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THE REDISTRIBUTIONAL IMPACT OF NON-LINEAR ELECTRICITY PRICING

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ABSTRACT

Utility regulators frequently focus as much or more on the distributional impact of electric rate structures as on their efficiency. The goal of protecting low-income consumers has become more central with recent increases in wholesale power costs and anticipation of significant costs of greenhouse gas emissions in the near future. These concerns have led to the widespread use of increasing-block pricing (IBP), under which the marginal price to the household increases as its daily or monthly usage rises. There is no cost basis for differentiating marginal price of electricity by consumption level, so perhaps nowhere is the conflict between efficiency and distributional goals greater than in the use of IBP. California has adopted some of the most steeply increasing-block tariffs in electric utility history. Combining household-level utility billing data with census data on income distribution by area, I derive estimates of the income redistribution effected by these increasing-block electricity tariffs. I find that the rate structure does redistribute income to lower-income groups, cutting the bills of households in the lowest income bracket by about 12% (about $5 per month). The effect would be about twice as large if not for the presence of another program that offers a different and lower rate structure to qualified low-income households. I find that the deadweight loss associated with IBP is likely to be large relative to the transfers. In contrast, I find that the means-tested program transfers income with much less economic inefficiency. A much larger share of the revenue redistributed by the IBP tariff, however, comes from the wealthiest quintile of households, so IBP may be a more progressive structure of redistribution. In carrying out the analysis, I also show that a common approach to studying (or controlling for) income distribution effects by using median household income within a census block group may substantially understate the potential effects.

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I. Introduction

With rising energy costs and growing awareness of the threat of climate change, policy makers are increasingly coming to the realization that retail energy prices are going to have to rise in order to reflect the full cost of consumption. At the same time, there is concern that higher energy prices – whether attributable to greenhouse gas policies, resource scarcity, or market power of sellers – will disproportionately impact the poor. In the electric utility sector, this tension between income distribution concerns and high energy prices has been recognized for decades. In the 1970s and 1980s these concerns led to widespread adoption of increasing-block pricing (IBP) of electricity – also commonly called inverted-block pricing, increasing-tier pricing, or lifeline rates (though some of these are means tested). Supporters of IBP argue that these tariffs promote conservation by setting high marginal prices for many consumers while protecting small energy consumers – who are presumed to be poorer on average – by keeping the price for a baseline level of consumption relatively low.[2]

California's regulated utilities adopted increasing-block residential electricity tariffs in the 1980s. Prior to the California electricity crisis in 2000-01, all three of the large regulated electric utilities in California—Pacific Gas & Electric (PG&E), Southern California Edison (SCE), and San Diego Gas & Electric (SDG&E)—had two-tiered residential rate structures where the marginal price in the second tier was 15%-18% higher than in the first tier. That was in line with the structure in many other states. One recent survey of 61 U.S. utilities (BC Hydro, 2008), found that about one-third of them use IBP for residential customers. Many more utilities and regulators are currently considering adopting IBP tariffs.

After the California electricity crisis, these three investor-owned utilities (IOUs) needed to raise substantial revenues, but regulators and state legislators were concerned about the impact on lower-income households. Regulators adopted a five-tier increasing-block retail pricing structure where the prices on the first two tiers were virtually frozen at pre-crisis levels and incremental revenue needs were to be collected by raising prices on tiers 3, 4 and 5. The result has been a much more extreme increasing-block tariff structure. By 2008, the price on the highest block—which is the marginal price for about 6%-9% of all residential customers—ranged from about 80% higher to more than triple the price on the lowest block, depending on the utility.

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[2] Declining-block pricing – under which the marginal price of electricity to the customer is lower for units of consumption beyond a certain baseline level – had been common in the 1960s and 70s. In the following decades, with increasing focus on conservation, it became seen as promoting wasteful consumption of power, despite the fact that a two-part tariff almost surely is a closer reflection than IBP of the true cost of serving a residential customer.

Regardless of one's views of the externality costs of electricity consumption and the need for conservation, it is clear that increasing-block electricity pricing distorts the relative marginal prices that different customers face.[3] Thus, the use of increasing-block pricing presents a classic tradeoff between efficiency and distributional effects in regulated tariff design. There is, however, very little firm evidence on the magnitude of this tradeoff, and none that is based on a large-scale systematic empirical study.

Combining residential bill data with income data at the census block group level, I first develop an approach that yields bounds on the income redistribution effects of these IBP tariffs. This approach and the resulting bounds are related to the literature on ecological regression.[4] Borrowing in part from that literature, I then develop a better estimate of redistribution based on those bounds. I find that low-income customers benefit from California's current steeply-tiered rate structure compared to the bills they would have paid under a flat rate tariff. If this were the only electricity program aimed at helping the poor, I find that IBP would lower the bills of SCE customers in the lowest income bracket (approximately a quintile) by $9-$11 per month, with somewhat smaller changes for the other two utilities.

Such analysis of transfers raises the question of the cost in terms of inefficient pricing. Under a wide range of demand elasticity assumptions, I calculate the deadweight loss that would result from IBP. For all of the plausible long-run elasticity scenarios, it seems very likely that the efficiency costs of IBP would be substantial compared to the redistributional impact. An interesting exception arises if the marginal cost of electricity were quite high (on the order of two to three times higher than wholesale electricity prices during the sample period), in which case the IBP tariffs that I study for California could actually reduce deadweight loss compared to a break-even flat-rate tariff. California and most other areas also have a low-income energy assistance program that offers lower rates to customers who meet some means test. I examined that program as well (called the CARE program in California), and find that it is likely more effective than IBP in redistributing income relative to the economic distortions it causes.

Separate from the analysis of electricity rates, this approach to analyzing redistributional effects has implications for a wide variety of studies that use census block group

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[3] Some have argued that heavy residential users impose higher costs per unit consumption. Such suggestions are based on the correlation between the timing of consumption patterns and overall use, but the increasing-block tariff takes no account of the timing of use so the connection is quite indirect. See Marcus (2007).

[4] See Goodman (1953), King (1997), Freedman (2004), and Wakefield (2004).

level data to look at the effect of business or public policies on income distribution or *vice versa*. Many studies use the median household income for a census block group to represent the income of all households in that area. I show, however, that there is very large heterogeneity of household incomes within census block groups and that the use of median household income greatly truncates the income distribution. Thus, studying available data on income distribution both across *and within* census block groups could be very informative, particularly for analyzing impacts on low-income households.

II. Previous Studies of Distributional Impacts of Non-Linear Electricity Pricing

An active literature on IBP in the U.S. existed in the late 1970s and 1980s. A pre-cursor is Feldstein (1972), who develops a model of the optimal tradeoff between a fixed and volumetric charge to recover utility costs when the regulator cares about both efficiency and equity. He then applies the model to Massachusetts using estimates of price and income elasticity of demand from another study. A number of later papers attempt to infer income transfers from simulations using their own or others' estimates of the income elasticity of demand. A few others combine billing data with household surveys of relatively small populations to infer the impact of IBP. Hennessy (1984) surveys this literature. Faruqui (2008) presents a recent analysis using the simulation approach, as well as a discussion of IBP policies among US utilities. Two other papers, Scott (1981) and Hennessy and Keane (1989), focus on "lifeline" plans that provide discounts for a limited quantity of electricity that are available on a means-tested basis.[5]

Inferring redistribution from estimates of income elasticity presents two problems. The first is that those estimates vary widely (with large standard errors) among refereed publications, implying huge variations in the redistribution effect of IBP. The income elasticities of residential demand reported in Taylor's (1975) survey of electricity demand estimation vary by nearly an order of magnitude, and other studies come to even more divergent estimates. The second problem is interpretation of the income elasticity estimates. The standard income elasticity estimate is an attempt to capture the (causal) partial derivative of electricity consumption with respect to income. To the extent that the regression controls for other factors, the parameter estimated on income does not capture indirect income effects that come about from house size, number of people living in the dwelling,

[5] Numerous studies outside the U.S. are concerned with the impact of non-linear electricity prices on the poor. Wodon, Ajwad, and Siaens (2003) and Al-Qudsi and Shatti (1987) present policy analyses of IBP in Honduras and Kuwait, respectively. Gibson and Price (1986) examine the distributional impact of two-part tariffs in the U.K. natural gas and electricity markets. Hancock and Price (1996) and Price and Hancock (1998) consider the distributional effects of market liberalization in the UK gas, telecom and electricity markets, including changes in the fixed and variable-rate components of the tariffs.

propensity to heat with electricity, and other factors. Nor does it capture factors that may have no causal link with low income, but are highly correlated with income and influence electricity use. For instance, controlling for weather in a standard electricity demand regression means that the income parameter does not capture the extent to which poor people may live in different areas with different weather than wealthier people. If the goal is to redistribute income to the poor through IBP, then the cross-sectional co-variation of income and usage is of interest, not the causal impact of income (directly or indirectly) on usage. The survey-based studies tend to capture this relationship more effectively than the regression/simulation studies, but the survey studies are based on much smaller samples than I am able to use in this case. In addition, while the surveys have individual household demographics, they suffer from lower response rates and greater selection issues than data from the census. The cost of using the census data is that questions are not as targeted and the data are not available at the household level for matching to electricity billing data.

III. Increasing-Block Residential Electricity Rates in California

The analysis in this study has been carried out for all three of the large regulated public utilities in California – Pacific Gas & Electric (PG&E), Southern California Edison (SCE), and San Diego Gas & Electric(SDG&E) – with fairly similar results. I focus in the body of the paper on SCE, but present the results for the other two utilities in the appendix. The conclusions are consistent across the three utilities.

The standard residential tariffs for SCE during 2006 are shown in the top left panel of Table 1.[6] The increasing-block tariff structure implies an increasing *marginal* price for electricity. A SCE customer whose consumption level puts him or her on the fifth tier, for instance, still pays the lower-tier rates for consumption up to 300% of baseline.[7]

The marginal rate that a residential customer pays increases as consumption increases relative to a "baseline" consumption level. A household's baseline allocation is supposed

[6] The tariff changed very slightly during 2006. Table 1 presents the time-weighted average tariff. These are just the volumetric electricity rates. SCE also had a small daily fixed charge, $0.03/day, which I assume is unchanged under the alternative tariffs that I consider. All three utilities also had minimum daily charges for electricity, but these were set at about the same level as the minimum daily usage cut off and that I impose below.

[7] For example, under the standard residential rate shown in Table 1, a SCE customer with a baseline consumption allocation of 300 kWh during a given billing period who actually consumes 1100 kWh would pay 11.62¢ for each of the first 300 kWh, 13.61¢ for each of the next 90 kWh, 22.01¢ for each of the next 210 kWh, 30.49¢ for each of the next 300 kWh, and 30.49¢ for each of the last 200 kWh. During 2006, the regulated prices on the fourth and fifth tier were equal, though that has not always been the case in earlier or succeeding years.

Tier	% of Baseline Quantity	Standard Residential Rate	CARE Low-income Rate
Actual 2006 tariff (time-weighted average in 2006)			
1	0-100%	$0.1162	$0.0834
2	100%-130%	$0.1361	$0.1053
3	130%-200%	$0.2201	$0.1691
4	200%-300%	$0.3049	$0.1717
5	300%+	$0.3049	$0.1717
Alternative Flat-Rate Tariff with CARE program			
	0%+	$0.1731	$0.1060

Tier	% of Baseline Quantity	Standard Residential Rate
Benchmark Five-Tier Tariff with no CARE program		
1	0-100%	$0.1069
2	100%-130%	$0.1268
3	130%-200%	$0.2108
4	200%-300%	$0.2956
5	300%+	$0.2956
Alternative Flat-Rate Tariff with no CARE program		
	0%+	$0.1592

Table 1: 2006 Southern California Edison Retail Electricity Rates

to correspond to a minimal basic electricity usage. The baseline, however, is the same for all residential customers in a region regardless of the size of the residence or the number of people who live there. Within the region, a studio apartment receives the same baseline allocation as a four-bedroom house.[8] Baseline allocations do differ by geographic regions within the utility area: SCE's service territory is divided into 6 different baseline regions. This is argued to reflect variation in basic electricity need due to climate differences, but in practice baselines are set based on different average usage across regions. As a result, variation is driven not only by climate differences, but also by wealth levels, average residence size, and choices to install air-conditioning.

Prior to the California electricity crisis in 2000-01, SCE had a two-tier rate structure with prices near those on the first two tiers of the structure shown in top panel of Table 1. All consumption above the baseline level was charged at the second-tier rate. After the extreme financial losses associated with the electricity crisis, the structure was changed to five tiers and rates were raised substantially for the third, fourth and fifth tiers. As a result, in 2006 the marginal price on the fourth and fifth tier was nearly three times higher than on the first tier. The same qualitative changes occurred at the other two regulated utilities in California, but the resulting rates are noticably different – more steeply tiered at PG&E, less so at SDG&E – owing in part to the differences in economic losses they incurred during the California electricity crisis.

Not all residential customers of the IOUs are on the standard tariff. The largest exception from the standard tariff is customers who are on the CARE (California Alternate Rates for Energy) program, which is an income-based program that offers lower rates to low-income customers.[9] At SCE, 25.2% of residential customers were on the CARE program in 2006.

[8] The baseline allocation is higher for approximately 10% of customers who have electric heating systems and some other electrical appliances.

[9] For 2006, a residence with one or two occupants had to have a household income no higher than $28,600

The CARE program is advertised as offering "a 20% discount" off the standard residential rates, but not all components of the bill are included in the discount, some components are not charged to CARE customers, and the exact implementation is quite complex. In practice, the discount is at least 20% and was up to 44% on marginal consumption at higher tiers during 2006, as shown in Table 1. Overall, because of the discount on each tier and the fact that CARE customers consumed a higher proportion of their power on lower tiers, the average price paid per kilowatt-hour was 39% lower for CARE customers than for customers on the standard residential rate.

A small number of customers are on special tariffs that incorporate time-of-use electricity pricing, interruptible air-conditioning use, mobilehome/RV/marina accounts, or other idiosyncratic rate structures. In aggregate, these nonstandard tariffs covered 1.4% of SCE's residential customers in 2006, who consumed 2.1% of residential power. Most of these customers still face a five-tier tariff, but with different baseline allocations and in some cases somewhat different rates on the tiers.

Regardless of the tariff that a customer is on, the customer has a baseline allocation and his or her monthly consumption can be allocated across the five tiers of the tariff. The top panel of Table 2 shows the total quantity of residential consumption that was billed on each of the tiers during 2006. The lower-income customers who are on the CARE program consume less on average than other residential customers, but there is substantial overlap in the distributions with many low-consuming customers who are not on CARE, and some CARE customers with consumption levels even out to the fifth tier. The bottom panel of Table 2 shows the proportion of households whose average daily consumption puts them on each of the five tiers in the rate structure.[10] Among SCE's non-CARE customers, for instance, 32.4% consume less than the baseline and therefore face the tier 1 price for their marginal consumption, while 11.3% consume more than 300% of baseline so face the tier 5 price for their marginal consumption.

With billing data alone, comparison of CARE to non-CARE customers is about all one can do to analyze the consumption patterns of richer versus poorer customers. This is, however, not the most useful comparison for analysis of the five-tier tariff system. At least four questions arise in examining the distributional impact of increasing-block pricing in electricity pricing: (1) how effectively does IBP redistribute income to poorer households

in order to qualify for CARE, with the threshold increasing by $5,000 for a third occupant, and by $6,900 for each additional occupant.

[10] To be precise, the bottom panel of Table 2 shows the customer-days weighted-average proportion of bills during 2006 for which marginal consumption was billed at each tier.

	Residential Usage (million-kWh)	Percentage of Residential Usage					CARE/Non-CARE Shares	
		tier 1	tier 2	tier 3	tier 4	tier 5	% Usage	% customers
Non-CARE	23,046	52.9%	10.7%	16.5%	10.9%	9.0%	79.3%	74.8%
CARE	6,016	66.0%	10.7%	13.5%	6.7%	3.1%	20.7%	25.2%

	Percentage of Customers on Each Tier for Marginal Consumption				
	tier 1	tier 2	tier 3	tier 4	tier 5
Non-CARE	32.4%	14.2%	25.0%	17.2%	11.3%
CARE	45.4%	16.7%	22.7%	10.9%	4.3%

NOTE: reported results drop household accounts with consumption of less than 1 kWh/day

Table 2: Distribution of SCE Residential Customer Consumption Across Tariff Tiers

(in the absence of any means-tested program, such as CARE)?; (2) what is the efficiency effect of such an IBP? (3) what impact does the CARE program have?; and (4) given the existence of the CARE program what is the incremental effect of IBP? I attempt to answer these questions by merging utility billing data with census data on income levels by census block group.

IV. Data Sources

The data for this analysis come from utility residential billing records and the U.S. census. Utility residential billing records were made available to the U.C. Energy Institute by all three of the large California investor-owned electric utilities on a confidential basis. The data used in this analysis include virtually all residential bills for 2006. Customers who were not individually metered, but instead are part of a "master-metered" building or other location, were not included in the data. In aggregate, such accounts constitute less than 3% of residential consumption at each of the utilities.

The data do not include the address or the name of the customer. They do, however, include the nine-digit ZIP code, which allows a fairly precise neighborhood matching with census data. The utility data also include usage on each of the five tiers, days in the billing period, tariff (including whether or not the customer is on the CARE program), total amount billed, and assigned baseline quantity.

Actual billing periods do not begin and end exactly at the beginning and end of the calendar year, so annual bills were created by interpolating usage and charges for bills that overlapped the beginning and end of the year.[11] I also dropped bills with consumption of

[11] For instance, a bill that included 13 days at the end of 2005 and 18 days at the beginning of 2006 was

less than 1 kWh/day. A refrigerator typically uses 1-2 kWh/day,[12] so it is implausible that an occupied primary residence would fall below 1 kWh/day. Dropping these observations should permit a closer match to the census data. Including these observations does not change the qualitative results, but it increases the number of customer-days by about 1.4%.

Summary household income data are available from the U.S. Census at the level of census block group (CBG), a geographic designation that on average includes about 600 households in California. Census block groups are considerably larger than the areas associated with nine-digit ZIP codes. Each nine-digit ZIP code is assigned to the CBG in which it was located.[13] The analysis presented here was then carried out at the CBG level. Results presented here use 2000 census data updated to 2007 by Geolytics, but the results are very similar if the analysis is based on the original 2000 data.[14]

Census Measures of Household Income

Household income data at the CBG level includes median household income and mean per capita income.[15] In economics, epidemiology, and other areas of research, these summary measures are frequently used by associating them with every household in the CBG.[16]

Unfortunately for such applications, there is considerable income heterogeneity within CBGs. This is evident from additional data released by the Census that break down households into very small income brackets for each CBG in the 2000 census. Because

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incorporated into the annual bill by adding 18/31 of the usage and 18/31 of the billed amount to the annual bill. Data for PG&E, unfortunately, did not extend beyond the end of 2006, so billing periods that ended after December 31, 2006 would be lost if I were to apply this procedure to PG&E. To greatly reduce this problem, the period of analysis for PG&E was shifted by one month and I instead studied December 2005-November 2006.

[12] See http://www.energystar.gov/index.cfm?fuseaction=refrig.display_products_html .

[13] A small number of customer records did not include a nine-digit ZIP code, or did not match to a nine-digit ZIP code in the census data. In the case of nine-digit ZIP codes that did not match to the census data, I used the numerically closest nine-digit ZIP code. In the case of having only a five-digit ZIP code, those customers were allocated probabilistically among all of the nine-digit ZIP codes within the five-digit ZIP code based on the share of households that were in each of the nine-digit ZIP codes.

[14] For details of the updating see, http://www.geolytics.com.

[15] Household income data from the U.S. Census are based on the "long form" questionnaire that is distributed to about 1/6 of all households.

[16] Examples in economics include hedonic real estate demand models, Bajari & Kahn (2008), auto demand, Busse, Silva-Risso and Zettelemeyer (2006), education valuation, Jacob & Lefgren (2007) and Hastings, Kane & Staiger (2005), local pollution impacts on housing, Gayer, Hamilton & Viscusi (2000), and effects of low income housing tax credits, Baum-Snow and Marion (2009). Of course, the importance of this simplification will differ depending on the empirical application.

