Energy Efficiency: The Bird's-Eye View

If energy efficiency policy works, it should be possible to detect its effect on aggregate demand.

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Originally published in The Electricity Journal, April 2018

In what has come to be known as the "Rosenfeld effect"—in deference to Arthur Rosenfeld, the University of California, Berkeley's physicist and influential member of the California Energy Commission, California's per-person electricity use has remained relatively steady since the mid-1970s, despite the proliferation of electricity-using devices. Meanwhile, the rest of the nation's electricity usage has risen. Today, California consumes nearly 40% less electricity per person than the national average.

Arthur (Art) Rosenfeld is widely known as a founding father of the energy efficiency movement. He earned that title for his many scientific contributions, especially in developing the now widespread energy efficiency performance standards for appliances and buildings. He also helped advance energy efficiency by conceiving a logical policy framework, built on economic and engineering principles, thus pioneering the 'Art' of Energy Efficiency—the title of his 1999 autobiography.[2]

Arthur Rosenfeld died last year, aged 91. In his memory, this article searches for a possible Rosenfeld effect beyond California. The article integrates ideas from econometric methods for forecasting electricity demand to build an analytic model that explains the relationship between retail electricity sales and investment in energy efficiency. It begins with a review of national trends in electricity intensity (measured as annual per-capita retail electricity sales) during the

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[2] Arthur Rosenfeld. "The Art of Energy Efficiency: Protecting the Environment with Better Technology." Annual Review of Energy and Environment. 24:33–82. 1999.

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decade ending in 2016, and uses the analytic model with data on 50 states and the District of Columbia to estimate the effect of publicly funded energy efficiency on these trends.

California: Special but not Unique

For four decades, efficiency has been a priority in California's energy policy and planning —a history quite visibly marked by continuous attempts at paving the way for greater efficiency—"curling" is the closest sports analogy that comes to mind.

California launched its first generation of utility electricity-efficiency programs and adopted the first electricity-efficiency building codes and appliance standards in the mid-1970s. Following the hiatus caused by restructuring of wholesale electricity markets in the 1990s, the energy crisis of 2001 and a growing awareness of climate change dangers reinvigorated interest in energy efficiency. In 2005, California designated efficiency as the resource-of-choice for meeting the state's future electric load growth. Two years later, the state established an incentive mechanism (the Risk-Reward Incentive Mechanism) to encourage the state's utilities to achieve higher savings. In 2008, the state adopted the California Long Term Energy Efficiency Strategic Plan, which established a roadmap for energy efficiency investments through 2020.

California's praised policy accomplishments have established the state as an example to follow in a national mission to control energy use and greenhouse gas emissions. The state also has been hailed as a model for other countries.[3]

Several attempts have been made to invalidate the causal link between stable trends in California's electricity use and the state's energy efficiency policies by offering alternative hypotheses to explain the divergence in California's per capita electricity use from the national average.

California, the skeptics have argued, is an exceptional state with distinctive characteristics—non-energy intensive industry, high electricity prices, smaller households, higher proportions of multifamily units in housing, a conservation ethic, and the natural advantage of a mild climate. Upon factoring in these structural and natural attributes, the critics have argued, differences between California's per-capita electricity use and that of other states disappear.[4] Others have suggested that California's flat per-capita electricity use has more to do with coincidental factors such as urbanization, the size of dwelling units, and the residential fuel mix, than with the effects of the state's energy efficiency policies.[5]

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3 The World Bank once praised California's utility demand-side management and efficiency standards for the stale's stable per-capita electricity demand. The World Bank, Development and Climate Change, Technology Report, The World Bank, Washington, DC, 2010, p. 215.

4 Mitchel, Cynthia. "Stabilizing California's Demand: The Real Reasons Behind the State's Energy Savings." Public Utilities Fortnightly. March 2009.

5 Sudarshan, Anant and James Sweeney. Deconstructing the Rosenfeld Curve: Understanding California's Low Per Capita Electricity Consumption. Stanford University. September 30, 2008.

Such reasoning has led critics to raise broader concerns about the effectiveness of California's policies, as other states—and countries—attempt to emulate them.[6] One critic has gone so far as charging that California's model is unrealistic not only for the nation, but following California's example would prove detrimental to the national interest by putting domestic firms at a global competitive disadvantage by increasing the cost of doing business.[7]

Amid these criticisms, California is doubling down on its energy efficiency policy. In the decade ending in 2016, California IOUs spent about $10.3 billion on electric energy efficiency and reported savings of about 3.4 billion kilowatt-hours. New legislation passed in 2015 calls for a doubling of savings by 2030.

