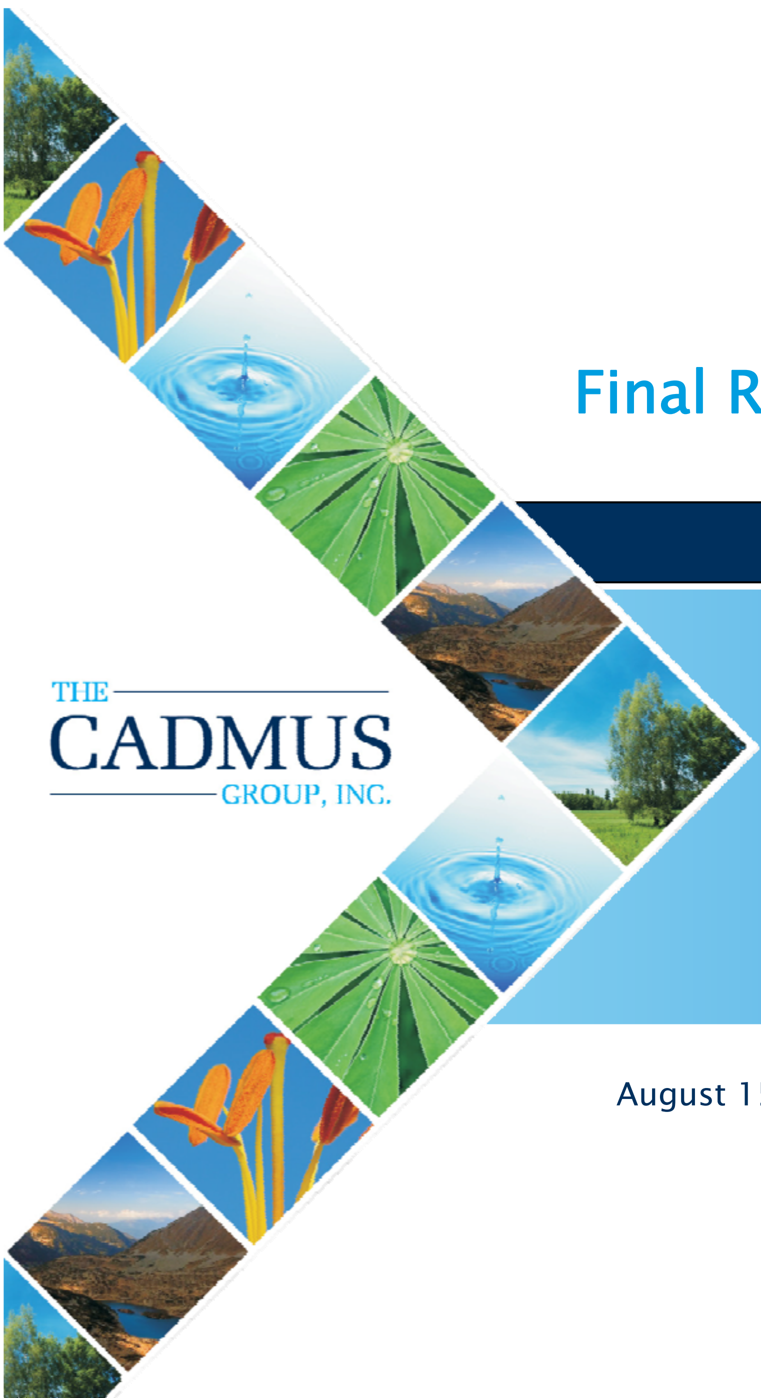

THE CADMUS GROUP, INC.

Final Report

White Paper

Critical Review and Recommendations for Top-Down Evaluations

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1. Introduction

This white paper reviews the conceptual underpinnings, analytic methods, and results of Top-Down (T-D) approaches to estimating the impacts of energy-efficiency programs, and explores their usefulness in addressing energy-efficiency policy issues in California. T-D methods use macro-level data (aggregated to the sector or geographic area) from energy use indicators to estimate energy savings.

Rationale

Energy savings and the cost-effectiveness of demand-side management (DSM) initiatives in general—and energy-efficiency programs in particular—have traditionally been evaluated using a broad range of analytic approaches based on engineering, statistics, market research, or combinations of these. Regardless of their field of origin and despite the diversity of methods used, these approaches are similar in one essential respect: they are structured according to a bottom-up (B-U) approach. As the term suggests, the B-U approach treats individual energy-efficiency measures, end uses, or programs as the primary units of analysis, and involves estimating savings from individual measures or programs, and aggregating results to produce estimates of system-wide load impacts.

The B-U approach has become the utility industry standard for measurement and verification of energy-efficiency program impacts, and is widely used in nearly all jurisdictions of the United States. This approach, however, does not have a unified methodology. Rather, it uses a multidisciplinary approach, relying on disparate analytic techniques to address specific evaluation issues, such as verification of gross savings, net-to-gross calculations, and attribution of savings impacts to utility programs.

Despite its history and broad appeal, the B-U approach has four general shortcomings.

1. First, it requires extensive primary data collection, and is therefore time and resource intensive.
2. Second, it may result in overstating savings since it fails to properly account for possible technical interactions among measures and programs—a particularly critical issue in large portfolios.
3. Third, in many cases, its application fails to properly account for confounding factors, such as rebound effects and self-selection.
4. Fourth, the B-U approach has inconsistent treatments or definitions 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 conventional B-U approach: 1) hybrid methods, combining features of the T-D and B-U approaches, and 2) T-D methods relying on macro-economic models of energy demand. We began research for this white paper by thoroughly examining a hybrid method using a quasi-experimental research design, which is widely used for estimating program-level impacts of energy-efficiency programs. The method involved a comparison of consumption for participants (treatment group) and a comparable sample of non-participants (comparison group) before and after a programmatic intervention to measure the program's net savings.

We evaluated the possibility of extending this general method to measure savings at the aggregate, portfolio level. By relying on pooled cross-sectional, time-series consumption records for participants and non-participants in a utility's programs over an extended period, net portfolio-level savings could be estimated at the utility level. The main advantage of this method is its low cost, both in terms of data requirements and computation. Further analysis, however, revealed several weaknesses of this approach in three critical respects:

1. For utilities with large portfolios and multiple programs being operated over a long period of time, such as with California's investor-owned utilities (IOUs), it would be difficult to employ this method because of the unavailability of customer data to properly assign customers to the treatment and comparison groups.
2. The research design does not allow for proper evaluation of the impacts of upstream programs, in which participants cannot be readily identified.
3. The research design fails to effectively account for the potential impacts of self-selection bias, and thus overstates the impacts.

In light of these considerations, during its 2010–2012 evaluation, measurement, and verification (EM&V) decision, the California Public Utilities Commission (CPUC) directed the Energy Division (ED) to explore, assess, and test 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 partly motivated by their 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 the CPUC's adoption of the California Energy Efficiency Strategic Plan, which is intended to set utility programs on a course towards market transformation.

Objectives

The CPUC has expressed interest in considering a full range of T-D evaluation methodologies, including, but not limited to: econometric and other forms of time series analysis; cross-sectional studies; panel studies; case study approaches; or "hybrid" combinations of B-U and T-D methods. These approaches should provide a reasonably accurate and reliable means of meeting three key objectives:

1. ***Estimation of energy savings attributable to IOU programs.*** Under the existing Risk Reward Incentive Mechanism (RRIM), IOUs can earn financial rewards or incur penalties for meeting or failing to meet energy-savings goals established by the state. Because RRIM financial rewards and penalties can potentially be large, the CPUC requires that IOU program savings be estimated and attributed as effectively as possible. Presently, IOU program savings are verified from the bottom-up on the basis of a large number of program evaluations, a lengthy and costly process. The CPUC is interested in

[1] California Public Utilities Commission. *Decision on Evaluation, Measurement, and Verification of California Energy Efficiency Programs.* Decision 10-10-033. October 28, 2010.

knowing 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.*** State Assembly Bill 32 requires California to reduce its greenhouse gas emissions to year 1990 levels 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 state's 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 and ensuring its generation resources are adequate to meet future demand. 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 few reliable, historical savings data are available on which to base the development of these future forecasts. T-D methods may help the CEC incorporate more accurate estimates of utility program savings into its forecasts.

Research Activities

For this white paper, Cadmus undertook several research activities. We reviewed T-D evaluation literature, which focuses on estimating utility program savings. We identified data sources, modeling and estimation approaches, key identifying assumptions, and important results. Chapter 2 presents our literature review findings.

We also evaluated T-D methods in consideration of their potential application to California policy. In Chapter 3, we describe the data requirements, applicability to different retail energy sectors in the state (e.g., residential, commercial), reliability of savings estimates, and potential policy applications. We close Chapter 3 with recommendations for potential T-D method applications in California.

In Chapter 4, we propose a follow-on study to estimate market gross savings in California using T-D methods. We describe data collection and preparation, model specification and estimation, and estimation of market gross savings.

Summary of Findings

There has been considerable interest over the past two decades in T-D approaches that are based on macro-economic energy demand models to measure the impacts of energy-efficiency and conservation programs, resulting in a significant body of research. This literature suggests that the T-D approach offers an appealing, low-cost alternative to the B-U approach. In addition, our main findings were:

- T-D evaluations have modest data requirements, and can be implemented inexpensively.
- T-D evaluations employ similar conceptual frameworks, data, and estimation approaches, which facilitates the ability to compare results between studies.

- Assumptions necessary for attributing savings to utility programs are strong, difficult to verify, and, in many instances, unlikely to be satisfied.
- Although the studies use similar data, model specifications, and estimation strategies, their results diverge significantly.
- The estimation of market gross savings poses some unique challenges related to naturally occurring and codes and standards savings.

These findings lead to the following observations:

- Limitations notwithstanding, T-D methods provide a potentially useful means of estimating utility program energy savings.
- Use of common data, model specifications, and estimation methods facilitates comparing results among studies.
- Our findings raise doubts about T-D methods' reliability for evaluating utility programs due to a lack of agreement among studies regarding estimated savings and cost-effectiveness, and the strong assumptions required to identify utility program savings. Researchers should carefully examine assumptions required to estimate savings.

Our main findings regarding assessment of the applicability of T-D evaluation to California include:

- Most data required for T-D evaluation in California are free and publicly available.
- Assumptions necessary to identify and estimate utility program savings may be satisfied, with the most likely results in the industrial sector, where codes and standards are not an issue.
- The uncertainty of T-D savings estimates can be described statistically, which is not true for the B-U approach. However, savings based on T-D approaches will likely be estimated imprecisely, limiting their potential policy applications.

From these findings, we draw the following conclusions:

- Implementing T-D savings evaluation in California would be inexpensive, especially compared to costs of estimating savings from the bottom up.
- T-D evaluation of utility savings can be reliably applied to the industrial sector. Concerns arise regarding the application of T-D methods to estimating utility savings in the residential and commercial sectors, due to the confounding impacts of codes and standards. Researchers should invest effort in developing reliable indicators of codes and standards savings for T-D models.
- Uncertainty about utility program savings from T-D evaluations can be incorporated into state forecasts of long-term demand.
- T-D approaches have important limitations, affecting their usefulness in certain policy areas. California policymakers should be aware of these limitations before applying results from T-D evaluation.

Based on our conclusions about the applicability of T-D methods to California policy, we offer the following recommendations:

- California should pursue T-D evaluation methods as a means of estimating historical energy savings for incorporation into CEC forecasts of long-term demand.
- California should be cautious about solely relying on T-D evaluation methods in attribution of energy savings to utility programs due to the imprecision of savings estimates; however, methods could be inexpensively used in conjunction with B-U methods to verify savings.
- California should continue researching the use of T-D methods in estimating market gross savings for tracking the state's progress in meeting its greenhouse gas reduction goals.

Research Proposal

Chapter 4 of this white paper presents a proposal for estimating market gross savings in California from the top-down. Based on our literature review and assessment of California's needs, we conclude that additional research on estimating market gross savings would have the greatest benefit to the state.

Our proposal describes a research plan, including data collection, and a methodology for estimating market gross savings. We also provide a budget, project timeline, and staffing plan.

2. Literature Review

Introduction

Over the last two decades, academics and policymakers have expressed growing interest in the use of T-D methods. Research in this area has been largely directed towards estimation of utility-sponsored energy-efficiency program savings. Little effort has been focused on estimating market-gross savings using T-D methods.

We begin this chapter by defining T-D evaluation methods and exploring their applications in estimating utility programs and market gross savings. We then look more closely at T-D model specifications and different energy use and energy-efficiency indicators. We also review assumptions necessary for identifying utility program savings impacts. Finally, we review findings from a number of papers using T-D methods.

Description of T-D Methods

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).

Applications of T-D Methods

In theory, T-D approaches can be used to estimate *market gross savings* or *utility program savings*. Market gross energy savings tend to be long lasting and result from a range of causes, including utility or public-funded energy-efficiency programs, government policies (such as building codes and appliance standards), and naturally occurring market adoption. In contrast, temporary reductions in energy use from changes in weather, income, energy prices, and other structural economic variables, such as in industry composition, generally do not qualify as market gross savings.

