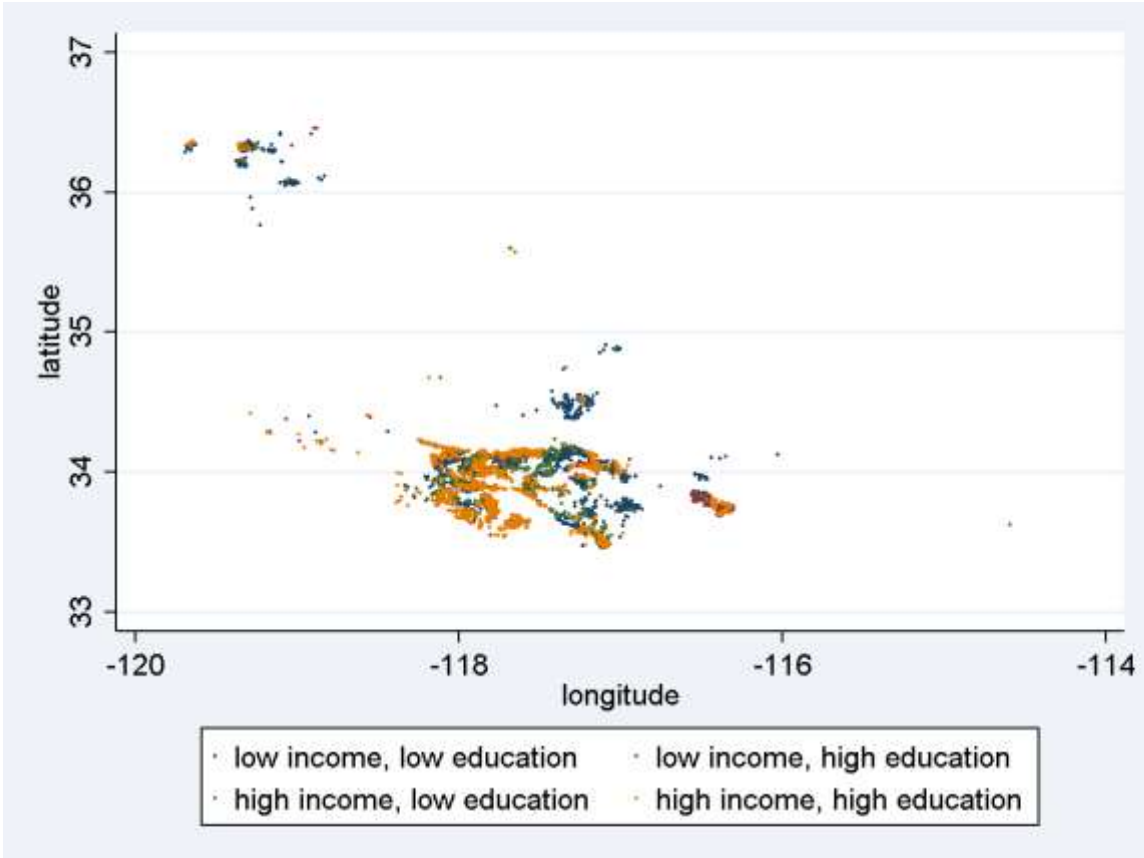
The structure of Table 7 is as follows. Column (1) reports the number of households in each category that participated in the program. Column (2) reports the participation rate for that group. Finally, column (3) reports the average annual electricity savings (in kWh) for program participants in that group.

Panel A reports estimates for all participating households. Overall, there were 7,284 households in this data that participated in the Quality Installation Program. This is about one-tenth of one percent of all 4.9 million residential customers in SCE territory. And, on average, program participants saved 398.6 kilowatt hours annually after replacing their central air conditioners. These results are identical to the baseline results from the second phase of the project (Chapter 3).

Panel B breaks participants into two categories on the basis of annual household income. Take-up is about twice as high for higher-income households. The pattern of high uptake among higher-income households has been previously noted with other similar programs (see, for example Borenstein and Davis, 2015) and is of great policy relevance. Average energy savings are larger in the lower-income category. Having completed additional analysis, however, the team believes this pattern is almost entirely due to climate. Lower-income households come disproportionately from the hot climate zones. With these paired comparisons climate is not controlled for, so these differences in Table 7 can reflect climate and other "lurking variables" rather than income itself. Indeed, when a single regression is run, it turns out that climate is a more important factor than income.

Panel C looks at educational attainment. Both take-up and savings are positively correlated with educational attainment. It is perhaps surprising that the income and educational attainment results appear to go in opposite directions. A map of the different categories (Figure 20) was examined and although income and educational attainment are strongly correlated, they are not perfectly correlated. In particular there are a large number of "low" income, high education zip codes in the Palm Spring area, potentially indicating retirees.

Figure 20: Quality Installation Program Participants, by Income and Education



SOURCE: Energy Institute at Haas

Table 7 Panel D examines climate zones. Take-up is near zero in the mild zones, and at .23% in the warm and hot areas. Savings are strongly correlated with climate zone. In the mild zones, the point estimate for savings is near zero and not statistically significant. Savings are larger in warm areas, and then much larger again in the hot areas, with average savings of almost 1,200 kilowatt hours annually. The team believes these are some of the most interesting results of the heterogeneity analysis, and of direct policy relevance.

Panels E and F look by race and household size. Overall smaller savings are found in zip codes which are more than 50% non-white and with larger households. Also notable is that the take-up rate is considerably smaller in zip codes that are more than 50% non-white.

As the truism goes, however, correlation is not causation. All of these patterns could reflect correlation between these characteristics and lurking variables. For example, the estimates for household income could be reflecting a correlation between income and climate zones, rather than any true causal impact of income. The large variation in savings by climate zone, in particular, is believed to drive most of these results.

