Do Energy Efficiency Investments Deliver at the Right Time?

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May 2017

Abstract

Electricity cannot be cost-effectively stored even for short periods of time. Consequently, wholesale electricity prices vary widely across hours of the day with peak prices frequently exceeding off-peak prices by a factor of ten or more. Most analyses of energy-efficiency policies ignore this variation, focusing on total energy savings without regard to when those savings occur. In this paper we demonstrate the importance of this distinction using novel evidence from a rebate program for air conditioners in Southern California. We estimate electricity savings using previously unavailable hourly "smart-meter" data and show that savings tend to occur during hours when the value of electricity is high. This significantly increases the overall value of the program, especially once we account for the large capacity payments received by generators to guarantee their availability in high-demand hours. We then compare this estimated savings profile with engineering-based estimates for this program as well as a variety of alternative energy-efficiency investments. The results illustrate a surprisingly large amount of variation in economic value across investments.

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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 tend to be very low. However, during peak hours prices rise substantially, frequently to two or three times the level of off-peak prices. Moreover, there are a small number of peak hours during the year when prices increase much more, often to ten or twenty times the level of off-peak prices. During these ultra-peak hours generation is operating at full capacity and there is little ability to further increase supply, making demand reductions 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 appliance energy-efficiency standards and building energy codes, 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 En-

[1] For appliance standards, see Commercial Package Air Conditioning and Heating Equipment and Warm Air Furnaces (81 *FR* 2420, 2016); Ceiling Fan Light Kits (81 *FR* 580, 2016); Single Package Vertical Air Conditioners and Heat Pumps (80 *FR* 57438, 2015); Commercial Clothes Washers (79 *FR* 12302, 2014); Residential Clothes Dryers and Room Air Conditioners (76 *FR* 22454, 2011); and Incandescent Lamps, Dishwashers, and Other Appliances (DOE 2009, Technical support document: Impacts on the Nation of the Energy Independence and Security Act of 2007). For residential building codes, see DOE, "Determination Regarding Energy Efficiency Improvements in the 2015 International Energy Conservation Code (IECC)", 80 *FR* 33250, 2015; and technical support documents cited therein. For commercial buildings, see DOE, "Determination Regarding Energy Efficiency Improvements in ANSI/ASHRAE/IES Standard 90.1–2013: Energy Standard for Buildings, Except Low-Rise Residential Buildings", 79 *FR* 57900, 2014. Citations with *FR* refer to the *Federal Register*.

[2] See, for example, California Public Utilities Commission, "Energy Efficiency Annual Progress Evaluation Report", March 2015; Public Service Commission of Maryland, "The EmPOWER Maryland Energy Efficiency Act Standard Report of 2015", April 2015; Mas-

ergy Modeling System lack temporal granularity altogether and instead model energy demand at the monthly or even annual level. With a few notable exceptions that we discuss later in the paper, there is surprisingly little attention both by policymakers and in the 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 impacts at the hourly level. The necessary high frequency data did not exist, since meters were only read once per billing cycle. This situation is rapidly changing. Today more than 40% of U.S. residential electricity customers have smart meters, up from less than 2% in 2007.[3]

In this paper we demonstrate the importance of accounting for the timing of energy savings using novel evidence from a rebate program for energy-efficient air conditioners in Southern California. Air conditioning is of large intrinsic interest because of the amount of energy consumption it represents. According to the Department of Energy, U.S. households use 210 million megawatt hours of electricity for air conditioning, 15% of total residential electricity demand.[4] We use hourly smart-meter data to estimate the change in electricity consumption after installation of an energy-efficient air conditioner.

With hourly smart-meter data from 6,000+ participants, we are able to precisely characterize the energy savings profile across seasons and hours of the day. We show that savings occur disproportionately during July and August, with 55% of total savings in these two months, and near zero savings between November and April. Energy savings are largest between 3 p.m. and 9 p.m., with peak savings between 6 p.m. and 7 p.m.. This pattern has important

sachusetts 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.

[3]U.S. Department of Energy, "Electric Power Annual 2015", Released November 2016, Tables 2.1 and 10.10.

[4]U.S. Department of Energy, "Annual Energy Outlook 2017", 2017.

implications for electricity markets given growing challenges with meeting electricity demand in the early evening (see, e.g., Denholm et al., 2015).

We then use price data from wholesale energy and forward capacity markets to quantify the economic value of these estimated savings. Savings are strongly correlated with the value of electricity, making the program about 40% more valuable than under a naive calculation ignoring timing. We call this difference a "timing premium." As we show, including capacity payments in this calculation is important. Most of the value of electricity in ultra-peak hours is captured by forward capacity payments to generators to guarantee their availability in these hours.

Finally we use engineering predictions to calculate timing premiums for a much larger set of energy-efficiency investments, both residential and non-residential. Overall, we find that there is a remarkably wide range of value across investments. Using data from six major U.S. electricity markets, we show that air conditioning investments have an average timing premium of 18%. For commercial and industrial heat pumps and chillers the average timing premiums are 21% and 17%, respectively. Other investments like refrigerators have timing premiums near or even below zero because savings are only weakly correlated with value. Lighting also does surprisingly poorly because savings are largest during evening and winter hours when electricity is less valuable.

These findings have immediate policy implications. Energy-efficiency is a major focus of global energy policy, so it is imperative that the benefits of demand reductions be accurately measured. Electric utilities in the United States, for example, spent $36 billion on energy-efficiency programs between 2006 and 2015, leading to more than 1.5 million gigawatt hours in reported electricity savings.[5] Yet virtually all analyses of these programs have ignored the timing of energy savings.

The paper proceeds as follows. Section 2 provides background about electricity

[5]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 2015 (Tables 10.6 and 10.7). Expenditures are reported in year 2015 dollars.

markets and energy efficiency. Section 3 describes our empirical application, estimating framework, and savings estimates. Section 4 measures the correlation between energy savings and the value of electricity, and calculates the timing premium for residential air conditioning. Section 5 then incorporates engineering predictions to calculate timing premiums for a much broader set of energy-efficiency investments. Section 6 concludes.

2 Background

2.1 Electricity Markets

Electricity is supplied in most markets by a mix of 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 generating units like natural gas combustion turbines and even oil-burning "peaker" plants, which have high marginal costs but low fixed costs. Beyond that the supply curve for electricity is perfectly vertical, reflecting the maximum total generating capacity.

This mix is necessary because electricity cannot be cost-effectively stored. 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 two 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 any plant's marginal cost.

An immediate implication of these features of electricity markets is that the value of demand reductions varies widely across hours. Most buyers do not see real-time prices (Borenstein, 2005; Borenstein and Holland, 2005; Holland and Mansur, 2006). Instead, many electric utilities have implemented demand response programs, optional critical peak pricing tariffs, and other policies aimed at curbing electricity demand during ultra-peak periods.

Wholesale energy 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 equaled average cost. In such a market, the hourly wholesale price represents the full value of avoided electricity consumption in any given hour.

The reality of electricity markets, even “deregulated” ones, is more complex. In many markets the amount of power plant capacity is set by regulation. 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.[6] Regulators set minimum “reserve margins” (generation capacity in excess of expected peak demand) that reduce the risk of electricity shortages below some target level, such as one event every ten years. These reserve margin requirements are implemented through dedicated capacity markets where generators commit to make their plants available to sell power during future periods.[7] The equilibrium capacity price just covers the shortfall between ex-

[6] In principle, household-level interruptible tariffs could solve this problem but they have historically been infeasible (although this may be changing with new technologies). Some electricity markets also include price caps, which can depress energy market revenues and create an additional rationale for market intervention.

[7] 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 we show later, 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. For more discussion of capacity markets see Bushnell (2005); Cramton and Stoft (2005); Joskow (2006); Joskow and Tirole (2007); Alcott (2013). Many electricity

pected energy market revenues and total cost for the marginal new power plant at the desired reserve margin. In the U.S., much of the price signal for new generation investments is communicated through capacity markets.

It is important to take capacity markets into account when measuring how the value of electricity varies across hours. As we will show 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 which receives a significant capacity payment for being available to be used only a very small number of hours each year. Accounting for these capacity payments increases the marginal cost of electricity in this handful of hours enormously, to potentially 50+ times the prices in the energy market.

In summary, the economic value of a demand reduction can be measured using prices from wholesale energy and capacity markets. The wholesale energy price reflects the economic value of a one-unit decrease in demand in the energy market. This is the marginal cost of the marginal generator in most hours, and the willingness to pay of the marginal buyer during hours when generation capacity is fully utilized. Demand reductions that occur during peak hours have additional value because they reduce the amount of capacity which needs to be procured in advance in the capacity market. On the margin, the value of avoided capacity purchases is given by the capacity price.

Finally, another important feature of electricity markets is large externalities. These external costs of energy production also vary across hours and across markets. Callaway et al. (2015) use site-level data on renewables generation and engineering estimates of the hourly load profiles for lighting to show how the total social value of those resources varies across U.S. markets. There

markets also provide additional payments for frequency regulation and other ancillary services, but these payments tend to be smaller than capacity payments and energy-efficiency is less well-suited for providing these services.

are large regional differences with particularly large external damages in the Midwest. In this paper, however, we limit our focus to private energy cost savings. Perhaps contrary to popular expectation, the large majority of the benefits from most energy-efficiency policies come from reduced private energy costs (Gayer and Viscusi, 2013). For example, nine new standards promulgated by the DOE in 2016 are predicted to achieve a total present value of $76 billion in energy cost savings, vs. $28 billion in avoided CO_2 emissions and $5 billion in avoided NO_x emissions.[8] That is, more than two-thirds of the benefits come from private energy cost savings. Moreover, the hourly variation in external costs is small relative to the hourly variation in electricity prices and capacity values. Private value varies across hours by a factor of ten or more, while emission rates vary only by about a factor of two between fossil-fuel plants. For both of these reasons, in this paper we focus exclusively on private costs and refer readers interested in externalities to Callaway et al. (2015).

2.2 Energy Efficiency

Energy is a widely-used input, both by firms in virtually all modern production processes and by consumers in the production of cooling, lighting, refrigeration, and other household services. Energy efficiency is the rate at which energy inputs are converted into these outputs. Households and firms can choose to improve energy efficiency through a variety of (usually capital-intensive) investments. The ultimate level of investment in energy efficiency depends on capital costs, energy prices, discount rates, and other factors.

Governments intervene in energy efficiency to reduce peak demand, increase "energy security", and reduce externalities from energy consumption. Most

[8]We made these calculations based on the nine new standards listed in DOE's February, 2016 and August, 2016 semi-annual reports to Congress. The rulemakings are Single Package Vertical Air Conditioners and Heat Pumps (80 *FR* 57438, 2015); Ceiling Fan Light Kits (81 *FR* 580, 2016); Refrigerated Beverage Vending Machines (81 *FR* 1028, 2016); Commercial Package Air Conditioning and Heating Equipment and Warm Air Furnaces (81 *FR* 2420, 2016); Residential Boilers (81 *FR* 2320, 2016); Commercial and Industrial General Pumps (81 *FR* 4368, 2016); Commercial Prerinse Spray Valves (81 *FR* 4748, 2016); Battery Chargers (81 *FR* 38266, 2016); and Dehumidifiers (81 *FR* 38338, 2016).

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 paper fits into a recent literature that emphasizes the importance of rigorous ex-post analyses of these programs using real market outcomes (Davis et al., 2014; Fowlie et al., 2015; Allcott and Greenstone, 2017).

The vast majority of existing economic analyses of energy efficiency have focused on total savings, rather than on when these savings occur (see e.g. 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. (2015)). A notable 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. Our paper in contrast is much more focused on the timing of energy savings and how this impacts the total value of energy-efficiency investments.

Like academic research, regulatory analyses conducted during the design and evaluation of energy efficiency policies have also overwhelmingly ignored the timing of savings. Minimum efficiency standards are probably the most pervasive form of government intervention in energy efficiency. There are standards for 40+ categories of residential and commercial technologies in the United States. Analyses of these 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. They find that energy-efficiency standards saved households and firms $60 billion in 2014. The DOE performs additional economic analyses every time a new standard is implemented but again, they emphasize total energy savings without regard to when they occur (see references in Footnote 1).

