Do low-income electricity subsidies change peak consumption behavior?

Evan D. Sherwin, Carnegie Mellon University, Dept. of Engineering and Public Policy, Pittsburgh, PA
Dr. Russell M. Meyer, NMR Group, Los Angeles, CA
Prof. Inês M. L. Azevedo, Carnegie Mellon University, Dept. of Engineering and Public Policy, Pittsburgh, PA

ABSTRACT

Increases in electricity consumption during peak hours place additional strain on the electric power system, which can be partially mitigated if foreseen years in advance. Smart meter data, with hourly resolution or better, allow improved characterization of the effects of various programs and other interventions on residential and system load shape. We characterize the load shape impacts of the California Alternate Rates for Energy (CARE) program, which provides 3.2 million households an average electric bill subsidy of 33% (Evergreen Economics 2013, 17). We use hourly electricity consumption data from roughly 30,000 randomly selected households from Pacific Gas and Electric service territory to estimate the hourly effect of enrollment in the CARE program on household electricity consumption using a fixed-effects regression model. We find that the CARE program is associated with an average increase in electricity consumption of 13% [11%, 16%]. The increase is relatively constant throughout the day, with no two hours statistically distinguishable from each other. We find suggestive evidence that the largest increase in electricity consumption in all three regions occurs between 7pm and 10pm, generally after summer peak demand. The overall increase is smallest in the cooler Coast, largest in the warmer Inland Hills, and in the middle in the hot Central Valley. These estimates of regional differences in the effect of the CARE program can help policy makers and utilities understand the energy effects of changes to low-income electricity subsidies.

Introduction and Background

Modern electric utilities are expected to reliably meet demand at all times with a fixed fleet of generators, and transmission and distribution infrastructure. Because electricity must enter the grid at the moment it is consumed, electricity consumption on or around peak consumption times can place much more demand on the system than off-peak consumption.

There is a substantial literature devoted to understanding the determinants of system-wide electric load shape, the distribution of electricity consumption over time. Several existing studies focus on bottom-up engineering estimates of the load shape effects of the dissemination of newer, more efficient appliances (James and Clement 2016; KEMA, Inc. 2009). More recent research attempts to measure the load shape effects of energy efficiency and demand response programs using hourly smart meter data (Boomhower and Davis 2016; Jessoe and Rapson 2014). Many residential utility programs were not designed to influence load shape, but likely have load shape effects nonetheless. We are not aware of any efforts to quantify these effects in the peer-reviewed literature.

Some of the largest such programs provide low-income households with various forms of energy assistance. These programs range from emergency bill assistance such as that available through the Low-Income Home Energy Assistance Program (ACF 2017), to weatherization and other efficiency measures such as California's Energy Savings Assistance program (Evergreen Economics 2013), to lump sum payments such as New York's Home Energy Assistance Program (NYOTDA 2017), to direct price subsidies such as the California Alternate Rates for Energy (CARE) program (Evergreen Economics 2013).

We study the residential load shape effect of the CARE program, an electricity and natural gas subsidy available to California households with income below 200% of the federal poverty level. The program, which subsidized electric service in 3.2 million households in 2012 (Evergreen Economics 2013, 17), provides a statewide average electric bill subsidy of 33%, or $29 per month (Evergreen Economics 2013, 18). Within the service territory of Pacific Gas & Electric, where our data come from, the average electric subsidy is 42%, or $40 per month (Evergreen Economics 2013, 18). California approved $4 billion in CARE expenditures for the 2012-2014 budget cycle, funded through a public purpose customer charge (Evergreen Economics 2013, 16).

The intended effect of this subsidy is to make energy more affordable for millions of families, allowing them to enjoy a higher quality of life by lowering the cost of important energy services, such as lighting, refrigeration, heating, and cooling. Economic first principles suggest that the program should increase electricity consumption according to a price elasticity of electricity of demand. However, the effects of the program on residential load shape, and indeed overall energy consumption are poorly understood.

We anticipate that the greatest increases in electricity consumption will largely occur before, and particularly after normal working hours of roughly 7:00am-6:00pm, with some adjustment on both ends to account for commute time. Depending on commute time, this would likely coincide with partial peak demand, from 6:00-9:30pm, but likely would not overlap with summer peak periods of 12:00-6:00pm (PG&E 2017c), which place greater strain on the electric power system. We do not have a firm prior expectation of the extent to which these changes in electricity consumption would be due to changes in household appliance stock or resident behavior.

We believe that an understanding of the load shape effects of low-income energy subsidies can provide utilities and energy policymakers with important insights, both for short-term and long-term planning. For example, deep decarbonization of the electric power system will likely require substantial investment in generation, transmission, and distribution infrastructure, which could easily raise the total cost of providing electric service. For instance, Southern California Edison’s recent proposal to upgrade its distribution system to enable further renewable integration and smart grid applications is estimated to cost $1.5-2.5 billion from 2018-2020 (Valberg, Torchia, and Dwyer 2015, 213). Low-income subsidies, such as the CARE program, help ensure that these costs are distributed equitably through society. Still, these subsidies likely affect electricity consumption behavior, and thus long-term infrastructure needs. These effects should be understood and accounted for in resource adequacy planning.