4.3.2 Single Regression

Table 8 examines the same heterogeneity but with a single regression which pits the different types of heterogeneity against each other in attempt to disentangle which factor is most important. In particular these are coefficient estimates and standard errors from a single least squares regression. As with Table 7, the dependent variable is average hourly electricity consumption and the regression includes household by hour-of-day by month-of-year, and week-of-sample by climate zone fixed effects.

Table 8: Take-Up and Energy Savings, Single Regression

	Average Annual Energy Savings (kWh/year)	
1[New Air Conditioner]	1.3	(16.3)
× Median Income > $75,000	-65.8	(10.5)
× College Completion > 30%	166.3	(10.4)
× Warm Climate Zone	378.0	(14.4)
× Hot Climate Zone	1,166.3	(21.4)
× > 50% Non-White	-190.6	(9.4)
× > 3 People per Household	-68.4	(9.8)

This table reports coefficient estimates and standard errors from a single least squares regression. As with Table 7, the dependent variable is average hourly electricity consumption and the regression includes household by hour-of-day by month-of-year, and week-of-sample by climate zone fixed effects. The difference is that the specification includes a set of interaction between 1[NewAirConditioner] and the different heterogeneous factors listed in the row headings. Due to computational constraints, the reported standard errors above are only approximate and were calculated assuming that the covariances are zero between all hour-of-day and month-of-year cells.

SOURCE: Energy Institute at Haas

The difference is that the specification includes a set of interaction between 1[*New Air Conditioner*] and six different heterogeneous factors listed in the row headings. Program participants belong to different categories for these different factors (for example, above median income, warm climate zone, more than three people per household), and the single regression is an attempt to tease out which factors are most significant.

The results are very interesting. Most significantly, the results show large variation in energy savings between mild, warm, and hot areas of Southern California Edison territory. On average, program participants in hot areas (Climate Zones 13, 14, and 15) save 1,166 kilowatt hours annually, compared to 378 kilowatt hours annually in warm areas (Climate Zones 9 and 10), and approximately zero average savings in mild areas (Climate Zones 6, 8, and 16). This central finding comes through in the single regression approaches, even after allowing for heterogeneity in these other factors.

The demographic factors are much less significant. While there were large differences for high- and low-income in the paired comparison, here the coefficient on high income is relatively small

(65). Thus, the single regression provides strong evidence that the difference observed in the paired comparison is driven by climate, rather than by the "true" effect of income. Results are similarly small, and of inconsistent pattern for the other demographic factors.

4.4 Conclusion

The main finding from the third phase of the project is that climate is the most important form of heterogeneity. On average, program participants in hot areas (Climate Zones 13, 14, and 15) save more than 1,100 kilowatt hours annually, compared to 300 kilowatt hours annually in warm areas (Climate Zones 9 and 10), and approximately zero average savings in mild areas (Climate Zones 6, 8, and 16).

These results imply that the Quality Installation Program is likely to be most cost-effective in the hot areas of SCE's territory. At some level, this makes intuitive sense. Where air conditioners are mostly heavily used, energy efficiency gains are most valuable and translate into the largest total savings in kilowatt hours.

Demographic factors strongly influence take-up, but not energy savings. For example, high-income households are approximately twice as likely to participate in the program as low-income households. This suggests that low-income households in hot areas would appear to be a particularly valuable potential target. There is also a strong equity argument for targeting these programs to underserved groups.

In terms of policy recommendations, it might make sense to consider eliminating the program in mild climate zones. These results indicate approximately zero average savings in mild areas (Climate Zones 6, 8, and 16), consistent with these units not being used enough hours of the year to generate substantial savings. In addition, it would make sense to perform additional analyses of the program in warm climate zones. Savings are modest enough in these areas that it calls for a full-scale cost-benefit analysis. Given scarce utility resources it makes sense to spend money where there is the biggest possible return on investment.

Critical for this broader analysis is the question of what fraction of participants are inframarginal "free riders," that is, those getting paid to do what they would have done anyway. The problem with inframarginal participants is that they add cost to the program without generating actual energy savings. This is an important consideration for all energy efficiency programs (Boomhower and Davis, 2014), but particularly when the average savings are relatively modest.

Potentially offsetting this concern about inframarginal participants is the fact that this program tends disproportionately to deliver energy savings during high-value hours. The second phase of the analysis (Chapter 3), that this significantly increases the overall value of the program, especially once the researchers accounted for the large capacity payments received by generators to guarantee their availability during high-demand hours. In particular, the program has a timing premium of 50%, delivering savings that are 50% more valuable than under a simple calculation that ignores timing.

More broadly, this work highlights the enormous potential of smart meter data. This econometric analysis would have been impossible just a few years ago with traditional monthly billing data, but today more than 50 million smart meters have deployed in the United States alone. This flood of high-frequency data can facilitate smarter, more evidence-based energy efficiency policies that are better integrated with market priorities. California can help lead the way on this type of smart meter analysis, both because of the innovative approaches through which California utilities make data available to researchers, and because of the California Energy Commission's long-standing support for evidence-based policy making.

GLOSSARY

Term	Definition
Capacity Markets	Markets where generators commit to offer power for sale during future periods. Capacity markets can be bilateral, such as in California, or centralized, such as PJM.
Heterogeneity Analysis	The heterogeneity analysis performed for this project involves splitting the participants into two subsets based on demographic differences. The regression is then run separately for each subset in order to determine how the program's impact differs between the two populations. Separate split regressions were run based on income, educational attainment, racial makeup of the zip code and average household size.
HVAC	Heating, ventilation and air conditioning
Inframarginal Participants	Participants who are getting paid by a program to do what they would have done otherwise.
IOU	investor-owned utility
Propensity Score Matching	Propensity score matching is a statistical matching technique that attempts to estimate the effect of a treatment by accounting for the characteristics that predict receiving the treatment.
Regression Discontinuity	Regression discontinuity (RD) is an analytical approach that can be used to estimate the impact of an intervention. An RD design can be used if the treatment a participant receives depends on cutoff criteria that are based on pre-treatment characteristics. An RD design is considered to be a quasi-experimental design because the population just above and below the cutoff are almost identical except that some are being treated and others are not. This means the treatment and control groups approximate random assignment, as would be the case in an experimental, randomized-controlled trial.
Reserve Margin	Generation capacity in excess of expected peak demand.
Timing Premium	The timing premium is the additional value of an energy efficiency upgrade attributable to the specific hours of the year when the upgrade saves energy. The timing premium is expressed as a percentage increase in value relative to an upgrade that saves the same amount of energy in total over a year, but saves a constant amount of energy in each hour of the year.