Another major category of policies are subsidies for energy-efficient technologies. This includes federal and state income tax credits for energy efficiency investments 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).[9]

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. Some recent federal energy efficiency standards consider seasonal differences, but still ignore the enormous variation within seasons and across hours of the day.[10] In addition, while the vast majority of third-party analyses of energy-efficiency programs ignore the timing of savings, a relevant exception is Evergreen Economics (2016), which compares random coefficients versus alternative models for estimating hourly savings for several California energy-efficiency programs.

3 Empirical Application

For our empirical application, we focus on a residential air conditioner program in Southern California. Section 3.1 briefly describes the program, Section 3.2 provides graphical evidence on average electricity savings, Sections 3.3 and 3.4 plot savings estimates by daily temperature and hour-of-day, respectively, and then Section 3.5 reports regression estimates of overall annual savings.

3.1 Program Background

Our empirical application is an energy-efficiency rebate program offered by Southern California Edison (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 the wholesale electricity

[9]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.

[10]For example, recent standards for Ceiling Fan Light Kits (81 *FR* 580, 2016).

market operated by the California Independent System Operator and sells it to residential, commercial, and industrial customers.

Known as the *Quality Installation Program*, this program provides incentives of up to $1,100 to households that install an energy-efficient central air conditioner. This program is of significant intrinsic interest because of the high level of energy consumption from air conditioning. In California, air conditioning is responsible for 10% of average residential electricity use and 15% of average commercial electricity use (California Energy Commission, 2012). 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 one of the fastest growing uses of electricity worldwide (Davis and Gertler, 2015).

The program is administered similarly to most U.S. energy-efficiency rebate programs. As with other programs, the household claims the rebate through the mail after the new air conditioner is installed. Also, as is typical with this type of program, the state utility commission compensates the utility for running the program by allowing it to pass on costs to ratepayers in the form of higher electricity prices. This particular program includes an additional focus on proper installation of the new air conditioner, which can further improve energy performance (California Public Utilities Commission, 2011).

The data consist of detailed information about program participants and hourly electricity consumption records. Our main empirical analyses are based on about 6,000 households who participated in the program between January 2012 and April 2015. The online appendix provides additional details, descriptive statistics, and results from alternative specifications including analyses which use data from matched non-participating households.

3.2 Event Study

Figure 1 plots estimated coefficients and 95% confidence intervals corresponding to a standard event study regression. The dependent variable is average hourly electricity consumption by household and year. The horizontal axis is the time in years before and after installation, normalized so that the year of installation is equal to zero. We include year by climate zone fixed effects to remove the effect of annual changes in average electricity consumption in each climate zone due to weather and other time-varying factors.

We include separate plots for summer and winter. For summer, we estimate the regression using July and August data from 2012 to 2015. We drop data from installations that occurred during August, September, and October to ensure that participants did not have new air conditioners during year -1. This exclusion is for the event study figure only; 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 decrease is about 0.2 kilowatt hours per hour. A typical LED lightbulb uses about 10 watts, so this decrease is equivalent to shutting off 20 LEDs. Electricity consumption is otherwise approximately flat before and after installation.

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 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.

These event study figures and estimates in later sections measure the electricity savings from a new air conditioner. This is different, however, from the causal effect of the rebate program. Many participants in energy-efficiency programs are inframarginal, getting paid for something they would have done anyway (Joskow and Marron, 1992). In the extreme, if all participants are inframarginal, a program can have no causal impact even though the subsidized activity creates large savings. Measuring the causal impact also requires figuring out how the program changed the *type* of appliances that were purchased. Recent studies have used regression discontinuity and other quasi-experimental techniques to tease out these causal effects and perform cost-benefit analysis (Boomhower and Davis, 2014; Houde and Aldy, Forthcoming).

3.3 Impacts by Local Temperature

A potential concern in our application is that participating households might have experienced other changes at the same time they installed a new air conditioner. For example, program participation might coincide with a home remodel or a new baby, both of which would affect electricity consumption. However, air conditioning has a very particular pattern of usage that we can use to validate our estimates. Unlike most other energy-using durable goods, air conditioner usage is highly correlated with temperature. Thus, we can validate our empirical approach by confirming that our estimated savings are large on hot days and near zero on mild days.

Figure 2 plots estimated electricity savings against daily mean temperature for each household's nine-digit zip code. We use daily mean temperature data at the four kilometer grid cell level from the PRISM Climate Group (PRISM, 2016). We report regression coefficients for 22 different temperature bins interacted with an indicator variable for after a new air conditioner is installed. So, for example, the left-most marker reports the effect of a new air conditioner on days when the temperature is below 40 degrees Fahrenheit. The regression is estimated at the household by day-of-sample level and includes household by month-of-year and day-of-sample by climate zone fixed effects.

On mild days, between 50 and 70 degrees Fahrenheit, estimated energy savings are zero or not statistically distinguishable from it. The lack of consumption changes on these days implies that participants are not simultaneously changing their stock or usage of refrigerators, lighting, or other appliances. From 70 to 100+ degrees, there is a steep, continuous relationship between temperature and energy savings, as expected from a new air conditioner. Air conditioner usage is largest on the hottest days, so energy-efficiency gains have the largest effect on these days. There is also a small decrease in consumption on days below 50 degrees. This might be explained by improvements to ductwork, insulation, thermostats, or other HVAC-related upgrades that in some cases occur as part of a new central air conditioner installation. This decrease is very small, however, relative to the energy savings on hot days.

3.4 Hourly Impacts by Season

Figure 3 plots estimated electricity savings by hour-of-day 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 during summer- or non-summer months, respectively. 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-of-sample by hour-of-day level and control for week-of-sample by climate zone 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. Overall, 55% of total savings occur during July and August.

3.5 Annual Average Savings

Table 1 reports regression estimates of annual average energy savings. The dependent variable in these regressions is average hourly electricity consumption measured at the household by week-of-sample by hour-of-day level. The covariates of interest are 288 indicator variables corresponding to the 24 hours of the day crossed with the 12 months of the year (for example, 1:00–2:00 p.m. in November), each interacted with an indicator variable for new air conditioner installation. We calculate annual savings by multiplying each coefficient by the number of days in the month, and summing the resulting values.[11]

In columns (1) and (2) the implied annual savings per household are 375 and 358 kilowatt hours per year, respectively. The difference between these two specifications is that the latter adds a richer set of time fixed effects. Finally, in column (3) we restrict the estimation sample to exclude, for each household, the eight weeks prior to installation. This might make a difference if an old air conditioner was not working or if the installation date was recorded incorrectly. The estimates are somewhat larger in column (3) but overall average savings are similar across the three columns.

Prior to installing a new air conditioner, program participants consumed an average of 9,820 kilowatt hours annually, so the estimate in column (3) implies a 4.4% decrease in household consumption.[12] A typical central air conditioner (3 ton, 13 SEER) in this region uses about 4,237 kilowatt hours per year, so the savings represent a 10% decrease in annual electricity consumption for air conditioning. This is broadly similar to what would be expected based on a simple engineering prediction. For example, a Department of Energy calculator shows that ignoring rebound and other factors a typical central air conditioner upgrade in Los Angeles saves 565 kilowatt hours per year.[13]

[11] Alternatively, one could use a single new appliance indicator variable to measure average savings across all hours, and then multiply by the number of hours in a year. However, this approach incorrectly weights hours of the year according to the composition of post-installation observations for each household. For example, since our data end in April 2015, a household that installed in late 2013 would be observed for two winters and one summer. This uneven weighting could potentially be addressed by restricting the sample to include exactly one year of post-installation data for each household and throwing out installations after April 2014; or by re-weighting across the sample to equalize the effective number of post-installation observations. We prefer to simply estimate average savings for each hour-of-day by month-of-year pair and sum up to annual savings. Moreover, we need these 288 separate estimates for the analyses in following sections.

[12] 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 impacts for this program using data from a much smaller number of homes, and also estimates savings for two other California energy-efficiency programs.

[13] Typical air conditioner electricity usage and predicted savings are from Energy Star Program, "Life Cycle Cost Estimate for 1 ENERGY STAR Qualified Central Air Conditioner(s)", 2013. https://www.energystar.gov/. These statistics assume replacement of a

4 The Value of Energy Efficiency

In this section we show that the value of electricity varies substantially across hours and we demonstrate the importance of accounting for this variation when valuing energy-efficiency investments. We start by incorporating data on wholesale electricity prices and capacity values (Section 4.1). Then, with the empirical application from the previous section, we measure the correlation between electricity savings and the value of electricity (Section 4.2) and we quantify the average value of savings (Section 4.3).

4.1 The Value of Electricity in U.S. Markets

Figure 4 plots hourly wholesale electricity prices and capacity values for two months-of-year (February and August) and for two major U.S. electricity markets (California/CAISO and Texas/ERCOT). We selected February and August because they tend to be relatively low- and high-demand months; adjacent months look similar. For each market we plot average prices by hour-of-day for 2011 through 2015. The energy and capacity price data that we use come from SNL Financial and the California Public Utilities Commission and are described in the online appendix. We include ERCOT because it is a particularly interesting point of comparison; since ERCOT has no capacity market, the full value of electricity is encoded in hourly energy prices.

For California, the figures plot average wholesale energy prices as well as four alternative measures of capacity value. As discussed in Section 2.1, capacity payments are made to electricity generators to remain open and available, thereby ensuring desired reserve margins. 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. ERCOT has no capacity market and, not coincidentally, has much higher energy market prices

3-ton 13 SEER unit with 3-ton 15 SEER without programmable thermostat before or after.

than California during peak hours.

In California, generation capacity is procured in advance at the monthly level. Capacity contracts obligate generators to be available every hour of one month. In order to value hourly energy savings, we need to allocate these monthly capacity costs across individual hours. We do this several ways and report the results of each. As we explain in more detail in the Appendix, the capacity value of a demand reduction in any hour depends on the probability that that hour is the peak hour. Our various approaches to allocating capacity value to hours involve different ways of calculating these probabilities. In our first approach, we use hourly load data to calculate the hour-of-the-day with the highest average load each month. We then divide the monthly capacity price evenly across all occurrences of that hour-of-day on weekdays. We allocate capacity costs to weekdays only because weekend and holiday loads are reliably smaller. In other specifications, we divide the capacity contract price evenly over 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. We calculate the historical likelihood that each hour-of-the-day was the daily peak hour, and allocate monthly capacity values to hours of the day proportionally according to these probabilities.

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 \$300 and \$600 per megawatt hour. 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. In addition, the general shape of the capacity-inclusive values for California matches the shape in Texas, providing some reassurance that our approach recovers a price shape that is similar to what would exist in an energy-only market.[14]

[14]We return to this point later, when we show that valuing energy savings using Texas electricity prices yields similar results to valuing savings using California energy and capacity prices. Of course, Texas and California have different load profiles and generation mixes,

The value of electricity in Texas surges in August to \$300+ during the late afternoon, considerably higher than the marginal cost of any generator.

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 (see, e.g., Blonz, 2016). 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. For example, one might argue that the recent influx of renewables into U.S. electricity markets has pushed capacity market prices 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 our calculations with updated data. Larger capacity prices would lead to larger variation in economic value between off-peak and peak, thus reinforcing our 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 and capacity requirements by 1.06 kilowatt hours. Line losses vary over time by an amount approximately proportional to the square of total generation. We incorporate these losses explicitly following Borenstein (2008) and, in practice, they range from 3.9% during off-peak periods to 10.3% during ultra-peak periods. Incorporating line losses thus further increases the variation in economic value between off-peak and peak.

4.2 Correlation between Savings and Value

Figure 5 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-

so California's wholesale prices would not exactly match those in Texas were California to eliminate its capacity market and price cap.

year pair (for example, 1:00–2:00 p.m. during November). The vertical axes show average hourly energy savings. These are the 288 coefficients from the regression described in Section 3.5. In Panel A, the horizontal axis shows average wholesale energy prices from California for 2011–2015. In Panel B, the horizontal axis shows energy and capacity values, using the probabilistic allocation method for capacity prices described in Section 4.1.

Several facts are apparent in Panel A. First, the summer months include many more high-price realizations than the winter months. We use dark markers to indicate April through September, and the number of intervals with energy prices above $40 per MWh is much higher during these summer months. Second, this energy-efficiency investment delivers much larger savings in the summer. We saw this before in Figure 3, with average savings in excess of 0.1 kilowatt-hours per hour in many summer hours.