Understanding California's experience is important. The state has served as a pioneer in energy efficiency and today provides a well-known case study, both within the United States and abroad. As other states and countries continue to adopt policies and programs similar to California, the need increases to effectively evaluate efficiency policies.

However, it appears that California may not be the only state experiencing declining electricity use. Data from the Energy Information Administration (EIA) shows that national, annual, per-capita retail electricity sales dropped from 12,300 kWh in 2006 to 11,650 kWh in 2016—a 5.3% at drop at an average annual rate of about 0.5%, as shown in Figure 1. Between 2006 and 2016, consumption declined in 41 states, including the District of Columbia, by just under 8% on average.

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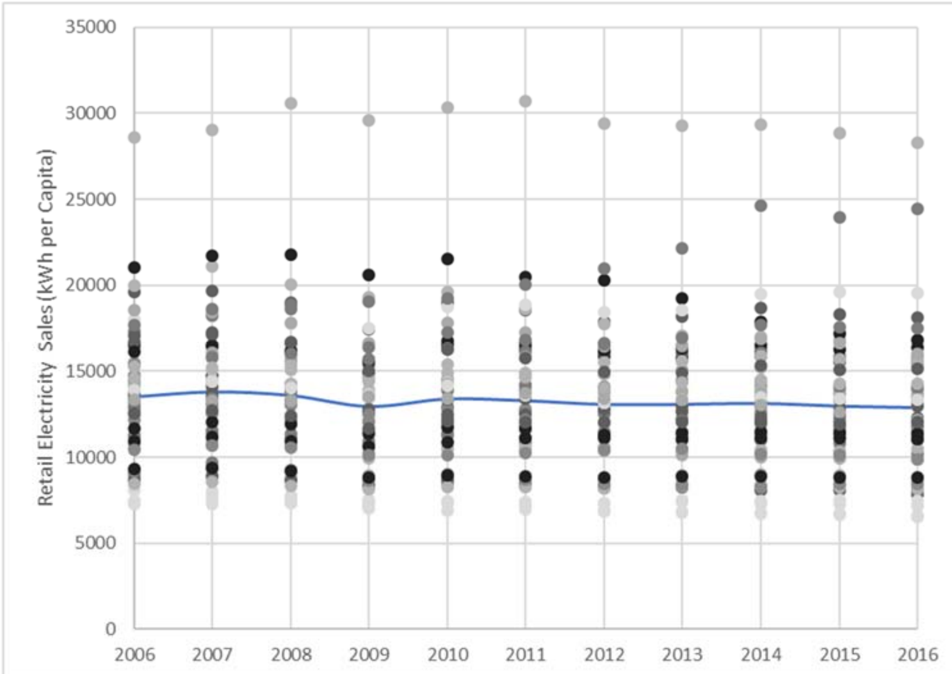
6 Levinson, Arik. *California Energy Efficiency: Lessons for the Rest of the World, or Not?* Georgetown Economics Department, Elsevier. 2014. http://faculty.georgetown.edu/aml6/pdfs&zips/CaliforniaEnergy.pdf

7 Clement, Jude. "Is California's Electricity Policy Really a Model for the United States?" Innovative Energy Policies. Ashdin Publishing. 2011.

Figure 1. Annual Per-Capita Retail Electricity Sales 2006–2016



Eight states showed a drop greater than California's, with Hawaii experiencing the largest drop at nearly 20%—almost twice that of California. Electricity consumption rose in 10 states by an average of 7%, ranging from almost 36% to less than 1%. North Dakota's per-capita electricity use climbed by 35.6%, the highest rate in the country, followed by South Dakota (9.0%), Louisiana (8.6%), and Iowa (6.4%). Electricity consumption also increased, though at more modest rates, in Mississippi (2.0%), Nebraska (3.2%), New Mexico (1.5%), New York (0.8%), and West Virginia (0.3%).

The Megawatt in a Negawatt

Since 2006, the American Council for an Energy Efficient Economy, ACEEE (which, incidentally, Arthur Rosenfeld founded), has published annual reports that benchmark state progress on policies that promote energy efficiency. The State Energy Efficiency Scorecard uses officially sanctioned data to rank states in six areas: utility-funded programs, transportation, building energy codes, combined heat and power, state policy initiatives, and appliance standards. The report's latest edition, published in September 2017,[8] identified Massachusetts, California, Rhode Island, Vermont, and Oregon as the top performers and cited Idaho, Florida, and Virginia as the most-improved states.

