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Evidence from Hourly Smart-Meter Data

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The Incentive to Overinvest in Energy Efficiency: Evidence From Hourly Smart-Meter Data

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Abstract

In most hours of most days, consumers of electricity pay a marginal price that exceeds the marginal social cost of providing that electricity. We show that such pricing schemes provide a large subsidy for energy efficiency investments. Using hourly smart-meter data for households facing increasing block prices, we estimate how air conditioner upgrades affect electricity use. We find that the average participating household reduces consumption by 5%. While the avoided consumption provides modest social cost savings by decreasing generation and pollution, we find that the private savings the households achieve on their energy bills exceed the social savings by 140%.

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Private investment in energy efficiency is widely believed to be inefficiently low, which has motivated policymakers to provide generous financial incentives to spur investment in efficiency upgrades. From 2005 through 2012, the U.S. Federal government provided tax credits worth \$13.7 billion to households making energy efficiency improvements (Borenstein and Davis (2015)). State and local governments are providing support as well. For example, California offers homeowners up to \$6,500 in rebates for investing in a wide range of energy efficiency upgrades.¹

Two arguments drive the belief that energy efficiency investment is too low. First, consumers do not bear the full cost of the pollution created by consuming energy. As a result, energy efficiency upgrades (e.g., improving a home’s insulation) provide external benefits that do not accrue to those making the investments. Second, additional market failures (e.g., imperfect information, principal-agent problems) can result in an “energy paradox” – a situation in which investment in energy efficiency falls below the privately optimal level, let alone the socially optimal level.²

We focus on a third market imperfection that is often overlooked, even though it has potentially large effects on the incentive to invest in energy efficiency. Specifically, consumers in the residential electricity sector typically face price schedules that differ from the first-best rate structure. In theory, efficient electricity rates consist of a fixed fee combined with a per kilowatt-hour (kWh) charge set equal to the social marginal cost (Coase (1946)). In practice, however, per kWh charges are not set equal to the social marginal cost. While the social marginal cost of providing electricity varies substantially across hours and across days, the vast majority of households face per kWh charges that are fixed over time. Moreover, a household’s per kWh rate often increases with its aggregate monthly consumption – a practice referred to as increasing block, or tiered, pricing.³ Under increasing block rate structures, the marginal price paid by households – particularly those households with relatively low electricity consumption – often falls below the social marginal cost during periods

¹For a description of “Energy Upgrade California”, see <http://www.energyupgradeca.org/home>.

²For overviews of the literature studying the energy paradox, see Allcott and Greenstone (2012), Gillingham and Palmer (2014), and Gerarden et al. (2015).

³Increasing block electricity prices are used throughout California as well as in many other locations. In a 2008 survey of 61 U.S. electric utilities (BC-Hydro (2008)), 25 employed increasing block pricing for residential consumers. Tiered rate structures are also common among gas and water utilities.

with high market demand. In contrast, among high consuming households, or during non-peak demand periods, marginal prices generally exceed the social marginal cost.

The main effect of an improvement in energy efficiency is reduced energy use. This reduction benefits private residents by lowering their monthly energy bills, whereas it benefits society by avoiding the resource and environmental costs of generating additional electricity. These private and social benefits are only guaranteed to equal each other if the retail price equals the social marginal cost of energy. Other potential benefits, such as increased comfort (e.g., making the home cooler), accrue equally to the homeowner and to society. Thus, the difference between the private bill savings and the social cost savings reveals the extent to which private incentives to invest in energy efficiency are distorted away from the efficient outcome.

In this paper, we examine how increasing block rate structures affect households' incentives to invest in energy efficiency. We focus on air conditioning (AC), which is the single largest source of U.S. residential electricity consumption.⁴ We find that, when a household is faced with increasing block prices, the private savings it receives by investing in an energy efficient AC unit dramatically exceed the social cost savings. This excess constitutes a subsidy to energy efficiency. Contrary to the belief that households are under-investing in energy efficiency, our results suggest that private investment in residential energy efficiency may in fact exceed the socially optimal level of investment.

We use data from a set of households in Sacramento, California that participated in an energy efficiency rebate program run by the local electric utility. During 2012 and 2013, over 6,000 homeowners received a rebate for installing a new, energy efficient AC unit. Rather than focusing on the impact of the rebate program, we are specifically interested in estimating how the AC upgrades affect electricity consumption within the participating households. To do so, we combine information on the dates the participating households receive their new AC units with smart meter data that records the hourly electricity consumption at each residence. By identifying how the participating households' electricity consumption changes after installing the new AC units, we estimate the energy savings provided by the energy efficient AC systems. Participating households reduce their estimated non-winter consumption by an average of

⁴For a breakdown of residential electricity consumption by use, see the U.S. Energy Information and Administration's "Annual Energy Outlook 2015".

1.3 kWh per day – roughly a 5% reduction in total consumption.

To quantify the social costs avoided by the reductions in consumption, it is crucial to know not only how much energy is saved, but also when the reductions occur. This is due to the fact that the social marginal cost of supplying electricity varies substantially over time. Previous studies providing ex-ante estimates of the energy savings achieved by residential efficiency upgrades have relied on billing-data which records monthly, household-level consumption.⁵ As a result, the previous studies have been unable to determine when, within a given month, the resulting energy savings take place. In contrast, the newly available smart meter data enables us to estimate precisely when the reductions in energy consumption occur at each individual home. We find that the energy savings are concentrated during the late evening hours of the hottest days – and in particular, in the households with high historical levels of consumption.

Combining our estimates of the energy saved during each individual hour with (1) the observed hourly wholesale electricity prices and (2) estimates of the hour-specific marginal external cost of supplying electricity, we quantify the social cost savings provided by the new AC units. High-consuming households are responsible for the majority of the energy savings, and we estimate that the energy efficient AC units reduce the social cost of supplying electricity to these homes by an average of \$11.44 per month. In contrast, under the increasing block rate structure paid by the households, we estimate that the electricity bills fall by an average of \$26.56 per month. These estimates highlight that, by creating marginal prices that regularly exceed the social marginal cost, the current rate structure is implicitly – and heavily – subsidizing energy efficiency investments.

We also predict the private savings under three counterfactual pricing policies that are being actively considered by utilities and policymakers throughout California and elsewhere. The alternative policies include (1) flat electricity rates, (2) a time-of-use plan that increases prices during the peak demand hours each day, and (3) a critical peak pricing plan that increases peak-period prices on days with the highest expected demand. Each of the policies would achieve the same revenue as the current tiered rates without requiring any

⁵For example, see Metcalf and Hassett (1999), Jacobsen and Kotchen (2013), Davis, Fuchs and Gertler (2014), Graff Zivin and Novan (2016), and Fowle, Greenstone and Wolfram (2015*b*).

changes to the existing fixed monthly charge. Importantly, each of the alternative policies removes the increasing block structure that causes the marginal price to increase with consumption. While the private cost savings are found to exceed the social cost savings by 132% under the existing rate structure, we estimate that the private savings would only exceed the social savings by 64% to 69% under the three alternative pricing policies. These results reveal that the increasing block rate structure is responsible for approximately half of the implicit subsidy energy efficiency investments are receiving. Much of the remaining half is driven by the fact that an inefficiently high share of revenue comes from per kWh charges.

This paper contributes to a growing literature highlighting the inefficiencies stemming from current residential energy rate structures. For example, Davis and Muehlegger (2010) stress that the combination of low fixed charges and high marginal prices results in inefficiently low energy consumption. Borenstein (2012) and Borenstein and Davis (2012) further demonstrate that increasing block rate structures can lead to an inefficient distribution of energy consumption across households.

These previous studies focus on how rate structures distort short-run energy consumption, but the rate structure may also impact the decision to invest in long-lived energy producing or consuming durables. For example, Borenstein (2015) demonstrates that California’s increasing block rate structures provide high consuming households with a strong incentive to invest in solar panels. Similarly, by directly comparing the private and social cost savings provided by AC upgrades, we show that the rate structures provide an implicit subsidy to residential energy efficiency. In particular, even without direct subsidies from the state and federal governments, the privately optimal level of residential energy efficiency exceeds the socially optimal level by a substantial amount. Recall, additional market failures (e.g., imperfect information, principal-agent problems) can depress actual investment below the privately optimal level. However, our results demonstrate that any such “energy paradox” would have to be widespread across households and large to justify the implicit subsidy created by the current increasing block rate structures.

The remainder of the paper proceeds as follows. Section 1 discuss the energy efficiency upgrades and consumption data we examine. Section 2 presents estimates of the energy savings achieved by the efficiency upgrades and Section 3 explores the private savings. Section 4 compares the estimates of the private

savings to estimates of the social costs avoided and Section 5 concludes.

1 Data Sources

1.1 Energy Efficiency Rebate Program

This paper focuses on households purchasing electricity from the Sacramento Municipal Utility District (SMUD). SMUD is a community-owned utility, which means that it is a nonprofit organization serving its local community. It is governed by an elected board of directors and can set rates and issue debt to achieve its stated purpose, which is “to enhance the quality of life for our customers and community through creative energy solutions.” Thus, in developing programs and setting rates, SMUD balances a broad set of objectives. These include maintaining competitive rates, reflecting the cost of energy when it is used, meeting the needs of customers with fixed low incomes or severe medical conditions, equitable allocation of costs, and encouraging energy efficiency.

As part of SMUD’s effort to encourage investment in energy efficiency, the utility provides customers with rebates for purchasing new, energy efficient appliances (e.g., refrigerators, water heaters, etc.) as well as rebates for carrying out energy efficient upgrades of their homes (e.g., improved insulation, new windows, duct sealing, etc.). Our analysis specifically examines the households that select to participate in SMUD’s central air conditioning (AC) rebate program. This program provides residential customers with rebates ranging from \$400 to \$2,000 for installing new central AC units that meet the EPA’s Energy Star standards.⁶

It is important to stress that the objective of our analysis is not to determine the impact of the AC rebate program. Instead, we are interested in understanding how installing a new, energy efficient AC unit affects the quantity of electricity consumed by a participating household. Specifically, we seek to estimate the difference in the amount of electricity consumed by a household that has installed a new AC unit relative to the quantity of electricity that would have been consumed had the household not upgraded to the new,

⁶To be classified as an Energy Star central AC unit, and to be eligible to receive a rebate from SMUD, an AC unit must have a Seasonal Energy Efficiency Ratio (SEER) that exceeds the federal minimum of SEER of 14.

energy efficient AC unit.⁷ Therefore, our estimates of the resulting changes in electricity consumption capture the impact of the physical AC upgrades as well as any resulting behavioral responses – that is, any “rebound” in post-upgrade electricity consumption – exhibited by the participating households.

We narrow our focus to the AC program participants for three main reasons. First, the central AC program is the largest in terms of number of participants amongst SMUD’s energy efficiency rebate programs. During 2012 and 2013, the period we examine, 6,142 single family households received a rebate for installing a new, energy efficient AC unit.⁸ Second, in the region we study, indoor temperature control is one of the largest sources of residential demand for electricity.⁹ As a result, improving the energy efficiency of the AC units has the potential to cause large changes in energy consumption – and in particular, during hot, summer days when California’s demand for electricity, and the cost of providing it, typically peaks. Finally, understanding the affects of installing energy efficient AC units provides insights into how a range of other investments, which are also intended to reduce cooling-related electricity demand (e.g., attic or wall insulation), will impact residential electricity consumption. However, unlike investments in factors like improved insulation, installing a new AC unit is a much more homogeneous treatment. As a result, we are able to carefully explore the extent to which the impact of a new AC unit varies across homes.

1.2 Electricity Consumption and Expenditures

To estimate the impact of installing an energy efficient AC unit on electricity consumption, we use household-level smart meter data.¹⁰ By the beginning

⁷In contrast, to estimate the impact of the rebate program, we would need to compare a household’s post-upgrade electricity consumption to the consumption that would have occurred in the absence of the AC rebate program. The important distinction is that the AC upgrade may still have occurred even without the rebate program. In this case, while the physical AC upgrade may alter electricity consumption, the rebate program itself would have had no impact on electricity consumption.

⁸We focus exclusively on premises that are classified as single-family units as opposed to multi-family, rental units. The classifications are provided by matching Sacramento County Assessor data to each premise in our sample.

⁹The California Energy Commission provides a summary of electricity consumed by end source at the following location: http://energyalmanac.ca.gov/electricity/electricity_stats/index.html.

¹⁰For security reasons, the smart meter data is matched to the energy efficiency program participation data using an anonymized premise ID. The individual names, addresses, and account numbers were removed before we received the data.

of January, 2012, each household in the SMUD service territory had a smart meter installed. In contrast to the previous analog meters, which were used to record electricity consumption over monthly intervals, the smart meters record each household’s consumption at the hourly frequency. For the period from January 1, 2012 through December 31, 2013, we observe the hourly consumption from each of the premises participating in the AC rebate program.

In addition to the smart meter data, we observe the household-level, monthly billing data. The billing data provides two key pieces of information. First, we observe if the SMUD account number at a premise changes. Often, this is a signal that a new owner is residing in the premise. To ensure that any of the observed changes in electricity consumption are not caused by a change in residence, we drop any premises that had multiple account numbers during the two year sample. Second, the billing data records the SMUD rate category in which each household is enrolled. In our sample, each household pays increasing block – or tiered – rates. For example, households in the standard rate class – which account for 92% of our sample – paid 9.89 cents per kWh on the first 700 kWh’s they consumed in a summer month and 18.03 cents per kwh on any additional electricity consumed.¹¹ During the period we examine (2012-2013), the monthly consumption at the participating households placed them in the second price tier 58% of the time. We use the information on the specific rate categories to estimate how the AC upgrades affect each participating household’s energy expenditures under the current tiered pricing regime.