The figure also includes least-squares fitted lines. The fitted line for April–September slopes steeply upward. In Panel A, predicted savings when energy prices are $55/MWh are twice as large as predicted savings at $35/MWh. The fitted line for winter, in contrast, is essentially flat. Savings are near zero in all winter hours, so there is little correlation between savings and price.

The same patterns are apparent in Panel B, but this panel emphasizes the importance of accounting for capacity values. During a few ultra-peak hours in the summer, generation capacity is extremely valuable and the value of energy surges to above $200/MWh. Air conditioner investments deliver above-average savings in these hours, so the correlation is again strongly positive.

4.3 Quantifying the Value of Energy Savings

Table 2 quantifies the value of the energy savings from this investment. To do this, we combine estimates of month-of-year by hour-of-day energy savings with month-of-year by hour-of-day prices. For these estimates we also differentiate between weekdays and weekends (including holidays). We estimate savings for 576 different month-of-year by hour-of-day by weekday/weekend periods using the same set of fixed effects as in column (3) of Table 1. Row (A) presents estimates of the annual value of these energy savings in dollars per megawatt-hour when we account for timing. Row (B) gives the naive value estimate when all savings are valued at load-weighted average annual prices. The five columns of the table use five different approaches for valuing electricity. In column (1) we use wholesale energy prices only, ignoring capacity values. Under this calculation the annual value of savings is $45 per megawatt hour. This is 12% higher than the row (B) calculation ignoring timing.

In columns (2) through (5) we incorporate capacity values. Each column measures the value of electricity using a different approach to allocating monthly capacity payments across hours, as described in Section 4.1. Incorporating capacity values significantly increases the value of air conditioner energy savings to $70 per megawatt-hour. Air conditioning investments save electricity during the hours-of-day and months-of-year when large capacity payments are needed to ensure that there is sufficient generation to meet demand. The naive calculation that ignores timing understates these capacity benefits. The naive estimate in Row (B) increases from $40 per year to $51 per year after including capacity value. This reflects the fact that most hours have zero capacity value, so the average across the year is relatively small.

Exactly how we account for capacity values has little impact, changing the estimated timing premium only slightly across columns (2) through (5). This is because the estimated energy savings are similar during adjacent hours, so spreading capacity costs across more peak hours does not significantly impact the estimated value of savings. In the results that follow we use the "top 3 hours" allocation (column (4)) as our preferred measure, but results are almost identical using the other allocation methods. In all four columns, accounting for timing increases the estimated savings value by about 37%.

The baseline values in row (B) are calculated using a load-weighted average electricity price. Electricity prices tend to be higher in high-load hours, so this load-weighted average is higher than an unweighted average. Many regulatory analyses (see citations in Section 1) use energy prices based on average revenue per megawatt hour, which is equivalent to using load-weighted averages. This implicitly assumes that the savings profile of the investment exactly matches the market-wide load profile. An alternative assumption is that energy savings are the same in all hours, which implies using an unweighted average of hourly prices. When we use this approach, the effect of accounting for timing is larger, with a timing premium (including capacity values) of 50%.

4.3.1 How Might These Values Change in the Future?

Environmental policies that favor renewable energy are expected to cause significant changes in electricity markets. California, for example, has a renewable portfolio standard which requires that the fraction of electricity sourced from renewables increase to 33% by 2020 and 50% by 2030. High levels of renewables penetration, and, in particular, solar generation, make electricity less scarce during the middle of the day, and more valuable in the evening after the sun sets. The expected steep increase in net load during future evening periods has prompted concern (CAISO, 2013).

To examine how this altered price shape could affect the value of energy efficiency, we performed an additional analysis using forecast prices and load profiles for California in 2024 from Denholm et al. (2015).[15] The authors provided us with monthly energy prices by hour-of-day, and net load forecasts by hour-of-day and season for a scenario with 40% renewable penetration. We calculated future capacity values by allocating current monthly capacity contract prices over the three highest net load hours of day in each future month. Under these assumptions, the timing premium increases from 37% to 50%.[16] This increase in value is due to increased solar penetration shifting peak prices further into the late afternoon and early evening, when energy savings from air conditioners are largest.

[15] In related work, Martinez and Sullivan (2014) uses an engineering model to examine the potential for energy efficiency investments to reduce energy consumption in California from 4:00 p.m. to 7:00 p.m. on March 31st (a typical Spring day), thereby mitigating the need for flexible ramping resources.

[16] Ignoring capacity value and using future energy prices only, the timing premium is 30%.

This estimate should be interpreted with caution. Predicting the future requires strong assumptions about electricity demand, natural gas prices, the deployment of electricity storage, and other factors. This calculation does, however, show how increased renewables integration can make it even more important to incorporate timing differences across investments. We are already seeing occasional negative wholesale prices in the middle of the day and this is expected to become more common, underscoring our central point that not all energy savings are equally valuable.[17]

5 Examining a Broader Set of Investments

Finally, in this section, we turn to engineering predictions from a broader set of energy-efficiency investments. We show that time profiles differ significantly between investments (Section 5.1) and that these different profiles imply large differences in value (Section 5.2).

5.1 Savings Profiles for Selected Investments

We next bring in engineering predictions of hourly savings profiles for air conditioning and a wide variety of other energy-efficiency investments. The engineering predictions that we use come from the *Database for Energy Efficient Resources* (DEER), a publicly-available software tool developed by the California Public Utilities Commission (CPUC).[18] These are *ex ante* predictions of energy savings, developed using a building simulation model that makes a variety of strong assumptions about building characteristics, occupant usage schedules, local weather, and other factors. The DEER predictions are not based on plug load monitoring or other empirical data. To our knowledge, this paper is the first attempt to verify these engineering predictions empirically

[17]Energy Information Administration. "Rising Solar Generation in California Coincides with Negative Wholesale Electricity Prices." Today in Energy, April 7, 2017.

[18]The *DEER* is used by the CPUC to design and evaluate energy-efficiency programs administered by California investor-owned utilities. For each energy-efficiency investment the DEER reports 8,760 numbers, one for each hour of the year. We use the savings profiles developed in 2013/2014 for the Southern California Edison service territory. See the Appendix and `http://deeresources.com` for data details.

using measured electricity consumption.[19]

Figure 6 compares our econometric estimates with engineering predictions for residential air conditioning investments in this same geographic area. Since our interest is in *when* savings occur, both panels are normalized to show the share of total annual savings that occur in each month and hour (Section 3.5 includes a comparison of total savings amounts). The two savings profiles are broadly similar, but there are interesting differences. First, the econometric estimates indicate peak savings later in the evening. The engineering predictions peak between 4 p.m. and 6 p.m., while the econometric estimates peak between 6 p.m. and 7 p.m. This difference is important and policy-relevant because of expected future challenges in meeting electricity demand during sunset hours, as discussed in the previous section.

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 predictions show savings quickly tapering off at night during the summer, reaching zero at midnight. It could be that the engineering predictions are insufficiently accounting for the thermal mass of 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 predictions 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 that almost all of the savings occur June through September with only modest savings in October and essentially zero savings in other months.

Differences between *ex ante* predictions and *ex post* econometric evaluations are not unusual for energy efficiency technologies (Davis et al., 2014; Fowlie et al., 2015; Allcott and Greenstone, 2017) or for other technologies such as

[19] An alternative to large-scale empirical analysis of billing data would be to use plug load monitoring studies of individual appliances within households. However, these studies tend to be small-scale and not representative. For example, Perez et al. (2014) examines plug-load data for air conditioning in 19 homes in Austin, Texas.

improved cookstoves (Hanna et al., 2016). These previous studies underscore the value of grounding *ex-ante* predictions using actual *ex-post* data from the field. In our case, however, we find that the *ex-ante* predictions and *ex-post* estimates for air conditioning predict broadly similar patterns for the timing of savings. This rough accuracy gives us confidence in using engineering-based savings profiles for a broader set of energy-efficiency investments in the analyses that follow.

Figure 7 plots hourly savings profiles for eight different investments, four residential and four non-residential. Savings profiles for additional energy-efficient investments are available in the online appendix. The profiles are remarkably diverse. The flattest profile is residential refrigeration, but even this profile is not perfectly flat. Savings from residential lighting investments peak between 8 p.m. and 9 p.m. all months of the year, while savings from residential heat pumps peak at night during the winter and in the afternoon during the summer. The non-residential profiles are also interesting, and quite different from the residential profiles. Whereas savings from residential lighting peak at night, savings from commercial and industrial lighting occur 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, savings from commercial and industrial heat pumps are assumed to peak only in the summer, unlike the residential heat pumps for which the engineering predictions assume both summer and winter peaks.

5.2 Comparing Investments

Table 3 reports timing premiums for this wider set of investments. Just as we did in Table 2, we calculate timing premiums as the additional value of each investment in percentage terms relative to a naive calculation that values savings using load-weighted average prices. As before, we value electricity using both wholesale prices and capacity payments, and we incorporate data not only from California but from five other U.S. markets as well, including Texas (ERCOT), the Mid-Atlantic (PJM), the Midwest (MISO), New York

(NYISO), and New England (NE-ISO). Capacity values are allocated to the three highest-load hours of the day in each month in CAISO and NYISO, and to the 36 highest hour-of-day by month-of-year pairs in PJM, MISO, and ISONE. See the online appendix for details.

The highest timing premiums are for residential air conditioning investments in California and Texas – two states that between them represent 21% of total U.S. population. This is true regardless of whether the econometric estimates or engineering predictions are used, and reflects the high value of electricity in these markets during summer afternoons and evenings. Residential air conditioning also has a significant but smaller timing premium in the Mid-Atlantic and Midwest.

Interestingly, the timing premiums for residential air conditioning are near zero in New York and New England. These markets have recently experienced high *winter* prices due to cold temperatures caused by a southward shift of the polar vortex (see, e.g. Kim et al., 2014). Natural gas pipeline capacity is limited in parts of the Northeast, so when heating increases there can be large spikes in electricity prices. Air conditioning investments provide little savings during these cold periods, resulting in low timing premiums. Premiums for the Northeast are particularly low with the econometric estimates, which show a very small share of savings occurring outside of June through September.

Other investments also have large timing premiums. Commercial and industrial heating and cooling investments, for example, have premiums of about 20%, reflecting the relatively high value of electricity during the day. This is particularly true in California and Texas (30+%), though premiums are also consistently high in the Mid-Atlantic, Midwest, and New York. Again, timing premiums are substantially lower in New England, reflecting the poor match between these investments and the winter peak.

Timing premiums for lighting and clothes washers are much smaller. The savings from these investments are not as strongly correlated with prices. Lighting, for example, does poorly because the savings occur somewhat after the system peak in all U.S. markets and disproportionately during the winter, when electricity is less valuable. This could change in the future as increased solar generation moves net system peaks later in the evening, but for the moment both residential and non-residential lighting have timing premiums near zero in all markets.

Residential heat pumps and refrigerators and freezers have consistently negative timing premiums. These investments are *less* valuable than implied by a naive calculation using load-weighted average prices. Heat pump investments deliver about half of their savings during winter nights and early mornings, when electricity prices are very low. Refrigerator and freezer investments deliver essentially constant savings and so do even worse than the baseline, which assumes that energy savings are proportional to total system load.

The timing premiums reported in this table rely on many strong assumptions. For example, we have econometric estimates for only one of the nine technologies, so these calculations necessarily rely heavily on the engineering predictions. We see empirical validation of savings profiles for other technologies as an important area for further research. In addition, although we have incorporated capacity payments as consistently as possible for all markets, there are differences in how these markets are designed that make the capacity payments not perfectly comparable. These important caveats aside, the table nonetheless makes two valuable points: (1) timing premiums vary widely across investments and, (2) market characteristics are important for determining the value of savings.

6 Conclusion

Hotel rooms, airline seats, restaurant meals, 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, the value of electricity is even more variable, often varying by a factor of ten or more within a single day. Moreover, this variability is tending to grow larger as a greater fraction of electricity comes from solar and other intermittent renewables. This feature of electricity markets is widely understood yet it tends 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.

In this paper, we've shown that accounting for timing matters. Our 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. We showed that energy-efficiency investments in air conditioning lead to a sharp reduction in electricity consumption in summer months during the afternoon and evening. We then used electricity market data 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 about 40%. Especially important in this calculation was accounting for the large capacity payments received by electricity generators. In most electricity markets in the U.S. and elsewhere, generators earn revenue through capacity markets as well as through electricity sales. These payments are concentrated in the highest demand hours of the year, making electricity in these periods much more valuable than is implied by wholesale prices alone. This emphasis on capacity markets is one of the significant contributions of our analysis, and we believe, an important priority for future research.

