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DO ENERGY EFFICIENCY INVESTMENTS DELIVER AT THE RIGHT TIME?

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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 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 so demand reductions are extremely valuable.

These features of electricity markets are well known, yet most analyses of energy-efficiency policies ignore this variation. When the U.S. Department of Energy (DOE) considers new 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 Energy Modeling System lack temporal granularity altogether and instead model energy demand

[1] For appliance energy standards, see Commercial Package Air Conditioning and Heating Equipment and Warm Air Furnaces (81 *FR* 2420, January 15, 2016); Ceiling Fan Light Kits (81 *FR* 580, January 6, 2016); Single Package Vertical Air Conditioners and Heat Pumps (80 *FR* 57438, September 23, 2015); Commercial Clothes Washers (79 *FR* 12302, March 3, 2014); Residential Clothes Dryers and Room Air Conditioners (76 *FR* 22454, April 21, 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 energy codes, see DOE, "Determination Regarding Energy Efficiency Improvements in the 2015 International Energy Conservation Code (IECC)", 80 *FR* 33250, June 11, 2015; and technical support documents cited therein. For commercial building energy codes, 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, September 26, 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; Massachusetts Energy Efficiency Advisory Council, "2013 Annual Report: Energy Efficiency Sets the Stage for Sustainable, Long-Term Savings", 2014; Northwest Power and Conservation Council, "2014 Achievements: Progress Toward the Sixth Plan's Regional Conservation Goals", November 2015; Consortium for Energy Efficiency, "2015 State of the Efficiency Program Industry", March 2016.

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 simply did not exist, since meters were only read once per billing cycle. This situation is rapidly changing. Today in the United States more than 40% of residential electricity customers have smart meters, up from less than 2% in 2007.[3]

In this 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. We use hourly smart-meter data to estimate the change in electricity consumption after installation of an energy-efficient air conditioner, and show that savings tend to occur disproportionately during July and August, and during the hours 3 p.m. to 9 p.m. With hourly data from 6,000+ participants, we are able to precisely characterize the savings profile both across seasons and hours of the day.

Our estimated time profile of energy savings is similar to *ex ante* engineering estimates, but there are several interesting differences. Most importantly, the econometric estimates indicate peak savings between 6 p.m. and 7 p.m., compared to between 4 p.m. and 5 p.m. in the engineering estimates. This seemingly small difference has important implications for electricity markets given growing concern about meeting electricity demand during the early evening hours as the sun sets and solar generation decreases (see, e.g., CAISO, 2013).

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 48% more valuable than under a naive calculation ignoring timing. As we demonstrate, including capacity payments is important in this calculation. Most of the value of electricity in ultra-peak hours is captured by forward capacity payments to generators to guarantee their availability.

Finally we compare air conditioning to a much larger set of energy-efficiency investments,

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

both residential and non-residential. Overall, there is a remarkably wide range of value across investments. Across six major U.S. markets, we find that air conditioning investments are on average 29% more valuable than under a naive calculation ignoring timing. For commercial and industrial heat pumps and chillers the "timing premiums" are 29% and 25%, respectively. Other investments like refrigerators and freezers have timing premiums below 5% because savings are only weakly correlated with value. Lighting also does surprisingly poorly, reflecting that savings occur disproportionately during evening and winter hours when electricity tends to be less valuable.

These findings have important policy implications. Energy-efficiency is a major focus of energy policy in the United States and other countries. 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 total electricity savings.[4] In addition, the U.S. Federal government has spent $12 billion since 2009 on income tax credits for residential energy-efficiency investments (Borenstein and Davis, 2015). Virtually all analyses of these programs have ignored the timing of energy savings.

The paper proceeds as follows. Section 2 provides background about electricity markets and energy-efficiency. Section 3 describes our empirical application, estimating framework, and savings estimates. Section 4 then examines the correlation between savings and the value of electricity, incorporating engineering-based estimated savings profiles from alternative energy-efficiency investments. Section 5 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.

[4] Tabulations by the authors based on data from U.S. Department of Energy, Energy Information Administration, "Electric Power Annual", 2012 (Tables 10.2 and 10.5) and 2015 (Tables 10.6 and 10.7). Expenditures are reported in year 2015 dollars.

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

The reality of electricity markets, even "deregulated" ones, is more complex. 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.[5] Regulators set minimum "reserve

[5]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.

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.[6] The equilibrium capacity price just covers the shortfall between expected energy market revenues and total cost for the marginal new power plant at the desired reserve margin. In the US, much of the price signal for new investment in electricity markets 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 hourly prices in the energy market.

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 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 stated benefits from most energy-efficiency policies come from reduced private energy costs (Gayer and Viscusi,

[6] For example, the California Public Utilities Commission adopts a forecast of peak demand for each month and requires utilities to enter into "resource adequacy" contracts to ensure that they can meet 115% of this demand. The payments in these contracts are very high in months when peak electricity demand is expected to be near total system capacity. As 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 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.

2013). For example, nine new standards promulgated by the DOE in 2016 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.[7] 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

Electricity is a widely-used input, both in manufacturing and 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 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, 2015). In this paper we extend that work to include the hourly shape of demand reductions.

The vast majority of existing economic analyses of energy efficiency have focused on total

[7] 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 individual rulemakings are Single Package Vertical Air Conditioners and Heat Pumps (80 *FR* 57438, September 23, 2015); Ceiling Fan Light Kits (81 *FR* 580, January 6, 2016); Refrigerated Beverage Vending Machines (81 *FR* 1028, January 8, 2016); Commercial Package Air Conditioning and Heating Equipment and Warm Air Furnaces (81 *FR* 2420, January 15, 2016); Residential Boilers (81 *FR* 2320, January 15, 2016); Commercial and Industrial General Pumps (81 *FR* 4368, January 26, 2016); Commercial Prerinse Spray Valves (81 *FR* 4748, January 27, 2016); Battery Chargers (81 *FR* 38266, June 16, 2016); and Dehumidifiers (81 *FR* 38338, June 31, 2016).

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)). An important exception is Novan and Smith (2016) which uses hourly data from a similar energy-efficiency program to illustrate important inefficiencies with current retail rate designs for electricity. 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 U.S. energy-efficiency standards saved households and firms $60 billion in 2014. The DOE performs additional economic analyses every time a new U.S. standard is implemented but again, the emphasis is on total energy savings without regard to when these savings 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, sales tax holidays, and, at the state level, utility-sponsored rebates and upstream manufacturer incentives. Most state utility commissions require these programs to be evaluated by third-party analysts. Although thousands of studies have been performed looking at subsidy programs, the vast majority focus on total energy savings (for example, see references cited in Footnote 2).[8]

There are exceptions. California requires that proposed utility-sponsored energy-efficiency programs be evaluated against engineering models of hourly electricity values before programs are implemented. California's Title 24 building efficiency standards also explicitly

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

consider time value. Some recent federal energy efficiency standards consider seasonal differences in savings values, but still ignore the enormous variation within seasons and across hours of the day.[9] In addition, while the vast majority of third-party analyses of energy-efficiency programs ignore the timing of savings, a notable 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 key features of 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.

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

The program is known as the *Quality Installation Program.* It provides incentives of up to $1,100 to households that install an energy-efficient central air conditioner. This program is an excellent empirical setting in which to examine the time-specific value of energy savings. Air conditioning is responsible for 10% of average residential electricity use and 15% of average commercial electricity use in California (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 projected to be one of the fastest growing uses of electricity worldwide (see, e.g., Davis and Gertler, 2015). This

[9] For example, the 2016 standards for Ceiling Fan Light Kits (81 *FR* 580, January 6, 2016).

large demand for air conditioning is concentrated in certain seasons of the year and hours of the day.

The *Quality Installation Program* is administered similarly to most energy-efficiency subsidy programs in the United States. As with other programs, the household claims the rebate through the mail after the new air conditioner is installed. And as with other programs, the state utility commission compensates SCE for running the program by allowing the utility to pass on costs to ratepayers in the form of higher electricity prices. The *Quality Installation Program* includes an additional focus on proper installation of the new subsidized central 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 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 incorporate data from non-participating households.

3.2 Event Study

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

Figure 1 describes the effect of new air conditioner installation on electricity consumption during the summer and winter, respectively. The horizontal axis is the time in years before and after installation, normalized so that the year of installation is equal to zero. The figure plots estimated coefficients and ninety-fifth percentile confidence intervals corresponding to event time indicator variables from the following regression,

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

The dependent variable y_{it} is average hourly electricity consumption for household i in year t and τ denotes the event year defined so that $\tau = 0$ is the exact year in which the new air conditioner was installed, $\tau = -3$ for three years before, $\tau = 3$ for three years after, and so on. We do not include an indicator variable for the year before installation ($\tau = -1$), so the other coefficients are measured relative to that year. We include year by climate zone fixed effects, ω_{ct}, to remove the effect of annual changes in average electricity consumption in each climate zone due to weather and other time-varying factors.

For summer, we estimate this regression using July and August data from 2012 to 2015 collapsed to the year-by-household level. The sample includes households who installed new air conditioners between January 2012 and April 2015. We drop data from installations that occurred during August, September, and October to ensure that participants did not have new air conditioners during the zero-year summer. This exclusion is for the event study figure only and these installations are included in all subsequent analyses.

The event study figure for summer shows a sharp decrease in electricity consumption in the year in which the new air conditioner is installed. The magnitude of the decrease is about 0.2 kilowatt hours per hour. A typical LED lightbulb uses about 10 watts, so this decrease is equivalent to shutting off 20 LEDs. Electricity consumption is otherwise approximately flat, both during the four years before and during the four years after.