A panel of smart meter data from northern California

In this work, we use a regionally stratified sample of smart meter data of approximately 30,000 households in Pacific Gas & Electric (PG&E) service territory from 2008 to 2011. The sample is drawn from all households in PG&E territory, including both single-family and multi-family residences. The data include 8,597 households from the Coast, 11,391 from the Inland Hills, and 10,217 from the Central Valley, three major climate regions in PG&E territory, displayed graphically in Figure 1A. This study period of 2008-2011 coincided with the roll-out of the smart meter program, so the number of households with smart meter readings in the dataset increases over time, as shown in Figure 1B.

The smart meter readings are communicated back to a base station, from which they are relayed back to PG&E. We use 15-minute smart meter readings, which we aggregate to hourly and daily.

This dataset includes two major household-related identifiers: a service point id, which identifies the location of the smart meter, and an account id, which identifies the customer (i.e., if a customer moves to a new house, the account id is maintained, but the customer will have a new service point id). Results below are in terms of electric service point id, which generally corresponds to a single household in a single location.

Households with smart meters were randomly sampled by PG&E at the end of the 2011. Data were gathered for each of these households for the duration of the period in which the household had an active smart meter. Figure 1B shows meter installation in our sample by region over time. As of August 2011, smart meters were installed for 4.7 million of PG&E's 5.25 million residential customers (IEE 2012, 8). As a result, the dataset should be an unbiased sample of households in each region at the end of 2011. Earlier data are unbiased only to the extent that PG&E's smart meter deployment program can be considered random. Other than the staged deployment across regions, this assumption is not contradicted by any of our findings, but without access to PG&E's internal documents, the possibility of non-random selection cannot be ruled out.

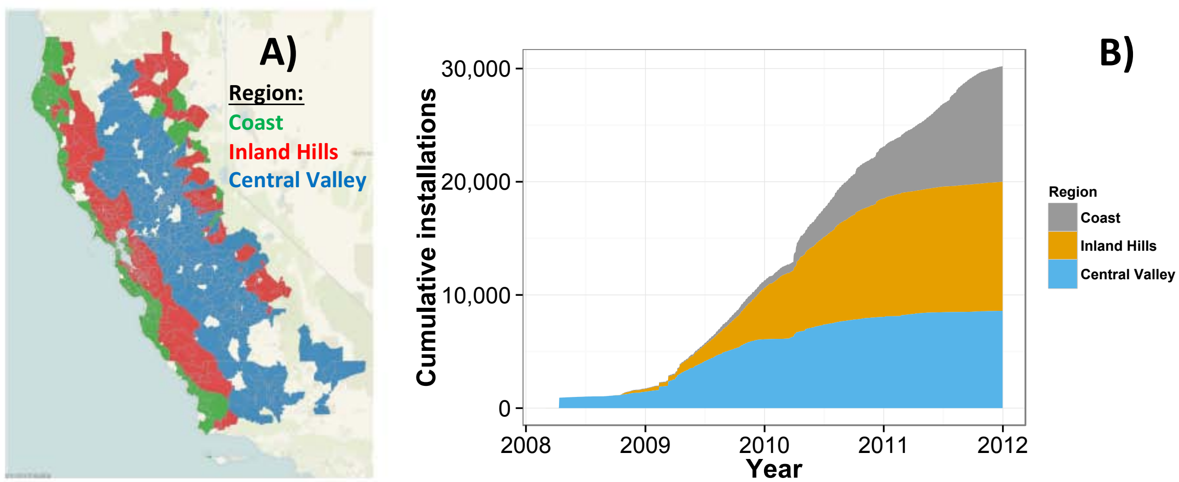

Figure 1. A) Regions in the PG&E service territory. PG&E randomly selected approximately 10,000 households from each of the region to construct the sample. Region classifications are based on climate, not geography, resulting in non-contiguous regions. Note: Figure from the Wharton Customer Analytics Initiative. B) Smart meter rollout for our sample, March 1, 2008 to December 31, 2011 by region. Deployment began in the Central Valley, followed by the Inland Hills, followed by the Coast. *Source:* (Meyer, Sherwin, and Azevedo 2017).

In Figure 1B, we show the deployment of the smart meter program observed in our sample. In our sample, smart meter deployment began in the Central Valley, followed by Inland Hills, and finally by the Coast region. Region classifications are based on climate, rather than explicit geography. As a result, some far inland households are classified as "Coast" due to moderate climate. Toward the end of our sample period (end of 2011) our sample contains about the same number of households in each climate region.

