Do Energy Efficiency Investments Deliver at the Right Time?[†]

By Judson Boomhower and Lucas Davis*

Most analyses of energy efficiency investments ignore that the value of electricity varies widely across hours. We show how much timing matters. Using novel hourly consumption data from an air conditioner rebate program in California, we find that energy savings are concentrated in high-value hours. This significantly increases the value of these investments, especially after we account for the large capacity payments that electricity generators receive to guarantee supply in peak hours. We then use engineering predictions to calculate timing premiums for a wide range of energy efficiency investments, finding substantial variation in economic value across investments. (*JEL* L94, L98, Q41, Q48)

U nlike 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 20 times the level of off-peak prices. During these ultra-peak hours, generation is operating at full capacity and there is little ability to further increase supply, making demand reductions extremely valuable.

These features of electricity markets are well known, yet most analyses of energy efficiency policies ignore this variation. For example, when the US Department of Energy (DOE) considers new appliance energy efficiency standards and building energy codes, they focus on total energy savings without regard to when these savings occur.[1] Similarly, when state utility commissions evaluate state and local energy efficiency programs, they typically focus on total energy savings, with little regard to timing.[2] With a few notable exceptions that we discuss later in the paper, there is surprisingly little attention both by policymakers and in the academic literature to how the value of energy efficiency depends on when savings occur.

In part, these limitations reflect historical technological constraints. Before smart meters and other advanced metering infrastructure, it was impossible to measure policy impacts at the hourly level. The necessary high frequency data did not exist since meters were only read once per billing cycle. This situation is rapidly changing. Today almost half of US residential electricity customers have smart meters, up from less than 2 percent in 2007.[3]

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

With hourly smart-meter data from 6,000+ participants, we are able to precisely characterize the energy savings profile across seasons and hours of the day. We show that savings occur disproportionately during July and August, with 55 percent of total savings in these two months, and near zero savings between November and April. Energy savings are largest between 3 PM and 9 PM, with peak savings between 6 PM and 7 PM. This pattern has important implications for electricity markets given growing challenges with meeting electricity demand in the early evening (see, e.g., Denholm et al. 2015).

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

[2] See, for example, California Public Utilities Commission, "2010–2012 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.

[3] US Department of Energy, "Electric Power Annual 2016," released December 2017, Tables 2.1 and 10.10.

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

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

Finally, we use engineering predictions to calculate timing premiums for a larger set of energy efficiency investments, both residential and nonresidential. Overall, we find that there is a remarkably wide range of value across investments. Using data from six major US electricity markets, we show that residential air conditioning investments have the highest average timing premium. Other high timing premiums are for commercial and industrial heat pumps, chillers, and air conditioners, all of which save energy disproportionately during peak periods. Other investments like refrigerators have timing premiums near or even below zero because savings are only weakly correlated with value. Lighting also does surprisingly poorly because savings are largest during evening and winter hours when electricity is less valuable.

These findings have immediate policy implications. Energy efficiency is a major focus of global energy policy, so it is imperative that the benefits of demand reductions be accurately measured. Electric utilities in the United States, for example, spent $41 billion on energy efficiency programs during the decade between 2007 and 2016, leading to more than 1.7 billion MWhs in reported electricity savings.[5] Yet virtually all analyses of these programs have ignored the timing of energy savings.

The paper proceeds as follows. Section I provides background about electricity markets and energy efficiency. Section II describes our empirical application, estimating framework, and savings estimates. Section III presents data on the value of electricity across hours, and calculates the timing premium for residential air conditioning. Section IV then incorporates engineering predictions to calculate timing premiums for a much broader set of energy efficiency investments. Section V concludes.

I. Background

A. *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. Beyond that, the supply curve for electricity is perfectly vertical, reflecting the maximum total generating capacity.

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[5] Tabulations by the authors based on data from US Department of Energy, Energy Information Administration, "Electric Power Annual 2012" (Tables 10.2 and 10.5) and 2016 (Tables 10.6 and 10.7). Expenditures are reported in year 2015 dollars.

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 marginal cost. But during peak hours, the marginal generator has a much higher marginal cost. There are also typically a small number of ultra-peak hours each year in which demand outstrips total generating capacity, leading the market to clear on the demand side and resulting in prices that can spike to many times any plant's marginal cost.

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 electricity generators would need when deciding whether to enter or exit. In a competitive market in long-run equilibrium, the number of generators would be determined by price competition and free entry. Additional generators would be built until the average price across all hours equaled average cost. In such a market, the hourly wholesale price would represent 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 total amount of generating capacity is set by regulation. Regulators set minimum "reserve margins" (generation capacity in excess of expected peak demand) that reduce the risk of electricity shortages below a target level, such as one event every ten years. A variety of economic justifications for these reserve requirements have been proposed, including externalities associated with system collapse and price caps in spot markets used to mitigate market power (Joskow 2006). These reserve margin requirements are implemented through dedicated capacity markets where generators commit to be available to sell power during future periods.[6] Existing generators and potential new entrants compete to sell capacity to the utilities obligated to purchase it. In theory, competition in the capacity market results in an equilibrium capacity price that just covers the "net cost of new entry" for the marginal generating unit at the desired reserve margin. The net cost of new entry is the shortfall between expected energy market revenues and total investment and operating costs for this marginal generator. If the capacity price were lower, not enough generators would enter the market to meet the reserve requirement. If a generator charged a higher capacity price, it would be undercut by competitors.

It is important to take capacity payments into account when measuring how the value of electricity varies across hours. In an energy-only market, increases in demand increase energy prices, which, in turn, induce additional investment

[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 percent of this demand. The payments in these contracts are 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 MWh 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), and Allcott (2013). Many electricity markets also provide additional payments for frequency regulation and other ancillary services, but these payments tend to be much smaller than capacity payments and energy efficiency is less well suited for providing these services.

in generation. With capacity markets, an increase in peak-period demand also increases the mandated quantity of capacity, increasing capacity prices. A binding capacity target actually decreases peak prices in the energy market because greater capacity reduces the frequency of scarcity pricing events. For example, one study found that moving from an energy-only market to a modest capacity target in Texas would be expected to create $3.2 billion in capacity payments while reducing energy market payments by $2.8 billion.[7] This shifting of peak-period costs into the capacity market means that considering only energy prices will systematically underestimate the value of electricity in peak hours.