Utility program energy savings result from utility programmatic interventions. They exclude savings from freeriders (program participants who would have installed program measures in a program’s absence) and include spillover savings (resulting from the adoption of non-program measures by program participant and nonparticipants). Interest in T-D methods has grown from policymakers’ and researchers’ concerns that B-U evaluations have not properly accounted for the effects of freeridership, spillover, and savings overlap. Such oversight has likely resulted in overstated utility savings (Arimura, Newell, and Palmer, 2009; Loughran and Kulick, 2004; Rivers and Jaccard, 2011).

We could not identify any researchers using T-D methods to estimate market gross savings. Researchers have focused on utility energy-efficiency programs for two reasons. First, from certain viewpoints, the measurement of savings impacts and cost-effectiveness of utility energy-efficiency programs have proved controversial for some time (Joskow and Marron, 1992; Nadel and Geller, 1996), and most efforts have been to measuring these impacts. However, we expect interest in T-D methods for market gross savings to grow as states establish greenhouse gas reduction goals and seek cost-effective methods for measuring their progress towards achieving those goals. Second, as we discuss, T-D methods are significantly more challenging to use for estimating market gross savings than to use for estimating utility savings.

Given the literature's emphasis on measuring utility savings, our literature review focuses on applying T-D methods in this area; however, many findings about T-D methods for estimating utility program savings can also be used to estimate market gross savings.

T-D Methods for Estimating Energy Savings

T-D studies use regression analyses of aggregate energy use data to estimate energy savings. Regression analysis offers a straightforward method for estimating the impacts of utility programs on different energy-use measures; changes in these measures reflect the influences of a large number of differing factors. Regression analysis allows for proper attribution of energy-use changes resulting from utility programs, codes and standards, and naturally occurring savings by controlling for a large number of different factors affecting energy use.

T-D Estimation of Utility Program Savings

T-D studies typically rely on energy use data and its drivers for a large number of geographic units (e.g., utility service territories, states, or provinces) over time. Most of these data can be acquired free-of-charge from the U.S. Department of Energy's Energy Information Administration. Energy use is modeled as a function of energy-efficiency investments and other time-varying factors affecting use, including price, weather, and income.

Typically, the model produces estimates using panel regression techniques, such as fixed-effects or first-differencing. Our research identified seven studies using T-D methods to estimate utility program savings (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). Table 2.1 summarizes the basic characteristics and primary findings from these studies.

Table 2.1 Summary of T-D Utility Program Energy Savings Papers

Study	Sector	Geographic Area and Years	Energy Use Indicator	Energy Efficiency	Main Findings
Parfomak and Lave (1996)	Commercial and industrial	39 U.S. utility service territories in 10 states, 1970–1993	Energy sales to commercial and industrial customers	Utility reported savings at meter	Average realization rate for commercial DSM programs of 99%.
Horowitz (2004)	Commercial	42 U.S. states,1989–2001	Commercial retail electricity sales/commercial sector income	DSM savings of statistically adjusted shipments of electronic ballasts	Average realization rate for commercial DSM programs of 54%.
Loughran and Kulick (2004)	All sectors	324 U.S. utilities, 1989–1999	Retail energy sales	DSM expenditures	DSM savings between 0.3% and 0.4% of electricity consumption.
Horowitz (2007)	Residential, commercial, and industrial	24 U.S. states, 1989–2001	Commercial sector retail electricity sales to state service sector income	Strong versus weak commitment	DSM resulting in reductions in electricity intensity of 4.4% in the residential sector, 8.1% in the commercial sector, 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	DSM 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	DSM savings of 1.1% of electricity consumption 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	DSM savings are statistically zero. Cost-effectiveness may be as high as $2/kWh

To illustrate a typical approach, the following model examines energy use in a sector (e.g., residential, commercial) for a large number of geographic areas (e.g., utility service territories), i=1, 2,..., N, over a number of years (t=1, 2, ..., T).

Let us suppose that annual energy use per consumption unit (e.g., capita) in area 'i' in year 't' can be modeled as follows:

$$e_{it} = \mathbf{W}_{it}'\gamma + \Sigma_{j=0}^{J}\delta_j D_{it-j} + \lambda_i + \mu_{it} \qquad \text{(Equation 2.1)}$$

Where:

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

$\mathbf{W}_{it}$ = vector of time-varying characteristics affecting energy use in geographic area 'i' during period 't,' including weather, income, electricity, and other energy source prices.

γ = vector of coefficients indicating the relationship between energy use and the characteristics of $\mathbf{W}_{it}$.

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 = geographic unit of analysis fixed effect, capturing the impacts of energy consumption characteristics that do not vary over time.

μ_{it} = the model's random error term, reflecting unobservable influences on energy use in area 'i' during year 't.'

In addition to the right-hand side variables listed above, 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 changes in prices, preferences, or time-varying factors (Auffhammer, Blumstein, and Fowlie, 2008; Horowitz, 2004; Loughran and Kulick, 2004; Rivers and Jaccard, 2011). As electricity demand derives from the use of long-lived appliances and equipment, adjustments lag as equipment and appliances are replaced gradually. Houthakker, Verlager, and Sheehan (1974) show how auto-regressive model specifications can be derived from a flow-adjustment demand model.

Time trend variables or time periods capture omitted time-varying covariates of consumption, such as changes in attitudes and in codes and standards (Loughran and Kulick, 2004, p. 38).

The 'δ' coefficient provides the main objects of interest in Equation 2.1. If D_{it-j} represents per capita DSM expenditures, the coefficient δ_{it-j} represents energy savings in period 't' per dollar of expenditures in period 't' through 'j.' If D_{it-j} represents per capita *ex ante* energy savings, δ_{it-j} represents the percentage of *ex ante* energy savings in period 't' through 'j' that are realized in period 't.'

Market Gross Savings

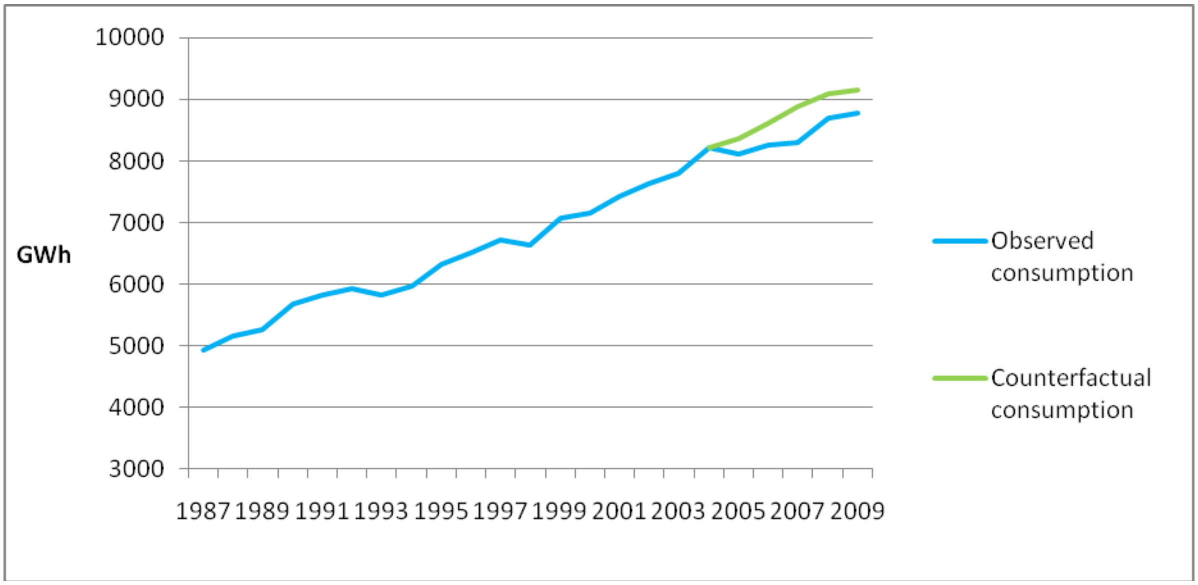
Market gross savings result from utility energy-efficiency programs, codes and standards, and naturally occurring adoption, and result in long-lasting savings, not short-term reductions in consumption from changes in weather, income, or energy prices. Natural adoption provides an important element of market gross savings, and depends on energy prices, environmental attitudes, energy-efficiency awareness, and the normal replacement of equipment and appliances at the end of their life cycles.

In theory, market gross savings can be estimated as the difference between reference (counterfactual) consumption (consumption in the absence of natural adoption, utility programs, and state codes and standards) and observed consumption. Such estimation could be accomplished via several steps:

1. Model energy consumption as a function of energy prices, income, weather, energy-efficiency investments, codes and standards, and, possibly, a polynomial time trend to obtain consumption elasticity.
2. Estimate consumption in the absence of naturally occurring measures, codes and standards, and utility programs, using the model coefficients. This would require choosing appropriate counterfactual values for prices, energy-efficiency programs, and codes and standards. A plausible counterfactual would use previous year energy prices, previous codes and standards, and zero energy-efficiency expenditures.
3. Estimate market gross savings as the difference between observed consumption and consumption without utility energy-efficiency programs, changes in codes and standards, or naturally occurring adoption.

Figure 2.1 illustrates the calculation of market gross savings. The blue line shows observed consumption and the green line shows consumption in the absence of market gross savings, which we calculated by setting market gross savings variables to zero or their previous period levels. The difference between the lines provides market gross savings.

Figure 2.1. Graphical Illustration of Estimating Market Gross Savings



Estimating market gross savings, however, may be difficult. First, price changes elicit responses along two margins: one permanent and qualifying as energy savings, and the other temporary and not qualifying. Increases in energy prices can lead to the adoption of energy-efficiency measures, which permanently reduce energy use and qualify as savings (the extensive margin). Price increases also reduce the usage intensity of existing appliances and equipment, which is temporary (the intensive margin) and does not qualify as energy savings. As the price variable coefficient captures both effects, estimates of savings impacts based on the coefficient would reflect long-term, short-term, and temporary consumption changes. Naturally occurring savings should capture only those savings from long-term responses to energy price changes. Dynamic demand models that enable the estimation of short- and long-term consumption elasticities are a potential solution to this problem (Houthakker, Verlager, and Sheehan, 1974; Bernstein and Griffin, 2005; Rivers and Jaccard, 2011).

The second way that estimating market gross savings may be difficult is that estimating savings from codes and standards has proved difficult in T-D models (Arimura, Newell, and Palmer, 2009; Aroonruengsawat, Auffhammer, and Sanstad, 2009). Specifically, it has been difficult to develop reliable indicators of energy savings from codes and standards for inclusion in the models as independent variables. We discuss this issue in our proposal in Chapter 4.

The third reason that estimating market gross savings may be difficult is that the polynomial time trend can be used to capture energy savings from naturally occurring adoption related to new attitudes and awareness. The time trend, however, may also include the effects of factors unrelated to energy efficiency and codes and standards, such as increasing adoption of energy-using consumer products (e.g., DVR players, cable boxes, and game consoles).

Energy Use Indicators

In Equation 2.1, the dependent variable e_{it} provides the energy use indicator, showing energy use per consumption or per unit of output (typically for one sector, which are residential, commercial, industrial, and agricultural, but sometimes for all sectors). Studying energy use in all sectors offers the advantage of comprehensiveness: it provides a complete picture of the relationships between energy consumption and energy efficiency in retail energy markets. Its disadvantage lies in the fact that the relationships between certain model variables may not apply across all sectors. For example, energy efficiency may be much more effective in some sectors than others, which is why researchers have adopted both approaches (as was shown in Table 2.1).

Many T-D studies express energy use relative to a consumption unit, such as population, or relative to a unit of output, such as gross state product (GSP). Energy-use indicators per consumption unit include energy use *per capita* in the residential sector or energy use *per square foot* of floor space in the commercial sector.

Normalizing energy this way offers two advantages. First, it controls for changes in energy use on the extensive margin: that is, changes in population or floor space. These changes contribute to energy use and must be accounted for, but they do not represent the primary objects of interest in the estimation. Second, expressing energy use on a per-unit basis facilitates the interpretation of results; it is much easier to understand the significance of energy reductions when results are expressed this way.

Several studies express energy use per unit of output, or energy use intensities. Examples include energy use per dollar of GDP or GSP, or energy use per unit of industrial output value added. Horowitz (2004) 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.

Normalizing energy use per unit of consumption or output also exacts costs in terms of the generality of the assumed relationship between energy use and the normalizing variable. Specifically, in a double-log model (such as that estimated by Arimura, Newell, and Palmer, 2009; Auffhammer, Blumstein, and Fowlie, 2008; Loughran and Kulick, 2004; and others), normalization imposes a unitary elasticity restriction. That is, the model assumes that a 1 percent increase in the normalizing variable results in a 1 percent increase in the energy-use indicator.[2] For example, using population as the normalizing variable implies that a 1 percent increase in population results in a 1 percent increase in energy use.

