Characterizing the association between low-income electric subsidies and the intra-day timing of electricity consumption

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Abstract
Electricity rate subsidies are an important policy mechanism to help low-income households afford necessary energy services, bringing substantial quality of life benefits to roughly 30% of California households. Resulting increases in consumption may unintentionally increase costly peak demand while also raising emissions of greenhouse gases and criteria air pollution from electricity generation, potentially motivating additional measures to shift consumption to hours with fewer unintended consequences. In a difference-in-differences study of interval data from over 30,000 northern California dwellings, we find that enrollment in the California Alternate Rates for Energy subsidy is associated with a $\sim 13\%$ increase in electricity consumption, varying modestly across regions and seasons, increasing by an additional $\sim 3\%$ during summer peak times. We find that peak demand costs associated with CARE are about $\$45$ M per year but could fall by $\sim 1/3$ with peak shifting to level demand.

1. Introduction
Modern energy services provide enormous quality of life benefits. For most households in the United States (US), energy utility bills are a small fraction of total income, about 2% on average (Drehobl and Ross 2016). However, for low-income households this energy burden can rise to 10% or higher, often forcing choices between vital energy services such as heating and cooling and other necessities such as food and medication (Liddell and Morris 2010, Liddell et al 2012, Brunner et al 2012, Drehobl and Ross 2016).

Many US states subsidize electricity for low-income households to ensure affordable access to important services (Landley and Rzad 2014). Improved energy access can bring substantial improvements in physical and mental health of adults and children and a host of other benefits (Skumatz 2014, Drehobl and Ross 2016).

Subsidies lower the price of electricity, thus encouraging increased consumption through a price elasticity of demand. This is the intended effect of such a policy. The resulting additional electricity generation may emit greenhouse gases (GHG) and criteria air pollutants into the atmosphere, causing climate and human health damages. This additional electricity use is not distributed uniformly throughout the day. This can have important consequences, as electricity consumption during peak times may require construction of expensive additional peaking generation or new electricity transmission and distribution capacity. Furthermore, in some regions the amount of emissions and damages varies quite substantially throughout the day as the mix of dispatched energy resources changes. Thus, the intra-day timing of any increase in electricity consumption matters both because of potential coincidence with peak demand periods and because more or less polluting electricity generators may be on the margin at a given time. The importance of the timing of electricity consumption may become even more pronounced in California and other regions with high levels of solar electricity and peak demand in the dim or dark evening.

Estimates of the price elasticity of electricity of demand, the marginal change in electricity consumption for a marginal change in price, vary widely. Estimates of the short-run elasticity, often defined as responses within the same month as a change in price, range from 0 and $-2.5$ with a median of $-0.35$
(Alberini et al. 2019, Espey and Espey 2004, Bernstein and Griffin 2006, Lijesen 2007, Paul et al. 2009, Azevedo et al. 2011, Alberini and Filippini 2011, Miller and Alberini 2016, Chang et al. 2016, Labandeira et al. 2017). In the long-run, generally timescales of months to years, estimates range from 0 to $-4.56$ (Alberini et al. 2019, Espey and Espey 2004, Bernstein and Griffin 2006, Lijesen 2007, Paul et al. 2009, Azevedo et al. 2011, Alberini and Filippini 2011, Miller and Alberini 2016, Chang et al. 2016, Labandeira et al. 2017), with a median around $-0.81$ (Espey and Espey 2004). This variation is due both to heterogeneity in price-responsiveness across different populations and to uncertainties inherent in observational causal inference. Estimates of the national-level price elasticity of demand tend to fall as national income rises (Chang et al. 2016), but the relationship between income and price elasticity is less clear at the household level.

Current estimates of the price elasticity of demand generally assume that the elasticity does not change throughout the day. This likely holds true for changes in electricity demand that do not depend on occupancy patterns, such as the purchase of a new refrigerator. However, lower electricity prices may encourage adoption or increased use of heating or cooling technologies or other more occupancy-dependent energy services, such as watching television. In such cases, electricity consumption would increase more when occupants are at home, e.g. weekday mornings or evenings.

The widespread deployment of advanced metering infrastructure (AMI) by many electric utilities over the past decade and a half facilitates more detailed analysis of intra-day variation in the effect of various interventions on residential electricity consumption (Cooper 2017). Jessoe and Rapson (2014) use a randomized controlled trial to estimate the intra-day responsiveness of household electricity consumption to critical peak pricing, in which electricity rates rise during anticipated peaks in system-wide electricity demand. Boomhower and Davis (2017) use quasi-experimental methods to estimate the timing of electricity savings from an air conditioner replacement program. Qiu and Kahn (2018) estimate hourly energy consumption effects of Energy Star and Leadership in Energy and Environmental Design (LEED) building certifications.