According to the Scorecard, utilities across the country spent $6.3 billion in 2016 on electric efficiency programs, a steady, four-fold increase from the $1.6 billion spent in 2006. As shown in Figure 2, these expenditures equaled 0.55% of utility retail revenues in 2006 and 1.7% in 2016.

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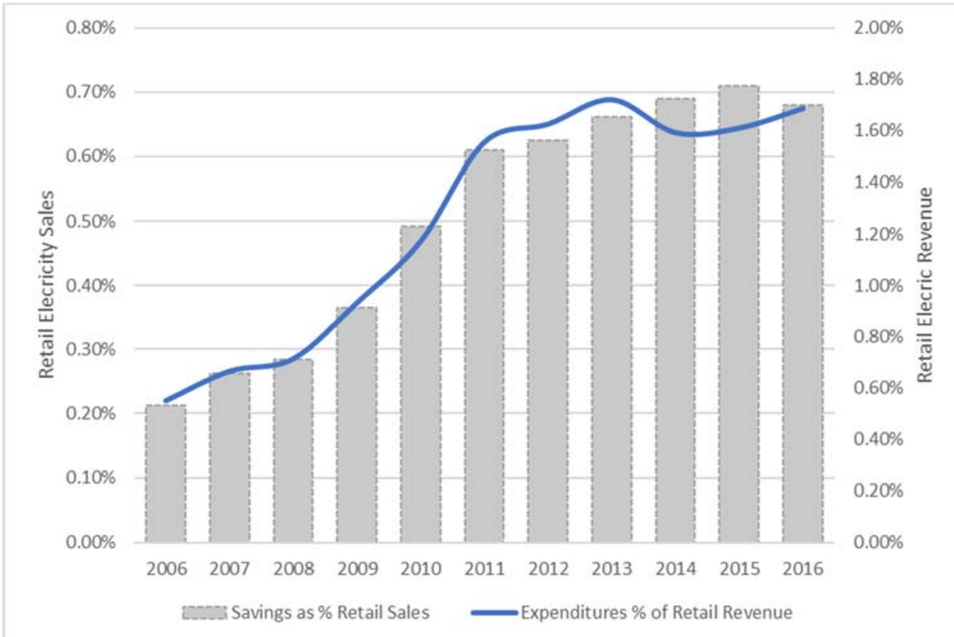
[8] ACEEE. 2017 State Energy Efficiency Scorecard, Report U1710. September 2017.

Reported savings also rose proportionately, from 7.8 million MWh in 2006 to 25.4 million MWh in 2016. From 2006 to 2016, these savings represent more than a three-fold increase from 0.21% to 0.68% of retail electricity sales, averaging at about 0.5% per year.

Figure 2. Annual Electric Efficiency Expenditures and Savings 2006–2016



Existence of an energy efficiency resource standard is a clear demarcation among states. In 2016, states with an EERS spent significantly more and produced higher savings, investing the equivalent of 2.6% of retail electric revenues and lowering retail sales by 1.2%. States without EERS obligations spent 0.8% of retail revenues and achieved proportionately lower savings of 0.3% of retail sales. Among states with an EERS, Texas ranked lowest in expenditures (0.6% of retail revenues) and savings (0.2% of retail revenues), on average, while Vermont counted as the most aggressive, with expenditures of 6.8% of retail revenues and savings at 2.5% of retail sales.

The correlation between expenditures and savings shows a slightly downward trend, suggesting declining returns on efficiency expenditures. The average cost of acquiring savings rose modestly between 2006 and 2016, perhaps reflective of depleting savings opportunities from low-cost measures, such as residential lighting.

The Trouble with Negawatts

Because energy savings cannot be observed directly, they must be estimated using engineering calculations or statistical inferences. Savings are typically first calculated for individual measures or projects, then aggregated to program or portfolio levels, awarding the scheme its moniker, the “bottom-up” approach. Bottom-up is not a unified methodology (although this has started to change); it is inconvenient to use and can be expensive. It also can misstate savings for failing to account for three issues that have vexed analysis and policy makers.