This assumption may be appropriate in some cases, but it is rarely stated or tested, and would result in biased DSM impact estimates if, for example, economies of scale in electricity

[2] Suppose log total energy consumption in a state sector is: $\ln(Y_t) = a + b_1 \ln(DSM_t) + b_2 \ln(Pop)_t + c\ln(X_t) + \varepsilon_t$
Subtracting $b_2\ln(Pop)_t$ from both sides results in: $\ln(Y_t) - b_2\ln(Pop)_t = a + b_1 \ln(DSM_t) + c\ln(X_t) + \varepsilon_t$
Most papers estimate: $\ln(Y_t/Pop_t) = a + b_1 \ln(DSM_t) + c\ln(X_t) + \varepsilon_t$
This formulation implies that $b_2=1$, (i.e., that sales are unit-elastic in the population).

consumption occurred.[3] In this case, it would be more appropriate to estimate relationships between energy use and energy efficiency directly by using total energy use as the dependent variable and a polynomial in population on the right-hand side of the estimating equation.

Energy-Efficiency Indicators

T-D studies have also used different indicators of energy-efficiency investments, including energy-efficiency expenditures, *ex ante* energy savings, and market transformation variables. For three reasons, most have used expenditures per unit of consumption or output (e.g., Auffhammer, Blumstein, and Fowlie, 2008; Rivers and Jaccard, 2011).

1. First, coefficients on expenditures have a simple cost-effectiveness interpretation. In log-linear models, the interpretation is the percent 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.
2. Second, 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.
3. Third, many studies rely on expenditures since they 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.

Nevertheless, while expenditure data can be a useful source of information about utility investments in energy efficiency, caution should be exercised in interpreting estimated utility program cost-effectiveness. For example, the model returns an estimate of average cost-effectiveness across utilities, ignoring potential differences in utilities' efficiency in operating their programs. Utility programs' cost-effectiveness also may change over time. Utilities typically invest in the most cost-effective options first. As time passes, however, fewer cost-effective opportunities are available, and program cost-effectiveness diminishes (Arimura, Newell, and Palmer, 2009). Most T-D studies do not specify models that capture differences between utility programs' maturities and life-cycles.

Another limitation in using expenditures is, as noted, some data are not disaggregated by sector or 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, and cost-effectiveness and program savings estimates may be biased downward.

[3] For example, total energy consumption may grow by less than 1 percent for every 1 percent increase in population, if the population increase is mostly in dense urban areas with electric space conditioning. Large commercial and multifamily residential buildings in dense urban areas would achieve the same cooling with total lower energy use than the same population in less dense urban, rural, and suburban areas.

An alternative measure of utility energy-efficiency investments uses utility *ex ante* 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 saving. This coefficient, multiplied by *ex ante* savings, produces an estimate of actual savings. A difficulty this approach presents, however, is that *ex ante* savings may not be estimated consistently over time or across utilities (Parfomak and Lave, 1996). This biases 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.[4] 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.

Assumptions Necessary to Identify Utility Program Savings Impacts in T-D Models

As noted, most T-D analyses specify consumption as a function of utility program savings, other time-varying factors (such as income and energy prices), and geographic area fixed effects. The model estimates use panel regression methods. Three assumptions are necessary to identify the impact of utility energy-efficiency programs on consumption:

1. Energy-efficiency expenditures must vary sufficiently over time;
2. Energy-efficiency expenditure variations must be exogenous to consumption; and
3. The model must not omit any variables correlated with energy-efficiency expenditures and consumption.

Violation of these assumptions results in biased estimates of utility program savings, undermining the results' internal validity. We discuss each of these assumptions below, along with the potential threats resulting from their violation.

Sufficient Variation in Energy-Efficiency Investments

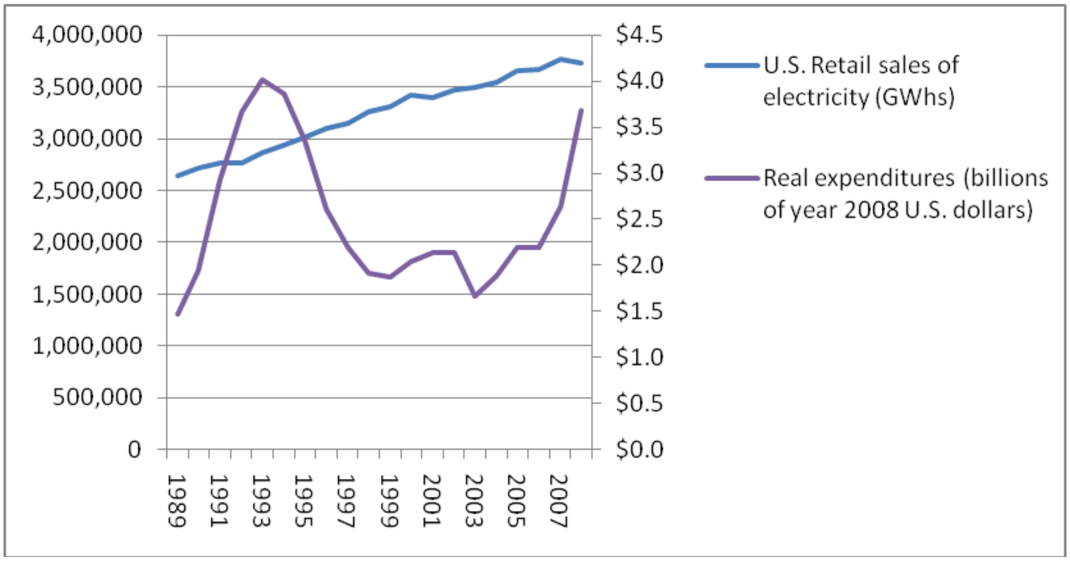
In T-D evaluations, identifying utility program savings requires variations over time in energy-efficiency expenditures within utility service territories, states, or provinces. The variation must be sufficiently large to estimate energy-efficiency programs' savings impacts.

Fortunately, from the standpoint of evaluation, significant variations in DSM spending have occurred over time. Much of this variation in spending has resulted from the restructuring of electricity markets in the late 1990s and 2000s, leading to a significant decrease in energy-efficiency interest and spending by utilities (Arimura, Newell, and Palmer, 2009, pp. 6-7; Rivers

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

and Jaccard, 2011, pp. 3-4). Figure 2.2 shows variations in real total DSM spending and total retail electricity sales in the United States between 1989 and 2008.

Figure 2.2. Real DSM Expenditures by U.S. Utilities, 1989–2008



Exogeneity of Variation in Energy-Efficiency Investments

Variation in energy-efficiency spending must be exogenous with consumption. In the context of Equation 2.1, it must be $E[\mu_{it}D_{it} \mid \mathbf{W}_{it}, \lambda_i] = 0$. Violation of this condition results in biased estimates of utility program impacts.

Such violations could arise for two reasons. First, selection in utilities energy-efficiency program offerings may not be random. For example, if only utilities that expect to save the most energy offer energy-efficiency programs, savings impacts would be biased upward. It could be argued that spending is partially or fully exogenous because, in many cases, utilities' energy-saving targets are mandated by regulation or legislation. However, selection may also occur at the regulatory level, whereby states with expectations of high or cost-effective energy savings mandate the most ambitious savings goals. Selection bias could also occur if utilities invest in energy efficiency only during periods when investments are expected to save a great deal of energy. In this case, savings impacts would also be biased upward.

The second reason energy-efficiency spending may not be exogenous to consumption is that attitudes towards energy efficiency and their impacts on energy consumption vary over time (resulting from environmental concerns). The correlation between energy consumption and energy-efficiency spending from unobserved attitudes about the environment would bias impacts of energy savings downward.

In theory, instrumental variables can be used to control for the endogeneity of consumption and energy-efficiency spending. To do this, analysts would need to find variables correlated with energy-efficiency expenditures, but not with consumption after controlling for other variables. However, in practice, it has proved difficult to find variables satisfying the necessary exclusion requirements (Rivers and Jaccard, 2011).

In practice, most studies have simply ignored the potential for endogenous energy-efficiency expenditures or assumed they were exogenous. In some circumstances, it may be possible to argue that DSM expenditures are effectively exogenous, and research design is quasi-experimental. For example, River and Jaccard (2011, p. 23) argue that energy-efficiency expenditures are largely driven by regulatory requirements and influential personalities, minimizing the extent of endogeneity.

Omitted Variables

Another condition necessary for identifying savings impacts of utility energy-efficiency programs is accounting for all variables correlated with energy-efficiency spending and consumption. If this condition does not hold, the condition $E[\mu_{it}D_{it} \mid \mathbf{W}_{it}, \lambda_i] = 0$ will be violated, and savings estimates will be biased.

In Equation 2.1, two types of omitted variables may potentially be omitted: those varying over time and those not varying. The cross-sectional fixed effects control for any correlation between utility or state time-invariant characteristics affecting consumption and energy-efficiency spending. These fixed effects could control for differences in attitudes and beliefs, home sizes and characteristics, and industrial composition.

The vector 'W' controls for observable factors that change over time. The most important such factors are income, weather, and prices. However, data on all time-varying factors affecting consumption may not be available. If missing variables do not correlate with energy-efficiency expenditures, the omission will be inconsequential. If missing variables are correlated with consumption, however, omitted variable bias will arise.

In most T-D studies, several factors correlated with energy-efficiency expenditures are ignored. First, there are state energy codes and equipment standards, which, as explained earlier, can substitute for utility energy-efficiency programs. To the extent correlation occurs between energy-efficiency programs and codes and standards, and the latter are unaccounted for in the model, the savings impact estimate will be biased. Accurate accounting of codes and standards effects is important due to the correlation between energy codes and standards resulting from their complementary relationship with utility investments, and savings from codes and standards substituting for utility investments. This has been of particular relevance in California, where utilities actively participate in developing and adopting codes and standards, and can claim such savings toward their mandated saving targets. In other states, such as Washington and Minnesota, utilities also are allowed to claim savings from codes and standards toward their targets.

Arimura, Newell, and Palmer (2009, p. 14) attempt to control for the influences of building codes by categorizing U.S. states according to the stringency of their building codes, and by including categorical variables in their model. However, as they note (p. 17), their "*admittedly blunt measure of code stringency is insufficient to detect any effect.*" Their measure may be too blunt in that it does not account for differences between state building code compliance and enforcement, which largely remains unknown.

A second omitted variable is the extent that states are affected by federal appliance standards. While all states are required to comply with federal standards, some are more affected by certain standards than others due to differences in economic, demographic, and climate characteristics.

For example, federal air conditioning standards are likely to have a greater effect on electricity consumption in states with warm climate than with mild climates. If states with high cooling demands also have more stringent energy codes, and codes are omitted from the model, the energy-efficiency savings estimate will be biased. T-D savings analyses have not controlled for the differential effects of federal standards on states energy consumption.

A third variable omitted is third-party, energy-efficiency expenditures by state or quasi-governmental bodies. Rather than requiring utilities to invest in energy efficiency, some states have authorized agencies using public benefit charges to fund energy-efficiency investments (such as: New York [NYSERDA]; Oregon [Energy Trust of Oregon]), and Wisconsin [Focus on Energy]). Arimura, Newell, and Palmer (2009, p. 37) collect data on DSM spending by such agencies, but express concern that some third-party expenditures may also be reported in utility energy-efficiency spending. To the extent that third-party spending correlates with utility expenditures and remains unaccounted for, omissions from models will bias energy-efficiency savings impact estimates.

In California, the major sources of third-party or non-utility energy-efficiency spending have been with American Recovery and Reinvestment Act funds, administered by the CEC, local government initiatives, and federal tax credits. In a T-D evaluation of energy savings in California, it would be important to collect data and control for spending from these sources.

Other Drivers of Energy Use

The regression model must also effectively control for other energy use drivers correlated with the programs. Most studies accomplish this by including geographic fixed effects (e.g., for utility service territory or state) and explicit controls for time-varying factors on the right-hand side of Equation 2.1, such as energy prices, income, and weather. Failure to include these variables from analysis could result in omitted-variable bias.

The most problematic time-varying consumption driver has been energy prices. While theory regarding price change effects on consumption is relatively straightforward, identifying and estimating these effects has proven difficult for several reasons.

1. First, in some markets, there has been relatively little movement in electricity's retail price over time, resulting in insufficient variation with which to identify price effects. Estimated price coefficients are commonly statistically insignificant or have the wrong signs due to a lack of price variation. The studies shown in Table 2.1 have largely overcome this problem by including a large number of cross-sectional units in their analyses.
2. Second, the relationship between prices and sales is endogenous, where each affects the other. In many markets, endogenous prices and consumption arise because of increasing block structures of utility rates (Borenstein, 2009; Ito, 2010). To estimate price effects on consumption, a source of price variations exogenous to sales is needed. Unfortunately, finding instruments for energy prices has been difficult. Most researchers have ignored this issue, though some have argued that prices are effectively exogenous to consumption (Rivers and Jaccard, 2001).