We then broadened the analysis to incorporate a wide range of energy-efficiency investments. Residential air conditioning has the highest average timing premium across markets, though this premium goes away in markets with high winter prices. Commercial and industrial heat pumps, chillers, and air conditioners also have high average premiums. Lighting, in contrast, does considerably worse, reflecting that these investments save electricity mostly during the winter and at night, when electricity tends to be less valuable. Finally, residential heat pumps have an average timing premium below zero, reflecting that these investments save energy at systematically low-value times.

These results have immediate policy relevance. For example, energy-efficiency programs around the world have tended to place a large emphasis on lighting.[20] 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. Another interesting example is the markedly lower timing premiums for air conditioning in the Northeast, where recent price spikes have tended to occur in the winter rather than the summer. Electricity prices necessarily reflect regional factors, so a one-size-fits-all approach to energy-efficiency fails to maximize the total value of savings. Rebalancing policy portfolios toward different investments and markets could increase the total value of savings. We find a remarkably wide range of timing premiums across investments so our results show that better optimizing this broader portfolio could yield substantial welfare benefits.

Our paper also highlights the enormous potential of smart-meter data. Our 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 been deployed in the United States alone. This flood of high-frequency data can facilitate smarter, more evidence-based energy policies that more effectively address market priorities.

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[20]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, compared to total residential net savings of 2.7 million kilowatt-hours. See California Public Utilities Commission 2015, "2010–2012 Energy Efficiency Annual Progress Evaluation Report."

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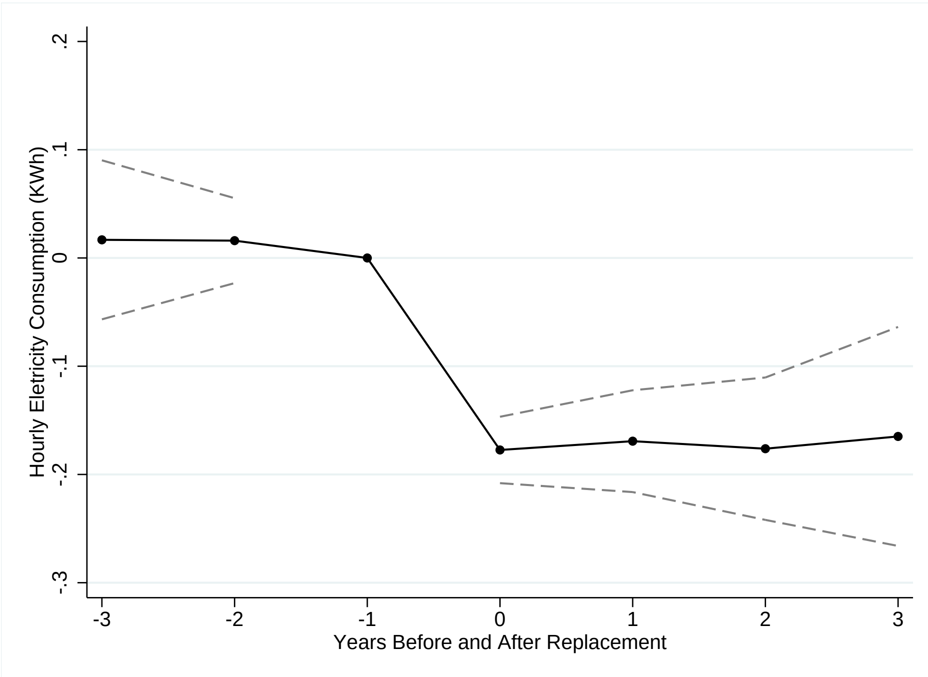
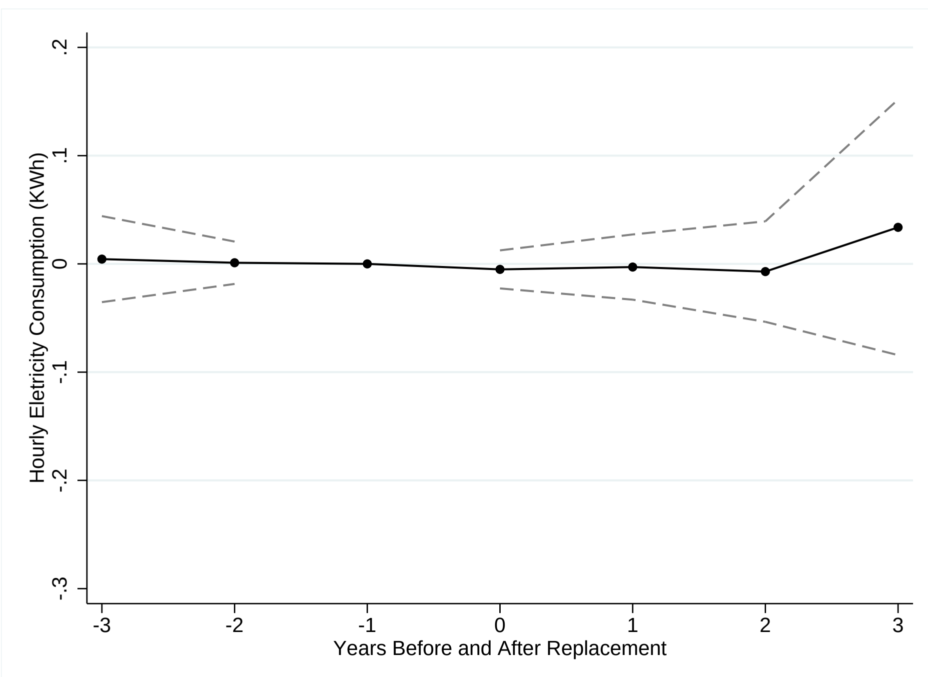
Figure 1: The Effect of New Air Conditioner Installation on Electricity Consumption

Summer

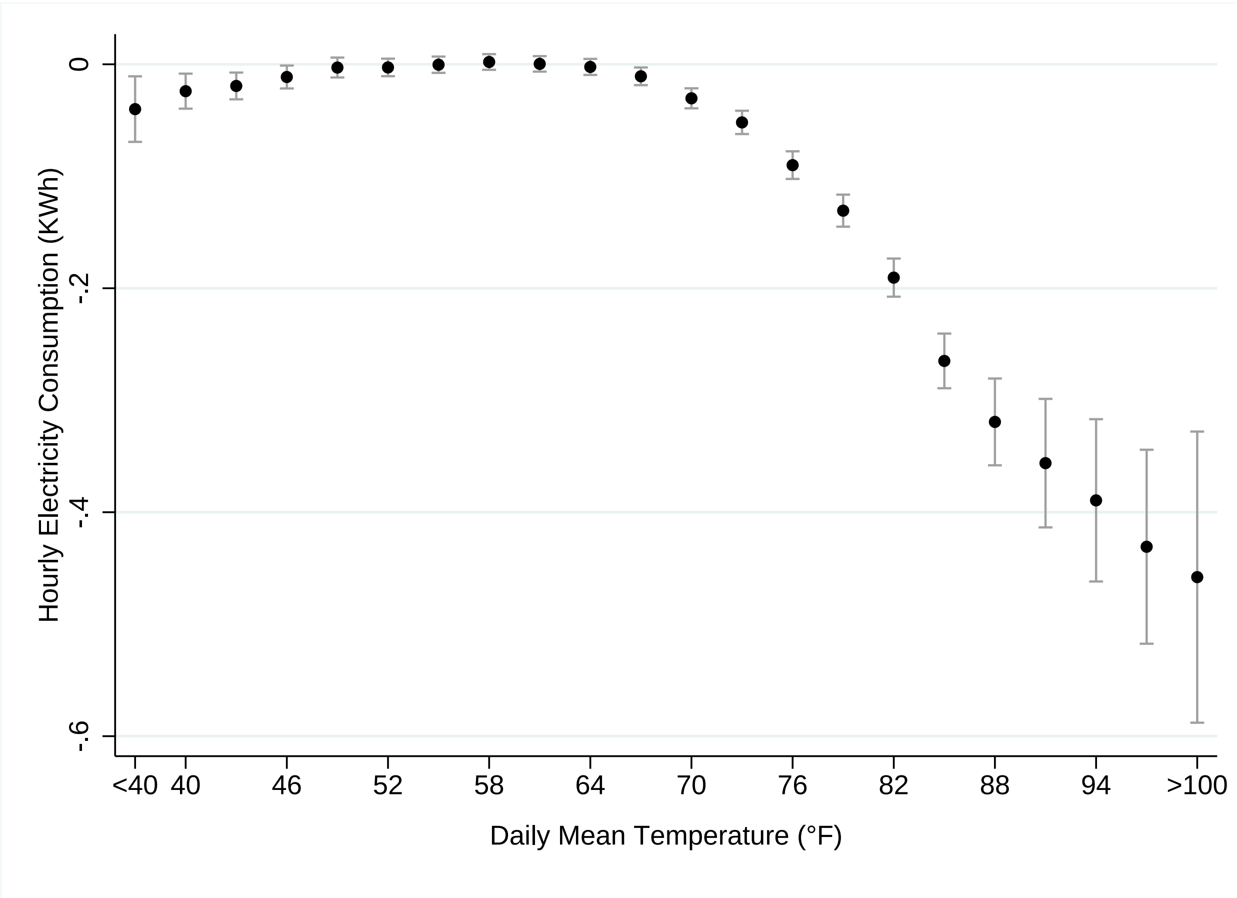


Winter



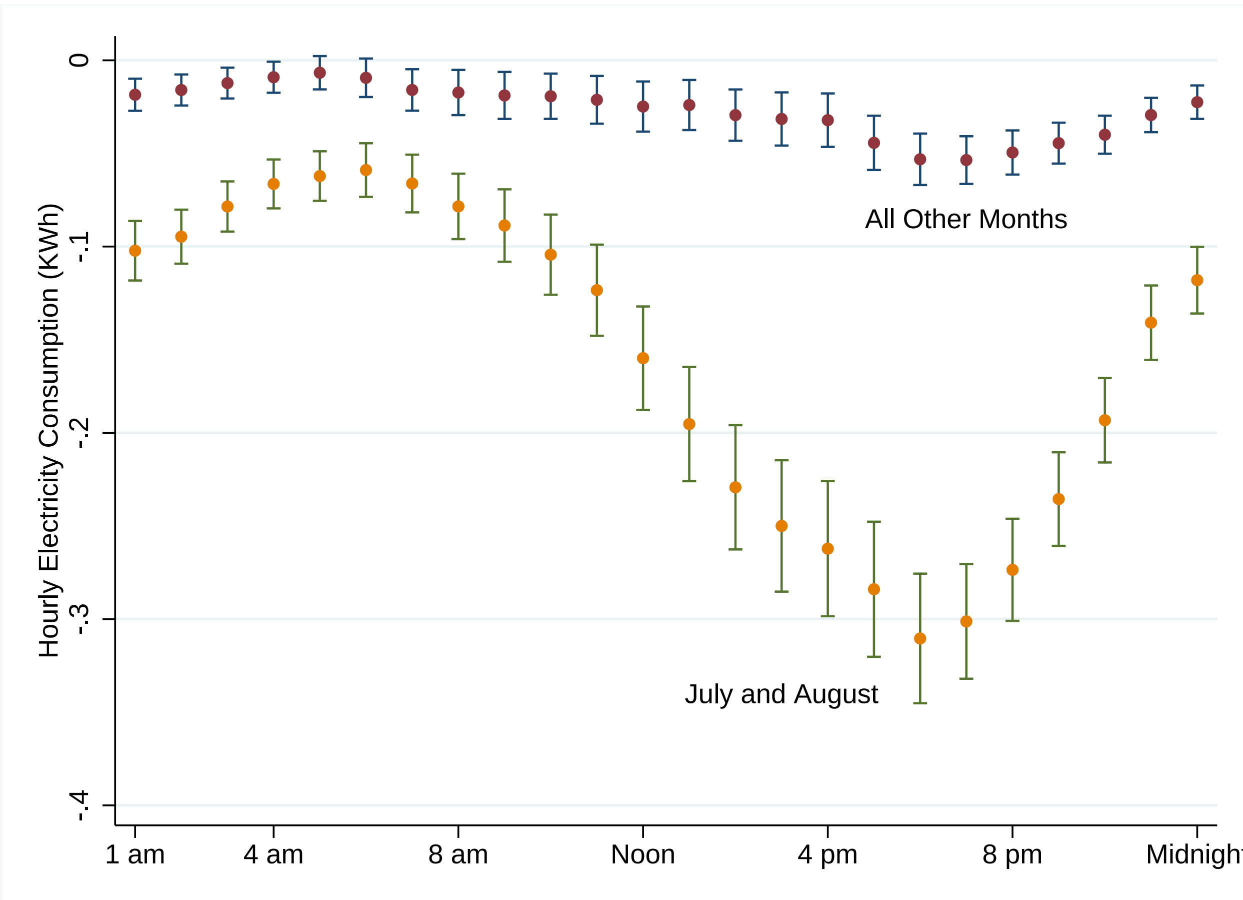
Notes: These event study figures plot estimated coefficients and 95% confidence intervals from two least squares regressions. The dependent variable is average electricity consumption during July and August and January and February, respectively, at the household by year level. Time is normalized relative to the year of installation ($t = 0$) and the excluded category is $t = -1$. The regressions include year by climate zone fixed effects. Standard errors are clustered by nine-digit zip code.