The event study figure for winter was constructed in exactly the same way but using data from January and February, and excluding data from installations that occurred during February, March, or April. As expected, winter consumption is essentially unchanged after the new air conditioner is installed. This is reassuring because it suggests that the sharp drop in electricity consumption during summer is indeed due to the new air conditioner and not some other unrelated change in household appliances or behavior.[10]

These event study figures and estimates in later sections measure the electricity savings from a new air conditioner installation. This is different, however, from the causal effect of the rebate program. Many participants in energy-efficiency programs are inframarginal, getting paid to do what they would have done otherwise (Joskow and Marron, 1992). Measuring the causal impact also requires figuring out how the program changed the *type*

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

of appliances that were purchased. In the extreme case in which all participants are inframarginal, a program may have no causal impact whatsoever, even while the savings from an investment are large. Recent studies have used regression discontinuity and other quasi-experimental techniques to attempt to tease out these causal effects and perform cost-benefit analysis (Boomhower and Davis, 2014; Houde and Aldy, Forthcoming).

3.3 Impacts by Local Temperature

As another validity test, we next examine the relationship between energy savings and daily outdoor 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 take-up might coincide with a home remodel or the arrival of 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 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.

We use daily mean temperature data at the four kilometer grid cell level from the PRISM Climate Group (PRISM Climate Group, 2016). Figure 2 plots estimated electricity savings against daily mean temperature for each household's nine-digit zip code. 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.

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 following air conditioner replacement. This may be explained by improvements to ductwork, insulation, thermostats, or other HVAC-related upgrades that could in some cases occur as part of a central air conditioner replacement.

3.4 Hourly Impacts by Season

Figure 3 plots estimated electricity savings by hour-of-day. We plot separate estimates for summer and non-summer months. The coefficients and standard errors for this figure are estimated using 48 separate least squares regressions. Each regression includes electricity consumption for a single hour-of-the-day and either summer- or non-summer months. For example, for the top left coefficient the dependent variable is average electricity consumption between midnight and 1 a.m. during non-summer months. All regressions are estimated at the household-by-week level and control for week-of-sample 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.

3.5 Regression Estimates

Finally, we turn to a regression framework for characterizing the distribution of energy savings across hours of the day and months of the year. Our regression equation can be described as follows,

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

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

All specifications include household by hour-of-day by month-of-year fixed effects, γ_{ihm}. That is, for each household we include 288 separate fixed effects that allow for differing household-level average consumption over the day and across the year. This allows for rich heterogeneity across households in typical seasonal electricity usage.

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

Table 1 reports estimates from three different specifications. For each specification we report average annual energy savings per household in kilowatt hours per year. Standard errors are clustered to allow for arbitrary error correlations at the nine-digit zip code level.

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 the 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 the 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 this is a 4.5% decrease in household consumption. 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, but slightly less than, 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.[11]

For computational reasons, we estimate all of these regressions using weekly average consumption at the household by hour-of-day level. Estimation with the hourly microdata is computationally demanding and does not yield different estimates. Using hourly microdata, household by month-of-year by hour-of-day fixed effects, hour-of-sample by climate zone fixed effects, and the sample exclusions in Column (3), the estimate of annual program savings is 442 kilowatt hours per year.

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 showing data on wholesale energy 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). With this proof of concept completed, we then turn to engineering estimates from a broader set of energy-efficiency investments. We show that the time profile differs significantly between investments (Section 4.4) and that these different profiles imply large differences in value (Section 4.5).

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-

[11] Typical central 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 3-ton 13 SEER unit with 3-ton 15 SEER without programmable thermostat before or after.

and high-demand months but adjacent months look similar. For each market we report average prices by hour-of-day for 2011 through 2015. The energy and capacity price data that we use come from SNL Financial and are described in the online appendix. We include ERCOT as a benchmark for our California capacity value estimates; because 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 higher energy market prices than California during peak hours.

In California, generation capacity is procured at the monthly level (that is, capacity contracts obligate generators to be available every hour of one month). In order to value energy savings in a given hour, we need to allocate these monthly capacity prices across individual hours. We do this in several different ways and report the results of each. In the first approach, we use hourly load data to calculate the hour-of-the-day with the highest average load each month. We then assign the capacity contract price for that month entirely to that hour-of-the-day. This means dividing the monthly contract price by the number of days in the month, and assigning the resulting amount to the peak hour. 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 prices 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 \$200 and \$600 per megawatt hour. And, overall, the pattern is very similar across the four approaches for allocating capacity value across hours. As expected, allocating the entire capacity value to the single highest-load hour results in the highest peak, though the other approaches have similar shapes. In addition, the general shape of the capacity-inclusive hourly values for California matches the shape in Texas, providing some reassurance that our allocation strategy recovers the price shape that would exist in an energy-only market.[12] The value of electricity in Texas surges in August to $200+ 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. This would address the concern that capacity markets may not be in long-run equilibrium, and thus may not reflect the true long-run cost of capacity. Some market participants have argued, for example, that the recent influx of renewables into U.S. electricity markets has pushed capacity market prices down below long-run equilibrium levels. If this is the case then over time entry and exit decisions should lead to increased capacity prices and it would be straightforward to repeat our calculations with updated data. Larger capacity prices would lead to larger variation in economic value between off-peak and peak, thus strengthening 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 4.4% during off-peak periods to 8.4% 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

[12] We return to this point later, when we show that valuing energy savings using the Texas price shape yields similar results to our approach using California energy and capacity prices.

corresponds to an hour-of-day by month-of-year pair (for example, 1:00–2:00 p.m. during November). The vertical axes show average hourly energy savings. These are the 288 β coefficients from estimating Equation 2. In Panel A, the horizontal axis shows average wholesale energy prices from California for 2010–2014. In Panel B, the horizontal axis shows energy and capacity values, using the probabilistic allocation method for capacity prices described in Section 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 blue markers to indicate April through September, and the number of intervals with energy prices above $40 per MWh is clearly higher during these summer months. Second, this energy-efficiency investment delivers 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 for April–September (in red) and October–March (in yellow). The fitted line for summer slopes steeply upward. In the top panel, predicted savings when energy prices are $55/MWh are twice as large as predicted savings at $35/MWh. The fitted line for winter, however, is essentially flat. This energy-efficiency investment delivers essentially zero electricity savings in all hours during the winter, so there is little correlation between savings and prices.

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

4.3 Quantifying the Value of Energy Savings

Table 2 quantifies the value of the energy savings from this investment. We report estimates using five alternative approaches for valuing electricity. In column (1) we ignore capacity values and use wholesale energy prices only. For each hour-of-day and month-of-year pair, we multiply our estimate of electricity savings in that period by the average wholesale price in the California market in that period. Summing up these hourly values across all days of the year gives the annual value of electricity savings. Dividing total annual value by total annual savings gives the average value of each megawatt hour saved, which is what we report in Row (A) of the table. Under this calculation that accounts for timing, the average value of savings is \$45 per megawatt hour. This is 17% higher than the naive value estimate using average annual prices and ignoring timing, as in Row (B).

In columns (2) through (5) we incorporate capacity values. Each column takes a different approach to allocating monthly capacity payments across hours of the day, as described in Section 4.1 and shown graphically in Figure 4. Incorporating capacity values significantly increases the value of air conditioning investments to \$68 per megawatt hour. This reflects the positive correlation between electricity savings and peak hours. 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 greatly understates these capacity benefits. The naive estimate in Row (B) increases only modestly from \$39 per megawatt hour to \$46 per megawatt hour after including capacity value. This reflects the fact that most hours have zero capacity value, so while a few peak hours have capacity values well above \$100 per megawatt-hour the average across the year is only about \$6.50 per megawatt hour.

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.[13]

[13] Results are also similar using alternative specifications that: 1) distinguish between weekdays and weekends/holidays, or 2) compare to load-weighted average prices. In the first of these, we account for weekends (including holidays) by estimating twice as many coefficients (576), one for each hour-of-day, month-of-year, and weekend or weekday combination. Savings are then valued using weekend- and weekday-specific hourly wholesale prices. Capacity values are assigned to weekdays only, consistent with the significantly higher level of net system load. This more complicated specification yields quite similar results, with a timing premium of 46% compared to 48% in the baseline specification. In the second of these, we compare our main estimates to load-weighted average prices instead of simple average prices. The load weights are calculated using hourly CAISO load from SNL. The timing premium relative to load-weighted average prices is 39%.

4.3.1 How Might These Values Change in the Future?

Air conditioners are long-lived investments, so it is also worth considering how the associated timing premiums could change in the future. Environmental policies that favor renewable energy technologies 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. These 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 (CAISO, 2013). The expected steep increase in net load during future evening periods has prompted concern among grid managers and policymakers.

To examine how this altered price shape could affect the value of energy efficiency, we performed a sensitivity analysis using forecast prices and load profiles for California in 2024 from Denholm et al. (2015).[14] 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 48% to 74%. Air conditioning efficiency improvements are even more valuable in this future scenario because increased solar penetration shifts peak prices further into the late afternoon and early evening, when energy savings are largest.

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 predicted future prices can be incorporated into this framework for evaluating potential impacts.

4.4 Savings Profiles for Selected Investments

We next bring in engineering estimates of hourly savings profiles for air conditioning and a wide variety of other energy-efficiency investments. We compare the engineering estimates

[14] 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.

for air conditioning to our econometric estimates. Then we use the engineering estimates for other investments to explore more broadly the question of whether energy efficiency delivers at the right time. The engineering estimates 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).[15] These are *ex ante* estimates of energy savings, constructed using weather data and engineering information on the technological characteristics of the different technologies.

Figure 6 compares our econometric estimates with engineering estimates 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-based savings estimates peak between 4 p.m. and 5 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 estimates show savings quickly tapering off at night during the summer, reaching zero at midnight. It could be that the engineering estimates are insufficiently accounting for the thermal mass of California homes and how long it takes them to cool off after a warm summer day. The econometric estimates also show greater concentration of savings during the warmest months. Both sets of estimates indicate July and August as the two most important months for energy savings. But the engineering estimates indicate a significant share of savings in all five summer months, and a non-negligible share of savings during winter months. In contrast, the econometric estimates show that almost all of the savings occur June through September with only modest savings in October and essentially zero savings in other months.