Data Sources

Most T-D studies have obtained macro sales (consumption) and utility program energy-efficiency expenditures or *ex ante* savings data from the U.S. Department of Energy's EIA. These data are self-reported by the utilities in survey forms EIA-826 and EIA-861, [5] and are known to have several issues (Horowitz, 2004; Arimura, Newell, and Palmer, 2009), including:

- Inconsistencies between utilities in reporting of sales by end-use sector. For example, some utilities may categorize certain customers as large commercial, while others may categorize them as industrial.
- Inconsistencies by utilities over time in reporting of sales by end-use sector.
- Varying quality in reports of energy-efficiency expenditures between utilities and over time.

Differences between utilities or changes in reporting practices over time means that consumption and energy-efficiency data series enter the models with error. 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.

Evidence from T-D Studies about Utility Program Savings Impacts

Questions about utility program savings and cost-effectiveness, based on conventional B-U evaluations, intensified in the 1980s and early 1990s. As Figure 2.2 above shows, DSM program expenditures increased rapidly, but some analysts believed insufficient evidence existed to justify such spending. A contentious point was how fully utility program evaluations accounted for freeridership. Many studies used discrete-choice analysis of utility program participation and electricity consumption to estimate program savings (Hartman, 1988; Train, 1988; Waldman and Ozog, 1996).

One of these studies' main conclusions was that freeriders accounted for a large share of utility program participation and savings. For example, Train's analysis of Southern California Edison's energy-efficiency program estimates that 70 percent of energy savings would have occurred in the program's absence (1988, p. 124). Furthermore, studies of utility energy-efficiency program accounting practices and incentives reinforced doubts about utility savings estimates (Joskow and Marron, 1992; Soft and Gilbert, 1994).

In their 1996 paper, "*How Many Kilowatts are in a Negawatt?*," Parfomak and Lave adopted a new approach to the question of utility savings, relying on time-series regressions of macro-level consumption data for a large number of utility service territories. Their panel regression of commercial and industrial sales on conservation expenditures and other consumption drivers involved 39 U.S. utility service territories between 1970 and 1993. Using a double-log model in the first differences, they found that consumption reductions from utility programs equaled 99

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[5] Form EIA-826 includes information about utility-level retail sales of electricity and associated revenue by end-use sector. Form EIA-861 includes information about electricity sales, revenues, customer counts, peak load, electric purchases, DSM programs, green pricing and net metering programs, and distributed generation capacity.

percent of what utilities claimed. Parfomak and Lave (1996) did not analyze impacts of energy-efficiency expenditures in the residential sector.

Almost a decade later, Horowitz (2004) performed a similar analysis of utility program savings in the U.S. commercial sector. He analyzed commercial electricity consumption in 42 states between 1989 and 2001, finding a significantly lower realization rate (54 percent) than Parfomak and Lave (1996). He speculated this was due to differences in model specifications, estimation samples, and time periods, or changes in the quality or implementation of DSM programs.

Noting persistent doubts about utility program savings in spite of Parfomak and Lave (1996) findings, Loughran and Kulick (2004) estimated utility program impacts on electricity consumption in all retail sectors. The authors modeled the first-difference of the log of retail electricity sales as a function of the first difference of the log of time-varying factors such as income, weather, and prices. The number of cross-sectional units in their sample was considerably larger than in the Parfomak and Lave (1996) study, including 324 utilities with positive DSM expenditures between 1992 and 1999. Loughran and Kulick found that energy-efficiency expenditures reduced consumption, but by a much smaller amount and with lower cost-effectiveness than claimed by utilities. Actual savings were approximately 20 to 25 percent of those claimed by utilities. Loughran and Kulick suggest utilities have not adequately accounted for freeridership in their savings estimates.

Auffhammer, Blumstein, and Fowlie (2008) used Loughran and Kulick's retail electricity sales data and model specifications, but reached an opposite conclusion. They pointed out two flaws in Loughran and Kulick's analysis and interpretation. First, in calculating an overall DSM savings rate, Loughran and Kulick did not report utility sales-weighted estimates of energy savings. Instead, they took an unweighted average of savings across all utilities. Second, Loughran and Kulick did not use the appropriate statistics in testing the hypothesis that true savings equal claimed savings. After using a sales-weighted estimate of savings and forming proper test statistics, Auffhammer, Blumstein, and Fowlie (2008) found that average utility reported savings fall within the 95 percent confidence interval for actual savings. Thus, they concluded they cannot reject the hypothesis that reported savings equal actual savings. They also found significantly higher program cost-effectiveness than Loughran and Kulick did.

Horowitz (2007) studied electricity consumption in the residential, commercial, and industrial sectors. He used difference-in-differences methods to estimate the impacts of energy-efficiency policies on electricity consumption between 1977 and 2003. He divided the estimation period (1977 to 2003) into pre (1977-1992) and post (after 1992) periods, corresponding to when a number of states made substantial commitments to energy-efficiency programs. Using energy savings data, he then classified each state as having strong, moderate, or weak commitments to energy-efficiency policy. Employing a difference-in-differences estimator to estimate savings impacts of strong DSM commitments in the post-period for the residential, commercial, and industrial sectors, Horowitz found that strong commitments to energy efficiency results in decreased energy intensity in the residential sector (4.4 percent), commercial sector (8.1 percent), and industrial sector (11.8 percent). However, in the residential sector, Horowitz found strong commitments to energy efficiency associated with increased electricity consumption.

Arimura, Newell, and Palmer (2009) also studied retail electricity consumption, but controlled for a number of factors affecting consumption that earlier studies ignored or were unable to control for. These factors include third-party DSM spending, codes and standards, and decoupling. For example, the authors created categorical variables for the stringency of state residential building codes. The variables were defined in regard to current and previous versions of the IECC.[6] They also allowed energy use to depend on energy-efficiency expenditures in a more flexible way than most previous studies. Using utility EIA data from 1989 to 2006, Arimura, Newell, and Palmer found DSM savings of 1.1 to 1.4 percent and predicted cost-effectiveness of 5.5 to 6.4 cents per kWh—savings that are significantly less and have a greater cost-effectiveness than reported by utilities.

Noting that researchers have not applied T-D evaluation to Canadian energy-efficiency programs, Rivers and Jaccard (2011) analyzed energy-efficiency program savings and cost-effectiveness in 10 Canadian provinces between 1990 and 2005. They found that DSM spending had a small and statistically insignificant impact on consumption. However, they also noted their finding come with a few caveats. First, their model does not control for potential endogeneity between programs spending and electricity consumption, or the impact of codes and standards and other government policies on consumption. Second, their measure of energy-efficiency investment includes energy-efficiency and demand-response expenditures.

Other Approaches to Estimating Utility Program Energy Savings

We identified several other methods for estimating energy savings that could serve as alternatives or supplement B-U approaches currently in use. One approach is exemplified by the discrete choice studies of Train (1988), Hartman (1988), and others. These studies use microeconomic data on utility customer consumption and program participation to estimate energy savings shares attributable to utility programs, freeridership, and natural market adoption.

A second approach is exemplified by a recent study by Sudarshan and Sweeney (2008), who estimated energy savings attributable to California state energy policies using macro data. The study explains the difference in per capita electricity consumption between California and the rest of the United States as a function of climate (and thus heating and cooling loads), water heating use, household income and size, industry type, and population distributions between rural and urban areas. After accounting for these factors, the authors argued that the remaining, unexplained difference between California and the rest of the United States can be attributed to policy differences. Sudarshan and Sweeney noted that their estimate of the unexplained consumption difference is similar to the CEC's estimates of savings from California policy.

The European Union (EU) also completed a study 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). This approach involved the construction of energy consumption indices for the most important end uses in the residential, industrial, transport, and service sectors. The end-use indices averaged to achieve a sector index, using the end uses' shares of consumption as weights. The advantage of the B-U energy-efficiency index in comparison to aggregated (T-D) indicators is they "*are cleaned from the structural changes and from other factors not related to energy efficiency (more appliances, more cars…)*" (Bosseboeuf, Lapillone, and Eichhammer, 2005, p. 1,128).

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6 The variables are not significant or have the wrong signs, casting doubt on how well they control for the impacts of building code stringency on energy consumption.

3. Top-Down Methods in the Context of California Energy-Efficiency Policy

Introduction

In the previous chapter, we reviewed T-D evaluation methods and their applications for estimating utility program and total market gross savings. We showed that T-D studies have resulted in a wide range of savings impact and cost-effectiveness estimates, despite employing similar research designs, analytic models, and data. We also found that assumptions necessary to identify utility programs' savings impacts are strong and difficult to verify. In spite of their reasonably sound conceptual underpinnings and analytic approaches, extreme differences in the results raises serious questions about these methods' reliability and appropriateness for energy-efficiency investment decision making.

In this chapter, we evaluate T-D methods and consider their potential use for energy-efficiency policymaking in California, particularly in the context of the three main research issues delineated in the RFP: estimating energy savings attributable to IOU programs; evaluating the state's progress toward achieving its greenhouse gas reduction goals; and forecasting.

In gauging the utility of this general approach, we examine the following standpoints: (1) data availability and collection; (2) applicability to different retail energy sectors; (3) reliability of savings estimates (bias and precision); and (4) policy applications.

Data Availability and Collection

Table 3.1 shows the data required to estimate utility program savings using T-D evaluation methods. Assuming the unit of analysis would be the utility service territory, only California utility service territories would be included in the analysis, and the data frequency would be annual. Fifteen data series would prove essential for estimating utility program savings in the residential, commercial, industrial, and agricultural sectors. All data series are available annually at utility service territory or county levels, except variables for codes and standards, which would have to be constructed. Also, data series at county levels would require being mapped to utility service territories.

Table 3.1. Data Sources for T-D Analysis

Data Series	Source	Availability	Applicable Sectors	Years
Energy sales	EIA Form 861, CEC, or utilities	Utility service territory and sector	All	1989–present
Population	U.S. Census Bureau	County/City/MSA	Residential	1970–present
Commercial floor space	CEC, McGraw-Hill Construction Dodge	County	Commercial	1977-present
Commercial value added/income/retail sales	U.S. Bureau of Economic Analysis	County	Commercial	1969–present
Electricity prices	EIA Form 826, CEC, or utilities	Utility service territory and sector	All	1989–present
Gas prices (estimated from revenues and sales)	EIA	Utility service territory and sector	All	1973–present
Personal income	U.S. Bureau of Economic Analysis	County	Residential, commercial	1969–present
Industrial value added/income	U.S. Bureau of Economic Analysis	County and NAICS	Industrial	1969–2000 (SIC); 2001–present (NAICS)
Farm income	U.S. Bureau of Economic Analysis	County	Agricultural	1969–present
Consumer or producer price index	U.S. Bureau of Economic Analysis	State	All	1989–present
Weather (HDDs, CDDs)	National Oceanic and Atmospheric Administration	Utility service territory	Residential, commercial, industrial, agricultural	1965–present
Appliance saturation	Residential Appliance Saturation Survey or Historical U.S. Census	Household	Residential	RASS (2003, 2009); U.S. Census (1970, 1980, 1990, 2000)
Energy-efficiency expenditures or *ex ante* savings	EIA Form 861, CEC, or CA IOUs	Utility service territory and sector	All	1989–present
State energy codes and standards	CEC	None	Residential, commercial, agricultural	1975–present
Federal energy codes and standards	U.S. Department of Energy	None	Residential, commercial, agricultural	1987-present

Most of these data series are publicly available for free. Energy consumption, prices, and efficiency expenditures for utility service territories and residential, commercial, and industrial sectors are available on the U.S. Department of Energy's EIA Forms 861 and 826. The CEC also has available sales data for IOU and non-IOU service territories starting from 1980, which could be used to construct consumption series for the California utility service territories.[7] Use of these data would alleviate many concerns about the quality and consistency of the EIA consumption data.

Data on annual energy-efficiency program expenditures can be obtained from the CEC or directly from the utilities. Average prices for each utility and sector could be 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.[8] Historical weather data on annual heating and cooling degree days are available 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 could be used to weight heating and cooling degree days in a regression analysis, are available from California's Residential Appliance Saturation Survey and from the U.S. Census. Details about California building codes and appliance standards and federal appliance standards are available from the CEC, the U.S. Department of Energy, and the Building Code Assistance Project.

As most required data are available electronically, data collection costs would be modest. Data preparation, however, would be more costly, facing three principal challenges. First, it would be desirable to construct consumption and energy-efficiency expenditure series at the utility service territory level, using data from the CEC or the utilities. Second, county- and other geographic-level data would have to be mapped to utility service territories, given that the largest utilities' service territories cover parts of many counties. This would require logical, consistent mapping methodologies. Third, variables would have to be constructed to account for the impacts of state and federal codes and standards on energy use in the residential and commercial sectors (Arimura, Newell, and Palmer, 2009; Aroonruengsawat, Auffhammer, and Sanstad, 2009; Jacobson and Kotchen, 2010).

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.

