The View from the Top: Application of Macro-Economic Models to Measure Energy-Efficiency Program Savings in California

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Abstract

Energy savings and the cost-effectiveness of energy-efficiency have traditionally been evaluated using a bottom-up (B-U) approach—a mix of techniques based on engineering, statistics, market research, or combinations of these. Despite its history and broad appeal, this approach has several shortcomings: It is time and resource intensive; it may overstate savings, since it does not properly account for technical measure interactions; it fails to properly account for confounding factors, such as rebound effects, self-selection, and persistence.

In light of these considerations, the California Public Utilities Commission (CPUC) decided to investigate the viability of using alternative top-down (T-D) approaches that employ aggregate consumption and macro-economic data to measure reductions in energy use resulting from energy-efficiency. The CPUC's funded a two-track effort to study the applicability of the T-D methods. The two studies apply similar analytic techniques to data compiled at these different geographical levels of resolution: ZIP Code and county/utility service area. This paper describes the scope of the project, reviews the literature on the T-D approach, and reports the preliminary results of the study based on the utility-level application of the approach. The early results of this study indicate the approach provides a useful, inexpensive complement to the B-U approach, although it is unlikely to replace it entirely. The T-D approach predicted annual savings equivalent to 1.8% of annual sales for California's three investor-owned utilities (IOUs). This estimate falls within 7% of the reported savings.

The Bottom-Up Method

The B-U approach to measurement and verification of energy-efficiency programs is widely used in nearly all jurisdictions in the United States. As the term suggests, this approach treats individual energy-efficiency measures, end uses, or programs as the primary units of analysis. It involves estimating savings from individual measures or programs and then aggregating the results to produce system-wide load impacts.

The B-U approach lacks a unified methodology; it is multidisciplinary, relying on disparate analytic techniques to address specific evaluation issues, such as verification of gross savings, net-to-gross calculations, and attribution of savings. Despite its history and broad appeal, the B-U approach has four general shortcomings, especially when applied to large portfolios of energy-efficiency programs.

1. It requires extensive primary data collection and, therefore, is both time- and resource-intensive.
2. It may result in overstating savings, since it fails to account properly for possible technical interactions among measures and programs—a particularly critical issue in large portfolios.
3. In many cases, its application fails to account properly for confounding factors, such as rebound effects and self-selection.
4. It lacks a consistent definition for and treatment of baseline, both across B-U studies and over time, and has failed to adequately account for measure retention and savings persistence.

Broadly speaking, there are two alternatives to the B-U approach: (1) T-D methods relying on macro-economic models of energy demand, and (2) hybrid methods that combine features of the T-D and B-U approaches.

The hybrid methods rely on statistical analysis of consumption within a quasi-experimental research framework. They involve a comparison of consumption for participants (the treatment group) and a comparable sample of nonparticipants (the comparison group) before and after a programmatic intervention to measure a program's net savings. Compared to the B-U approach, the hybrid methods are more convenient and less expensive to implement, but they are unsuitable for evaluating large portfolios.

In the case of large portfolios and multiple programs operated over a long time—such as those of California's investor-owned utilities(IOUs)—it would be difficult to employ this method because of a lack of sufficient data to assign customers appropriately to the treatment and comparison groups. Moreover, the research design does not allow for proper evaluation of the impacts of upstream programs (in which participants cannot be readily identified).It also fails to account effectively for the potential impacts of self-selection bias and, thus, overstates the impacts.

In light of these considerations, the CPUC directed—during its 2010-2012 evaluation, measurement, and verification (EM&V) decision–its Energy Division (ED) to explore using T-D approaches. This entailed assessing and testing the viability of using alternative T-D approaches that use aggregate consumption data to measure reductions in energy consumption due to the various energy-efficiency programs and efforts in California.[1] The CPUC's decision was also motivated in part by these factors: (1) an interest in developing robust methods to assess the progress of achieving carbon emission reductions resulting from the energy-efficiency requirement of the state Assembly Bill 32;and (2) the CPUC's adoption of the California Energy Efficiency Strategic Plan, which is intended to set utility programs on a course towards market transformation.