Since 1989, California has had a low-income electricity subsidy, now known as the California Alternate Rates for Energy (CARE) (CPUC 1989, 2001, 2002, 2005, Gallagher 2007). See the SI, section S1 (available online at stacks.iop.org/ERL/15/094089/mmedia) for further historical and demographic information. In 2012, 32% of California households were eligible for CARE (Evergreen Economics 2013). In 2011, enrollment in CARE reached 93% of the identified number of eligible California households, doubtless providing substantial quality-of-life benefits (Evergreen Economics 2013). CARE disbursements, funded through general electricity rates, were $1.3 billion in 2016 (Evergreen Economics 2013). The large scale of the program highlights the importance of understanding its effects on electricity demand, particularly given that a flat-rate subsidy may encourage extra consumption at peak or high-pollution times that could otherwise be shifted to lower-impact times.

In this work, we do not focus on the obvious value to society of having energy subsidies for low-income households. Instead, we focus on understanding if there is an opportunity to reduce unintended consequences in terms of peak demand and emissions if that induced consumption is shifted to hours with lower unintended negative consequences. We estimate the association between enrollment in the CARE subsidy and electricity consumption, capturing intra-day variation using data from 2008 to 2011, a period during which CARE enrollment expanded substantially (CPUC 2008). Although this observational analysis cannot ultimately claim causality due to potential selection bias concerns, we attempt as best we can to approximate the price elasticity of demand using available data. This yields insight into possible intra-day variation in household price responsiveness. We then determine the climate, human health, and peak capacity costs associated with the measured increase and thus gain intuition into whether accounting for such intra-day variation would change estimates of the climate, human health, and resource adequacy costs and benefits of changes in electricity pricing for low-income households in California. The program is clearly an important policy mechanism to provide affordable energy services where they are the most needed, but there could be opportunities to ensure that the added consumption is concentrated in hours where the peak demand, environmental, and human health costs are lower. The aim of this study is not to perform a benefit-cost assessment of the CARE program but to provide policy makers with insights into potential unintended consequences to mitigate while maintaining equity goals and the important main goal of the program—affordable access to necessary energy services.

2. Materials and methods

2.1. Hourly panel of household electricity consumption
We use hourly electricity consumption data from a random sample of roughly 30,000 households in northern California, acquired from the PG&E service territory through the Wharton Customer Analytics Initiative. Data include enrollment and disenrollment dates for the CARE program and several other utility programs, as well as dates of participation in rebate programs for energy-efficient appliances and services. These data also include each household’s census block, which allows matching
both to neighborhood-level demographics from the 2010 Census and to temperature data from nearby weather stations (Census 2012, Menne et al 2012).

AMI was installed at dwellings during the study period of 2008–2011. For each dwelling, hourly data in our panel begin after the installation of AMI, which was staged across the three regions of the Central Valley, Inland Hills, and Coast, shown in the SI, sections S2.1 and S2.2. As a result, the panel is unbalanced, with two or more years of data from most Central Valley dwellings and less than one year of data for most dwellings on the Coast. See the SI, section S2 for further discussion of the dataset.

Households also had access to several other utility programs offered through PG&E. These included energy efficiency rebates, an air conditioner demand response program, a seasonal bill smoothing program, and several others. These programs are described further in the SI, section S2.6.

2.2. Difference-in-differences regression

We estimate the increase in electricity consumption associated with CARE enrollment using a difference-in-differences model, described in equation (1):

\[
\ln(y_{ith}) = \beta_{ith}^\text{CARE} \cdot 1_{ith} \cdot T_{ith > 65^\circ F} + \alpha \cdot T_{ith} \cdot 1_{ith} \cdot T_{ith < 65^\circ F} + \gamma_j + \omega_h + \epsilon_{ith}
\]

where \(y_{ith}\) is electricity consumption in kWh by dwelling \(i\) in day-of-sample \(t\) in hour-block \(h\), where the day is divided into eight three-hour blocks, starting at 12 am. The three-hour blocks from 3 pm to 6 pm and 6 pm to 9 pm roughly correspond with peak electricity pricing periods in PG&E’s current residential time-of-use rates, which are offered at 3 pm–8 pm or 4 pm–9 pm (PG&E 2019). We consider \(\ln(y_{ith})\) as the independent variable both because we ultimately aim to estimate a price elasticity of demand using log-arithmetic coefficients and because the distribution of electricity consumption across dwellings is approximately lognormal (see the SI, section S3). The term ‘dwelling’ refers to a residence while ‘household’ refers to the inhabitants.