[7] The CEC developed data series at the planning area level, which is similar but slightly different than the utility service territory. In the industrial sector, their data are further broken out into 28 different NAICS/SIC code level classifications. In the commercial sector, CEC data are broken out into building types. They constructed these series by requesting billing data directly from the utilities. The billing data could be used to form consistent consumption series.

[8] Regional Economic Accounts are available at: http://www.bea.gov/regional/reis/

Applicability to Different Sectors

T-D evaluation methods could be applied to the residential, commercial, and industrial sectors, and possibly to the agricultural sector. Table 3.2 shows the data series required for differing retail sectors.

Table 3.2 Data Availability and Variable Definitions by Sector

Data Series	Residential	Commercial	Industrial	Agricultural
Energy sales	x	x	x	?
Population	x			
Commercial value added/income/retail sales		x		
Commercial floor space		x		
Industrial value added/income			x	
Farm income				x
Electricity prices	x	x	x	x
Gas prices	x	x	x	x
Personal income	x	x		x
Weather (HDDs, CDDs)	x	x	x	x
Appliance saturations	x			
Energy-efficiency expenditures or *ex ante* savings	x	x	x	x
State energy codes and standards	x	x		
Federal energy codes and standards	x	x		

We are uncertain about the feasibility of estimating a model for the agricultural sector due to the unavailability of sales data. EIA does not report sales on the agricultural sector, so these sales data would have to be collected from the CEC or California utilities. Another potential obstacle is that agricultural sales data may include sales to food processors. It will be necessary to closely investigate how any of the agricultural energy sales series were constructed.

Table 3.3 shows possible model specifications for each sector.

Table 3.3. Top-Down Model Specifications

Variable	Residential	Commercial	Industrial	Agricultural
Dependent variable (energy-use indicator)	Energy sales per capita	Energy sales per dollar of valued added in the commercial sector or energy sales per floor space	Energy sales per dollar of valued added in the industrial sector	Energy sales per dollar of income in the agricultural sector
Energy-efficiency indicator	Energy-efficiency expenditures per capita	Energy-efficiency expenditures per dollar of value added in the commercial sector	Energy-efficiency expenditures per dollar of value added in the industrial sector	Energy-efficiency expenditures per dollar of income in the agricultural sector
Other controls	Personal income, electricity price, gas price, weather, codes and standards (lagged building starts)	Personal income, electricity price, gas price, weather, codes and standards	National GDP, manufacturing employment, electricity prices, natural gas prices, weather	National GDP, electricity prices, gas prices, weather

Notes: All models would include utility service territory fixed effects, and could be estimated with a time trend or lagged values of the dependent variable.

In the residential sector, the dependent variable would be energy sales per capita, and the energy-efficiency indicator would be efficiency expenditures per capita. The main controls would be electricity prices, gas prices, weather, and variables for codes and standards.

Two concerns arise with the residential model. First, because many utility consumers face increasing block tariffs for electricity (Borenstein, 2009; Ito, 2010), electricity prices and consumption would be endogenous. An instrumental variables approach may be necessary to estimate price effects (Aroonruengsawat, Auffhammer, Sanstad, 2009). Second, and of greater concern, would be adequately controlling for savings impacts from codes and standards.

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

The industrial sector best lends itself to T-D evaluation, as codes and standards are less important. The dependent variable would be energy use per dollar of value added, and energy efficiency would be expenditures per dollar of value added. The biggest concern with the industrial model would be how to control for changes in energy intensities unrelated to energy efficiency, and from shifts in the types of industry over time. For example, it is well known that industry has left California, and the companies that remain may be less energy-intensive than their predecessors. Manufacturing employment and capital indicators could be employed to account for these shifts. The industrial sector model would also include the national gross domestic product to reflect the strength and demand for industrial goods in the national economy.

Sales in the agricultural sector will be driven by irrigation and possibly light food processing. A potential confounding problem this model faces is that some food processing classifies as agricultural and some as industrial. The dependent variable would be sales per dollar of value added or farm income. The energy-efficiency indicator would be expenditures per dollar of value added. Codes and standards would not be a significant issue, but it might be necessary to control for changes over time in the shares of different crops grown, which would affect irrigation demand.

Reliability of T-D Evaluation Methods

At the beginning of this chapter, we noted that T-D evaluations of utility programs have resulted in a wide range of savings estimates. While it is not possible to diagnose with certainty the causes of these differences, they raise questions about the methods' reliability for estimating savings. Reliability concerns include whether regression analysis results in a parameter estimate (i.e., a savings realization rate or energy savings per dollar expenditure) equal to the true parameter. It also raises concerns regarding the savings estimate's precision for use in potential policy applications.

In the literature review, we described the following three assumptions necessary to identify savings impacts from utility energy-efficiency programs:

- Energy-efficiency expenditures must vary sufficiently over time.
- Energy-efficiency expenditures variations must be exogenous to consumption.
- Factors correlated with energy-efficiency expenditures and consumption must not be omitted from the model.

In this section, we examine whether these assumptions are likely to remain viable in T-D evaluation of California utility program savings. It would also be important for evaluators using T-D methods to test these assumptions.

Between 1989 and 2009, significant variations in energy-efficiency expenditures occurred. These variations should be sufficient to identify utility programs' savings impacts on consumption.

The second assumption concerns the exogeneity of utility expenditures. In the literature review, we described threats to the validity of this assumption, including selection by utilities in energy-efficiency spending and the impacts of time-varying attitudes towards energy efficiency and the environment on consumption and energy-efficiency spending. Program spending selection, however, would likely present less of an issue in California than in other states. Since the 1970s, California utility energy-efficiency investments have largely been driven by responses of state policy to national and state energy supply crises in the 1970s, late 1990s, and early 2000s (Eom and Sweeney, 2009; Kavalec and Schultz, 2011, pp. 2-4). This means that energy-efficiency spending is more likely to be exogenous with consumption. Another factor mitigating the potential for endogenous energy-efficiency expenditures is the largest IOUs, which account for 70 percent of state electricity sales, are regulated by the same agency, the CPUC, and face similar incentives to invest in energy-efficiency programs.

The third assumption concerns possible omissions of variables correlated with consumption and energy-efficiency expenditures. Omitted variable bias is most likely to arise in the residential and commercial sector models, given the difficulty in capturing significant savings impacts of state and federal codes and standards, and their potential correlation with energy-efficiency expenditures. T-D studies have employed time trends, dummy variables for code stringency, or composite variables of stringency and compliance to measure savings. Our results indicate that developing a reliable indicator of codes and standards savings impacts may be possible.

Overall, we found that necessary identification assumptions are likely to be satisfied in California. Endogenous energy-efficiency spending and omitted variable bias do not appear to be significant concerns, perhaps excepting codes and standards. These issues are more likely to arise in studies involving a larger number of cross-sectional units, where energy-efficiency spending is likely to be determined endogenously in some areas.

Uncertainty and Precision of Savings Estimates

Precision refers to the statistical certainty with which the savings impacts of utility energy-efficiency programs are measured. Precision is usually expressed in terms of a confidence or probability that true savings lies within a distance of the savings estimate. Many T-D evaluations have reported fairly imprecise savings estimates, casting doubt on the usefulness of this approach for many California policy purposes (Auffhammer, Blumstein, and Fowlie, 2008; Rivers and Jaccard, 2011). Nevertheless, it is should be noted that T-D evaluation would make it possible to quantify uncertainty statistically, which cannot be accomplished with current B-U approaches.

To illustrate why precision may limit application of T-D models, consider a recent CEC workshop (May 25, 2011) on estimating historical energy-efficiency impacts for use in long-term demand forecasting.[9] At the workshop, CEC staff presented preliminary estimates of California utility program savings from a T-D regression analysis of the natural logarithm of per capita income on DSM expenditures per capita, a time trend, and other control variables in natural log form (including electricity rate, natural gas rate, cooling degree days, and heating degree days).[10] The estimate of the coefficient on DSM expenditures per capita was -0.0011, with an estimated standard error of 0.00052. The point estimate implies that a one-dollar increase in per capita DSM spending would correlate to an 0.11 percent decrease in per capita consumption. As Table 3.4 shows, with state per capita consumption of 7,037 kWh in 2009, this would imply cost-effectiveness of 7.74 kWh of savings per dollar, or 12.9 cents per kWh.[11]

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[9] May 25, 2011, IEPR Staff Workshop on Historical Energy Efficiency Estimate and Update to the 2009 California Energy Demand Forecast. Documents from the workshop are available here: http://www.energy.ca.gov/2011_energypolicy/documents/2011-05-25_workshop/

[10] Results are available at: http://www.energy.ca.gov/2011_energypolicy/documents/2011-05-5_workshop/presentations/Estimating_Historical_Efficiency_Program_Impacts_Chris_Kavalec.pdf.

[11] This is an approximation of per capita savings, as 2009 consumption includes energy-efficiency expenditure impacts.

Table 3.4. Precision of T-D Savings Estimates

	Point Estimate	LB 95% CI	UB 95% CI
Retail sales (MWh)[1]	259,583,623	259,583,623	259,583,623
2009 population[2]	36,887,615	36,887,615	36,887,615
Per capita consumption (kWh)	7,037	7,037	7,037
Predicted per capita savings per dollar expenditures (kWh)[3]	7.741	14.778	0.549
Cost per kWh savings (cents)	12.918	6.767	182.183
SCE DSM expenditures 2009[4]	$225,000,000	$225,000,000	$225,000,000
SCE claimed savings (MWh)[4]	1,704,000	1,704,000	1,704,000
Model predicted IOU savings (MWh)	1,741,694	3,325,053	123,502

Sources:
1. EIA Form 861, 2009.
2. U.S. Census, http://www.census.gov/popest/eval-estimates/eval-est2010.html.
3. Calculation based on results in Kavalec presentation (slide 21) to CEC, May 25, 2011, http://www.energy.ca.gov/2011_energypolicy/documents/2011-05-25_workshop/presentations/Estimating_Historical_Efficiency_Program_Impacts_Chris_Kavalec.pdf.
4. 2009 SCE Annual Report, http://eega2006.cpuc.ca.gov/DisplayAnnualReport.aspx?ID=7.

To illustrate the uncertainty of regression-based utility program savings, we estimated 2009 SCE energy savings using the cost-effectiveness point estimate and lower and upper bounds of the 95 percent confidence interval. In 2009, SCE reported DSM expenditures of $225 million and first-year savings of 1,704 GWHs using B-U calculations. Based on SCE's expenditures, the model predicts total electricity savings of 1,741 GWH, just 2 percent more than savings calculated using the B-U method.

Although this comparison of T-D and B-U savings addresses just one utility and year, it suggests that T-D approaches may be able to predict savings accurately. Nevertheless, we know there is approximately a 95 percent probability that true utility program cost-effectiveness lies in the interval [-0.21%, -0.0078%]. If we calculate total savings at the lower and upper bounds of the confidence interval for cost-effectiveness, we get saving of 3,325 GWH and 123 GWH, respectively. Thus, there is a 95 percent probability that true savings fall between 7 percent and 195 percent of reported savings. This would create substantial uncertainty in savings estimation for use in California policy.

Policy Applications

As noted, T-D methods offer several potential applications to California policy, including attribution of utility program savings, tracking of market gross savings and progress towards meeting greenhouse gas reduction goals, and forecasting the state's long-term energy demand.

Attribution of Utility Program Savings

We foresee two potential problems with applying T-D methods of attribution of savings to California IOU programs. First, substantial uncertainty will likely be present in savings estimates, as the preceding example using CEC results demonstrated. This would make it difficult to use T-D savings estimates as a basis for rewarding or penalizing IOUs for their programs' performance. Second, T-D evaluation may not measure values evaluators need: the impact of utility programs in the most recent program cycle. T-D methods provide an estimate of the *average* cost-effectiveness or savings over the estimation period, for utility service territories in the estimation sample. Estimates of average savings may differ greatly from true savings in the most recent evaluation cycle. Changes in energy-efficiency program cost-effectiveness over the estimation period would have to be ruled out using statistical tests.

Estimation of Market Gross Savings and Greenhouse Gas Reduction Goals

T-D methods could be used to track market gross savings and progress towards achieving California's greenhouse gas reduction goals, though there would be challenges to achieving this end. As discussed in the literature review, a difficulty in estimating market gross savings is measuring naturally occurring savings, which arise from changes in energy prices, attitudes, and awareness. In T-D models, prices and time trends normally capture these naturally occurring savings, but they also capture other consumption impacts unrelated to market gross savings. More research about estimating these savings will have to be completed before T-D methods can be applied reliably in this area.

Demand Forecasting

T-D evaluation could be applied to estimating historical utility program energy savings for use in developing long-term demand forecasts in California. A benefit of applying T-D methods in this way is the ability to quantify and incorporate uncertainty from energy efficiency in the forecast. This is not possible with B-U savings estimates. Further, although substantial uncertainty exists, T-D evaluation may provide a more reliable means of predicting future utility program savings as a function of expected future utility program expenditures.

Summary of Findings

Based on our analysis of T-D methods and their potential policy applications in California, we determined the following findings.