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

B. *Energy Efficiency*

Energy efficiency has become a major focus of policymakers at all levels of government. For example, the US government spent $12 billion on federal energy efficiency tax credits between 2009 and 2012 (Borenstein and Davis 2016), and state utility commissions oversee $6 billion annually in electric utility sponsored energy efficiency programs.[8] Supporters of these policies argue that they are a "win-win," reducing energy expenditures while also reducing externalities, decreasing peak demand, and increasing "energy security." Economists have argued that these objectives may be accomplished more efficiently through policies like emissions taxes and real-time pricing of electricity (Borenstein 2005, Borenstein and Holland 2005, and Holland and Mansur 2006), but these approaches tend to be less politically palatable than energy efficiency.[9]

Our argument is that it is important to account for timing when measuring the benefits of energy efficiency policies. Most previous economic analyses of energy efficiency ignore this variation, focusing on total savings, rather than on when these savings occur. See, for example, Dubin, Miedema, and Chandran (1986); Metcalf and Hassett (1999); Davis (2008); Arimura et al. (2012); Jacobsen and Kotchen (2013); Davis, Fuchs, and Gertler (2014); Levinson (2016); Houde and Aldy (2017); Allcott and Greenstone (2017); and Fowlie, Greenstone, and Wolfram (2018).

An important exception is Novan and Smith (2018), which uses hourly data from a similar energy efficiency program to illustrate important inefficiencies with current

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[7] The Brattle Group, 2014. "Estimating the Economically Optimal Reserve Margin in ERCOT." page viii.

[8] US Department of Energy, Energy Information Administration, "Electric Power Annual 2016," Table 10.6.

[9] Another policy alternative that is technologically promising but politically unpopular is centralized control of devices like refrigerators, electric vehicle chargers, and air conditioners to smooth demand second-by-second (Callaway and Hiskens 2011).

retail rate designs for electricity. They point out that many households pay a marginal price for electricity that exceeds the marginal social cost of electricity, leading households to have too much incentive to invest in energy efficiency. In the program they evaluate, the private savings exceed social value by an average of 140 percent. Our paper in contrast is much more focused on the timing of energy savings and how this impacts the economic value of energy efficiency investments.

Most government and regulatory analyses also ignore the timing of savings. For example, in the United States there are minimum efficiency standards for 40+ categories of residential and commercial technologies. The US Department of Energy performs an economic analysis every time a new standard is implemented, but these analyses are based on total energy savings without regard to when those savings occur (see references in footnote 1). Moreover, "meta-analyses" like Meyers et al. (2016), typically add up the benefits from standards by multiplying total energy savings by annual energy prices, thus ignoring the correlation between savings and the value of energy.

Another major category of policies are subsidies for energy efficient technologies. This includes federal and state income tax credits for energy efficiency investments and, at the state level, utility-sponsored rebates and upstream manufacturer incentives. Most state utility commissions require these programs to be evaluated by third-party analysts. Although thousands of studies have been performed looking at subsidy programs, the vast majority focus on total energy savings (for example, see references cited in footnote 2).[10]

There are exceptions. California requires that proposed utility-sponsored energy efficiency programs be evaluated against engineering models of hourly electricity values before programs are implemented. California's Title 24 building efficiency standards also explicitly consider time value. Some recent federal energy efficiency standards consider seasonal differences, but still ignore the enormous variation within seasons and across hours of the day.[11] In addition, while the vast majority of third-party analyses of energy efficiency programs ignore the timing of savings, a relevant exception is Evergreen Economics (2016), which compares random coefficients versus alternative models for estimating hourly savings for several California energy efficiency programs.

C. *Externalities*

Another important feature of electricity markets is externalities. These external costs of energy production also vary across hours and across markets. Callaway, Fowlie, and McCormick (2018) uses 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 US regional power systems. They find that variation in avoided carbon dioxide emissions per MWh is limited across

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[10] 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.

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

resources within a region, but is significant across regions. For example, they find that avoided carbon dioxide emissions per MWh in the Midwest are more than double that in California.

Perhaps contrary to popular expectation, the large majority of the benefits from most energy efficiency policies come from reduced private energy costs, not externality reductions (Gayer and Viscusi 2013). For example, nine new standards promulgated by the DOE in 2016 are predicted to achieve a total present value of $76 billion in energy cost savings, versus $28 billion in avoided CO_2 emissions and $5 billion in avoided NO_x emissions.[12] That is, more than two-thirds of the benefits come from private energy cost savings.

In addition, the hourly variation in external costs is much smaller than the hourly variation in private energy costs. In most markets, the marginal generating unit is essentially always a coal- or natural gas-fired generator (renewables have zero marginal cost and are thus essentially always inframarginal in terms of dispatch). That fact means that the possible variation in marginal external costs across hours of the day or seasons of the year is bounded by the difference in emissions rates between a relatively clean combined cycle natural gas turbine and a higher-emitting coal steam generator, which is roughly a factor of two.[13] Empirical studies of emissions externalities find relatively little variation in marginal emissions rates across hours of the day or seasons of the year (Graff Zivin, Kotchen, and Mansur 2014; Callaway, Fowlie, and McCormick 2018). Callaway et al. (2018) finds that the difference between the highest and lowest season by hour-of-day emissions rates is only about 22 percent in California, 27 percent in the Midwest, and 55 percent in Texas. In comparison, the season-by-hour average energy price differences that we discuss in this paper are greater than 1,000 percent.

In summary, the total externality benefits of energy efficiency investments are substantially smaller than the total private cost savings, and the time profile of externality reductions is much flatter than the time profile of private energy costs. For that reason, in this paper, we focus exclusively on private costs and refer readers interested in externalities to Callaway, Fowlie, and McCormick (2018).

II. Empirical Application

For our empirical application, we focus on a residential air conditioner program in Southern California. Section IIA briefly describes the program, Section IIB provides graphical evidence on average electricity savings, Sections IIC and IID plot savings

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

[13] For carbon dioxide, a typical coal plant emits 0.94 kg per kWh, while a typical combined cycle natural gas plant emits 0.41 kg per kWh. EIA Electric Power Annual 2016, released December 2017. Calculations based on Tables 8.2 and A.3.

estimates by daily temperature and hour-of-day, respectively, and then Section IIE reports regression estimates of overall annual savings.