While the vast majority of residential consumers in California currently pay tiered electricity prices, several alternative pricing strategies are receiving serious consideration. First, following the passage of AB-327, the California Public Utilities Commission is considering a move towards “flatter” tiered rate profiles that remove the steep, increasing block rate structures used throughout much of California. In addition, with the increased penetration of smart-meters, wider use of dynamic electricity pricing is also being considered. For example, SMUD recently conducted a pilot study to examine how customers

¹¹The rates, and the threshold between tier 1 and tier 2 consumption, are not constant across households. For example, low income households are eligible to receive a 30% reduction on their rate for all tier 1 and some tier 2 consumption through the Energy Assistance Program (EAPR). Roughly 7% of our sample paid EAPR rates. In addition, households with electric well pumps – roughly 1% of the sample – pay the tier 1 rate on the first 1,000 kWh’s of consumption during summer months.

would respond to possible TOU or CPP policies. Under the TOU plan examined, households were charged \$0.27 per kWh for electricity consumed between 4:00pm and 7:00pm on non-holiday, summer (June through September) weekdays. Under the CPP plan, SMUD selected up to 12 event days from June through September on which wholesale prices were expected to be the highest. On those days, consumers paid \$0.75 per kWh for electricity used between 4:00pm and 7:00pm.

To explore how the private savings provided by the AC upgrades would differ if the households did not pay the current increasing block prices, we estimate the private bill savings the households would receive had the customers been faced with one of three alternative pricing strategies during 2013. The first is similar to the SMUD pilot study's TOU policy which charged a peak price from 4:00pm to 7:00pm during the summer months. The second alternative policy is a CPP plan that follows the design of the SMUD pilot study's CPP policy. Finally, we consider a hypothetical flat-rate policy which charges a constant per kWh price. The key similarity among the three hypothetical pricing policies is that each one of them would remove the increasing tiered rates.

1.3 Wholesale Prices and Air Pollution

In addition to estimating the impact of the new AC units on private electricity expenditures, we also quantify the social cost savings achieved during 2013 by installing the energy efficient AC units. To estimate the social costs avoided, we use data from two additional sources. First, to estimate the private generation costs that are avoided, we use information on the hourly wholesale electricity prices in the Sacramento region. Specifically, we use the hourly average locational marginal prices (LMP) reported by the California Independent System Operator (CAISO). Given that the vast majority of electricity is procured through the day-ahead market, we elect to use the prices in the day-ahead market. For comparison, we also estimate the private generation costs avoided using observed prices from the real-time market and find very similar results.

To highlight the variation in the wholesale prices, Figure 1 summarizes the minimum and maximum wholesale prices by hour, as well as the 25th, 50th, and 75th percentiles, during the non-winter months (April through October) –

precisely when the new AC units have the potential to reduce the electricity required for cooling. During 2013, the median hourly prices reach a minimum of 3 cents per kWh (\$30 per MWh) during the 4am hour and a maximum of 4.7 cents per kWh during the 5pm hour. There is even greater variation in the prices across days. For example, during the 5pm hour, the hourly average LMP varies between 3.3 cents per kWh and 16.6 cents per kWh. The magnitude of the temporal variation in marginal prices highlights why it is crucial to determine when the energy savings occur in order to estimate the generation costs avoided by energy efficiency upgrades.

If the new AC units reduce electricity consumption, the avoided generation costs may only account for a portion of the avoided social costs because the external pollution costs created by generating electricity can also be reduced. However, quantifying the avoided external costs is complicated by the fact that there are existing environmental policies that may interact with the reductions in electricity demand. In particular, California implemented a CO₂ cap-and-trade program beginning in January of 2013. If the CO₂ cap ultimately proves to be a binding regulation, meaning that the business-as-usual emissions would exceed the cap, then a marginal decrease in electricity demand among the SMUD customers will not affect the aggregate emissions of CO₂ over the period the cap is set. Alternatively, if the cap is not set at a binding level, then reductions in electricity demand can provide real reductions in CO₂ emissions.

Given the uncertainty surrounding California's business-as-usual CO₂ emissions (e.g., Borenstein et al. (2015)), we choose to take a conservative approach. Specifically, we assume that the CO₂ cap is not binding and we estimate the upper bound of the social costs avoided by the new, energy efficient AC units during 2013. To quantify the reduction in the pollution costs under the assumption that the CO₂ cap is not binding, we must estimate the quantity of pollution avoided by the AC upgrades. To do so, we collect information on the hourly emissions of CO₂, NO_x, and SO₂ emitted throughout the western U.S. from the Environmental Protection Agency's Continuous Emissions Monitoring Systems (CEMS). As several recent studies highlight (Siler-Evans, Azevedo and Morgan (2012), Carson and Novan (2013), Graff Zivin, Kotchen and Mansur (2014), Jacobsen (2014), Callaway, Fowlie and McCormick (2015)), the quantity of pollution avoided by a marginal decrease in electricity generation varies across hours. Following the methodology from these previous studies, we estimate hour-specific marginal emission rates and use these estimates to predict

the avoided pollution.

2 Impact of Energy Efficiency on Consumption

To determine how the new, energy efficient AC units affect electricity use, we estimate the average change in consumption that occurs after the participating households receive new AC units. We begin this section by presenting a pooled model for estimating average effects. Then, we augment the basic model to allow for heterogeneous impacts across temperature and hour of day.

2.1 Econometric Specification

To examine the average impact of the AC upgrades on the participating households' daily electricity consumption, we estimate the following pooled household fixed effects model:

$$Cons_{i,d} = \alpha_i + \gamma \cdot Post_{i,d} + \boldsymbol{\theta} \cdot \mathbf{W}_d + \varepsilon_{i,d}, \quad (1)$$

where i indexes each individual household that receives a new AC unit and d indexes each day during the two year sample. $Cons_{i,d}$ represents the total consumption (kWh) for household i on day d . \mathbf{W}_d , which is discussed in greater detail below, is a flexible spline function controlling for temperature driven shifts in electricity demand. Finally, $Post_{i,d}$ indicates household i 's treatment status. Although the information we observe identifies each premise that participates in the AC rebate program, we do not know the exact dates that the new AC units are installed. Instead, we observe the dates that the rebates are mailed to each of the participating households. Therefore, $Post_{i,d}$ switches from 0 to 1 beginning on the day household i 's AC rebate was sent. The key coefficient of interest, γ , represents the average change in a participating household's daily electricity consumption following the date the AC rebate is sent to the homeowner.

Given that the new AC units will be installed prior to the date the rebates are sent, $Post_{i,d}$ will equal zero on an unknown number of days when premise i had in fact already received a new AC unit. By including these post-upgrade observations during the pre-treatment period (i.e. when $Post_{i,d} = 0$), we would

expect to understate any energy savings provided by the new AC units.¹² However, we know anecdotally that the lag between the mailing dates and the physical upgrades are typically quite short (e.g., two to three weeks). Moreover, due to the program requirements, the lag between the installation and the rebate date cannot exceed 90 days. To examine the extent to which our imperfect measure of the treatment date can impact our estimate of the average effect of the AC units, we present several estimates of Eq. (1), each time dropping anywhere between 0 and 90 days worth of observations immediately preceding the observed rebate dates. Given that the rebate date had to occur within 90 days of the actual AC upgrade, dropping 90 days prior to the rebate date ensures that $Post_{i,d}$ will accurately separate the observations for each premise into pre and post-upgrade periods. By accurately separating the pre and post-upgrade observations, we will be able to interpret the coefficient γ as the average change in a participating household’s daily electricity consumption following the AC upgrade.

To identify the average impact of the AC upgrades, we use within-household variation in the daily level of electricity consumption. Therefore, it is important to control for time-varying determinants of electricity demand that could be correlated with the timing of the AC upgrades. In the region we study, the weather – and in particular, the temperature – is the key factor driving daily variation in electricity consumption. To control for temperature driven shifts in electricity demand, Eq. (1) includes the average daily temperature in Sacramento (T_d).¹³ The daily temperature enters the model in piecewise linear form with three knot points (at 63°F, 70°F, and 75°F).¹⁴ Specifically,

¹²It is also possible that a household installs a new, energy efficient AC unit in response to their existing AC unit breaking. As a result, the electricity consumption during the days immediately preceding $Post_{i,d}$ switching from 0 to 1 could be lower than would be expected if the existing AC unit was still functioning. In this case, we would expect to overestimate the energy savings provided by the new AC unit relative to the previous, functioning AC unit.

¹³We use NOAA data that records the temperature from the Sacramento International Airport. Rather than using the average daily temperatures, a number of alternative strategies were also considered – including using the individual hourly temperatures, or the daily maximum and minimum temperatures. However, the average daily temperature turns out to be very highly correlated with the hourly temperatures. For each of the 24 hours of the day, we calculate a correlation coefficient between the average daily temperature and the hour-specific temperature. Across the 24 hours of the day, the correlation coefficients never fall below 0.81 and, on average, equal 0.92.

¹⁴63°F, 70°F, and 75°F are approximately the 25th, 50th, and 75th percentiles of average daily temperatures between April and October – the non-winter months which we ultimately focus on in the empirical analysis.

\mathbf{W}_d represents the following 5×1 vector:

$$\mathbf{W}_d = \begin{bmatrix} 1 \\ \min(T_d, 63) \\ \min(\max(T_d - 63, 0), 70 - 63) \\ \min(\max(T_d - 70, 0), 75 - 70) \\ \max(T_d - 75, 0) \end{bmatrix}. \quad (2)$$

We must also account for the possibility that households choosing to install a new, energy efficient AC unit may also be making other energy efficiency upgrades to their homes. In an effort to focus solely on the impacts of the AC upgrades, we drop any households that participate in multiple SMUD rebate programs. Additionally, we must address the possibility that some households receiving a new AC unit may be replacing a heat-pump. In contrast to AC units, which are used only for cooling, heat-pumps use electricity for cooling and heating. Therefore, a household that replaces a heat-pump with a new AC unit will likely achieve a reduction in cooling-related electricity consumption – which is caused by the new AC unit – as well as a reduction in heating-related electricity consumption – which is not caused by the new AC unit, but rather by a switch from electric to natural gas heating.¹⁵

To ensure that any electricity savings caused by a switch to natural gas heating are not attributed to the impact of a new AC units, we place two additional restrictions on our sample. First, we drop all households enrolled in SMUD’s electric-heat rate plan. The electric-heat rate plan, which allows households to consume more electricity at the low, baseline price during the winter months, is only open to households using electricity as their primary energy source for heating. Therefore, dropping these homes removes the premises that are likely to have heat-pumps to begin with. Second, to account for the fact that some eligible households will not enroll in the electric-heat rate program, we drop the five coldest months (November through March) from the analysis and focus exclusively on the warmer months when cooling-driven demand shifts may occur.¹⁶ In the end, the dataset we examine includes 5,423 single family households that each receive new AC units at some point during 2012 and 2013.

¹⁵We do not observe natural gas consumed by the households in our dataset.

¹⁶The five excluded months are the only months with average daily temperatures below 60°F.

Of course, there are a range of other time-varying determinants of electricity demand that could be correlated with the timing of the AC upgrades. If any time-varying determinants of demand are correlated with the timing of the AC upgrades, then our estimates of the resulting energy savings could be biased. While we are unable to control for all time-varying electricity demand shifters, the very detailed, hourly consumption data we observe enables us to carefully examine the temporal heterogeneity in the impacts of the AC upgrades. In particular, our subsequent results reveal that, after receiving an energy efficient AC unit, a participating household’s electricity consumption falls specifically during the time periods when AC units are used for temperature control – e.g., on the warmest summer days and during the afternoon and evening hours when Sacramento temperatures reach their peak. In contrast, electricity consumption is unaffected on the cooler summer days and during the temperate morning hours. These results provide strong evidence that, rather than being driven by omitted variable bias, our estimates are uncovering the impacts of the AC upgrades on the participating households’ electricity consumption.

2.2 Pooled Model Results

We first estimate Eq. (1) using all of the daily observations from April through October of 2012 and 2013 for the 5,423 households participating in the AC upgrade program. The first column of Table 1 presents the estimate of the average change in daily electricity consumption that occurs following the observed AC rebate dates. The reported standard errors are robust to heteroskedasticity and to two-way clustering by household and week-by-year. On average, a participating household’s daily consumption falls by 1.24 kWh following the AC rebate date. To give a sense of the magnitude of this change, during the months examined, the median daily consumption among the participating households is 24 kWh.

Recall, each premise will already have their new AC unit installed for an unobserved number of days immediately prior to the rebate date. As a result, the average post-rebate reduction of 1.24 kWh’s per day likely understates the average energy savings caused by the new AC units. To account for this, we also estimate Eq. (1) dropping the 14, 30, 60, or 90 days immediately preceding the observed rebate dates. Columns two through five of Table 1 present the

resulting estimates. Consistent with the fact that AC upgrades occur up to 90 days prior to the rebate date, as the number of dropped pre-rebate observations grows, the estimates of the average change in electricity consumption become more negative. Dropping the 90 days immediately preceding the rebate-dates, we estimate that, on average, daily electricity consumption falls by 1.41 kWh following the installation of a new AC unit. The results presented in Table 1 also reveal that the majority of the jump in the estimate of γ is achieved simply by dropping the first 30 pre-rebate days for each household. This finding corroborates the anecdotal evidence suggesting that the majority of households receive their rebates within the first month following the AC upgrade.