Data Collection and Preparation

- T-D evaluation of California energy savings would be inexpensive, especially compared to the costs of estimating savings from the bottom up.
- Most required data are free and publicly available.
- Significant effort would be required to prepare data for analysis; particularly in developing a reliable indicator of codes and standards savings for T-D analysis.

Applicability to Different Sectors

- T-D evaluation could be applied to the residential, commercial, and industrial sectors.
- Application to the agricultural sector would depend on the availability of sales data for agricultural customers.
- T-D evaluation could be applied most reliably to the industrial sector. Evaluation of the residential and commercial sectors would have to account for codes and standards savings.

Reliability

- Potential bias in T-D savings estimates resulting from selection and omitted variables is not significant.
- Uncertainty can be measured statistically, but precision of savings estimates remains a concern.

Policy Applications

- The most promising application for T-D methods would be in estimating historical savings impacts of utility programs for use in forecasting long-term demand. T-D evaluation would enable the CEC to quantify uncertainty from energy efficiency in such forecasts.
- T-D methods may not be appropriate for attributing utility energy savings due to imprecision in savings and cost-effectiveness estimates, and such estimates may not reflect savings during the most recent evaluation cycles.

Recommendation to CPUC

Based on these findings, Cadmus makes the following recommendations to the CPUC regarding application of T-D evaluation methods:

- California should apply T-D evaluation methods in estimating historical energy savings for developing forecasts of long-term demand. Applying T-D evaluation towards this purpose would enable the CEC to quantify uncertainty from energy efficiency in its forecasts, and would create opportunities to refine T-D methods for potential use in other policy areas.
- California should not rely solely on T-D evaluation methods for attributing energy savings to utility programs. These methods, however, could be used to verify savings estimated from the bottom-up. One possible approach would be to perform both T-D and B-U evaluations only for programs with the largest savings.
- California should continue to explore the application of T-D methods to the estimation of market gross savings for measuring progress towards meeting the state’s greenhouse gas reduction goals. However, too many uncertainties about measuring naturally occurring savings preclude reliance solely on these methods.

4. Proposal

Introduction

CPUC has expressed interested in developing cost-effective, reliable means of estimating energy savings from utility programs, state and federal codes and standards, and naturally occurring measures. T-D evaluation methods could potentially satisfy this need. In our assessment of T-D evaluation's applicability to California policy, we concluded that some T-D applications are potentially promising.

In this proposal, we describe a plan for estimating the total market gross savings in California using T-D methods. To our knowledge, researchers have not applied T-D evaluation to estimating market gross savings in California or other states. We believe research on estimating market gross savings would have great benefit for California, which must track its progress towards meeting greenhouse gas reduction goals.

In addition to representing a new application of T-D evaluation to a policy objective, our research would also improve existing T-D evaluation methods. In estimating market gross savings that account for naturally occurring savings—which can result from changes in energy prices and changes in awareness and attitudes towards energy efficiency—presents significant challenges. Researchers have measured naturally occurring savings by estimating the impacts of price changes on energy consumption. However, price changes result in two types of changes: 1) transitory, short-term changes in energy use from shifts in the intensity of existing equipment use, which would not qualify as energy savings from a market gross perspective; and 2) more permanent changes in energy use through the adoption of new and more efficient equipment and measures. We propose a method of separately estimating short- and long-term price impacts on consumption, and counting only the long-term impacts in estimating market gross savings.

In addition to improving the estimation of naturally occurring savings, estimating the total market gross savings in California using T-D methods would improve the existing methods for estimating codes and standards impacts on consumption. In our literature review, we found a weakness of existing studies in their inability to rigorously account for the impacts of codes and standards. We propose developing a rigorous measure of codes and standards impacts for use in T-D models, based on building activity or appliance saturation, climate, and compliance and enforcement.

Finally, our approach would reduce bias and increase the precision of savings estimates by employing data from the California utilities (rather than the EIA) to construct the macro consumption and energy-efficiency expenditure series. Use of such data would reduce the amount of measurement error on both sides of our regression equation.

The main outcome of this research will be a T-D estimate of market gross savings in each California retail energy sector (residential, commercial, industrial, and agricultural) between 2006 and 2010. We will estimate and report savings estimates for components of market gross savings, which include savings from utility programs, codes and standards, and naturally occurring adoption. To check our savings estimates' plausibility, we will compare the results to the CPUC and CEC savings estimates.

A technical description of our proposed research approach, a staffing plan, and a budget follows.

Technical Approach and Project Tasks

In our analysis, we will estimate market gross savings in each of California's retail electricity sectors between 2006 and 2010. Our approach relies only on California utility data. Using data for other utilities or applying results from existing T-D evaluations would prove inappropriate, as the resulting estimates would represent average savings for a wide range of utility service territories and states, having very different market conditions and utility program experiences than in California.

We will estimate separate models for each of the four main utility customer sectors, and will report market gross savings. This approach would allow the impacts of energy-efficiency expenditures to vary across sectors, yielding more precise estimates of market gross savings and cost-effectiveness.

The analysis unit will be the utility service territory, which will increase the number of observational units, allowing for more precise estimates while limiting the pilot's cost. In 2009, 75 electric distribution companies served California retail customers (EIA Form 861, File 2, 2009). However, just 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 percent of all retail sales. Our sample will include these five largest utilities, plus other large municipal utilities, including the City of Santa Clara, the City of Anaheim, and the City of Riverside—each of which account for approximately 1 percent of state electricity sales. We will explore the feasibility of increasing the estimation sample to include smaller utility service territories. Our ability to increase the number of utility service territories in the estimation will depend on the costs necessary to clean and prepare the data.

We will estimate the model using annual data between 1989 and 2010, to alleviate concerns about the quality of data before this period and because many of the model's variables are not available at higher frequencies.[12] With eight utility service territories in the estimation sample, the number of observations would be 168.

Task 1: Project Initiation Meeting

The project would kick-off with a meeting between Cadmus and the CPUC and KEMA project management team. At this meeting, we will review and confirm the project objectives, tasks, deliverables, and deadlines. Cadmus will then revise the work plan accordingly for delivery to the project management team.

Deliverable: A revised work plan.

Task 2: Data Collection and Preparation

Cadmus will collect data to estimate market gross savings in the residential, commercial, industrial, and agricultural sectors. Required data, described in the previous chapters, includes information about annual energy-use indicators, utility program expenditures, weather, energy prices, consumer and producer prices, other drivers of consumption, and codes and standards for at least eight California utility service territories between 1989 and 2010 (and possibly for more

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12 EIA Form 861, annual utility DSM expenditure data are typically released between November and December of the following year (source: personal communication with EIA staff, May 25, 2011).

utilities).[13] We will collect the data from the EIA, the U.S. Census Bureau, the Bureau of Economic Analysis, the National Oceanic and Atmospheric Administration, and the CEC. In all, we will collect or construct approximately 40 data series at the utility service territory or county level.

An important feature of our proposal is the use of utility billing data to construct the macro consumption data series and energy-efficiency expenditure series. By constructing the series, rather than relying on EIA data, we will increase the precision of our utility program savings estimates, and reduce bias from measurement error in energy expenditures.

Cadmus will request annual customer billing data between 1989 and 2010 for the California utilities in our estimation sample from the CEC, which obtained that data directly from the utilities. For each utility and each retail sector, Cadmus will aggregate the billing data to estimate annual consumption. The CEC has classified commercial customers by building type and industrial customers by SIC/NAIC code. Cadmus will use this information to develop a consistent series of customers over time.

Cadmus will check the consistency and completeness of all data series, identify any issues, and analytically determine how any data flaws may affect savings estimates. For example, from previous T-D evaluations of utility program expenditures, we observed issues such as an uneven quality of self-reported utility expenditures. Error in the reporting of utility energy-efficiency expenditures is expected to bias down the estimated cost-effectiveness. Instrumental variables can be used in this situation. Nevertheless, in general, we do not anticipate significant problems with these series.

As the analysis unit will be the utility service territory, Cadmus will map data reported at other levels, such as county, to utility service territories. For weather, Cadmus will estimate a population-weighted average or an appliance saturation-weighted average of heating and cooling degree days from weather stations in each utility service territory. For income and other variables reported at the county level, Cadmus will estimate population or other appropriate unit-weighted averages.[14]

Cadmus will adjust all nominal economic series, such as energy-efficiency expenditures, energy prices, and incomes, for changes in price levels over time using consumer and producer price indexes.

Quantifying Impacts of Codes and Standards

A weakness of existing T-D savings evaluations has been their inability to fully account for the savings impacts of codes and standards. As part of our research, Cadmus will develop indicators

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[13] The eight included utility service territories would be: Pacific Gas & Electric Co.; Southern California Edison Co.; The City of Los Angeles; San Diego Gas and Electric; Sacramento Municipal Utility District; City of Santa Clara; City of Anaheim; and City of Riverside.

[14] If all of a utility's service territory is contained in one county, that county average would be the average in the utility service territory. If a utility service territory comprises all or parts of two counties, we would estimate the real personal income at the utility service territory level as a weighted average of the county average real personal incomes with weights equal to each county's share of the population in the utility service territory. Cadmus would require utility customer counts by retail sector and by county or zip code to perform these calculations.

to quantify the impacts of state building codes and federal and state appliance standards on energy consumption. These indicators would be independent variables in the regression model. In constructing such indicators, Cadmus will build on our experience evaluating savings from energy codes and standards in California during the 2006–2008 evaluation cycle.

The requirements for measuring the consumption impacts of state building codes are affected by building activity, code stringency, and compliance and enforcement. As building activity and code stringency vary between regions, savings impacts of codes and standards will vary across utility service territories.

Cadmus can measure new construction using annual data on building permits in California counties, which are available online from Moody's Analytics Economy or McGraw-Hill. This variable would change over time and across regions. It is well known that building permits provide an imperfect measure of building activity; so Cadmus will look for more reliable construction indicators before turning to building permits. We will measure code stringency as the difference between stringency in the current year and stringency under the previous code. This variable would change over time and across climate zones. Compliance and enforcement are expected to vary over time and space, but are difficult or impossible to measure. However, as we will draw the estimation sample only from one state, we expect that compliance and enforcement with building codes will not vary significantly across utility service territories.

We will capture building code impacts by including new construction and an interaction variable between new construction and a measure of code stringency as independent variables. New construction would capture additional consumption from growth in building stock. The interaction variable would capture consumption impacts of a more stringent building code. We would measure savings relative to the previous building code.

Task 3: Model Development and Analytic Framework

Primarily, our research will estimate first-year total market gross electricity savings, defined as first-year energy savings drawn from the following sources:

- Utility energy-efficiency programs.
- State and federal appliance standards and state building codes; the latter are first-year savings from new construction.
- Naturally occurring measures resulting from changes in energy prices and changes in attitudes and awareness.

To estimate savings from these sources, Cadmus will use the following steps:

1. Estimate a dynamic regression model of energy use (Houthakker, Verlager, and Sheehan, 1974) as a function of lagged energy use, energy prices, a time trend, codes and standards, energy-efficiency expenditures, and other observable variables affecting demand. We will estimate this model in reduced form, yielding short- and long-term consumption elasticities for each independent variable.
2. Using the regression results, estimate consumption rates in absence of naturally occurring measures, codes and standards, and utility programs for each utility service territory in the state.

3. Estimate total market gross savings as the difference between counterfactual and observed consumption.
4. Estimate state market gross savings by adding up market gross savings over the utility service territories.

Model Specification

In the following model, 'i' indexes a utility service territory and 't' represents time. For each retail energy sector 'j' (suppressed), we will estimate an energy-use regression model with the following form:

$$\ln(kWh_{it}) = \theta\ln(kWh_{it-1}) + \gamma_e\ln(p_{e,it}) + \gamma_g\ln(p_{g,it}) + \beta\ln(I_{it}) + \omega_h\ln(HDD_{it}) + \omega_c\ln(CDD_{it}) + \Sigma_{k=0}^{K}\delta_k EE_{it-k} + \eta NC_{it} + \mu(NC_{it} * Code_{it}) + \tau(TimeTrend_t) + \lambda_i + \mu_{it} \quad \text{(Equation 4.1)}$$

where the variables are defined as follows:

$\ln(kWh_{it})$ is the natural logarithm of electricity use for utility service territory 'i', where i=1, 2, …N, in year 't.' The right-hand side of Equation 4.1 includes a lagged value of the dependent variable. The lag captures partial adjustments of electricity demand over time due to fixed investments in home appliances and energy-using equipment in businesses (Houthakker, Verlager, and Sheehan, 1974). In this white paper's appendix, we show in the above model with a lagged dependent variable, where the long-run price elasticity of demand equals $\gamma_e/(1-\theta)$ (Houthakker, Verlager, and Sheehan, 1974; Bernstein and Griffin, 2005; Rivers and Jaccard, 2011). This coefficient could be used to estimate naturally occurring savings from changes in electricity prices.

$p_{e,it}$ is the electricity price for utility service territory 'i' in period 't.' The coefficient γ_e shows the short-run price elasticity of demand.