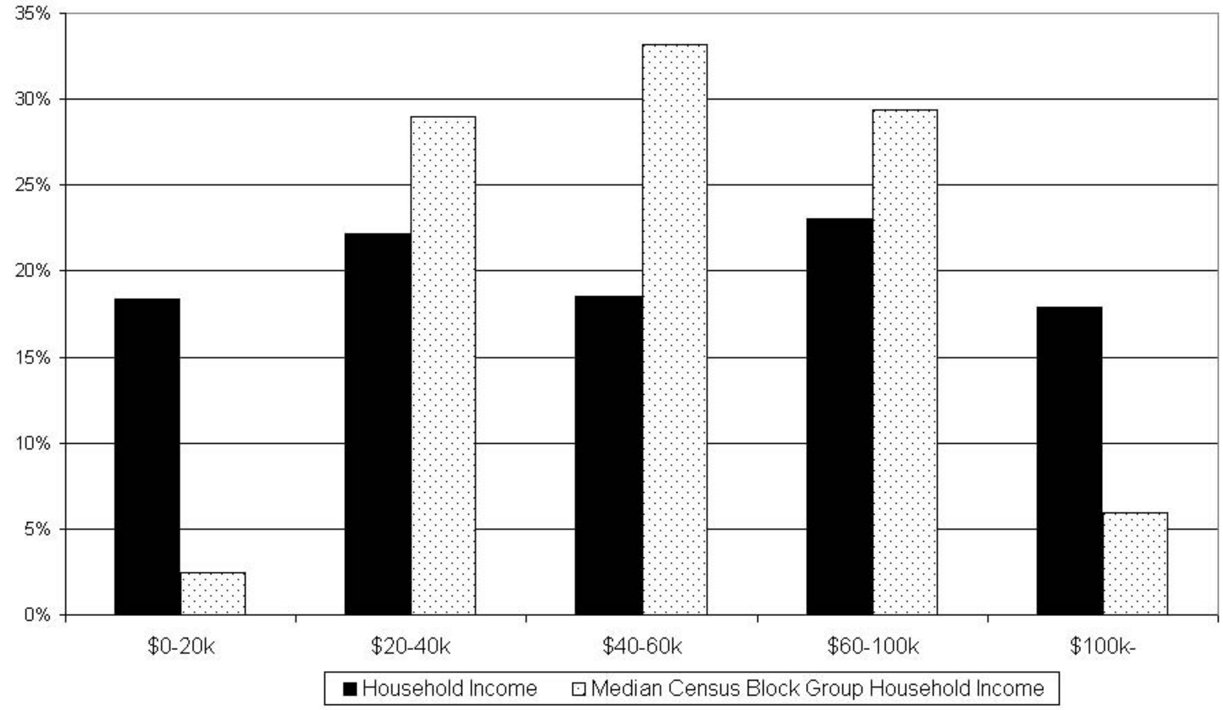

Figure 1: Distribution of Household Income and Median Household Income (weighted by households) By Census Block Group

many brackets have zero households in many CBGs and because this is a 17% sample, not a census, I aggregate the data to 5 income brackets that are approximate quintile breaks: \$0-\$20,000, \$20,000-\$40,000, \$40,000-\$60,000, \$60,000-\$100,000, and over \$100,000. In the 17768 census block groups I consider in California — those served by the three investor-owned utilities — the breakpoints between these categories correspond to the 18th, 41st, 59th and 82nd percentiles in the distribution of household income.

It would be very convenient for this analysis if all of the population in a given CBG fell into one of these income brackets, but that is far from the case. Looking at the shares of households in each bracket, one can calculate a Herfindahl index to measure concentration of households within the income brackets for a given CBG. This index is the sum of the squared shares of population in each bracket. With five income groups, it has a minimum of 0.2 (if households within a CBG were evenly divided across the five brackets) and a maximum of 1 (if households were all in the same bracket). Calculating this index for the census block groups I examine in California, the average value is 0.29, indicating more dispersion than if the population within each CBG were evenly divided across any three income brackets (which would yield a value of 0.333).

Because of this within-CBG dispersion, assigning to every household within a CBG the median household income or mean per capita income for that CBG substantially understates the variance in the distribution at the household level. More extreme high and low income levels are underrepresented. Figure 1 illustrates this effect by showing the households-weighted distribution of median household incomes within CBGs and the assignment of individual households to each of the five income brackets. About 18% of households report income below $20,000, but only about 2.5% of households live in CBGs with a median income below $20,000.

Thus, it will be important for this analysis to account for income heterogeneity within the CBGs. I do that in a variety of ways, as explained in section VI.

V. Creating Benchmark and Counterfactual Bills

I begin the analysis by constructing the bills that each customer would face under alternative tariff structures. Essentially, this amounts to calculating the alternative tariff structures under the constraint that they all generate the same total revenue. Implicit in this exercise is the assumption that demand is completely inelastic, so that a customer will consume the same quantities regardless of which tariff they face. Obviously, this is not realistic if customers exhibit some elasticity with respect to the marginal price variation after controlling for the system average price. I return to this issue in section VIII, reestimating the impact for a range of elasticities and explaining why the effect of this change is quite small.

I focus first on a simple case in which there is no means-tested (*e.g.,* CARE) program. A hypothetical five-tier tariff structure is created by subtracting a constant from each tier of the non-CARE tariff resulting in a tariff structure that generates the same total revenue as under the actual tariffs under the current participation in the CARE program.[17] The resulting tariff "Benchmark Five-Tier Tariff with No CARE Program" is shown at the top of the right-hand panel of Table 1. From this alternative five-tier tariff, it is straightforward to generate a flat electricity rate for comparison.[18] Focusing on this case,

[17] I construct the benchmark five-tier tariff by subtracting a constant from the actual tariff, because the CARE program is funded in part from non-CARE residential energy by a flat per-kWh charge. Over half of the CARE funding comes from commercial/industrial/agricultural customers. For the purpose of this study, I hold that transfer between customer classes constant and assume that all rate changes must be revenue-neutral among residential customers.

[18] I also create a two-tiered tariff with an 18% step between the tiers, which more closely reflects the IBPs in use in many other states as well as the structure that existed in California prior to the 2000-01 electricity crisis. Results for this tariff are presented in the appendix.

without the complexity of an overlapping means-tested program, allows a clear analysis of the impact of a steeply increasing tiered rate structure alone. In section IX, I reintroduce the means-tested program.

With these tariffs, the quantities consumed by each customer, and the assumption of no demand elasticity, it is straightforward to generate the total amount each customer would be billed under each of these tariffs. The more challenging aspect of the analysis is to match customers with income brackets, as is discussed in the next section.

VI. Matching Households to Income Brackets

As explained earlier, with very high accuracy each customer can be matched to a census block group and the census data include the distribution of household income across income brackets. The income brackets are helpful in capturing the tails of the distribution, but they are especially useful if one can use other information to allocate households within a CBG across the income brackets. Household electricity usage is potentially such complementary information. Though estimates of the income elasticity of demand for electricity vary widely, they are nearly all positive and significantly different from zero.[19]

The same positive relationship seems likely to hold within census block groups. Unfortunately, I could find no direct studies of the level of that correlation within a CBG or, more specifically for this analysis, how closely the ranking of households by usage would correspond to the ranking by income. Nor do the data for this study allow such inference.

There are, however, two cases that can be easily studied and imply bounds (of a sort I describe below) on the degree of redistribution associated with the different tariffs. Variants of this approach may be usable in accounting for within-CBG income dispersion in studying the impact of many policy changes on people of different income.

First, one can assume that within a CBG, usage is completely uncorrelated with household income. It is possible that income and electricity usage could be negatively correlated within CBGs, but a negative correlation is not supported by any empirical studies of larger populations. Under the assumption of zero correlation, households could be randomly allocated across income brackets within the CBG in proportion to the census data share of households within each income bracket. It may at first appear that this is nearly equivalent to assigning median household income to all households, but this approach still allocates

[19] Every study I have found estimates a positive long-run income elasticity of demand for electricity, though the estimates range at least from 0.2 to 1.6. See Taylor (1975), Herriges & King (1994), and Kamerschen & Porter (2004).

many more households to very low-income and high-income categories than does the median household income. Thus, if the goal is to examine the change in electricity costs with particular focus on low-income households, this approach would still be more informative. Since there is very likely some positive correlation between income and electricity usage, this "random-rank method" is likely to incorrectly associate too many poor households with high usage and too many wealthy households with low usage within each CBG.

At the opposite extreme, one can assume that usage is perfectly rank correlated with household income within a CBG. Households can then be ranked by usage and allocated across income brackets in proportion to the census data shares such that every member of a lower income bracket has lower household electricity usage than any member of a higher income bracket. In reality, the rank correlation is certainly not perfect, so this "usage rank method" will incorrectly associate too many poor households with low usage and too many wealthy households with high usage within each CBG. Note again that this allocation is only occurring *within* each CBG, so either approach will still capture the income redistribution *across* CBGs that results from different average income and usage levels.

This bounding approach is closely related to the techniques of ecological or aggregate regression.[20] In an ecological regression there are only categorical share data for the two variables, usually by spatial areas of aggregation – such as a CBG or county.[21] In this analysis, I have individual level data on the "predictor" variable, electricity consumption, though there is still no ability to directly match the individual consumption data to invidivual data on the "response variable," which is income.[22] Instead, I have only aggregate share data on the response variable, which is shares of the population that fall into each income bracket. The random-rank method described above corresponds closely to the "neighborhood model" regression approach described by Freedman (2004). The underlying assumption is that within-neighborhood variation is not helpful in identifying the relationship, *i.e.,* that within-neighborhood variation in the electricity consumption is orthogonal to income. My approach differs somewhat, because the effect of interest in this

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[20] Freedman (2004) gives a concise overview of ecological regression.

[21] A representative topic in ecological regression would be to infer the share of blacks who are registered Republicans from data by voting precinct on the share of adults registered Republican and the share of adults who are black. In broad terms, the ecological regression literature is an investigation of what can be learned from a regression of share-Republican on share-black and how such a regression can produce biased estimates of the propensity of blacks to register Republican.

[22] The "predictor" and "response" terminology comes from Wakefield (2004). He is careful to point out that the relationship need not be causal.

case – the change in electricity bill – is a mechanical function of the variable for which individual data are available – electricity usage – so a regression to estimate an average relationship is not necessary. Instead, both the random-rank method and the usage-rank method are numerical calculations.

Both the random-rank and the usage rank methods are related to the "method of bounds" suggested by Duncan and Davis (1953). In the standard 2-groups/2-states model in ecological regression, the minimum and maximum possible propensity of one group to be in either state can be calculated from the aggregate shares of the groups and the states. For instance, if the share of registered Republicans in a precinct is 30% and the share of registered black voters is 80%, then the share of black voters who are registered Republicans must lie between 12.5% ($\frac{10}{80}$, if all non-black voters are Republican) and 37.5% ($\frac{30}{80}$, if all non-black voters are not Republican).

Similarly, given the aggregate income distribution in a CBG, one could construct the minimum and maximum consumption of the customers in any one income bracket by assigning the highest-usage or lowest-usage bills within the CBG to that income bracket. In practice, given that the income elasticity of demand is widely believed to be positive throughout the income distribution, it seems the most plausible bound is one in which customers are assigned monotonically by usage to the income brackets. The opposite bound would be a monotonic inverse assignment by usage, but that bound is obviously much less helpful than the random-rank approach if we are fairly certain that electricity usage is non-decreasing with income. So, the random-rank and usage rank approaches are a practical adaptation of the method of bounds to this dataset and policy question.

The inference from this bounding method is limited, however, by two factors. First, in a 5-group application such as the present case, the switch from random ranking to usage ranking only has clear implications for the lowest and highest groups. The random-rank method understates the degree of usage differentition across income groups within the CBG, so it would understate average usage of the highest-income group and overstate average usage of the lowest-income group.[23] The usage rank method overstates average usage of the highest-income group and understates average usage of the lowest-income group. For the three "interior" income brackets, however, the change from applying these approaches will depend on the particular distributions of usage and income.

Second, the goal of this investigation is to analyze bill *changes* due to the tariff change (not usage or bill *levels*). Only if the impact of the policy change (in this case, the change

[23] This is the case assuming that the true within-CBG correlation between income and usage is positive.

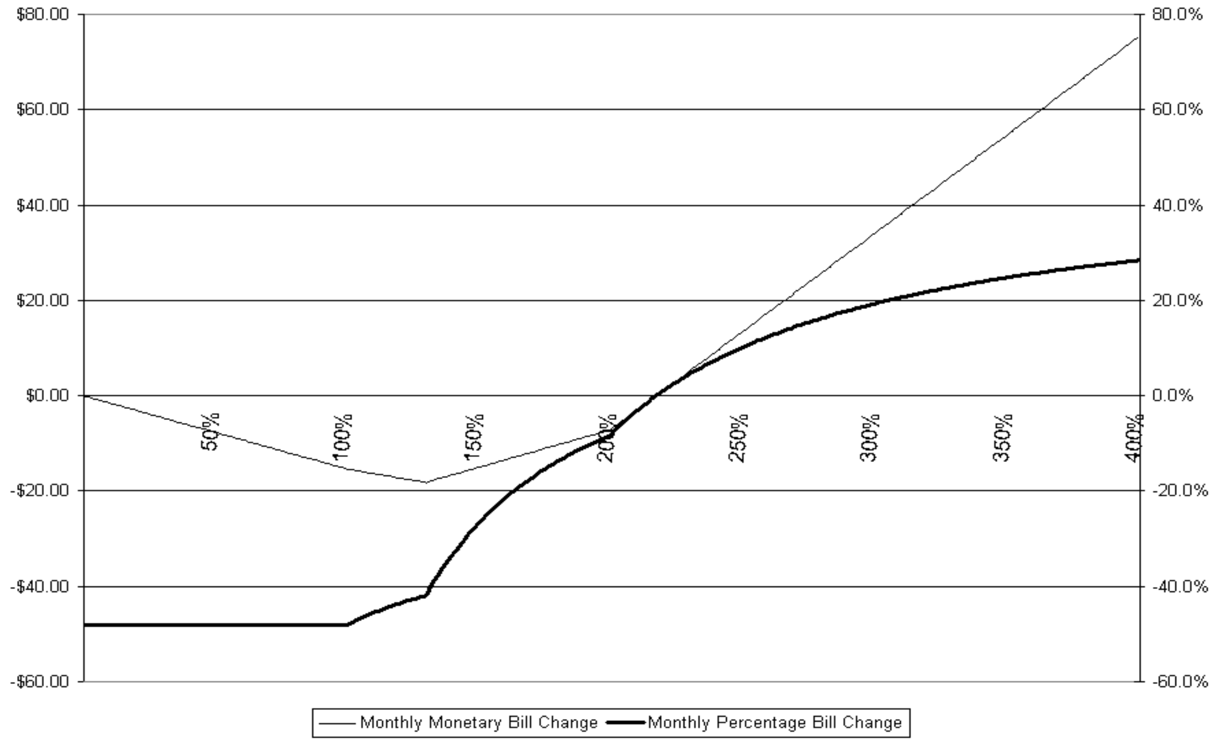

Figure 2: Monetary and Percentage Change in SCE Bill Due to Switch from Flat-Rate to 5-Tier Tariff as a Function of Consumption/Baseline Ratio

in tariff structure) is monotonic in the observed predictor variable (in this case, household electricity consumption) would these two approaches produce upper and lower bounds on the redistributional impact of the policy, at least for the lowest and highest income brackets where the approaches do place bounds on the usage of members of these groups. In this case, if the change to an IBP tariff had a monotonically increasing effect on bills as usage increased, then the "random-rank method" would provide a lower bound on the policy's impact (on the top and bottom income brackets) and the "usage rank method" would provide an upper bound.

That is in fact the case in studying the *proportional* change in bills. As shown in figure 2 for SCE, the percentage bill change is constant out to 100% of baseline, and then increases monotonically beyond 100% of baseline. As a result, the "random-rank method" will provide a lower bound on the percentage decrease that lowest income households will face and the percentage increase that the highest income households will face. The "usage rank method" will provide upper bounds on each.

The analysis of the monetary (*i.e.,* measured in dollars, not proportional) bill change by income bracket is less straightforward because the monetary bill change is not monotonic in usage, as is also shown in figure 2 for SCE. The change is necessarily zero for a zero-consumption customer and decreases linearly over the 0-100% of baseline range, for which the per-kWh price change is constant. In fact, the bill change grows more negative out to a consumption level equal to 130% of baseline – nearly coincident with the median usage level – and rises after that. As a result, the change from random ranking to usage ranking does not necessarily increase the assumed within-CBG correlation between income and size of the bill *change* a customer would face from the new policy.

Nonetheless, I proceed with these two approaches because they provide benchmarks for at least the lowest and highest income brackets and, more importantly, because they are the basis for a refinement I develop in the next section that attempts to improve on the bounding approach.

Before applying the random and usage ranking approaches, I make one further adjustment due to an additional piece of information that is available in this empirical application: the billing data indicate whether or not each household is participating in the CARE program, which indicates a much higher probability of being poor. This adjustment is described in detail in the appendix. Essentially, for each CBG I allocate slots within each of the five income brakcets to CARE and non-CARE customers based on earlier studies of the rate of CARE penetration among eligible customers. Within each CBG, I then allocate "CARE slots" among CARE customers and "non-CARE slots" among non-CARE customers based on the random or usage ranking methods. This adjustment for CARE participation does not have a large impact in the random-rank and usage-rank boundary cases, but it does tend to reduce slightly the differences between the two ranking approaches. It will be more relevant in the subsequent analysis where I compare the redistributional impacts of IBP and a means-tested program like CARE.[24]

Results

Under each of the within-CBG ranking methods, Table 3 presents the average annual electricity bills in each of the income brackets under the benchmark five-tier tariff and the alternative revenue-neutral flat tariff, each applied to all residential customers. Unfortunately, these bounds do not narrow the range of the redistributional impact as much as one would like.[25] Changing from a flat rate tariff to the benchmark 5-tier tariff lowers

[24] At this point, I am using the CARE participation information only to identify households that are more likely to be low income. For now, all customers are still assumed to be subject to the same tariff for the purpose of the redistribution calculations.

[25] This is consistent with the difficulty that Freedman (2004) reports with the method of bounds in

	Income Range	Share of Customers	Average Daily Use (kWh)	Average Annualized Bill Flat	5-tier	Dollar Change	Percent Change
random	$0-$20k	17.9%	16.98	$986	$908	-$78	-8.0%
rank	$20k-$40k	22.1%	17.93	$1,041	$985	-$57	-5.5%
method	$40k-$60k	18.9%	19.34	$1,124	$1,104	-$19	-1.7%
	$60k-$100k	23.7%	20.86	$1,212	$1,237	$25	2.0%
	>$100k	17.4%	23.85	$1,386	$1,527	$141	10.2%
usage	$0-$20k	17.9%	8.85	$514	$365	-$149	-28.9%
rank	$20k-$40k	22.1%	14.56	$846	$696	-$150	-17.7%
method	$40k-$60k	18.9%	16.61	$965	$834	-$131	-13.6%
	$60k-$100k	23.7%	21.90	$1,272	$1,201	-$72	-5.6%
	>$100k	17.4%	38.08	$2,212	$2,797	$585	26.4%

Excludes bills with daily consumption < 1kWh/day

Includes all CARE and non-CARE customers, all on no-CARE-program rates from table 1

Table 3: SCE Average Bill By Income Bracket Under Benchmark 5-Tier and Flat-Rate Tariffs Using Random-Rank and Usage-Rank Methods for Within-CBG Allocation

the annual bills of households in the lowest income bracket by between 8% and 29% on average.[26] The $78 to $149 range of monetary bill decline are not strict bounds due to the non-monotonic relationship between consumption level and monetary bill change, but they reinforce the point that the bounds offer less guidance than one would hope for. The tables in the appendix also includes results for a two-tier tariff approach with an 18% differential between the baseline price and the second-tier price. This is similar to the tariffs that the California utilities offered prior to the 2000-01 electricity crisis, and much closer to the sort of IBP schedules that are being utilized, or are being considered, in a number of other states. The results for such a two-tier tariff fall between the flat-rate and five-tier tariff results, but are much closer to the flat-rate results.

VII. Refining the Redistribution Estimates

Besides suggesting very different redistributional impacts, the two approaches to allocating customers to income brackets within census block groups imply substantial differences in other attributes, including average consumption quantities and average monthly bill. Under the usage-rank method, households in the highest bracket are estimated to consume on average over four times as much electricity and pay over seven times higher bills (under IBP) as those in the lowest bracket. The random-rank method, however, implies very different distributions across the income brackets: households in the highest bracket consume on average only 41% more electricity and pay only 68% higher bills than those in

ecological regression.

[26] Even these bounds assume that the correlation is positive.

the lowest bracket. These implied average differences in ancillary attributes can be used to calibrate the within-CBG allocation of households to income brackets and potentially obtain a better estimate of income redistribution than either approach affords in isolation. Conceptually, if one knew the actual average consumption or average bill by income bracket, one could use some weighting of the random ranking and usage ranking to develop redistribution estimates that matched the actual distribution of these attributes as closely as possible.