A. *Program Background*

Our empirical application is an energy efficiency rebate program offered by Southern California Edison (SCE), a major investor-owned utility. The program provides incentives of up to $1,100 to households that install an energy efficient central air conditioner. This program is of significant intrinsic interest because of the high level of energy consumption from air conditioning. In California, air conditioning is responsible for 10 percent of average residential electricity use and 15 percent of average commercial electricity use (California Energy Commission 2012).

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

The data consist of detailed information about program participants and hourly electricity consumption records. Our main empirical analyses are based on 5,973 households who participated in the program between January 2012 and April 2015. Participants tend to consume more electricity than other SCE customers, particularly during the summer, and are less likely to be on SCE's low-income tariff. The online Appendix provides these descriptive statistics, additional details, and results from alternative specifications including analyses that use data from matched nonparticipating households.

B. *Event Study*

Figure 1 plots estimated coefficients and 95 percent confidence intervals corresponding to a standard event study regression. The dependent variable is summer average hourly electricity consumption by household and year. The horizontal axis is the time in years before and after installation, normalized so that the year of installation is equal to zero. We include year by climate zone fixed effects to remove the effect of annual changes in average electricity consumption in each climate zone due to weather and other time-varying factors. We estimate the regression using July and August data from 2012 to 2015. We drop data from installations that occurred during August, September, and October to ensure that participants did not have new air conditioners during year -1. This exclusion is for the event study figure only; these installations are included in all subsequent analyses.

The event study figure shows a sharp decrease in electricity consumption in the year in which the new air conditioner is installed. The decrease is about 0.2 kilowatt hours (kWh) per hour. A typical LED lightbulb uses about
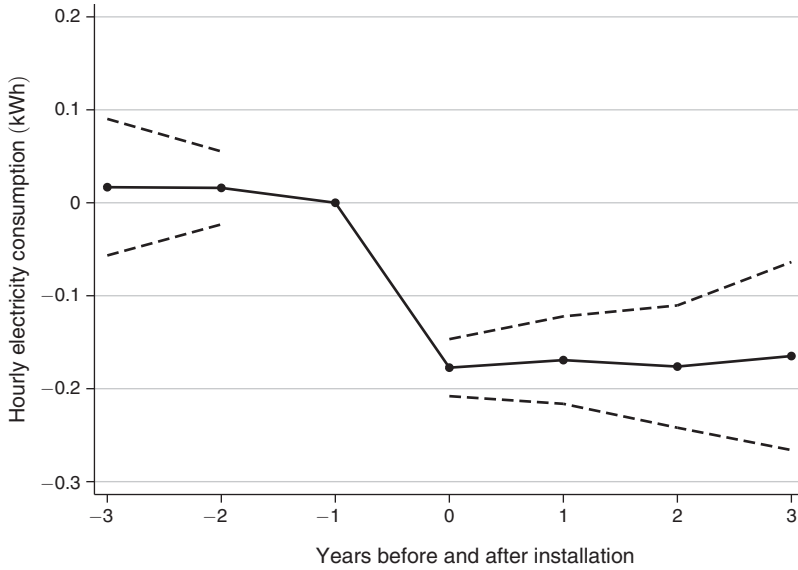
FIGURE 1. EVENT STUDY FIGURE FOR ELECTRICITY CONSUMPTION

Notes: This event study figure plots estimated coefficients and 95 percent confidence intervals from a least squares regression. The dependent variable is average hourly electricity consumption during July and August at the household-by-year level. Time is normalized relative to the year of installation ($t = 0$) and the excluded category is $t = -1$. The regression includes year by climate zone fixed effects. Standard errors are clustered by nine-digit zip code.

10 watts, so this decrease is equivalent to shutting off 20 LEDs. These households use an average of 1.5 kWh/hour during July and August, so this is approximately a 13 percent decrease. In the event study figure, electricity consumption is otherwise approximately flat before and after installation.

The online Appendix includes a similar event study figure for January and February electricity consumption. As expected, winter consumption is essentially unchanged after the new air conditioner is installed. These event study figures and the estimates in later sections measure the electricity savings from a new air conditioner. This is different, however, from the causal effect of the rebate program. Many participants in energy efficiency programs are inframarginal, getting paid for something they would have done anyway (Joskow and Marron 1992). In the extreme, if all participants are inframarginal, a program can have no causal impact even though the subsidized activity creates large savings. Measuring the causal impact also requires figuring out how the program changed the *type* of appliances that were purchased. Recent studies have used regression discontinuity and other quasi-experimental techniques to tease out these causal effects and perform cost-benefit analysis (Boomhower and Davis 2014, Houde and Aldy 2017).

C. *Impacts by Local Temperature*

A potential concern in our application is that participating households might have experienced other changes at the same time they installed a new air

conditioner. For example, program participation might coincide with a home remodel or a new baby, both of which would affect electricity consumption. However, air conditioning has a very particular pattern of usage that we can use to validate our estimates. Unlike most other energy-using durable goods, air conditioner usage is highly correlated with outdoor temperature. Thus, we can validate our empirical approach by confirming that our estimated savings are large on hot days and near zero on mild days.

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

On mild days between 50 and 70 degrees Fahrenheit, energy savings are precisely estimated zeros. The lack of savings on these days is reassuring because it suggests 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, approximately linear relationship between temperature and energy savings, as expected from a new air conditioner. Air conditioner usage increases with outdoor temperature, so energy efficiency gains have the largest effect on these days. There is also a small decrease in consumption on days below 50 degrees. This might be explained by improvements to ductwork, insulation, thermostats, or other HVAC-related upgrades that in some cases occur as part of a new central air conditioner installation. This decrease is very small, however, relative to the energy savings on hot days. Thus, overall, the impacts by temperature corroborate our empirical approach, providing evidence that our estimates are not confounded by simultaneous changes in other categories of energy use.

D. *Hourly Impacts by Season*

Figure 3 plots estimated electricity savings by hour-of-day for summer- and non-summer months. The coefficients and 95 percent confidence intervals for this figure are estimated using 48 separate least squares regressions. Each regression includes electricity consumption for a single hour-of-the-day during summer or non-summer months, respectively. For example, for the top left coefficient, the dependent variable is average electricity consumption between midnight and 1 AM during non-summer months. All regressions are estimated at the household by week-of-sample by hour-of-day level and control for week-of-sample by climate zone and household by month-of-year fixed effects.