PG&E Energy Efficiency and DSM Programs

During the study period, PG&E had several programs, such as energy efficiency, demand side management (DSM) and low-income programs. We control for participation in each of these programs to better isolate the effect of CARE. Key programs active during the period of observation include:

The **California Alternate Rates for Energy** (CARE) program is an energy subsidy, providing an average discount of 33% for low-income households in PG&E territory (Evergreen Economics 2013, 18). As mentioned before, we expect enrollment to increase electricity consumption due to lower prices.

The **Balanced Payment Plan** (BPP) program provides a bill smoothing service, in which the monthly bill is based on average consumption in the previous year. We expect this program to increase electricity consumption, particularly in the Central Valley, where the program allows households to smooth payment for highly seasonal electricity consumption.

The **Smart AC** demand response program provides a one-time $50 incentive payment, in exchange for installation of a device on the cooling unit that allows PG&E to cycle the unit off for up to 15 of every 30 minutes during peak load events. The program itself likely decreases electricity consumption, but in our model may find a positive association with electricity consumption, as this program is essentially an indicator for the presence of air conditioning, and we are not separately controlling for the presence of air conditioning.

Rebate programs subsidize appliances, other residential energy-consuming devices, and retrofits. Customers receive efficiency rebates only after purchasing qualifying equipment or services and submitting an application to PG&E. Households are eligible to participate in the rebate programs multiple times. Our previous work has shown that rebate participation in this sample is associated with increases in electricity consumption in the Coast and Inland Hills, with no discernable effect in the Central Valley (Meyer, Sherwin, and Azevedo 2017). We believe this is due to households either purchasing appliances that they did not have before, or keeping and using older, more inefficient versions of the newly-purchased appliance.

The **Climate Smart** program allows households to purchase carbon offsets through PG&E via their monthly utility bill. We expect this price increase to translate to a decrease in electricity consumption.

The **Direct Access** program allows customers to purchase their electricity from alternative (non-PG&E) power providers. New customers have not been able to join the Direct Access program since the California energy crisis in 2001, though existing customers have been able to remain in the program. We expect that customers who remain on this program are receiving lower electricity rates than they would otherwise, providing an incentive for increased electricity consumption.

The **Smart Rate** program provides customers with a 3-cent per kWh discount in exchange for accepting a 60 cent per kWh rate during summer peak hours. We expect this program, which was relatively new during the sample, to correlate with in a decrease in electricity consumption. The price signal could either encourage an increase or a reduction in overall electricity consumption.

The **Energy Savings Assistance (ESA)** Program provides free energy efficiency measures to households that meet similar eligibility criteria to the CARE program. Unfortunately, we do not have data on participation in this program. As of 2012, 59% of eligible households had participated in the ESA program (Evergreen Economics 2013, iv). This likely biases our results downward, as we cannot distinguish between increases in electricity consumption due to CARE, and decreases due to ESA.

PG&E Customers

The original dataset provided by PG&E includes smart meter electricity reading information and program enrollment. However, it does not include information on demographics at the household level. To overcome this limitation, we complement our dataset with 2010 Census data at the census block level. In Table 1, we provide the summary statistics of the census block data associated with each household in our sample. To be clear, if a household is associated with a location in census block *a*, we then associate that household observation with the median household value in census block *a*. The information displayed in Table 1 thus shows the median values for several demographic quantities across the sample of census block median characteristics for each household by climate region (Central Valley, Inland Hills, Coast and overall).

We observe that there are key differences across climate regions, with median home values in census blocks in the Inland Hills and the Coast regions being almost twice as large as those in the Central Valley. Similarly, the levels of median income in Census blocks in Central Valley are lower than in the Inland Hills or the Coast. The number of renters is higher in the Coast region, where the median home values are the highest. There is a striking difference in poverty rates between regions. The fraction of households below 150% of the federal poverty level is twice as high in the Central Valley as in the Inland Hills.

Table 1. Summary statistics for 2010 census block neighborhoods of households in the sample*. The Central Valley has the lowest incomes and home values. Below, "Poor" is defined as household income below 150% of the federal poverty level.

	Central Valley	Inland Hills	Coast	Overall
Median Home Value*	282,000	586,000	597,000	479,000
Median Income*	51,800	78,500	63,400	65,600
Median % Renters	34	32	51	38
Median % Poor	12	6	9	8
Median % w/ Bachelors (or higher)	17	38	40	32
Number of households	8,597	11,391	10,217	30,426

* These values are medians from our sample of Census block neighborhood medians. The values are top-coded by the US Census at $1M and $250k, respectively. We report the values rounded to the nearest $1000 for median home value, and to the nearest $100 for median income values. *Source:* (Meyer, Sherwin, and Azevedo 2017).

Electricity consumption in our sample by income and region

In Figure 2 we illustrate the daily electricity consumption over time and by climate region in our sample. We observe that the Coast has lower overall electricity consumption than the Inland Hills or the Central Valley, likely due in part to milder weather. We also note that the distribution of daily electricity consumption is tighter for the Coast and Inland Hills when compared to the daily distributions of electricity consumption for households in Central Valley. The summer spikes (largely attributable air conditioner use) are also notable in the Central Valley region. The large summer peak in the Central Valley illustrates the disproportionate contribution of that region to the overall residential peak consumption.