Figure 2: Electricity Savings by Temperature



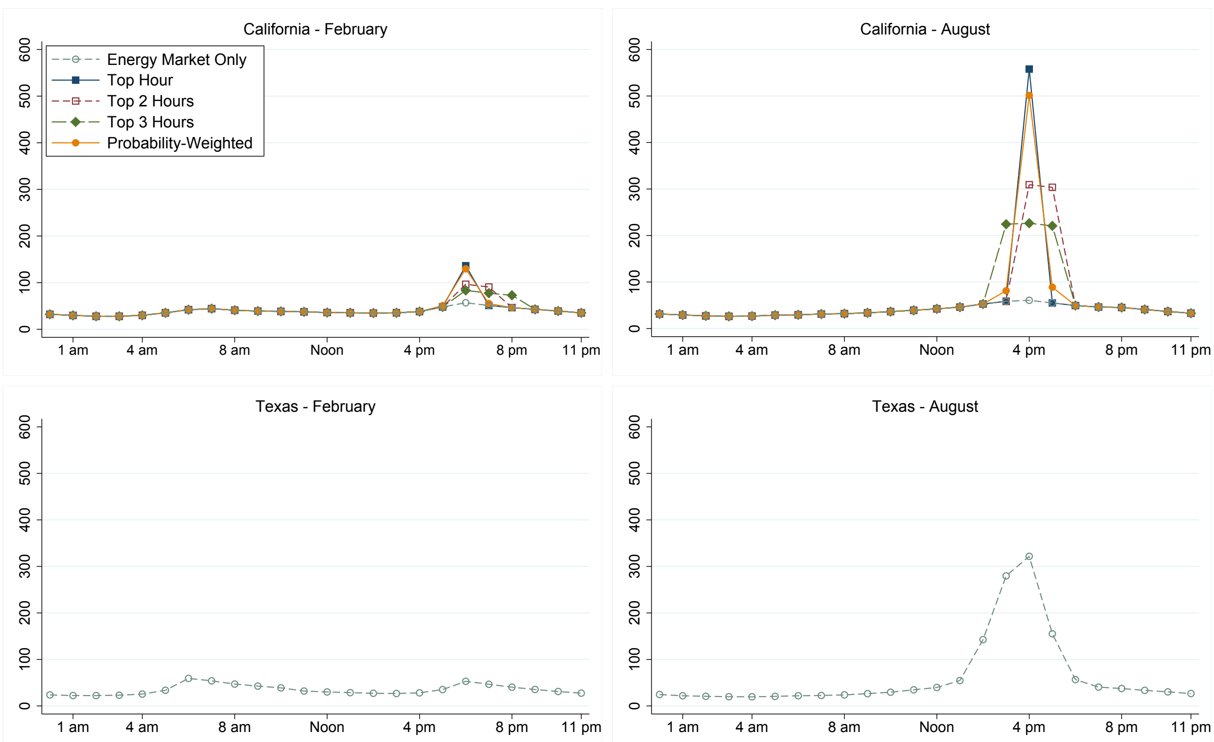
Notes: This figure plots regression coefficients and 95% confidence intervals from a single least squares regression. The dependent variable is average electricity consumption at the household by day-of-sample level. Coefficients correspond to 22 indicator variables for daily mean temperature bins, interacted with an indicator variable for after a new air conditioner installation. Each temperature bin spans three degrees; the axis labels show the bottom temperature in each bin. The regression also includes household by month-of-year and day-of-sample by climate zone fixed effects. Temperature data come from PRISM, as described in the text. Standard errors are clustered by nine-digit zip code.

Figure 3: Electricity Savings by Hour-of-Day



Notes: This figure plots estimated coefficients and 95% 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 horizontal axis. All regressions are estimated at the household by week-of-sample by hour-of-day level and control for week-of-sample by climate zone and household by month-of-year fixed effects. The sample includes all households who installed a new air conditioner between 2012 and 2015, and all summer- or non-summer months, as indicated. Standard errors are clustered by nine-digit zip code.

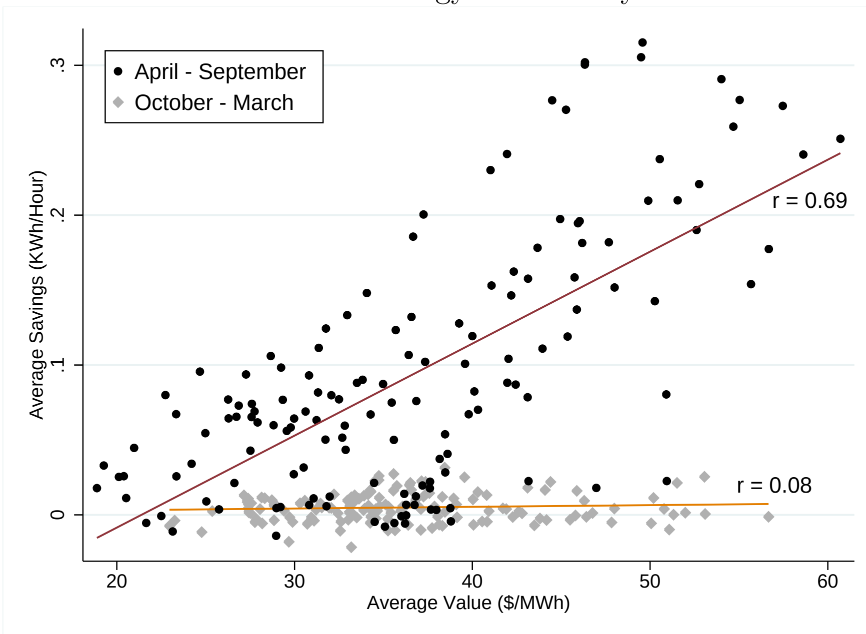
Figure 4: Wholesale Electricity Prices and Capacity Values



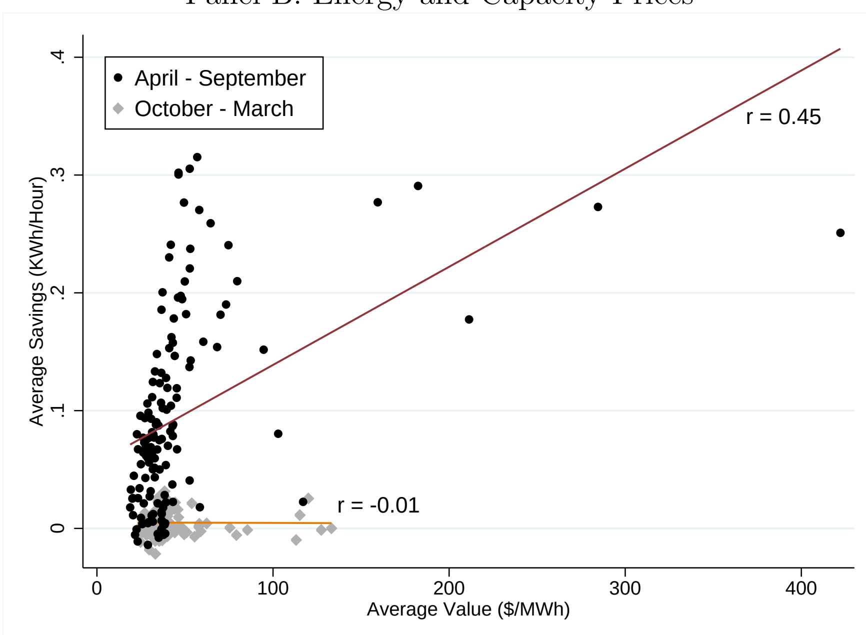
Notes: This figure shows the average hourly value of electricity in February and August in California and Texas, under various assumptions about capacity value in California. The vertical axis units in each figure are dollars per megawatt-hour. The hour labels on the horizontal axis refer to the beginning time of each one-hour interval. See text for details.

Figure 5: Correlation Between Savings and Prices, By Season

Panel A. Energy Prices Only



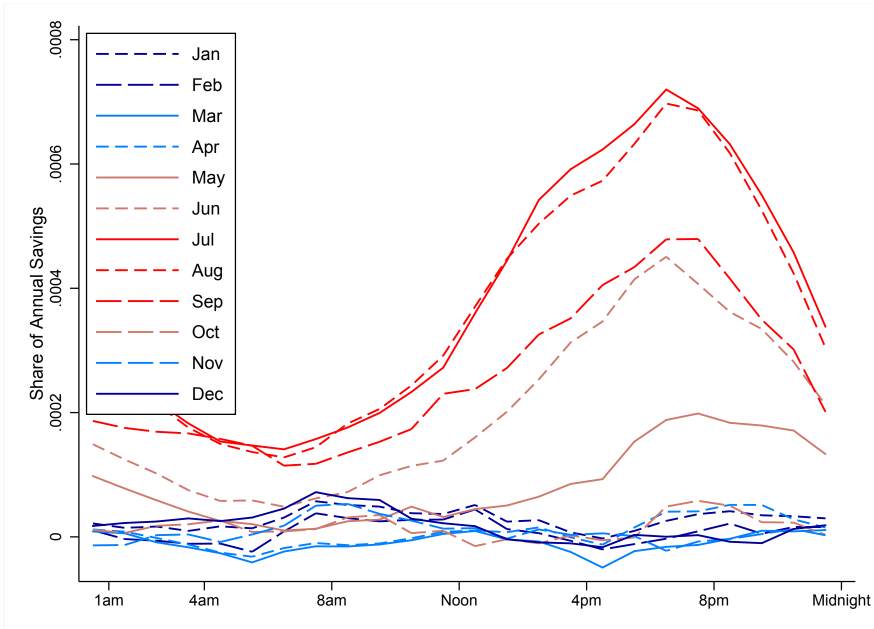
Panel B. Energy and Capacity Prices



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 (e.g. 1–2 p.m. during November). Electricity savings are estimated using a regression which controls for household by hour-of-day by month-of-year 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 2011–2015. 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.