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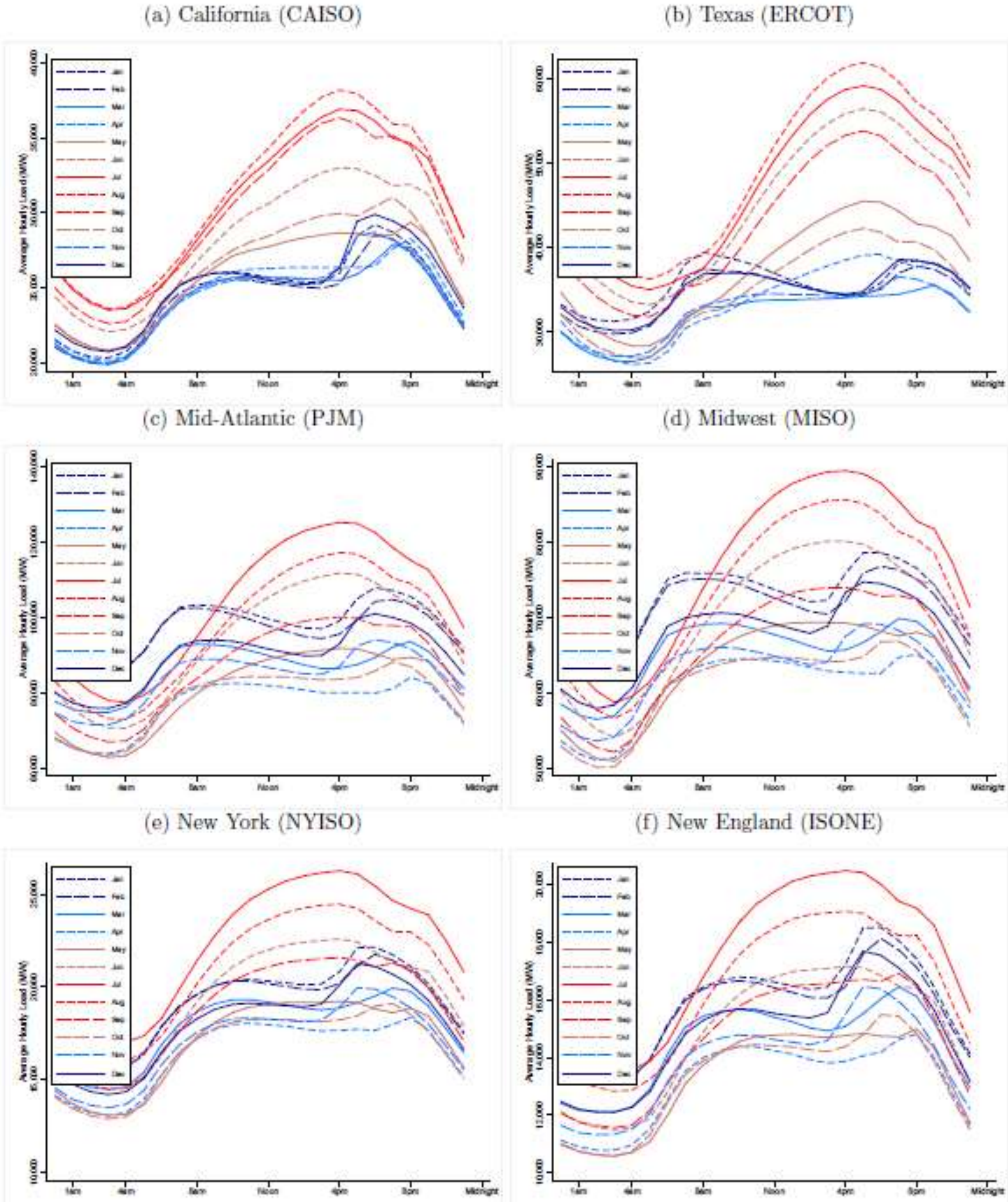
APPENDIX A: Electricity Market Data

A.1 Wholesale Electricity Prices and Load

Hourly wholesale price data are day-ahead prices from SNL Financial and are for 2011-2015. For California, the analysis uses California ISO market at the SP-15 node. For New England, the analysis uses ISO-NE real-time prices at the H Internal hub. For Texas, the analysis uses ERCOT real-time prices at the HB North hub. For New York, the analysis uses NYISO real-time prices at the J Hub. For PJM, the analysis uses prices at the Western hub. For MISO, the analysis uses prices at the Illinois hub. All times in the report are reported in local prevailing time: Standard Time or Daylight Time according to which is in effect. The load data in each market comes from the SNL hourly “Actual Load" series for 2011-2015. Figure A-1 plots hourly average load pro profiles by month-of-year for each market.

Figure A-1: Load Profiles in Six Major U.S. Electricity Markets



SOURCE: Energy Institute at Haas

A.2 Capacity Prices

Capacity values were calculated for each electricity market under a range of assumptions. For each market, the researchers used auction or regulatory data to infer monthly or annual capacity prices, and allocated those values across hours based on historical hourly load. Capacity market institutions vary across regions, so capacity values are not perfectly comparable across markets. However, the research team has attempted to use relatively comparable data and methods and to be transparent about their exact sources and calculations.