Who enrolls in energy efficiency, DSM and low income programs?

In Figure 3, we show the share of enrollment for all programs over time in our sample. We observe that the California Alternate Rates for Energy (CARE) program is the most prevalent program, with enrollments reaching 30% of the entire sample of households. This share is remarkable, as households must have income below 200% of the federal poverty level, or qualify for another means-tested low-income program such as Medicaid, to be eligible for CARE (Evergreen Economics 2013, 15). Of course, the goal of the CARE program is not to reduce electricity consumption or promote energy efficiency, but instead to ensure that low income households have affordable access to energy services.

By the end of 2011, 9% of households have participated in an energy efficiency rebate program, making it the second largest program in terms of peak participation. The Balanced Payment Plan (BPP), which provides a bill smoothing service, in which PG&E calculates the household's average monthly utility bill and the customer pays a flat amount for each monthly billing cycle, comes third in terms of peak program participation, capturing less than 8% of all households in our sample at any point in time.

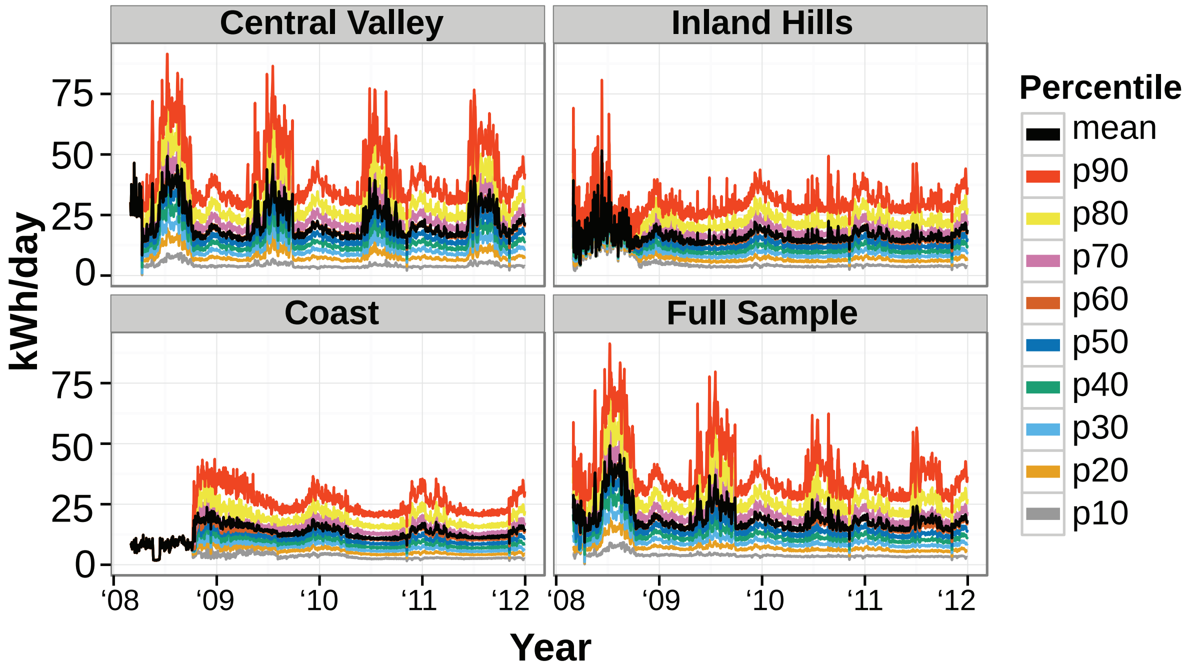

Figure 2. Deciles of daily household electricity consumption by region, from the 10th percentile to the 90th percentile, with the mean in black. All three regions have a small sample size in the first several months to one year, resulting in poorly-defined percentiles in some cases. *Source:* (Meyer, Sherwin, and Azevedo 2017).