I return momentarily to the question of how to estimate averages of these ancillary attributes by income bracket. For now, assume that one knew the average of ancillary attribute ϕ for each income bracket, $\bar{\phi}_b$, within the population of households the utility serves and that the random-rank and usage-rank methods each produced an implied $\tilde{\phi}_b$ for each imcome bracket. I develop a weighting of the random-rank and usage-rank methods in order to find the weight that minimizes a metric of the difference between the resulting $\tilde{\phi}$ vector and the $\bar{\phi}$ vector.

To be concrete, with N households in a CBG, they are assigned integer rankings from 1 to N, which are then used to assign them to the income bracket slots as was described earlier. In the case of random ranking, these integer ranks are assigned based on random number generation, while in the case of usage ranking, they are assigned in order of average daily usage. For any weighting factor w, where $0 \leq w \leq 1$, each household is assigned a weighted ranking value, $v_h = (1-w) \cdot r_{rh} + w \cdot r_{uh}$, where r_{rh} and r_{uh} are the integer rankings from the random-rank and usage-rank methods, respectively. They are then assigned to the income bracket slots based on the ranking of their v_h values. Every w yields a vector of $\tilde{\phi}_b(w)$ attributes across income brackets. Table 3 shows the two attributes, average daily usage and average monthly bill, for $w = 0$ (random rank) and $w = 1$ (usage rank). It is straightforward to calculate these average attribute values for any w, which I do for every $-1 < w < 1$ at increments of 0.01.

For each possible w, I then calculate the goodness-of-fit measure

$$G(w) = \sum_{b=1}^{5} s_b \cdot [\tilde{\phi}_b(w) - \bar{\phi}_b]^2$$

where s_b is the share of the population in income bracket b. The value of w that minimizes G is then $w*$, the weighting of the random-rank and usage-rank methods that best calibrates the ancillary attribute.

Unfortunately, no data are available for which I can generate exact calculations of either average usage or average bill by income bracket. However, two different approaches are feasible using different samples from the census. I describe each approach briefly here and in more detail in the appendix. The estimates from these approaches then are used as the $\bar{\phi}_b$ for determining $w*$, while accounting for the fact that they are statistical estimates.

Method A: Calibration using CBG-level income data and ecological regression

The billing data can be used to generate average household consumption by CBG and the long-form census data discussed earlier report the distribution of households across incomes brackets by CBG. Thus, average household consumption by income bracket can be estimated as an ecological regression problem, with the accompanying bias issues associated with this method.

In this formulation, a customer h whose income falls in bracket b consumes $q_{hb} = \bar{q_b} + \epsilon_h$ where $\bar{q_b}$ is the mean of consumption of customers in bracket b, and ϵ is orthogonal to customer income bracket over the entire population, by definition, because $\sum_h \epsilon_h = 0$ within each income bracket. Therefore, in a CBG, g, with H households the average consumption per household, $\bar{q_g}$, will be

$$\bar{q_g} = \sum_{b=1}^{5} \bar{q_b} s_{bg} + \frac{\sum_{h=1}^{H} \epsilon_h}{H}, \qquad [1]$$

where s_{bg} are the shares of customers in each income bracket within that CBG. One could estimate an ecological regression with observations at the census block group level, g,

$$\bar{q}_g = \sum_{b=1}^{5} \alpha_b s_{bg} + \eta. \qquad [2]$$

The α_b are then the least-squares estimates of income bracket mean consumption levels that generate the set of mean household consumption levels across the CBGs. The goal here is not to estimate the full causal model for $\bar{q}_g$, but rather to extract the best estimate of the mean consumption within each income bracket. Therefore, we are not, for instance, interested in the fact that wealthy people on average tend to own more air conditioning units, live in larger houses, or live in detached dwellings, and that it is these factors that directly raise household electricity demand.

The ecological regression literature points out two likely causes of bias from this sort of regression of aggregates. The first is common omitted variable bias. This will occur if differentiation in average consumption across CBGs is affected by another CBG-level factor that is correlated with the s_b. For instance, if wealthy people tend to live in milder climates, then it may appear that CBGs with more wealthy people consume less power, leading to downward biased estimates of consumption $\bar{q}_b$ for higher income brackets and upward biased estimates for lower income brackets. I control for climate by including heating and cooling degree days for the local area interacted with population shares in each income bracket so that, for instance, hot weather is allowed to affect the consumption of wealthy households differently than poor households.

The second source of possible bias, known as contextual bias, occurs if the relationship between the predictor variable and the response variable is itself dependent on the shares of the population that fall into each category of the predictor.[27] In the current analysis, the bias would occur, for instance, if among all lowest-bracket income households, those living in a predominantly wealthy CBG consumed more electricity on average than those living in a predominantly poor CBG. If people of all income brackets tended towards consumption levels similar to others in their CBG, then failing to capture this contextual effect, would lead to an overestimate of the average consumption of high-income households and underestimate the consumption of low-income households.[28]

In the standard 2-groups/2-states ecological model, contextual bias is very difficult to overcome, because the "context" – the breakdown of the area's population across groups – is perfectly correlated with the share of either group. For example, if all voters are grouped into black or white, then every voting precinct with 30% black voters is a precinct with 30% black and 70% white voters. With five groups, as is the case in this analysis, the hope for identifying the ecological parameter improves because there is no such perfect correlation. For instance, in one CBG the lowest income bracket could be 15% of the population with the rest spread evenly across the other four brackers, while in another CBG the lowest bracket could again be 15%, but the entire rest of the population could be in the second lowest income bracket. The predictor variable for the lowest bracket would be the same, but the context would be different, thus allowing separate identification of the two effects, subject to the usual caveat about functional form assumptions.

I implement this strategy by extending [2] to include not just the share of customers in each income bracket, but interaction of these shares with the median household income in the CBG. The regression, reported in the appendix, yields estimates of average daily

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27 The absence of such a relationship is known as the "constancy assumption." See Freedman, 2004.

28 For instance, consider two equal-sized CBGs, one 80% poor/20% rich with average daily consumption of 10 and one 40% poor/60% rich with average daily consumption of 20. If rich/poor have independent consumption – no contextual effect – these data would imply that the average daily consumption of rich households is 30 and average daily consumption of poor households is 5. If, in fact, consumption is 100% contextual – all households in a CBG have the same expected consumption regardless of wealth – this implies that rich households have an average daily consumption of 17.5 and poor households 13.3333.

electricity consumption for households in each of the five income brackets, the $\bar{\phi}_b$, which are a function of both the direct income share parameters and the parameters on the median household income and weather interaction effects. The goodness-of-fit measure G is calculated for every possible w and the w that minimizes G is w^*. For SCE, this procedure yields an estimated $w^* = 0.27$.

The estimate of interest, however, is not w^* itself, but average bill changes by income bracket, which are a highly nonlinear and possibly even non-monotonic function of w^*. Thus, bill changes implied by the point estimate of w^* might not be reliable estimates, and would almost certainly be improved upon by taking into account the entire distribution of the w^* estimate. Since w^* is the result of minimizing a function of estimated parameters, it is possible to generate a distribution of the estimated w^* with standard bootstrap methods. From 1000 bootstrap estimates of the ecological regression, the resulting distribution of w^* implies a 95% confidence interval of $[0.06, 0.44]$ – so both the random-rank results and the usage-rank results are rejected – a mean estimate of $w^* = 0.27$, and a median estimate of $w^* = 0.28$.

Each w value is uniquely associated with a ranking of customers for allocation across the income brackets and therefore generates a unique set of changes to the average bills of customers in each bracket. So, a distribution of the w^* estimates implies a distribution of the estimated bill changes. In Table 4, I report the mean and 95% confidence interval of those distributions. For the lowest income bracket, this approach results in an expected monetary bill change of $-\$129$ per year, a drop of slightly less than \$11 per month. The distribution is skewed, however, with a 95% confidence interval of $[-\$142, -\$92]$. Most of the weight of the w^* distribution is associated with bill declines that are slightly larger than the point estimate, but both tails of the w^* distribution have smaller (in absolute value) changes and one tail (towards random rank) has much smaller changes. The distribution of percentage bill changes does not exhibit nearly as much skewness, with a mean of -16.5% and a 95% confidence interval of $[-21.3\%, -9.7\%]$. For both the monetary and percentage bill changes for the lowest income bracket, the random-rank and usage-rank results lie outside the 95% confidence intervals. This is also true for the second lowest and the highest income bracket. As shown in the appendix, the estimated bill changes are somewhat smaller for PG&E and substantially smaller for SDG&E. SDG&E's smaller impact is probably explained in part by the fact that it has a less-steep IBP tariff, but PG&E's tariff is steeper than SCE's yet appears to redistribute income less effectively.

The results for all three utilities confirm that moving from a flat rate tariff to IBP on average generates statistically significant transfers from the two wealthiest income brackets,

	Income Range	Share of Customers	Average Daily Use (kWh)	Average Annualized Bill: Flat	*5-tier*	Dollar Chg	95% conf intvl	Percent Change	95% conf intvl	Aggregate Annual Chg ($M)
random	$0-$20k	17.9%	16.98	$986	$908	-$78		-8.0%		-$57
rank	$20k-$40k	22.1%	17.93	$1,041	$985	-$57		-5.5%		-$51
method	$40k-$60k	18.9%	19.34	$1,124	$1,104	-$19		-1.7%		-$15
	$60k-$100k	23.7%	20.86	$1,212	$1,237	$25		2.0%		$24
	>$100k	17.4%	23.85	$1,386	$1,527	$141		10.2%		$99
weighted	**$0-$20k**	**17.9%**	**13.66**	**$794**	**$665**	**-$129**	**[-$146, -$92]**	**-16.5%**	**[-21.3%, -9.7%]**	-$93
rank	**$20k-$40k**	**22.1%**	**16.80**	**$976**	**$884**	**-$92**	**[-$119,-$58]**	**-9.5%**	**[-12.9%, -5.6%]**	-$82
method A	**$40k-$60k**	**18.9%**	**19.31**	**$1,122**	**$1,090**	**-$32**	**[-$66, -$18]**	**-2.9%**	**[-6.1%, -1.6%]**	-$24
	$60k-$100k	**23.7%**	**21.27**	**$1,236**	**$1,261**	**$25**	**[$19. $26]**	**2.0%**	**[1.5%, 2.2%]**	$24
	>$100k	**17.4%**	**28.19**	**$1,638**	**$1,889**	**$251**	**[$155, $347]**	**15.2%**	**[10.9%, 19.0%]**	$177
weighted	**$0-$20k**	**17.9%**	**15.20**	**$883**	**$772**	**-$111**	**[-$116, -$106]**	**-12.6%**	**[-13.3%, -11.8%]**	-$80
rank	**$20k-$40k**	**22.1%**	**17.57**	**$1,021**	**$953**	**-$68**	**[-$71, -$64]**	**-6.6%**	**[-7.0%, -6.2%]**	-$61
method B	**$40k-$60k**	**18.9%**	**19.55**	**$1,136**	**$1,117**	**-$19**	**[-$19, -$18]**	**-1.6%**	**[-1.7%, -1.6%]**	-$14
	$60k-$100k	**23.7%**	**20.97**	**$1,218**	**$1,244**	**$26**	**[$26, $26]**	**2.2%**	**[2.1%, 2.2%]**	$25
	>$100k	**17.4%**	**25.76**	**$1,496**	**$1,682**	**$186**	**[$176, $195]**	**12.4%**	**[11.9%, 12.8%]**	$131
usage	$0-$20k	17.9%	8.85	$514	$365	-$149		-28.9%		-$108
rank	$20k-$40k	22.1%	14.56	$846	$696	-$150		-17.7%		-$134
method	$40k-$60k	18.9%	16.61	$965	$834	-$131		-13.6%		-$100
	$60k-$100k	23.7%	21.90	$1,272	$1,201	-$72		-5.6%		-$69
	>$100k	17.4%	38.08	$2,212	$2,797	$585		26.4%		$412

Excludes bills with daily consumption < 1kWh/day

Includes all CARE and non-CARE customers, all on no-CARE-program rates from table 1

Table 4: SCE Average Bill By Income Bracket Under Benchmark and Alternative Flat-Rate Tariff Using Random-Rank, Usage-Rank and Weighted-Rank Within-CBG Allocation Methods

mostly from the wealthiest bracket, to the three poorer income brackets, mostly to the two lowest. Among the slightly more than 4 million full-year-equivalent SCE customers in the dataset,[29] those monetary redistribution estimates represent aggregate annual transfers shown in the right-hand column of Table 4.

Method B: Calibration using average bill by income bracket

An alternative calibration approach uses a different dataset from the census, the American Community Survey, which is an approximately 1% household survey that asks more detailed consumption questions, including both the household's income and its monthly expenditures on electricity. Location data for these households are much less precise, so they cannot be grouped by CBG or matched with certainty to SCE's service territory in

[29] This is the total number of customer-days in the dataset divided by 365.

some cases. As described in the appendix, I weight household observations by the probability that they lie in SCE's service territory based on zip code coverage data. I then use these data to estimate average household monthly bill by income bracket and calculate the goodness-of-fit measure against the average household monthly bills by income bracket that are implied by each possible w value.

The advantage of this calibration approach is that it is based on a direct survey of households that includes both of the variables of interest, income and the attribute used for calibration. No ecological regression is needed. The disadvantage of this approach is that it relies on household reporting of not just annual income, but also average monthly electricity bill. It seems quite likely that this would be a fairly noisy measure. The estimation, however, is a regression of monthly bill on income bracket dummies, so the recall error on monthly bill may not be a problem if it is orthogonal to income. If income is reported with error, however, the estimates will tend to understate the actual bill differences across income brackets and bias downward estimates of w^*.[30] Likewise, the weighted location matching could bias the estimates, though it is difficult to know in which direction.

Just as with the ecological regression approach, this approach yields a point estimate of w^* and a distribution of the parameter estimate using the bootstrap method. Due to the large dataset – about 40,000 households in SCE territory – and simple mean calculation, however, the distribution is quite narrow. For SCE, the estimated w^* is 0.13 with a 95% confidence interval of $[0.11, 0.16]$.[31] The implied annual bills and transfers are shown in Table 4. Even with a mean w^* estimate much closer to zero (random rank) than one (usage rank), the estimates of transfers for the lowest and highest income brackets are substantially different from the random rank results.

The random rank method is based on the same assumption of within-CBG orthogonality between electricity consumption and income as one would be making if one used median household income by CBG. The difference between the results using the random rank method and the results from the weighted ranking methods provide a guide to the bias caused by this orthogonality assumption in this particular empirical investigation. The size of this bias for other studies, of course, will vary depending on the degree of actual within-CBG correlation between income and the variable of interest.

30 Recall bias is probably much less of an issue with the ecological regression calibration method. Even if individual households recall their income with error, the shares of households in each bracket are likely to be fairly accurate so long as the recall errors are uncorrelated.

31 In the 1000 bootstrap estimates, the mean w^* is 0.14 and median is 0.14.

It is important to note again two central assumptions on which these results are based, perfectly inelastic demand and no other program for low-income customers. In the next two sections, I address and relax these assumptions.

VIII. Demand Elasticity and the Efficiency Costs of Income Redistribution

In this section, I show that incorporating reasonable elasticity estimates changes the income redistribution results fairly little, but does suggest that the efficiency costs of an IBP tariff may be substantial in comparison to the redistribution that is accomplished.

Incorporating demand elasticity requires two critical pieces of data: the elasticity of demand and the marginal cost for marginal changes in production. Unfortunately, reliable estimates of the relevant elasticity for this analysis are difficult to come by and the true long-run marginal cost of electricity production and delivery is the subject of quite a bit of disagreement. Therefore, I proceed by analyzing the results over a range of demand elasticity and marginal cost assumptions.

In this analysis, the assumption about price elasticity also requires an assumption about the price to which customers respond. Do consumers actually respond to the marginal price they end up facing at the end of the billing period? Or do they respond to average price, or to some weighted average of the marginal price in the neighborhood of their typical consumption? In ongoing research, I am exploring this topic in detail.[32] For the purpose of these calculations, I make the conventional assumption that consumers respond to actual *ex post* marginal price for the billing period. I then examine a range of demand elasticities from zero (the previous results) to -0.3, in all cases assuming a constant elasticity functional form of demand. Longer run estimates of electricity demand elasticity are generally at the more elastic end of this range (or even larger, in absolute value), but they have not explicitly examined how well customers understand the IBP tariff and whether they would demonstrate the same elasticity in response to large changes in marginal price that have fairly small effects on the average price that most customers face.[33]

In order to maintain the assumption that the tariff change is profit-neutral for the utility, analysis of the consumer surplus change with non-zero demand elasticity also requires an

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[32] See Borenstein (2009).

[33] A further complication is that elasticities may differ in a way that is correlated with household consumption, but reliable estimates of such differences do not exist. It is also certainly possible that the constant elasticity functional form of demand is not the most accurate description, but unfortunately existing research does not provide very useful guidance on this subject either.

assumption about the marginal cost of quantity changes. For this analysis, I start out with the assumption that the long-run marginal cost of incremental quantity changes is equal to the average cost under the existing tariffs, which is equal to the average price under the assumption that the existing tariff is break-even. This is the flat-rate tariff in the previous section, in the case of SCE, \$0.1592/kWh. One could argue that this is too high – because this price included covering sunk losses from the 2000-01 California electricity crisis (and some long-term contracts signed shortly after) or because there are economies of scale in at least the electricity distribution activity – or too low – due to constraints on the expansion of cost-effective generation, for instance from regulatory constraints on building new fossil fuel power plants or new transmission lines.[34] I return below to the robustness of the results to different marginal cost assumptions. I show that for small elasticities the income redistribution results are less sensitive than one might expect to the MC assumption, because it affects only the cost change that results from the *net* change in quantity as some consumers increase consumption when their marginal price falls and others decrease consumption as their marginal price rises. The analysis of the deadweight loss from IBP, however, is much more sensitive to marginal cost.

The approach I take is to calculate the change in consumption of each consumer in each billing period when the tariff changes from the flat-rate tariff to the benchmark 5-tier tariff that is shown in Table 1. Because the actual quantities observed were for customers facing the 5-tier tariff, however, the quantities consumed under the alternative flat rate tariff depend on the elasticity assumption. Total consumption tends to be larger under the flat rate tariff because about half of the customers are on blocks 3, 4, or 5, while the other half of customers are on blocks 1 or 2 for marginal consumption. The customers on blocks 3, 4, and 5 are large-demand customers and see a substantially lower marginal price with a flat rate tariff, while those on blocks 1 and 2 are small customers and see a somewhat higher marginal price under a flat rate tariff. Because output expands under the flat rate compared to the five-tier tariff, the break-even flat rate tariff must rise if marginal cost is above average cost or fall if marginal cost is below average cost.

[34] One possible benchmark for the marginal cost of power is the regulator's analysis. The California Public Utilities Commission each year creates a "Market Price Referent" (MPR) that is used as an indicator price below which offers to the utilities from merchant generators will automatically be considered just and reasonable by the regulator. The Market Price Referent in 2006 for long-term power purchases was about \$0.085/kWh. This is a wholesale power price, however, and does not include transmission and distribution (T&D, including billing) costs. T&D costs average about \$0.04/kWh and the marginal cost is probably somewhat lower than that, though not all regulatory analysts would agree that marginal T&D costs are below average. Still, a long-run marginal cost of between \$0.11 and \$0.12 is fairly defensible if one excludes environmental externalities that are not priced in the MPR. If greenhouse gases were priced at \$30/ton – which is in the range contemplated in current proposed legislation – this would raise the cost of power by about 1.5 cents per kWh in California because that would be the emissions cost of a gas-fired power plant that is most often setting the market price.

For brevity, I focus here on results using calibration method A, the ecological regression results. Using method B, calibrating on reported monthly electricity bill in the ACS, yields similar results, though all redistribution effects are smaller.