Figure 6: Comparing Estimates of Electricity Savings

Econometric Estimates



Engineering Predictions

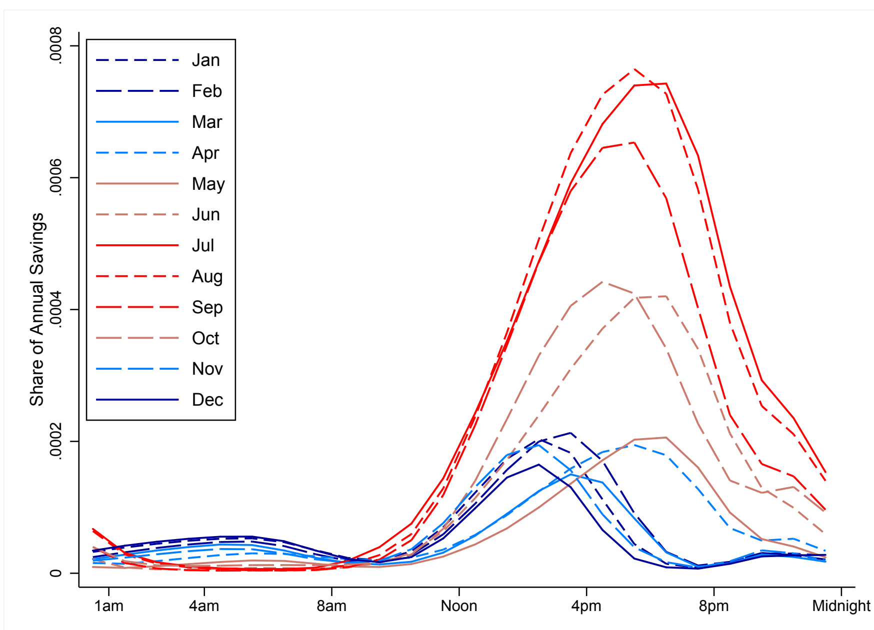


Figure 7: Savings Profiles for Selected Energy-Efficiency Investments

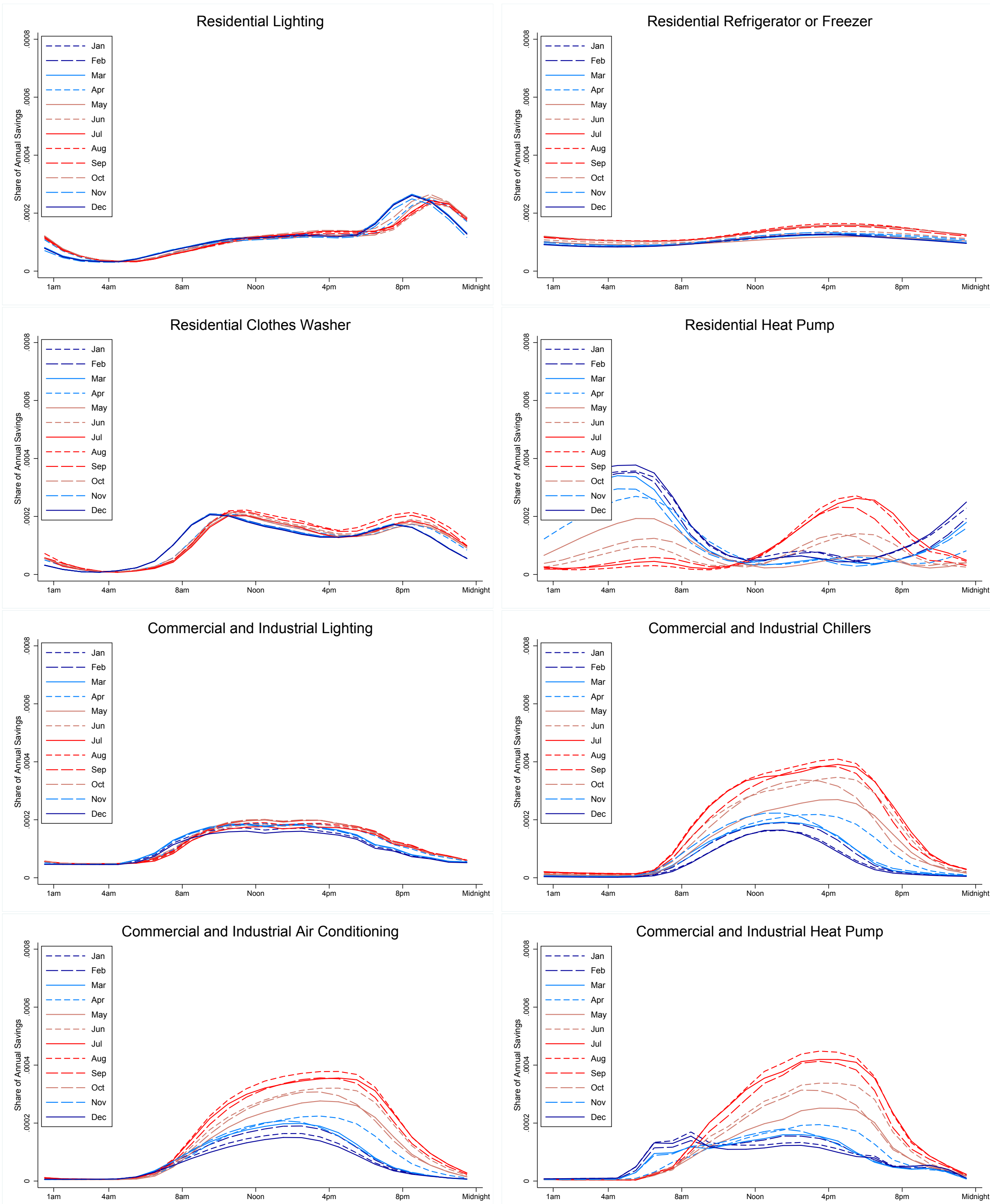


Table 1: Average Energy Savings from a New Central Air Conditioner

	(1)	(2)	(3)
Energy Savings Per Household (kWh/year)	375.3	358.0	436.3
	(32.2)	(32.2)	(36.0)
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
Number of observations	28.6 M	28.6 M	27.3 M
Number of households	5,973	5,973	5,972

Notes: This table reports results from three 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 energy savings is calculated as the weighted sum of these 288 estimates, where the weights are the number of days in each calendar month. Standard errors are clustered by nine digit zip code. The regressions are estimated using data from 2012 to 2015 for all participating households.

Table 2: Does Energy Efficiency Deliver at the Right Time?

	Energy Prices Only	Energy Plus Capacity Prices, Various Assumptions			
		Capacity Value in Top 3% of Hours	Capacity Value in Top 6% of Hours	Capacity Value in Top 9% of Hours	Capacity Value Allocated Probabilistically
	(1)	(2)	(3)	(4)	(5)
Average Value of Savings ($/MWh)					
(A) Accounting for Timing	$45.09	$69.78	$70.60	$69.92	$69.87
(B) Not Accounting for Timing	$40.31	$51.06	$51.01	$50.96	$51.03
Timing Premium ($\frac{A-B}{B}$)	12%	37%	38%	37%	37%

Notes: These calculations are made using estimated energy savings for each hour-of-day by month-of-year by weekday/weekend period from the full regression specification as in Column (3) in Table 1. Energy and capacity prices are from the California electricity market (CAISO). See the text and appendix for all sources and additional details. 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. Row (B) calculations use a load-weighted average of hourly prices.

Table 3: Timing Premiums for Selected Energy-Efficiency Investments

	California (CAISO)	Texas (ERCOT)	Mid-Atlantic (PJM)	Midwest (MISO)	New York (NYISO)	New England (ISONE)	Average
			A. Residential				
Air Conditioning (Econometric Estimates)	37%	39%	17%	14%	0%	1%	18%
Air Conditioning	56%	53%	23%	18%	18%	10%	30%
Lighting	3%	-5%	-2%	-1%	1%	-1%	-1%
Clothes Washers	2%	2%	4%	7%	6%	4%	4%
Heat Pump	-1%	-1%	-4%	-5%	-6%	-3%	-3%
Refrigerator or Freezer	-1%	-5%	-5%	-3%	-4%	-6%	-4%
			B. Commercial and Industrial				
Heat Pump	32%	31%	18%	17%	17%	10%	21%
Chillers	27%	26%	14%	15%	12%	5%	17%
Air Conditioners	25%	24%	14%	15%	13%	6%	16%
Lighting	3%	0%	1%	4%	4%	0%	2%

Notes: This table reports estimated timing premiums for nine energy-efficiency investments. As in Table 2, the timing premium is the additional value (in percentage terms) compared to an investment with a savings profile equal to the load profile. That is, an investment which reduced energy demand by the same percentage in all hours would have a timing premium of 0%. Except for the first row (econometric estimates for air conditioning), all estimates are based on engineering predictions of savings profiles from the California Public Utility Commission's Database for Energy Efficient Resources. Values are estimated using wholesale energy prices and capacity prices from six major U.S. markets as indicated in row headings. See text for details. The final column is the simple average across markets.

A Electricity Market Data

A.1 Wholesale Electricity Prices and Load

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

A.2 Capacity Prices

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

ERCOT has no capacity market so capacity values are equal to zero in all hours. In all other markets, generation capacity is procured in advance at the monthly or annual level, and capacity contracts obligate generators to be available every hour during that period. Specifically, California (CAISO) and New York (NYISO) have monthly contracts, whereas the Midwest (MISO), Mid-Atlantic (PJM), and New England (ISONE) have annual contracts. In order to value energy savings in a given hour, we need to allocate these capacity prices across individual hours. We do this several ways and report the results of each. The amount of capacity to be purchased each period is determined by the regulator's forecast of peak demand. If the precise hour of the peak could be predicted with certainty, that one hour would have capacity costs equal to the contract price, and capacity costs for all other hours would be zero. Changing demand in any of these other hours would have no effect on the capacity market. In reality, it is impossible to perfectly predict the day on which the peak will occur because of uncertainty in weather and other factors. The expected capacity value of a one megawatt-hour demand reduction in any hour is equal to the capacity price times the probability that that hour will be the peak hour. Our various approaches to allocating capacity value involve different ways of calculating these probabilities.

For markets with monthly capacity contracts, we start by using hourly load data to calculate the hour-of-the-day with the highest average load each month. We then divide the monthly capacity price evenly across all occurrences of that hour-of-day on weekdays. We allocate capacity costs to weekdays only, because weekend and holiday loads are reliably smaller. This approach assigns capacity values to the top 3% of all hours in each month, see column (2) of Table 2. For the alternative approaches, in columns (3) and (4), we divide the capacity contract price evenly over the top two or three hours-of-the-day with the highest load each month. The final approach in Column (5) treats each day of load data as a single observation of daily load shape in a given month. We calculate the likelihood between 2011 and 2015 that each hour-of-the-day was the daily peak hour, and allocate monthly capacity values to hours of the day proportionally according to these probabilities. For example, during February in the CAISO market, 6:00 p.m. was the highest-demand hour on 92% of days from 2011–2015. Consequently, we assign 92% of the February contract price to the 6:00 - 7:00 p.m. hour.

For markets with annual capacity contracts, our calculations are very similar, except we assign capacity values to the highest- load hours of the year, rather than to the highest-load hours of the month. Specifically, we allocate annual capacity payments to the top 36 hour-of-day by month-of-year pairs, equivalent to about 6% of all hours throughout the year.

We adjust for reserve margins in all calculations. For every unit of forecast peak demand, regulators require more than one unit of forward capacity purchases (the difference being the required reserve margin). California's reserve margin is 15%, and other markets are similar. Therefore, we increase all capacity values by 15% to reflect that each unit of demand reduction reduces capacity requirements by 1.15 units.

A.2.1 Capacity Market Data

California (CAISO)

CAISO differs from the other markets in that capacity is procured through bilateral contracts, rather than through a centralized auction. The California Public Utilities Commission (CPUC) surveys utilities to track capacity contract prices. We use 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. We use the 85th-percentile values, on the reasoning that these provide a conservative estimate of the marginal cost of procuring capacity. We 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, though most of the reported transactions are for 2013–2015 (page 29, Figure 9).

New York (NYISO)

Capacity prices for New York come from SNL Financial and are for 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.

New England (ISO-NE)

Capacity prices for New England come from SNL Financial and are for ISO-NE's annual forward capacity auctions for 2013 through 2016. We use the simple average of prices across all zones.

Mid-Atlantic (PJM)

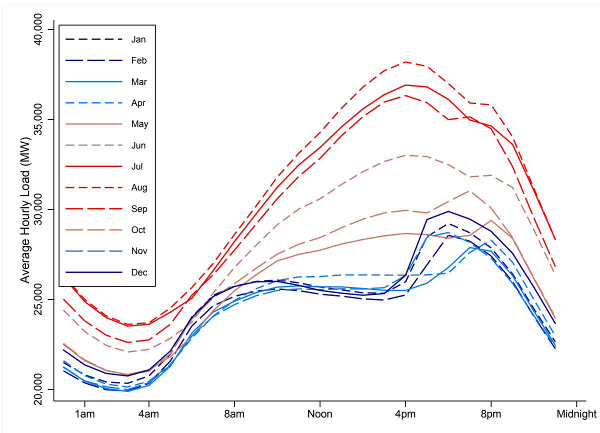
Capacity prices for PJM are from SNL Financial and are market clearing prices from the annual Base Residual Auction. We use the simple average across years and geographic zones for 2013–2016.