\(CARE_{ith}\) is CARE enrollment status of dwelling \(i\) in day-of-sample \(t\). This is an indicator variable, which takes the value of 1 when a dwelling is enrolled in the program and 0 otherwise. \(T_{ith}\) is the temperature at dwelling \(i\) in day-of-sample \(t\) in hour-block \(h\), using the average temperature from the three weather stations closest to the census block of dwelling \(i\) across the three hours in the hour-block, with data from the National Oceanic and Atmospheric Administration, described further in the SI, section S2.4 (Menne et al 2012). \(1_{ith > 65^\circ F}\) and \(1_{ith < 65^\circ F}\) are indicator functions for whether the average temperature in hour-block \(h\) is above or below 65\(^\circ\)F. This piecewise linear representation of temperature response accounts for heating and cooling, mimicking degree-days. \(\gamma_j\) is a fixed effect term for dwelling \(i\) in hour-block-of-day \(h\), \(\omega_h\) is a fixed effect term for hour-block \(h\) of week/weekend-of-sample \(j\) (with separate fixed effects for weekdays and weekends). \(\epsilon_{ith}\) is an error term corresponding to dwelling \(i\) in day-of-sample \(t\) in hour-block \(h\).

We use a slightly modified equation, equation (2), inspired in part by Boomhower and Davis, to estimate the intra-day consumption increase associated with CARE (Boomhower and Davis 2017). See the SI, section S4 for key differences between this specification and theirs.

\[
\ln(y_{ith}) = \beta_{ith}^\text{CARE} \cdot 1_{ith} + \alpha \cdot T_{ith} \cdot 1_{ith} \cdot T_{ith > 65^\circ F} + \alpha \cdot T_{ith} \cdot 1_{ith} \cdot T_{ith < 65^\circ F} + \gamma_j + \omega_h + \epsilon_{ith}
\]

Note that \(\beta_{ith}^\text{CARE}, \gamma_j, \text{ and } \omega_h\) are indexed by hour-block, meaning that they capture intra-day variation. \(1_{ith}\) is an indicator for the hour-block of the day.

These regression specifications are slightly different than in our preregistration, primarily for computational reasons. See the SI, section S5 for further discussion.

In the main analysis, we use the Full sample, including dwellings that never enrolled in CARE, those that enrolled in CARE during the study period, and those that are enrolled in CARE throughout the entire study period. As a result, some enrolled dwellings have no pre-treatment data. Including these dwellings helps capture any differential trends in electricity consumption between CARE and non-CARE dwellings, such as income shocks that disproportionately affect low-income households. In all cases, we use cluster-robust and heteroskedasticity-robust standard errors, clustering at the dwelling-level.

In addition to a specification that uses the Full sample, we also independently consider dwellings in the Coast, Inland Hills, and Central Valley, and compute separate estimates for the two seasons in PG&E’s current time-of-use rates, Summer (June-September) and Winter (October-May) (PG&E 2019). Note that time-invariant rates were overwhelmingly predominant during the study period (PG&E 2019).

2.3. Estimating externalities

To understand the societal implications of time-varying electricity consumption changes associated with CARE enrollment, we provide a very first-order estimate of corresponding electric power system peak capacity costs and the climate change and human health damages. We compare estimated costs using both time-invariant and intra-day estimates, in part to determine whether using intra-day estimates substantially changes estimates of external costs.

In the base case, we estimate the marginal damages associated with changes in intra-day electricity consumption using hourly emission factors from (Azevedo et al 2020) for the Western Electricity Coordinating Council (WECC) in 2011. Marginal
emission estimates for greenhouse gases and criteria pollutants are based on regression analysis of historical electricity generation patterns, described in (Siler-Evans et al 2012) with changes described in the documentation of the online tool (Azevedo et al 2020). Marginal human health damage estimates use the AP2 integrated assessment model, which links emissions in a particular location to human health damages (Muller 2017). See the SI, sections S6 and S9 for further discussion of the methods used to compute marginal damages and sensitivity analyses using average emission factors and the EASIUR damages model (Heo and Adams 2015).

We place a cost value on greenhouse gas and criteria pollutant emissions using a social cost of carbon of $2010/40t(CO_2)$ and a value of statistical life of $8.8$ M for consistency with the damage factors from Azevedo et al, recognizing that policy makers may wish to use different values for each (Azevedo et al 2020). Climate and human health damages, as well as peak electricity costs, are reported in 2010 dollars for consistency with (Azevedo et al 2020).