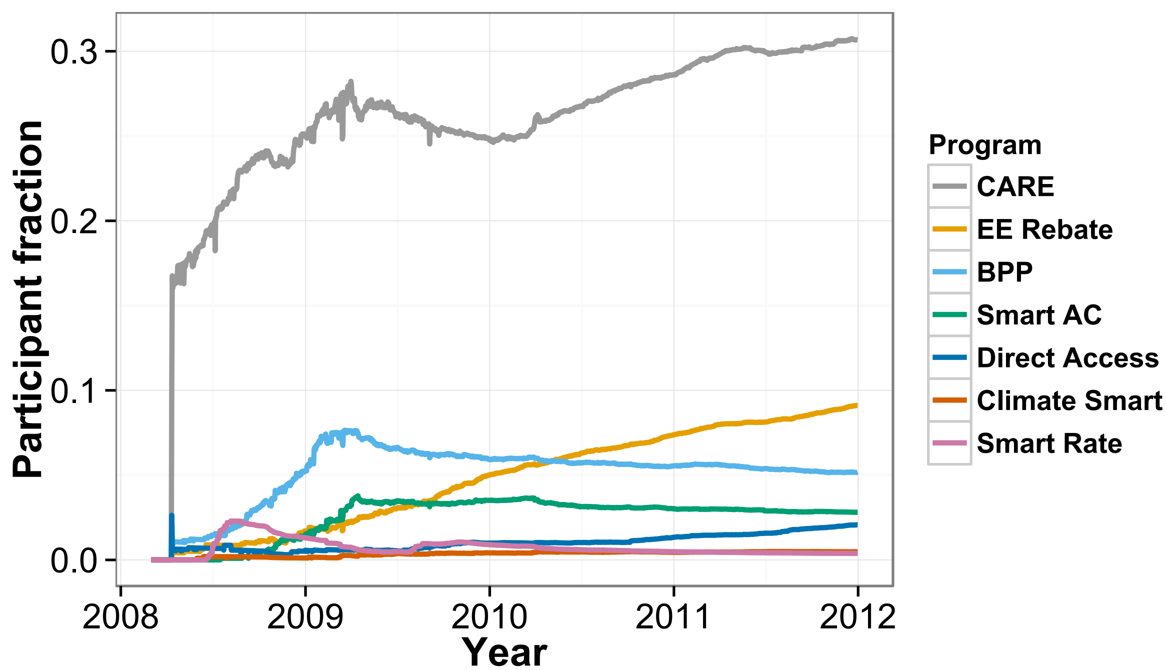

Figure 3. Enrollment rates in PG&E programs as a fraction of households in the dataset over time. The CARE low-income subsidy is by far the most prevalent. Energy efficiency rebates and the Balanced Payment Plan, BPP, are a distant second, followed by Smart AC. *Source:* (Meyer, Sherwin, and Azevedo 2017).

In Figure 4, we display CARE program enrollment by region and income to understand differences in CARE participation by these factors. The values represent the share of households in the dataset that were participating the CARE program at that point in time.

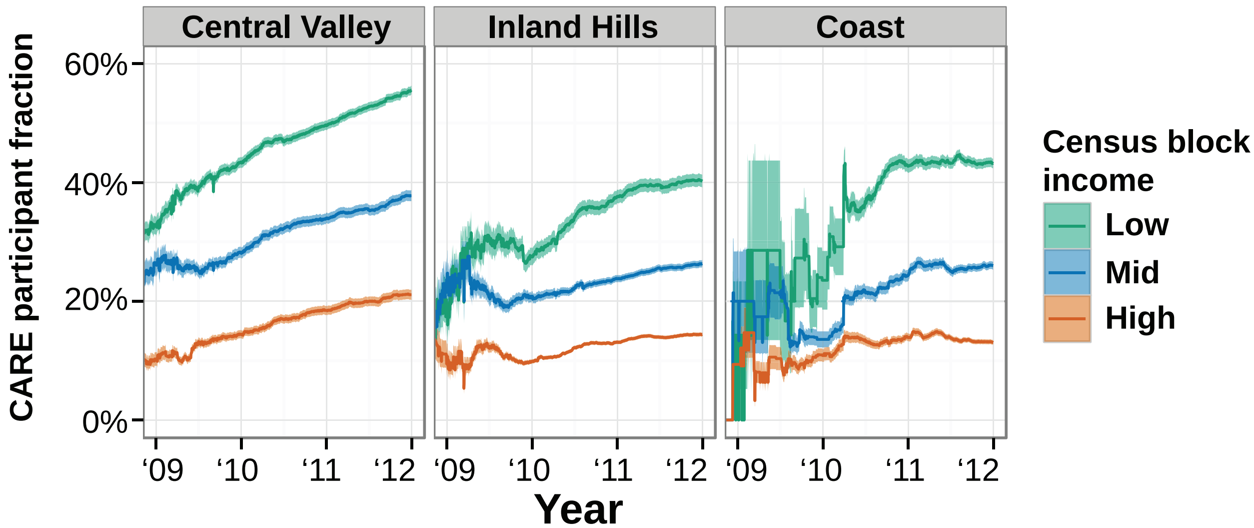

Figure 4. Enrollment rate in the CARE program as a fraction of all households in the dataset over time, by region and median census block median income, with thresholds of $52,252.33 and $81,572.00, the 1/3 and 2/3 fractiles of households in our sample respectively. Shaded areas are the 95% probability interval, considering sample error. Many CARE participants live outside low-income Census blocks. *Source:* (Sherwin, Azevedo, and Meyer 2017).