[15]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.

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, 2015) or for other frequently-subsidized technologies such as 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 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 estimates assume both summer and winter peaks.

4.5 Comparing the Value of Alternative Investments

Finally, we calculate 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 ignores timing. 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.

Table 3 compares investments and markets. Each column is a different U.S. market. Each row is a different energy-efficiency investment. The first row uses our econometric estimates, and all other rows use the engineering savings profiles described in Section 4.4. We present estimates for California (CAISO), Texas (ERCOT), the Mid-Atlantic (PJM), the Midwest (MISO), New York (NYISO), and New England (NE-ISO). See the appendix for details on prices in these additional markets. 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 (ERCOT has no capacity market).

Air conditioning investments in California and Texas have the highest timing premiums. This is true regardless of whether the econometric or engineering estimates are used, and reflects the relatively high value of electricity in these markets during summer afternoons and evenings. In other U.S. markets air conditioning has a timing premium greater than zero, but nowhere else is the value as high as in California and Texas (states that between them represent 21% of total U.S. population).

Other investments also have large timing premiums. Commercial and industrial heating and cooling investments, for example, all return premiums of about 25%, reflecting the relatively high value of electricity during the day. This is particularly true in CAISO and ERCOT (30+%).

The timing premiums of other investments, like refrigerators and freezers, are much lower. The savings from these investments are only weakly correlated with system load. Lighting, as well, does surprisingly poorly as the savings occur somewhat after the system peak in all U.S. markets and disproportionately during the winter, when electricity tends to be less valuable. This could change in the future as increased solar generation moves net system peaks later in the evening, but for the moment both residential and non-residential lighting have timing premiums of about 10% or below in all markets. There are no investments with negative timing premiums, reflecting the fact that all of these investments are at least weakly positively correlated with demand (no investment disproportionately saves energy in the middle of the night, for example).

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 estimates. In addition, although we have incorporated capacity payments similarly 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) that timing premiums vary widely across investments and that, (2) these broad patterns are likely to be similar across U.S. markets.

5 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 found 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 50%. 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.

We then broadened the analysis to incorporate a wide range of different energy-efficiency investments. For every single investment which we consider, the energy savings are at least weakly positively correlated with energy value. Thus, ignoring timing understates the value of all energy-efficiency investments, though to widely varying degrees. Residential air conditioning has an average timing premium of 29% across markets. Commercial and industrial heat pumps, chillers, and air conditioners have 25-30% average premiums. Lighting, in contrast, does considerably worse with a 8-10% average premium, reflecting that these investments save electricity mostly during the winter and at night, when electricity tends to be less valuable. Finally, refrigerators and freezers have average premiums below 5%, as would be expected for an investment that saves approximately the same amount of electricity at all hours of the day.

These results have immediate policy relevance. For example, energy-efficiency programs around the world have tended to place a large emphasis on lighting.[16] 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. Rebalancing policy portfolios toward different investments could increase the total value of savings. We find a remarkably wide range of timing premiums across investments so our results suggest 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 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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[16]For example, in California, 81% of estimated savings from residential energy efficiency programs come from lighting. Indoor lighting accounted for 2.2 million kilowatt-hours of residential net energy savings during 2010–2012. Total residential net savings were 2.7 million kilowatt-hours. California Public Utilities Commission 2015. "2010–2012 Energy Efficiency Annual Progress Evaluation Report."

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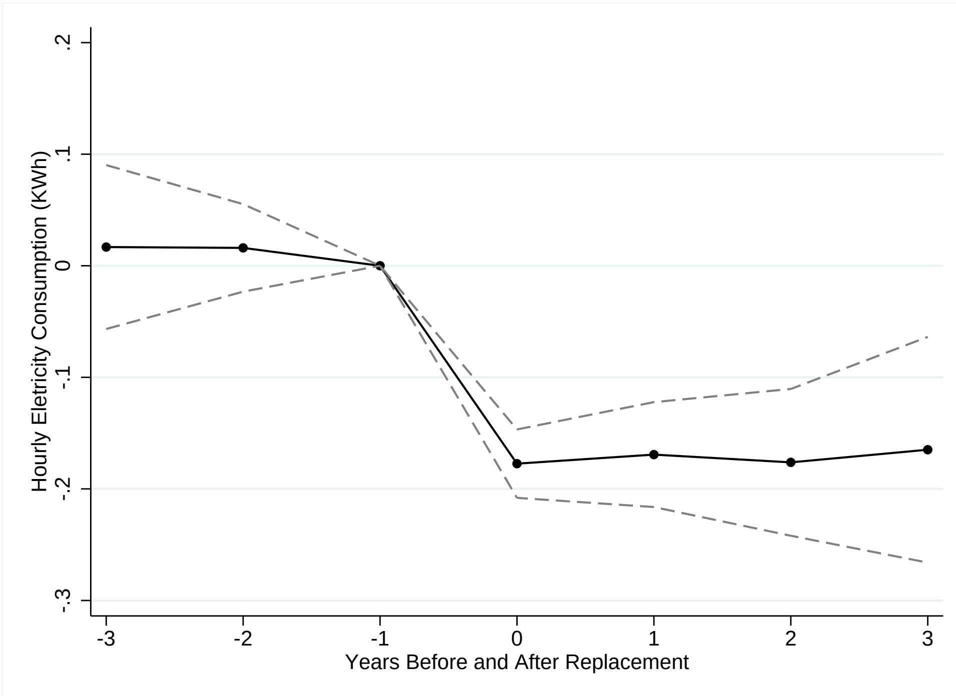
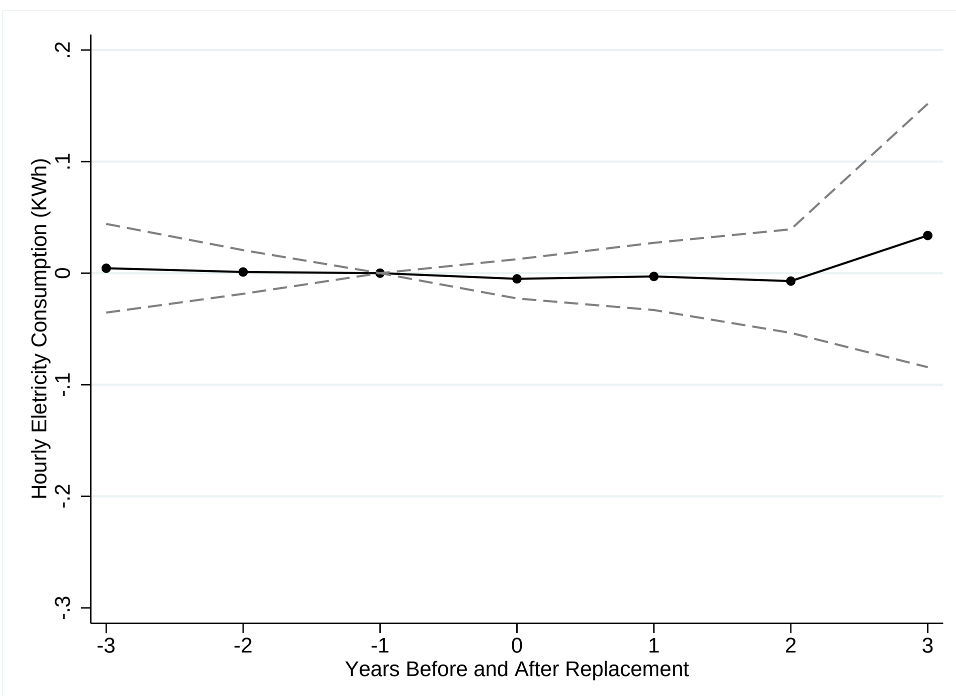
Figure 1: The Effect of New Air Conditioner Installation on Electricity Consumption