Midwest (MISO)

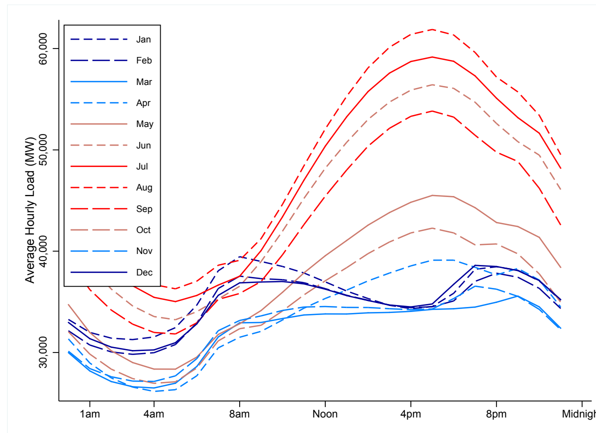
Capacity prices for MISO are from SNL Financial and are annual capacity auction prices for 2013 through 2016. We use the simple average of prices across all zones.

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

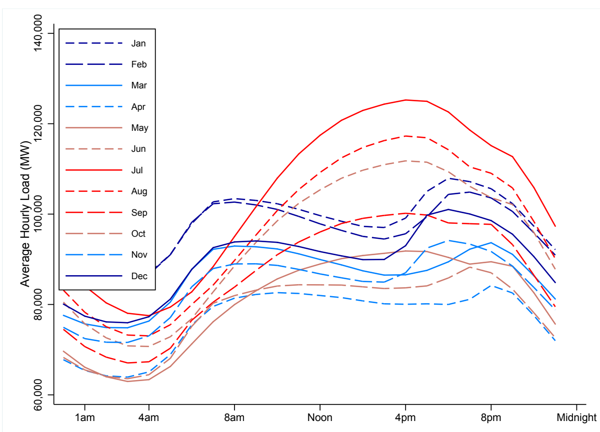
(a) California (CAISO)



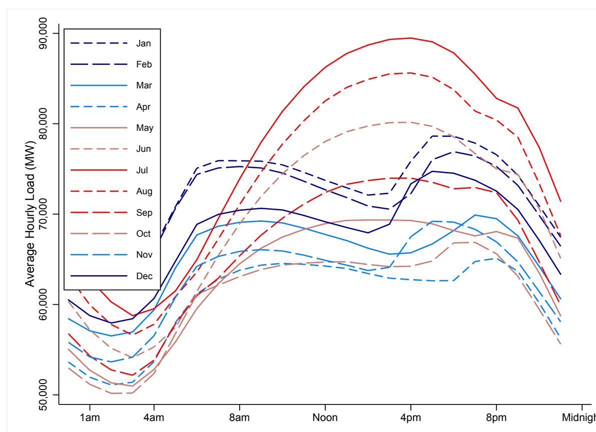
(b) Texas (ERCOT)



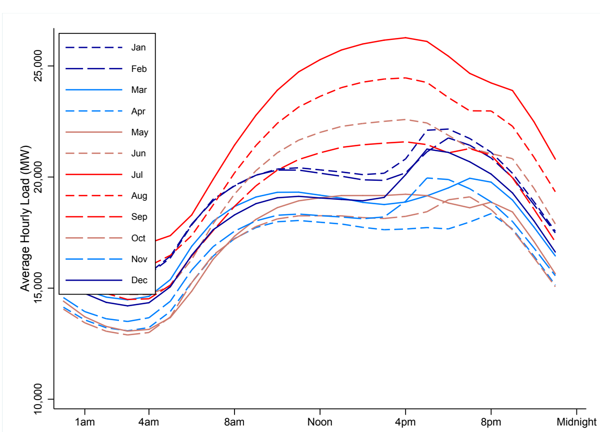
(c) Mid-Atlantic (PJM)



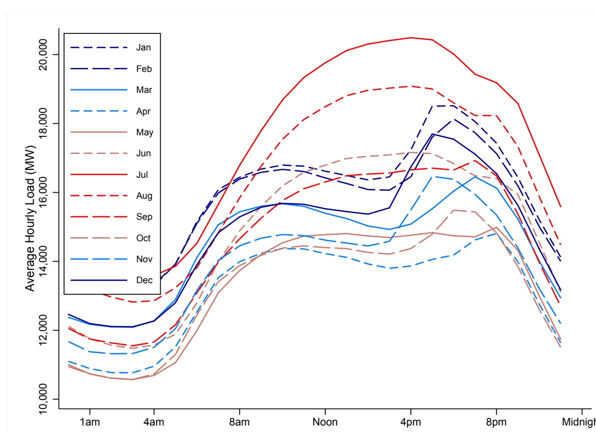
(d) Midwest (MISO)



(e) New York (NYISO)



(f) New England (ISONE)



B Additional Data Description

B.1 Program Data

The program data describe all 10,848 households who participated in the *Quality Installation Program* program between 2010 and 2015. These data were provided by Southern California Edison. We drop 968 duplicate participant records. These records have the exact same account number as other participant records, so are clear duplicates. We also drop an additional 291 households who 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. We further drop 2,431 households who participated before the start of 2012; we use electricity consumption data beginning in 2012, so these early participants would not contribute to our savings estimates. We also drop an additional 757 households who installed rooftop solar at any time during our sample period; rooftop solar dramatically changes household net electricity consumption (we only observe net consumption, not generation and consumption separately) so we drop these households to avoid biasing our savings estimates. In addition, we drop 60 households for whom we do not have a nine-digit zip code; a nine-digit zip code is required for merging with temperature data, and we cluster all standard errors at the nine-digit zip code. We successfully merged 94% of the participant records to the electricity consumption data, so we are left with a total of 5,973 participants in our analysis dataset. Appendix Figure 2 shows the pattern of participation between 2012 and 2015.

B.2 Electricity Consumption Data

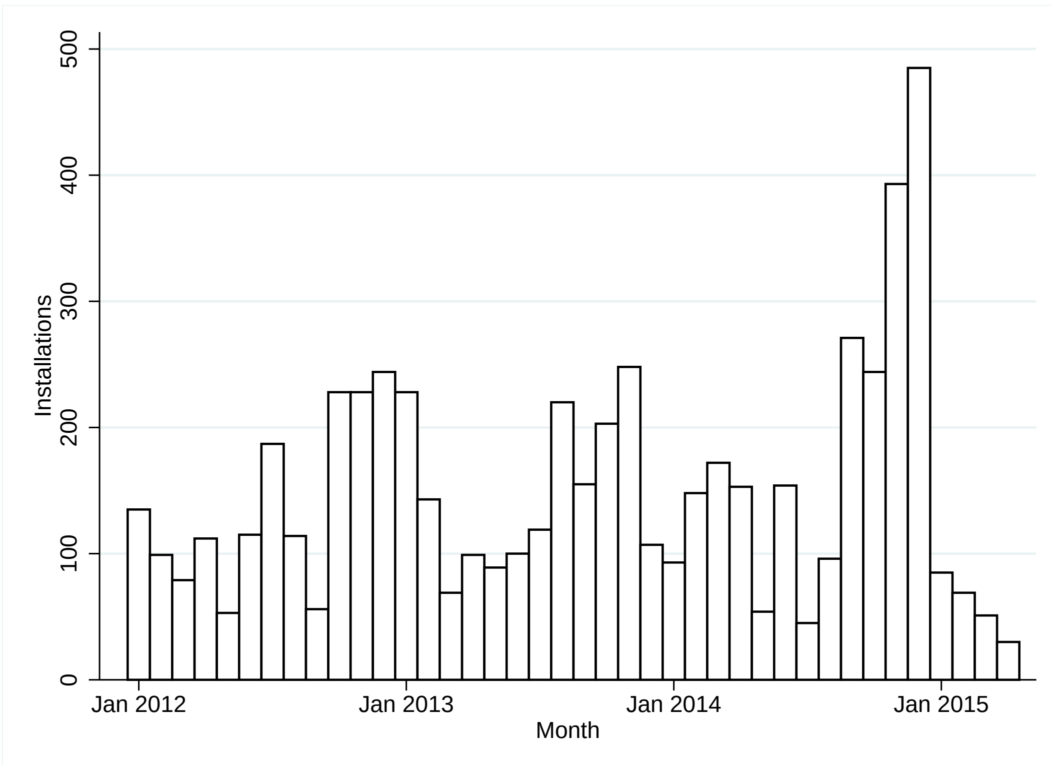
The electricity consumption data describe hourly electricity consumption for all program participants. We were provided with the complete history of hourly consumption for these households beginning when each household received a smart meter and continuing until August 2015, or, in some cases, somewhat before August 2015. Most Southern California Edison customers received a smart meter for the first time in either 2011 or 2012. Appendix Figure 3 shows the number of participants with smart meter billing data during each week of the sample.

B.3 Engineering-Based Savings Profiles

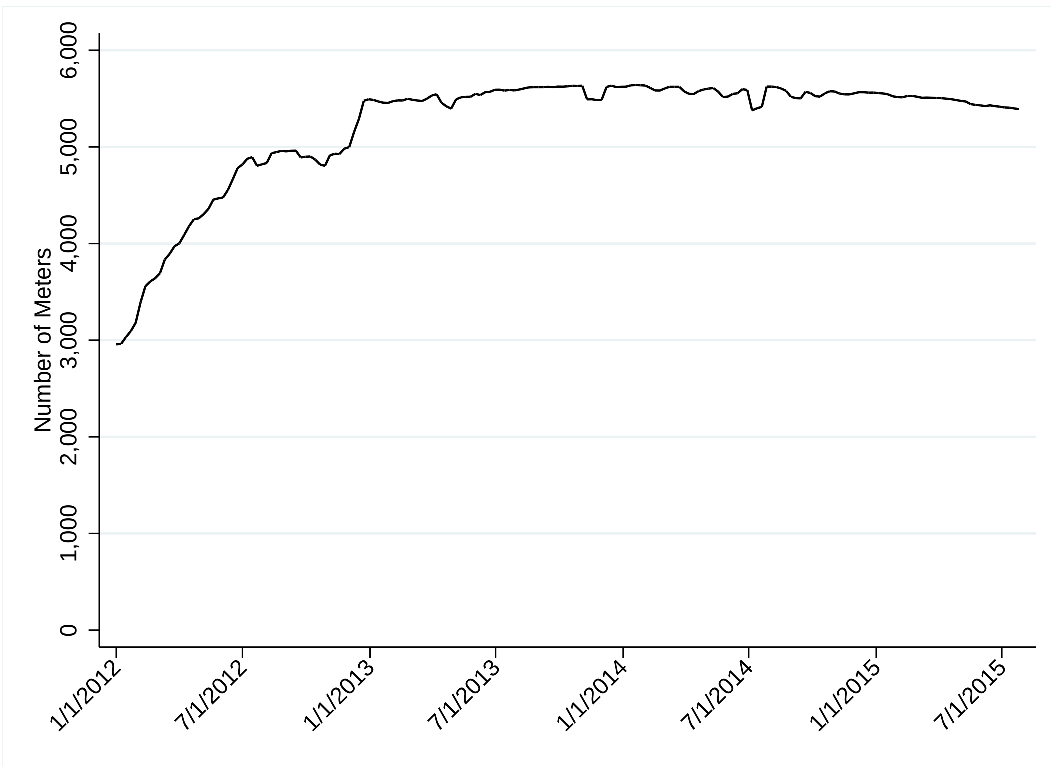
Appendix Figure 4 plots savings profiles for eight additional energy-efficiency investments. These figures are constructed in exactly the same way as Figure 7, and describe five residential investments and three commercial/industrial investments. As described in the paper, these engineering-based savings profiles come from the Database for Energy Efficient Resources (DEER), maintained by the California Public Utilities Commission. We use values developed in 2013/2014 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. We use these data 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. We do not make any adjustments to the DEER profiles in our main specifications. If we do impose a "shift" during Daylight Time, the estimated timing premiums for DEER investments change only slightly.