A.2.1 California (California ISO)

There is no capacity auction in California ISO, but the CPUC surveys utilities to track bilateral capacity contract prices. The analysis uses monthly capacity contract prices from the CPUC "2013-2014 Resource Adequacy Report," page 28, Table 13. This document reports average, 85th-percentile, and maximum contract prices for each month. The researchers use the 85th-percentile values, on the reasoning that these provide a conservative estimate of the marginal cost of procuring capacity (The researchers could instead use the maximum, but choose the 85th percentile to limit the influence of potential outlier observations). These reported prices include capacity contracts from 2013 through 2017. However, most of the reported transactions are for 2013-2015 (page 29, Figure 9).

A.2.2 New York (NYISO)

Capacity prices for New York come from NYISO's monthly spot capacity auctions for the NYCA region from May 2013 through April 2016. This auction runs two to four days prior to the beginning of the month being transacted for. NYISO also runs auctions for six-month "strips" of summer or winter capacity, as well as additional monthly auctions one to five months in advance.

A.2.3 New England (ISO-NE)

Capacity prices for New England come from ISO-NE's annual "forward capacity auctions" for 2013 through 2016, as reported by SNL Financial. The analysis uses the simple average of prices across the several zones in the market.

A.2.4 Mid-Atlantic (PJM)

Capacity prices for PJM are "Market Clearing Prices" from the annual "Base Residual Auction." The analysis uses the simple average across years and geographic zones for 2013-2016. Data are from SNL Financial.

A.2.5 Midwest (MISO)

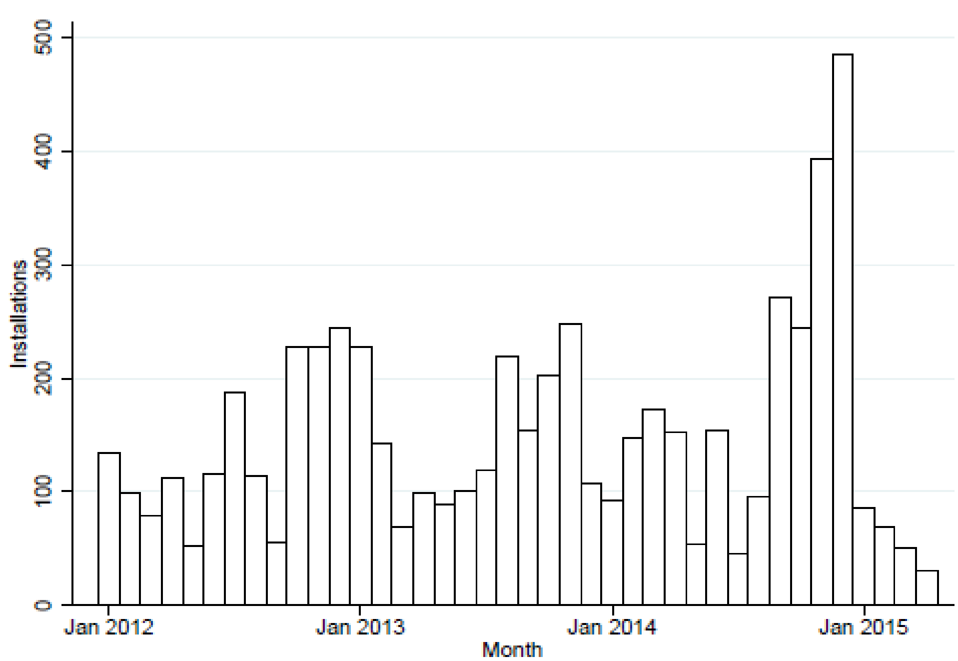
Capacity prices for MISO come from annual capacity auction prices for 2013 through 2016. The analysis uses the simple average of prices across the several geographic zones. Data are from SNL Financial.

APPENDIX B: Additional Data Description

B.1 Program Data

The program data describe all 10,848 households that participated in the Quality Installation Program between 2010 and 2015. These data were provided by Southern California Edison. The researchers drop 968 duplicate participant records. These records have the exact same account number as other participant records, so are clear duplicates. The researchers also drop an additional 291 households that installed a new heat pump rather than a new central air conditioner; the expected energy savings for heat pumps follows a very different temporal pattern than the temporal pattern for air conditioning so it does not make sense to include these participants. The researchers further drop 2,431 households that participated before the start of 2012; electricity consumption data begins in 2012, so these early participants would not contribute to the savings estimates. The researchers also drop an additional 757 households that installed rooftop solar at any time during the sample period; rooftop solar dramatically changes household net electricity consumption (the consumption data is net consumption, not generation and consumption separately) so the analysis drops these households to avoid biasing the savings estimates. In addition, the researchers drop 60 households for whom there are no nine-digit zip codes; a nine-digit zip code is required for merging with temperature data, and the analysis clusters all standard errors at the nine-digit zip code. The analysis successfully merged 94% of the participant records to the electricity consumption data, so a total of 5,973 participants are left in the analysis dataset. Figure B-1 shows the pattern of participation between 2012 and 2015.