The figure reveals large differences in savings across seasons and hours. During July and August there are large energy savings, particularly between noon and 10 PM. Savings reach their nadir in the summer at 6 AM., which is typically the coolest time of the day. During non-summer months savings are
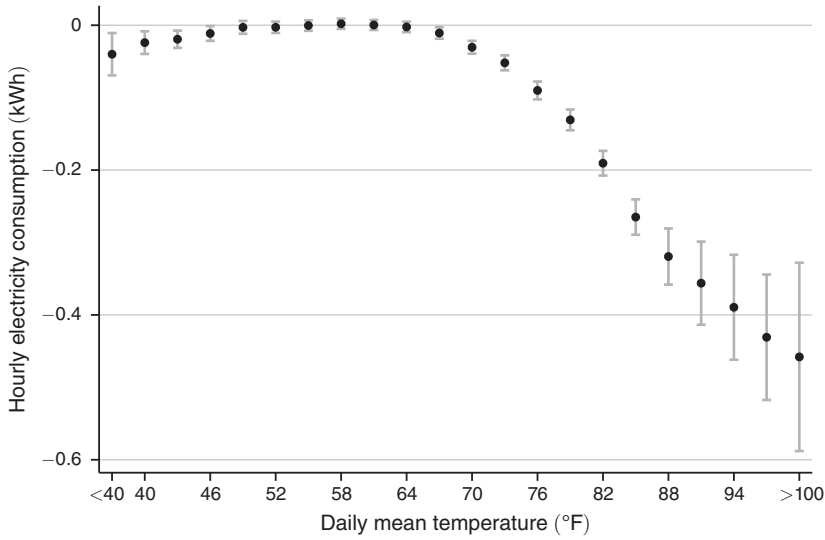
FIGURE 2. ELECTRICITY SAVINGS BY TEMPERATURE

Notes: This figure plots regression coefficients and 95 percent confidence intervals from a single least squares regression. The dependent variable is average electricity consumption at the household by day-of-sample level. Coefficients correspond to 22 indicator variables for daily mean temperature bins, interacted with an indicator variable for after a new air conditioner installation. Each temperature bin spans three degrees; the axis labels show the bottom temperature in each bin. The regression also includes household by month-of-year and day-of-sample by climate zone fixed effects. Temperature data come from PRISM, as described in the text. Standard errors are clustered by nine-digit zip code.
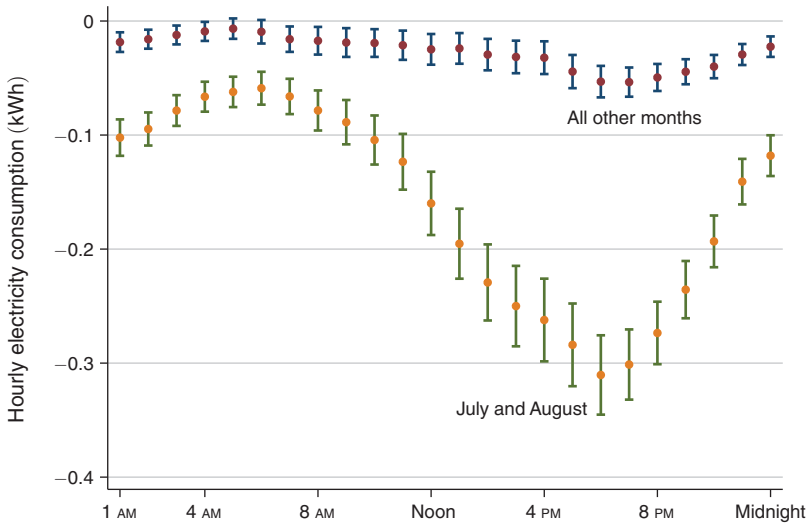
FIGURE 3. ELECTRICITY SAVINGS BY HOUR-OF-DAY

Notes: This figure plots estimated coefficients and 95 percent confidence intervals from 48 separate least squares regressions. For each regression, the dependent variable is average electricity consumption during the hour-of-the-day indicated along the horizontal axis. All regressions are estimated at the household by week-of-sample by hour-of-day level and control for week-of-sample by climate zone and household by month-of-year fixed effects. The sample includes all households who installed a new air conditioner between 2012 and 2015, and all summer or non-summer months, as indicated. Standard errors are clustered by nine-digit zip code.

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 FE	Yes	Yes	Yes
Week-of-sample by hour-of-day FE	Yes		
Week-of-sample by hour-of-day by climate zone FE		Yes	Yes
Drop 8 weeks pre-installation			Yes
Observations	28.6M	28.6M	27.3M
Number of households	5,973	5,973	5,972

Notes: This table reports results from three separate regressions. The dependent variable in all regressions is average hourly electricity consumption measured at the household by week-of-sample by hour-of-day level. The main variables of interest in these regressions are 288 month-of-year by hour-of-day indicators interacted with an indicator for observations after a new air conditioner installation. Annual energy savings is calculated as the weighted sum of these 288 estimates, where the weights are the number of days in each calendar month. Standard errors are clustered by nine-digit zip code. The regressions are estimated using data from 2012 to 2015 for all participating households.

much smaller, less than 0.05 kWh/hour, compared to 0.2 to 0.3 kWh/hour during afternoon and evening hours in July and August. Overall, 55 percent of total savings occur during July and August.

E. *Annual Average Savings*

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

In columns 1 and 2, the implied annual savings per household are 375 and 358 kWh/year, respectively. The difference between these two specifications is that the latter adds a richer set of time fixed effects. Finally, in column 3, we restrict the estimation sample to exclude, for each household, the eight weeks prior to installation. This might make a difference if an old air conditioner was not working or if the installation date was recorded incorrectly. The estimates are somewhat larger in column 3, but overall average savings are similar across the three columns. Prior to installing a new air conditioner, program participants consumed an average of 9,820 kWh/year, so the estimate in column 3 implies a 4.4 percent decrease in household consumption.[14]

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[14] These estimates of aggregate program impact are quantitatively similar to estimates in SCE-sponsored Evergreen Economics (2016) based on a random coefficients model. The Evergreen study estimates impacts for this program using data from a much smaller number of homes.

III. The Value of Energy Efficiency

In this section, we show that the value of electricity varies substantially across hours, and we demonstrate the importance of accounting for this variation when valuing energy efficiency investments. We start by incorporating data on wholesale electricity prices and capacity values to establish the hourly variation in private energy costs (Section IIIA). Then, we use those prices and the empirical application from the previous section to calculate the timing premium for air conditioners under a range of assumptions (Section IIIB).