The first problem is the technical interaction effect, which arises when installing multiple efficiency measures together. Electricity end uses tend to function interdependently—higher efficiency in one end use affects electric loads in another end use. By simply adding savings from individual measures, the bottom-up approach can overstate or understate savings, sometimes by a wide margin.[9]

This approach also fails to address two issues that complicate public policy in more areas than energy efficiency. The first is attribution—separating the direct effects of an energy efficiency policy or program from observed (gross) changes in consumption by accounting for the influence of coincidental factors unrelated to the program, such as price change. The resulting net-to-gross ratio has become a singularly charged topic in energy efficiency policy, especially in states where utilities face strict savings targets. Further clouding the issue, non-programmatic effects are extremely difficult to define, and there are no completely satisfactory ways of measuring them.

The second problem is rebound,[10] which can erode savings. Rebound can occur at two levels. On a consumer level, this can be a direct effect (i.e., turning up the heat or air conditioning in a newly insulated house) or indirect (spending money saved on bills for purchasing other goods that, presumably, take energy to produce). On a macro-economic level, improved efficiency could lead to lower prices and, thus, higher demand. Unlike attribution, which is almost routinely estimated and applied to adjust savings, rebound remains an insufficiently researched and controversial topic.

One way to work around problems posed by rebound is to measure efficiency's effects on aggregate demand. Unlike its bottom-up counterpart, this "top-down" method uses a conventional energy demand forecasting framework to estimate savings directly. The approach employs a simple rationale: given increasingly large expenditures, if energy efficiency influences electricity use, it should be possible to detect it in aggregate electricity sales data. As aggregate demand already reflects the influence of factors that might confound bottom-up saving estimates, the approach effectively avoids them. Utility planners find this method especially appealing because it operates consistently with conventional load forecasting methods and readily blends into a utility's resource planning process.

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9 Haeri, Hossein. "Energy Efficiency: The Art of Measurement." Public Utilities Fortnightly. January 2018.

10 Rebound is also known as "Jevons' Paradox," after the British economist William Jevons. In his 1865 book, *The Coal Question*, Jevons observed that steam engines' efficiency led to much more widespread use, accelerating coal depletion in England.

Roughly 10 top-down energy efficiency studies have been conducted in the United States, Canada, and Europe, starting with the groundbreaking work by Perfomak and Lave in 1996.[11,12] Though these studies employ generally similar methods, they differ in several respects, such as aggregation levels (e.g., sector, utility, or state), choice of analysis units, and definitions of energy efficiency activity. Utility retail sales serve as the common metric for the dependent variable, but it is expressed in different ways: either in absolute terms or as intensity, normalized to different bases, such as population, total manufacturing output, aggregate income, gross state domestic product, or floorspace over a unit of time (typically, day or year). Energy efficiency policy typically enters the equation as expected electricity savings or expenditures (often expressed in per-capita or unit of output).

These studies, however, come to drastically different conclusions. Estimates for savings realization rates (the fraction of reported savings attributable to energy efficiency policies and programs—a common evaluation metric) range from nearly 100%[13] to 0%.[14] The stark differences in results highlights the difficulties in measuring energy efficiency's impacts and amplifies the controversy that has surrounded this.

The Top-Down View

In top-down analysis, regression analysis of aggregate electricity demand has served as the method of choice. A variant of econometric models for forecasting electricity demand, the approach combines economic theory with statistical methods to produce one or more equations that estimate the effects of energy efficiency policy on aggregate electricity use, controlling for the effects of other natural, demographic, and economic drivers of electricity demand. In its simplest form, the causal relationship between energy efficiency and electricity use may be expressed as:

(1) $$E_{it} = \beta X_{it} + \gamma EE_{it} + \varepsilon_{it}$$

Here, the dependent variable E represents electricity use, X is a series of predictors of electricity demand, EE is a proxy for energy efficiency policy, and ε is random disturbance from unobservable influences on electricity use. Subscripts i and t denote the level of aggregation (e.g., state) and the unit of time (e.g., year), respectively. The Beta coefficients measure the marginal effect of X predictors on electricity demand. The coefficient of interest in this equation

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11 Parfomak, Paul W., and Lester Lave. "How Many Kilowatts Are in a Negawatt? Verifying the Ex-Post Estimates of Utility Conservation Impacts at a Regional Level." Energy Journal 17 (4). 1996.