I_{it} is the 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.

EE_{it-k} is the 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_{it} is new construction in utility service territory 'i' in year 't.' The coefficient η shows the short-run elasticity of consumption with respect to new construction.

$Code_{it}$ measures the stringency of the current building code relative to the previous building code in year 't.' The coefficient μ shows the short-run elasticity of new construction as a function of building code stringency (relative to the previous code).

$TimeTrend_t$ is a time trend variable, which equals one in 1989, and increases by one unit annually. It represents the impact of a growing awareness of energy efficiency and changing attitudes about consumption. The coefficient τ represents the short-run impact of changing awareness over the year on consumption. Depending on the number of utility service territories included in the analysis, it may be possible to include time fixed effects instead of a time trend. [15]

λ_i is a component of the error term, reflecting utility-specific, time-invariant, unobservable characteristics. We estimate the contributions of these characteristics with a set of dummy variables for the utility service territories:

$$\sum_{i=1}^{N} \pi_i d_{it}$$

where $d_{it}=1$ if $U_i=i$; and $d_{it}=0$ otherwise, where U indicates the utility service territory number. The coefficient π_i represents the impact of these characteristics on consumption in utility service territory 'i.'

μ_{it} is the error term for utility service territory 'i' in year 't.'

To estimate the long-run elasticity of consumption with respect to an independent variable, we divide the variable's estimated coefficient by one minus the estimate of θ. Table 4.1 summarizes model specifications for the residential and other retail sectors.

Table 4.1 Model Specifications

Variable	Residential	Commercial	Industrial	Agricultural
Dependent variable (energy-use indicator)	Energy sales	Energy sales	Energy sales	Energy sales
Lagged value of dependent variable	Yes	Yes	Yes	Yes
Time trend	Yes	Yes	Yes	Yes
Other controls	Lagged and current energy-efficiency expenditures in the residential sector, personal income, electricity price, gas price, weather, population, new construction, interaction between codes and standards stringency and new construction	Lagged and current energy-efficiency expenditures in the commercial sector, personal income, dollar of valued added in commercial sector or energy sales per floor square footage, space electricity price, gas price, weather, new construction, interaction between new construction and codes and standards stringency	Lagged and current energy-efficiency expenditures in the industrial sector, dollars of value added in industrial sector, national GDP, manufacturing employment, electricity prices, natural gas prices, weather	Lagged and current energy-efficiency expenditures in the agricultural sector, income in agricultural sector, national GDP, electricity prices, gas prices, weather

Notes: All models would include utility service territory fixed effects.

Equation 4.1 is expected to be the main estimating equation; however, Cadmus will estimate other model specifications to test the results' sensitivity and robustness.

[15] Cadmus will also consider including utility-specific time trends to capture heterogeneity in naturally occurring trends.

Task 4: Model Estimation

Cadmus will estimate retail sector models using 21 years (1989–2010) of annual data for at least the eight largest utility service territories in California (and possibly including a larger number of territories). We will include utility fixed effects to capture any unobservable, time-invariant characteristics affecting consumption.

Following a procedure described by Greene (1997, pp. 640-641) and employed by Rivers and Jaccard (2011) for dynamic panel models, we will use instrumental variables to estimate the first difference of the retail sector models. Instrumental variable estimation is necessary because a lagged dependent variable in a panel regression model results in correlation with the disturbance term.[16]

In addition, several assumptions must hold for unbiased estimates of the model coefficients:

1. Energy prices and energy-efficiency expenditures are exogenous to energy use.
2. Any variables correlated with the explanatory variables in the model are included in the model (no omitted variable bias).
3. The error term is not auto-correlated (Wooldridge, 2002).

Cadmus will test these identifying assumptions to the extent possible, and control for any violations of assumptions. For example, we will test the model for evidence of auto-correlated errors (Wooldridge, 2002). The log-log model specification should help us control for heteroskedasticity.

Cadmus will also test the reasonableness of estimated coefficients by comparing them to other studies. A large body of literature estimates short- and long-term price elasticities, income elasticity, and energy-efficiency cost-effectiveness.

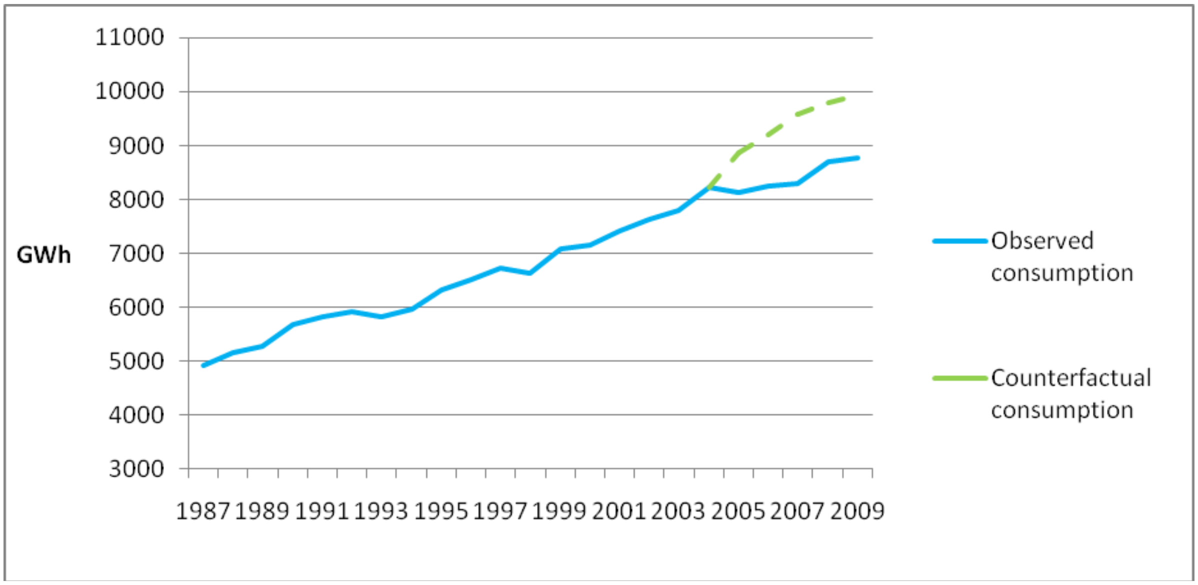
Estimating Total Market Gross Savings

We will use the model results to estimate total market gross savings, which are the sum of permanent or long-term reductions in consumption from energy-efficiency spending, codes and standards, attitudes and awareness, and energy prices. We will estimate market gross savings as the sum of these components. The difference between observed consumption and market gross savings equals what consumption would have been if energy savings activities did not occur.

Figure 4.1 illustrates the calculation of market gross savings for an example utility. The blue line shows actual consumption in a retail sector. The dashed green line shows an estimate of consumption without energy-saving activities. The difference between the lines is what we will be estimating: market gross savings.

[16] This procedure was developed in Nickell (1981) and Arellano and Bond (1991). For instruments, we will use twice-lagged differences or levels of the dependent variable.

Figure 4.1. Illustration of Estimation of Market Gross Savings



To estimate market gross savings, it will be necessary to select reference values or baselines for the components of market gross savings (i.e., what utility expenditures, building codes and standards, energy prices, and attitudes would have been in absence of the energy savings activities). Table 4.2 shows likely reference points and how we will calculate the percentage of savings impact for each component.

We will estimate savings impacts of utility energy-efficiency programs using zero energy-efficiency expenditures as a reference point. We will estimate savings from changes in attitudes and awareness assuming their previous year's values. We will estimate naturally occurring savings from price changes using the previous year's price as the reference value. We will estimate savings from codes and standards using the previous building code or appliance standard as a baseline. For building codes, savings will be the amount of new construction times the differences in savings between buildings constructed under the most recent code and those constructed under the previous code.

Table 4.2 Components of Market Gross Savings

Market Gross Savings Components	Long-Term Elasticity from Model	Interpretation	Reference Value for Measuring Impact	How Savings Are Estimated (E^*_{it} = long-term consumption)
Energy-efficiency expenditures	$\delta_0/(1-\sigma)$	Long-term percentage change in consumption from a one dollar increase in energy-efficiency expenditures	Zero expenditures	E^*_{it} x $(\delta_0/(1-\sigma))$ x (ΔEE_{it})
Attitudes and awareness	$\tau/(1-\sigma)$	Long-term percentage change in consumption from changes in attitudes and awareness over the year	Previous year	E^*_{it} x $(\tau/(1-\sigma))$
Prices	$\gamma_\varepsilon/(1-\sigma)$	Long-term elasticity of demand	Previous year	E^*_{it} x $(\gamma_e/(1-\sigma)$ x $(\Delta p_{e,it}/p_{e,it})$
Codes and standards	$\mu/(1-\sigma)$	Long-term elasticity of new construction as a function of building code stringency (relative to the previous code)	Previous code or standard	E^*_{it} x $(\mu/(1-\sigma))$ x NC_{it} x $\Delta Code_{it}$

Using these reference points, we will estimate the savings from each component, which only include the long-term impacts of prices, energy-efficiency spending, attitudes, and codes and standards on consumption. In the Appendix, we derive expressions for the long-term savings in a dynamic consumption model. The last column in Table 4.2 shows these expressions.

First-year market gross savings for utility 'i' in year 't' (mgs_{ti}) is the sum of the component savings.[17] First-year market gross savings in California in year 't' would equal the sum of first-year market gross savings in the California utility service territories, where i=1, 2, …, N:

$$MGS_t = \Sigma_{i=1}^{N} mgs_{ti}$$

Cadmus will use this methodology to estimate the component savings and market gross savings for each California retail energy sector between 2006 and 2010. We will also estimate the uncertainty of our savings estimates. Finally, we will gauge the reasonableness of our results by comparing them to savings estimates from other studies.

Task 5: Reporting

Cadmus will present a detailed draft report summarizing our research efforts, and will submit it to the CPUC and other stakeholders for comment. The report will include a detailed description of the data collection and preparation effort; the analytical approach, including model specification and estimation; and the savings estimates. The report will also discuss requirements

17 When E^*_{it} is desired or permanent consumption, market gross savings are the sum of naturally occurring savings, energy-efficiency savings, and codes and standards savings, equal to E^*_{it} $*[(\gamma_e/(1-\sigma)*(\Delta p_{e,it}/p_{e,it}) + \tau/(1-\sigma) + (\delta_t/(1-\sigma))*\Delta EE_{it}) + (\mu/(1-\sigma))*NC_{it}*\Delta Code_{it}] = e^{(\ln(Eit) - (1-\sigma)\ln(Eit-1))/\sigma} * [((\gamma_e/(1-\sigma))*(\Delta p_{e,it}/p_{e,it}) + \tau/(1-\sigma) + (\delta_t/(1-\sigma))*\Delta EE_{it}) + (\mu/(1-\sigma))*NC_{it}*\Delta Code_{it}]$. See the Appendix for derivation.

for California to annually estimate market gross savings. Cadmus will deliver a final report, incorporating comments from stakeholders and the CPUC.

Deliverables: Draft and final reports.

Task 6: Workshop Presentation

Cadmus will present the results of our research at a CPUC public workshop. We will use comments from the public presentation and from CPUC reviewers to revise the report.

Project Tasks and Timeline

Figure 4.2 shows the project timeline. The project would kick-off with a meeting between Cadmus and CPUC staff and consultants to confirm the objectives and deliverables for the project. We anticipate that the project will take seven months to complete.

Figure 4.2. Project Timeline

Task	Sep-11	Oct-11	Nov-11	Dec-11	Jan-12	Feb-12	Mar-12
Task 1: Project Initiation Meeting							
1. Meeting between Cadmus and CPUC team							
2. Development of revised workplan							
Deliverable: Revised workplan based on kick-off meeting							
Task 2: Data Collection and Preparation							
1. Data collection							
2. Data prepared for analysis							
3. Develop indicator for codes and standards impacts							
Task 3: Model Development							
1. Develop model specifications							
Task 4: Model Estimation and Savings Analysis							
1. Estimate model							
2. Estimate market gross savings and uncertainty							
3. Compare to other studies and robustness checks							
Task 5: Reporting							
1. Write draft report							
2. Revise final report							
Deliverable: Draft final report							
Deliverable: Final report							
Task 6: Workshop Presentation							
1. Present findings to CPUC and stakeholders							

Team Member Qualifications

About The Cadmus Group, Inc.

The Energy Services Group at Cadmus, which will perform the services specified in the RFP, is located at 720 SW Washington Street, Suite 400, in Portland, Oregon, 97205. The main telephone number for our office is 503-228-2992.

Cadmus' principal-in-charge for this project will be Dr. Hossein Haeri, who can be reached via the main telephone number or his e-mail address: hossein.haeri@cadmusgroup.com.

Description of Cadmus Qualifications

Cadmus' highly qualified staff includes expert program evaluators, economists, statisticians, engineers, and energy analysts. Our proposed team for this project (shown in Table 4.3) provides expertise and in-depth knowledge regarding California energy-efficiency evaluations and methods. This core team will be supported by Cadmus research analysts and associates, as needed.