To provide additional evidence regarding when the actual AC upgrades occur, we reestimate Eq. (1) allowing γ to flexibly vary across the months leading up to, and following, the observed AC rebate dates. Specifically, we estimate the following model:

$$Cons_{i,d} = \alpha_i + \sum_{m=-7}^{-1} \gamma_m \cdot Pre_{i,d,m} + \sum_{m=1}^7 \gamma_m \cdot Post_{i,d,m} + \boldsymbol{\theta} \cdot \mathbf{W}_d + \varepsilon_{i,d}. \quad (3)$$

Rather than including a single treatment indicator, we now include a set of dummy variables $\{Pre_{i,d,m}\}$ which separate the days immediately preceding each household’s observed rebate date into 7 mutually exclusive 30-day pre-rebate windows. Thus, γ_{-1} represents the average change in a household’s daily electricity consumption that occurs during the first 30 days preceding the AC rebate dates while γ_{-2} represents the average change in daily consumption during the window 30 to 60 days prior to the rebate dates. In addition, we include 7 post-rebate dummy variables $\{Post_{i,d,m}\}$ which separate the observations following each household’s rebate date into 30-day windows representing 1, 2, 3, 4, 5, 6, or 7+ months after the rebate date. All of the changes are measured relative to the daily consumption that occurs on days eight or more months (i.e. more than 240 days) prior to the households’ rebate dates.

Figure 2 presents the 14 points estimates of the pre and post-rebate γ_m values from Eq. (3) along with the corresponding 95% confidence intervals – which are again robust to heteroskedasticity and clustering at the household and week-by-year levels. Focusing on the pre-rebate months, there is evidence that the AC upgrades occur largely during the first 30 days prior to the AC rebate date. On average, households reduce their daily consumption by 0.91 kWh during the first pre-rebate month. This estimated reduction is approxi-

mately two-thirds as large as the average daily energy savings during the first post-rebate month (1.42 kWh/day). This is consistent with approximately two thirds of the daily observations during the first pre-rebate month coming from households which had already received a new, energy efficient AC unit.

While there is strong evidence that AC upgrades take place during the 30 days immediately preceding the AC rebate dates, Figure 2 reveals that more than 30 days before the observed AC rebate dates (i.e. during pre-rebate months 2 through 7), there are no significant changes in the average level of electricity consumption. These findings, combined with the estimates presented in Table 1, suggest that we can quite accurately separate the daily observations into pre-upgrade and post-upgrade observations by (A) continuing to use the $Post_{i,d}$ indicator to reflect whether a household has been treated with a new AC unit, and (B) dropping the 30 days immediately preceding each individual household's observed rebate date. Throughout the remainder of our analysis, we follow this procedure to estimate the impact of the AC upgrades.

In addition to shedding light on when the AC upgrades occur, the results presented in Figure 2 also provide evidence that the estimated changes in consumption are being caused by the AC upgrades as opposed to an alternative, time-varying household characteristic that we cannot observe. If the consumption changes were instead being driven by a confounding variable that is simply correlated – but not perfectly – with the timing of the AC upgrades, then we might expect to see significant changes in consumption that occur prior to the AC upgrades – that is, during the period of time more than 30 days before the AC rebate dates. However, there are no significant changes in consumption preceding the first pre-rebate month when the AC upgrades largely occur. Moreover, if the AC upgrades were being performed prior to other household changes that could affect electricity demand (e.g., new household members, retirements, income changes, etc.), then we might expect that the estimated consumption changes during the post-rebate months would vary over time as the confounding demand shifts occur. However, during each of the post-rebate months, there is a very stable reduction in the average daily electricity consumption.

2.3 Heterogeneity in Energy Savings Over Time

A key advantage of the hourly smart meter data is that it allows us to estimate not only how much energy is conserved, but also when the energy savings occur – both across hours of the day as well as on different days within a month. This is valuable for two main reasons. First, given that the marginal cost of supplying electricity varies substantially across time, understanding when the reductions in consumption occur plays an important role in determining the social costs that are avoided. Second, by uncovering when the energy savings occur, we can provide additional evidence that our estimation strategy is uncovering the consumption changes caused by the AC upgrade. In particular, if the reductions in consumption are caused by installing energy efficient AC units, then we would expect the energy savings to be concentrated during the late afternoon hours when demand for cooling is the highest. Moreover, we would expect the energy savings to be concentrated on the hottest days.

To examine how the energy savings vary across hours of the day, we estimate the following model separately for each hour of the day:

$$Cons_{i,h,d} = \alpha_{i,h} + \gamma_h \cdot Post_{i,d} + \boldsymbol{\theta}_h \cdot \mathbf{W}_d + \varepsilon_{i,h,d}, \quad (4)$$

where $Cons_{i,h,d}$ now represents the electricity consumed at household i during hour h of day d and $\alpha_{i,h}$ is a household fixed effect that is allowed to vary across hours of the day. To account for the fact that the upgrades occur prior to the observed rebate dates, we drop all observations from the 30 days immediately preceding each household’s rebate date. Estimating Eq. (4) separately for each hour of the day results in 24 point estimates of γ_h , the average impact of a new AC unit on consumption during hour h .

Figure 3 displays the point estimates of the average change in consumption by hour as well as the corresponding 95% confidence intervals. The results reveal that the largest energy savings caused by the AC upgrades occur during the late afternoon and nighttime hours. In contrast, during the morning hours, the estimated energy savings are small and statistically insignificant. These findings are consistent with the daily temperature patterns in Sacramento. During the summer months observed during our sample (June through September, 2012 and 2013), the average hourly temperature during the 5pm hour (hour 17) was 90°F – the highest across all hours – and remained above 75°F through the 9pm hour. In contrast, during the morning hours (6am

through 10am), the average hourly temperature during the summer months is 64°F. Therefore, if the new, energy efficient AC units are reducing the electricity required for cooling the homes, we would expect to see energy savings occurring during the late afternoon/evening hours when the demand for cooling is the highest. In addition, we would expect to see very little energy savings during the cool morning hours – which is precisely what we see in Figure 3.

It is also important to note that the energy savings are not confined between 4:00pm and 7:00pm (hours 16, 17, and 18) when demand on the California grid typically peaks – and consequently, when wholesale electricity prices are at their highest. Instead, the post-7pm hours display the largest average energy savings. This suggests that a large share of the energy savings take place during hours when the private marginal generation costs are relatively low.

If the AC upgrades are reducing the electricity consumed to cool homes, then we would expect the energy savings to not only vary across hours of the day, but also across days with different average temperatures. To directly examine how the quantity of energy saved varies with the daily temperature, we estimate the following model separately for each hour of the day:

$$Cons_{i,h,d} = \alpha_{i,h} + \beta_h \cdot \mathbf{W}_d \cdot Post_{i,d} + \theta_h \cdot \mathbf{W}_d + \varepsilon_{i,d}. \quad (5)$$

In Eq. (5), β_h is a 1×5 vector of coefficients which specifies the average change in electricity consumption during hour h as a function of the average daily temperature. To highlight the heterogeneity in the resulting energy savings, we report two specific hours of the day – 8am, when the minimum average energy savings occurs, and 8pm, when the maximum average energy savings occurs. Again, we drop all observations from the 30 days immediately preceding each household’s rebate date. The standard errors are robust to heteroskedasticity and are clustered at the household and week-by-year levels.

Figure 4 displays the estimates of the average hourly change in electricity consumption, following the receipt of an AC rebate, on days with average temperatures ranging from 52°F to 86°F.¹⁷ The estimates reveal that, regardless of the average daily temperature, the new AC units do not affect the average level of electricity consumed during the 8am hour. This is consistent with households not using their AC units for cooling during the morning hours. In

¹⁷These temperatures represent the 1st and 99th percentiles of the average daily temperatures during April through October of 2012 and 2013.

contrast, during the 8pm hour, we find that the new AC units provide significant energy savings on days when the average temperature exceeds 72°F. Moreover, as the temperature increases beyond 72°F, the average energy savings during the 8pm hour increase.

The results presented thus far reveal that the new AC units have very heterogeneous impacts on electricity consumption during different hours and across different days. In the following section, we extend the analysis to explore how the energy conserved varies across households. Using our household specific estimates, we predict the resulting private savings the households receive on their monthly electricity bills.

3 Private Cost Savings from Energy Efficiency

In this section, we present estimates of the private savings households receive on their electricity bills following the installation of the energy efficient AC units. Specifically, we consider the following question. How much would each household pay for electricity had their new, energy efficient AC unit been in place for all of Summer 2013 and how much would they have paid if they did not have the new AC unit during Summer 2013?

We first estimate the pre-upgrade and post-upgrade expenditures that would occur under the actual tiered pricing structure that each household was subject to during 2013. We then present estimates of the expenditures that would have occurred under three alternative, revenue-neutral pricing plans: (1) a TOU pricing plan that increases summer rates during the peak afternoon hours, (2) a CPP plan that increases rates during the peak hours on the hottest summer days, and (3) a simple flat retail price policy. We focus specifically on the expenditure changes during four summer months (June through September) for two key reasons. First, these summer months have the highest temperatures, and therefore, the energy efficient AC units have the clearest potential to affect electricity consumption. Second, following the TOU and CPP policies that SMUD examined in their recent pilot study (SMUD (2014)), the simulated TOU and CPP pricing plans only alter the electricity prices during these summer months.

3.1 Household-Level Consumption Changes

To estimate the average private savings achieved by installing the new AC units, we first estimate how electricity consumption at each participating household changes. Using these estimates, we then compute how each individual household’s expenditure on electricity is affected by the new AC units and then summarize the predicted private savings across households. This approach allows households that experience larger energy savings following an AC upgrade to be in a different pricing tier from those with smaller savings. If, for example, households that save the most energy are also more likely to pay the higher tiered price, then simply multiplying the pooled estimates of the energy savings by the average retail price will underestimate the private savings provided by the new AC units.

To determine how each household’s electricity consumption is affected by the new AC units, we estimate the following model separately for each premise and for each hour of the day:

$$Cons_{i,h,d} = \alpha_{i,h} + \beta_{i,h} \cdot \mathbf{W}_d \cdot Post_{i,d} + \theta_{i,h} \cdot \mathbf{W}_d + \varepsilon_{i,h,d}, \quad (6)$$

where $Cons_{i,h,d}$ represents the electricity consumed at household i during hour h of day d and \mathbf{W}_d is again specified by Eq. (2). To estimate the models, we use observations from April through October of 2012 and 2013, excluding the 30 days immediately preceding each household’s observed rebate date. To ensure that we observe summer consumption before and after the AC upgrade, we focus exclusively on the 2,496 households that received a rebate for their new AC unit between June 16, 2012 and July 4, 2013.¹⁸

Combining the estimates $\{\hat{\alpha}_{i,h}, \hat{\beta}_{i,h}, \hat{\theta}_{i,h}\}$ with the observed daily temperatures from June 1, 2013 through September 30, 2013, we can predict the expected pre-upgrade consumption, i.e., the consumption that would occur without the new AC unit, and the expected post-upgrade consumption, i.e., the consumption that would be observed after the AC unit is installed, for each household and for each hour. Specifically, the estimated pre-upgrade and post-upgrade consumption levels for household i during hour h of day d are

¹⁸Using only rebates inside this window ensures that the pre-rebate and post-rebate observations have a common support over the range of temperatures.

given by:

$$\text{Pre-Upgrade Consumption}_{i,h,d} = \hat{\alpha}_{i,h} + \hat{\theta}_{i,h} \cdot \mathbf{W}_d \quad (7)$$

$$\text{Post-Upgrade Consumption}_{i,h,d} = \hat{\alpha}_{i,h} + \hat{\theta}_{i,h} \cdot \mathbf{W}_d + \hat{\beta}_{i,h} \cdot \mathbf{W}_d. \quad (8)$$

The first column of Table 2 presents the average pre and post-upgrade electricity consumption among the 2,496 households examined. Our results reveal that, on average, the energy efficient AC units reduce a household’s summer consumption by 1.13 kWh per day.¹⁹ There is, however, considerable heterogeneity in the estimated energy savings across households. To highlight this heterogeneity, we separate the households into three groups – low, medium, and high electricity users. To create these groups, we first aggregate each household’s consumption during the summer (June through September) of 2011 – prior to the 2012 and 2013 period when we observe the households’ hourly consumption.²⁰ The ‘Low’ consumption group includes the households that, on average, use less than 25 kWh per day during the summer of 2011. These low users account for approximately 33% of the households. The ‘Medium’ consumption group, approximately 50% of the homes, uses between 25 kWh and 50 kWh per day. Finally, the ‘High’ consumption group, the remaining 17% of households, uses more than 50 kWh per day.