Project Objectives

To obtain reasonably accurate and reliable means of meeting three key policy objectives, the CPUC expressed an interest in considering a full range of T-D evaluation methodologies:

1. ***Estimation of energy savings attributable to programs operated by California's IOUs.*** Under the existing Risk Reward Incentive Mechanism (RRIM), IOUs can earn financial rewards for meeting—or incur penalties for failing to meet—energy-savings goals established by the state. The CPUC is interested in whether T-D evaluation methods can supplement or substitute existing methods, possibly reducing evaluation costs and time.

2. ***Assessment of the state's progress toward achieving its greenhouse gas reduction goals.*** The California State Assembly Bill 32 requires the state to reduce its greenhouse gas emissions to the levels of the year 1990 by year 2020. An integral component of the state's plan for achieving this goal is to reduce electricity and gas consumption in the retail sector. T-D methods could be used in assessing the progress towards this goal. Such progress would be measured in terms of the *market-gross* savings of electricity and gas consumption.

3. ***Forecasting energy-efficiency programs, codes and standards, and naturally occurring savings for use in developing long-term forecasts of state electricity demand.*** The California Energy Commission (CEC) is responsible for forecasting the state's electricity demand to ensure electric resource adequacy. In 2003, the state declared energy efficiency as a "resource of first choice," meaning that energy-efficiency investments will continue to grow. Demand forecasters must incorporate energy-efficiency growth into their forecasts, but there are few reliable, historical savings data available on which to base the development of these forecasts.

The Top-Down Approach

[1] California Public Utilities Commission (CPUC).*Decision on Evaluation, Measurement, and Verification of California Energy Efficiency Programs,* Decision 10-10-033.October28, 2010.

Among academics and policy makers, there has been considerable interest over the past two decades in T-D approaches based on macro-economic energy demand models to measure the impacts of energy-efficiency and conservation programs. As a result, there is a significant body of research in this area, which has largely been directed towards estimating savings from utility-sponsored, ratepayer-funded energy-efficiency programs.

T-D methods use macro-level data (aggregated to the sector and/or geographic area) on energy use indicators to estimate energy savings. These data contrast with those from customer, end use, or measure levels, which are commonly employed in B-U energy consumption studies. Energy-use indicators measure energy intensity through energy consumption per specific units (e.g., capita, square foot) or unit of output (e.g., industrial value added, gross domestic product) over a specified period of time (typically a year).

Regression analysis of aggregate energy use has been the primary method in T-D analysis. This method offers a straightforward means of estimating the impacts of utility programs on different energy-use metrics while controlling for exogenous factors that affect energy consumption. Thus, regression analysis provides a reasonable framework for attribution of changes in energy-use to utility programs, codes and standards, and naturally occurring conservation.

Typically, the regression model is estimated using panel regression techniques, such as fixed-effects or first-differencing.

Equation 1 represents a typical specification for a regression model to analyze energy use in a particular sector for a large number of utilities over time.

$$\text{(Equation 1)} \quad e_{it} = \mathbf{W}_{it}'\boldsymbol{\gamma} + \Sigma_{j=0}^{J}\delta_j D_{it-j} + \lambda_i + \mu_{it}$$

where:

e_{it} = energy use indicator, typically expressed in natural logarithmic form.

W_{it} = vector of time-varying characteristics in utility service area "i" during period "t" affecting energy use, such as weather, income, electricity, and other energy source prices.

γ = vector of coefficients indicating the relationship between energy use and the characteristics of W_{it}.

D_{it-j} = measure of energy-efficiency program expenditures in the period "t" through "j." One or more lags control for the impacts of past investments on current energy use. The coefficient δ_j, where j=1 to J, shows the impacts of contemporaneous and past utility energy-efficiency investments on energy use.

λ_i = utility-specific fixed effect, capturing the impacts of energy consumption characteristics that do not vary over time.