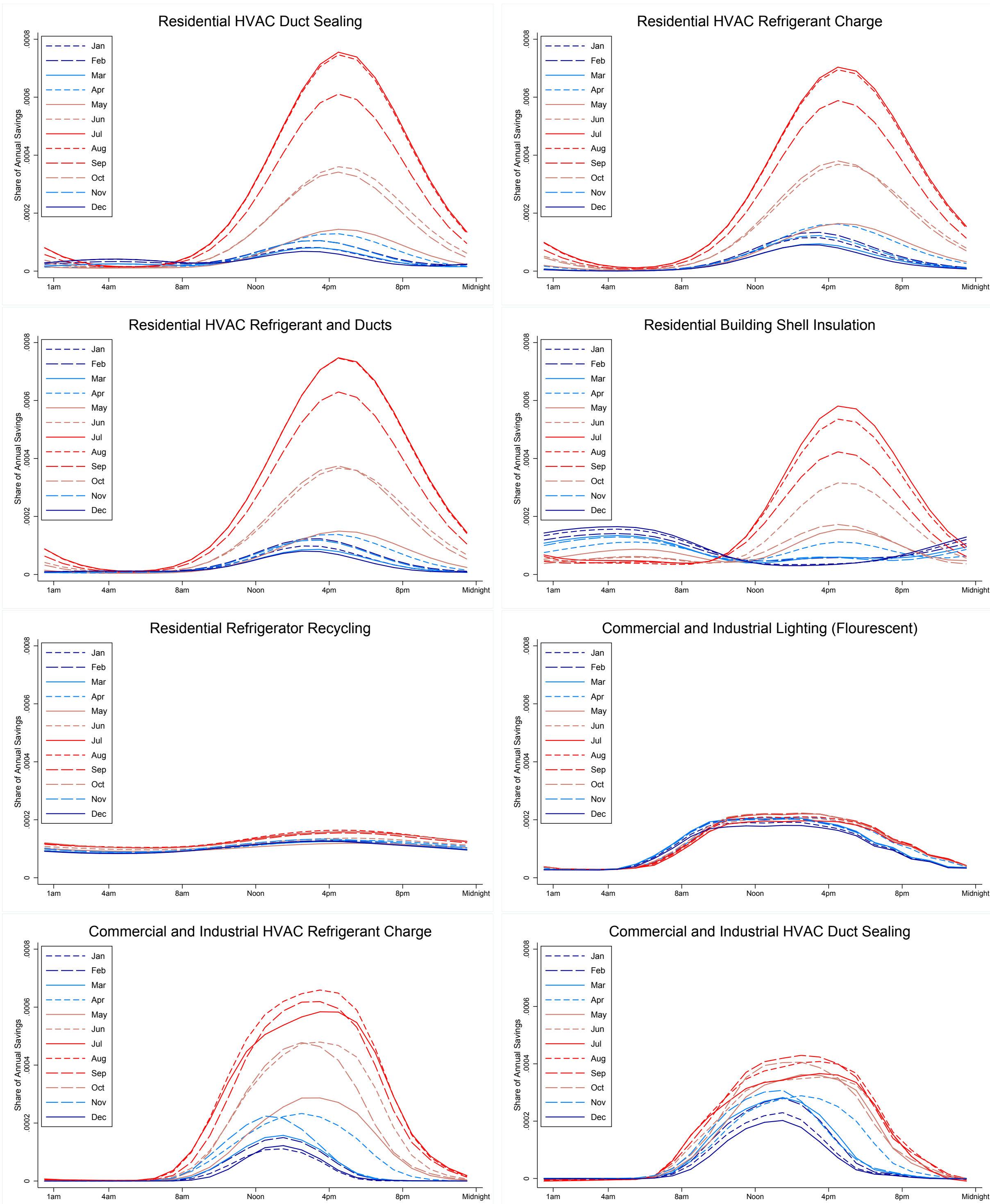
Appendix Figure 2: Histogram of Installation Dates



Appendix Figure 3: Number of Participants with Smart Meter Data



Appendix Figure 4: Savings Profiles for Additional Energy-Efficiency Investments



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 our 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 the paper 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.

Appendix Table 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. We were provided with data from a 5% random sample of Southern California Edison 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 we selected non-participants based on zip codes. In particular, for each participant, we 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 we excluded households with rooftop solar or a missing nine-digit zip code, just as we did for participants.

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.

We used these alternative samples to construct alternative estimates of several of our main results. Appendix Figure 5 plots event study estimates analogous to Figure 1 in the paper. Whereas the event study figure in the paper 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. These alternative event studies follow a very similar pattern to the event study figures in the paper. 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 the paper. Moreover, the pattern for winter is very similar to the event study figure in the paper, with no change when the new air conditioners are installed.

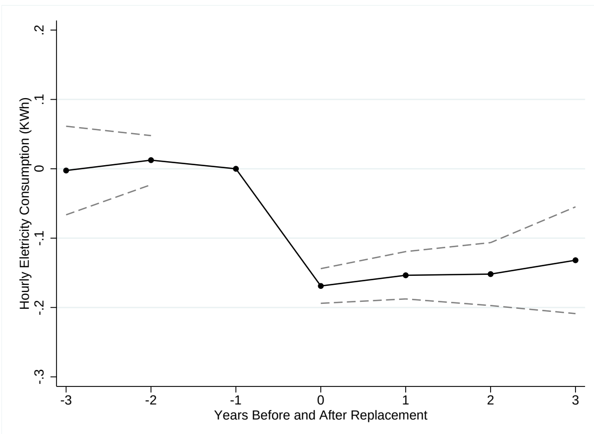
Next, Appendix Table 2 reports regression estimates of total energy savings from new air conditioner installation. This table is constructed in exactly the same way as Table 1, but estimated using data from both participants and non-participants. Including data from non-participants has little overall effect. The estimates are slightly larger, but the pattern across specifications is similar, increasing when dropping eight weeks pre-installation in Column (3).

Finally, Appendix Figure 6 plots estimates of energy savings by month-of-year and hour-of-day. These figures are constructed in exactly the same way as Figure 6, 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.

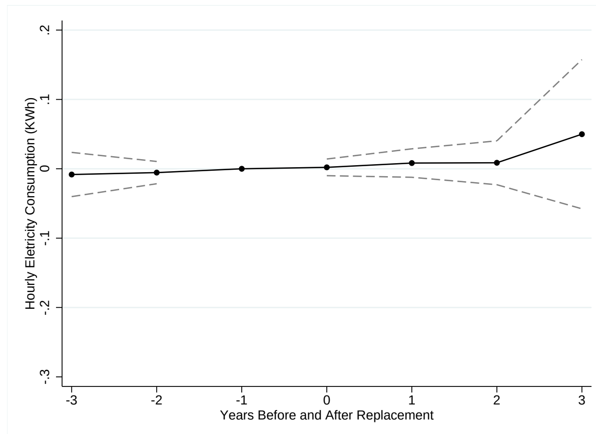
Appendix Figure 5: Event Study Figures, Alternative Specifications

Random Sample of Non-Participants

Summer

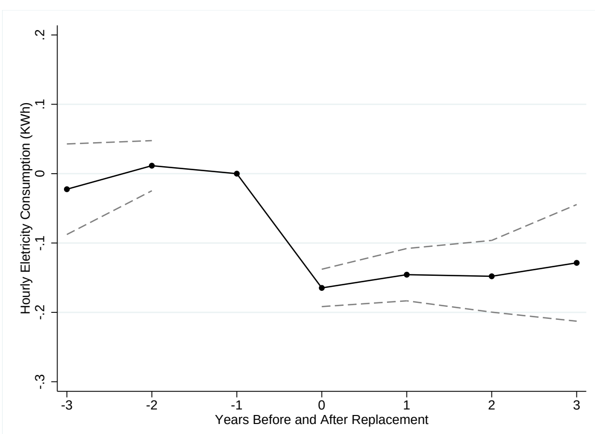


Winter

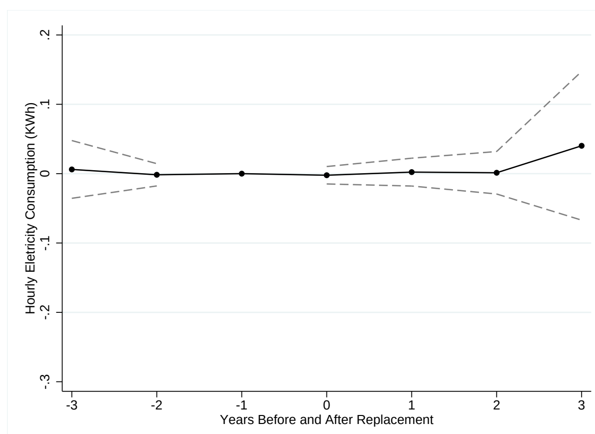


Matched Sample of Non-Participants

Summer

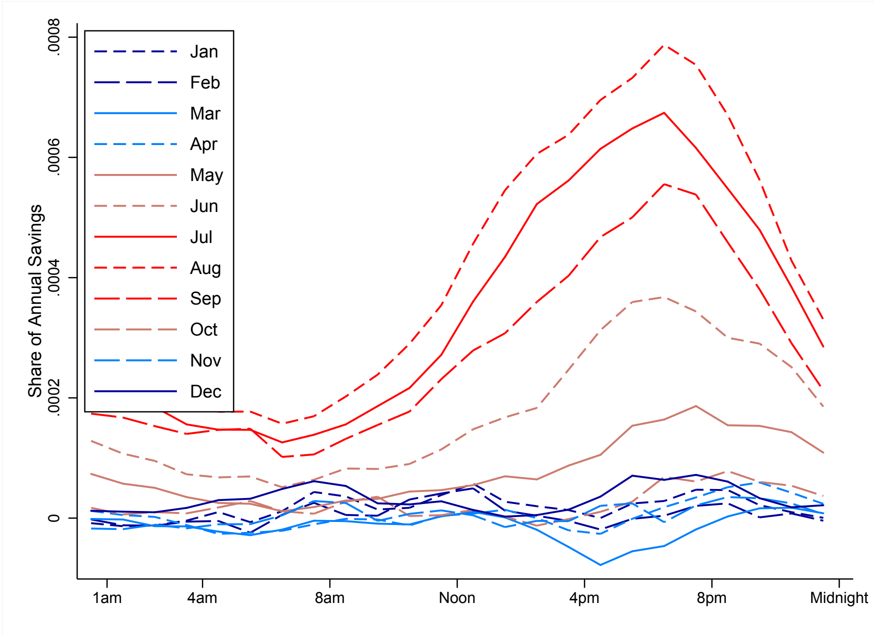


Winter

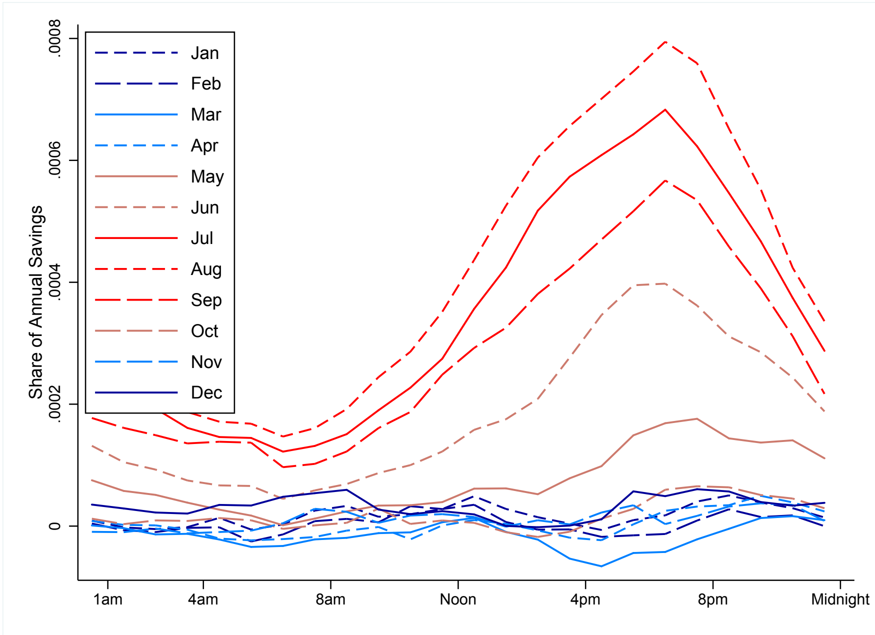


Appendix Figure 6: Econometric Estimates of Electricity Savings, Alternative Specifications

Random Sample of Non-Participants



Matched Sample of Non-Participants



Appendix Table 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.

Appendix Table 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 1 in the paper 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, we restrict these regressions to a 50% random sample of participating households along with an equal number of non-participating households.