The last three columns of Table 2 summarize the estimates of the pre and post-upgrade electricity consumption across the three different consumption groups. On average, the new AC units save households in the High consumption group 4.95 kWh per day. Households in the Medium consumption group save an average of 1.47 kWh per day. Finally, households in the Low consumption group actually increase electricity usage by an average of 0.70 kWh per

¹⁹This estimate differs from the pooled FE estimates presented in Table 1 for a couple of reasons. First, the household-specific estimates focus only on the impact of the AC units during the four summer months, and specifically, only in a subset of the participating households. Second, by solving for the simple mean of the household-specific, average energy savings, we are now placing an equal weight on the average change in electricity consumption that occurs at each household. In contrast, the pooled FE model places a greater weight on the energy savings achieved by households that receive their AC upgrade in the middle of sample period.

²⁰To calculate the 2011 summer consumption, we utilize the monthly billing data. While all of the households we examine reside in their home for all of 2012 and 2013, not all were in the home during the summer of 2011. As a result, our sample shrinks to 2,437 households. For households that have billing periods that don’t align with the calendar months, we uniformly allocate consumption to a calendar month based on the share of the billing period occurring in each given month.

day.²¹ To highlight when these consumption changes occur, we solve for the average pre-upgrade and post-upgrade consumption for each hour of the day and for each of the three consumption groups. Figure 5 displays the hour-specific average consumption levels. Consistent with the results presented in Figure 3, the estimated savings among the Medium and High consumption households occurs most heavily in the very late evening hours.

The large standard deviations presented in Table 2 reveal that, even after controlling for a household’s historical consumption, a considerable amount of heterogeneity still remains in the estimated energy savings. Some of the remaining heterogeneity can be explained by observable factors. For example, controlling for historical usage, smaller premises tend to save more energy after installing a new AC unit. To highlight this point, we separate the households into three groups – premises that are smaller than 1,335 square feet (the smallest 25% of homes), premises that are between 1,335 and 2,111 square feet, and premises that are larger than 2,111 square feet (the largest 25% of homes).

Table 3 displays the average impact the new AC units have on daily electricity consumption within households in each size and consumption bin. The largest average energy savings occur in small, high consuming households.²² Intuitively, small homes that consume a large amount of electricity in the summer have a high demand for cooling – and therefore, save the most energy by installing an efficient AC unit. In contrast, homes with low historical summer consumption are more likely to have either very inefficient AC units, that are used infrequently, or perhaps no functioning AC unit at all. As a result, these households are the most likely to increase their cooling-related energy use following the installation of a new AC unit. Moreover, Table 3 highlights

²¹To examine whether the pattern in the average consumption changes across groups is being driven in part by mean reversion in the household-level electricity consumption, we use an alternative approach to classify households as low, medium, and high consumers. We use billing data to calculate the average daily consumption during three individual summers (2009, 2010, and 2011). Low consuming households are then defined as those that have an average daily consumption below 25 kWh during each of the three historical summers. High consuming households are all households that have an average daily consumption above 50 kWh during each of the three summers. Medium consuming households are all other households. Table A1 presents the average consumption changes across the three consumption groups. The average changes are very similar to the results presented in Table 2.

²²Again, to demonstrate that the pattern in the average energy savings is not driven by mean reversion in household-level electricity consumption, we also present estimates using the alternative approach – which uses the average daily consumption during each individual summer from 2009 through 2011 – to classify households as low, medium, and high consuming households. The analogous results are presented in A2.

that the potential for an increase in consumption is the most pronounced in homes with more square footage to cool. Combined, the pattern exhibited by these estimates provides further evidence that our empirical approach is in fact uncovering the impacts of the AC units.

3.2 Private Cost Savings Under Increasing Block Pricing

Using the preceding estimates of the household-level consumption changes, we can predict how the AC upgrades affect monthly electricity expenditures under the existing increasing block, or tiered, rates. To estimate the expenditure impacts, we assume that customers are billed by the calendar month. For June, July, August, and September of 2013, we estimate the monthly aggregate pre-upgrade and post-upgrade consumption that would occur at each household by summing the hourly estimates of the pre-upgrade and post-upgrade consumption. Next, using the resulting monthly consumption estimates, we calculate the electricity bills each household would pay with and without the new AC units. To calculate the bills, we use information on the actual rates paid by each household. Recall, households in the standard rate category – which accounts for the majority of homes in our sample – pay 9.89 cents per kWh on the first 700 kWh consumed during a summer month and 18.03 cents per kWh on any additional electricity consumed.²³

The first column of Table 4 summarizes the estimates of the monthly expenditure changes under the actual tiered pricing policy. Without the new AC units, the households would pay an average summer bill of \$125.58 per month. With the energy efficient AC units, the households average monthly bill falls to \$119.12 – an average private savings of \$6.46 per month. Again, these predicted savings are very heterogeneous across the households. Within the Low consumption group, the new AC units increase the average monthly bill by \$3.95. In the Medium consumption group, the monthly bills fall by an average of \$7.03. Finally, within the High consumption group, the new AC units cause the monthly expenditures to fall by \$26.56.

The variation in the average expenditure changes across the low, medium, and high users is largely driven by the differences in the amount of energy con-

²³Households also pay a fixed charge of \$12 per month. Given that the fixed charge is unaffected by the energy efficient AC units, we don't include the \$12 charge in our predicted electricity expenditures.

served by the new AC units. On average, high consuming households save the most energy, and therefore, save the most on their bills. However, some of the variation in the private savings is driven by the increasing block rate structure. Given that high consuming households are almost exclusively in the top price tier, conserving a kWh of electricity results in the maximum potential private savings. Dividing the estimates of the average monthly expenditure changes by the average monthly consumption changes, we find that households in the high consumption group save an average of 17.95 cents per kWh conserved. In contrast, households in the medium consumption group save an average of 17.30 cents per kWh conserved. Finally, households in the low consumption group spend an average of 12.39 cents per kWh on their increased usage following the AC upgrade. The following subsection examines how removing the increasing block price structure would affect the private savings provided by the AC investments.

3.3 Private Cost Savings Under Alternative Pricing Strategies

In addition to the existing tiered prices, we examine how three alternative pricing policies would affect the private savings provided by the new AC units. The first alternative policy roughly follows the TOU plan SMUD recently explored during a Smart Pricing pilot study. The TOU policy we simulate charges customers \$0.27 per kWh for electricity used between 4:00pm and 7:00pm during the summer months (June through September).²⁴ To compare the savings from the TOU policy to the 2013 tiered prices, we set the rate during the off-peak hours at \$0.093 per kWh to ensure that the pre-upgrade bills would, on average, equal \$125.58 per month as they do under the tiered prices. To choose this off-peak rate, we assume that the pre-upgrade consumption would be unchanged, regardless of how the prices change.

The second alternative policy we simulate is a CPP program. Again, we build on the CPP policy examined in the Smart Pricing pilot study. On the 13 hottest days during Summer 2013, the peak (4:00pm to 7:00pm) rates increase to \$0.75 per kWh. During all remaining hours, we set a single, flat price of

²⁴The actual Smart Pricing pilot study only increased the peak hour prices on non-holiday weekdays. Rather than estimating how each individual household's demand for electricity differs by weekdays and weekends, we instead assume that, under our TOU plan, the peak hour prices increase regardless of the day of week.

\$0.089 per kWh. This non-CPP period rate is again chosen to ensure that the pre-upgrade bills are on average \$125.58/month. The third alternative policy we simulate is a flat price (\$0.128 per kWh) that is constant across all hours and all days. We choose the flat rate for the simulation to once again ensure that the average pre-upgrade bills are identical across each simulated policy under the assumption that the quantity consumed is the same.

Recall, each household in our sample paid SMUD’s tiered rates. If these customers faced different prices, then they may have used a different amount of electricity – both pre and post-upgrade. For example, the TOU pricing plan charges a higher price during peak hours and a lower price in off-peak hours. We may expect households to adjust, for example, the thermostat on their air conditioner to use less energy in peak hours and more in off-peak hours. To account for these potential behavioral responses, we present several estimates of the private savings assuming that the households’ elasticity of demand ranges from perfectly inelastic – i.e., the pre and post-upgrade consumption is unaffected by prices – to an elasticity of -0.09 – i.e., a 1% increase in the price during a given hour leads to a 0.09% decrease in the hourly consumption.²⁵ Moreover, we assume that a household’s hourly consumption only responds to the contemporaneous price – not prices during other hours. In the recent pilot study (SMUD (2014)), households served by SMUD were estimated to have a price elasticity of demand of approximately -0.06 during peak hours. Therefore, the range of elasticities that we consider includes values that are more and less elastic than the best estimate available. Ultimately, our subsequent estimates of the private savings are largely unaffected by the assumed elasticity of demand.

To simulate the counterfactual pre and post-upgrade consumption levels under the alternative policies, we must also impose an assumption regarding the price to which consumers respond. For our calculations, we assume that consumers respond to the actual ex post marginal prices during each month. However, Ito (2014) provides evidence that consumer behavior is more consistent with them responding to the average monthly price. Compared to the marginal price changes between the current tiered prices and the simulated policies, the average monthly prices will be much more stable. Therefore, our

²⁵The specific elasticity of demand is also assumed to be constant across each energy service demanded by the household (e.g., cooling, lighting, etc.). This approach is consistent with previous studies estimating residential electricity expenditures under counterfactual pricing strategies. For example, see Borenstein (2012).

simulation strategy, which assumes customers respond to the marginal price, will likely overstate how sensitive our consumption and expenditure estimates are to the choice of the elasticity of demand.

To estimate the expenditure changes under the three alternative policies, we use our estimates of the household-level pre-upgrade consumption ($Q_{0,t}$) during hour t and post-upgrade consumption ($Q_{1,t}$) under the observed tiered prices – Eq. (7) and Eq. (8), respectively. Assuming the price elasticity of demand is η , the pre-upgrade consumption under the new pricing policy can be approximated as follows:

$$\text{Pre-Upgrade Consumption} \approx Q_{0,t} + \frac{\partial Q}{\partial P} \Delta P_{0,t} = Q_{0,t} \cdot \left(1 + \eta \frac{\Delta P_{0,t}}{P_{0,t}}\right), \quad (9)$$

where $P_{0,t}$ is the pre-upgrade price during hour t and $\Delta P_{0,t}$ is the change in the pre-upgrade price due to the new pricing policy. Similarly, the post-upgrade consumption under the new pricing policy can be approximated by the following expression:

$$\text{Post-Upgrade Consumption} \approx Q_{1,t} + \frac{\partial Q}{\partial P} \Delta P_{1,t} = Q_{1,t} \cdot \left(1 + \eta \frac{\Delta P_{1,t}}{P_{1,t}}\right), \quad (10)$$

where $P_{1,t}$ is the post-upgrade price, which may differ from $P_{0,t}$ if the upgrade moves the household into a different tier, and $\Delta P_{1,t}$ is the change in the post-upgrade price.

Using Eq. (9) and Eq. (10), we predict the pre and post-upgrade consumption under each alternative policy for each household during the peak and off-peak hours between June 1, 2013 and September 30, 2013. To do so, we first compute the resulting percentage changes in pre and post-upgrade prices ($\Delta P_0/P_0$ and $\Delta P_1/P_1$) during the peak and off-peak periods that would occur under each alternative policy. Assuming $\eta = \{0, -0.03, -0.06, \text{ or } -0.09\}$, we are able to simply scale the original estimates of Q_0 and Q_1 to predict the new pre and post-upgrade quantities under the new pricing policies. Multiplying the new peak and off-peak quantities by the new prices and aggregating across days, we are able to estimate the monthly pre and post-upgrade bills each household would pay under the alternative pricing policies.

The last three columns of Table 4 present the estimates of the average impact the new AC units would have on the household’s monthly bills during Summer 2013 under TOU, CPP, and flat retail rates. Assuming demand is

perfectly inelastic ($\eta = 0$), households would save an average of \$4.37/month under the TOU plan, \$5.81/month under the CPP plan, and \$4.39/month under the flat retail rates. As the assumed elasticity of demand moves away from zero, the estimated average private savings increases slightly under the TOU and flat rate policies and decreases under the flat rate policy.

Overall, the estimates reveal that, aggregating across all households, the private savings provided by the new AC units are the greatest under the current tiered pricing structure. This outcome is driven by two factors. First, the majority of energy savings comes from the high consuming households. Under tiered pricing, these households typically pay the higher tiered rate, even during the off-peak hours. The second factor is that the majority of energy savings occur after 7:00pm – i.e. during the off-peak hours. As a result, with tiered prices, the off-peak energy savings in the high consuming households provides a relatively large reduction in their bills. In contrast, these off-peak energy savings will become less valuable privately under the TOU, CPP, and flat rate policies.

The estimates presented in Table 4 also highlight how the private savings vary across the three consumption groups. Regardless of the policy, the high consuming households receive the largest average private savings from the new AC units. Comparing the expenditure changes across the different pricing policies, the gap between the private savings under tiered prices and the alternative policies is most pronounced for the high consumption group. The new AC units reduce the monthly expenditures within the high consuming households by an average of \$26.56 per month – roughly 40% more than the private savings under the alternative policies (\approx \$19/month). Again, these households almost exclusively pay the second tier price under the increasing block rates. Therefore, reducing consumption in these households results in the largest private savings.

4 Social Cost Savings from Energy Efficiency

The preceding estimates quantify the private cost savings that households receive during the summer of 2013 by installing new, energy efficient AC units. In this section, we compare the private cost savings to estimates of the social cost savings. Specifically, we quantify the reduction in the private generation costs and the external pollution costs that occur during the summer of 2013

as the result of a household installing a new, energy efficient AC unit. It is important to note that reducing energy demand can provide additional, long-run social cost savings by delaying required investments in generation and transmission capacity. To account for these additional cost savings, we also present estimates of the avoided generation capacity investment costs.