μ_{it} = the error term, reflecting unobservable influences on energy use in utility "i" during year "t."

In addition to these explanatory variables, many T-D studies include one or more lagged values of the dependent variable, a time trend, or time period fixed effects. The lagged values for the dependent variable capture the partial adjustment of electricity demand to various determinants of energy consumption, such as prices, tastes, preferences, or time-varying factors. As electricity demand derives from the use of long-lived appliances and equipment, adjustments lag when equipment and appliances are replaced gradually. Time trend variables or time periods capture omitted time-varying covariates of consumption, such as changes in attitudes and in codes and standards.

The "δ" coefficient provides the main objects of interest in Equation 1. For example, if D_{it-j} represents per-capita expenditures on energy efficiency, the coefficient δ_{it-j} is interpreted as energy savings in period "t" per dollar of expenditures in period "t" through "j." If D_{it-j} represents expected (*ex-ante*) per-capita energy savings, δ_{it-j} represents the fraction of expected energy savings in period "t" through "j" that are realized in period "t."

Review of Past Research

Since 1996, seven studies have attempted to estimate the energy savings of utility-sponsored energy-efficiency programs using T-D methods (Arimura, Newell, and Palmer, 2009; Auffhammer, Blumstein, and Fowlie, 2008; Horowitz, 2004; Horowitz, 2007; Loughran and Kulick, 2004; Parfomak and Lave, 1996; Rivers and Jaccard, 2011). T-D studies have also used different indicators of energy-efficiency investments, including energy-efficiency expenditures, *ex ante* energy savings, and market transformation variables. Expenditures per unit of consumption or capita have been a common representation of investment (e.g., Auffhammer, Blumstein, and Fowlie, 2008; Rivers and Jaccard, 2011) for three reasons:

- First, coefficients on expenditures have a simple cost-effectiveness interpretation. In log-linear models, the interpretation is the percentage change in savings per dollar. In double-log models, interpretation is the elasticity of savings with respect to expenditures. Given the intense interest in the cost-effectiveness of utility energy-efficiency programs, many researchers naturally chose to quantify energy-efficiency investments in terms of expenditures.
- Second, the utility annual DSM expenditures are readily available on the U.S. Department of Energy's Energy Information Agency (EIA) Form 861, which has reported data on DSM expenditures for most of the nation's utilities since 1989.
- Third, many studies rely on expenditures since these can be represented consistently over time. With proper adjustments for differences in price, energy-efficiency expenditures can be compared over time and across geographic areas.

The use of expenditure as a measure of energy-efficiency activity does, however, pose certain interpretation challenges. For example, the model returns an estimate of average cost-effectiveness across utilities, ignoring potential differences in utilities' efficiency in operating their programs. Also, a utility program's cost-effectiveness may change over time. Typically, utilities invest in the most cost-effective options first. Over time, fewer cost-effective opportunities are available, so cost-effectiveness declines (Arimura, Newell, and Palmer, 2009). Most T-D studies do not specify models that capture differences between utility programs' maturity and life-cycle.

Another limitation in using expenditures is that some data are not disaggregated by sector or by spending on energy-efficiency or demand-response programs (Horowitz, 2004; Rivers and Jaccard, 2011). As T-D studies seek to measure energy savings or energy-efficiency program cost-effectiveness, energy-efficiency expenditures offer the proper measure. When including demand-response spending on expenditures, energy-efficiency expenditures may be measured with error, possibly resulting in a downward bias of the cost-effectiveness and program savings estimates.

An alternative measure of utility energy-efficiency investments uses utility *e xante* savings estimates. Typically, these are based on engineering studies (Parfomak and Lave, 1996, adopt this approach). As with energy-efficiency expenditures, the coefficient on the *ex ante* savings model has a straightforward interpretation: it is the average realization rate for *ex ante* utility program savings. This coefficient, multiplied by *ex ante* savings, produces an estimate of actual savings. However, a difficulty presented by this approach is that *ex ante* savings may not be estimated consistently over time or across utilities (Parfomak and Lave, 1996). Consequently, that can bias the realization rate estimate. Horowitz

(2004) observes that the quality of utility savings data declined during deregulation and industry restructuring in the late 1990s, as DSM fell out of favor.