We estimate peak electricity capacity costs at $150/kW-yr (in 2010 dollars) based on the cost of new entry for a natural gas combustion turbine plus transmission and distribution capacity costs from PG&E (CPUC 2018). Capacity costs use estimates of the increase in electricity consumption associated with CARE enrollment from 6 pm to 9 pm, capturing much of PG&E’s residential peak pricing period in both the 3 pm–8 pm and 4 pm–9 pm options available to customers (PG&E 2019). See the SI, section S6 for further details.

2.4. Limitations
This analysis is an observational study of a mature utility program attempting to characterize what is fundamentally a causal relationship between electric subsidies and electricity consumption. As a result, there is substantial potential for selection bias and, in this case, we were not able to identify a clear natural experiment or other technique that would enable a convincing improvement over the rich fixed effects difference-in-differences model in equations (1) and (2). Thus, we are not able to claim causality, although this analysis attempts to control for selection issues.

The SI, section S7, details some of the key limitations of the dataset, such as confounding of CARE enrollment with unobserved changes in income and employment status and lack of access to transparent electricity rate information. We apply a battery of robustness checks in the SI, section S8.3 to investigate the potential influence of different model specifications and data subsets on our results. SI section S7 also explains why we think it is unlikely that selection effects explain the intra-day variation in the increase in demand associated with CARE. In addition, we would ideally use a more recent data set. However, acquiring high-resolution interval data for tens of thousands of customers with detailed information indicating program enrollment, income status, and census block-level demographics is extremely difficult and this remains one of the only such data sets in existence for research purposes.

3. Results
CARE enrollment is widespread and varies by region. Table 1 shows that 30% of the full sample is enrolled in CARE, with 44% enrollment in the agricultural Central Valley, which has lower average incomes, home values, and education levels than the Coast and Inland Hills, which together include most of the wealthy San Francisco Bay Area. Still, even in census blocks with relatively high incomes, CARE participation is at least 10% in all three regions. See the SI, section S2.3 for further details.

Although CARE participants have slightly (3–6%) higher average electricity consumption in the Central Valley and Coast, they consume 7% less electricity than non-CARE households in the Inland Hills. Note that these figures are per household, not per capita. We do not have household size data, but because the CARE income eligibility threshold increases with household size, CARE households are likely larger on average, possibly further reducing relative per capita electricity consumption. In addition, median consumption for CARE customers is lower in all regions, suggesting that the distribution of CARE electricity consumption in the Central Valley has a heavy right tail.

3.1. Regression results
Participation in the CARE program is associated, as expected, with an overall increase in electricity consumption. Using the time-invariant difference-in-differences model in equation (1), see Materials and methods, this increase is 12.7% [10.2%, 15.1%] across the full sample. Table 2 shows increases ranging from 9.7% [3.8%, 16.0%] on the cool Coast to 14.9% [10.7%, 19.3%] in the warm Inland Hills, with a rise of 11.9% [8.6%, 15.3%] in the hot Central Valley. CARE participation is associated with a greater increase in the Summer (June-September), 14.4% [11.0%, 17.9%] than in the Winter (October-May), 12.3% [9.7%, 14.9%] (PG&E 2019). See the SI, section S8.1 for discussion of temperature coefficients.

There is significant intra-day variation in all cases, shown in figure 1, based on equation (2) in Materials and methods. In the Full sample, the baseline increase, from 12 am to 3 am, is 11.7% [9.2%, 14.2%], statistically indistinguishable from the time-invariant estimate. However, there are statistically significant increases in electricity consumption from 6 pm to 9 pm, and 9 pm to 12 am of 2.7% [1.1%, 4.4%] and 2.6% [1.5%, 3.7%], respectively, leading to net
increases in consumption of 14.4% [11.4%, 17.5%] and 14.3% [11.5%, 17.1%]. An increase in a particular hour-block is statistically significant if its 95% confidence interval does not overlap the baseline value, the black dashed line in figure 1. Thus, in the Full sample the increase in consumption is 20% greater during the peak hours of 6–9 pm than from 12 am to 3 am.

The consumption increase associated with CARE is significantly higher from 6 pm to 9 pm than from 12 am to 3 am for all seasons and all regions except the Central Valley. As in the time-invariant cases, the baseline increase is greatest in the Summer, 12.6% [9.2%, 16.0%], and in the Inland Hills, 13.5% [8.9%, 18.3%], with 6 pm–9 pm values at 16.6% [12.5%, 20.8%] and 18.2% [12.5%, 24.1%], respectively. However, in regional regressions by season, shown in the SI, section S8.3.17, table S7, all regions see a significant incremental increase in electricity consumption during peak times during the Summer.