4.1 Estimating the Avoided Social Costs

To quantify the generation and pollution costs that are avoided by installing energy efficient AC units in the participating households, we again use our estimates of the hourly consumption changes for each individual household. Recall from Eq. (6), the expected impact of a new, energy efficient AC unit on household i 's consumption during hour h , on a day when the average temperature is T degrees, is equal to $\beta_{i,h} \cdot \mathbf{W}_d$, where \mathbf{W}_d is specified by Eq. (2). Define $\rho_{h,d}$ as the marginal private cost of supplying electricity during hour h of day d and $\mu_{h,d}$ as the marginal external cost of electricity. Therefore, installing an energy efficient AC unit in household i will cause the social cost of consuming electricity during hour h of day d to change by the following amount:

$$\Delta \text{Social Cost}_{i,h,d} = (\rho_{h,d} + \mu_{h,d}) \cdot \beta_{i,h} \cdot \mathbf{W}_d. \quad (11)$$

To estimate for the impact of the AC units on the social costs during the summer of 2013, we need estimates of the marginal private costs (ρ) and the marginal external costs of electricity (μ). To estimate the hourly marginal private costs, we use the observed wholesale prices recorded by the California Independent System Operator (CAISO). Specifically, we use the average hourly locational marginal price (LMP) paid for electricity in SMUD's service region in the day-ahead market.²⁶ Absent any market imperfections, these hourly LMP's would reflect the marginal private cost of electricity. However, if suppliers can exert market power, then the observed LMP's will represent an upper bound on the marginal private costs.²⁷

To produce estimates of the marginal external cost of supplying elec-

²⁶We also provide estimates using the average hourly prices in the real time market as proxied for the avoided generation costs.

²⁷Borenstein (2008) uses a similar approach to estimate the market value of solar PV production in California. In addition to the potential for market power, Borenstein highlights that the wholesale prices may deviate from the true marginal cost if there is a shortage or surplus of generation capacity.

tricity to the SMUD region, we follow the approach used in several recent studies (Siler-Evans, Azevedo and Morgan (2012), Carson and Novan (2013), Graff Zivin, Kotchen and Mansur (2014), Jacobsen (2014), Callaway, Fowle and McCormick (2015)). We first assume that a marginal decrease in consumption in SMUD’s service territory can result in a marginal decrease in electricity generation from anywhere throughout the Western Interconnection – roughly speaking, Montana, Wyoming, Colorado, New Mexico, and the states to the west of these.²⁸ In addition, we assume that a marginal decrease in electricity consumption during any given hour will be met by a marginal decrease in production from dispatchable, fossil-fuel generators – i.e., sources like nuclear and hydroelectric are assumed to never be on the margin. Under these two assumptions, we can predict how a marginal decrease in electricity consumption in the SMUD region will affect the total external cost of generating electricity simply by estimating how the external costs change in response to a marginal decrease in fossil generation in the Western Interconnection. It is important to note that, compared to relatively clean, natural gas dominated generation capacity in California, the fossil capacity throughout the rest of the Western Interconnection is typically more emission intensive – due largely to the presence of coal fired units outside of California. As a result, by assuming that marginal changes in Sacramento demand could always be met by a change in generation anywhere throughout the West, our estimates effectively provide an upper bound on the quantity of pollution avoided.

To estimate the marginal external cost of consuming electricity in the SMUD region, we utilize hourly data from the EPA’s Continuous Emissions Monitoring Systems. The CEMS data records the hourly gross generation and emissions of CO₂, NO_x, and SO₂ from nearly every fossil fuel generator in the U.S.²⁹ To convert the hourly emissions into an estimate of the hourly external cost, we use estimates of the marginal external damages of the three observed pollutants. For CO₂, we present results using two different external damage estimates. We use a central cost estimate of \$38 per ton of CO₂ and a high cost estimate of \$100 per ton of CO₂.³⁰

²⁸The continental U.S. is split up into three interconnections: the Eastern, Western, and Texas Interconnections. Within each interconnection, electricity is generated at a synchronized frequency. Therefore, as long as transmission constraints are not binding, electricity can be traded throughout a given interconnection.

²⁹Other pollutants are not recorded at the hourly level by the EPA, and therefore, we are restricted to focus on these three pollutants in this analysis.

³⁰These estimates are motivated by the Interagency Working Group’s estimates of the

For NO_X and SO_2 , the marginal external damage will vary based on when and where the pollutants are emitted. To capture some of this variation in the marginal external damages, we use estimates from Banzhaf and Chupp (2012). The authors use a Tracking and Analysis Framework to produce estimates of the average marginal cost of emitting a ton of NO_X or SO_2 in each individual state. For example, emitting a ton of NO_X in Montana causes an estimated damage of \$1,104 – the minimum among the Western Interconnection states. In contrast, emitting a a ton of NO_X in California creates an estimated social cost of \$6,199 – the maximum among the Western Interconnection states.³¹ To estimate the total hourly external cost of generation, we first multiply the emissions from each state by the state-specific marginal external damages. We then aggregate across states to predict the total external cost of generating electricity in the Western Interconnection during each individual hour of each day during summer 2013.³²

As previous studies highlight, the marginal external cost of generating electricity varies across time (Siler-Evans, Azevedo and Morgan (2012), Carson and Novan (2013), Graff Zivin, Kotchen and Mansur (2014), Jacobsen (2014), Callaway, Fowlie and McCormick (2015)). This temporal variation stems from the fact that different fossil fuel units, which potentially have very heterogeneous emission intensities, will be on the margin at different points in time. To capture the potential temporal heterogeneity in the marginal external cost, we estimate the following model:

$$\text{External Cost}_{h,d} = \alpha_h + \gamma_h \cdot \text{Generation}_{h,d} + \varepsilon_{h,d}, \quad (12)$$

where $\text{External Cost}_{h,d}$ represents the total external cost of the pollution emitted by fossil fuel generating units in the Western Interconnection during hour h of day d and $\text{Generation}_{h,d}$ equals the aggregate gross generation from the corresponding fossil units during the same hour. We estimate the model

social cost of carbon (IAWG (2013)). For the 2015 social cost of carbon, the IAWG reports a central estimate of \$38 per ton of CO_2 and an upper estimate of \$109 per ton.

³¹The estimates of the external costs of SO_2 range from \$201 per ton (in Montana) and \$475 per ton (in California).

³²While this approach will not capture the full range of heterogeneity in the marginal damages caused by emitting SO_2 and NO_X at different times in different locations, this ultimately will have very little impact on the estimates of the marginal external damages caused by generating electricity. This is due to the fact that the external costs are dominated by the social cost of the CO_2 emitted. For example, at an estimated cost of \$38/ton of CO_2 , emissions of CO_2 account for an average of 95% of the hourly external pollution cost.

using hourly observations from June 1, 2013 through September 30, 2013.

From Eq. (12), the coefficient γ_h represents the average change in the total external cost caused by a marginal change in gross generation – not electricity consumption – during hour h of a day during summer 2013. While our resulting estimates of the marginal external cost of consumption abstract from variation in the marginal external cost across days, they do capture the within day variation. To ultimately arrive at an estimate of the average marginal external cost incurred by consuming a unit of electricity, two adjustments must be made. First, we need to account for the fact that a portion of the gross generation is consumed at the generating units. Typically, the net output from a fossil fuel unit will be roughly 5% less than the gross generation. Second, a portion of the net electricity produced is lost during the transmission and distribution process. Following Graff Zivin, Kotchen and Mansur (2014), we use the estimated loss rate of 9.6% from Stephan and Sullivan (2008). Therefore, to estimate how the external pollution costs are affected by a marginal change in SMUD consumption, we must scale the estimates of γ_h up by (1.05×1.096) .

Assuming the marginal private cost of generating electricity is equal to the LMP, and using our estimates of the marginal external costs of consumption, we can estimate how a new, energy efficient AC unit changes the social cost of providing electricity to household i during hour h of day d from the following expression:

$$\Delta \widehat{\text{Social Cost}}_{i,h,d} = (LMP_{h,d} + \hat{\gamma}_h \cdot (1.05 \times 1.096)) \cdot \hat{\beta}_{i,h} \cdot \mathbf{W}_d, \quad (13)$$

where $LMP_{h,d}$ represents the locational marginal price in the SMUD region, $\hat{\gamma}_h$ represents the estimate of the hour-specific marginal external cost of generation from Eq. (12), and $\hat{\beta}_{i,h} \cdot \mathbf{W}_d$ is the estimate of the change in hourly consumption from Eq. (6). Aggregating the hourly, household-level estimates of the generation and pollution cost changes specified by Eq. (13), we predict how the new AC units change the monthly social cost of providing electricity during June, July, August, and September of 2013 for each of the 2,496 households that received a rebate between June 16, 2012 and July 4, 2013.

In addition to the avoided generation and pollution costs, the energy efficient AC units can also provide social cost savings by reducing, or deferring, the required investment in generation capacity.³³ To get a sense of how large these

³³There can also be reductions, or deferments, in the required investment in distribution

additional social cost savings may be, we use the observed contract prices from California’s Resource Adequacy Program (CPUC (2015*a*)). Specifically, we assume that the avoided social cost from reducing peak demand by a kilowatt (kW) is equal to \$2.66 per month – which is the average monthly contracted price for capacity, in dollars per kW, from 2013 through 2017 in the Northern Zone of California.³⁴

In California, the peak demand for electricity generally occurs during the 5pm hour on summer days. The results from Figure 5 reveal that, during the 5pm hour of the 2013 summer months, medium consuming households reduce electricity consumption by an average of 0.07 kWh and high consuming households reduce electricity consumption by an average of 0.26 kWh. To estimate the cost of the avoided capacity, we can simply multiply the average reductions in 5pm summer consumption by the average monthly cost of capacity (\$2.66 per/kW).³⁵ Using this approach, we estimate that, on average, medium consuming households that install an energy efficient AC unit provide additional social cost savings of \$0.19/month and high consuming households provide an additional social cost savings of \$0.70/month. Low consuming households that install an energy efficient AC are predicted to increase the monthly social costs by an additional \$0.29.

4.2 Comparison of Private and Social Cost Savings

Figure 6 presents the average change in the monthly social cost of supplying electricity to a participating household.³⁶ For the sake of comparison, the figure also presents the estimates from the top panel of Table 4 – the average monthly private savings achieved by the participating households under each

infrastructure. However, Cohen, Kauzmann and Callaway (2015) estimate that, in the vast majority of locations, these cost savings are likely to be negligible.

³⁴The average contract price for capacity is presented in Table 11 of the CPUC’s 2013-2014 Resource Adequacy Report.

³⁵This approach assumes that the hourly reduction in consumption at a participating household is uniformly distributed across the hour. That is, on average, a high consuming household’s consumption falls by 0.31 kW for the entire hour.

³⁶To estimate the monthly household-level social costs avoided, we sum the estimates of the hourly avoided generation and pollution costs (Eq. (12)) over each calendar month and add the estimates of the change in monthly capacity costs. The simple means of the household-level average monthly avoided generation, pollution, and capacity costs are individually presented in Table A3. In addition, Table A3 demonstrates that the estimates of the avoided generation costs are effectively unchanged when we use the average hourly real-time prices instead of the day-ahead prices.

of the retail pricing policies.³⁷ Assuming the external cost of CO₂ is \$38 per ton, our results reveal that the new AC units reduce the total social cost of providing electricity to a participating household by an average of \$2.69 per month – of which \$1.62 is avoided private generation costs, \$0.96 in avoided external pollution costs, and \$0.11 is avoided generation capacity costs.³⁸ In contrast, under the existing tiered electricity prices, households save an average of \$6.46 on their monthly bills. While the participating households save an average of over 17 cents per kWh conserved, society only saves an average of 7.6 cents per kWh conserved.

Figure 6 also compares the average social and private cost savings separately for the three consumption groups. Focusing first on the high consumption group – which accounts for approximately two-thirds of the total energy savings – we find that the energy efficient AC units reduce the social cost of providing electricity to a high consuming household by an average of \$11.44 per month, assuming that the social cost of CO₂ is \$38/ton. If the external cost of CO₂ is assumed to be \$100/ton, the AC units will instead reduce the average monthly social costs by \$18.01. Even using the high estimate for the social cost of carbon, the private savings provided by the AC units are still larger. Recall, under the existing tiered prices, a high consuming household saves an average of \$26.56 per month.

Within the 50% of households that fit into the medium consumption group, the same pattern is displayed. The average monthly private savings exceed the average social savings by 110%, assuming a social cost of CO₂ of \$38/ton. In the lowest consuming households, the average monthly private expenditures increase by \$3.95 under the observed tiered prices. In contrast, the energy efficient AC units only increase the average monthly social cost by \$2.41.

The differences between the private and social cost changes are driven by the fact that the marginal price paid for electricity exceeds the social marginal cost of supplying electricity during the vast majority of hours. As a result, reductions in energy consumption caused by the new AC units reduce the private expenditures by more than the social costs. Similarly, increases in energy consumption caused by the new AC units lead to larger increases in

³⁷The estimates of the private savings achieved under the three counterfactual policies are made assuming a price elasticity of demand of zero.

³⁸If CO₂ imposes an external cost of \$100 per ton, the AC units will reduce the monthly social costs by an average of \$4.23 – the avoided external pollution costs increase to an average of \$2.50/month.

private expenditures.