Summer

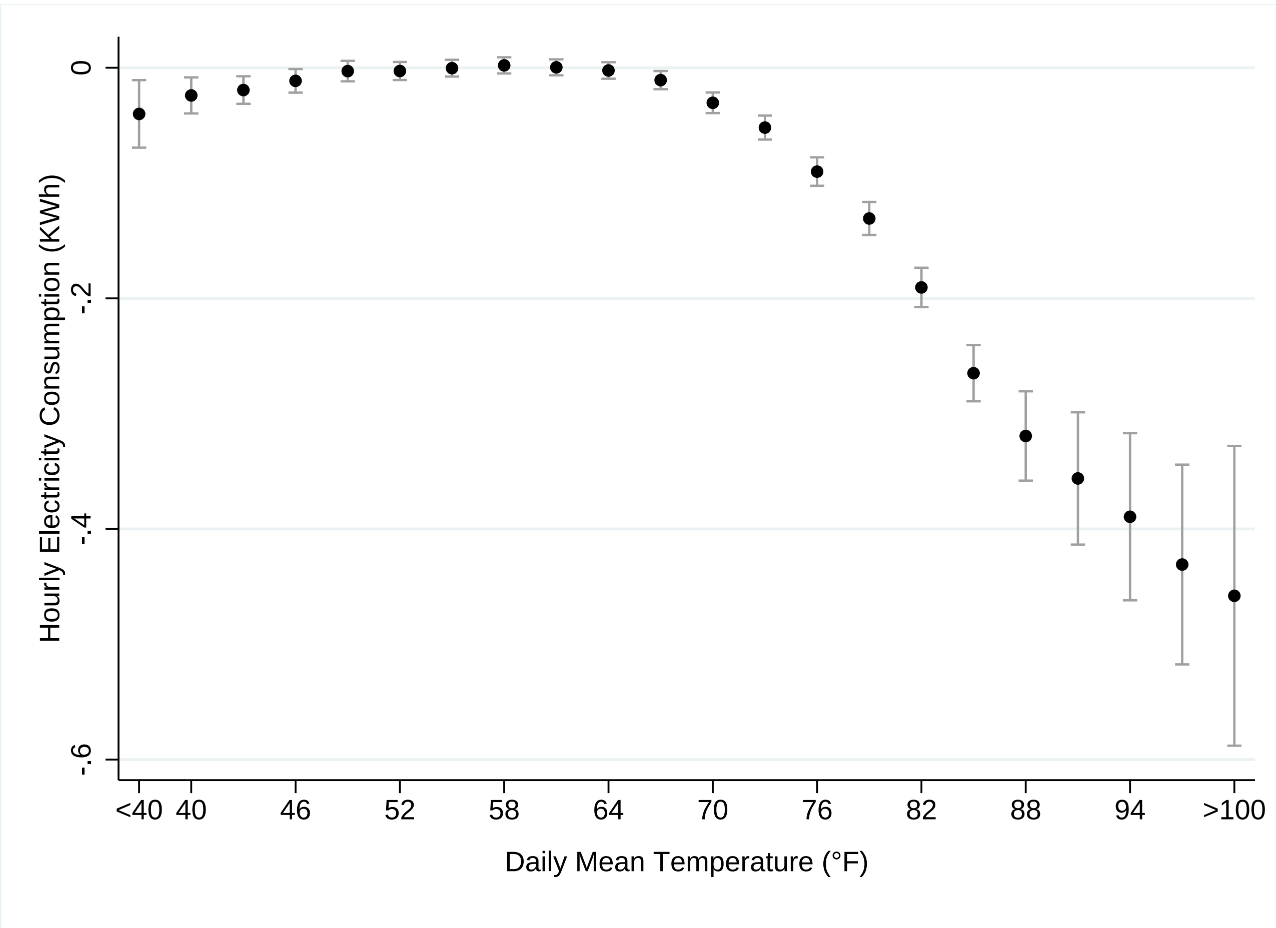


Winter



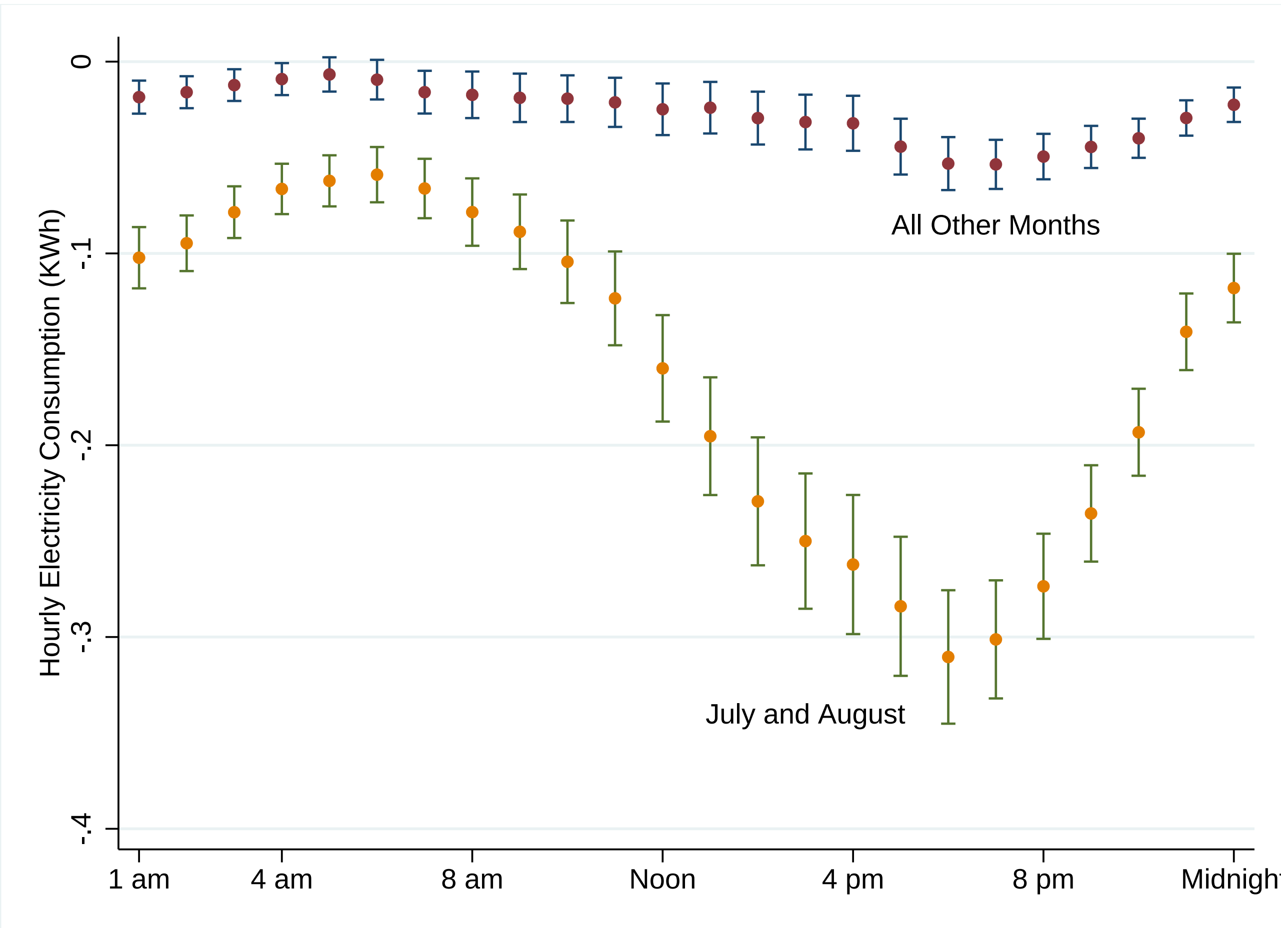
Notes: These event study figures plot estimated coefficients and ninety-fifth percentile confidence intervals describing average hourly electricity consumption during July and August and January and February, respectively, before and after a new energy-efficient air conditioner is installed. Time is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

Figure 2: Electricity Savings by Temperature



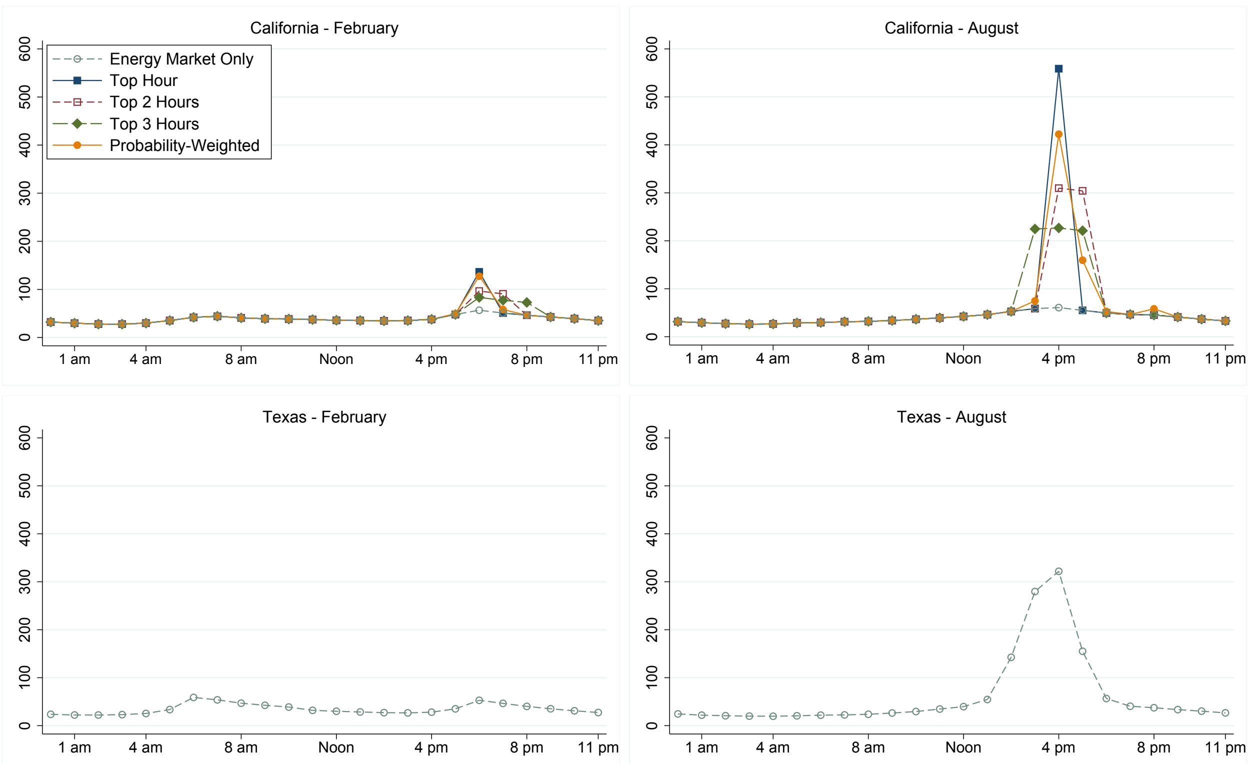
Notes: This figure plots regression coefficients and ninety-fifth percentile confidence intervals from a single least squares regression. The dependent variable is average electricity consumption at the household by day-of-sample level. Coefficients correspond to 22 indicator variables for daily mean 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 fixed effects and day-of-sample by climate zone fixed effects. Temperature data come from PRISM, as described in the text. Standard errors are clustered at the nine digit zip code level.