3.2. Elasticity estimation
We use the above estimates to compute the implicit price elasticity of electricity demand. Lacking detailed rate information, we assume all CARE households receive PG&E’s average discount of 42% (Evergreen Economics 2013). Thus, the Full Sample time-invariant effect of 12.7% [10.2%, 15.1%] translates to a price elasticity of electricity demand of −0.30 [−0.24, −0.36]. This is within the range of estimates for the short-run and long-run price elasticity of demand. It is slightly below, but not statistically distinguishable from the median short-run estimate from the literature of −0.35, and well below the median estimate of the long-run price elasticity of demand of −0.81 (Espey and Espey 2004).
3.3. Peak electricity demand, climate, and human health, and externalities

This increase in electricity consumption is associated with increased demand for costly peak electricity generation and transmission and distribution capacity and climate and human health damages. Note that this exercise treats the estimated increase in consumption associated with CARE as though it were causal, both to give a rough estimate of potential externalities associated with CARE, while decidedly not conducting a more comprehensive welfare analysis as in (Borenstein 2012), and to gain intuition into whether accounting for intra-day variability in the price elasticity of demand is likely to substantially change estimates of externalities.

The time-invariant Full sample increase for PG&E’s 1.53 M CARE customers in 2011 corresponds to an annual increase in demand of 1.2 TWh [1.0 TWh, 1.5 TWh] and 203 MW [164 MW, 243 MW] of incremental peak demand (Evergreen Economics 2013).

This increase in electricity consumption is associated with capacity costs, shown in figure 2(A), greater than or roughly equal to combined climate and human health damages in all cases, with a maximum value of ∼$45 M based on the estimated effect of CARE in the Summer from 6 pm to 9 pm. Using the Full Sample and a time-invariant estimate, costs are ∼$30 M. The mean estimates for time-invariant and intra-day specifications differ by as much as ∼$6 M in the Summer case, or ∼$15 M if Summer intra-day estimates are compared to Full sample time-invariant estimates, 2.1% of total CARE expenditures (Evergreen Economics 2013). These changes are still within the confidence intervals of the intra-day and time-invariant estimates. However, the incremental increase in capacity cost is likely statistically significant in the sense that the increase over the baseline from 6 pm to 9 pm is statistically significant in all cases but the Central Valley. See the SI, section S6.5 for further discussion of statistical significance.

Climate and human health damages are on the order of in the tens of millions of dollars per year. Figure 2(B) estimates climate damages associated with a time-invariant elasticity at ∼$26 M. Figure 2(C) shows human health damages in the Full Sample at ∼$14 M from human health effects of criteria air pollutants.

In all regions and seasons, the increases in climate and human health damages are statistically significant in the sense that the confidence intervals do not contain zero. See the SI, section S6.5 for further discussion of statistical significance. However, using intra-day or time-invariant elasticities results in essentially identical estimates of mean damages, within 6%, with strongly overlapping confidence intervals. The magnitude of damages in figure 2(C) is weighted by the population in each region and the fraction of the year in each season, described further in the SI, section S6.

As a sensitivity analysis, we also consider marginal damages from Azevedo et al assuming the same increase in electricity consumption occurred in 2018 in WECC, which experienced a 10% decline in greenhouse gas emissions intensity and a 50% decline in average pollution-related damages per MWh from 2011 to 2018 (Azevedo et al 2020). This is reflected in a fall in overall health damages of 26% for time-invariant and 35% for intra-day estimates. As a sensitivity, we compare results using average, rather than marginal emissions factors and the EASIUR integrated assessment model, with qualitatively similar results in all cases (Heo and Adams 2015). See the SI, section S9 for further details.

3.4. Robustness checks

In an attempt to bound potential selection issues as much as possible, we apply the intra-day regression,
Estimated annual externality costs. Comparison of societal costs associated with (A) increases in peak electricity consumption, (B) marginal climate damages from greenhouse gas emissions, and (C) human health damages from criteria pollutant emissions attributable to the estimated increase in electricity consumption associated with CARE during 2011, assuming a social cost of carbon of $40/t(CO₂), an $8.8 million value of statistical life, and a capacity cost of $150/kW-yr (all in 2010 dollars) (CPUC 2018), described in section S6.3. Regional and seasonal estimates consider effects only in the corresponding subpopulation and season. Capacity costs assume the increase from 6 pm to 9 pm translates to an increase in system-wide peak demand. Red and blue dots represent the mean and 95% confidence interval using intra-day or time-invariant estimates of the consumption increase associated with CARE enrollment. Note that capacity costs, the largest component in all cases, are up to ~$7 M higher using intra-day estimates. This rises to ~$15 M if Summer intra-day estimates are compared to Full sample time-invariant estimates. See the SI, section S8.3 for further discussion of statistical significance. Climate and health damages are essentially identical in both time resolutions despite accounting for different marginal pollution from the electric grid at different times.