While the deviations between the private and social cost changes are caused by charging relatively high average per kWh rates, the increasing block price structure exaggerates the differences between the private and social cost savings. This is especially true among the high consuming households, the set of homes that are almost exclusively paying the higher tiered rate. The effect of the increasing block rate structure can be seen by comparing the private savings under the existing tiered prices to the private savings that would occur under the TOU, CPP, or flat rate policies – each of which removes the increasing block rates. Assuming CO₂ has an external cost of \$38/ton, the average private savings among the high consuming households is 132% larger than the average social savings under the tiered rates. In contrast, under the simulated TOU, CPP, and flat rate policies, the private savings are only 66%, 69%, and 64% larger than the avoided social costs.

4.3 Discussion

Upgrading residential energy efficiency (e.g., installing energy efficient AC units) requires sizable upfront investments. In return, the upgrades provide a variety of future expected benefits. From the perspective of the private homeowners making the investments, these benefits include increased welfare from additional consumption of energy services (e.g., making homes cooler during the summer) as well as reductions in their monthly energy bills. From society's perspective, the stream of potential benefits include the same welfare increases from the increased consumption of energy services. However, the magnitude of the social benefits do not depend on the reductions in household energy bills. Instead, the social benefits depend on the resource and pollution costs avoided by reducing energy consumption.

Our results reveal that, in regions where households pay high average per kWh charges and increasing block energy prices, the private savings achieved by investing in energy efficiency can dramatically exceed the social cost savings. It is of course important to stress that our estimates of the social cost savings provided by the AC upgrades are conditional on the California market conditions during the sample period. As the stock of generating capacity changes, or as fuel prices change, the social marginal cost of producing electricity can change – which may in turn alter the social benefits provided by

energy efficiency upgrades. Nonetheless, if households continue to face increasing block rate structures that regularly charge marginal prices in excess of the social marginal cost, the privately optimal level of residential energy efficiency will exceed the socially optimal level.

By itself, this does not necessarily imply that the actual level of private investment will be inefficiently high. If additional market failures contribute to the existence of an energy paradox, then investment in energy efficiency will lag behind the privately optimal level. However, even in the presence of an energy paradox, it is difficult to justify the implicit subsidy generated by the increasing block rate structure on the grounds of economic efficiency. The available evidence reveals that the investment inefficiencies stemming from an energy paradox are unlikely to be large (Allcott and Greenstone (2012)). In contrast to claims of widespread underinvestment in residential energy efficiency (e.g., McKinsey (2009)), the observed low investment levels can instead be largely explained by factors including overstated potential energy savings (Metcalf and Hassett (1999), Fowle, Greenstone and Wolfram (2015*b*), Graff Zivin and Novan (2016)) as well as unaccounted for, hidden upgrade costs (Fowle, Greenstone and Wolfram (2015*a*)). These findings suggest that, in the setting we examine, the implicit subsidy generated by the current rate structure – which leads to private savings that exceed the social savings by over 130% – is inefficiently large.

Even if we were to assume that a sufficiently large energy paradox exists, the implicit subsidy created by the increasing block rate structure is simply not an efficient tool for addressing the energy paradox. Surveys of the energy paradox literature (e.g., Gillingham and Palmer (2014)) highlight several potential market failures that can contribute to low private investment in energy efficiency. These include imperfect information about potential savings, principal-agent problems (i.e. the landlord-tenant problem), and liquidity constraints. Rather than directly addressing these potential market failures, however, the implicit energy efficiency subsidy generated by increasing block rates serves as a very blunt, and very inefficient, policy tool. In particular, the implicit subsidy does not specifically target the customers underinvesting in energy efficiency.³⁹ For example, we may expect that an energy paradox results in the greatest underinvestment among lower income, credit constrained

³⁹Allcott, Knittel and Taubinsky (2015) highlight this inefficiency which is inherent in direct energy efficiency subsidies as well.

households. However, the implicit subsidy created by the high marginal prices does not target this set of consumers – it is provided to all households that reduce consumption and is largest for those that reduce consumption the most.

While our results reveal that SMUD’s standard residential rate structure – a fixed monthly fee of \$12 combined with a two-tiered, increasing block per kWh charge – creates a large, implicit subsidy for energy efficiency, customers throughout the rest of California have faced even more extreme tiered rate schedules with higher marginal prices. For example, at the beginning of 2015, households purchasing electricity from one of California’s big three large investor-owned utilities (IOUs) – i.e. PG&E, SCE, and SDG&E – faced increasing block price schedules with four or more tiers. In particular, PG&E customers consuming in the highest tier faced a marginal price of \$0.33/kWh and SDG&E customers in the top tier paid a marginal price of over \$0.42/kWh.⁴⁰ As a result, residential customers served by the big three utilities have historically received even larger implicit subsidies for investments made in energy efficiency. As a result, residential customers served by the big three utilities have historically received even larger implicit subsidies for investments made in energy efficiency.

Moving forward, the residential rate structures charged by California’s IOUs are undergoing changes. Following a recent ruling by the California Public Utility Commission (CPUC (2015*b*)), the IOUs are beginning a transition towards residential rate structures very similar to the SMUD rate structure examined in this paper. Specifically, the CPUC has mandated that the IOUs move to a two-tiered rate schedule with fixed charges of \$10 per month. While these changes can be expected to reduce the implicit subsidy for energy efficiency, our analysis of the private savings achieved under the SMUD rate structure reveals that the implicit subsidies will nonetheless remain quite large.

Looking farther down the road, the CPUC has also mandated that California’s IOUs begin charging a default time-of-use (TOU) rate plan for residential consumers by 2019. Moreover, on August 15, 2013 the SMUD Board of Directors voted to phase out the residential tiers by 2017 and to begin preparing

⁴⁰Similar to SMUD, the IOUs each receive the majority of their revenue from the per kWh charges as opposed to fixed fees. At the beginning of 2015, PG&E customers on the standard tiered rate schedule paid a minimum of \$4.44/month while SDG&E customers paid a minimum of \$5.10/month. If not binding, the minimum charges serve as fixed fees. SCE customers on the standard residential tiered rate plan paid a fixed charge of \$0.93/month.

for time-of-use rates. Our results highlight that TOU rates, which remove the increasing block structure currently in place, will substantially reduce the implicit subsidy currently provided for energy efficiency upgrades. However, if the TOU rate plans continue to include low fixed monthly fees, and therefore generate revenue mainly from the per kWh charges, then our estimates highlight that a large financial incentive to invest energy efficiency will still be created. Ultimately, our results provide support for moving towards residential energy rate structures that align marginal prices with marginal costs. Doing so requires not only removing increasing block rates, but also increasing the share of revenue generated by fixed fees.

5 Conclusion

In this paper, we have compared the private and social cost savings achieved by investing in residential energy efficiency. Using hourly, household-level smart meter data from Sacramento, we are able to estimate not only how much electricity households save by installing new, energy efficient AC units, but also when the energy savings occur. These estimates enable us to predict how much the new AC units reduce the participating households' monthly electricity bills. In addition, by combining the estimated energy savings with (1) observed wholesale electricity prices and (2) estimates of the marginal external cost of the pollution created, we are able to quantify the social cost savings provided by the new AC units.

Our estimates reveal that, after installing an energy efficient AC unit, a participating household's non-winter electricity consumption fell by an average of 1.3 kWh per day – approximately a 5% reduction in total consumption. Under the current residential electricity rate structure, which combines low fixed monthly fees with increasing block prices, the participating households saved an average of \$6.46 per month. In contrast, the estimated social costs savings were only \$2.69 per month. The gap between the private and social cost savings is even more pronounced among the households with high historical levels of electricity consumption – the homes that account for the vast majority of the energy savings. On average, a high consuming household's monthly electricity bill fell by \$26.56 while the social costs only fell by an average of \$11.44 per month. These results highlight that, by setting the marginal price above the marginal social cost of supplying electricity, the current residential

rate structure leads to an outcome in which the privately optimal level of investment in energy efficiency exceeds the socially optimal level.

In many regions, regulators and policymakers are actively debating making changes to existing residential energy rate structures. In California in particular, the Public Utility Commission has recently mandated that the investor-owned utilities begin to charge flatter tiered electricity prices with slightly larger fixed fees. However, the results presented in this paper demonstrate that, even after these changes, homeowners still have a large incentive to overinvest in energy efficiency.

References

- Allcott, Hunt, and Michael Greenstone.** 2012. “Is There an Energy Efficiency Gap?” *Journal of Economic Perspectives*, 26(1): 3–28.
- Allcott, Hunt, Christopher Knittel, and Dmitry Taubinsky.** 2015. “Tagging and Targeting of Energy Efficiency Subsidies.” *American Economic Review*, 105(5): 187–91.
- Banzhaf, Spencer H., and Andrew B. Chupp.** 2012. “Fiscal federalism and interjurisdictional externalities: New results and an application to US Air pollution.” *Journal of Public Economics*, 96(5): 449–464.
- BC-Hydro.** 2008. “2008 Residential Inclining Block Rate Application.” British Columbia Utilities Commission, <http://www.bcuc.com/ApplicationView.aspx?ApplicationId=187>.
- Borenstein, Severin.** 2008. “The Market Value and Cost of Solar Photovoltaic Electricity Production.” *Center for the Study of Energy Markets*.
- Borenstein, Severin.** 2012. “The Redistributive Impact of Nonlinear Electricity Pricing.” *American Economic Journal: Economic Policy*, 4(3): 56–90.
- Borenstein, Severin.** 2015. “The Private Net Benefits of Residential Solar PV: And Who Gets Them.” *Energy Institute at Haas Working Paper #259*.
- Borenstein, Severin, and Lucas W Davis.** 2012. “The Equity and Efficiency of Two-Part Tariffs in US Natural Gas Markets.” *Journal of Law and Economics*, 55(1): 75–128.
- Borenstein, Severin, and Lucas W Davis.** 2015. “The Distributional Effects of US Clean Energy Tax Credits.” In *Tax Policy and the Economy, Volume 30*. University of Chicago Press.

- Borenstein, Severin, James Bushnell, Frank A Wolak, and Matthew Zaragoza-Watkins.** 2015. “Expecting the Unexpected: Emissions Uncertainty and Environmental Market Design.” National Bureau of Economic Research.
- Callaway, Duncan, Meredith Fowlie, and Gavin McCormick.** 2015. “Location, location, location: The variable value of renewable energy and demand-side efficiency resources.” Energy Institute at Haas – Working paper 264.
- Carson, Richard T., and Kevin Novan.** 2013. “The Private and Social Economics of Bulk Electricity Storage.” *Journal of Environmental Economics and Management*.
- Coase, Ronald H.** 1946. “The Marginal Cost Controversy.” *Economica*, 13.
- Cohen, M., P. Kauzmann, and D. Callaway.** 2015. “Economic Effects of Distributed PV Generation on California’s Distribution System.” Energy Institute at Haas Working Paper – 260.
- CPUC.** 2015*a*. “The 2013-2014 Resource Adequacy Report.” Public Utilities Commission of the State of California.
- CPUC.** 2015*b*. “Decision on Residential Rate Reform for Pacific Gas and Electric Company, Southern California Edison Company, and San Diego Gas & Electric Company and Transition to Time-of-Use Rates.” Public Utilities Commission of the State of California.
- Davis, Lucas W., Alan Fuchs, and Paul Gertler.** 2014. “Cash for Coolers: Evaluating a Large-Scale Appliance Replacement Program in Mexico.” *American Economic Journal: Economic Policy*, 6(4): 207–238.
- Davis, Lucas W, and Erich Muehlegger.** 2010. “Do Americans consume too little natural gas? An empirical test of marginal cost pricing.” *The RAND Journal of Economics*, 41(4): 791–810.
- Fowlie, Meredith, Michael Greenstone, and Catherine Wolfram.** 2015*a*. “Are the Non-Monetary Costs of Energy Efficiency Investments Large? Understanding Low Take-Up of a Free Energy Efficiency Program.” *American Economic Review*, 105(5): 201–04.
- Fowlie, Meredith, Michael Greenstone, and Catherine Wolfram.** 2015*b*. “Do Energy Efficiency Investments Deliver? Evidence from the Weatherization Assistance Program.”
- Gerarden, Todd D, Richard Newell, Robert Stavins, and Robert C Stowe.** 2015. “An Assessment of the Energy-Efficiency Gap and its Implications for Climate-Change Policy.” National Bureau of Economic Research.