Horowitz (2004) employs creative approaches to quantifying energy-efficiency and market transformation investments. In his analysis of the commercial sector, he uses statistically adjusted U.S. Census data on electronic fluorescent lighting ballast shipments to approximate utility spending on market transformation programs.[2] Also, in analyzing electricity savings in the residential, commercial, and industrial sectors, Horowitz (2007) uses EIA data on utility-reported energy savings to classify states by their commitment to DSM programs. Table 1 summarizes the basic characteristics and primary findings from these studies.

Table 1. Summary of T-D Utility Program Energy Savings Studies

Study	Sector	Study Sample and Timeframe	Energy Use Indicator	Energy Efficiency	Main Findings
Parfomak and Lave (1996)	Commercial, industrial	39 U.S. utility service territories in 10 states, 1970–1993	Energy sales to commercial and industrialcustomers	Utility reported savings	Average realization rate for commercial programs of 99%
Horowitz (2004)	Commercial	42 U.S. states,1989–2001	Commercial retail electricity sales/ commercial sector income	Savings of adjusted shipments of electronic ballasts	Average realization rate for commercial programs of 54%
Loughran and Kulick (2004)	All sectors	324 U.S. utilities, 1989–1999	Retail energy sales	DSM expenditures	Savings between 0.3% and 0.4% of consumption
Horowitz (2007)	Residential, commercial, industrial	24 U.S. states, 1989–2001	Commercial sector retail electricity sales to state service sector income	Strong versus weak commitment	Reductions in electricity intensity of 4.4% in the residential, 8.1% in the commercial and 11.8% in the industrial sector
Auffhammer, Blumstein, and Fowlie (2008)	All sectors	324 U.S. utilities, 1989–1999	Retail energy sales	DSM expenditures	Savings between 0.5% and 2.8% of electricity consumption
Arimura, Newell, and Palmer (2009)	All sectors	513 U.S. utilities, 1989–2006	Retail energy sales	DSM expenditures per customer	Savings of 1.1% in electricity use at a cost to utilities of $0.064/kWh
Rivers and Jaccard (2011)	All sectors	10 Canadian provinces, 1990–2005	Retail energy sales per capita	DSM expenditures per capita	Statistically zero savings, per-unit cost of conserved energy may be as high as $2/kWh

Although similar in their methods, the seven studies are different in several respects, particularly in the way they define energy use indicators and characterize energy-efficiency programs. In some cases energy use is normalized to a consumption unit (such as population) or relative to a unit of output (such as gross state product—GSP). Energy-use indicators per unit of consumption include energy use *per capita* in the residential sector and energy use *per square foot* of floor space in the commercial sector.

Other studies expressed energy use per unit of output, or energy use intensities (such as energy use per dollar of GDP or GSP), or energy use per unit of industrial output value added. Horowitz (2004)

2 Horowitz's critical assumption is that electronic ballast shipments from market transformation programs closely track other market transformation activities.

uses energy use per unit of income in the commercial and industrial sectors as an energy-use indicator. The advantage of this approach is that it account for changes in the sectors' size and its effect on energy consumption. Thus, it effectively controls for changes in energy use resulting from structural changes in the economy, such as relocations of industries. A disadvantage of energy use intensities is that they remain sensitive to the composition of energy-using firms in the industry. Energy-intensive firms may account for a smaller share of value added over time, decreasing the sector's energy intensity for reasons unrelated to efficiency.

The seven studies also used different indicators of energy-efficiency activity, including energy-efficiency expenditures, *ex ante* energy savings, and market transformation variables. Expenditure per unit of consumption or output, however, is the most common approach to representing energy-efficiency activity (e.g., Auffhammer, Blumstein, and Fowlie, 2008; Rivers and Jaccard, 2011). One advantage of using expenditure is that the coefficient on the expenditure term has a straightforward interpretation as the per-unit cost of conserved energy.