Figure 3: Electricity Savings by Hour-of-Day



Notes: This figure plots estimated coefficients and ninety-fifth percentile confidence intervals from 48 separate least squares regressions. For each regression, the dependent variable is average electricity consumption during the hour-of-the-day indicated along the horizontal axis. All regressions are estimated with household-by-week observations and control for week-of-sample by climate zone and household by month-of-year fixed effects. The sample for all regressions 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.

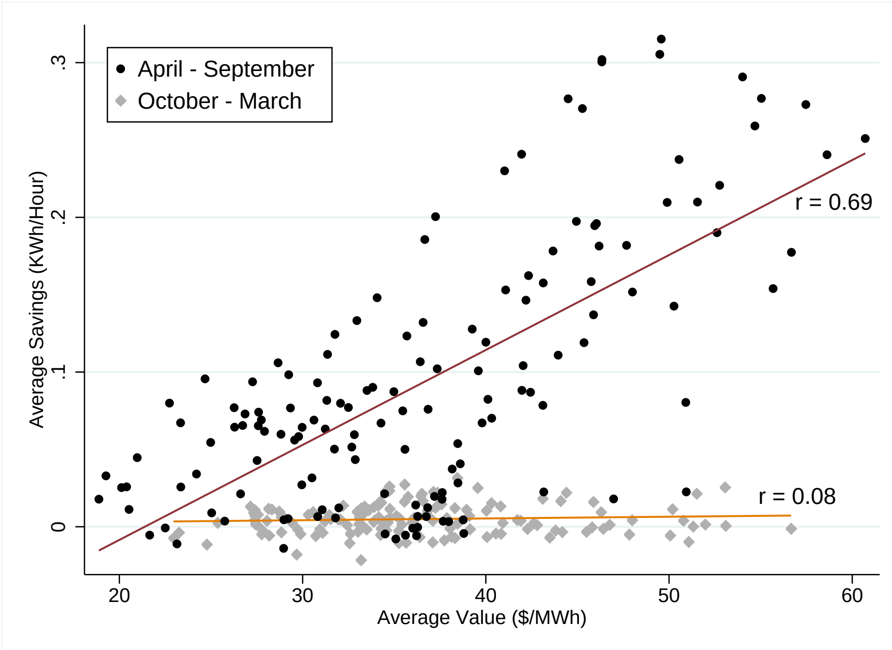
Figure 4: Wholesale Electricity Prices and Capacity Values



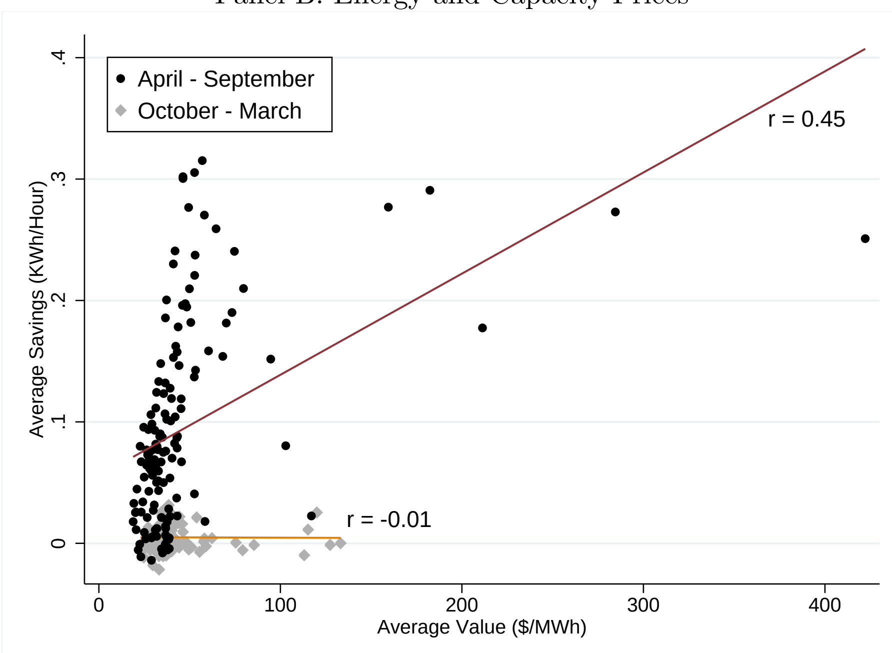
Notes: This figure shows the average hourly value of electricity in February and August in California and Texas, under various assumptions about capacity value in California. The vertical axis units in each figure are dollars per megawatt-hour. The hour labels on the horizontal axis refer to the beginning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