- Gillingham, Kenneth, and Karen Palmer.** 2014. “Bridging the Energy Efficiency Gap: Policy Insights from Economic Theory and Empirical Evidence.” *Review of Environmental Economics and Policy*, ret021.
- Graff Zivin, Joshua, and Kevin Novan.** 2016. “Upgrading Efficiency and Behavior: Electricity Savings from Residential Weatherization Programs.” *Energy Journal*.
- Graff Zivin, Joshua, Matthew Kotchen, and Erin Mansur.** 2014. “Temporal and Spatial Heterogeneity of Marginal Emissions: Implications for Electric Cars and Other Electricity-Shifting Policies.” *Journal of Economic Behavior and Organization*, 107: 248–268.
- IAWG.** 2013. “Interagency Working Group – Technical Update of the Social Cost of Carbon for Regulatory Impact Analysis - Under Executive Order 12866.”
- Ito, Koichiro.** 2014. “Do Consumers Respond to Marginal or Average Price? Evidence from Nonlinear Electricity Pricing.” *The American Economic Review*, 104(2): 537–563.
- Jacobsen, Grant D.** 2014. “Estimating End-Use Emissions Factors For Policy Analysis: The Case of Space Cooling and Heating.” *Environmental Science & Technology*.
- Jacobsen, Grant D., and Mathew J. Kotchen.** 2013. “Are Building Codes Effective at Saving Energy? Evidence from Residential Billing Data in Florida.” *Review of Economics and Statistics*, 95(1): 34–49.
- McKinsey.** 2009. “Unlocking Energy Efficiency in the US Economy.” http://www.mckinsey.com/client_service/electric_power_and_natural_gas/latest_thinking/unlocking_energy_efficiency_in_the_us_economy.
- Metcalf, Gilbert E., and Kevin A. Hassett.** 1999. “Measuring the Energy Savings from Home Improvement Investments: Evidence from Monthly Billing Data.” *Review of Economics and Statistics*, 81(3): 516–528.
- Siler-Evans, Kyle, Ines Azevedo, and M. G. Morgan.** 2012. “Marginal Emissions Factors for the US Electricity System.” *Environmental Science & Technology*, 46(9): 4742–4748.
- SMUD.** 2014. “Smart Pricing Options Final Evaluation.”
- Stephan, Craig H, and John Sullivan.** 2008. “Environmental and energy implications of plug-in hybrid-electric vehicles.” *Environmental Science & Technology*, 42(4): 1185–1190.

Table 1: Average Change in Daily Electricity Consumption (kWh)

| | Number of Days Dropped Prior to Rebate Date | | | | |
|---------------------------|---|-------------------|-------------------|-------------------|-------------------|
| | 0 days | 14 days | 30 days | 60 days | 90 days |
| Post | -1.24** (0.38) | -1.31** (0.39) | -1.35** (0.41) | -1.38** (0.43) | -1.41** (0.44) |
| Temperature < 63°F | -0.03 (0.03) | -0.03 (0.03) | -0.02 (0.03) | -0.02 (0.03) | -0.02 (0.03) |
| 63°F < Temperature < 70°F | 0.74** (0.08) | 0.74** (0.08) | 0.74** (0.08) | 0.73** (0.08) | 0.73** (0.08) |
| 70°F < Temperature < 75°F | 1.48** (0.12) | 1.48** (0.12) | 1.48** (0.12) | 1.49** (0.12) | 1.48** (0.12) |
| Temperature ≥ 75°F | 1.87** (0.07) | 1.88** (0.07) | 1.88** (0.07) | 1.88** (0.07) | 1.87** (0.07) |
| N | 2,315,443 | 2,269,904 | 2,217,566 | 2,117,423 | 2,016,834 |
| Within R ² | 0.41 | 0.41 | 0.41 | 0.41 | 0.41 |

Each model is estimated using household fixed effects. Standard errors are robust to heteroskedasticity and clustering at the household and week-by-year level. * = Significant at the 5% level; ** = Significant at the 1% level.

Table 2: Pre and Post-Upgrade Consumption Under Tiered Prices

| | All Households | Consumption Group | | |
|-------------------------------|------------------|-------------------|-----------------|------------------|
| | | Low | Medium | High |
| Average Consumption (kWh/day) | | | | |
| <i>Pre-Upgrade</i> | 32.56 (16.68) | 17.86 (6.29) | 34.14 (8.39) | 59.35 (16.16) |
| <i>Post-Upgrade</i> | 31.43 (15.22) | 18.82 (6.79) | 32.79 (8.27) | 54.48 (16.61) |
| <i>Change</i> | -1.13 (7.02) | 0.96 (4.95) | -1.35 (6.34) | -4.87 (10.21) |
| Number of Households | 2,496 | 826 | 1,220 | 391 |

The point estimates represent the simple average of the household-level, mean pre and post-upgrade daily consumption levels from June 1, 2013 through September 30, 2013. The Change point estimates provide the simple average of the household-level, mean changes in daily electricity consumption following the upgrades. The standard deviations represent the standard deviation among the household-level mean daily consumption levels and changes.

Table 3: Heterogeneity in Average Consumption Changes

| Home Size | Avg. Change in Consumption (kWh/day) | | |
|--|--------------------------------------|------------------------------------|----------------------------|
| | Low Group (< 25 kWh/day) | Medium Group (25 to 50 kWh/day) | High Group (50 kWh/day) |
| Small ($< 1,335$ ft ²) | 0.78 (4.66) | -1.54 (6.66) | -8.80 (7.90) |
| Medium (1,335 to 2,111 ft ²) | 0.98 (4.77) | -1.60 (6.31) | -5.49 (10.75) |
| Large ($> 2,111$ ft ²) | 1.45 (6.69) | -0.58 (6.01) | -4.20 (9.48) |

The point estimates represent the simple average of the household-level, mean change in daily electricity consumption over the period from June 1, 2013 through September 30, 2013. The standard deviations represent the standard deviation among the household-level mean daily consumption changes.

Table 4: Change in Average Monthly Expenditure by Policy

| Elasticity | Consumption Group | Tier | TOU | CPP | Flat |
|-----------------|-----------------------|------------------|------------------|------------------|------------------|
| $ \eta = 0.0$ | <i>All Households</i> | -\$6.46 (35) | -\$4.37 (29) | -\$5.81 (29) | -\$4.39 (27) |
| | <i>Low Group</i> | \$3.95 (21) | \$4.16 (20) | \$2.96 (22) | \$3.56 (19) |
| | <i>Medium Group</i> | -\$7.03 (33) | -\$5.48 (26) | -\$7.50 (27) | -\$5.18 (24) |
| | <i>High Group</i> | -\$26.56 (55) | -\$19.01 (40) | -\$19.35 (39) | -\$18.73 (39) |
| $ \eta = 0.03$ | <i>All Households</i> | -\$6.46 (35) | -\$4.37 (28) | -\$5.52 (27) | -\$4.43 (27) |
| | <i>Low Group</i> | \$3.95 (21) | \$4.01 (20) | \$2.77 (20) | \$3.50 (18) |
| | <i>Medium Group</i> | -\$7.03 (33) | -\$5.39 (26) | -\$6.96 (25) | -\$5.16 (24) |
| | <i>High Group</i> | -\$26.56 (55) | -\$19.02 (40) | -\$18.82 (38) | -\$18.87 (39) |
| $ \eta = 0.06$ | <i>All Households</i> | -\$6.46 (35) | -\$4.39 (28) | -\$5.23 (25) | -\$4.46 (27) |
| | <i>Low Group</i> | \$3.95 (21) | \$3.86 (19) | \$2.58 (17) | \$3.43 (18) |
| | <i>Medium Group</i> | -\$7.03 (33) | -\$5.31 (26) | -\$6.41 (24) | -\$5.14 (24) |
| | <i>High Group</i> | -\$26.56 (55) | -\$19.03 (40) | -\$18.29 (37) | -\$19.02 (40) |
| $ \eta = 0.09$ | <i>All Households</i> | -\$6.46 (35) | -\$4.40 (27) | -\$4.94 (24) | -\$4.50 (27) |
| | <i>Low Group</i> | \$3.95 (21) | \$3.71 (18) | \$2.39 (15) | \$3.37 (18) |
| | <i>Medium Group</i> | -\$7.03 (33) | -\$5.23 (25) | -\$5.87 (22) | -\$5.13 (24) |
| | <i>High Group</i> | -\$26.56 (55) | -\$19.04 (40) | -\$17.76 (35) | -\$19.16 (40) |

The estimate represent the mean of the household-level average change in the monthly expenditure, during June through September of 2013, that is caused by installing a new AC unit. The standard deviations of the electricity expenditures represent the standard deviations of the household-level average monthly expenditures changes.

Day-Ahead Locational Marginal Prices (April - October, 2013)

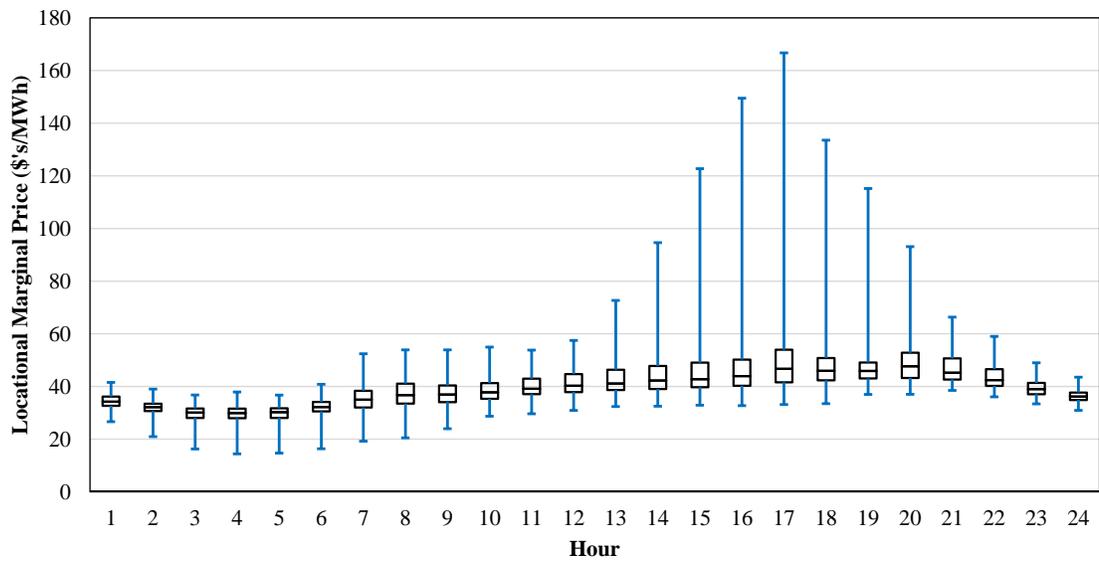


Figure 1: The graph summarizes the Day-Ahead market Location Marginal Prices in the SMUD region from April, 2013 through October, 2013. The box-and-whisker plots display the minimum and maximum hourly prices as well as the 25th, 50th, and 75th percentiles of the hourly prices.

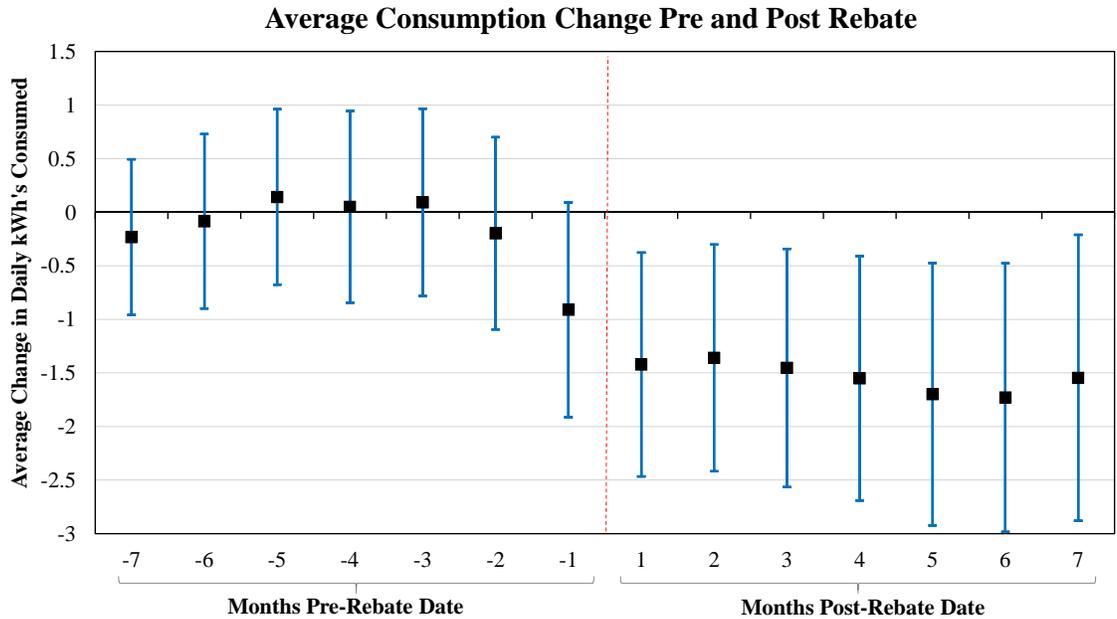


Figure 2: The graph displays the point estimates, and the corresponding 95% confidence intervals, of the average change in the daily electricity consumption during the months before and after the AC rebates are sent. The first “pre-rebate month” (month= -1) includes all observations during the 30 days immediately preceding the date each households’ AC rebate is sent. The first “post-rebate month” (month= 1) includes all observations during the first 30 days following each households’ AC rebate date. The changes are measured relative to the average daily consumption on days 8 or month months prior to the AC rebate being sent. The confidence intervals are robust to heteroskedasticity and clustering at the household level and across households within each week-by-year.