As shown in Table 1, the seven studies reach dramatically different conclusions. For example, savings realization rates range from nearly 100% (Parfomak and Lave, 1996) to zero (Rivers and Jaccard, 2011). The stark differences between the results highlights a long-standing controversy in the energy-efficiency policy arenas about utility program savings and cost-effectiveness, based on conventional B-U evaluations. One contentious point has been how fully utility program evaluations have accounted for freeridership.

- In one study (Train 1988), an analysis of an energy-efficiency program in Southern California estimated that 70% of energy savings would have occurred in the program's absence (1988, p. 124).
- In another study, which analyzed data from 39 utilities for the years from 1970 to 1993 (Parfomak and Lave 1996), the estimated energy-efficiency savings were equivalent to 99% of what utilities had reported.
- Almost a decade later, Horowitz (2004) performed a similar analysis of utility program savings in the U.S. commercial sector and found a significantly lower realization rate of 54%.
- Noting persistent doubts about utility program savings, one study (Loughran and Kulick2004) analyzed data from between 1992 and 1999 for a large sample of 324 utilities. The study found significantly lower savings, ranging from 20% to 25% of those claimed by utilities.
- A recent study (Rivers and Jaccard 2011) analyzed energy-efficiency program savings and cost-effectiveness in 10 Canadian provinces between 1990 and 2005. The study found that energy-efficiency spending had a small and statistically insignificant impact on consumption.

For a large number of utilities, states, and provinces, most of the top-down studies have relied on energy use data and its drivers over time. Energy use is modeled as a function of investments in energy efficiency and other time-varying factors affecting use, including price, weather, and income. Macro sales (consumption) and utility energy-efficiency expenditures or *ex ante* savings data are typically those available from the EIA—which has well-known limitations due to reporting inconsistencies among utilities. Differences between utilities' reporting practices or changes in reporting practices over time means that consumption and energy-efficiency data series enter the models with error. The error in the reporting of sales will be absorbed by the error term and will result in less-precise coefficient estimates. The consequence of measurement error in energy-efficiency expenditures is more serious, as it will result in estimation bias of utility program savings realization rates or cost-effectiveness.

The European Union (EU) has also completed studies investigating the use of energy-efficiency indices for verifying member-country compliance with EU energy savings goals (Bosseboeuf, Lapillone, and Eichhammer, 2005; Lapillonne, Bosseboeuf, and Thomas, 2009). These studies constructed energy consumption indices for the most important end uses in the residential, industrial, transport, and service sectors. Using the end uses' shares of consumption as weights, the end-use indices were averaged to achieve a sector index. The advantage using such indices to aggregated (T-D) indicators is that, presumably, they help control for structural changes and other factors unrelated to energy efficiency.

Applying the Top-Down Approach

Data Development

Data development is the greatest obstacle to applying the T-D approach at the state level, even in large states such as California. According to EIA (Form 861), there were 75 investor-owned and municipal electric distribution companies serving California retail customers in 2010. However, five utilities—Pacific Gas & Electric Co., Southern California Edison Co., the City of Los Angeles, San Diego Gas and Electric, and Sacramento Municipal Utility District—accounted for 82% of all retail sales.

To increase the sample size, this study also contained a number of municipal utilities, the largest of which (City of Santa Clara, the City of Anaheim, and the City of Riverside) account for approximately 1% of electricity sales in the state. The data were compiled for the period from 1989 to 2010, due to concerns over the quality of data prior to 1989. With eight utility service territories in the estimation sample, the number of observations was 168. Table 2 shows the elements and sources of the data compiled for the study.