We find that participation in the CARE program is prevalent across all three regions, but, unsurprisingly, overwhelmingly concentrated in low median income census blocks. CARE enrollment also increases substantially over the study period in all groups except high-income Census blocks on the Coast. In households in low-income Census blocks in the Central Valley, CARE enrollment grows from just over 30% in 2009 to over 50% in 2011 (see Figure 4A). Similarly, in Census blocks with low median income in the Coast and Inland Hills, CARE program participation exceeds 40% in analogous households. The substantial increase in CARE enrollment over time may be attributable in part to the 2008 Financial Crisis, and the subsequent Great Recession.

Notably, in Census blocks with mid-range median income range, participation in CARE is still very high (about 40% in 2011 in the Central Valley, and about 20% in the Coast and Inland Hills regions). Even high-income Census blocks see CARE enrollment rates between 10% and 20% in 2011. Relatively high CARE enrollment in even relatively affluent areas is likely both a measure of local income inequality, and a product of language in CARE eligibility criteria that allows households participating in various social assistance programs to enroll in CARE regardless of income (PG&E 2017a). This may also reflect the program's randomized ex-post income verification process, which only selects a fraction, approximately 8% of participants annually, to verify eligibility for the program (Clopton 2016, 282).

Methods

Because these data are observational, we must employ quasi-experimental methods, designating treatment and control groups, to estimate the effect of the CARE program on load shape and energy consumption. Due to an essentially flat overall time trend in electricity consumption, we apply the fixed-effects model below, as opposed to a difference-in-differences model, with the regression specification below. Our treatment group is all households actively enrolled in CARE (N ≈ 10,000). Our control group is all households not actively enrolled in CARE (N ≈ 25,000), including households that never enroll in CARE (N ≈ 20,000), and households that eventually enroll in CARE (N ≈ 5,000). Our model is:

$$\ln\left(kWh_{i,t,h}\right) = \alpha + \beta_j\left(Temp_{i,t,h}\right)_j + \gamma\left(CARE_{i,t}\right) + \delta_k(Time_t)_k + \zeta(TimeTrend_t) + \varphi_q\left(Program_{i,t}\right)_q + u_i + \varepsilon_{i,t}$$

$ln(kWh_{i,t,h})$ is the natural log of household electricity consumption for household i, in day t, in hour h. α is a constant. $(Temp_{i,t,h})_j$ is hourly linear and quadratic temperature controls, separately considering temperatures below or above 15 degrees C, using the index j to denote high or low temperature. $CARE_{i,t}$ indicates whether household i is enrolled in CARE on day t. $(Time_t)_k$ includes indicator variables for the day of the week and month of the year. $TimeTrend_t$ is a time trend that captures any longer-term secular trend not included in day-of-week or month-of-year indicator variables. $(Program_{i,t})_q$ indicates whether household i is enrolled in program q on day t. u_i controls for time-invariant household-level differences, such as different baseline levels of electricity consumption. $\varepsilon_{i,t}$ is an error term, assumed to be normally distributed with mean zero.

Limitations

This fixed-effects model controls for differences between households that do not changes over time, such as whether the unit is a single-family or multi-family home. Limiting factors include unobserved variables that change differently over time for different households. The most important such variables include income and household occupancy, both of which are used to determine eligibility for the CARE program. For example, a family that has an additional child may become eligible for CARE as a result. In this case, it would not be possible to distinguish between a change in electricity consumption due to CARE, or due to the additional occupant of the household. The reverse is also true for households that experience a reduction in household size. As a result, the direction of the effect of this limitation on our results is not clear.

Similarly, changes in household income have the potential to bias the results in the either direction. If a household loses income, it may become eligible for CARE, but may also reduce electricity consumption due to the income elasticity of demand. The opposite is also true, for a household that experiences an increase in income, and subsequently becomes ineligible for CARE. Given that the sample contains the Financial Crisis and subsequent Great Recession, household incomes likely do change substantially over time. Literature estimates of the short-run income elasticity of electricity demand have a median of 0.15, a minimum of 0.04, and a maximum of 3.48 (Espey and Espey 2004, 66). Estimates of the long-run income elasticity of demand have a median of 0.92, a minimum of 0.02, and a maximum of 5.73 (Espey and Espey 2004, 66). Bounding the effect of this limitation will require combining these elasticities with further analysis of the income dynamics of low-income and middle-income households.

Lastly, our results assume plausibly random deployment of smart meters. Apart from regionally staged deployment, we find no evidence of major non-randomness in important ways, but this cannot be ruled out. If deployment was not plausibly random, this could result in bias in either direction.

Results

We find that enrollment in the CARE program is associated with a significant increase in electricity consumption across the full sample, with a coefficient, shown in Table 2, of 0.12 [0.10, 0.15] (95% confidence interval), equivalent to an increase of 13% [11%, 16%]. Given the average bill subsidy of 42% (Evergreen Economics 2013, 18), this corresponds to a price elasticity of demand of roughly 0.25, consistent with the mean short-run elasticity estimate from the literature (Espey and Espey 2004, 66). In the three regions, the corresponding coefficients are 0.12 [0.085, 0.15] in the Central Valley, 0.16 [0.12, 0.20] in the Inland Hills, and 0.11 [0.04, 0.17] on the Coast.