12 For a review of these studies and references see Haeri, Hossein, Jim Stewart, Seth Kadish, and Ayat Osman. *The View from the Top: Application of Macro-Economic Models to Measure Energy-Efficiency Program Savings in California.* Proceedings, International Energy Program Evaluation Conference, Chicago. 2013.

13 Parfomak, Paul W. and Lester Lave. op. cit.

14 Rivers, Nic and Mark Jaccard. "Electric Utility Demand Side Management in Canada." The Energy Journal. Vol. 32, No. 4. 2011.

is γ which measures the marginal effect of energy efficiency on electricity use ($\partial E/\partial EE$), holding other variables constant.

Drawing on the many lessons provided by previous studies, we expand this basic demand equation, so it includes key determinants of electricity sales, including efficiency. The resulting equation represented is a reasonably complete formulation that explains electricity sales with several notable features.

We use per-capita retail electricity sales as a proxy for electricity demand. We recognize that this may present a disadvantage in that electric intensity is sensitive to a state's composition of economic sectors. The presence of a large, electricity-intensive manufacturing sector can skew per-capita electricity use. Decline in the industrial sector can also decrease per-capita energy intensity for reasons unrelated to efficiency. To overcome this, we include gross domestic product (GDP) as an indicator of broad economic activity that drives electricity demand.

Expenditures on efficiency serves as the instrument for expressing energy efficiency activity in the model. The advantage in using expenditures is that the variable's estimated coefficient is easily understood as the per-unit cost of conserved energy. In log-log models, the interpretation is the elasticity of demand: the percent change in electricity demand for a one percent change in energy efficiency expenditures.[15]

Improved efficiency has a lasting effect on electricity use: an efficiency measure installed today continues to produce savings over the measure's useful life. The simplest way of expressing this dynamic relationship is to include a lag distribution relating energy efficiency to electricity demand—a distributed lag (DL) model. Thus, instead of a single expression describing the effects of EE on E ($\partial Et/\partial EE$), a finite sequence of expressions ($\partial Et/\partial EEt+s$, where s is a finite number) would describe the cumulative effects of EE on E. These are called 'dynamic multipliers' or 'dynamic elasticities' when working with log-log specifications.

Annual energy efficiency expenditures, however, tend to correlate over time, especially in states with mandated saving targets spanning multiple years. High correlation among regressors implies multicollinearity, which leads to unreliable coefficients. Distributed lag models also inevitably result in loss of data and degrees of freedom: every lag term results in the loss of one

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15 Expected electricity savings from the bottom-up evaluation provide one way of expressing energy efficiency policy, EE. This offers an advantage in that estimated coefficients can be interpreted as a savings realization rate, the fraction of expected savings reflected in electricity demand. It also presents a drawback: bottom-up savings are assumed to involve measurement error, which presents serious consequences as it results in estimation bias.

set of cross-sectional observations in the panel data, a potentially serious problem in panels with a short time dimension. Both problems become less severe by restricting the lag terms.[16]

There is also the reciprocal relationship between energy efficiency and price elasticity of electricity demand to be accounted for. Price elasticity is decisive in consumers' adoption of energy-efficient appliances. Energy efficient appliances, on the other hand, serve as a substitute for energy consumption when energy prices rise. The model includes a lagged value of average retail electricity rates to allow estimations of short-run ($\beta 2$) and long-run ($\beta 2 + \beta 3$) elasticity of demand. This assumes that electricity demand adjusts gradually to price changes through a stock-flow process, where "stock" refers to energy-consuming appliances that a consumer owns (e.g., air conditioners) and "flow" refers to how much the consumer uses the appliance. Through this process, the consumer has immediate control over setting the thermostat that regulates the air conditioner, but the consumer takes longer to achieve a greater change in electricity use by replacing the air conditioner.

The demand relationship also includes fixed-effects terms to differentiate three states with somewhat unique characteristics that noticeably influenced the results. Wyoming's industrial sector accounts for 60% of statewide electricity consumption (compared to 27% nationwide), which distorts per-capita consumption (Figure 1). North Dakota had the highest increase in per-capita electricity use (Figure 3), partly due to the state's booming oil and gas industry and partly due to its historically low electricity rates. Hawaii stands out as the only state with zero heating degrees.