Table 2. Data Sources for the California T-D Analysis

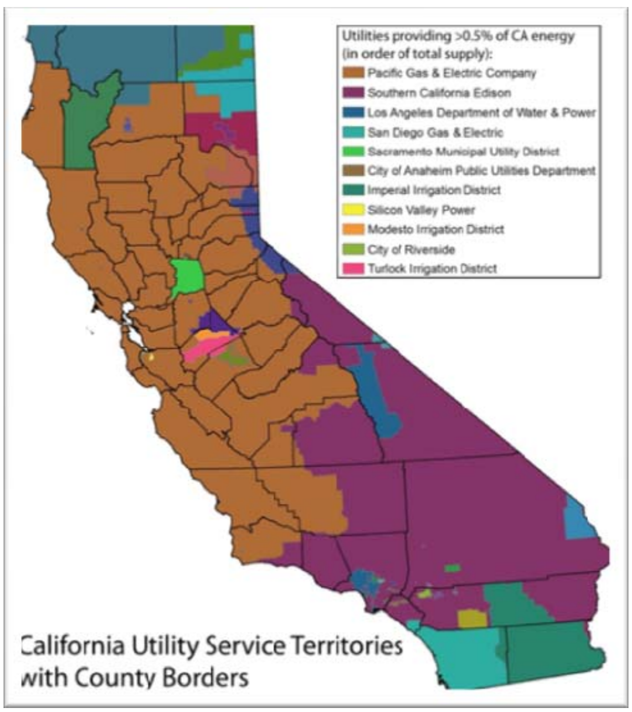
Data Series	Source	Availability	Period
Energy sales	EIA Form 861, CEC, or utilities	Utility service territory and sector	1989–present
Population	U.S. Census Bureau	County/City/MSA	1970–present
Commercial floor space	CEC, McGraw-Hill Construction Dodge	County	1977-present
Commercial value added/income/retail sales	U.S. Bureau of Economic Analysis	County	1969–present
Electricity prices	EIA Form 826, CEC, or utilities	Utility service territory and sector	1989–present
Gas prices (estimated from revenues and sales)	EIA	Utility service territory and sector	1973–present
Personal income	U.S. Bureau of Economic Analysis	County	1969–present
Industrial value added/income	U.S. Bureau of Economic Analysis	County and NAICS	1969–2000 (SIC); 2001–present (NAICS)
Farm income	U.S. Bureau of Economic Analysis	County	1969–present
Consumer or producer price index	U.S. Bureau of Economic Analysis	State	1989–present
Weather (HDDs, CDDs)	National Oceanic and Atmospheric Administration	Utility service territory	1965–present
Appliance saturation	Residential Appliance Saturation Survey or Historical U.S. Census	Household	RASS (2003, 2009); U.S. Census (1980, 1990, 2000)
Energy-efficiency expenditures or savings	EIA Form 861, CEC, or CA IOUs	Utility service territory and sector	1989–present
State energy codes and	CEC	None	1975–present

standards			
Federal energy codes and standards	U.S. Department of Energy	None	1987-present

Most of these data series are free and publicly available. Energy consumption, prices, and efficiency expenditures for utility service territories and the residential, commercial, and industrial sectors are available on the U.S. Department of Energy's EIA Forms 861 and 826. The California Energy Commission (CEC) also has available sales data—starting in 1980—for IOU and municipal utilities. These data could be used to construct consumption series for the California utility service territories, which could alleviate many concerns about the quality and consistency of the EIA consumption data.

Data preparation proved to be a challenge primarily due because information on many of the variables essential to estimating a macro-economic model of energy consumption are available at different geographic levels. For example, energy use and energy-efficiency expenditures are most reliably available at the utility service area level, while macro-economic indicators of economic activity and demographics are compiled at the county and census tract levels. Unfortunately, there is no standard means for converting data from one geographic level. Since the various geographic units do not overlap (as shown in Figure 1), data need to be transformed from one level to another, which increases the potential for error.

Figure 1. Geographical Levels of Data Reporting



Data Sources

Data were obtained from a variety of sources.

- Average prices for each utility and sector were estimated from annual utility revenue and sales data.