A. *The Value of Electricity in US Markets*

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

For California, the figures plot average wholesale energy prices as well as four alternative measures of capacity value. The hourly variation in energy-only prices in California is substantially smaller than in Texas, where the value of electricity in August afternoons surges to over $300, well above the marginal cost of any generator. This difference across markets is partly due to California's mandated capacity targets, which shift peak-period costs from energy to capacity markets as we discussed in Section IA. These capacity payments are made to electricity generators to remain open and available, thereby ensuring desired reserve margins during peak demand periods.

In California, generation capacity is procured in advance at the monthly level. Capacity contracts obligate generators to be available every hour of one month. In order to value hourly energy savings, we need to allocate these monthly capacity costs across individual hours. We do this several ways and report the results of each. As we explain in more detail in the online Appendix, the capacity value of a demand reduction in any hour depends on the probability that that hour is the peak hour. Our various approaches to allocating capacity value to hours involve different ways of calculating these probabilities. In our first approach, we use hourly load data to calculate the hour-of-the-day with the highest average load each month. We then divide the monthly capacity price evenly across all occurrences of that hour-of-day on weekdays. We allocate capacity costs to weekdays only because weekend and holiday loads are reliably smaller. In other specifications, we divide the capacity contract price evenly over the top two or three hours-of-the-day with the highest load each month. The final approach treats each day of load data as a single observation of daily load shape in a given month. We calculate the historical
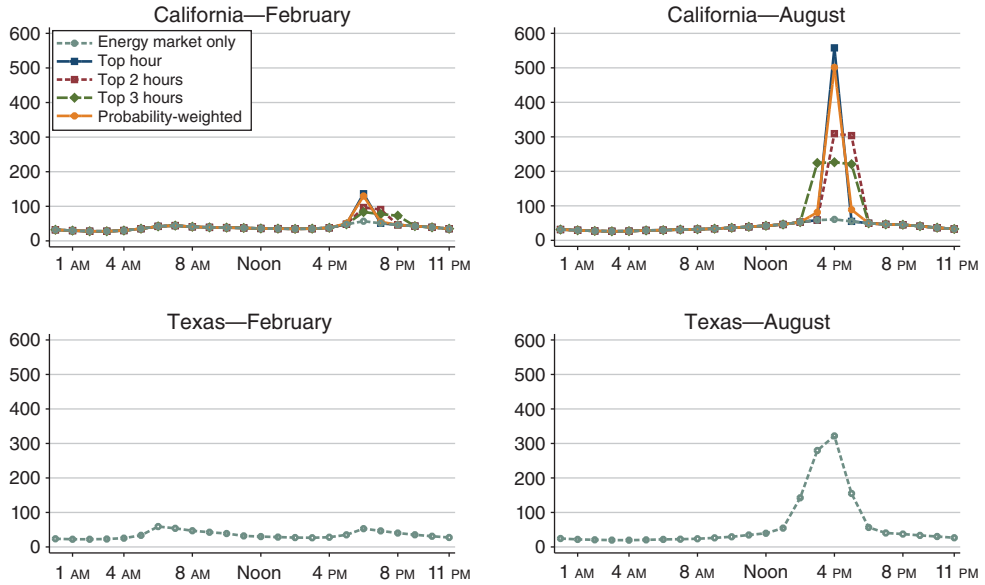
FIGURE 4. WHOLESALE ELECTRICITY PRICES AND CAPACITY VALUES

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 MWh. The hour labels on the horizontal axis refer to the beginning time of each one-hour interval. See text for details.

likelihood that each hour-of-the-day was the daily peak hour, and allocate monthly capacity values to hours of the day proportionally according to these probabilities.

Incorporating capacity values substantially increases the value of electricity during peak periods. In California during August, for example, capacity values increase the value of electricity during peak evening hours to between \$300 and \$600/MWh. Overall, the pattern is similar across the four approaches for allocating capacity value across hours. As expected, allocating the entire capacity value to the single highest-load hour results in the highest peak, though the other approaches have similar shapes. In addition, the general shape of the capacity-inclusive values for California matches the shape in Texas, providing some reassurance that our approach recovers a price shape that is similar to what would exist in an energy-only market.

Our treatment of capacity values in the empirical analysis is guided by the economic model of capacity markets that we described in Section IA and the online Appendix. The workings of capacity markets in practice may diverge from that model in ways that would affect our analysis. For example, one might argue that capacity markets may not be in long-run equilibrium due to the recent influx of renewables in US markets. Or that practical details of capacity auction design may impede participation by some potential entrants (Joskow 2006). If either of these is the case, capacity prices should be expected to converge to equilibrium levels over time as entry and exit occur and regulators improve market design. It would be straightforward to repeat our calculations with updated data. Alternatively, one

could attempt to value capacity using engineering assumptions about the cost of new electricity generating equipment like a natural gas combustion turbine plant (see, e.g., Blonz 2016). Our judgment is that our approach based on observed market outcomes, while potentially imperfect, is the best available way to capture capacity values in this analysis.

The calculations which follow also account for line losses in electricity transmission and distribution. In the United States, an average of 6 percent of electricity is lost between the point of generation and the point of consumption (DOE 2016, Table 7.1), so 1.0 kWh in energy savings reduces generation and capacity requirements by 1.06 kWh. Line losses vary over time by an amount approximately proportional to the square of total generation. We incorporate these losses explicitly following Borenstein (2008) and, in practice, they range from 3.9 percent during off-peak periods to 10.3 percent during ultra-peak periods. Incorporating line losses thus further increases the variation in economic value between off-peak and peak, albeit only modestly.

B. *Quantifying the Value of Energy Savings*

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

In columns 2 through 5, we incorporate capacity values. Each column measures the value of electricity using a different approach to allocating monthly capacity payments across hours, as described in Section IIIA. Incorporating capacity values significantly increases the value of air conditioner energy savings to $70/MWh. 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 calculations that ignore timing significantly understate these capacity benefits.

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 9 percent of hours" allocation (column 4) as our preferred measure, but results are almost identical using the other allocation methods. In all four columns, accounting for timing increases the estimated savings value by about 37 percent.