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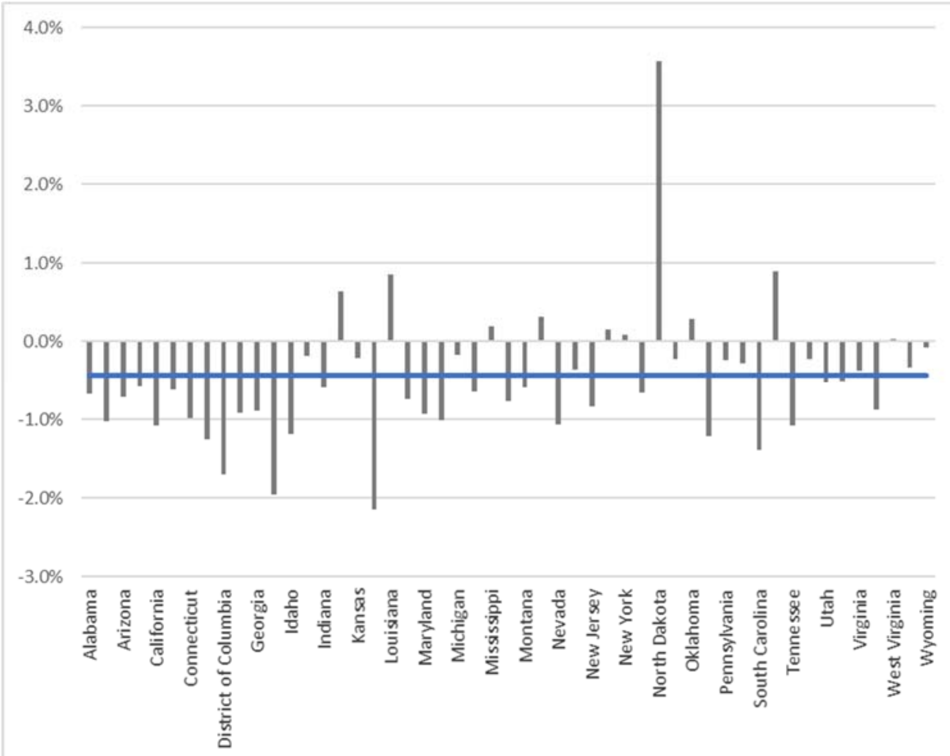
[16] A model that incorporates a lagged independent variable as a predictor—the so-called autoregressive (AR) model—provides another way of capturing this dynamic relationship. Alternatively, features of AR and DL models may be combined to form a so-called autoregressive distributed lag (ARDL) model.

Figure 3. Average Annual Change in Retail Electricity Sales 2006–2016



Finally, the model includes a trend variable (t) to capture omitted time-varying covariates of electricity sales, such as changes in appliance codes and in standards and attitudes.

Parsing the Policy Impacts

We estimated the demand model's parameters using panel data on 50 states and the District of Columbia from 2006 to 2016, with 561 observations. These data were compiled from five sources. ACEEE's Scorecard data provided energy efficiency expenditures and expected savings, obtaining these data from state government agencies, utilities, or program administrators in states where energy efficiency is administered through statewide public benefits charges. Where savings are reported as gross reduction in energy use, ACEEE converts the data into net savings, using a net-to-gross adjustment factor of 0.9 (lowered slightly to 0.87 in 2016). According to ACEEE, the adjustment factor has been applied to all or a portion of savings reported by one-half of the states.

The scorecard data was relatively clean, with a few exceptions where savings or expenditures appeared anomalous or changed inexplicably from one year to the next.[17] Screening the data for these anomalies resulted in the loss of 54 observations, an attrition of about 10%. Data on

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[17] According to ACEEE, the most common reason for such discrepancies are instances where a previous year's data is used for scoring purpose in the Scorecard. These cases are generally corrected subsequently when new data becomes available.

other variables were obtained from the EIA, the U.S. Census Bureau, the U.S. Bureau of Economic Analysis, and the National Oceanic and Atmospheric Administration.

All variables, except the trend and binary variables (adoption of 2012 IECC and fixed state effect variables), were transformed into logarithms—a common way of handling a potentially non-linear relationship between the independent and dependent variables, and a convenient means of transforming a variable's skewed distribution into an approximately normal pattern. We used an error-correction procedure to address an autoregressive (serially-correlated) error term, a common problem in time-series data, to estimate the model's coefficients.

The results indicate satisfactory outcomes. As shown in Table 1, the estimated coefficient of determination (R2) suggests the model fits the data well, explaining 82% of observed variations in per-capita electricity sales. The causal directions, as indicated by the estimated coefficients' signs, operate as theory predicts and are statistically significant for all predictor variables.