Figure 5: Correlation Between Savings and Prices, By Season

Panel A. Energy Prices Only



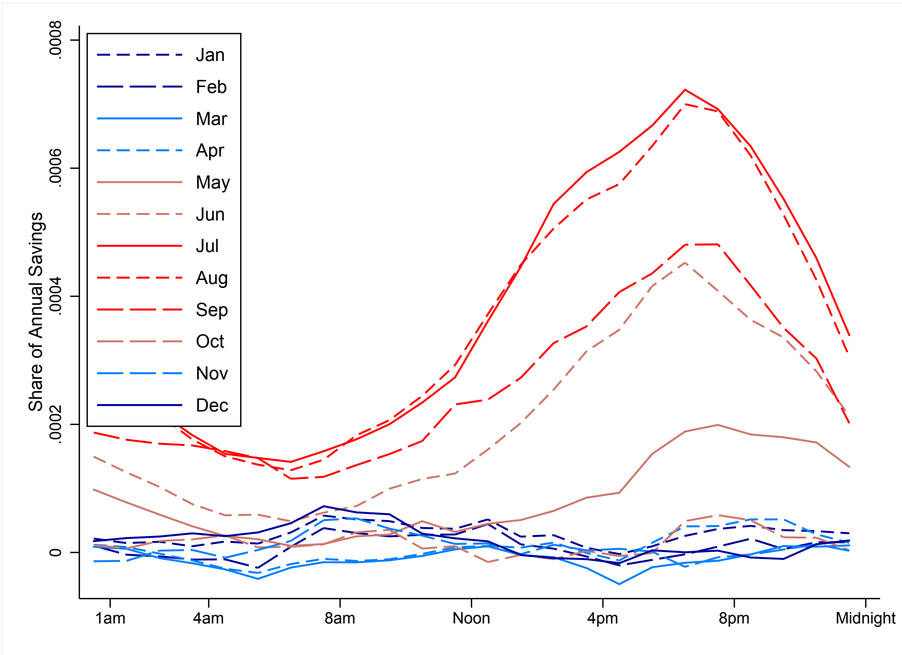
Panel B. Energy and Capacity Prices



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 Estimates

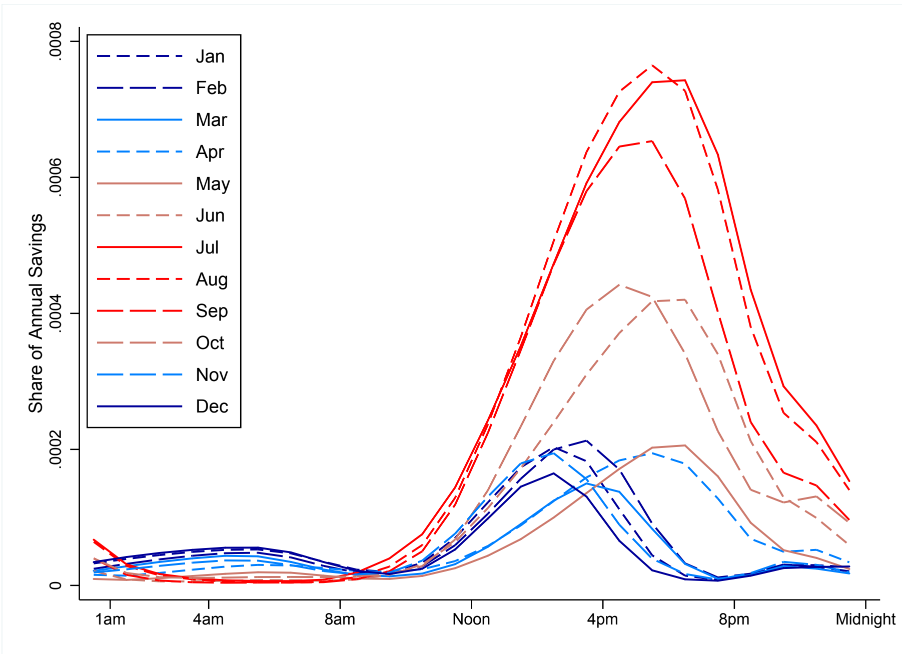


Figure 7: Savings Profiles for Selected Energy-Efficiency Investments

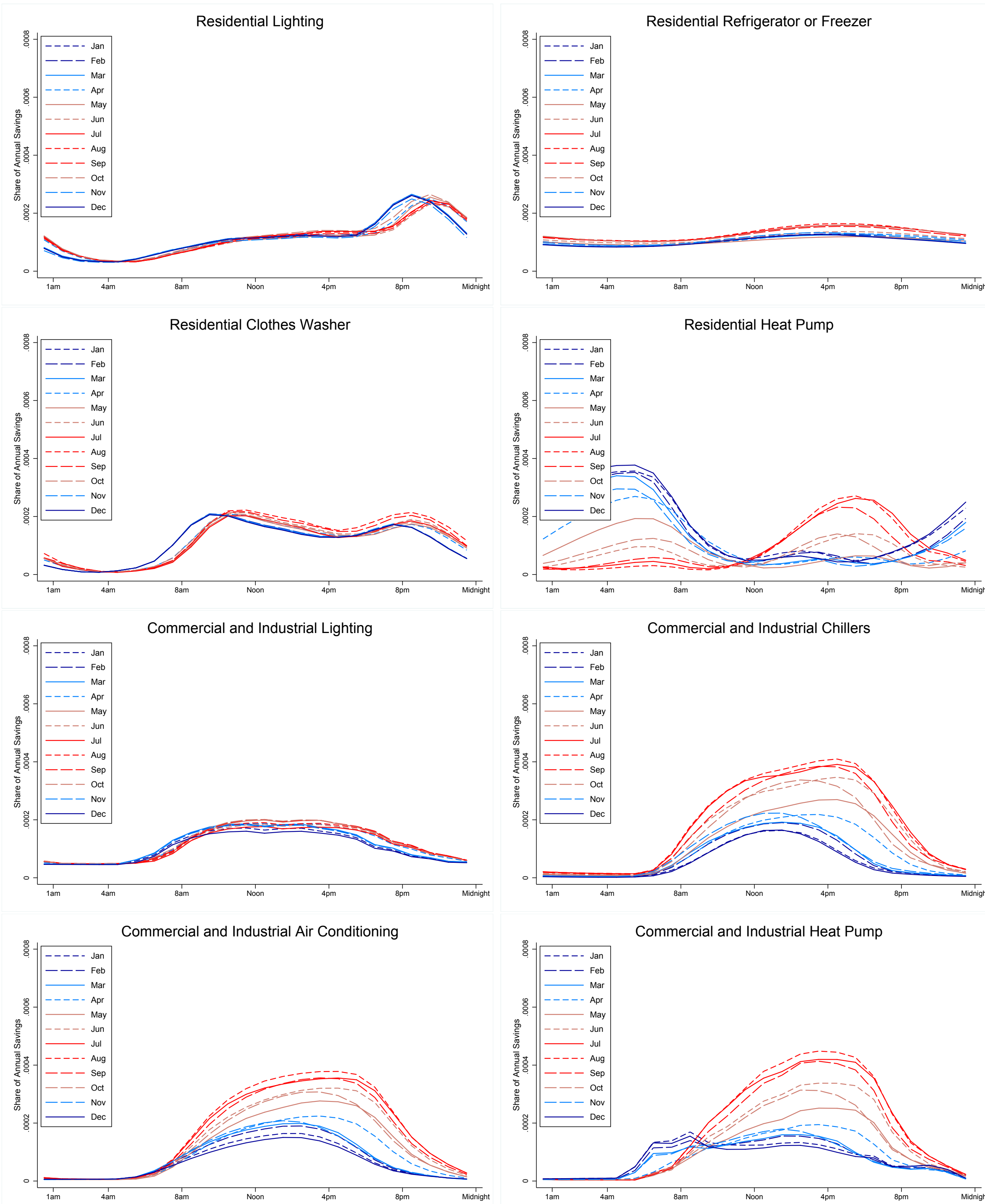


Table 1: Average Energy Savings from a New Central Air Conditioner

	(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 average energy savings is calculated as the weighted sum of these 288 estimates. 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 4% of Hours	Capacity Value in Top 8% of Hours	Capacity Value in Top 12% of Hours	Capacity Value Allocated Probabilistically
	(1)	(2)	(3)	(4)	(5)
Average Value of Savings ($/MWh)					
(A) Accounting for Timing	$45.20	$67.66	$68.26	$67.80	$68.05
(B) Not Accounting for Timing	$38.71	$45.76	$45.75	$45.75	$45.75
Timing Premium ($\frac{A-B}{B}$)	17%	48%	49%	48%	49%

Notes: These calculations were made using estimated energy savings for each hour-of-day by month-of-year from the full regression specification as in Column (3) in Table 1. Energy prices are wholesale electricity prices from the California electricity market (CAISO-SP15-Day Ahead Market) between January 2011 and December 2015. Capacity prices are based on Resource Adequacy contract prices reported in California Public Utilities Commission, "2013–2014 Resource Adequacy Report". In Columns (2), (3), and (4), monthly capacity prices are allocated evenly across the one, two, and three (respectively) hours of the day with the highest average load each month. In Column (5), monthly capacity prices are allocated to hours of the day based on their historical probability of containing the monthly peak load event. Hourly load data are from SNL Financial.

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)	48%	54%	30%	21%	11%	9%	29%
Air Conditioning	64%	69%	33%	25%	26%	18%	39%
Lighting	12%	7%	7%	5%	9%	8%	8%
Clothes Washers	10%	14%	13%	13%	14%	13%	13%
Refrigerator or Freezer	7%	7%	3%	3%	3%	2%	4%
Heat Pump	6%	10%	4%	0%	3%	5%	5%
			B. Commercial and Industrial				
Heat Pump	38%	47%	27%	23%	23%	16%	29%
Chillers	34%	41%	23%	21%	18%	11%	25%
Air Conditioners	32%	39%	23%	21%	20%	13%	25%
Lighting	11%	13%	10%	9%	10%	8%	10%

Notes: This table reports the estimated timing premiums for nine energy efficiency investments. As in the final row of Table 2, the statistics in each cell of this table represent the additional value (in percentage terms) compared to an investment with a completely flat savings profile. Except for the first row (econometric estimates for air conditioning), all estimates are based on engineering estimates of savings profiles 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 price data are day-ahead prices from SNL Financial and are for 2011–2015. For California, we use CAISO market at the SP-15 node. For New England, we use ISO-NE real-time prices at the H Internal hub. For Texas, we use ERCOT real-time prices at the HB North hub. For New York, we use NYISO real-time prices at the J Hub. For PJM, we use prices at the Western hub. For MISO, we use 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 for each electricity market 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 hourly 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 exact sources and calculations.

A.2.1 California (CAISO)

There is no capacity auction in CAISO, but the California Public Utilities Commission (CPUC) surveys utilities to track bilateral 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. However, most of the reported transactions are for 2013–2015 (page 29, Figure 9).

A.2.2 New York (NYISO)

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

A.2.3 New England (ISO-NE)

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

A.2.4 Mid-Atlantic (PJM)

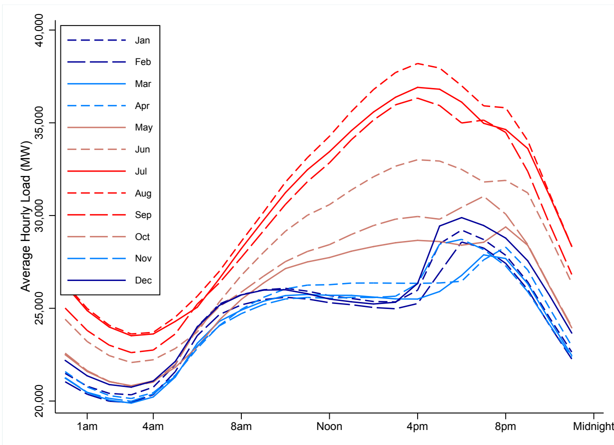
Capacity prices for PJM are "Market Clearing Prices" from the annual "Base Residual Auction." We use the simple average across years and geographic zones for 2013–2016. Data are from SNL Financial.

A.2.5 Midwest (MISO)

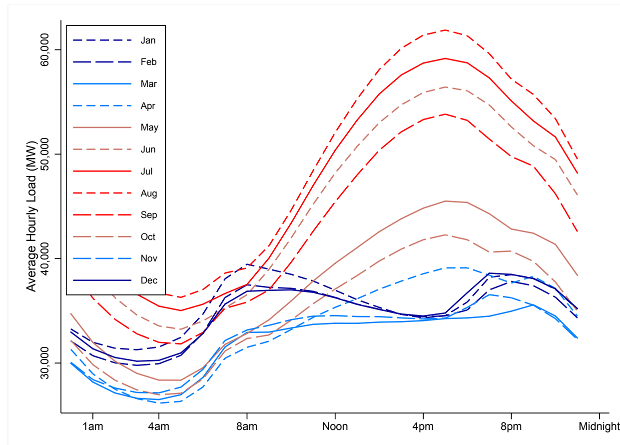
Capacity prices for MISO come from annual capacity auction prices for 2013 through 2016. We use the simple average of prices across the several geographic zones. Data are from SNL Financial.

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

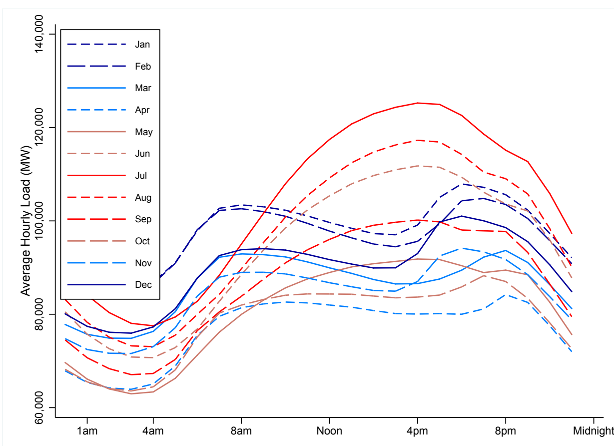
(a) California (CAISO)



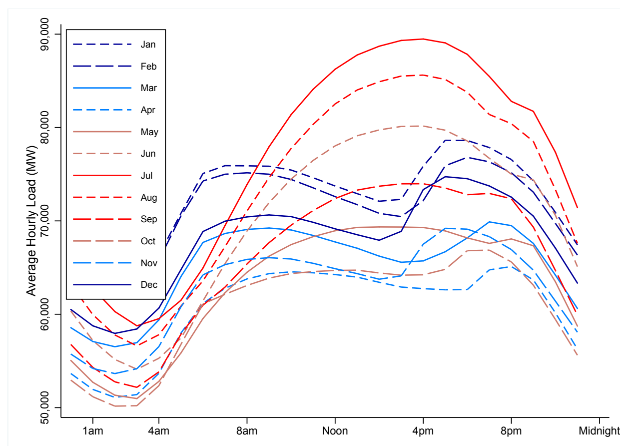
(b) Texas (ERCOT)