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

		Energy plus capacity prices, various assumptions			
	Energy prices only (1)	Capacity value in top 3% of hours (2)	Capacity value in top 6% of hours (3)	Capacity value in top 9% of hours (4)	Capacity value allocated probabilistically (5)
Average value of savings ($/MWh)					
(A) Accounting for timing	$45.09	$69.78	$70.60	$69.92	$69.87
(B) Not accounting for timing	$40.31	$51.06	$51.01	$50.96	$51.03
Timing premium $\left(\dfrac{A-B}{B}\right)$	12%	37%	38%	37%	37%

Notes: These calculations are made using estimated energy savings for each hour-of-day by month-of-year by weekday/weekend period from the full regression specification as in column 3 in Table 1. Energy and capacity prices are from the California electricity market (CAISO). See the text and online Appendix for all sources and additional details. In columns 2, 3, and 4, monthly capacity prices are allocated evenly across the one, two, and three (respectively) hours of the day with the highest average load each month. In column (5), monthly capacity prices are allocated to hours of the day based on their historical probability of containing the monthly peak load event. Row (B) calculations use a load-weighted average of hourly prices.

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

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

To examine how this altered price shape could affect the value of energy efficiency, we performed an additional analysis using forecast prices and load profiles for California in 2024 from Eichman et al. (2015).[15] The authors

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

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 percent renewable penetration. We calculated future capacity values by allocating current monthly capacity contract prices over the three highest net load hours of day in each future month. Under these assumptions, the timing premium increases from 37 percent to 50 percent. This increase in value is due to increased solar penetration shifting peak prices further into the late afternoon and early evening, when energy savings from air conditioners are largest.

This estimate should be interpreted with caution. Predicting the future requires strong assumptions about electricity demand, natural gas prices, the deployment of electricity storage, and other factors. This calculation does, however, show how increased renewables integration can make it even more important to incorporate timing differences across investments.

IV. Examining a Broader Set of Investments

Finally, in this section, we incorporate engineering predictions from a broad set of energy efficiency investments. We start by comparing the engineering predictions to our econometric estimates for air conditioning (Section IVA). We then examine engineering predictions for other technologies, showing that time profiles differ significantly between investments (Section IVB) and that these different profiles imply large differences in economic value (Section IVC).

A. *Engineering Predictions for Air Conditioning*

The engineering predictions that we use come from the Database for Energy Efficient Resources (DEER), a publicly available software tool developed by the California Public Utilities Commission (CPUC).[16] These are ex ante predictions of energy savings, developed using a building simulation model that makes strong assumptions about building characteristics, occupant usage schedules, local weather, and other factors. To our knowledge, this paper is the first attempt to verify these engineering predictions empirically using measured electricity consumption.

Figure 5 compares our econometric estimates with engineering predictions for residential air conditioning investments in this same geographic area. Since our interest is in *when* savings occur, both panels are normalized to show the share of total annual savings that occur in each month and hour. The two savings profiles are broadly similar, but there are interesting differences. First, the econometric estimates indicate peak savings later in the evening. The engineering predictions peak between 4 PM and 6 PM, while the econometric estimates peak between 6 PM and 7 PM. This difference is important and policy-relevant because of expected

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[16] 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. See the online Appendix and http://deeresources.com for details.

Panel A. Econometric estimates
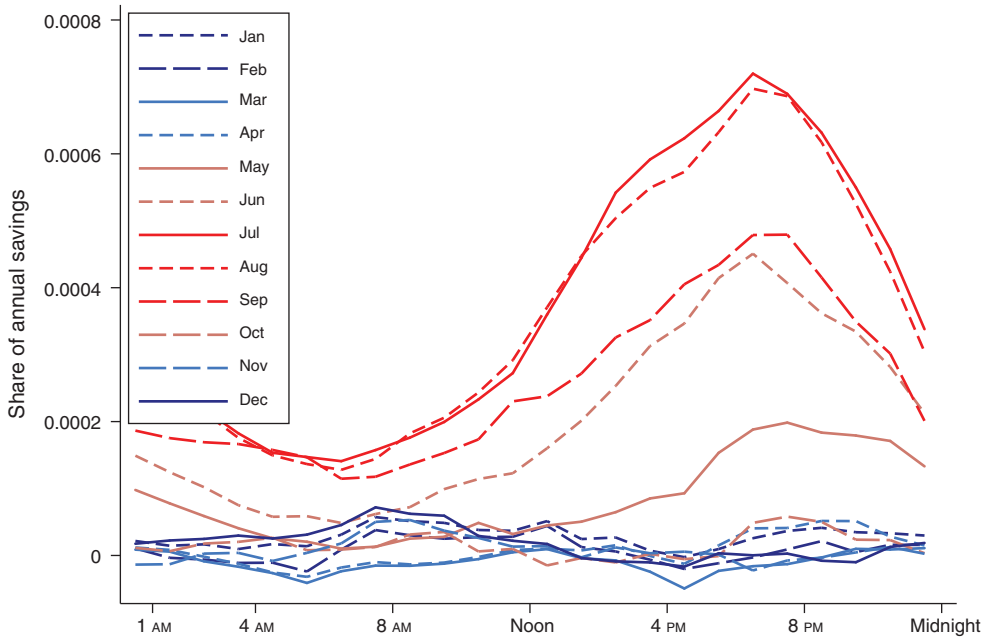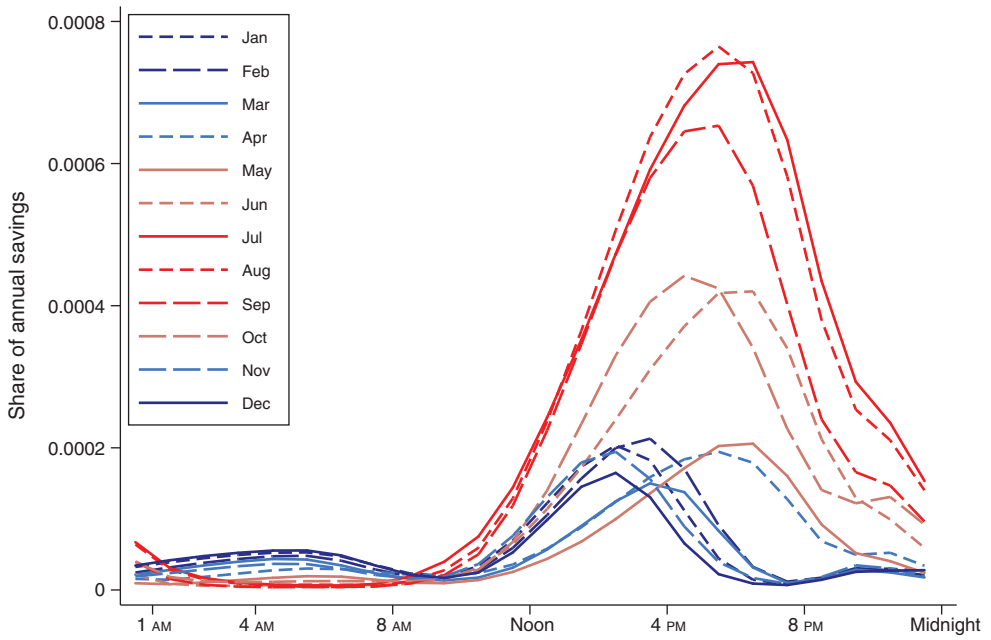