Figure B-1: Histogram of Installation Dates

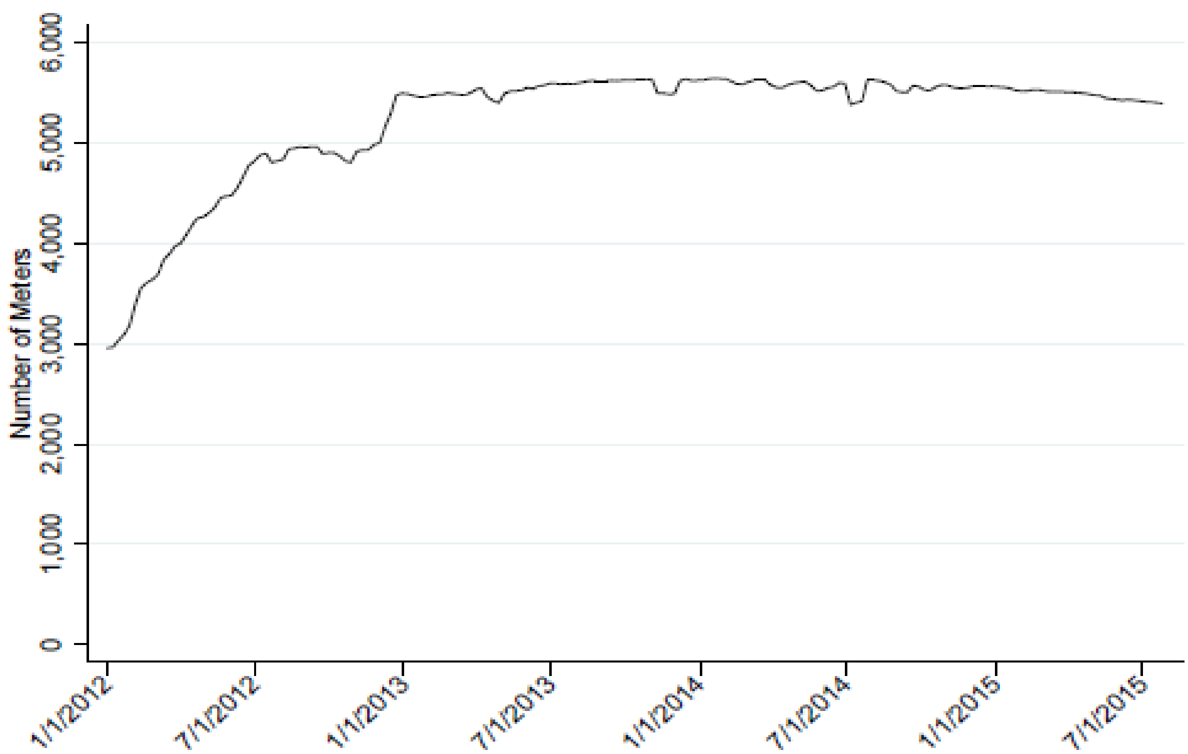


SOURCE: Energy Institute at Haas

B.2 Electricity Consumption Data

The electricity consumption data describe hourly electricity consumption for all program participants. SCE provided the research team with the complete history of hourly consumption for these households beginning when each household received a smart meter and continuing until August 2015, or, in some cases, somewhat before August 2015. Most Southern California Edison customers received a smart meter for the first time in either 2011 or 2012. Figure B-2 shows the number of participants with smart meter billing data during each week of the sample.