The changes in annual average household consumer surplus by income bracket are shown in the middle columns of Table 5. The second panel (in bold) of Table 5 displays results under the assumption that marginal cost is \$0.1592/kWh, the actual average revenue per kWh that SCE collected. The top panel shows results under the alternative assumption that $MC =$\$0.1092/kWh, five cents lower and possibly a more accurate indication of marginal cost if no environmental costs are incurred. The third panel shows results under the alternative assumption that $MC =$\$0.2092/kWh, five cents higher and potentially more accurate if expansion of generation, transmission, and distribution is severely constrained or environmental costs are very high.[35]

Focusing first on the middle columns of the second panel, the $\epsilon = 0$ column replicates the results from Table 4, though with the sign reversed because I am now considering change in consumer surplus rather than the change in the bill. The next three columns to the right show the change in average household consumer surplus under increasing elasticity assumptions. They indicate that incorporating more elastic demand changes the results but not the qualitative inference.[36] Over the alternative elasticity assumptions from zero to -0.3, the estimated average consumer surplus gain for households in the poorest income bracket due to the IBP tariff are all in the range of about \$9-\$11 per month, which is 16% to 19% of their estimated bills under the existing 5-tier tariff.[37]

Incorporating the elasticity of electricity demand leads to the question of the tradeoff between income redistribution and economic efficiency. The four right-hand columns present the aggregate transfers, in millions of dollars per year, to or from each income bracket,

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[35] Raising the marginal cost of production by five cents due to greenhouse gas emissions alone, however, would require a price on GHGs of around \$100 per ton of CO_2 equivalent.

[36] Incorporating demand elasticity necessarily, by revealed preference, makes more positive (or less negative) the change in consumer surplus caused by a change from the observed price structure and associated quantities to any given alternative. In this case, the sign of this effect is ambiguous, however, because I am evaluating the change *from* a hypothetical alternative flat rate *to* the IBP price structure at which quantity has been actually observed. That is, the change in elasticity assumption pivots the demand curve around the point at which it is intersecting the 5-tier price schedule.

[37] In examining consumption responses to changes in the tariff, these calculations ignore income effects. Even for customers in the lowest income bracket these are likely to be very small, amounting to about 1% of their income. Estimates of the income elasticity of demand vary greatly, but even if it assumed to be 1.5 in the long run – which is towards the high end of the distribution of estimates in the literature – the quantity effect from the income change would be in the noise of these estimates.

taking into account the share of households in each bracket. Because these calculations were carried out for a break-even utility, the difference in deadweight loss between the IBP tariff and the flat rate is simply the aggregate change in consumer surplus that occurs with the switch from one to the other. This is shown in the row beneath the four right-hand columns.

For example, with a demand elasticity of -0.1, switching from a flat rate tariff to the 5-tier tariff raises deadweight loss by $67 million per year, reducing the consumer surplus of households in the two highest income brackets by $240 million per year (=$198+$42), while increasing by $173 million per year the consumer surplus of households in the other three income brackets, with $160 million per year of that going to households in the two lowest income brackets. The second row beneath the right-hand columns reports the ratio of the dealweight loss to the amount of income transfered to households in the two lowest income brackets, *i.e.,* households with annual income below $40,000 per year. This seems to be a somewhat inefficient redistributional program. The 0.42 ratio is slightly higher than the range of many estimates of the marginal cost of public funds. Those estimates generally do not include the increase or decline in distortion that could result from the distribution of those funds to lower income households, through for instance either reductions in payroll taxes or distorted prices on subsidized goods.[38] The ratio, however, is much higher if the elasticity of demand is -0.2 or -0.3. The ratios are substantially higher (ranging from roughly 0.77 to 4.06) for PG&E which has a steeper IBP tariff, and about the same (ranging from 0.35 to 1.31) for SDG&E.

Conceptually, the deadweight loss impact of a switch from a flat rate to an IBP tariff can be decomposed into the resulting inter-buyer misallocation of any given total quantity of electricity – which results from buyers facing heterogeneous prices for marginal purchases under IBP – and inefficient aggregate consumption of electricity – which results from the marginal price differing from marginal cost. The flat rate tariff is clearly more efficient in terms of inter-buyer misallocation, but it may be more or less efficient than the IBP tariff in terms of optimizing total consumption, depending on how closely each tariff reflects marginal cost across all consumers. In the case of the second panel in Table 5 the flat rate tariff is reducing deadweight loss to zero by setting price equal to marginal cost for all customers.

Though it may be tempting to conclude that the case in which the flat rate tariff is equal to marginal cost maximizes the deadweight loss advantage of a flat rate tariff over

[38] See Ballard & Fullerton (1992) and Snow & Warren (1996).

MC=0.1092		Change in Annual Average Household Consumer Surplus From Switch to 5-tier tariff				Change in Aggregate Annual Consumer Surplus ($M/yr) From Switch to 5-tier tariff			
Income Range	Share of Customers	ε=0	ε=-0.1	ε=-0.2	ε=-0.3	ε=0	ε=-0.1	ε=-0.2	ε=-0.3
$0-$20k	17.9%	$129	$114	$97	$80	$93	$82	$70	$58
$20k-$40k	22.1%	$92	$71	$49	$25	$82	$64	$44	$22
$40k-$60k	18.9%	$32	$5	-$23	-$54	$24	$4	-$18	-$41
$60k-$100k	23.7%	-$25	-$56	-$89	-$126	-$24	-$53	-$85	-$120
>$100k	17.4%	-$251	-$298	-$348	-$403	-$177	-$210	-$245	-$284
Aggregate Increase in DWL from IBP ($M/yr)						$0	$113	$234	$365
Ratio of DWL to transfers to two lowest income brackets						0.00	0.77	2.05	4.56
Flat-rate Price						$0.1592	$0.1577	$0.1560	$0.1543

MC=0.1592		**Change in Annual Average Household Consumer Surplus From Switch to 5-tier tariff**				**Change in Aggregate Annual Consumer Surplus ($M/yr) From Switch to 5-tier tariff**			
Income Range	**Share of Customers**	**ε=0**	**ε=-0.1**	**ε=-0.2**	**ε=-0.3**	**ε=0**	**ε=-0.1**	**ε=-0.2**	**ε=-0.3**
$0-$20k	**17.9%**	**$129**	**$121**	**$113**	**$105**	**$93**	**$88**	**$82**	**$76**
$20k-$40k	**22.1%**	**$92**	**$81**	**$69**	**$57**	**$82**	**$72**	**$62**	**$51**
$40k-$60k	**18.9%**	**$32**	**$16**	**$1**	**-$16**	**$24**	**$13**	**$0**	**-$12**
$60k-$100k	**23.7%**	**-$25**	**-$44**	**-$63**	**-$83**	**-$24**	**-$42**	**-$60**	**-$79**
>$100k	**17.4%**	**-$251**	**-$281**	**-$313**	**-$345**	**-$177**	**-$198**	**-$220**	**-$243**
Aggregate Increase in DWL from IBP ($M/yr)						$0	**$67**	**$136**	**$207**
Ratio of DWL to transfers to two lowest income brackets						**0.00**	**0.42**	**0.95**	**1.63**
Flat-rate Price						**$0.1592**	**$0.1592**	**$0.1592**	**$0.1592**

MC=0.2092		Change in Annual Average Household Consumer Surplus From Switch to 5-tier tariff				Change in Aggregate Annual Consumer Surplus ($M/yr) From Switch to 5-tier tariff			
Income Range	Share of Customers	ε=0	ε=-0.1	ε=-0.2	ε=-0.3	ε=0	ε=-0.1	ε=-0.2	ε=-0.3
$0-$20k	17.9%	$129	$128	$128	$128	$93	$93	$92	$92
$20k-$40k	22.1%	$92	$90	$87	$87	$82	$80	$78	$78
$40k-$60k	18.9%	$32	$27	$21	$21	$24	$20	$16	$16
$60k-$100k	23.7%	-$25	-$32	-$40	-$40	-$24	-$31	-$38	-$38
>$100k	17.4%	-$251	-$266	-$281	-$281	-$177	-$187	-$198	-$198
Aggregate Increase in DWL from IBP ($M/yr)						$0	$24	$49	$49
Ratio of DWL to transfers to two lowest income brackets						0.00	0.14	0.29	0.29
Flat-rate Price						$0.1592	$0.1606	$0.1620	$0.1633

MC=0.2592		Change in Annual Average Household Consumer Surplus From Switch to 5-tier tariff				Change in Aggregate Annual Consumer Surplus ($M/yr) From Switch to 5-tier tariff			
Income Range	Share of Customers	ε=0	ε=-0.1	ε=-0.2	ε=-0.3	ε=0	ε=-0.1	ε=-0.2	ε=-0.3
$0-$20k	17.9%	$129	$135	$140	$144	$93	$98	$101	$104
$20k-$40k	22.1%	$92	$98	$103	$107	$82	$88	$92	$95
$40k-$60k	18.9%	$32	$37	$40	$43	$24	$28	$31	$33
$60k-$100k	23.7%	-$25	-$21	-$19	-$17	-$24	-$20	-$18	-$16
>$100k	17.4%	-$251	-$251	-$253	-$255	-$177	-$177	-$178	-$179
Aggregate Increase in DWL from IBP ($M/yr)						$0	-$16	-$28	-$37
Ratio of DWL to transfers to two lowest income brackets						0.00	-0.09	-0.15	-0.18
Flat-rate Price						$0.1592	$0.1619	$0.1645	$0.1669

Table 5: Change in Consumer Surplus Switching from Flat-rate to 5-tier Tariff Under Alternative Demand Elasticities (Weighted Ranking Method A - calibration from ecological regression)

increasing-block pricing, that is not the case. In this empirical analysis, the deadweight loss *difference* is even larger if marginal cost is lower. While a lower marginal cost (holding constant the firm's total cost at the observed quantities) increases deadweight loss under flat rate pricing, in this case it increases the deadweight loss under the IBP structure by even more. This difference is shown in the top panel of Table 5, where for a given elasticity, the deadweight loss difference is substantially larger than in the second panel. The intuition here is that the deadweight loss induced by moving the marginal price slightly above or below marginal cost is second order, but increases with the square of that difference. Thus, the change in deadweight loss if marginal cost is $0.1092 instead of $0.1592 is quite large for customers who are out on the fifth tier paying around $0.30 per kWh.

Conversely, if marginal cost is well above average cost, the case shown in the bottom panels, increasing-block pricing induces much less deadweight loss because the many customers out on the higher tiers (who are also the high-use consumers) are facing prices that are much closer to marginal cost. An intuitive extreme case would be if all customers were on the fifth tier and marginal cost were equal to the fifth tier price, but the firm was still breaking even due to marginal cost being well above average cost. In that case, the increasing-block pricing would eliminate deadweight loss, while switching to a break-even flat-rate tariff would induce substantial deadweight loss.

In fact, in the present case, if the marginal cost were $0.2592/kWh (the bottom panel), a switch from a break-even flat-rate tariff to the benchmark 5-tier tariff would reduce deadweight loss while also transferring income from richer to poorer households. This was almost certainly not the case for California in 2006, though it is worth keeping in mind for cases in which firms have fairly low historical costs but face severe constraints on output expansion. On the other hand, if marginal cost were actually in the range of $0.11-$0.16, as seems likely to have been the case for SCE in 2006, increasing-block pricing was probably a fairly inefficient way of transferring income to poorer households.[39] The results for PG&E and SDG&E indicate the same tradeoff: the deadweight loss cost of redistributing income through IBP is fairly high if marginal cost is below average cost, but is lower if marginal cost is above average cost and could be negative if marginal cost were around $0.25/kWh or higher.

It is worth noting two considerations that this analysis does not incorporate. First, the deadweight loss calculations assume that there are no other distortions in the economy, but in fact we start from a situation far from the first best due to taxes on labor and other commodities. Intuitively, the distortion due to above-marginal-cost pricing of elec-

[39] This discussion ignores the "conservation motive" that is frequently suggested as another reason for using IBP. It is difficult to reconcile such arguments with a marginal cost that is well below the highest-tier prices unless one incorporates behavioral considerations. If a very high marginal price gets households to make energy efficiency investments that actually pay off even if price equals the much-lower true social marginal cost – but for some reason households were unwilling to make these investments under a less extreme marginal price – then the analysis would be more favorable to IBP.

tricity exacerbates the pre-existing labor supply distortion resulting from income taxes by reducing the real after-tax wage.[40] Below-marginal-cost pricing of electricity for some customers, however, may reduce the pre-existing labor supply distortion. The net impact of these effects is difficult to calculate, but it is worth pointing out that the customers charged above-marginal-cost electricity prices are disproportionately those who already face high marginal tax rates on labor, while those charged below-marginal-cost prices tend to be in lower marginal tax brackets and are thus likely to engender smaller pre-existing distortions from the tax on labor. So it seems likely that incorporating this indirect tax distortion would raise the estimated deadweight loss. Second, there is significant theoretical and empirical support for the idea that customers do not respond to the *ex post* observed marginal price that they face, but rather to some average of marginal prices over at the range of potential consumption, or to just an average price for the month.[41] These effects could reduce the deadweight loss from IBP.[42]

IX. Increasing-Block Pricing Versus A Tariff for Low-Income Households

While IBP is generally aimed at protecting low-income customers, many policymakers and economists argue for a means-tested program for the poor rather than a price schedule that distorts prices for all consumers and only redistributes to the poor indirectly through the correlation with usage. And, of course, virtually all economists would prefer to see lump-sum transfers, rather than price distortions. Means-tested programs, however, raise their own set of concerns, most notably the difficulty in identifying and enrolling low-income, and only low-income, customers. Nearly every state has some form of means-tested assistance for energy bills in addition to the federal government's Low Income Home Energy Assistance Program (LIHEAP).[43]

The CARE (California Alternate Rates for Energy) program in California is a discounted electricity tariff targeted at low-income households. As shown in Table 1, the CARE program is also an increasing-block price schedule for electricity, but each block's price is

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[40] See Bovenberg and Goulder (1996).

[41] See Shin (1985), Borenstein (2009) and Ito (2010) on electricity. Saez (2002) explores a closely related issue in income tax effects.

[42] If customers respond to the "proximate marginal price" in the range of their expected consumption, then this would probably change the deadweight loss calculation very little, but if they actually respond to their average price over the whole billing period, then for a given demand elasticity, IBP would create substantially less deadweight loss than calculated here.

[43] Summaries of each state's programs are at http://liheap.ncat.org/sp.htm .

discounted off of the standard residential tariff. The discounts are not the same on each tier. Thus, the CARE program delivers a lower average electricity price and a different structure of increasing-block pricing.

Despite the lower prices offered under CARE, the utilities have had a difficult time getting all or nearly all of the eligible customers to sign up for the program. After many years of significant efforts by the utilities and independent poverty-assistance programs, the utilities report penetration rates among eligible households of 70%-80%. Unfortuately, those figures probably overstate the program effectiveness because they are calculated by dividing the number of CARE participants by an estimate of the number of eligible households. Implicitly, such a calculation assumes that all households on CARE are eligible, but some data suggest that the reality may be substantially different, as discussed in the appendix. Nonetheless, for this analysis, I base my calculations on the reported figures recognizing that the results probably overstate the degree of income redistribution accomplished by the CARE program.

To examine the transfers resulting from CARE, it is useful to separate the lower *average* price from the increasing-block nature of each tariff. To do this, I first consider the case of different flat-rate tariffs for CARE and non-CARE customers. Once again assuming zero demand elasticity, it is straightforward to create separate revenue-neutral flat-rate tariffs for each group. These are shown in the lower left-hand panel of Table 1. CARE participation is indicated in the billing data for each household, so one can then easily assess the change in each household's bills with the introduction of the CARE program under a flat-rate tariff, and under a 5-tier tariff.[44]

Table 6 shows the average annual bills by income bracket under four alternative scenarios using the ecological regression calibration method.[45] The effect of the CARE program and 5-tier tariff on average bills by income bracket are shown separately and combined in the right-hand columns, both as monetary and percentage changes from the flat-tariff/No-

[44] Throughout this study, I have assumed that tariff changes would be revenue neutral. That is unlikely to be exactly true with CARE, because more than half of the subsidy comes from surcharges on commercial, industrial, and agricultural electricity bills. However, it is impossible to predict how a change in the CARE program would alter the cross-subsidies between these customer classes, and very difficult to determine how the impact of bill changes among these non-residential customer classes is shared among households of different income brackets. Therefore, I maintain the assumption that changes in CARE would be financed by changes in the non-CARE residential rates. Absent elastic responses, this is equivalent to assuming that the incidence of changes in electricity costs for non-residential customers are borne entirely by residential customers of the same utility and allocated in the same proportion as their residential electricity bills.

[45] Results using both calibration methods for all three utilities are shown in the appendix.

	Average Annualized Bill				Monetary Bill Chage from No-CARE/Flat			Percentage Bill Chage from No-CARE/Flat		
	No-CARE		with CARE		No-CARE	w/CARE	w/CARE	No-CARE	w/CARE	w/CARE
Income Range	Flat Tariff	5-tier Tariff	Flat Tariff	5-tier Tariff	5-tier Tariff	Flat Tariff	5-tier Tariff	5-tier Tariff	Flat Tariff	5-tier Tariff
$0-$20k	$794	$665	$618	$558	-$129	-$176	-$236	-16%	-22%	-30%
$20k-$40k	$976	$884	$865	$808	-$92	-$111	-$168	-9%	-11%	-17%
$40k-$60k	$1,122	$1,090	$1,158	$1,108	-$32	$36	-$15	-3%	3%	-1%
$60k-$100k	$1,236	$1,261	$1,339	$1,328	$25	$103	$92	2%	8%	7%
>$100k	$1,638	$1,889	$1,781	$1,985	$251	$143	$347	15%	9%	21%

All results are from weighted rank method A - calibrated from ecological regression results
Excludes bills with daily consumption < 1kWh/day
Includes all CARE and non-CARE customers

Table 6: Estimated Average Annual Bills With and Without IBP and CARE

CARE results. A flat-rate tariff for both non-CARE and CARE customers – maintaining the average discount of 39% for CARE customers that results from the current program – would reduce the average bill for households in the lowest income bracket to $618 versus $665 if the IBP tariff was offered, but with no means-tested program. Of course, such a comparison depends entirely on the size of the CARE discount and the steepness of IBP.

Some other insights from Table 6 are likely to be more general, however. Comparing the bill changes from No-CARE/5-tier with those from CARE/flat-rate, it is apparent that a substantially smaller share of the funds that CARE redistributes come from the very wealthiest customers. Rather, the cost of the transfers are shared more by households in the next highest income bracket and even in the middle bracket. In that sense, a CARE-like program may be less progressive than IBP. This result, which holds true for all three utilities, reflects the fact that the CARE program is financed by raising price for all non-CARE customers by the same amount per kilowatt-hour. The IBP, however, lowers price for baseline energy by raising it the most for the heaviest users, who are disproportionately from the highest income bracket.

The IBP and CARE programs are substitutes to some extent, so the presence of the CARE program lowers the incremental redistributive effect of the IBP (and *vice versa*). The additional impact of the IBP given the CARE program is to lower the average bill of households in the lowest income bracket by $60/year or about $5 per month, about 10% of the bill they would face without IBP.

While the CARE program and IBP do redistribute income from wealthier to poorer customers, they both also distort prices and potentially lower economic efficiency. Table 7 carries out the same type of elasticity adjustment and deadweight-loss analysis for SCE's CARE program that Table 5 presented for SCE's increasing-block pricing. Comparing Table 7 with Table 5, however, suggests that the induced deadweight loss is likely to be much smaller per dollar transfered with the CARE program. The deadweight loss is drastically lower if marginal cost is around average cost or lower, the top two panels. Even if marginal cost is slightly over \$0.20/kWh, CARE creates less than half as much deadweight loss per dollar transfered. If marginal cost is even higher, however, the ability of IBP to reflect high marginal cost while maintaining a lower average price can make it more attractive.[46]

These results are based on a 78% CARE penetration rate among eligible customers, as reported by SCE for 2006, which probably overstates participation by low-income households, as explained in the appendix. Using an adjusted penetration rate of 65% (discussed in the appendix) reduces the efficiency dominance of the CARE program somewhat, but still suggests that it creates much less inefficiency for a given transfer to the lowest income bracket than does IBP.[47]

A complete comparison between IBP and CARE would require a much more extensive study of the eligibility and consumption of households on CARE. Faced with great difficulty signing up customers who qualify for the lower rates, utilities and the regulator in California have focused more on reducing the number of eligible customers who don't take advantage of the program than on tracking down ineligible customers who do. Nonetheless, over the plausible range on CARE penetration rates and likely marginal costs, CARE redistributes more income to the lowest income bracket per dollar of deadweight loss created than does IBP. Under CARE, however, more of the funds for that redistribution come from middle-income households and less from wealthy households.

Besides the difficulty in accurately identifying truly eligible customers, CARE-like programs also may have higher "customer acquistion" and administration costs. In fact, program administrative costs should be considered in analyzing both IBP and CARE. No data are available on the additional administrative cost of IBP versus a flat-rate tariff, though it seems likely to be quite small due to the fact that it is mandatory and calculated automatically in the billing process. In contrast, the utilities file detailed reports on their CARE program administration costs. For 2006, SCE reported its costs were \$4.2 million of

[46] These deadweight loss calculations raise the same issue of pre-existing labor market distortions as in the previous section, though the correlation between high prices and high marginal tax brackets is probably not as great in this case. Another possible distortion, however, is the disincentive to increase income if it would disqualify one from the CARE program. Still, such an effect is likely to be very small in most cases given the size of electricity bill savings relative to the potential chang in income and, more importantly, due to the extremely weak enforcement of the income eligibility rules for CARE.