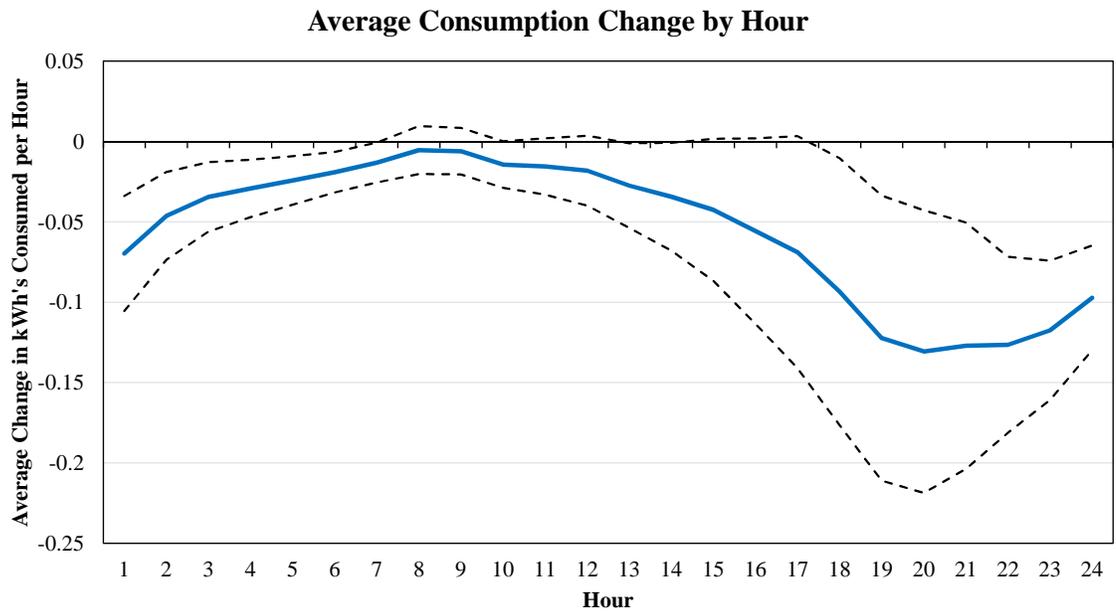


Figure 3: The graph displays the point estimates, and the corresponding 95% confidence intervals, of the average hourly changes in a household's energy consumption following an AC upgrade. The confidence intervals are robust to heteroskedasticity and clustering at the household level and across households within each week-by-year. To produce the point estimates, the observations from the 30 days preceding each households' AC rebate date are removed from the sample.

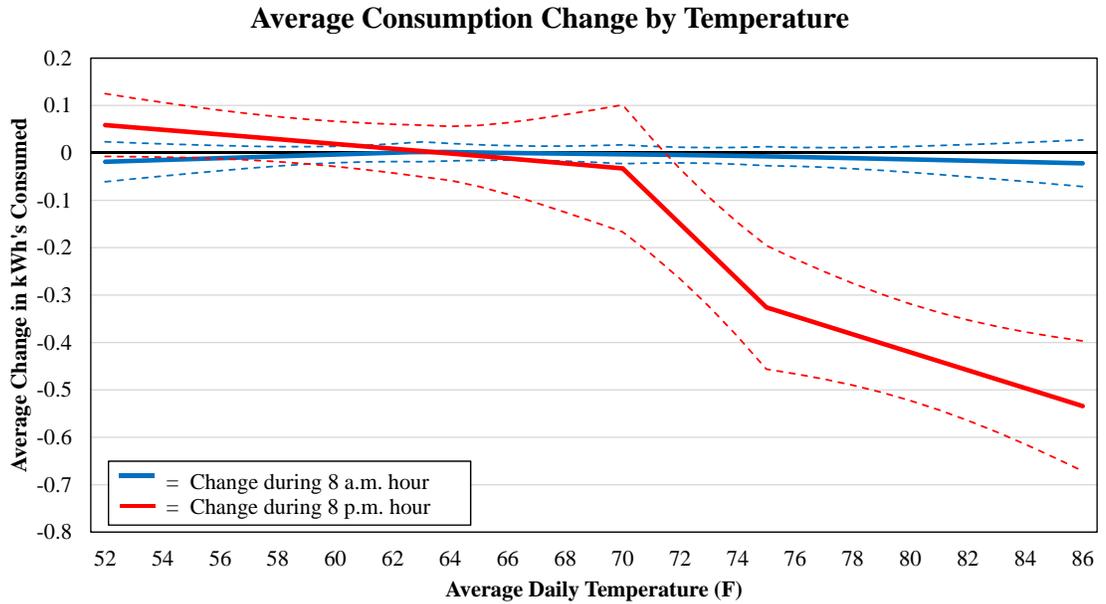


Figure 4: The graph displays the point estimates, and the corresponding 95% confidence intervals, of the average hourly changes in a household's electricity consumption following an AC upgrade during two different hours – 8am and 8pm – as a function of the average daily temperature. The confidence intervals are robust to heteroskedasticity and clustering at the household level and across households within each week-by-year. To produce the point estimates, the observations from the 30 days preceding each households' AC rebate date are removed from the sample.

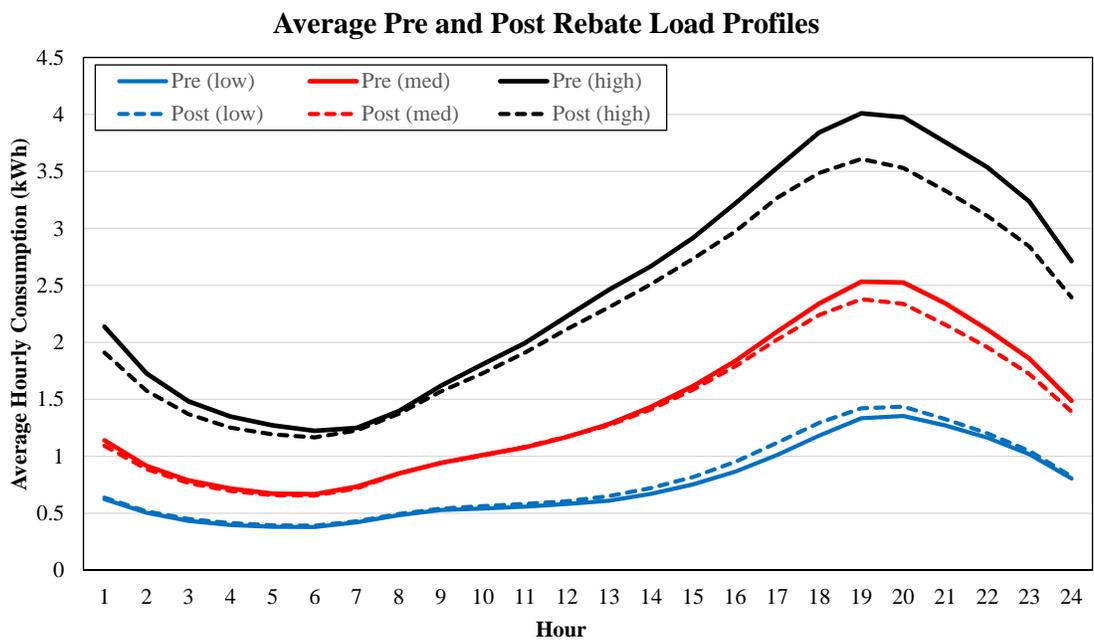


Figure 5: The graph displays the group-level averages of the expected hourly pre-rebate and post-rebate consumption during the summer of 2013.

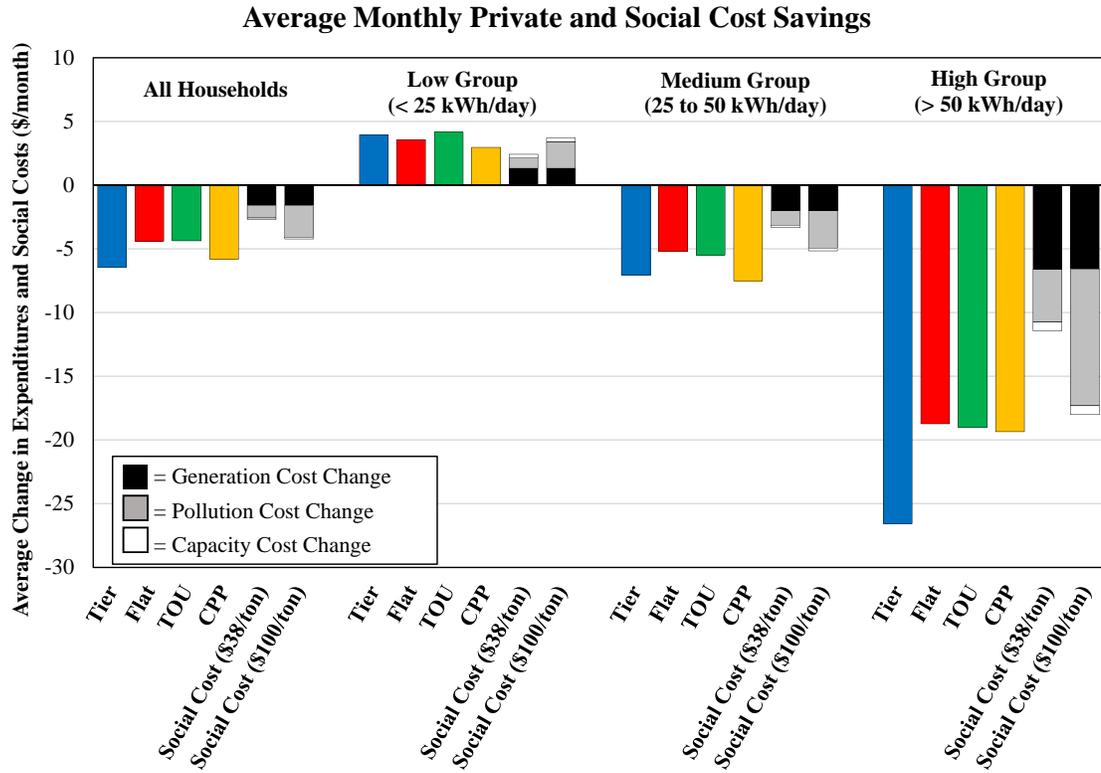


Figure 6: The figure presents the average monthly private savings under the actual tiered rates as well as under three alternative pricing policies. To calculate the bill changes under the TOU, CPP, and flat rate policies, the elasticity of demand is assumed to be zero in the plotted results. The figure also presents the average monthly change in the social costs of supplying electricity. The social cost changes are broken down to display the avoided generation costs and the avoided pollution costs – assuming that the social cost of CO₂ is \$30/ton.

Table A1: Pre and Post-Upgrade Consumption (by 2009-11 Consumption)

| | Consumption Group | | |
|-------------------------------|-------------------|------------------|------------------|
| | Low | Medium | High |
| Average Consumption (kWh/day) | | | |
| <i>Pre-Upgrade</i> | 16.58 (5.18) | 34.00 (10.29) | 62.83 (17.06) |
| <i>Post-Upgrade</i> | 17.37 (5.91) | 32.42 (9.26) | 58.39 (17.20) |
| <i>Change</i> | 0.79 (4.46) | -1.59 (6.43) | -4.45 (10.67) |
| Number of Households | 575 | 1,360 | 253 |

The point estimates represent the simple average of the household-level, mean pre and post-upgrade daily consumption levels from June 1, 2013 through September 30, 2013. The Change point estimates provide the simple average of the household-level, mean changes in daily electricity consumption following the upgrades. The standard deviations represent the standard deviation among the household-level mean daily consumption levels and changes.

Table A2: Heterogeneity in Consumption Changes (by 2009-11 Consumption)

| Home Size | Avg. Change in Consumption (kWh/day) | | |
|--|--------------------------------------|------------------------------------|----------------------------|
| | Low Group (< 25 kWh/day) | Medium Group (25 to 50 kWh/day) | High Group (50 kWh/day) |
| Small (< 1,335 ft ²) | 0.53 (3.99) | -1.60 (6.58) | -8.40 (8.90) |
| Medium (1,335 to 2,111 ft ²) | 0.82 (4.26) | -1.75 (6.40) | -5.47 (11.71) |
| Large (> 2,111 ft ²) | 1.77 (7.06) | -1.22 (6.38) | -3.82 (9.45) |

The point estimates represent the simple average of the household-level, mean change in daily electricity consumption over the period from June 1, 2013 through September 30, 2013. The standard deviations represent the standard deviation among the household-level mean daily consumption changes.

Table A3: Change in Monthly Average Generation and Pollution Costs

| Group | Generation Cost Change | | Pollution Cost Change | | Capacity Cost Change |
|-----------------------|------------------------|---------------------|--|--|---|
| | Day-Ahead Market | Real Time Market | Central Case (CO ₂ = \$38) | High Cost (CO ₂ = \$100) | Capacity Contracts (\$2.66/kW-month) |
| <i>All Households</i> | -\$1.62 (9.63) | -\$1.64 (9.47) | -\$0.96 (5.94) | -\$2.50 (15.39) | -\$0.11 (1.67) |
| <i>Low Group</i> | \$1.32 (7.00) | \$1.28 (6.96) | \$0.80 (4.17) | \$2.09 (10.82) | \$0.29 (1.14) |
| <i>Medium Group</i> | -\$2.01 (8.78) | -\$2.06 (8.65) | -\$1.14 (5.36) | -\$2.96 (13.90) | -\$0.19 (1.58) |
| <i>High Group</i> | -\$6.61 (13.64) | -\$6.51 (13.28) | -\$4.13 (8.67) | -\$10.70 (22.45) | -\$0.70 (2.47) |

The point estimates represent the mean of the household-level average change in daily consumption from June, 2013 through September, 2013. The standard deviations represent the standard deviation among the household-level average daily consumption changes.