Panel B. Engineering predictions

FIGURE 5. COMPARING ESTIMATES OF ELECTRICITY SAVINGS

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 significant savings during summer nights even well after the peak, whereas the engineering predictions show savings quickly tapering off after 8 PM during the summer, reaching near zero at midnight. This suggests that the engineering predictions may be insufficiently accounting for the thermal mass of homes and how long it takes them to cool off after a warm summer day.

Overall, the econometric estimates also show a greater concentration of savings during the warmest months. Both sets of estimates indicate July and August as the two most important months for energy savings. But the engineering predictions indicate a significant share of savings in all five summer months, and a non-negligible share of savings during winter months. In contrast, the econometric estimates show that almost all of the savings occur June through September with only modest savings in October and essentially zero savings in other months.

B. *Savings Profiles for Other Investments*

Figure 6 plots hourly savings profiles for eight different investments, four residential and four nonresidential. Savings profiles for additional energy efficiency 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 PM and 9 PM 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 nonresidential 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 savings are much more concentrated during summer months. Finally, savings from commercial and industrial heat pumps peak in the summer, while savings from residential heat pumps peak in the winter.

How much should we trust these engineering predictions? Several recent econometric evaluations of energy efficiency investments have shown that ex post measured savings can differ significantly from ex ante predictions (Davis, Fuchs, and Gertler 2014; Levinson 2016; Allcott and Greenstone 2017; and Fowlie, Greenstone, and Wolfram 2018). For example, Fowlie, Greenstone, and Wolfram (2018) finds that energy savings in the US weatherization program are only about one-third of predicted savings. If engineering predictions fail to accurately predict the *level* of energy savings, it would seem prudent to be skeptical about the accuracy of these models for predicting *when* these savings occur.

Still, it is worth pointing out that, at least in our case, the estimated timing of savings corresponds well with the ex ante predictions. We pointed out several modest differences, but the broader pattern is quite similar with savings concentrated in summer months, mostly during the afternoon and evening. As additional

Panel A. Residential lighting

Panel B. Residential refrigerator or freezer

Panel C. Residential clothes washer

Panel D. Residential heat pump

Panel E. Commercial and industrial lighting

Panel F. Commercial and industrial chillers

Panel G. Commercial and industrial air conditioning
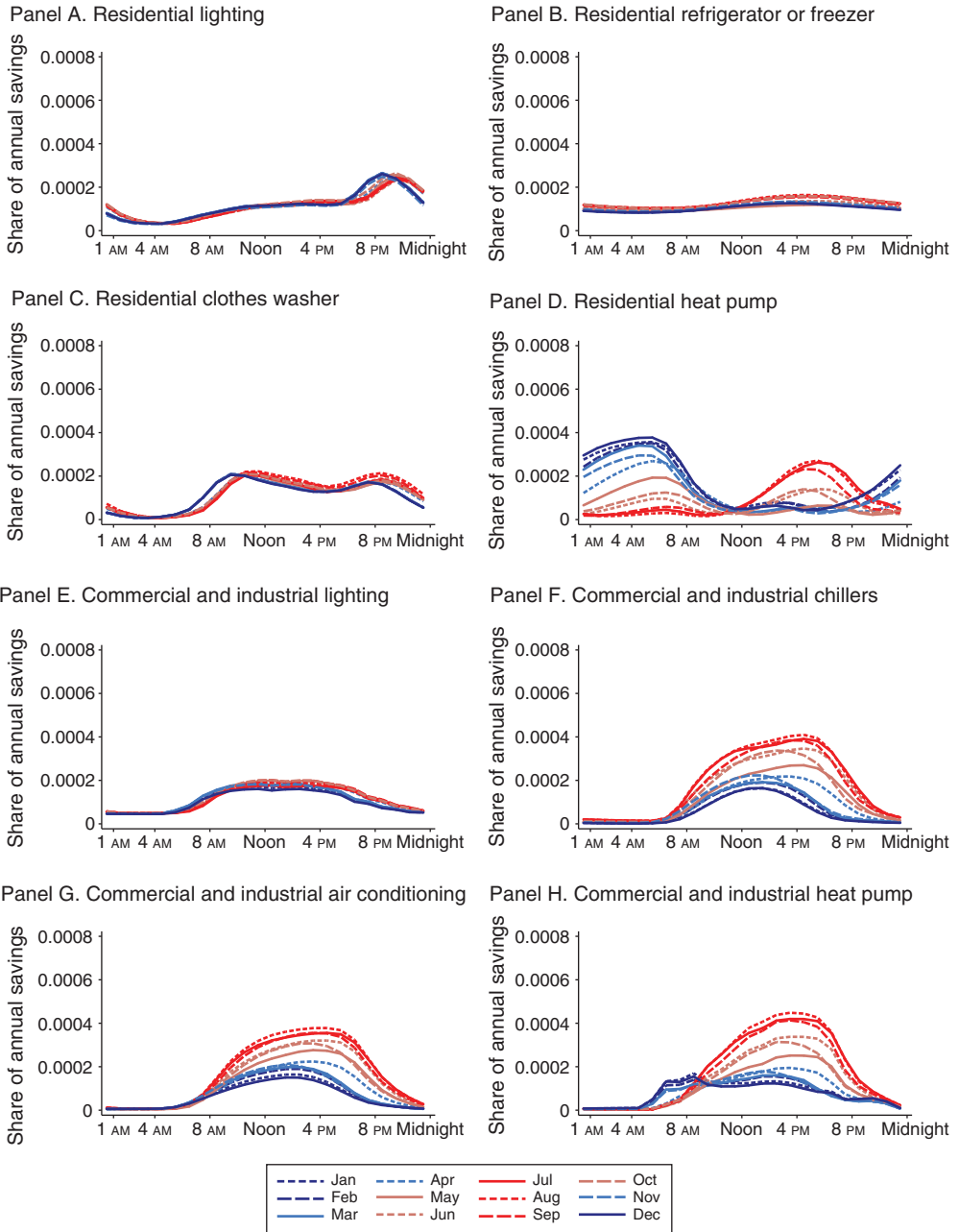
Panel H. Commercial and industrial heat pump

Figure 6. Savings Profiles for Selected Energy Efficiency Investments

ex post studies become available, it will be important to validate these engineering estimates; but in the meantime, we proceed to go ahead and perform additional analyses using the engineering-based savings profiles.