- Annual residential, commercial, industrial, and farm income data are available from the Bureau of Economic Analysis Regional Economic Accounts at the county level.
- Historical weather data on annual heating and cooling degree days were obtained from the National Oceanic and Atmospheric Administration's National Climate Data Center.
- Historical data on the saturation of central air conditioning units and gas and electric heat, which can be used to weight heating and cooling degree days in a regression analysis, were obtained from California's Residential Appliance Saturation Survey (RASS) and from the U.S. Census.
- Historical data on residential and non residential new construction was obtained from McGraw Hill.
- Details about California building codes and appliance standards and federal appliance standards were obtained from the CEC, the U.S. Department of Energy, and the Building Code Assistance Project.

Accounting for the effects of codes and standards presented an additional challenge in the study. While California is subject to state building codes and state and federal appliance standards, some areas are more affected by codes and standards than others. For example, pool pump standards would be expected to have their greatest impact in the southern part of the state, where most pools are located. Similarly, areas with higher building activity would experience greater savings from building codes. Measuring savings impacts from California utility programs would require accounting for these differences.

Model Specification and Estimation

The application of the T-D method in California will focus on estimating the impacts of energy-efficiency investments at the aggregate level and residential and non residential sectors. We aggregated the commercial, industrial, and agricultural sectors because utility energy efficiency program expenditures are typically reported at the non residential level. Table 3 shows possible model specifications for each sector. All economic series were expressed in real terms.

Table 3. Top-Down Model Specifications

Variable	Aggregate	Residential	Nonresidential
Dependent variable (energy-use indicator)	Energy sales per capita	Energy sales per capita	Energy sales per unit of floor area
Energy-efficiency indicator	Energy-efficiency expenditures per capita	Energy-efficiency expenditures per capita	Energy-efficiency expenditures per unit of floor area
Other controls	Personal income, electricity price, natural gas price, weather, residential and non residential new construction	Real personal income, electricity price, natural gas price, weather, residential new construction, central air conditioning saturation, electric heat saturation	Personal income, electricity price, gas price, weather, nonresidential new construction

In the total utility sales model, the dependent variable is energy sales per capita, and the energy-efficiency indicator is efficiency expenditures per capita. The main controls are personal income, electricity prices, gas prices, weather, and residential and non residential new construction to capture the impacts of building codes.

In the residential sector, the dependent variable is also energy sales per capita, and the energy-efficiency indicator is efficiency expenditures per capita. The main controls are electricity prices, gas prices, weather, and residential new construction.

The non residential sector has a similar model specification: the dependent variable is energy sales per foot of floor space, and the energy-efficiency indicator is expenditures per foot of floor area. Modeling and estimation issues in the commercial sector are similar to those in the residential sector. Prices may be endogenous due to increasing block tariffs, and the impacts of building codes would be difficult to account for.

Preliminary Results

The results of the literature review and the planning and data development work completed to date indicate the T-D approach is a viable method for estimating aggregate, system-wide effects of energy-efficiency investments. This is particularly true for estimating market gross savings as a means of measuring progress toward California's greenhouse gas reduction goals. Data has been prepared to allow estimation of models for each fuel and retail sectors, with the following basic form:

$$\ln(kWh_{it}) = \sigma\ln(kWh_{it-1}) + \gamma_e\ln(p_{e,it}) + \gamma_g\ln(p_{g,it}) + \beta\ln(I_{it}) + \omega_h\ln(HDD_{it}*EHSAT) + \omega_c\ln(CDD_{it}*CACSAT) + \Sigma_{k=0}^{K}\delta_k EE_{it-k} + \Sigma_{m=1}^{M}\eta_m\ln(NC_{mit}) + \tau(TimeTrend_t) + \lambda_i + \mu_{it}$$

where,

$\ln(kWh_{it})$ is the natural logarithm of per-capita energy use for utility service territory "i," where i=1, 2, …N, in year "t."

$p_{e,it}$ is the electricity price for utility service territory "i" in period "t." The coefficient γ_e shows the short-run price elasticity of demand.

$p_{g,it}$ is the gas price for utility service territory "i" in period "t." The coefficient γ_g shows the short-run price elasticity of demand.