Figure B-2: Number of Participants with Smart Meter Data



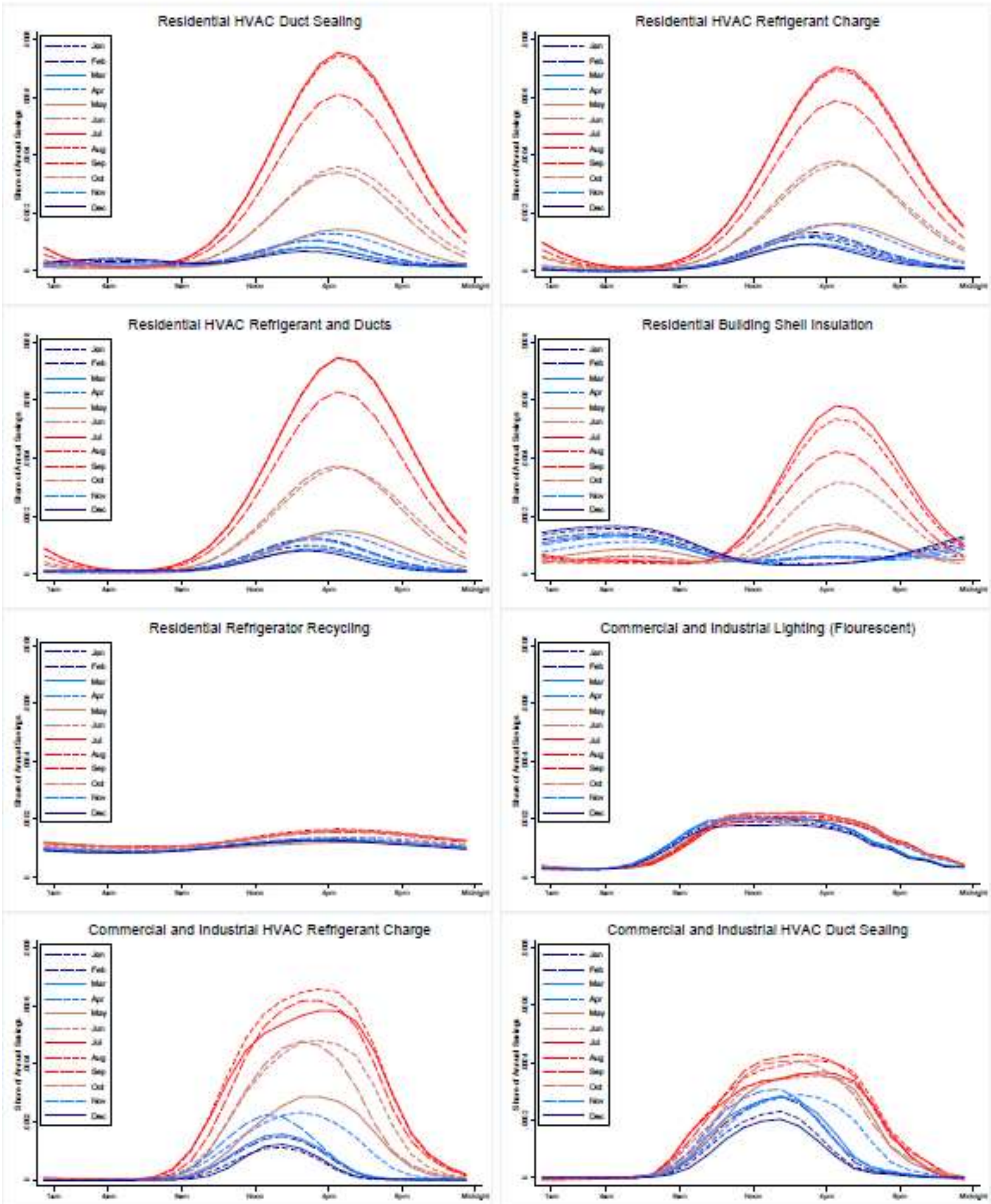
SOURCE: Energy Institute at Haas

B.3 Engineering-Based Savings Profiles

Figure B-3 plots savings profiles for eight additional energy efficiency investments. These figures are constructed in exactly the same way as Figure 19, and describe vive residential investments and three commercial/industrial investments. As described in the paper, these engineering-based savings profiles come from the Database for Energy Efficient Resources (DEER), maintained by the California Public Utilities Commission. Values developed in 2013/2014 are used for DEER 2011, reported in the file DEER2011-HrlyProfiles-SCE.xls. For each energy efficiency investment the DEER reports 8,760 numbers, one for each hour of the year. These data are used to construct average hourly profiles by month. These savings profiles are intended to reflect average impacts in Southern California Edison territory.

The underlying model that generates the DEER hourly profiles does not account for daylight savings time. Building occupants are assumed to observe Standard Time for the full year. As a result, the model inputs for physical phenomena such as solar angle and temperature are correct, but inputs related to human schedules, like building opening times, are off by one hour. Some analysts adjust for daylight savings after the fact by “shifting" the DEER profile one hour: that is, replacing predicted savings for all hours during Daylight Time with predicted savings one hour later. This corrects building schedules but introduces error in physical factors. Whether such a shift helps or hurts accuracy depends on whether building schedules or physical factors are more important in determining hourly savings. This analysis does not make any adjustments to the DEER profiles in the main specifications. If a “shift" is imposed during Daylight Time, the estimated timing premiums for DEER investments change only slightly.

Figure B-3: Savings Profiles for Additional Energy Efficiency Investments



SOURCE: Energy Institute at Haas

APPENDIX C: Alternative Specifications Using Data from Non-Participants

This section presents estimates from alternative specifications which incorporate electricity consumption data from non-participating households. Overall, these alternative estimates are quite similar to the main estimates in the paper.

The key challenge in Chapter 3's empirical analysis is to construct a counterfactual for how much electricity the participants would have consumed had they not installed a new air conditioner. The analyses in Chapter 3 construct this counterfactual using data from participants only, exploiting the natural variation in the timing of program participation to control for trends in electricity consumption, weather, and other time-varying factors. An alternative approach, however, is to estimate the model using data from both participants and non-participants.

There are advantages and disadvantages with this alternative approach. The potential advantage of including non-participant data is that these data may help better control for trends in electricity consumption, weather, and other time effects, while also potentially improving the precision of the estimates. The disadvantage is that non-participants tend to be quite different from participants, making them potentially a less valid counterfactual. Without any ex ante reason to prefer one approach over the other, it makes sense to report estimates from both approaches.

Table C-1 provides descriptive statistics. The columns refer to three different samples. The first column describes the 5,973 participants used for the main estimates in the paper. The second column describes a random sample of non-participants. Southern California Edison provided data from a 5% random sample of the utility's residential customers who did not participate in the program, and this is a random subset of 5,973 households from that sample. Finally, the third column describes a matched sample of non-participants. For the matched sample the researchers selected non-participants based on zip codes. In particular, for each participant, the analysis randomly selected a non-participant from the same nine-digit zip code, or five-digit zip code when nine-digit zip code is not available. Weather is a major determinant of electricity consumption so this matching ensures that comparison households are experiencing approximately the same weather as the treatment households. In addition, households in close geographic proximity tend to have similar income and other demographics. Some non-participants matched to more than one participant, yielding 5,633 unique households in the matched sample of non-participants. For both random and matched samples households with rooftop solar or a missing nine-digit zip code were excluded, just as was done for participants.

Table C-1: Smart Meter Data, Descriptive Statistics

	Participants (1)	Random Sample of Non-Participants (2)	Matched Sample of Non-Participants (3)	p-Value: Column 1 vs Column 2 (4)	p-Value: Column 1 vs Column 3 (5)
Mean Hourly Electricity Consumption					
All Months	1.076	0.878	1.025	0.000	0.000
Summer Months (July and August)	1.521	1.205	1.480	0.000	0.000
Winter Months (January and February)	0.852	0.729	0.806	0.000	0.000
Type of Electricity Tariff					
Proportion on Low-Income Tariff	0.128	0.303	0.254	0.000	0.000
Proportion on All-Electric Tariff	0.020	0.101	0.065	0.000	0.000