Table 1. Regression Results

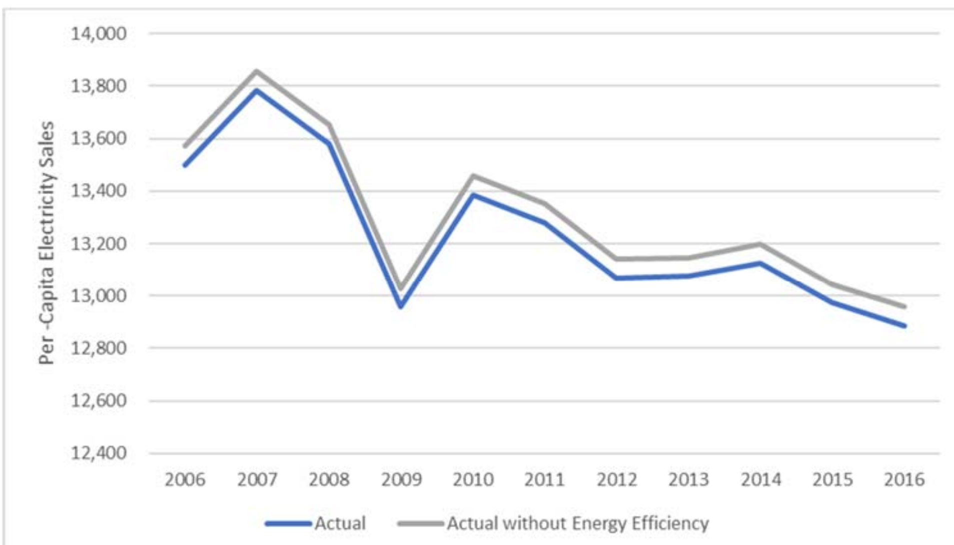
Variables	Mean Value	Estimated Coefficient	t statistic	p value
Per-Capita Retail Electricity Sales (kWh)	12,918.1			
Intercept		8.23	21.80	<.0001
Independent Variables:				
Per-Capita Energy-Efficiency Expenditures (2016 Dollars)	14.9	-0.047	-3.76	0.000
Per-Capita Energy-Efficiency Expenditures (Lagged-1)	13.7	-0.024	-1.97	0.049
Time Trend		0.012	4.01	<.0001
Adoption of 2012 IECC Building Code		-0.103	-2.65	0.008
Per-Capita Gross Domestic Product (GDP)	49,440.8	0.183	6.02	<.0001
Average Retail Electricity Rate (2016 $/kWh)	0.11	-0.427	-3.30	0.001
Average Retail Electricity Rate, Lagged-1 (2016 $/kWh)	0.10	-0.392	-3.16	0.002
Average Retail Natural Gas Rate ($/MCF)	9.6	0.159	4.34	<.0001
Annual Cooling Degree Days (CDD)	1,174.0	0.075	7.07	<.0001
Annual Heating Degree Days (HDD)	5,144.9	0.032	1.83	0.068
Binary Variable Hawaii = 1, 0 Otherwise		0.311	2.24	0.026
Binary Variable North Dakota = 1, 0 Otherwise		0.268	5.29	<.0001
Binary Variable Wyoming = 1, 0 Otherwise		0.684	12.98	<.0001
Autoregressive Error Term (AR1)		0.215	4.21	<.0001
Durbin-Watson Statistic				1.92
R^2				0.82

The results show a small, positive, and statistically significant upward trend in per-capita electricity sales. Adoption of the 2012 IECC building code appears to have a material and statistically significant effect on retail electricity sales. Both short-run and long-run price elasticities with values of 0.43 and 0.82 are statistically significant. These estimates are in line with the EIA's latest short-term and long-term average elasticities of 0.24 and 0.61, excluding the industrial sector.[18] It is reasonable to expect that once the industrial sector's typically higher price elasticity is factored in, the economy-wide estimates would be close.

The coefficients of interest for current-year and lagged per-capita expenditures on electric energy efficiency show a small, but statistically significant impact. The estimated coefficients suggest that increasing per-capita energy efficiency expenditures by 1% (approximately $0.15) can be expected to decrease per-capita retail electricity sales by 0.047% in the short run and 0.072% (0.047+0.024, from Table 1) in the long run. This figure translates into long-run, per-capita savings of just over 62 (0.072 * 12,918.1 / $14.9) kWh from every 1% increase in expenditures. Considering the margins of error associated with the long-term coefficient, we can say in more precise statistical terms that every 1% increase in expenditures can be expected to produce a 37 kWh to 87 kWh reduction in retail electricity sales, on average.