I_{it} is the personal income for utility service territory "i" in period "t." The coefficient β is the short-run income elasticity of demand.

HDD_{it} and CDD_{it} are, respectively, the annual heating and cooling degree days for utility service territory "i" in period "t." The coefficients ω_H and ω_C indicate the short-run elasticity of consumption with respect to annual degree days.

$EHSAT_{it}$ is the electric heat saturation in utility service area "i" in period "t."

$CACSAT_{it}$ is the central air conditioning saturation in utility service area "i" in period "t."

EE_{it-k} is the per capita energy-efficiency expenditures in utility service territory "i" in period "t-k." The coefficient δ_j shows the short-run percentage reduction in per capita consumption in period "t" from a one-dollar increase in energy-efficiency expenditures in period "t-k."

NC_{mit} is cumulative new construction in utility service territory "i" in year "t" built since the building code m, m=1, 2, …M. The coefficient η shows the short-run elasticity of current consumption with respect to new construction built under code m or the incremental effect of building code m on consumption.

$TimeTrend_t$ is a time trend variable, which equals one in 1990 and increases by one unit annually.

λ_i is a component of the error, reflecting utility-specific, time-invariant characteristics. (We control for these unobservable characteristics by including utility fixed effects or estimating the first difference of the regression model.)

μ_{it} is the error term for utility service territory "i" in year "t."

In the dynamic demand model, the long-run elasticity of consumption with respect to an independent variable is obtained by dividing the variable's estimated coefficient by one minus the estimate of σ.

Model Estimation

The specified model was estimated under different assumptions as to the speed at which consumption adjusts to changes in prices, incomes, etc., using alternative lagged structures for the dependent variable. Potential autocorrelation was addressed by using an order one autoregressive process and estimating the models by FGLS. The final estimation sample included data for 29 California utilities (including the five largest utilities: PG&E, SDG&E, SCE, LADWP, and SMUD). Utilities having very small service areas were eliminated, as it was often difficult to estimate their populations reliably.

Preliminary Savings Estimates

Using the specification outlined above, aggregate energy savings were estimated for PG&E, SDG&E, and SCE in each year between 2006 and 2010. These results are preliminary and may change as this research proceeds. The model predicted the following:

- For the PG&E programs, annual savings of 1,081 GWh or 1.2% of consumption, increasing to over 3% of consumption in 2010, as expenditures more than doubled.
- For SCE, estimates showed savings of 1.2% for 2006, decreasing to about 0.5% in 2008, and rising to 2.3% in 2010.
- SDG&E's savings were estimated at 1.2% of consumption in 2006, reaching a maximum of 3.8% in 2008.

For all IOU programs, the model predicted savings of 1.2% in 2006 and 2.7% in 2010.

For all utilities, the model performed better at predicting aggregate savings over multiple years. For example, the model predicted PG&E's programs saved 9,079 GWh between 2006 and 2010, slightly 0.2% higher than what was reported by the utility during this period (9,064 GWh). The predicted five-year savings for SCE and SDGE were not as precise. The model under-predicted SCE's and over-predicted SDGE's savings. However, over time and across the three utilities, the model performed relatively well. It estimated IOU program savings between 2006 and 2010 were 17,516 GWh, which is approximately 7% lower than what was reported by the utilities for the period.

Next Steps

Data collection and preparation have proven to be the key element in the analysis, requiring significantly greater effort than previously expected. This is particularly the case, given the objectives to estimate the aggregate effects at the utility and sector levels, which reduce the number of observations. Potentially, this will reduce the efficiency of the estimated parameters and the precision of the saving impacts.

The planning and data development phases of the project are now nearly complete, and estimation of electricity savings at the sector level has already begun. Once sector-level electric models are estimated, the focus will shift to developing estimates of natural gas savings. According to the project's timeline, the final results of the project are expected to be available in July 2012. The final report on the project will be published by CPUC and will be available on the California Measurement Advisory Council's (CALMAC's) Website: www.calmac.org.

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