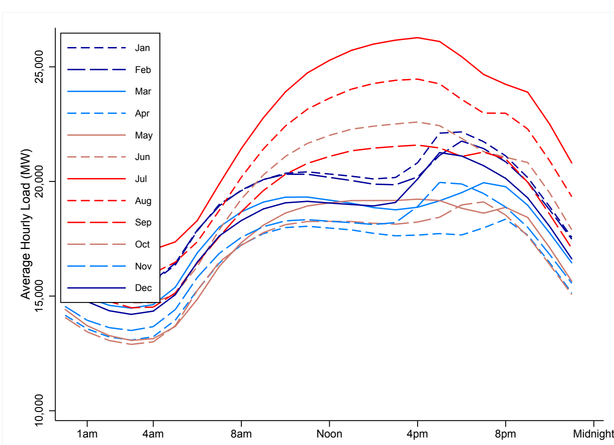
(c) Mid-Atlantic (PJM)



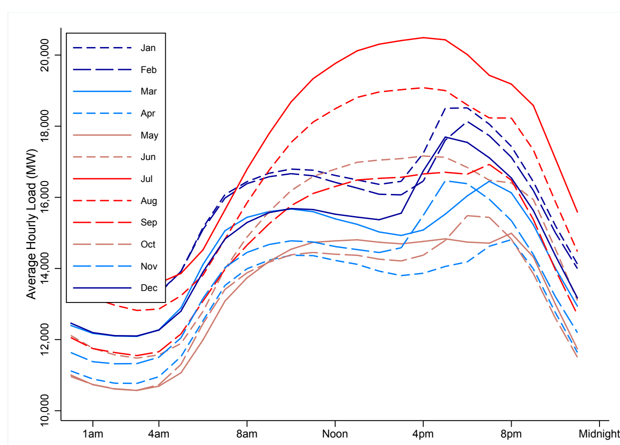
(d) Midwest (MISO)



(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

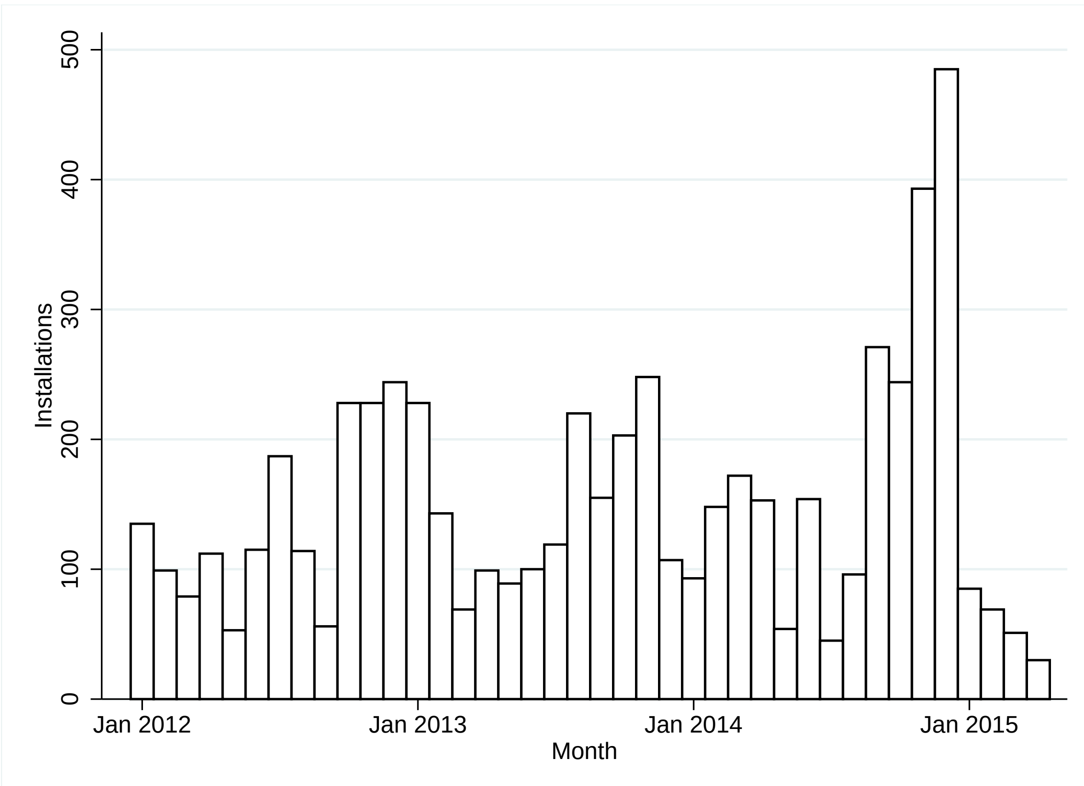
The electricity consumption data describe hourly electricity consumption for all program participants. We were provided with the complete history of hourly consumption for these households beginning when each household received a smart meter and continuing until August 2015, or, in some cases, somewhat 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

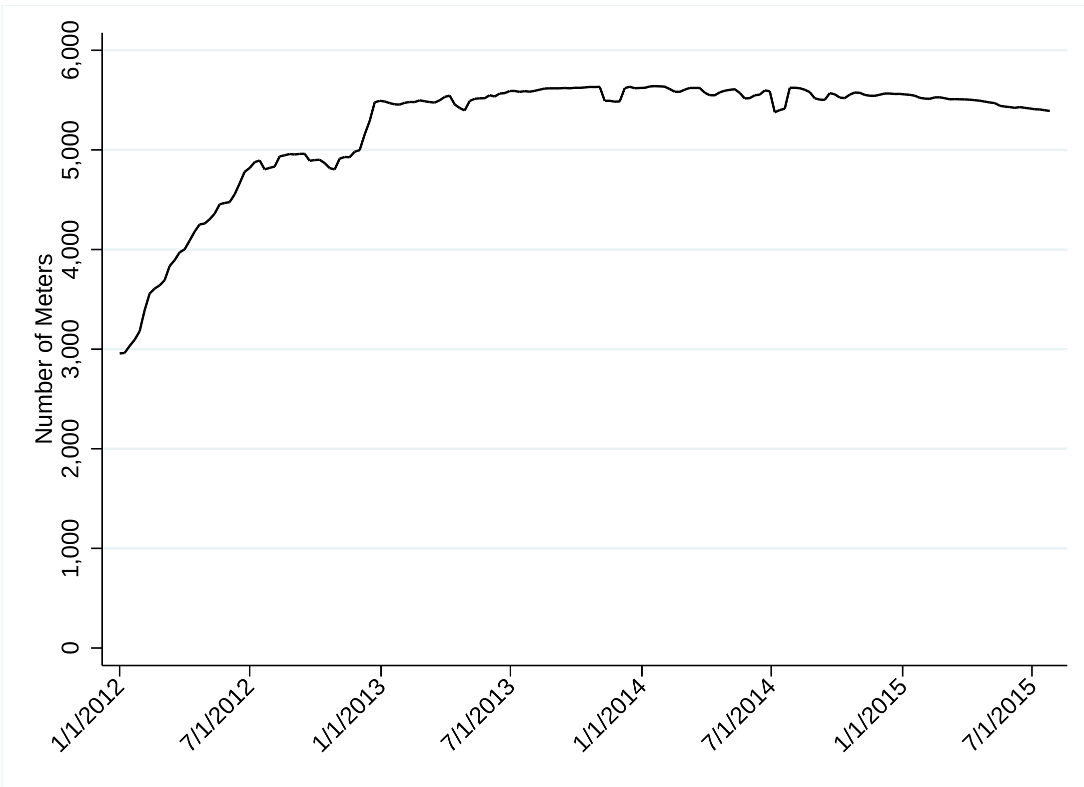
Appendix Figure 4 plots savings profiles for eight additional energy-efficiency investments. These figures are constructed in exactly the same way as Figure 7, and describe five residential investments and three commercial/industrial investments. As described in the paper, these engineering-based savings 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.

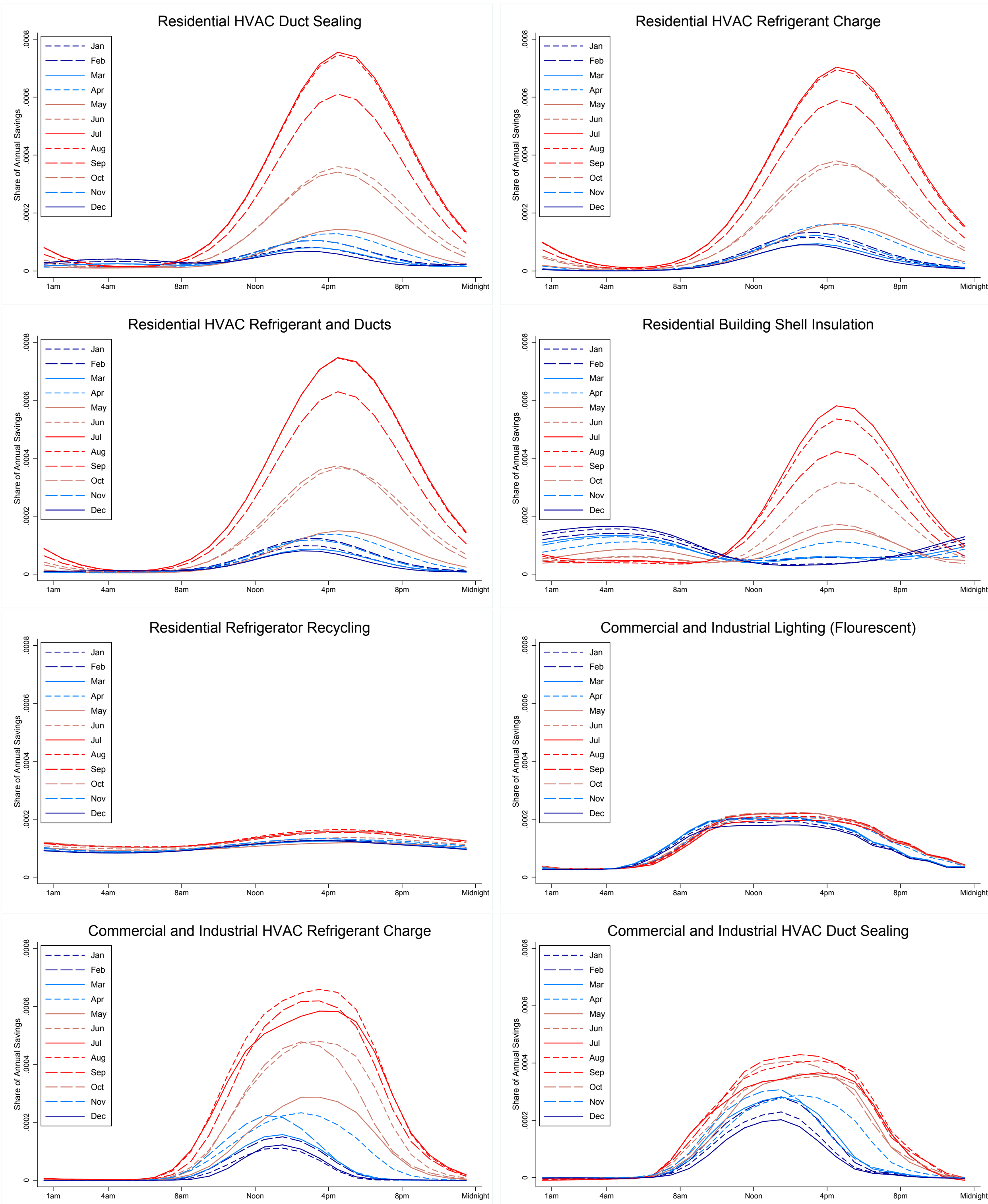
Appendix Figure 2: Histogram of Installation Dates