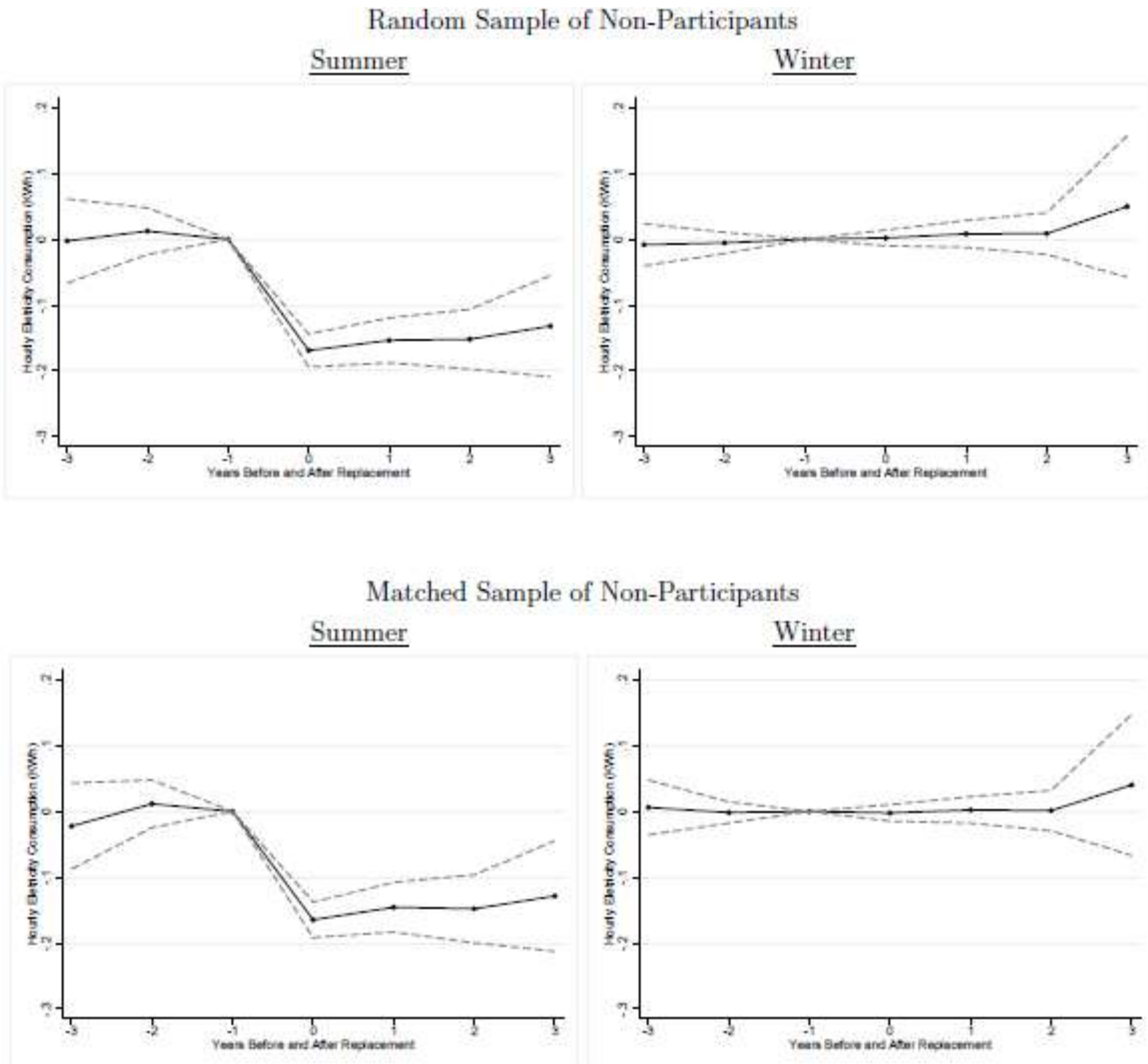
Notes: Columns (1), (2), and (3) report the variables listed in the row headings for the group listed at the top of the column. There are a total of 5,973 participants and an equal number of non-participating households in the random and matched samples. Electricity consumption is measured in kilowatt hours. Columns (4) and (5) report p-values from tests that the means in the subsamples are equal.

SOURCE: Energy Institute at Haas

Across all households, mean hourly electricity consumption is about one kWh per hour. Participants tend to consume more than non-participants, especially during summer months. But this appears to be largely a question of geography and the pattern of consumption in the matched sample is much more similar to participants. More generally, the characteristics of the matched sample are more similar but not identical to the characteristics of participants. Among participants, 13% are on the low-income tariff, compared to 30% in the random sample and 25% in the matched sample. Similarly, only 2% of participants are on the all-electric tariff, compared to 10% in the random sample and 6.5% in the matched sample.

The researchers used these alternative samples to construct alternative estimates of several of the main results. Figure C-1 plots event study estimates analogous to Figure 14 in Chapter 3. Whereas the event study figure in Chapter 3 is estimated using data from participants only, these are estimated using data from both participants and non-participants. The plots on the top include the random sample of non-participants while the plots on the bottom include the matched sample.

Figure C-1: Event Study Figures, Alternative Specifications



SOURCE: Energy Institute at Haas

These alternative event studies follow a very similar pattern to the event study figures in Chapter 3. Summer consumption drops sharply in the year that the new air conditioners are installed and the magnitude of this decrease is 0.2 kilowatt hours per hour, identical to the decrease in the event study figure in Chapter 3. Moreover, the pattern for winter is very similar to the event study figure in Chapter 3, with no change when the new air conditioners are installed.

Next, Table C-2 reports regression estimates of total energy savings from new air conditioner installation. This table is constructed in exactly the same way as Table 4, but estimated using data from both participants and non-participants.

Table C-2: Average Energy Savings, Alternative Specifications

	(1)	(2)	(3)
Random Sample of Non-Participants			
Energy Savings Per Household (kWh/year)	494.4	435.8	507.3
	(42.8)	(42.6)	(47.5)
Number of observations	27.0 M	27.0 M	26.4 M
Number of households	5,976	5,976	5,975
Matched Sample of Non-Participants			
Energy Savings Per Household (kWh/year)	447.9	434.5	503.4
	(43.3)	(42.8)	(47.3)
Number of observations	27.2 M	27.2 M	26.6 M
Number of households	5,893	5,893	5,892
Household by hour-of-day by month-of-year fixed effects	Y	Y	Y
Week-of-sample by hour-of-day fixed effects	Y		
Week-of-sample by hour-of-day by climate zone fixed effects		Y	Y
Drop 8 weeks pre-installation			Y

Notes: This table reports results from six separate regressions and is identical to Table 4 in Chapter 3 except for the sample includes data on non-participating households. In particular, Panel A includes a random sample of non-participating households and Panel B includes a matched sample of non-participating households in which the non-participating households are drawn from the same nine digit zip code as participating households. For computational reasons, these regressions are restricted to a 50% random sample of participating households along with an equal number of non-participating households.