Table 2. Effects of CARE programs on average household electricity consumption, coefficient estimates. CARE enrollment has the largest effect in the Inland Hills. Climate Smart is omitted in the Inland Hills and Coast due to collinearity with other covariates.

	Dependent Variable: ln(kWh/day)			
Independent Variable	Full Sample	Central Valley	Inland Hills	Coast
CARE	$1.2\text{x}10^{-1}$** ($1.2\text{x}10^{-2}$)	$1.2\text{x}10^{-1}$** ($1.7\text{x}10^{-2}$)	$1.6\text{x}10^{-1}$** ($2.0\text{x}10^{-2}$)	$1.1\text{x}10^{-1}$** ($3.2\text{x}10^{-2}$)
Rebate	$5.8\text{x}10^{-2}$** ($1.3\text{x}10^{-2}$)	$2.2\text{x}10^{-2}$ ($2.3\text{x}10^{-2}$)	$6.9\text{x}10^{-2}$** ($1.7\text{x}10^{-2}$)	$1.1\text{x}10^{-1}$** ($3.0\text{x}10^{-2}$)
BPP	$6.6\text{x}10^{-2}$** ($2.0\text{x}10^{-2}$)	$2.9\text{x}10^{-2}$ ($2.6\text{x}10^{-2}$)	$1.6\text{x}10^{-1}$** ($4.0\text{x}10^{-2}$)	$1.5\text{x}10^{-1}$** ($5.0\text{x}10^{-2}$)
Climate Smart	$-2.2\text{x}10^{-1}$ ($1.9\text{x}10^{-1}$)	$-1.8\text{x}10^{-1}$ ($1.9\text{x}10^{-1}$)	Omitted	Omitted
Direct Access	$8.1\text{x}10^{-2}$** ($3.0\text{x}10^{-2}$)	$1.0\text{x}10^{-1}$* ($4.7\text{x}10^{-2}$)	$6.0\text{x}10^{-3}$ ($3.1\text{x}10^{-2}$)	$1.1\text{x}10^{-1}$ ($7.0\text{x}10^{-2}$)
Smart AC	$4.7\text{x}10^{-2}$ ($2.6\text{x}10^{-2}$)	$5.6\text{x}10^{-2}$ ($3.6\text{x}10^{-2}$)	$2.6\text{x}10^{-2}$ ($2.8\text{x}10^{-2}$)	$3.0\text{x}10^{-1}$ ($2.8\text{x}10^{-1}$)
Smart Rate	$1.2\text{x}10^{-2}$ ($4.3\text{x}10^{-2}$)	$3.3\text{x}10^{-2}$ ($6.3\text{x}10^{-2}$)	$-3.6\text{x}10^{-2}$ ($4.2\text{x}10^{-2}$)	$7.3\text{x}10^{-2}$ ($2.7\text{x}10^{-2}$)
Daily Temperature Controls	Included	Included	Included	Included
Month Dummies	Included	Included	Included	Included
Day of Week Dummies	Included	Included	Included	Included
Intercept	2.7** ($9.6\text{x}10^{-3}$)	2.8** ($1.3\text{x}10^{-2}$)	2.6** ($1.3\text{x}10^{-2}$)	2.3** ($2.7\text{x}10^{-2}$)
Observations	18,329,664	7,222,330	7,323,276	3,659,844
# of groups, total	30,385	8,586	11,377	10,203
R^2 within	0.058	0.104	0.0272	0.026
R^2 between	0.032	0.003	0.0049	0.021
R^2 overall	0.046	0.055	0.013	0.0228

Robust and clustered standard errors in parentheses
** p<0.01, *p<0.05

Figure 5 shows the estimated increase in electricity consumption due to CARE on an hourly basis, and by region. These full sample results present suggestive evidence that the measured increase in electricity consumption is higher later in the day, with the increase in electricity consumption between 8pm and 11pm roughly a third higher than the increase at 3am. The smallest increase, a coefficient of 0.09 [0.07, 0.12], or 9.7% [7.5%, 12.1%] occurs at 3am, while the highest increase, 13.3% [11.6%,16.4%], occurs at 9pm. Although each of the hourly coefficients is strongly statistically different from zero (p<0.001), the difference between any pair of hours is not statistically significant. Summer peak hours in California fall between noon and 6pm, with a partial peak ending at 9:30pm (PG&E 2017c). As a result, the largest increases in CARE electricity consumption do not coincide with the absolute peak demand, but are split between partial-peak and off-peak demand.