Figure 2.

4. Conclusions and policy implications

Subsidies are a highly effective tool for ensuring affordable access to energy services for low-income households, which significantly improves quality of life in numerous ways (Skumatz 2014, Drehobl and Ross 2016). We find, unsurprisingly, that enrollment in a major low-income electricity subsidy is associated with an increase in electricity consumption, suggesting that the subsidy is indeed expanding access to energy services.

The magnitude of this increase, which implies a price elasticity of −0.30, is well within the range in the existing literature, very close to close to the median estimate for the short-run price elasticity of −0.35, and substantially below the median estimate for long-run elasticity of −0.81 (Espey and Espey 2004). −0.30 is the high-end estimate of price elasticity used in Borenstein’s analysis comparing the welfare impacts of equity-based electricity rate designs. Generalized across the PG&E customer base, this 13% increase in electricity consumption corresponds to an extra ~1.2 TWh per year, or roughly a medium-sized 200 MW power plant.

Our results suggest that the effect of the CARE subsidy may vary throughout the day, with modest but significant increases in consumption in the evenings in most cases, coinciding with California’s peak electricity demand (PG&E 2019). Both the baseline and the early evening increase are greatest in the Summer, which are, together with seasonal regressions in the SI, section S8.3.17, suggestive of increased use of air conditioning. See the SI, section S10 for further details.

The general agreement of our estimates with the price elasticity of demand literature supports the validity of the estimation strategy employed in this study. However, as in all observational studies, selection bias and other confounding factors could push these estimates upward or downward. The robustness checks suggest that the true value could be roughly 30% lower or 50% higher. In addition, households may respond differently to a low-income subsidy than...
they would to an equivalent simple change in price. See the SI, section S7 for further details. Thus, we do not claim that our results are causal, only our best attempt toward causality given the reality of messy observational data. Even if these results were definitively causal, they may or may not generalize to intra-day responses to changing price signals throughout the day, such as time-of-use pricing, as there is evidence that residential customers respond to average electricity price, i.e. bills, rather than marginal prices (Ito 2014).

The estimated intra-day climate, human health, and summer peak capacity externality costs associated with this increase in electricity consumption represent 3.7%, 2.0% and 6.3% of PG&E’s 2012 expenditures on the CARE program, respectively, totaling 12.0% of expenditures (Evergreen Economics 2013). These externalities are substantial, particularly given that the human health effects of electricity generation are often disproportionately borne by low-income households (Drehobl and Ross 2016).

Switching from time-invariant to intra-day estimates can materially increase estimates of peak capacity costs. However, the magnitude of the climate and human health damages does not vary substantially between the two. Thus, understanding time variation in household responsiveness to electricity prices can inform resource adequacy planning and procurement, particularly if a utility is considering implementing a new subsidy or other change in rates.

Note that because CARE is financed through a charge levied on non-CARE customers, this is an upper bound on the net externalities of the CARE program, as non-CARE customers may also reduce consumption in response to resulting higher prices. Non-CARE customers will likely be less responsive to prices as electricity expenditures represent a smaller fraction of income (Drehobl and Ross 2016).

Although we do not attempt a full welfare calculation, note that CARE brings California’s already high electricity rates closer to local marginal cost during off-peak time periods, potentially improving social welfare and encouraging beneficial electrification (Borenstein and Bushnell 2018). Note that peak capacity costs would fall by $\frac{1}{3}$ if the increase in consumption were flattened to a fixed $\frac{12}{13}$ proportional increase at all hours of the day. See Borenstein (2012) and Levinson and Silva (2019) for further discussion of the equity implications of subsidies and other redistributive electricity rate designs such as inclined block pricing (Borenstein 2012, Levinson and Silva 2019). Time-varying electric rates, such as California’s recent move to default time-of-use pricing for all customers, may allow utilities to maintain robust energy services for low-income households while, when possible, shifting consumption away from high-externality times (PG&E 2020). In addition, the apparent role of air conditioning in this increase highlights the potential importance of low-income energy efficiency programs such as California’s Energy Savings Assistance (ESA) Program (Evergreen Economics 2013).