[47] The lower penetration rate yields virtually the same deadweight loss as in Table 7, but reduces the transfers by about 15%.

MC=0.1092		Change in Annual Average Household Consumer Surplus From adding CARE program				Change in Aggregate Annual Consumer Surplus ($M/yr) From adding CARE program			
Income Range	Share of Customers	ε=0	ε=-0.1	ε=-0.2	ε=-0.3	ε=0	ε=-0.1	ε=-0.2	ε=-0.3
$0-$20k	17.9%	$176	$178	$182	$186	$127	$129	$131	$134
$20k-$40k	22.1%	$111	$114	$117	$120	$99	$102	$104	$107
$40k-$60k	18.9%	-$36	-$37	-$38	-$40	-$27	-$28	-$29	-$30
$60k-$100k	23.7%	-$103	-$108	-$113	-$118	-$99	-$103	-$108	-$113
>$100k	17.4%	-$143	-$151	-$160	-$171	-$101	-$106	-$113	-$120
Aggregate Increase in DWL from CARE ($M/yr)						$0	$7	$14	$22
Ratio of DWL to transfers to two lowest income brackets						0.00	0.03	0.06	0.09
Flat-rate Price - Standard Residential						$0.1731	$0.1717	$0.1703	$0.1687
Flat-rate Price - CARE participants						$0.1060	$0.1052	$0.1043	$0.1033

MC=0.1592		**Change in Annual Average Household Consumer Surplus From adding CARE program**				**Change in Aggregate Annual Consumer Surplus ($M/yr) From adding CARE program**			
Income Range	**Share of Customers**	**ε=0**	**ε=-0.1**	**ε=-0.2**	**ε=-0.3**	**ε=0**	**ε=-0.1**	**ε=-0.2**	**ε=-0.3**
$0-$20k	**17.9%**	**$176**	**$180**	**$184**	**$189**	**$127**	**$130**	**$133**	**$137**
$20k-$40k	**22.1%**	**$111**	**$114**	**$118**	**$122**	**$99**	**$102**	**$105**	**$109**
$40k-$60k	**18.9%**	**-$36**	**-$38**	**-$40**	**-$42**	**-$27**	**-$29**	**-$30**	**-$32**
$60k-$100k	**23.7%**	**-$103**	**-$109**	**-$116**	**-$123**	**-$99**	**-$104**	**-$111**	**-$117**
>$100k	**17.4%**	**-$143**	**-$154**	**-$165**	**-$177**	**-$101**	**-$108**	**-$116**	**-$125**
Aggregate Increase in DWL from CARE ($M/yr)						**$0**	**$9**	**$19**	**$29**
Ratio of DWL to transfers to two lowest income brackets						**0.00**	**0.04**	**0.08**	**0.12**
Flat-rate Price - Standard Residential						**$0.1731**	**$0.1735**	**$0.1739**	**$0.1743**
Flat-rate Price - CARE participants						**$0.1060**	**$0.1062**	**$0.1065**	**$0.1067**

MC=0.2092		Change in Annual Average Household Consumer Surplus From adding CARE program				Change in Aggregate Annual Consumer Surplus ($M/yr) From adding CARE program			
Income Range	Share of Customers	ε=0	ε=-0.1	ε=-0.2	ε=-0.3	ε=0	ε=-0.1	ε=-0.2	ε=-0.3
$0-$20k	17.9%	$176	$181	$186	$192	$127	$131	$135	$139
$20k-$40k	22.1%	$111	$115	$119	$123	$99	$102	$106	$110
$40k-$60k	18.9%	-$36	-$38	-$41	-$44	-$27	-$29	-$31	-$34
$60k-$100k	23.7%	-$103	-$111	-$118	-$127	-$99	-$106	-$113	-$121
>$100k	17.4%	-$143	-$156	-$169	-$182	-$101	-$110	-$119	-$128
Aggregate Increase in DWL from CARE ($M/yr)						$0	$11	$23	$34
Ratio of DWL to transfers to two lowest income brackets						0.00	0.05	0.09	0.14
Flat-rate Price - Standard Residential						$0.1731	$0.1751	$0.1771	$0.1790
Flat-rate Price - CARE participants						$0.1060	$0.1072	$0.1085	$0.1096

MC=0.2592		Change in Annual Average Household Consumer Surplus From adding CARE program				Change in Aggregate Annual Consumer Surplus ($M/yr) From adding CARE program			
Income Range	Share of Customers	ε=0	ε=-0.1	ε=-0.2	ε=-0.3	ε=0	ε=-0.1	ε=-0.2	ε=-0.3
$0-$20k	17.9%	$176	$182	$188	$194	$127	$132	$136	$140
$20k-$40k	22.1%	$111	$115	$119	$124	$99	$103	$107	$111
$40k-$60k	18.9%	-$36	-$39	-$43	-$46	-$27	-$30	-$32	-$35
$60k-$100k	23.7%	-$103	-$112	-$121	-$130	-$99	-$107	-$116	-$124
>$100k	17.4%	-$143	-$158	-$172	-$187	-$101	-$111	-$121	-$131
Aggregate Increase in DWL from CARE ($M/yr)						$0	$14	$27	$39
Ratio of DWL to transfers to two lowest income brackets						0.00	0.06	0.11	0.16
Flat-rate Price - Standard Residential						$0.1731	$0.1767	$0.1800	$0.1831
Flat-rate Price - CARE participants						$0.1060	$0.1082	$0.1102	$0.1121

Table 7: Change in Consumer Surplus Switching from No-CARE to w/CARE With Flat-rate Tariff Under Alternative Demand Elasticities (Weighted Ranking Method A - calibration from ecological regression)

which about two-thirds were "outreach" and "processing, certification and verification."[48] In comparing the deadweight loss calculations in Tables 5 and 7, however, adding $4.2

[48] See Southern California Edison (2007).

million to the CARE costs doesn't qualitatively change the analysis.

X. Conclusion

Increasing-block pricing has long been seen as a way to ensure nearly every household can afford a basic quantity of electricity while raising additional revenue from wealthier customers. As electricity costs rise, due to increases in fuel prices and additional greenhouse gas permit costs, electric utilities and their regulators are again focusing on ways to balance equity concerns with efficiency and the need to meet the company's budget constraints. As a result, there is renewed interest in IBP. The IBP tariffs currently in use by California's large utilities increase marginal price with usage much more steeply than other current or proposed IBP tariffs in other states, so they are a useful guidepost to the effects that such tariffs may have.

While it is generally agreed that wealthier customers on average consume larger quantities of electricity per person, it is less clear how strong that association is between wealth and household consumption after adjusting for differential numbers of household members. The impact of the steeply-tiered rates in protecting low-income customers is also no doubt mitigated by the existence of the CARE program that offers lower rates to low-income households in California. Similar programs exist in most states in the U.S.[49]

With access to residence-level electricity consumption, but only census block group data on income distribution, I have attempted to create an effective matching of households to incomes in order to infer the income redistribution impact of alternative electricity tariffs. Some previous studies facing similar challenges have assigned the median household income of each census block group to all households in the CBG. Actual household incomes within CBGs, however, are quite heterogeneous. Matching to median income compresses the apparent income distribution substantially and does not take account of the within-CBG correlation of household incomes with the program variable of interest. The approach explored here seems likely to be adaptable to other situations in which household-level data are available on the program variable, but income data are not.

I find that California's IBP tariffs do redistribute income on average from wealthier to poorer households, but the effect is fairly modest. This is due in part to the CARE program, which targets a lower overall electricity tariff at households that are deemed to be low income. If the CARE program were not present, I find that the IBP would reduce

[49] In California, eligibility criteria for CARE have been expanded since 2000 leading to a more than doubling of participation in the program between 2000 and 2006.

the bills of households in the lowest income bracket (approximately a quintile) by \$9-\$11 per month or around 13%-16%. The redistributional impact of the current CARE program by itself is probably somewhat larger than the impact of the steep IBP tariffs in California, but the two programs are partial substitutes in redistributing income, so combining them benefits low income households by substantially less than the sum of their separate effects.

I find that most income redistribution under IBP comes from households in the top income bracket, while the CARE program spreads the contribution burden more evenly among middle income and wealthy households, so IBP does seem to be more progressive. The CARE program, however, creates substantially less deadweight loss, because the prices that would result from the CARE program alone would more closely reflect the current marginal cost of electricity. Thus, it seems that if marginal cost is near or well below average cost, a mean-tested tariff for poor households is likely to be a more economically efficient way to ease the burden of electricity costs for low-income customers. If a utility is facing marginal cost well above average cost, however, IBP tariffs can potentially both benefit low-income households and reduce deadweight loss by setting high marginal prices for most customers.

Two issues that have not been addressed here are worth at least a brief mention. First, the redistributional analysis has focused on reducing average energy costs for low-income households, an issue of "vertical equity" in public finance terms. There are also potentially important issues of horizontal equity if similarly positioned households – where position can include both income and electricity "need" – are treated differently in terms of prices or, perhaps, bills. Applying horizontal equity concepts to increasing-block pricing is complex. The challenge is also apparent with means-tested programs, such as CARE. If imperfect information or aversion to sharing household details causes some eligible customers to enroll in CARE while others don't, that too raises issues of horizontal equity.

Second, I have not addressed the question of why electricity regulators should consider income distribution or affordability of electricity at all in setting tariff structures. The standard economic argument is that such issues are best addressed through economy-wide tax policy, not in the pricing of specific goods. While there is a great deal of logic and intellectual support for that framework, there is little indication that it is winning the argument in the regulatory arena. The fact is that nearly all electricity regulators feel pressure or the desire to address the issue of affordability of this specific good. The aim of this paper is to provide information that can at least allow that goal to be pursued more efficiently.

Appendix A: Details of Within-CBG Ranking Methods

In this appendix, I describe in detail the calibration methods based on ecological regression estimation of household usage and based on average bill by income category infered from the American Community Survey. First, I explain how CARE participation information is integrated into all of the within-CBG ranking. This applies to the usage-rank and random-rank methods as well as the calibration methods.

Utilization of CARE participation information in ranking methods

Reports from the utilities suggest that the CARE participation rate was 70%-80% among eligible households in 2006. The figures, however, appear to come from dividing the number of participating households by an estimate of the number of eligible households, based on census data. Implicitly, that assumes that all households on CARE are eligible. There is some evidence that this is not a good approximation.

One issue is that households may be qualified when they sign up, but then become ineligible due to an income increase or a decrease in the number of household residents. The calculation implicitly assumes that households report immediately when they become ineligible, which seems to be fairly rare. Instead, it appears from CARE dropout rates, which spike at the end of the two-year eligibility recertification period, that households that are no longer eligible simply do not recertify at renewal time. Given that 5% to 10% of households that are on CARE do not recertify when their renewal is required, it seems quite likely that at least a few percent of households on CARE have become ineligible since they enrolled.

In addition, some households may not be eligible at the time they join. The sign-up process requires a statement of eligibility, but does not require supporting evidence to be submitted. Much of CARE enrollment comes from contacting households that have qualified for other low-income programs, but one can also sign up through the websites of the utilities or by mail. In their monthly and annual reports, the utilities report the results of random eligibility verification which is requested from about 1% of participants annually. A surprisingly high number of participants selected for the random verification do not respond to the request for supporting information, over half in 2006 for SCE and PG&E, about one-quarter for SDG&E, and as a result are subject to being dropped from the CARE program (though it is unclear how quickly that happens). A much smaller share are found to be ineligible based on documentation submitted. It is difficult to know how many of the non-respondents are unable or unwilling to provide documentation, but are actually eligible. Still, that seems unlikely to be the explanation for all of the non-respondents.

Despite these concerns, in the study I have assumed a CARE penetration rate based on 78% participation (for SCE) for the algorithm described below. Based on the failure to recertify at the two-year interval and the low rate of response to requests for eligibility for verification, it seems that a participation rate of 65% is quite plausible, but there has been no study of ineligible participants on CARE.[50] A lower rate of CARE participation would mean that fewer of the households in the lowest income bracket and more of the households in higher income brackets are assumed to be CARE participants. Assuming that fewer of the CARE participants are in the lowest bracket leads to the conclusion of somewhat higher redistribution resulting from increasing-block pricing. If a much larger share of CARE participants were actually ineligible, then the redistributive impact of CARE would be smaller than is commonly assumed and the redistributive impact of increasing-block pricing would be greater than I have concluded.

To incorporate the CARE information and allocate CARE customers across income brackets, the CBG income distribution data are first used to determine the share of the households in the CBG that will fall into each of the five income brackets. From the billing data, we know the total number of CARE customers in the CBG. So, starting from the lowest income bracket 78% of the household "slots" are allocated to CARE customers.[51]

For instance, if the total number of CARE customers in the CBG is less than 78% of the household "slots" in the lowest income bracket, then all CARE customers are assumed to fall in the lowest income bracket.[52] If the total number of CARE customers in the CBG is greater than 78% of the household slots in the lowest bracket, then 78% of the slots in that bracket are allocated to CARE customers and remaining CARE customers are carried over to the second lowest income bracket. The same algorithm is then applied to the second lowest income bracket and if there are remaining customers, they are carried over to the third lowest income bracket, and so on. In the extremely small number of cases where this algorithm yielded leftover CARE customers beyond the highest income bracket, *i.e.,* the number of CARE customers exceeded 78% of the total number of households that received utility bills in the CBG, the CARE customers were simply divided proportionately across the population.

To be concrete, assume that a census block group has H households that receive electricity bills and the billing data indicate that H_c of them are on the CARE program. Assume that, according to the census, the shares of population in the income brackets are $s_1, ..., s_5$ where s_1 is the lowest income bracket. Finally, assume that the share of customers eligible for CARE who actually sign up, *i.e.,* the CARE participation rate, is p. Then, with s_{ic} representing the share of all customers in the CBG who are in income bracket i and are on the CARE program, the allocation can be broken into six cases:

[50] There are many reasons that an eligible household might not respond to the request for verification, including language barriers, concern about privacy, and undocumented immigration status.

[51] I present the algorithm in terms of household "slots," but it is somewhat more complicated because many households are in the sample for less than the full 365 days of the year. In practice, this means that household-days, rather than households, are allocated across the income brackets.

[52] Virtually all of these customers should be signing up for the CARE program, but the participation rate is well below 100%, as discussed above.

1. If $Hps_1 > H_c$ then $s_{1c} = \frac{H_c}{H},\ s_{2c} = s_{3c} = s_{4c} = s_{5c} = 0;$

2. If $Hps_1 < H_c < Hp(s_1 + s_2)$ then $s_{1c} = ps_1,\ s_{2c} = \frac{H_c - s_{1c}H}{Hs_2},\ s_{3c} = s_{4c} = s_{5c} = 0;$

3. If $Hp(s_1 + s_2) < H_c < Hp(s_1 + s_2 + s_3)$ then
$s_{1c} = ps_1,\ s_{2c} = ps_2,\ s_{3c} = \frac{H_c - (s_{1c} + s_{2c})H}{Hs_3},\ s_{4c} = s_{5c} = 0;$

4. If $Hp(s_1 + s_2 + s_3) < H_c < Hp(s_1 + s_2 + s_3 + s_4)$ then
$s_{1c} = ps_1,\ s_{2c} = ps_2,\ s_{3c} = ps_3,\ s_{4c} = \frac{H_c - (s_{1c} + s_{2c} + s_{3c})H}{Hs_4},\ s_{5c} = 0;$

5. If $Hp(s_1 + s_2 + s_3 + s_4) < H_c < Hp(s_1 + s_2 + s_3 + s_4 + s_5)$ then
$s_{1c} = ps_1,\ s_{2c} = ps_2,\ s_{3c} = ps_3,\ s_{4c} = ps_4,\ s_{5c} = \frac{H_c - (s_{1c} + s_{2c} + s_{3c} + s_{4c})H}{Hs_5};$

6. If $Hp < H_c$ then $s_{1c} = \frac{H_c}{H}s_1,\ s_{2c} = \frac{H_c}{H}s_2,\ s_{3c} = \frac{H_c}{H}s_3,\ s_{4c} = \frac{H_c}{H}s_4,\ s_{5c} = \frac{H_c}{H}s_5.$

For each case, the share of all customers who are in income bracket i and are not on the CARE program, is $s_{in} = s_i - s_{ic}$.

This approach determined the average CARE penetration in each income bracket. That average rate was assumed to hold in every CBG up to a constant mulitplier. So, for instance, if applying these penetration rates within a CBG would create fewer CARE customers than were actually in the CBG, penetration rates in all income brackets were scaled up to exactly match the actual number of CARE customers. Wherever possible, the ratio of penetration rates across income categories was held constant. In the instances where this was not possible because it implied a penetration rate of greater than 100%, that income bracket was assumed to be 100% CARE customers and the "overflow" was allocated to the other brackets so as to maintain their relative penetration rates. The share of all customers allocated to each income bracket who are on CARE using this allocation approach is shown in Table 6.

Detailed description of weighted ranking method A: ecological regression

To obtain estimates of average electricity usage by income bracket, I run the following regression with observations at the census block group level (CBG):

$$\bar{q}_g = \sum_{b=1}^{5} \big[\alpha_b s_{bg} + \beta_b s_{bg} HI_g + \gamma_{1b} s_{bg} CDD_g + \gamma_{2b} s_{bg} CDDsq_g + \gamma_{3b} s_{bg} HDD_g + \gamma_{4b} s_{bg} HDDsq_g\big] + \eta \qquad [A1]$$

where HI_g is the median household income in census block group g, CDD is the sum of daily cooling degree days in the CBG, $CDDsq$ is the sum of squares of daily cooling degree days in the CBG (*i.e.*, $\sum_{t=1,365} CDD_t^2$, not $(\sum_{t=1,365} CDD_t)^2$), HDD is the sum of daily heating degree days in the CBG, $HDDsq$ is the sum of squares of daily heating degree days in the CBG.

The top panel of Table A1 shows the results of this regression for SCE. The estimated average consumption of a household in income bracket b in census block group g is then

$$\hat{\bar{q}_{bg}} = \hat{\alpha_b} + \hat{\beta_b} HI_g + \hat{\gamma_{1b}} CDD_g + \hat{\gamma_{2b}} CDDsq_g + \hat{\gamma_{3b}} HDD_g + \hat{\gamma_{4b}} HDDsq_g. \qquad [A2]$$

.

Using the coefficients from [A2], the estimated average consumption of households in income bracket b is then

$$\hat{\bar{\bar{q}}}_b = \hat{\alpha_b} + \hat{\beta_b} H\bar{I}_b + \hat{\gamma_{1b}} C\bar{D}D_b + \hat{\gamma_{2b}} C\bar{D}Dsq_b + \hat{\gamma_{3b}} H\bar{D}D_b + \hat{\gamma_{4b}} H\bar{D}Dsq_b. \qquad [A3]$$

where $H\bar{I}_b$ is the weighted-average median household income where the weights are the share of bracket b customers in each census block group and likewise for the other terms (thus the b subscripts on the right-hand side variables).[53]

The resulting $\hat{\bar{\bar{q}}}_b$ are shown just below the regression in Table A1. Each possible weighting of the usage and random ranks, w, generates a within-CBG ranking of households by income and a resulting $\tilde{\bar{q}_{bg}}(w)$ for each income bracket in each CBG. From these, I calculate the weighted-average systemwide $\tilde{\bar{q}}_b(w)$, which are then used to calculate the goodness-of-fit measure

$$G = \sum_{b=1}^{5} s_b \cdot [\tilde{\bar{q}}_b(w) - \hat{\bar{\bar{q}}}_b]^2$$

where s_b is the share of the population in income bracket b. The value of w that minimizes G is then w^*, the weighting of the random-rank and usage-rank methods that best calibrates the ancillary attribute. 1000 bootstrap estimates of equation $[A1]$ then yield the distribution of w^* from which the distribution of income transfers are derived.

Detailed description of weighted ranking method B: survey on average electricity bill

The American Community Survey yields approximately 120,000 household surveys for California during 2006. The only location information for each household is the Public Use Microdata Area (PUMA), each of which includes about 100,000 households, so many PUMAs overlap the boundary of each utility's service territory and there is no way to know which households in those PUMAs are in the utility's territory. To match households to service territories, I first extract from the billing data 7-digit zip codes for each utility's service area.[54] I then match them to the 7-digit zip codes included in each PUMA. If the utility shows residential customers in ϕ percent of the 7-digit zip codes included in

[53] For each of the three utilities, the median household income interaction terms, as well as the cooling degree days and heating degree days interaction terms, were jointly significant.