Comparing these predicted values with actual reported annual per-capita savings of 70.7 kWh savings obtains a savings realization rate between 52% and 123%, or nearly 90%, on average. This suggests that publicly funded energy efficiency programs historically have achieved approximately 90% of claimed NET savings. Significantly, we find that savings from energy efficiency account for slightly more than the observed 5.1% average annual reduction in sales from 2006 to 2016 (Figure 4).

Figure 4. Per-Capita Electricity Sales with and without Energy Efficiency 2006–2016



Given average expenditures of $14.9 per capita, the results also suggest a first-year cost of conserved electricity of $0.24 ($14.94 / 62) per kWh. Assuming a weighted average measure life of 11 years (typical of most energy efficiency program portfolios) and an annual discount rate of 6%, this translates to a levelized cost of electricity savings slightly over $0.03 per kWh, a price well below the $0.54 per kWh generation cost of an advanced combined-cycle gas turbine,

[18] U.S. Energy Information Administration. *Price Elasticities for Energy Use in Buildings of the United States*. October 2014. EIA reported elasticities only for the residential and commercial sectors.

which energy efficiency is likely to replace.[19] The picture further improves upon factoring in the benefits of avoided transmission and distribution line losses.

More than Meets the Eye

"The method of science," as the philosopher of science Karl Popper once put it, "is the method of bold conjectures and ingenious and severe attempts to refute them." In energy efficiency, the conjecture is that energy efficiency leads to permanent reductions in energy use. With growing investments in energy efficiency and the wider implications of energy savings in electric system planning as well as broader climate policies, justified concerns exist regarding performance of publicly funded efficiency—that investments in energy efficiency will use scarce resources to the detriment of other worthy causes. Thus, it is understandable that attempts have been made (some more severe than ingenious) to dispute California's claim to a direct link between the state's energy efficiency policies and flat electricity demand.

The study's results show that California's experience is not an aberration, but the consequence of efficiency policies and programs that have blanketed the country over the past decade—and hence reflective of a more widespread Rosenfeld effect. This should come as good news not only to policy-makers, who have advocated efficiency, but to everyone who believes that energy efficiency has a role in mitigating climate change.

A reminder of energy efficiency's importance came on February 27, 2018, when the United Nations Environmental Program published its seventh annual emissions gap report. With an estimated emissions reduction potential of 4.1 GtCO2/year, energy efficiency in buildings and industry is regarded as a major contributor to the globe's ability to meet the Paris Agreement's 2030 emissions reduction goals. Per the study's results, in 2016, the nation's publicly funded efficiency programs produced 22.4 million MWh in electricity savings—roughly 3.5 Rosenfelds.[20] Assuming average emissions of nearly 1 pound per kWh, based on the country's generation mix, these savings helped avoid nearly 22.4 million tons of carbon dioxide. Granted, this will not save the world on its own, but it goes a long way in signaling what is possible for the rest of the world.

This research takes the practice of macroeconomic analysis of energy efficiency's impacts one step further, just as earlier studies have done. It is, after all, through such empirical examinations that the science (and art) of energy efficiency can progress. In the process, we hope to have also shed light on the effectiveness of bottom-up methods for measuring and reporting energy savings.

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19 Reported elasticities are only for the residential and commercial sectors. U.S. Energy Information Administration. "Levelized Cost and Levelized Avoided Cost of New Generation Resources." The Annual Energy Outlook. 2017.

20 In 2010, a group of scientists proposed naming a measurement unit after him. They defined the Rosenfeld as electricity savings of 3 billion kilowatt-hours per year, the amount needed to replace annual generation of a 500-megawatt coal-fired power plant.

As more states have embraced energy efficiency and have adopted stricter methods for monitoring their results, the difference between bottom-up and top-down methods has become less a question of the bottom-up methods' accuracy and more a matter of how well they are executed. The macro-economic approach does not represent a substitute for the bottom-up approach because measuring impacts is just one of the many purposes bottom-up evaluations serve, but it is worthwhile confirmatory exercise that can be easily incorporated into the econometric forecasting models most utilities use. It also offers regulators and policy makers further proof of energy efficiency's efficacy, helping them exercise due diligence without unduly undermining the good policies they have enacted.