In addition, the benefits of affordable access to energy services, such as improved physical and mental health and reduced reliance on high-interest short-term loans, are not quantified in this study or in the above studies and may well outweigh the both the direct and external costs of the program (Skumatz 2014, Drehobl and Ross 2016).

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**Data availability statement**

The data that support the findings of this study are available from the corresponding author upon reasonable request. Household electricity consumption and other household-level data were provided by Pacific Gas and Electric Company through the Wharton Customer Analytics Initiative via a non-disclosure agreement. Temperature data were provided by the National Oceanographic and Atmospheric Administration and are publicly available (Menne et al 2012). Census block demographic information are from the 2010 US Census and are publicly available (Census 2012). Code and data behind figures and tables are available at https://github.com/esherwin/CARE_ERL.

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References

Alberini A and Filippini M 2011 Response of residential electricity demand to price: the effect of measurement error Energy Econ. 33 889–95
Alberini A, Khymych O and Šásky M 2019 Response to extreme energy price changes: evidence from Ukraine Energy J. 20
Azevedo I L, Horner N C, Sier-Evers K and Vaishnav P T 2020 Electricity Marginal Factor Estimates (https://cdm.shinyparts.io/MarginalFactor/
Azevedo J M L, Morgan M G and Lave L 2011 Residential and regional electricity consumption in the U.S. and EU: how much will higher prices reduce CO2 emissions? Electr. J. 24 21–29
Bernstein M A and Griffin J M 2006 Regional Differences in the Price-Elasticity of Demand for Energy (http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.464.7523&rep=rep1&type=pdf)
Boommaker J and Davis J W 2017 Do energy efficiency investments deliver at the right time? Working Paper No. w23097 (https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2907900)
Borenstein S 2012 The redistributive impact of nonlinear electricity pricing Am. Econ. J.: Econ. Policy 4 56–90
Borenstein S and Bushnell J 2018 Do Two Electricity Pricing Wrongs Make a Right? Cost Recovery, Externalities, and Efficiency (Cambridge, MA: National Bureau of Economic Research) (www.nber.org/papers/w24756.pdf)
Brummer K-M, Spitzer M and Christanell A 2012 Experiencing fuel poverty. Coping strategies of low-income households in Vienna/Austria Energy Policy 49 53–59
Census 2012 United States Summary: 2010 Population and Housing Unit Counts (Washington, D.C.: U.S. Census Bureau) (www.census.gov/prod/cen2010/p2-1.pdf)
Chang Y, Choi Y, Kim C S, Miller J I and Park J Y 2016 Disentangling temporal patterns in elasticities: a functional panel coefficient analysis of electricity demand Energy Econ. 60 232–43
Cooper A 2017 Electric Company Smart Meter Deployments: Foundation for a Smart Grid (Washington, D.C.: The Edison Foundation: Institute for Electric Innovation) Electric Company Smart Meter Deployment: Foundation for a Smart Grid (www.edisonfoundation.net/-/media/Files/IEI/publications/IEI_Smart-Meter-Report-2017_FINAL.ashx)
CPUC 1989 Decision 89-09-044 Final Opinion (San Francisco, CA: California Public Utilities Commission) (ftp://ftp2.cpuc.ca.gov/Legacy/CPUC/decisionsAndResolutions/Decisions/Decisions_D840200_to_D8921077/D8909044_19890907_18807009.pdf)
CPUC 2001 Decision 01-05-033 May 3, 2001 (San Francisco, CA: California Public Utilities Commission) (http://docs.cpuc.ca.gov/word_pdf/FINAL_DECISION/6860.pdf)
CPUC 2002 Decision 01-05-033 July 17, 2002 (San Francisco, CA: California Public Utilities Commission) (http://docs.cpuc.ca.gov/published/final_decision/17665-07.htm)
CPUC 2005 Opinion Approving 2006–2007 Low Income Programs and Funding for The Larger Energy Utilities and Approving New Low Income Energy Efficiency Program Measures for 2006 (San Francisco, California, USA: California Public Utilities Commission) (http://docs.cpuc.ca.gov/word_pdf/FINAL_DECISION/52148.doc)