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
Panel A. Residential							
Air conditioning (econometric estimates)	37%	39%	17%	14%	0%	1%	18%
Air conditioning	56%	53%	23%	18%	18%	10%	30%
Lighting	3%	−5%	−2%	−1%	1%	−1%	−1%
Clothes washers	2%	2%	4%	7%	6%	4%	4%
Heat pump	−1%	−1%	−4%	−5%	−6%	−3%	−3%
Refrigerator or freezer	−1%	−5%	−5%	−3%	−4%	−6%	−4%
Panel B. Commercial and industrial							
Heat pump	32%	31%	18%	17%	17%	10%	21%
Chillers	27%	26%	14%	15%	12%	5%	17%
Air conditioners	25%	24%	14%	15%	13%	6%	16%
Lighting	3%	0%	1%	4%	4%	0%	2%

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

C. *Comparing Investments*

Table 3 reports timing premiums for this wider set of investments. Just as we did in Table 2, we calculate timing premiums as the additional value of each investment in percentage terms relative to a naive calculation that values savings using load-weighted average prices. As before, we value electricity using both wholesale prices and capacity payments, and we incorporate data not only from California but from five other US markets as well, including Texas (ERCOT), the Mid-Atlantic (PJM), the Midwest (MISO), NY (NYISO), and New England (ISONE). Capacity values are allocated to the three highest-load hours of the day in each month in CAISO and NYISO, and to the 36 highest hour-of-day by month-of-year pairs in PJM, MISO, and ISONE. See the online Appendix for details.

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

Interestingly, the timing premiums for residential air conditioning are much smaller in New York and New England. These markets have recently experienced high *winter* prices due to cold temperatures caused by a southward shift of the polar

vortex (see, e.g., Kim et al. 2014). Natural gas pipeline capacity is limited in parts of the Northeast, so when heating increases, there can be large spikes in electricity prices. Air conditioning investments provide little savings during these cold periods, resulting in low timing premiums. Premiums for the Northeast are particularly low with the econometric estimates, which show a very small share of savings occurring outside of summer months.

Other investments also have large timing premiums. Commercial and industrial heat pumps, chillers, and air conditioners all have premiums of about 20 percent, reflecting the relatively high value of electricity during the day. This is particularly true in California and Texas (24+ percent), though premiums are also consistently high in the Mid-Atlantic, Midwest, and New York. Again, timing premiums are substantially lower in New England, reflecting the poor match between these investments and the winter peak.

Timing premiums for lighting are close to zero. Residential lighting peaks in the evening, somewhat after the system peak in all US markets and is used disproportionately during the winter, when electricity is less valuable. This could change in the future as increased solar generation moves peak prices later in the evening, but for the moment both residential and nonresidential lighting have timing premiums near zero in all markets.

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

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

V. Conclusion

Hotel rooms, airline seats, restaurant meals, and many other goods are more valuable during certain times of the year and hours of the day. The same goes for electricity. If anything, the value of electricity is even more variable, often varying by a factor of ten or more within a single day. Moreover, this variability is tending to grow larger as a greater fraction of electricity comes from solar and other intermittent renewables. This feature of electricity markets is widely understood yet it tends to be completely ignored in analyses of energy efficiency

policy. Much attention is paid to quantifying energy savings, but not to *when* those savings occur.

In this paper, we've shown that accounting for timing matters. Our empirical application comes from air conditioning, one of the fastest growing categories of energy consumption and one with a unique temporal "signature" that makes it a particularly lucid example. We showed that energy efficiency investments in air conditioning lead to a sharp reduction in electricity consumption in summer months during the afternoon and evening. We then used electricity market data to document a strong positive correlation between energy savings and the value of energy.

Overall, accounting for timing increases the value of this investment by about 40 percent. An important part of this calculation was accounting for the large capacity payments received by electricity generators. In most electricity markets in the United States 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 energy efficiency investments. Residential air conditioning has the highest average timing premium across markets, though this premium goes away where the value of electricity peaks in the winter. Commercial and industrial heat pumps, chillers, and air conditioners also have high average premiums. Lighting, in contrast, does considerably worse, reflecting that these investments save electricity mostly during the winter and at night, when electricity tends to be less valuable.

These results have immediate policy relevance. For example, energy efficiency programs around the world have tended to place a large emphasis on lighting.[17] These programs may well save a large amount of electricity, but they do not necessarily do so during time periods when electricity is the most valuable. Another interesting example is the markedly lower timing premiums for air conditioning in the Northeast, where recent price spikes have tended to occur in the winter rather than the summer. Electricity prices necessarily reflect regional factors, so a one-size-fits-all approach to energy efficiency fails to maximize the total value of savings. We find a remarkably wide range of timing premiums across investments and markets so our results suggest that better optimizing this portfolio could yield substantial welfare benefits.

Our paper also demonstrates the wide-reaching potential of smart-meter data. Our econometric analysis would have been impossible just a few years ago with traditional electricity billing data, but today more than 50 million smart meters have been deployed in the United States alone. This flood of high-frequency data can facilitate smarter, more evidence-based energy policies that more effectively address market priorities.

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[17] For example, in California, 81 percent of estimated savings from residential energy efficiency programs come from lighting. Indoor lighting accounted for 2.2 million kWh of residential net energy savings during 2010–2012, compared to total residential net savings of 2.7 million kWh. See California Public Utilities Commission 2015, "2010–2012 Energy Efficiency Annual Progress Evaluation Report."

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