[54] I use 7-digit zip code because 9-digit zip codes include many building-specific or other small area designations in which there are no residences.

PUMA$_j$, then each household in PUMA$_j$ is given weight ϕ. The census also reports household weights that align the demographics of the sample with the demographics of the PUMA. The overall weighting of each observation is the product of these two weights. When multiplied by the households in the survey, this yields about 1% as many households in the survey as each utility actually serves.

Each household reports a monthly average electricity expenditure and an annual income. To get comparable income brackets to the long-form census data, I break the ACS survey households into five income brackets at the same percentiles as resulted from the breaks used for the redistribution categories, *e.g.,* in the case of SCE, at 17.9%, 40.0%, 58.9% and 82.6%. These yielded income breaks very close to, but not exactly the same as the $20,000, $40,000, $60,000 and $100,000 breaks. The results are barely changed using the same dollar breaks rather than the same percentile breaks.

With the household level monthly average electricity bill B_i and the household income bracket, I take means by weighted OLS estimation (to facilitate the bootstrap w^* calibration) on all households that have positive weight:

$$B_i = \alpha_1 I_1 + \alpha_2 I_2 + \alpha_3 I_3 + \alpha_4 I_4 + \alpha_5 I_5 + \epsilon \qquad [A4]$$

where I_n are dummy variables for the five income brackets into which the household might fall. The bottome panel of Table A1 reports the regression results for SCE. The coefficients in this case require no translation; they are the estimated mean bills by income bracket.

The goodness-of-fit calculation and bootstrap estimation of the distribution of w^* are then analogous to method A. Before the goodness-of-fit calculations, however, I make two additional adjustments to account for the fact that these are imperfectly reported household electricity billing data that are then being compared to actual usage data reported by the utility. First, household bills include daily connection charges as well as energy charges, so I add the daily connection charges to the bills that were calculated from the utility data. Second, even after correcting for daily connection charges, the survey reports of bills are substantially higher on average than the utility data. This is particularly true for PG&E and SDG&E, which send combined bills for gas and electricity.[55] Because of the squared losses nature of G, a misalignment of the distributions could distort the goodness-of-fit calculation, so I scale all of the utility-based bills up so that they have the same mean for each utility as the average bill reported in the ACS survey for (probabilistically weighted) households in the utility's service territory. This adjustment turns out, however, to have very little effect.[56]

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[55] This raises interesting cognition and salience issues that I am pursuing in a separate project.

[56] One further adjustment was to correct for the ACS top coding of monthly electricity bills at $540 per month, which creates a spike in the bill distribution at $540. From the utility billing data, I calculated the average bill for all customers with average monthly bills at or above $540 per month and then raised every survey reported bill of $540 to that calculated average.

Linear regression
Dependent Variable: CBG-level average daily usage

Number of obs	=	7307
F(29, 7277)	=	281.03
Prob > F	=	0.0000
R-squared	=	0.6305
Root MSE	=	4.5091

used	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
incsh1	12.85795	4.645283	2.77	0.006	3.751844	21.96405
incsh2	-8.668455	6.842066	-1.27	0.205	-22.08089	4.743979
incsh3	-5.398217	8.862259	-0.61	0.542	-22.77082	11.97438
incsh4	37.72531	7.580835	4.98	0.000	22.86467	52.58594
incsh5	-2.047782	6.758522	-0.30	0.762	-15.29644	11.20088
incsh1hh	.0000695	.0000461	1.51	0.131	-.0000208	.0001598
incsh2hh	.0001998	.0000582	3.44	0.001	.0000858	.0003138
incsh3hh	.000023	.0000606	0.38	0.704	-.0000957	.0001417
incsh4hh	-.0000279	.0000461	-0.61	0.545	-.0001184	.0000625
incsh5hh	.0002861	.0000299	9.57	0.000	.0002275	.0003447
incsh1CDD	-.0012894	.0040555	-0.32	0.751	-.0092393	.0066605
incsh2CDD	.0046847	.0064313	0.73	0.466	-.0079225	.0172919
incsh3CDD	.0029377	.0065664	0.45	0.655	-.0099343	.0158096
incsh4CDD	-.005609	.0060889	-0.92	0.357	-.017545	.006327
incsh5CDD	-.0254187	.0073676	-3.45	0.001	-.0398614	-.010976
incsh1CDDsq	.0001171	.0002042	0.57	0.566	-.0002831	.0005173
incsh2CDDsq	-.0000957	.0003307	-0.29	0.772	-.000744	.0005526
incsh3CDDsq	.0001438	.000328	0.44	0.661	-.0004993	.0007868
incsh4CDDsq	.0003045	.0003261	0.93	0.350	-.0003347	.0009438
incsh5CDDsq	.0021699	.0004424	4.90	0.000	.0013027	.0030371
incsh1HDD	-.0027365	.0032033	-0.85	0.393	-.009016	.003543
incsh2HDD	.008265	.0042177	1.96	0.050	-2.94e-06	.016533
incsh3HDD	.0134115	.0059132	2.27	0.023	.0018199	.025003
incsh4HDD	-.0147387	.005279	-2.79	0.005	-.025087	-.0043903
incsh5HDD	.0074028	.0044665	1.66	0.097	-.0013528	.0161584
incsh1HDDsq	.0001316	.0001147	1.15	0.251	-.0000933	.0003566
incsh2HDDsq	-.0001589	.0001457	-1.09	0.275	-.0004445	.0001267
incsh3HDDsq	-.0004003	.0002125	-1.88	0.060	-.0008168	.0000162
incsh4HDDsq	.0005271	.0002039	2.59	0.010	.0001275	.0009268
incsh5HDDsq	-.0000504	.0001865	-0.27	0.787	-.0004161	.0003152

Implied Daily Average Usage by Income Bracket (kWh/day):
(1) 14.787307 (2) 15.908655 (3) 15.889795 (4) 21.391435 (5) 27.921385

Linear regression
Dependent Variable: Monthly Average Electricity Bill

Number of obs	=	60226
F(4, 60221)	=	657.60
Prob > F	=	0.0000
R-squared	=	0.0868
Root MSE	=	104.34

elep	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
IncBracket1	65.98634	.9160116	72.04	0.000	64.19096	67.78173
IncBracket2	78.3088	.9751486	80.30	0.000	76.39751	80.22009
IncBracket3	93.38179	1.317554	70.88	0.000	90.79938	95.9642
IncBracket4	114.8657	1.255318	91.50	0.000	112.4053	117.3262
IncBracket5	161.9275	1.919041	84.38	0.000	158.1662	165.6888

TABLE A1: Regressions for Weighted-Ranking Methods A and B
(Note: reported R-squared and F values are for regressions with constant term)

Appendix B-1: Tables for Pacific Gas & Electric

Tier	% of Baseline Quantity	Standard Residential Rate	CARE Low-income Rate
Actual 2006 tariff (time-weighted average in 2006)			
1	0-100%	$0.1143	$0.0832
2	100%-130%	$0.1299	$0.0956
3	130%-200%	$0.2178	$0.0956
4	200%-300%	$0.2987	$0.0956
5	300%+	$0.3394	$0.0956
Alternative Flat-Rate Tariff with CARE program			
	0%+	$0.1643	$0.0874
Alternative Two-Tier Tariff with CARE program			
1	0-100%	$0.1527	$0.0824
2	100%+	$0.1801	$0.0972

Tier	% of Baseline Quantity	Standard Residential Rate
Benchmark Five-Tier Tariff with no CARE program		
1	0-100%	$0.1024
2	100%-130%	$0.1180
3	130%-200%	$0.2059
4	200%-300%	$0.2868
5	300%+	$0.3275
Alternative Flat-Rate Tariff with no CARE program		
	0%+	$0.1498
Alternative Two-Tier Tariff with no CARE program		
1	0-100%	$0.1395
2	100%+	$0.1647

Table 1: 2006 Pacific Gas & Electric Retail Electricity Rates

	Residential Usage (million-kWh)	Percentage of Residential Usage					CARE/Non-CARE Shares	
		tier 1	tier 2	tier 3	tier 4	tier 5	% Usage	% customers
Non-CARE	24,312	57.7%	10.7%	15.5%	9.2%	6.8%	81.1%	79.2%
CARE	5,660	66.2%	10.2%	13.2%	6.7%	3.7%	18.9%	20.8%

	Percentage of Customers on Each Tier for Marginal Consumption				
	tier 1	tier 2	tier 3	tier 4	tier 5
Non-CARE	38.4%	14.3%	24.1%	15.1%	8.2%
CARE	47.6%	15.5%	21.5%	11.0%	4.5%

NOTE: reported results drop household accounts with consumption of less than 1 kWh/day

Table 2: Distribution of PG&E Residential Customer Consumption Across Tariff Tiers

	Income Range	Share of Customers	Average Daily Use (kWh)	Average Annualized Bill *Flat*	*2-tier*	*5-tier*	Change from Flat to 5-tier: Dollar Chg	95% conf intvl	Percent Change	95% conf intvl
random	$0-$20k	17.0%	17.69	$967	$958	$916	-$51		-5.3%	
rank	$20k-$40k	20.5%	18.49	$1,011	$1,006	$979	-$32		-3.2%	
method	$40k-$60k	18.0%	19.08	$1,043	$1,042	$1,032	-$10		-1.0%	
	$60k-$100k	23.6%	19.68	$1,075	$1,078	$1,084	$8		0.8%	
	>$100k	20.9%	20.92	$1,143	$1,153	$1,216	$73		6.4%	
weighted	**$0-$20k**	**17.0%**	**14.61**	**$799**	**$782**	**$701**	**-$98**	**[-$117, -$70]**	**-12.4%**	**[-17.0%, -7.7%]**
rank	**$20k-$40k**	**20.5%**	**17.53**	**$958**	**$949**	**$899**	**-$59**	**[-$88, -$35]**	**-6.2%**	**[-9.8%, -3.5%]**
method A	**$40k-$60k**	**18.0%**	**19.06**	**$1,042**	**$1,040**	**$1,023**	**-$19**	**[-$42, -$11]**	**-1.8%**	**[-4.2%, -1.0%]**
	$60k-$100k	**23.6%**	**20.03**	**$1,095**	**$1,098**	**$1,106**	**$11**	**[$9, $12]**	**1.0%**	**[0.7%, 1.1%]**
	>$100k	**20.9%**	**23.97**	**$1,310**	**$1,331**	**$1,451**	**$141**	**[$89, $209]**	**10.7%**	**[7.5%, 14.3%]**
weighted	**$0-$20k**	**17.0%**	**16.31**	**$892**	**$879**	**$816**	**-$76**	**[-$81, -$70]**	**-8.5%**	**[-9.3%, -7.7%]**
rank	**$20k-$40k**	**20.5%**	**18.28**	**$999**	**$994**	**$962**	**-$38**	**[-$40, -$35]**	**-3.8%**	**[-4.1%, -3.5%]**
method B	**$40k-$60k**	**18.0%**	**19.17**	**$1,048**	**$1,047**	**$1,037**	**-$11**	**[-$10, -$11]**	**-1.0%**	**[-1.0%, -1.0%]**
	$60k-$100k	**23.6%**	**19.79**	**$1,082**	**$1,084**	**$1,092**	**$10**	**[$10, $11]**	**1.0%**	**[0.9%, 1.0%]**
	>$100k	**20.9%**	**22.03**	**$1,204**	**$1,218**	**$1,301**	**$96**	**[$89, $103]**	**8.0%**	**[7.5%, 8.4%]**
usage	$0-$20k	17.0%	8.88	$485	$461	$354	-$132		-27.1%	
rank	$20k-$40k	20.5%	14.37	$785	$766	$661	-$124		-15.8%	
method	$40k-$60k	18.0%	16.15	$883	$865	$768	-$115		-13.0%	
	$60k-$100k	23.6%	20.67	$1,130	$1,124	$1,042	-$87		-7.7%	
	>$100k	20.9%	33.52	$1,832	$1,893	$2,259	$427		23.3%	

Excludes bills with daily consumption < 1kWh/day

Includes all CARE and non-CARE customers, all on no-CARE-program rates from table 1

Distribution of w* for weighted rank method A
(calibrated from ecological regression results)

Point Estimate	0.21
Mean of bootstrap	0.23
Median of bootstrap	0.23
95% conf interval	[0.07,0.38]

Distribution of w* for weighted rank method B
(calibrated from American Community Survey)

Point Estimate	0.10
Mean of bootstrap	0.10
Median of bootstrap	0.10
95% conf interval	[0.07,0.12]

Table 4: PG&E Average Bill By Income Bracket Under Benchmark and Alternative Flat-Rate Tariff Using Random-Rank, Usage-Rank and Weighted-Rank Within-CBG Allocation Methods

	Income Range	Share on CARE	Average Annualized Bill: No-CARE Flat Tariff	No-CARE 2-tier Tariff	No-CARE 5-tier Tariff	with CARE Flat Tariff	with CARE 2-tier Tariff	with CARE 5-tier Tariff	Monetary Bill Chage from No-CARE/Flat: No-CARE 5-tier Tariff	w/CARE Flat Tariff	w/CARE 5-tier Tariff	Percentage Bill Chage from No-CARE/Flat: No-CARE 5-tier Tariff	w/CARE Flat Tariff	w/CARE 5-tier Tariff
weighted	$0-$20k	64.9%	$799	$782	$701	$587	$577	$545	-$98	-$212	-$254	-12%	-27%	-32%
rank	$20k-$40k	38.6%	$958	$949	$899	$854	$847	$811	-$59	-$104	-$147	-6%	-11%	-15%
method A	$40k-$60k	9.1%	$1,042	$1,040	$1,023	$1,085	$1,080	$1,050	-$19	$43	$8	-2%	4%	1%
	$60k-$100k	1.0%	$1,095	$1,098	$1,106	$1,193	$1,192	$1,182	$11	$98	$88	1%	9%	8%
	>$100k	0.0%	$1,310	$1,331	$1,451	$1,437	$1,456	$1,555	$141	$127	$245	11%	10%	19%
weighted	$0-$20k	64.9%	$892	$879	$816	$673	$667	$645	-$76	-$219	-$247	-9%	-25%	-28%
rank	$20k-$40k	38.6%	$999	$994	$962	$904	$901	$883	-$38	-$95	-$117	-4%	-9%	-12%
method B	$40k-$60k	9.1%	$1,048	$1,047	$1,037	$1,099	$1,096	$1,076	-$11	$51	$28	-1%	5%	3%
	$60k-$100k	1.0%	$1,082	$1,084	$1,092	$1,179	$1,179	$1,170	$10	$98	$88	1%	9%	8%
	>$100k	0.0%	$1,204	$1,218	$1,301	$1,321	$1,333	$1,396	$96	$117	$191	8%	10%	16%

All results are from weighted rank method
Excludes bills with daily consumption < 1kWh/day
Includes all CARE and non-CARE customers

Table 6: PG&E Estimated Average Annual Bills With and Without IBP and CARE

MC=0.0998

		Change in Annual Average Household Consumer Surplus From Switch to 5-tier tariff				Change in Aggregate Annual Consumer Surplus ($M/yr) From Switch to 5-tier tariff			
Income Range	Share of Customers	ε=0	ε=-0.1	ε=-0.2	ε=-0.3	ε=0	ε=-0.1	ε=-0.2	ε=-0.3
$0-$20k	17.0%	$98	$79	$59	$38	$71	$57	$43	$27
$20k-$40k	20.5%	$59	$35	$8	-$21	$52	$18	-$11	-$42
$40k-$60k	18.0%	$19	-$10	-$42	-$76	$14	-$8	-$32	-$59
$60k-$100k	23.6%	-$11	-$43	-$78	-$116	-$11	-$43	-$78	-$117
>$100k	20.9%	-$141	-$185	-$232	-$285	-$126	-$165	-$207	-$254
Aggregate Increase in DWL from IBP ($M/yr)						$0	$141	$286	$444
Ratio of DWL to transfers to two lowest income brackets						0.00	1.87	8.94	-29.84
Flat-rate Price						$0.1498	$0.1481	$0.1464	$0.1445

MC=0.1498

		Change in Annual Average Household Consumer Surplus From Switch to 5-tier tariff				**Change in Aggregate Annual Consumer Surplus ($M/yr) From Switch to 5-tier tariff**			
Income Range	**Share of Customers**	**ε=0**	**ε=-0.1**	**ε=-0.2**	**ε=-0.3**	**ε=0**	**ε=-0.1**	**ε=-0.2**	**ε=-0.3**
$0-$20k	**17.0%**	**$98**	**$88**	**$77**	**$67**	**$71**	**$64**	**$56**	**$48**
$20k-$40k	**20.5%**	**$59**	$45	$30	$14	**$52**	**$39**	**$26**	**$13**
$40k-$60k	**18.0%**	**$19**	**$1**	**-$17**	**-$36**	**$14**	**$1**	**-$13**	**-$28**
$60k-$100k	**23.6%**	**-$11**	**-$31**	**-$52**	**-$73**	**-$11**	**-$31**	**-$52**	**-$74**
>$100k	**20.9%**	**-$141**	**-$170**	**-$201**	**-$233**	**-$126**	**-$152**	**-$179**	**-$207**
Aggregate Increase in DWL from IBP ($M/yr)						**$0**	**$80**	**$162**	**$248**
Ratio of DWL to transfers to two lowest income brackets						**0.00**	**0.77**	**1.97**	**4.06**
Flat-rate Price						**$0.1498**	**$0.1498**	**$0.1498**	**$0.1498**

MC=0.1998

		Change in Annual Average Household Consumer Surplus From Switch to 5-tier tariff				Change in Aggregate Annual Consumer Surplus ($M/yr) From Switch to 5-tier tariff			
Income Range	Share of Customers	ε=0	ε=-0.1	ε=-0.2	ε=-0.3	ε=0	ε=-0.1	ε=-0.2	ε=-0.3
$0-$20k	17.0%	$98	$96	$93	$91	$71	$69	$68	$66
$20k-$40k	20.5%	$59	$55	$50	$44	$52	$48	$43	$39
$40k-$60k	18.0%	$19	$12	$4	-$4	$14	$9	$3	-$3
$60k-$100k	23.6%	-$11	-$20	-$29	-$38	-$11	-$20	-$29	-$39
>$100k	20.9%	-$141	-$157	-$173	-$189	-$126	-$140	-$154	-$169
Aggregate Increase in DWL from IBP ($M/yr)						$0	$34	$69	$106
Ratio of DWL to transfers to two lowest income brackets						0.00	0.29	0.62	1.01
Flat-rate Price						$0.1498	$0.1511	$0.1526	$0.1540

MC=0.2498

		Change in Annual Average Household Consumer Surplus From Switch to 5-tier tariff				Change in Aggregate Annual Consumer Surplus ($M/yr) From Switch to 5-tier tariff			
Income Range	Share of Customers	ε=0	ε=-0.1	ε=-0.2	ε=-0.3	ε=0	ε=-0.1	ε=-0.2	ε=-0.3
$0-$20k	17.0%	$98	$103	$107	$111	$71	$75	$78	$80
$20k-$40k	20.5%	$59	$64	$67	$69	$52	$56	$58	$60
$40k-$60k	18.0%	$19	$21	$23	$24	$14	$16	$18	$19
$60k-$100k	23.6%	-$11	-$9	-$9	-$9	-$11	-$9	-$9	-$9
>$100k	20.9%	-$141	-$144	-$148	-$153	-$126	-$129	-$132	-$136
Aggregate Increase in DWL from IBP ($M/yr)						$0	-$9	-$13	-$14
Ratio of DWL to transfers to two lowest income brackets						0.00	-0.07	-0.10	-0.10
Flat-rate Price						$0.1498	$0.1525	$0.1552	$0.1577

Table 5: PG&E Change in Consumer Surplus Switching from Flat-rate to 5-tier Tariff Under Alternative Demand Elasticities (Weighted Ranking Method A - calibration from ecological regression)

MC=0.0.998

Income Range	Share of Customers	Change in Annual Average Household Consumer Surplus From adding CARE program ε=0	ε=-0.1	ε=-0.2	ε=-0.3	Change in Aggregate Annual Consumer Surplus ($M/yr) From adding CARE program ε=0	ε=-0.1	ε=-0.2	ε=-0.3
$0-$20k	17.0%	$212	$217	$224	$231	$154	$158	$162	$167
$20k-$40k	20.5%	$104	$107	$110	$113	$91	$93	$96	$99
$40k-$60k	18.0%	-$43	-$45	-$48	-$52	-$33	-$35	-$37	-$40
$60k-$100k	23.6%	-$98	-$103	-$110	-$117	-$99	-$104	-$111	-$118
>$100k	20.9%	-$127	-$136	-$146	-$157	-$113	-$121	-$130	-$140
Aggregate Increase in DWL from CARE ($M/yr)						$0	$9	$19	$31
Ratio of DWL to transfers to two lowest income brackets						0.00	0.03	0.07	0.12
Flat-rate Price - Standard Residential						$0.1643	$0.1630	$0.1617	$0.1602
Flat-rate Price - CARE participants						$0.0874	$0.0867	$0.0860	$0.0852