CPUC 2008 Decision on Large Investor-Owned Utilities’ 2009–11 Low Income Energy Efficiency (LIEE) and California Alternate Rates for Energy (CARE) Applications (San Francisco, CA: California Public Utilities Commission) (http://docs.cpuc.ca.gov/published/FINAL_DECISION/93648.htm)
CPUC 2018 2018 Avoided Cost Calculator (San Francisco, California: California Public Utilities Commission, prepared by Energy + Environmental Economics) (www.cpuc.ca.gov/General.aspx?id=5267)
Drehobl A and Ross L 2016 How Energy Efficiency Can Improve Low Income and Underserved Communities (Washington, D.C.: American Council for an Energy-Efficient Economy) (https://aceee.org/sites/default/files/publications/research_reports/u1602.pdf)
Espey J A and Espey M 2004 Turning on the lights: a meta-analysis of residential electricity demand elasticities J. Agric. Appl. Econ. 36 65–81
Evergreen Economics 2013 Needs Assessment for the Energy Savings Assistance and the California Alternate Rates for Energy Programs (Portland, OR: Evergreen Economics) (www.calmac.org/publications/LINA_report_-_Volume_1_-_final.pdf)
Gallagher S H 2007 Clarification of Domestic Multifamily Accommodations/Eligibility for the California Alternate Rates for Energy Discount (Rosemead, CA: California Public Utilities Commission) (www.sce.com/NR/cf$ts/m2/pdf/2162-E.pdf)
Heo J and Adams P 2015 EASIUR User’s Guide Version 0.2 (Pittsburgh, PA, USA: Carnegie Mellon University) (https://barney.ce.cmu.edu/~jinhyok/easiur/EASIUR-Users-Guide-200505-Jinhyok.pdf)
Itu K 2014 Do consumers respond to marginal or average price? Evidence from nonlinear electricity pricing Am. Econ. Rev. 104 537–63
Jesse K and Rapson D 2014 Knowledge is (Less) Power: experimental evidence from residential energy use Am. Econ. Rev. 104 1417–38
Labandeira X, Labeaga J M and López-Otero X 2017 A meta-analysis on the price elasticity of energy demand Energy Policy 102 549–68
Landley A and Rza Y 2014 (Washington, D.C.: U.S. Department of Health and Human Services, Office of the Assistant Secretary for Planning and Evaluation) (https://aspe.hhs.gov/basic-report/approaches-low-income-energy-assistance-funding-selected-states)
Levinson A and Silva E 2019 The electric gini: income redistribution through energy prices Working paper 35 26385
Liddell C and Morris C 2010 Fuel poverty and human health: A review of recent evidence Energy Policy 38 2987–97
Liddell C, Morris C, Mckenzie S J P and Rae G 2012 Measuring and monitoring fuel poverty in the UK: national and regional perspectives Energy Policy 49 27–32
Lijesen M G 2007 The real-time price elasticity of electricity Energy Econ. 29 249–58
Menne M J et al 2012 Global Historical Climatology Network - Daily, Version 3 (California) (https://data.nodc.noaa.gov)
Meyer R M 2014 A Analysis of Selected Regulatory Interventions to Improve Energy Efficiency (Pittsburgh, PA: Carnegie Mellon University)
Miller M and Alberini A 2016 Sensitivity of price elasticity of demand to aggregation, unobserved heterogeneity, price trends, and price endogeneity: evidence from U.S. Data Energy Policy 97 235–49
Muller N Z 2017 AP2 Model (https://public.tepper.cmu.edu/~nnmuller/AP2Model.aspx)
Paul A C, Myers E C and Palmer K L 2009 A partial adjustment model of U.S. Electricity demand by region, season, and sector SSRN Electron. J. 1 08–50
PG&E 2019 Take Control with Time-of-Use Rate Plans (Sacramento, CA: Pacific Gas and Electric Co) (www.pge.com/en_US/residential/rate-plans/rate-plan-options/time-of-use-base-plan/time-of-use-plan.page)
PG&E 2020 Residential Rate Changes: 2020 (San Francisco, CA: Pacific Gas and Electric) (www.pge.com/en_US/residential/rate-plans/how-rates-work/rate-changes/residential-rate-changes/residential-rate-changes.page)
Qiu Y and Kahn M E 2018 Better sustainability assessment of green buildings with high-frequency data Nat. Sustain. 1 642–9
Siler-Evans K, Azevedo I L and Morgan M G 2012 Marginal emissions factors for the U.S. Electricity system Environ. Sci. Technol. 46 4742–8

Skumatz L A 2014 Non-Energy Benefits/Non-Energy Impacts (NEBs/NEIs) and Their Role & Values in Cost-Effectiveness Tests: State of Maryland (Superior, CO: Natural Resourced Defense Council, prepared by Skumatz Economic Research Associates Inc) (http://energyefficiencyforall.org/sites/default/files/2014_%20NEBs%20report%20for%20Maryland.pdf)