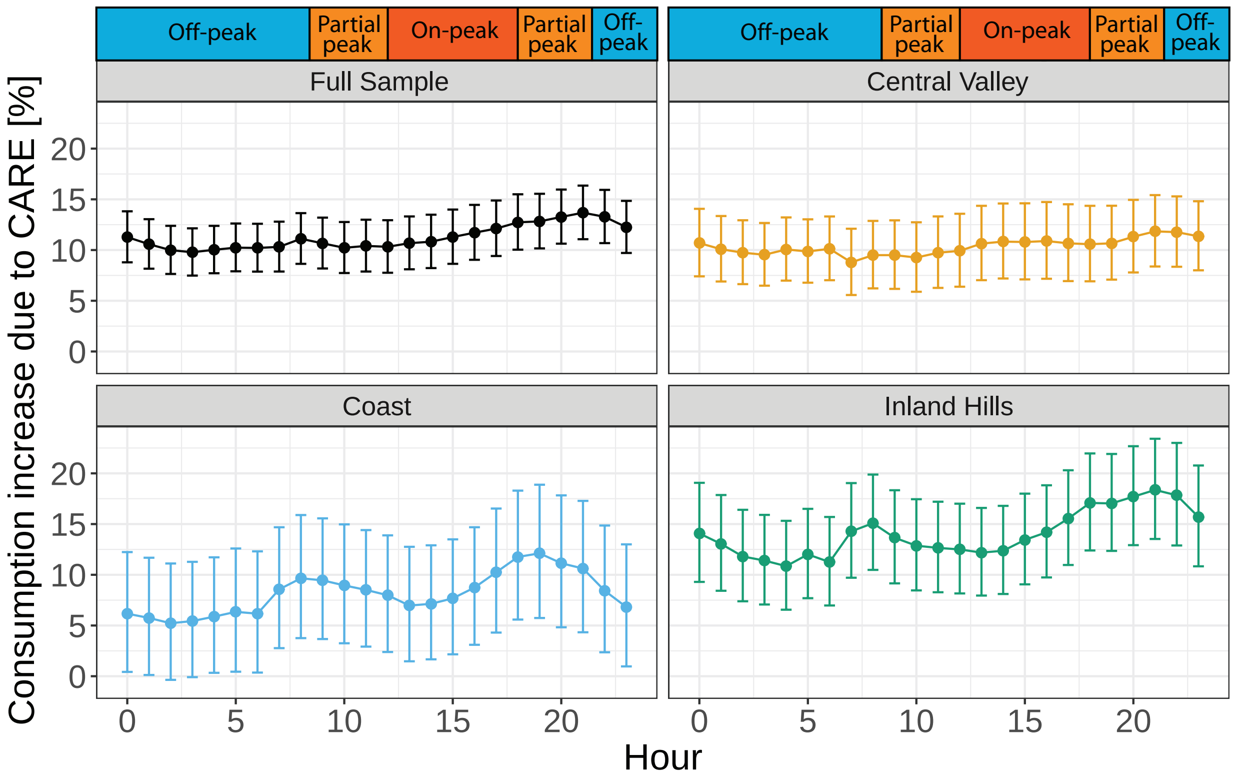

Figure 5. Hourly percent change in electricity consumption associated with enrollment in the CARE low-income energy subsidy program, derived from fixed-effects regression coefficients. In the full sample CARE enrollment is associated with a statistically significant increase of roughly 12% for all hours of the day, with a trough of 9.7% [7.5%, 12.1%] at 3am, and a peak increase, 13.3% [11.6%, 16.4%], at 9pm. CARE has the smallest effect on the on the Coast, with the highest effect in the Inland Hills.

When each of the three regions is considered individually, the results are similar. Figure 5 shows that there is an increase in electricity consumption associated with CARE in each region, and no pair of hours is statistically distinguishable from another. We see suggestive evidence that the morning and evening effects, which coincide with partial peak, but not with the overall system-level peak (PG&E 2017c), are more pronounced in the Inland Hills and on the Coast, and that the effect of the CARE program is greater in the Inland Hills than in the Central Valley or Coast.

Conclusions and Policy Implications

This analysis demonstrates that a major low-income energy subsidy is, unsurprisingly, associated with a modest but non-trivial increase in electricity consumption. This is an indication that these programs are in fact working as intended, ensuring that households have affordable access to important energy services.

Our analysis of differences in the timing of increases in consumption, the load shape effects of the CARE program, suggests that the CARE program does not appear to be placing disproportionate strain on the electric power system during peak consumption periods. The largest increases in electricity consumption associated with the CARE program come at times that are generally somewhat later than peak consumption, but do coincide somewhat with partial peak demand. With that said, the electric power system, and its peaks, may change substantially as additional distributed energy resources are deployed to the grid.

More detailed analysis, likely with a richer dataset, is needed to more accurately characterize both the magnitude of these load shape effects, and the causal mechanisms behind the observed changes in electricity consumption behavior. Such an effort would likely be supplemented with surveys or interviews with occupants of low-income households about their energy consumption habits, and their perceived sensitivity to electricity price in decision-making.

Smart meter data present a historically unparalleled opportunity to characterize and understand residential electricity consumption behavior. We hope this analysis will help energy decision makers more accurately understand and model interactions between low-income subsidies, overall electricity demand, and long-term electric power infrastructure needs.

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