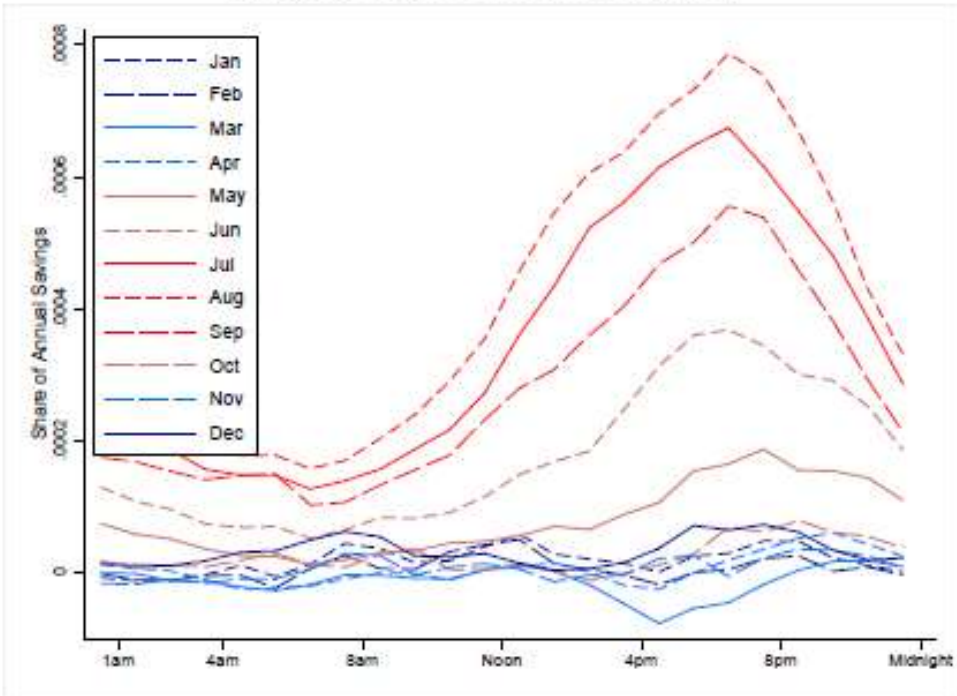
SOURCE: Energy Institute at Haas

Including data from non-participants has little overall effect. The estimates are slightly larger, but the pattern across specifications is similar, increasing when dropping eight weeks pre-installation in Column (3).

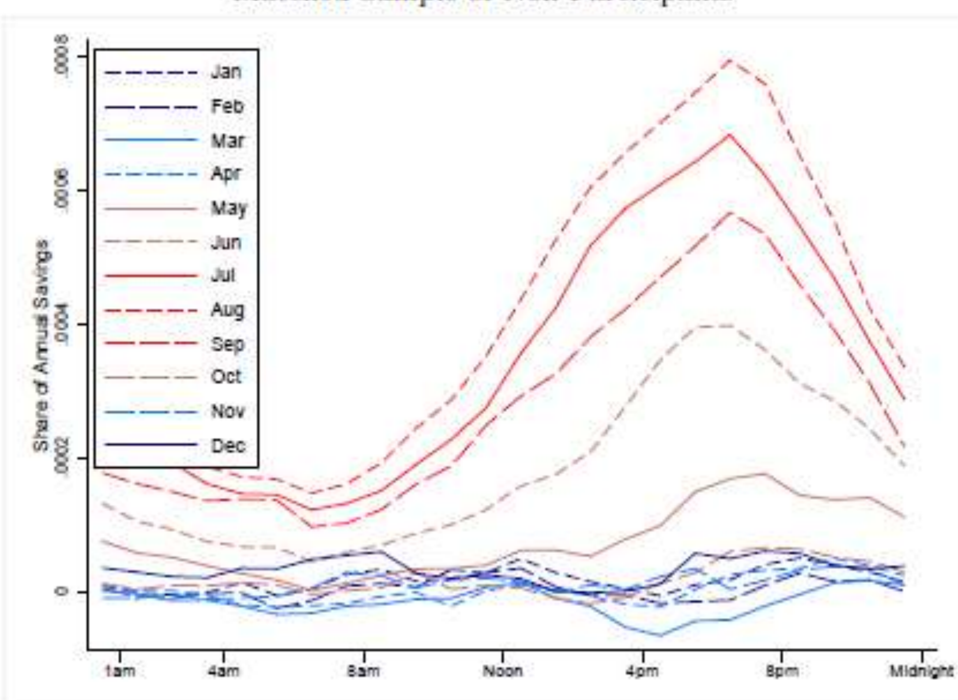
Finally, Figure C-2 plots estimates of energy savings by month-of-year and hour-of-day. These figures are constructed in exactly the same way as Figure 18, but are estimated using data from both participants and non-participants. Overall, including data from non-participants has very little effect on the temporal pattern of savings. Electricity savings still tend to occur disproportionately during July and August, and during the hours 3 p.m. to 9 p.m. In addition, during winter months the estimates remain very close to zero during all hours of the day. Moreover, the random and matched samples yield virtually identical estimates across hours and months.

Figure C-2: Econometric Estimates of Electricity Savings, Alternative Specifications

Random Sample of Non-Participants



Matched Sample of Non-Participants



SOURCE: Energy Institute at Haas