MC=0.1498

Income Range	Share of Customers	Change in Annual Average Household Consumer Surplus From adding CARE program ε=0	ε=-0.1	ε=-0.2	ε=-0.3	Change in Aggregate Annual Consumer Surplus ($M/yr) From adding CARE program ε=0	ε=-0.1	ε=-0.2	ε=-0.3
$0-$20k	17.0%	$212	$219	$227	$235	$154	$159	$164	$170
$20k-$40k	20.5%	$104	$107	$111	$114	$91	$94	$97	$100
$40k-$60k	18.0%	-$43	-$47	-$51	-$56	-$33	-$36	-$39	-$43
$60k-$100k	23.6%	-$98	-$105	-$113	-$122	-$99	-$106	-$114	-$124
>$100k	20.9%	-$127	-$138	-$151	-$164	-$113	-$123	-$134	-$146
Aggregate Increase in DWL from CARE ($M/yr)						$0	$13	$27	$42
Ratio of DWL to transfers to two lowest income brackets						0.00	0.05	0.10	0.16
Flat-rate Price - Standard Residential						$0.1643	$0.1648	$0.1655	$0.1663
Flat-rate Price - CARE participants						$0.0874	$0.0877	$0.0881	$0.0885

MC=0.1998

Income Range	Share of Customers	Change in Annual Average Household Consumer Surplus From adding CARE program ε=0	ε=-0.1	ε=-0.2	ε=-0.3	Change in Aggregate Annual Consumer Surplus ($M/yr) From adding CARE program ε=0	ε=-0.1	ε=-0.2	ε=-0.3
$0-$20k	17.0%	$212	$220	$229	$239	$154	$160	$166	$173
$20k-$40k	20.5%	$104	$107	$111	$115	$91	$94	$97	$101
$40k-$60k	18.0%	-$43	-$48	-$53	-$59	-$33	-$37	-$41	-$45
$60k-$100k	23.6%	-$98	-$107	-$117	-$127	-$99	-$108	-$118	-$128
>$100k	20.9%	-$127	-$141	-$155	-$170	-$113	-$125	-$138	-$152
Aggregate Increase in DWL from CARE ($M/yr)						$0	$16	$33	$51
Ratio of DWL to transfers to two lowest income brackets						0.00	0.06	0.13	0.19
Flat-rate Price - Standard Residential						$0.1643	$0.1666	$0.1690	$0.1714
Flat-rate Price - CARE participants						$0.0874	$0.0886	$0.0899	$0.0912

MC=0.2498

Income Range	Share of Customers	Change in Annual Average Household Consumer Surplus From adding CARE program ε=0	ε=-0.1	ε=-0.2	ε=-0.3	Change in Aggregate Annual Consumer Surplus ($M/yr) From adding CARE program ε=0	ε=-0.1	ε=-0.2	ε=-0.3
$0-$20k	17.0%	$212	$222	$232	$242	$154	$161	$168	$175
$20k-$40k	20.5%	$104	$108	$112	$116	$91	$94	$98	$101
$40k-$60k	18.0%	-$43	-$49	-$55	-$61	-$33	-$38	-$42	-$47
$60k-$100k	23.6%	-$98	-$109	-$120	-$131	-$99	-$110	-$121	-$132
>$100k	20.9%	-$127	-$143	-$159	-$175	-$113	-$127	-$142	-$156
Aggregate Increase in DWL from CARE ($M/yr)						$0	$20	$39	$59
Ratio of DWL to transfers to two lowest income brackets						0.00	0.08	0.15	0.21
Flat-rate Price - Standard Residential						$0.1643	$0.1682	$0.1720	$0.1757
Flat-rate Price - CARE participants						$0.0874	$0.0895	$0.0915	$0.0935

Table 7: PG&E Change in Consumer Surplus Switching from No-CARE to w/CARE With Flat-rate Tariff Under Alternative Demand Elasticities (Weighted Ranking Method A - calibration from ecological regression)

Appendix B-2: Tables for San Diego Gas & Electric

Tier	% of Baseline Quantity	Standard Residential Rate	CARE Low-income Rate
Actual 2006 tariff (time-weighted average in 2006)			
1	0-100%	$0.1287	$0.1026
2	100%-130%	$0.1488	$0.1187
3	130%-200%	$0.2312	$0.1758
4	200%-300%	$0.2401	$0.1764
5	300%+	$0.2571	$0.1776
Alternative Flat-Rate Tariff with CARE program			
	0%+	$0.1690	$0.1168
Alternative Two-Tier Tariff with CARE program			
1	0-100%	$0.1565	$0.1115
2	100%+	$0.1846	$0.1316

Tier	% of Baseline Quantity	Standard Residential Rate
Benchmark Five-Tier Tariff with no CARE program		
1	0-100%	$0.1245
2	100%-130%	$0.1446
3	130%-200%	$0.2270
4	200%-300%	$0.2359
5	300%+	$0.2529
Alternative Flat-Rate Tariff with no CARE program		
	0%+	$0.1622
Alternative Two-Tier Tariff with no CARE program		
1	0-100%	$0.1508
2	100%+	$0.1779

Table 1: 2006 San Diego Gas & Electric Retail Electricity Rates

	Residential Usage (million-kWh)	Percentage of Residential Usage					CARE/Non-CARE Shares	
		tier 1	tier 2	tier 3	tier 4	tier 5	% Usage	% customers
Non-CARE	6,255	55.5%	10.3%	15.3%	10.0%	8.9%	87.0%	82.4%
CARE	931	73.6%	9.1%	10.4%	4.7%	2.2%	13.0%	17.6%

	Percentage of Customers on Each Tier for Marginal Consumption				
	tier 1	tier 2	tier 3	tier 4	tier 5
Non-CARE	38.9%	13.9%	22.6%	14.5%	10.2%
CARE	59.2%	14.7%	16.8%	6.8%	2.5%

NOTE: reported results drop household accounts with consumption of less than 1 kWh/day

Table 2: Distribution of SDG&E Residential Customer Consumption Across Tariff Tiers

	Income Range	Share of Customers	Average Daily Use (kWh)	Average Annualized Bill *Flat*	*2-tier*	*5-tier*	**Change from Flat to 5-tier** Dollar Chg	95% conf intvl	Percent Change	95% conf intvl
random	$0-$20k	16.4%	13.65	$808	$794	$753	-$55		-6.8%	
rank	$20k-$40k	22.4%	15.00	$888	$879	$852	-$36		-4.1%	
method	$40k-$60k	18.9%	16.57	$981	$979	$968	-$13		-1.3%	
	$60k-$100k	23.8%	18.27	$1,082	$1,086	$1,096	$14		1.3%	
	>$100k	18.5%	21.36	$1,265	$1,285	$1,353	$88		7.0%	
weighted	**$0-$20k**	**16.4%**	**12.47**	**$738**	**$721**	**$672**	**-$66**	**[-$89, -$27]**	**-9.5%**	**[-16.2%, 3.0%]**
rank	**$20k-$40k**	**22.4%**	**14.57**	**$863**	**$852**	**$817**	**-$45**	**[-$78, -$32]**	**-5.3%**	**[-10.3%, -3.5%]**
method A	**$40k-$60k**	**18.9%**	**16.52**	**$979**	**$975**	**$962**	**-$16**	**[-$36, -$13]**	**-1.7%**	**[-3.8%, -1.3%]**
	$60k-$100k	**23.8%**	**18.42**	**$1,091**	**$1,095**	**$1,105**	**$14**	**[$12. $15]**	**1.3%**	**[1.1%, 1.4%]**
	>$100k	**18.5%**	**22.79**	**$1,350**	**$1,376**	**$1,462**	**$112**	**[$59, $195]**	**8.1%**	**[5.1%, 11.0%]**
weighted	**$0-$20k**	**16.4%**	**12.23**	**$724**	**$706**	**$652**	**-$72**	**[-$67, -$79]**	**-10.0%**	**[-11.6%, 8.9%]**
rank	**$20k-$40k**	**22.4%**	**14.79**	**$876**	**$866**	**$835**	**-$41**	**[-$39, -$46]**	**-4.7%**	**[-5.3%, -4.4%]**
method B	**$40k-$60k**	**18.9%**	**16.64**	**$986**	**$983**	**$972**	**-$14**	**[-$13, -$14]**	**-1.4%**	**[-1.4%, -1.4%]**
	$60k-$100k	**23.8%**	**18.35**	**$1,086**	**$1,091**	**$1,101**	**$14**	**[$14. $15]**	**1.3%**	**[1.3%, 1.4%]**
	>$100k	**18.5%**	**22.71**	**$1,345**	**$1,370**	**$1,454**	**$109**	**[$101, $121]**	**8.1%**	**[7.7%, 8.7%]**
usage	$0-$20k	16.4%	6.49	$384	$360	$301	-$83		-21.6%	
rank	$20k-$40k	22.4%	10.63	$630	$604	$530	-$100		-15.9%	
method	$40k-$60k	18.9%	13.44	$796	$770	$688	-$108		-13.5%	
	$60k-$100k	23.8%	19.18	$1,136	$1,132	$1,089	-$47		-4.1%	
	>$100k	18.5%	35.02	$2,074	$2,157	$2,438	$364		17.6%	

Excludes bills with daily consumption < 1kWh/day

Includes all CARE and non-CARE customers, all on no-CARE-program rates from table 1

Distribution of w* for weighted rank method A
(calibrated from ecological regression results)

Point Estimate	0.08
Mean of bootstrap	0.09
Median of bootstrap	0.07
95% conf interval	[-0.20,0.38]

Distribution of w* for weighted rank method B
(calibrated from American Community Survey)

Point Estimate	0.10
Mean of bootstrap	0.11
Median of bootstrap	0.10
95% conf interval	[0.07,0.16]

Table 4: SDG&E Average Bill By Income Bracket Under Benchmark and Alternative Flat-Rate Tariff Using Random-Rank, Usage-Rank and Weighted-Rank Within-CBG Allocation Methods

	Income Range	Share on CARE	**Average Annualized Bill** No-CARE Flat Tariff	No-CARE 2-tier Tariff	No-CARE 5-tier Tariff	with CARE Flat Tariff	with CARE 2-tier Tariff	with CARE 5-tier Tariff	**Monetary Bill Chage from No-CARE/Flat** No-CARE 5-tier Tariff	w/CARE Flat Tariff	w/CARE 5-tier Tariff	**Percentage Bill Chage from No-CARE/Flat** No-CARE 5-tier Tariff	w/CARE Flat Tariff	w/CARE 5-tier Tariff
weighted	$0-$20k	58.5%	$738	$721	$672	$639	$631	$612	-$66	-$99	-$126	-9%	-13%	-17%
rank	$20k-$40k	30.6%	$863	$852	$817	$822	$815	$792	-$45	-$41	-$71	-5%	-5%	-8%
method A	$40k-$60k	5.1%	$979	$975	$962	$1,004	$998	$977	-$16	$25	-$1	-2%	3%	0%
	$60k-$100k	0.6%	$1,091	$1,095	$1,105	$1,134	$1,134	$1,131	$14	$43	$40	1%	4%	4%
	>$100k	0.0%	$1,350	$1,376	$1,462	$1,406	$1,427	$1,497	$112	$56	$147	8%	4%	11%
weighted	$0-$20k	58.5%	$724	$706	$652	$624	$615	$591	-$72	-$101	-$133	-10%	-14%	-18%
rank	$20k-$40k	30.6%	$876	$866	$835	$836	$830	$810	-$41	-$39	-$66	-5%	-4%	-8%
method B	$40k-$60k	5.1%	$986	$983	$972	$1,011	$1,006	$987	-$14	$26	$2	-1%	3%	0%
	$60k-$100k	0.6%	$1,086	$1,091	$1,101	$1,129	$1,129	$1,127	$14	$43	$41	1%	4%	4%
	>$100k	0.0%	$1,345	$1,370	$1,454	$1,401	$1,421	$1,488	$109	$56	$144	8%	4%	11%

All results are from weighted rank method
Excludes bills with daily consumption < 1kWh/day
Includes all CARE and non-CARE customers

Table 6: SDG&E Estimated Average Annual Bills With and Without IBP and CARE

MC=0.1122

Income Range	Share of Customers	Change in Annual Average Household Consumer Surplus From Switch to 5-tier tariff				Change in Aggregate Annual Consumer Surplus ($M/yr) From Switch to 5-tier tariff			
		ε=0	ε=-0.1	ε=-0.2	ε=-0.3	ε=0	ε=-0.1	ε=-0.2	ε=-0.3
$0-$20k	16.4%	$66	$58	$48	$39	$13	$11	$9	$7
$20k-$40k	22.4%	$45	$35	$23	$11	$12	$18	-$11	-$42
$40k-$60k	18.9%	$16	$3	-$11	-$25	$4	$1	-$2	-$6
$60k-$100k	23.8%	-$14	-$29	-$45	-$62	-$4	-$8	-$12	-$17
>$100k	18.5%	-$112	-$132	-$154	-$177	-$24	-$28	-$33	-$38
Aggregate Increase in DWL from IBP ($M/yr)						$0	$7	$49	$96
Ratio of DWL to transfers to two lowest income brackets						0.00	0.24	-27.18	-2.74
Flat-rate Price						$0.1622	$0.1612	$0.1601	$0.1588

MC=0.1622

Income Range	**Share of Customers**	**Change in Annual Average Household Consumer Surplus From Switch to 5-tier tariff**				**Change in Aggregate Annual Consumer Surplus ($M/yr) From Switch to 5-tier tariff**			
		ε=0	**ε=-0.1**	**ε=-0.2**	**ε=-0.3**	**ε=0**	**ε=-0.1**	**ε=-0.2**	**ε=-0.3**
$0-$20k	**16.4%**	**$66**	**$62**	**$59**	**$55**	**$13**	**$12**	**$11**	**$10**
$20k-$40k	**22.4%**	**$45**	**$40**	**$35**	**$30**	**$12**	**$10**	**$9**	**$8**
$40k-$60k	**18.9%**	**$16**	**$10**	**$3**	**-$3**	**$4**	**$2**	**$1**	**-$1**
$60k-$100k	**23.8%**	**-$14**	**-$22**	**-$29**	**-$37**	**-$4**	**-$6**	**-$8**	**-$10**
>$100k	**18.5%**	**-$112**	**-$123**	**-$134**	**-$146**	**-$24**	**-$26**	**-$29**	**-$31**
Aggregate Increase in DWL from IBP ($M/yr)						**$0**	**$8**	**$16**	**$24**
Ratio of DWL to transfers to two lowest income brackets						**0.00**	**0.35**	**0.77**	**1.31**
Flat-rate Price						**$0.1622**	**$0.1622**	**$0.1622**	**$0.1622**

MC=0.2122

Income Range	Share of Customers	Change in Annual Average Household Consumer Surplus From Switch to 5-tier tariff				Change in Aggregate Annual Consumer Surplus ($M/yr) From Switch to 5-tier tariff			
		ε=0	ε=-0.1	ε=-0.2	ε=-0.3	ε=0	ε=-0.1	ε=-0.2	ε=-0.3
$0-$20k	16.4%	$66	$67	$68	$68	$13	$13	$13	$13
$20k-$40k	22.4%	$45	$46	$46	$46	$12	$12	$12	$12
$40k-$60k	18.9%	$16	$16	$16	$16	$4	$4	$3	$3
$60k-$100k	23.8%	-$14	-$15	-$15	-$16	-$4	-$4	-$4	-$4
>$100k	18.5%	-$112	-$114	-$117	-$119	-$24	-$24	-$25	-$25
Aggregate Increase in DWL from IBP ($M/yr)						$0	$0	$1	$2
Ratio of DWL to transfers to two lowest income brackets						0.00	0.01	0.04	0.06
Flat-rate Price						$0.1622	$0.1633	$0.1643	$0.1652

MC=0.2622

Income Range	Share of Customers	Change in Annual Average Household Consumer Surplus From Switch to 5-tier tariff				Change in Aggregate Annual Consumer Surplus ($M/yr) From Switch to 5-tier tariff			
		ε=0	ε=-0.1	ε=-0.2	ε=-0.3	ε=0	ε=-0.1	ε=-0.2	ε=-0.3
$0-$20k	16.4%	$66	$71	$76	$80	$13	$14	$14	$15
$20k-$40k	22.4%	$45	$51	$56	$60	$12	$13	$14	$16
$40k-$60k	18.9%	$16	$22	$27	$31	$4	$5	$6	$7
$60k-$100k	23.8%	-$14	-$8	-$3	$2	-$4	-$2	-$1	$0
>$100k	18.5%	-$112	-$106	-$101	-$96	-$24	-$23	-$22	-$21
Aggregate Increase in DWL from IBP ($M/yr)						$0	-$7	-$12	-$17
Ratio of DWL to transfers to two lowest income brackets						0.00	-0.25	-0.43	-0.57
Flat-rate Price						$0.1622	$0.1643	$0.1661	$0.1677

Table 5: SDG&E Change in Consumer Surplus Switching from Flat-rate to 5-tier Tariff Under Alternative Demand Elasticities (Weighted Ranking Method A - calibration from ecological regression)

MC=0.1122		Change in Annual Average Household Consumer Surplus From adding CARE program				Change in Aggregate Annual Consumer Surplus ($M/yr) From adding CARE program			
Income Range	Share of Customers	ε=0	ε=-0.1	ε=-0.2	ε=-0.3	ε=0	ε=-0.1	ε=-0.2	ε=-0.3
$0-$20k	16.4%	$99	$101	$102	$103	$19	$19	$19	$20
$20k-$40k	22.4%	$41	$41	$42	$42	$11	$11	$11	$11
$40k-$60k	18.9%	-$25	-$26	-$27	-$28	-$6	-$6	-$6	-$6
$60k-$100k	23.8%	-$43	-$44	-$46	-$48	-$12	-$12	-$13	-$13
>$100k	18.5%	-$56	-$58	-$61	-$63	-$12	-$12	-$13	-$14
Aggregate Increase in DWL from CARE ($M/yr)						$0	$1	$1	$2
Ratio of DWL to transfers to two lowest income brackets						0.00	0.02	0.04	0.07
Flat-rate Price - Standard Residential						$0.1690	$0.1680	$0.1669	$0.1658
Flat-rate Price - CARE participants						$0.1168	$0.1161	$0.1154	$0.1146

MC=0.1622		**Change in Annual Average Household Consumer Surplus From adding CARE program**				**Change in Aggregate Annual Consumer Surplus ($M/yr) From adding CARE program**			
Income Range	**Share of Customers**	**ε=0**	**ε=-0.1**	**ε=-0.2**	**ε=-0.3**	**ε=0**	**ε=-0.1**	**ε=-0.2**	**ε=-0.3**
$0-$20k	**16.4%**	**$99**	**$101**	**$103**	**$105**	**$19**	**$19**	**$20**	**$20**
$20k-$40k	**22.4%**	**$41**	**$41**	**$42**	**$43**	**$11**	**$11**	**$11**	**$11**
$40k-$60k	**18.9%**	**-$25**	**-$26**	**-$28**	**-$29**	**-$6**	**-$6**	**-$6**	**-$6**
$60k-$100k	**23.8%**	**-$43**	**-$45**	**-$47**	**-$49**	**-$12**	**-$12**	**-$13**	**-$13**
>$100k	**18.5%**	**-$56**	**-$59**	**-$62**	**-$65**	**-$12**	**-$13**	**-$13**	**-$14**
Aggregate Increase in DWL from CARE ($M/yr)						**$0**	**$1**	**$2**	**$3**
Ratio of DWL to transfers to two lowest income brackets						**0.00**	**0.03**	**0.06**	**0.09**
Flat-rate Price - Standard Residential						**$0.1690**	**$0.1692**	**$0.1693**	**$0.1695**
Flat-rate Price - CARE participants						**$0.1168**	**$0.1169**	**$0.1170**	**$0.1171**