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.

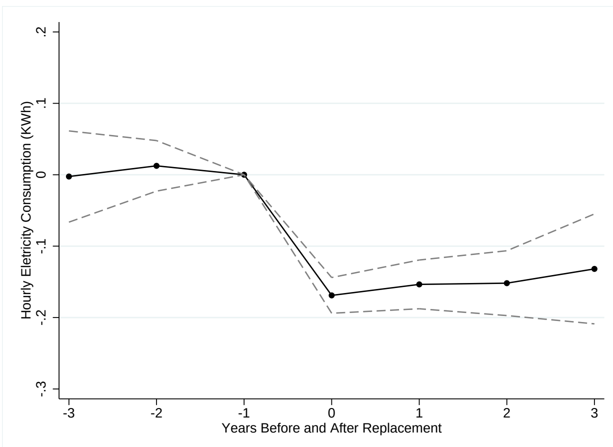
Next, Appendix Table 2 reports regression estimates of total energy savings from new air conditioner installation. This table is constructed in exactly the same way as Table 1, but estimated using data from both participants and non-participants. Including data from non-participants has little overall 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.

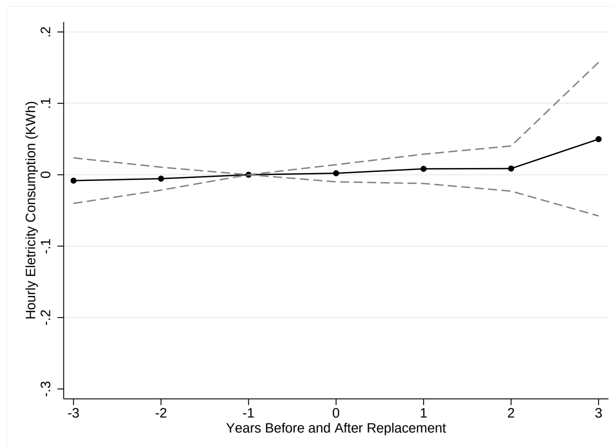
Appendix Figure 5: Event Study Figures, Alternative Specifications

Random Sample of Non-Participants

Summer

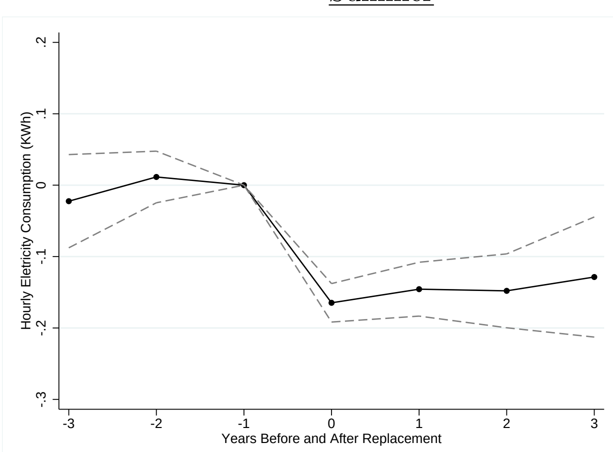


Winter

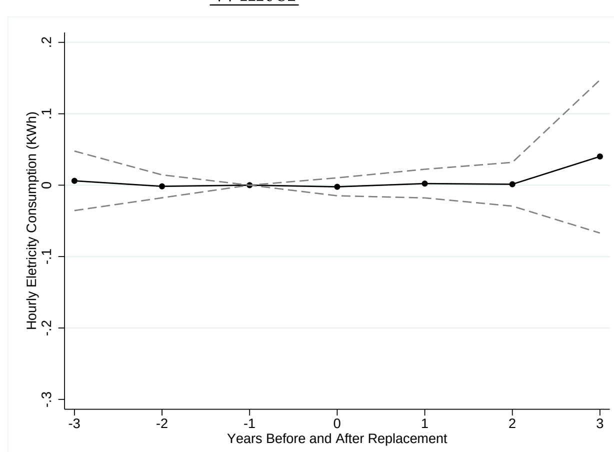


Matched Sample of Non-Participants

Summer

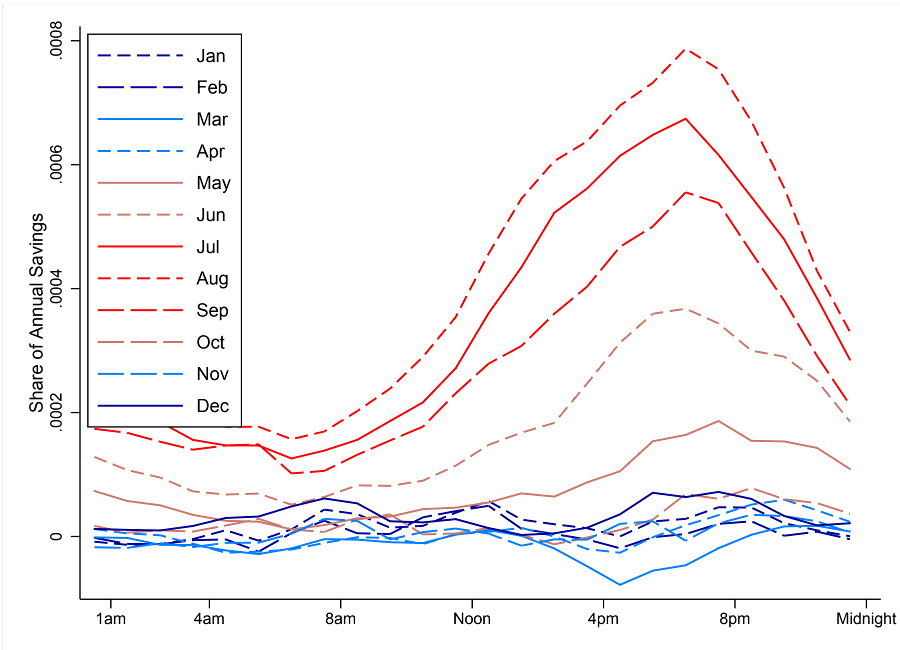


Winter

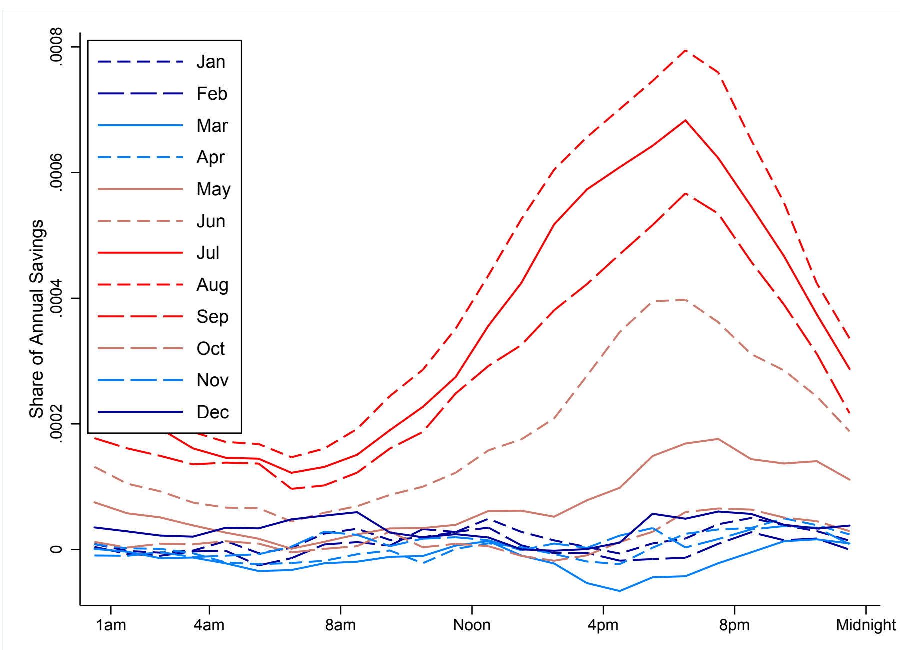


Appendix Figure 6: Econometric Estimates of Electricity Savings, Alternative Specifications

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.