MC=0.2122		Change in Annual Average Household Consumer Surplus From adding CARE program				Change in Aggregate Annual Consumer Surplus ($M/yr) From adding CARE program			
Income Range	Share of Customers	ε=0	ε=-0.1	ε=-0.2	ε=-0.3	ε=0	ε=-0.1	ε=-0.2	ε=-0.3
$0-$20k	16.4%	$99	$102	$104	$106	$19	$19	$20	$20
$20k-$40k	22.4%	$41	$41	$42	$43	$11	$11	$11	$11
$40k-$60k	18.9%	-$25	-$27	-$28	-$29	-$6	-$6	-$6	-$6
$60k-$100k	23.8%	-$43	-$45	-$48	-$50	-$12	-$12	-$13	-$14
>$100k	18.5%	-$56	-$59	-$63	-$66	-$12	-$13	-$13	-$14
Aggregate Increase in DWL from CARE ($M/yr)						$0	$1	$2	$3
Ratio of DWL to transfers to two lowest income brackets						0.00	0.04	0.07	0.10
Flat-rate Price - Standard Residential						$0.1690	$0.1703	$0.1715	$0.1726
Flat-rate Price - CARE participants						$0.1168	$0.1177	$0.1185	$0.1193

MC=0.2622		Change in Annual Average Household Consumer Surplus From adding CARE program				Change in Aggregate Annual Consumer Surplus ($M/yr) From adding CARE program			
Income Range	Share of Customers	ε=0	ε=-0.1	ε=-0.2	ε=-0.3	ε=0	ε=-0.1	ε=-0.2	ε=-0.3
$0-$20k	16.4%	$99	$102	$104	$106	$19	$19	$20	$20
$20k-$40k	22.4%	$41	$41	$42	$43	$11	$11	$11	$11
$40k-$60k	18.9%	-$25	-$27	-$29	-$30	-$6	-$6	-$6	-$7
$60k-$100k	23.8%	-$43	-$46	-$48	-$51	-$12	-$13	-$13	-$14
>$100k	18.5%	-$56	-$60	-$64	-$67	-$12	-$13	-$14	-$14
Aggregate Increase in DWL from CARE ($M/yr)						$0	$1	$3	$4
Ratio of DWL to transfers to two lowest income brackets						0.00	0.04	0.08	0.12
Flat-rate Price - Standard Residential						$0.1690	$0.1713	$0.1734	$0.1752
Flat-rate Price - CARE participants						$0.1168	$0.1184	$0.1198	$0.1211

Table 7: SDG&E Change in Consumer Surplus Switching from No-CARE to w/CARE With Flat-rate Tariff Under Alternative Demand Elasticities
(Weighted Ranking Method A - calibration from ecological regression)

Appendix B-3: Tables for Southern California Edison

Tier	% of Baseline Quantity	Standard Residential Rate	CARE Low-income Rate
Actual 2006 tariff (time-weighted average in 2006)			
1	0-100%	$0.1162	$0.0834
2	100%-130%	$0.1361	$0.1053
3	130%-200%	$0.2201	$0.1691
4	200%-300%	$0.3049	$0.1717
5	300%+	$0.3049	$0.1717
Alternative Flat-Rate Tariff with CARE program			
	0%+	$0.1731	$0.1060
Alternative Two-Tier Tariff with CARE program			
1	0-100%	$0.1595	$0.0999
2	100%+	$0.1883	$0.1179

Tier	% of Baseline Quantity	Standard Residential Rate
Benchmark Five-Tier Tariff with no CARE program		
1	0-100%	$0.1069
2	100%-130%	$0.1268
3	130%-200%	$0.2108
4	200%-300%	$0.2956
5	300%+	$0.2956
Alternative Flat-Rate Tariff with no CARE program		
	0%+	$0.1592
Alternative Two-Tier Tariff with no CARE program		
1	0-100%	$0.1474
2	100%+	$0.1739

Table 1: 2006 Southern California Edison Retail Electricity Rates

	Residential Usage (million-kWh)	Percentage of Residential Usage					CARE/Non-CARE Shares	
		tier 1	tier 2	tier 3	tier 4	tier 5	% Usage	% customers
Non-CARE	23,046	52.9%	10.7%	16.5%	10.9%	9.0%	79.3%	74.8%
CARE	6,016	66.0%	10.7%	13.5%	6.7%	3.1%	20.7%	25.2%

	Percentage of Customers on Each Tier for Marginal Consumption				
	tier 1	tier 2	tier 3	tier 4	tier 5
Non-CARE	32.4%	14.2%	25.0%	17.2%	11.3%
CARE	45.4%	16.7%	22.7%	10.9%	4.3%

NOTE: reported results drop household accounts with consumption of less than 1 kWh/day

Table 2: Distribution of SCE Residential Customer Consumption Across Tariff Tiers

	Income Range	Share of Customers	Average Daily Use (kWh)	Average Annualized Bill *Flat*	*2-tier*	*5-tier*	Change from Flat to 5-tier: Dollar Chg	95% conf intvl	Percent Change	95% conf intvl
random	$0-$20k	17.9%	16.98	$986	$974	$908	-$78		-8.0%	
rank	$20k-$40k	22.1%	17.93	$1,041	$1,033	$985	-$57		-5.5%	
method	$40k-$60k	18.9%	19.34	$1,124	$1,121	$1,104	-$19		-1.7%	
	$60k-$100k	23.7%	20.86	$1,212	$1,217	$1,237	$25		2.0%	
	>$100k	17.4%	23.85	$1,386	$1,406	$1,527	$141		10.2%	
weighted	**$0-$20k**	**17.9%**	**13.66**	**$794**	**$771**	**$665**	**-$129**	**[-$146, -$92]**	**-16.5%**	**[-21.3%, -9.7%]**
rank	**$20k-$40k**	**22.1%**	**16.80**	**$976**	**$962**	**$884**	**-$92**	**[-$119,-$58]**	**-9.5%**	**[-12.9%, -5.6%]**
method A	**$40k-$60k**	**18.9%**	**19.31**	**$1,122**	**$1,118**	**$1,090**	**-$32**	**[-$66, -$18]**	**-2.9%**	**[-6.1%, -1.6%]**
	$60k-$100k	**23.7%**	**21.27**	**$1,236**	**$1,241**	**$1,261**	**$25**	**[$19. $26]**	**2.0%**	**[1.5%, 2.2%]**
	>$100k	**17.4%**	**28.19**	**$1,638**	**$1,675**	**$1,889**	**$251**	**[$155, $347]**	**15.2%**	**[10.9%, 19.0%]**
weighted	**$0-$20k**	**17.9%**	**15.20**	**$883**	**$865**	**$772**	**-$111**	**[-$116, -$106]**	**-12.6%**	**[-13.3%, -11.8%]**
rank	**$20k-$40k**	**22.1%**	**17.57**	**$1,021**	**$1,010**	**$953**	**-$68**	**[-$71, -$64]**	**-6.6%**	**[-7.0%, -6.2%]**
method B	**$40k-$60k**	**18.9%**	**19.55**	**$1,136**	**$1,134**	**$1,117**	**-$19**	**[-$19, -$18]**	**-1.6%**	**[-1.7%, -1.6%]**
	$60k-$100k	**23.7%**	**20.97**	**$1,218**	**$1,223**	**$1,244**	**$26**	**[$26, $26]**	**2.2%**	**[2.1%, 2.2%]**
	>$100k	**17.4%**	**25.76**	**$1,496**	**$1,524**	**$1,682**	**$186**	**[$176, $195]**	**12.4%**	**[11.9%, 12.8%]**
usage	$0-$20k	17.9%	8.85	$514	$485	$365	-$149		-28.9%	
rank	$20k-$40k	22.1%	14.56	$846	$822	$696	-$150		-17.7%	
method	$40k-$60k	18.9%	16.61	$965	$944	$834	-$131		-13.6%	
	$60k-$100k	23.7%	21.90	$1,272	$1,271	$1,201	-$72		-5.6%	
	>$100k	17.4%	38.08	$2,212	$2,297	$2,797	$585		26.4%	

Excludes bills with daily consumption < 1kWh/day

Includes all CARE and non-CARE customers, all on no-CARE-program rates from table 1

Distribution of w* for weighted rank method A
(calibrated from ecological regression results)

Point Estimate	0.27
Mean of bootstrap	0.27
Median of bootstrap	0.28
95% conf interval	[0.06,0.44]

Distribution of w* for weighted rank method B
(calibrated from American Community Survey)

Point Estimate	0.13
Mean of bootstrap	0.14
Median of bootstrap	0.14
95% conf interval	[0.11,0.16]

Table 4: SCE Average Bill By Income Bracket Under Benchmark and Alternative Flat-Rate Tariff Using Random-Rank, Usage-Rank and Weighted-Rank Within-CBG Allocation Methods

			Average Annualized Bill						Monetary Bill Chage from No-CARE/Flat			Percentage Bill Chage from No-CARE/Flat		
		Share	No-CARE			with CARE			No-CARE	w/CARE	w/CARE	No-CARE	w/CARE	w/CARE
	Income	on	Flat	2-tier	5-tier	Flat	2-tier	5-tier	5-tier	Flat	5-tier	5-tier	Flat	5-tier
	Range	CARE	Tariff	tariff	Tariff	Tariff	tariff	Tariff	Tariff	Tariff	Tariff	Tariff	Tariff	Tariff
weighted	$0-$20k	69.9%	$794	$771	$665	$618	$606	$558	-$129	-$176	-$236	-16%	-22%	-30%
rank	$20k-$40k	47.1%	$976	$962	$884	$865	$856	$808	-$92	-$111	-$168	-9%	-11%	-17%
method A	$40k-$60k	11.3%	$1,122	$1,119	$1,090	$1,158	$1,151	$1,108	-$32	$36	-$15	-3%	3%	-1%
	$60k-$100k	0.6%	$1,236	$1,241	$1,261	$1,339	$1,338	$1,328	$25	$103	$92	2%	8%	7%
	>$100k	0.0%	$1,638	$1,675	$1,889	$1,781	$1,813	$1,985	$251	$143	$347	15%	9%	21%
weighted	$0-$20k	69.9%	$883	$865	$772	$699	$690	$654	-$112	-$184	-$229	-13%	-21%	-26%
rank	$20k-$40k	47.1%	$1,021	$1,010	$953	$920	$914	$885	-$68	-$101	-$136	-7%	-10%	-13%
method B	$40k-$60k	11.3%	$1,136	$1,134	$1,117	$1,181	$1,176	$1,144	-$18	$45	$8	-2%	4%	1%
	$60k-$100k	0.6%	$1,218	$1,223	$1,244	$1,320	$1,320	$1,312	$26	$102	$93	2%	8%	8%
	>$100k	0.0%	$1,496	$1,524	$1,682	$1,627	$1,650	$1,770	$186	$131	$273	12%	9%	18%

All results are from weighted rank method
Excludes bills with daily consumption < 1kWh/day
Includes all CARE and non-CARE customers

Table 6: SCE Estimated Average Annual Bills With and Without IBP and CARE

MC=0.1092

Income Range	Share of Customers	Change in Annual Average Household Consumer Surplus From Switch to 5-tier tariff ε=0	ε=-0.1	ε=-0.2	ε=-0.3	Change in Aggregate Annual Consumer Surplus ($M/yr) From Switch to 5-tier tariff ε=0	ε=-0.1	ε=-0.2	ε=-0.3
$0-$20k	17.9%	$129	$114	$97	$80	$93	$82	$70	$58
$20k-$40k	22.1%	$92	$71	$49	$25	$82	$64	$44	$22
$40k-$60k	18.9%	$32	$5	-$23	-$54	$24	$4	-$18	-$41
$60k-$100k	23.7%	-$25	-$56	-$89	-$126	-$24	-$53	-$85	-$120
>$100k	17.4%	-$251	-$298	-$348	-$403	-$177	-$210	-$245	-$284
Aggregate Increase in DWL from IBP ($M/yr)						$0	$113	$234	$365
Ratio of DWL to transfers to two lowest income brackets						0.00	0.77	2.05	4.56
Flat-rate Price						$0.1592	$0.1577	$0.1560	$0.1543

MC=0.1592

Income Range	**Share of Customers**	**Change in Annual Average Household Consumer Surplus From Switch to 5-tier tariff ε=0**	**ε=-0.1**	**ε=-0.2**	**ε=-0.3**	**Change in Aggregate Annual Consumer Surplus ($M/yr) From Switch to 5-tier tariff ε=0**	**ε=-0.1**	**ε=-0.2**	**ε=-0.3**
$0-$20k	**17.9%**	**$129**	**$121**	**$113**	**$105**	**$93**	**$88**	**$82**	**$76**
$20k-$40k	**22.1%**	**$92**	**$81**	**$69**	**$57**	**$82**	**$72**	**$62**	**$51**
$40k-$60k	**18.9%**	**$32**	**$16**	**$1**	**-$16**	**$24**	**$13**	**$0**	**-$12**
$60k-$100k	**23.7%**	**-$25**	**-$44**	**-$63**	**-$83**	**-$24**	**-$42**	**-$60**	**-$79**
>$100k	**17.4%**	**-$251**	**-$281**	**-$313**	**-$345**	**-$177**	**-$198**	**-$220**	**-$243**
Aggregate Increase in DWL from IBP ($M/yr)						$0	**$67**	**$136**	**$207**
Ratio of DWL to transfers to two lowest income brackets						**0.00**	**0.42**	**0.95**	**1.63**
Flat-rate Price						**$0.1592**	**$0.1592**	**$0.1592**	**$0.1592**

MC=0.2092

Income Range	Share of Customers	Change in Annual Average Household Consumer Surplus From Switch to 5-tier tariff ε=0	ε=-0.1	ε=-0.2	ε=-0.3	Change in Aggregate Annual Consumer Surplus ($M/yr) From Switch to 5-tier tariff ε=0	ε=-0.1	ε=-0.2	ε=-0.3
$0-$20k	17.9%	$129	$128	$128	$128	$93	$93	$92	$92
$20k-$40k	22.1%	$92	$90	$87	$87	$82	$80	$78	$78
$40k-$60k	18.9%	$32	$27	$21	$21	$24	$20	$16	$16
$60k-$100k	23.7%	-$25	-$32	-$40	-$40	-$24	-$31	-$38	-$38
>$100k	17.4%	-$251	-$266	-$281	-$281	-$177	-$187	-$198	-$198
Aggregate Increase in DWL from IBP ($M/yr)						$0	$24	$49	$49
Ratio of DWL to transfers to two lowest income brackets						0.00	0.14	0.29	0.29
Flat-rate Price						$0.1592	$0.1606	$0.1620	$0.1633

MC=0.2592

Income Range	Share of Customers	Change in Annual Average Household Consumer Surplus From Switch to 5-tier tariff ε=0	ε=-0.1	ε=-0.2	ε=-0.3	Change in Aggregate Annual Consumer Surplus ($M/yr) From Switch to 5-tier tariff ε=0	ε=-0.1	ε=-0.2	ε=-0.3
$0-$20k	17.9%	$129	$135	$140	$144	$93	$98	$101	$104
$20k-$40k	22.1%	$92	$98	$103	$107	$82	$88	$92	$95
$40k-$60k	18.9%	$32	$37	$40	$43	$24	$28	$31	$33
$60k-$100k	23.7%	-$25	-$21	-$19	-$17	-$24	-$20	-$18	-$16
>$100k	17.4%	-$251	-$251	-$253	-$255	-$177	-$177	-$178	-$179
Aggregate Increase in DWL from IBP ($M/yr)						$0	-$16	-$28	-$37
Ratio of DWL to transfers to two lowest income brackets						0.00	-0.09	-0.15	-0.18
Flat-rate Price						$0.1592	$0.1619	$0.1645	$0.1669

Table 5: SCE Change in Consumer Surplus Switching from Flat-rate to 5-tier Tariff Under Alternative Demand Elasticities (Weighted Ranking Method A - calibration from ecological regression)

MC=0.1092		Change in Annual Average Household Consumer Surplus From adding CARE program				Change in Aggregate Annual Consumer Surplus ($M/yr) From adding CARE program			
Income Range	Share of Customers	ε=0	ε=-0.1	ε=-0.2	ε=-0.3	ε=0	ε=-0.1	ε=-0.2	ε=-0.3
$0-$20k	17.9%	$176	$178	$182	$186	$127	$129	$131	$134
$20k-$40k	22.1%	$111	$114	$117	$120	$99	$102	$104	$107
$40k-$60k	18.9%	-$36	-$37	-$38	-$40	-$27	-$28	-$29	-$30
$60k-$100k	23.7%	-$103	-$108	-$113	-$118	-$99	-$103	-$108	-$113
>$100k	17.4%	-$143	-$151	-$160	-$171	-$101	-$106	-$113	-$120
Aggregate Increase in DWL from CARE ($M/yr)						$0	$7	$14	$22
Ratio of DWL to transfers to two lowest income brackets						0.00	0.03	0.06	0.09
Flat-rate Price - Standard Residential						$0.1731	$0.1717	$0.1703	$0.1687
Flat-rate Price - CARE participants						$0.1060	$0.1052	$0.1043	$0.1033

MC=0.1592		Change in Annual Average Household Consumer Surplus From adding CARE program				Change in Aggregate Annual Consumer Surplus ($M/yr) From adding CARE program			
Income Range	Share of Customers	ε=0	ε=-0.1	ε=-0.2	ε=-0.3	ε=0	ε=-0.1	ε=-0.2	ε=-0.3
$0-$20k	17.9%	$176	$180	$184	$189	$127	$130	$133	$137
$20k-$40k	22.1%	$111	$114	$118	$122	$99	$102	$105	$109
$40k-$60k	18.9%	-$36	-$38	-$40	-$42	-$27	-$29	-$30	-$32
$60k-$100k	23.7%	-$103	-$109	-$116	-$123	-$99	-$104	-$111	-$117
>$100k	17.4%	-$143	-$154	-$165	-$177	-$101	-$108	-$116	-$125
Aggregate Increase in DWL from CARE ($M/yr)						$0	$9	$19	$29
Ratio of DWL to transfers to two lowest income brackets						0.00	0.04	0.08	0.12
Flat-rate Price - Standard Residential						$0.1731	$0.1735	$0.1739	$0.1743
Flat-rate Price - CARE participants						$0.1060	$0.1062	$0.1065	$0.1067

MC=0.2092		Change in Annual Average Household Consumer Surplus From adding CARE program				Change in Aggregate Annual Consumer Surplus ($M/yr) From adding CARE program			
Income Range	Share of Customers	ε=0	ε=-0.1	ε=-0.2	ε=-0.3	ε=0	ε=-0.1	ε=-0.2	ε=-0.3
$0-$20k	17.9%	$176	$181	$186	$192	$127	$131	$135	$139
$20k-$40k	22.1%	$111	$115	$119	$123	$99	$102	$106	$110
$40k-$60k	18.9%	-$36	-$38	-$41	-$44	-$27	-$29	-$31	-$34
$60k-$100k	23.7%	-$103	-$111	-$118	-$127	-$99	-$106	-$113	-$121
>$100k	17.4%	-$143	-$156	-$169	-$182	-$101	-$110	-$119	-$128
Aggregate Increase in DWL from CARE ($M/yr)						$0	$11	$23	$34
Ratio of DWL to transfers to two lowest income brackets						0.00	0.05	0.09	0.14
Flat-rate Price - Standard Residential						$0.1731	$0.1751	$0.1771	$0.1790
Flat-rate Price - CARE participants						$0.1060	$0.1072	$0.1085	$0.1096

MC=0.2592		Change in Annual Average Household Consumer Surplus From adding CARE program				Change in Aggregate Annual Consumer Surplus ($M/yr) From adding CARE program			
Income Range	Share of Customers	ε=0	ε=-0.1	ε=-0.2	ε=-0.3	ε=0	ε=-0.1	ε=-0.2	ε=-0.3
$0-$20k	17.9%	$176	$182	$188	$194	$127	$132	$136	$140
$20k-$40k	22.1%	$111	$115	$119	$124	$99	$103	$107	$111
$40k-$60k	18.9%	-$36	-$39	-$43	-$46	-$27	-$30	-$32	-$35
$60k-$100k	23.7%	-$103	-$112	-$121	-$130	-$99	-$107	-$116	-$124
>$100k	17.4%	-$143	-$158	-$172	-$187	-$101	-$111	-$121	-$131
Aggregate Increase in DWL from CARE ($M/yr)						$0	$14	$27	$39
Ratio of DWL to transfers to two lowest income brackets						0.00	0.06	0.11	0.16
Flat-rate Price - Standard Residential						$0.1731	$0.1767	$0.1800	$0.1831
Flat-rate Price - CARE participants						$0.1060	$0.1082	$0.1102	$0.1121

Table 7: SCE Change in Consumer Surplus Switching from No-CARE to w/CARE With Flat-rate Tariff Under Alternative Demand Elasticities (Weighted Ranking Method A - calibration from ecological regression)

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