Table 4.3. The Cadmus Team

Name and Title	Project Role	Recent Relevant Project Experience
Dr. Hossein Haeri, Principal	Principal-in-charge: Responsible for the overall effort; primary contact for quality assurance.	Utility market studies, resource planning, impact assessment, and market transformation. Also statistical data modeling.
Dr. James Stewart, Senior Economist	Project manager: Responsible for managing day-to-day activities; primary contact for project matters.	Demand response and energy-efficiency program evaluations, behavioral (OPOWER) program impact evaluation, CPUC Codes and Standards Program evaluation, and CPUC Residential New Construction program market effects evaluation.
Dr. M. Sami Khawaja, Vice President	Technical expert: Provides expert knowledge regarding top-down evaluation methodologies.	Statistical analysis of DSM program impacts, adjunct professor of statistics and econometrics.
Dr. Allen Lee, Principal	Technical expert: Provides expert knowledge regarding quantification of codes and standards impacts.	Evaluation of California IOU Codes and Standards Program and studies of code compliance in New York and Montana.

Brief Biographies

Dr. Hossein Haeri, a principal at Cadmus, has nearly 25 years of experience in DSM planning, market transformation, evaluation, and quantitative assessment. His expertise covers utility resource planning, energy-efficiency performance verification, load research, and economic and statistical analysis. He has worked with government agencies, nonprofit organizations, and utility companies to aid them in performing market studies, formulating policies and business strategies, planning and executing programmatic initiatives, and evaluating the outcomes and effectiveness of such initiatives.

Dr. Haeri's most relevant work includes leading the preparation of DSM plans for Alliant Energy and Con Edison of New York; filing testimony on behalf of the utilities with regulatory commissions in Iowa and New York; and multi-sector assessments of energy-efficiency and demand response for Alliant, MidAmerican, and Aquila in Iowa; PacifiCorp; Puget Sound Energy; Snohomish County Public Utility District; Seattle City Light; Duke Power; and Ameren Utilities, among others. His work addresses both theoretical and analytic aspects, as well as practical applications of various approaches to energy resource planning, market transformation, and performance assessment. He has worked extensively on the development of cost-effective approaches to data development that takes full advantage of available information, including integration methods for data collection and analysis.

Dr. Haeri is an adjunct assistant professor at Portland State University, where he helped found the graduate program in Applied Energy Economics, and now teaches courses in Policy and Regulation. He holds a bachelor's degree in quantitative social research from the University of Oregon, and a doctorate in regional science from Portland State University.

Dr. James Stewart, a senior economist and senior associate at Cadmus, specializes in econometric and statistical analysis. Dr. Stewart conducts quantitative and qualitative data analysis for a broad range of projects, including program evaluations, impact evaluations, demand forecasting, and potentials assessments. He has creatively employed a range of statistical and econometric methods to identify program impacts, and is proficient in programming with SAS, STATA, Microsoft Excel®, and MATLAB.

Dr. Stewart's research, published in several peer-reviewed journals, involves studying household decision-making, collective action problems, administrative rulemaking, and applying a range of econometric methods (such as discrete choice, instrumental variables, selection, and quantile regression models).

Dr. Stewart holds a doctorate in economics from Northwestern University and a bachelor's in economics from the University of Pennsylvania. Before joining Cadmus, he was an assistant professor of economics and a Thormand A. Miller and Walter Mintz Professor of economic history at Reed College. He has taught econometrics, microeconomics, game theory, and U.S. and European economic history.

Dr. M. Sami Khawaja, a vice president at Cadmus, oversees the firm's Energy Services Group (formerly Quantec, LLC), which currently has a professional staff of more than 130. Dr. Khawaja has more than 25 years of economic consulting experience, and he specializes in forecasting, market transformation assessment, pricing, cost/benefit analysis, and statistical and quantitative analysis for utilities and government agencies. He is also nationally recognized as a leader of program design and evaluation methods.

Dr. Khawaja is well versed in commonly used sampling techniques for load research, including ratio-based sampling and model based statistical sampling. His extensive experience in statistical sampling design has ranged from simple random sampling for residential surveys to more sophisticated sampling design for quality control of large commercial and industrial programs.

In addition to being one of the authors of the International Performance Measurement and Verification Protocol, Dr. Khawaja co-authored the Program Impact Evaluation Guide for the public-private collaborative National Action Plan for Energy Efficiency. In early 2011, he served as the lead author on the Impact Evaluation Guide for the Electric Power Research Institute.

An adjunct professor of economics at Portland State University, Dr. Khawaja teaches quantitative economics and statistics. He is one of the founders of the Applied Energy Economics and Policy graduate certificate program at Portland State University.

Dr. Allen Lee, a principal at Cadmus, has more than 25 years of experience designing, managing, and providing technical leadership on a wide range of projects and programs involving energy policy, energy efficiency, renewables, environmental analysis, and sustainability. Dr. Lee has brought multidisciplinary expertise to challenging research projects for public and private sector clients, and has been directly involved in formulating public policy for public agencies.

Dr. Lee has participated in the development, adoption, implementation, and evaluation of energy-efficiency building codes and appliance standards. While at the CEC, he oversaw the development and implementation of the nation's first building energy codes and appliance standards. In support of the U.S. Department of Energy, he assisted with the development of national residential energy-efficiency codes, and managed development of the first software-based building energy standard for federal residential buildings.

Dr. Lee has also managed the impact and process evaluations of codes and standards programs in several states. He recently completed a multiyear evaluation of the impacts of the California utilities' Codes and Standards Program. He is managing a study of residential code compliance in Montana, as well as an evaluation of training and support program impacts on code compliance in New York. Dr. Lee also conducted a study of the costs and benefits of adopting appliance standards in Idaho.

Dr. Lee has doctorate and master's degrees in policy analysis from the RAND Graduate School. He also has a masters in aerospace engineering from the University of Southern California, and a bachelors in engineering from Caltech.

5. References

Arimura, Toshi H., Richard G. Newell, and Karen Palmer. *Cost Effectiveness of Electricity Energy Efficiency Programs.* Resources for the Future Discussion Paper 09-48. 2009.

Arellano, M. and S. Bond. *Some Test of Specification for Panel Data: Monte Carol Evidence and an Application to Employment Questions.* The Review of Economic Studies 58 (2), 277-297. 1991.

Aroonruengsawat, Anin, Maximilian Auffhammer, and Alan H. Sanstad. *The Impact of State Level Building Codes on Residential Electricity Consumption.* UC Berkeley ARE Mimeo. 2009.

Auffhammer, Maximilian, Carl Blumstein, and Meredith Fowlie. *Demand-Side Management and Energy Efficiency Revisited.* The Energy Journal 29 (3), 91-103. 2008.

Bernstein, Mark A. and James Griffin. *Regional Differences in the Price-Elasticity of Demand for Energy*. Rand Technical Report. Prepared for National Renewable Energy Laboratory. 2005.

Borenstein, Severin. *To What Electricity Price Do Consumers Respond?* University of California Energy Institute working paper. 2009. Available at: *www.econ.yale.edu/seminars/apmicro/am09/borenstein-090514.pdf*.

Bosseboeuf, Didier, Bruno Lapillone, and Wolfgang Eichhammer. *Measuring Energy Efficiency Progress in the EU: The Energy Efficiency Index Odex.* ECEEE 2005 Summer Study 5211. 2005.

Eom, J. and J.L. Sweeney. *Shareholder Incentives for Utility-Delivered Energy Efficiency Programs in California*, working paper, 2009.

Greene, William. Econometric Analysis. Upper Saddle River, New Jersey: Prentice-Hall. 1997.

Hartman, Raymond S. *Self-Selection Bias in the Evolution of Voluntary Energy Conservation Programs.* Review of Economics and Statistics 70 (3), 448-458. 1988.

Horowitz, Marvin J. *Electricity Intensity in the Commercial Sector: Market and Public Program Effects*. The Energy Journal 25 (2), 115-137. 2004.

Horowitz, Marvin J. *Changes in Electricity Demand in the United States from the 1970s to 2003.* The Energy Journal 28 (3), 93-119. 2007.

Houthakker, H.S., Philip K. Verlager, Jr., and Dennis P. Sheehan. *Dynamic Demand Analyses for Gasoline and Residential Electricity.* American Journal of Agricultural Economics 56 (2), 412-418. 1974.

Ito, Koichiro. *Do Consumers Respond to Marginal or Average Price? Evidence from Nonlinear Electricity Pricing*. University of California Department of Agricultural and Resource Economics working paper. 2010. Available at: http://ecnr.berkeley.edu /vfs/PPs/Ito-Koi/web/JMP_Koichiro_Ito_UC_Berkeley_2010_1116.pdf.

Jacobson, Grant D. and Matthew J. Kotchen. *Are Building Codes Effective at Saving Energy? Evidence from Residential Billing Data in Florida.* NBER working paper, 16194. 2010.

Joskow, Paul and Donald Marron. *What Does a Negawatt Really Cost? Evidence from Utility Conservation Programs.* The Energy Journal 13, 41-74. 1992.

Kavalec, Chris and Don Schultz. *Efficiency Programs: Incorporating Historical Activities into Energy Commission Demand Forecasts.* California Energy Commission Draft Staff Paper 200-2011-005-SD. 2011.

KEMA, The Cadmus Group, Inc., Itron, and Nexus Market Research. *Impact Evaluation – Volume III. Codes and Standards (C&S) Programs Impact Evaluation, 2006-2008*. San Francisco: California Public Utility Commission. 2010.

Lapillonne, Bruno, Didier Bosseboeuf, Stefan Thomas. *Evaluation and Monitoring for the EU Directive on Energy End Use Efficiency and Energy Services: Top Down Evaluation Methods of Energy Savings Summary Report.* Wuppertal Institute for Climate, Environment, and Energy. 2009.

Loughran David S. and Jonathan Kulick. *Demand-Side Management and Energy Efficiency in the United States.* The Energy Journal 25 (1), 19-41. 2004.

Nadel, Steven and H. Geller. *Utility DSM: What Have We Learned? Where Are We Going?* Energy Policy 24 (4), 289-302. 1996.

Nickell, S. *Biases in Dynamic Models with Fixed Effects*. Econometrica 49 (6), 1417-1426. 1981.

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.

Rivers, Nic and Mark Jaccard. *Electric Utility Demand Side Management in Canada.* Forthcoming in The Energy Journal. 2011.

Soft, Steven and Richard J. Gilbert. *A Review and Analysis of Electric Utility Conservation Incentives.* Yale Journal on Regulation 11 (1), 1-40. 1994.

Sudarshan, Anant and James Sweeney. *Deconstructing the Rosenfeld Curve.* Stanford University Precourt Institute for Energy Efficiency working paper. 2008.

Train, Kenneth E.. *Incentives for Energy Conservation in the Commercial and Industrial Sectors.* The Energy Journal 9 (3), 113-128. 1988.

Waldman, Donald M. and Michael T. Ozog. *Natural and Incentive Induced Conservation in Voluntary Energy Management Programs.* Southern Economic Journal 62 (4), 1054-1071. 1996.

Wooldridge, Jeffrey M. Econometric Analysis of Cross Section and Panel Data. Cambridge: MIT Press. 2002.

Appendix A. Dynamic Model of Energy Use

This appendix shows the derivation of a dynamic macro model of energy consumption and outlines that the short- and long-term elasticities of demand can be estimated from a reduced form of the model. This dynamic demand framework was proposed in Houthakker, Verlager, and Sheehan (1974) and applied by Bernstein and Griffin (2005) and Rivers and Jaccard (2011), among other researchers. It is based on the idea that in the short-term, consumer are limited in their abilities to adjust their energy consumption due to costly fixed investments in appliances and other energy using equipment.

Suppose that desired energy consumption (E^*) in utility service territory 'i' in year 't' is a Cobb-Douglas function of energy price, income, weather, and population. E^* is the consumption that would result if energy users could instantaneously adjust their consumption without cost. For ease of exposition, we omit the other variables (gas prices, codes and standards, time trend):

$$E^*_{it} = g(p_{e,it}, I_{it}, W_{it}, EE_{it}, P_{it})$$
$$= e^{EEit\varphi} p_{e,it}^{\xi} I_{it}^{\nu} W_{it}^{\alpha} P_{it}^{\phi}$$

If 'g' is included in log-linear form, the coefficient on electricity price $p_{e,it}$ represents the long-term price elasticity of demand. The coefficients on the other variables would also represent long-term elasticities.

However, consumers cannot achieve their desired consumption in each period due to fixed investments in appliances and other energy using equipment. To capture this inability, we assume that consumption adjusts between years according to the following relationship:

$$E_{it}/E_{it-1} = (E_{it}^*/E_{it-1})^{\sigma}$$

where E_{it} is the energy consumption in year 't.' The parameter σ, which is in the interval (0,1), indicates the speed with which the adjustment process occurs. A value close to 1 indicates that the adjustment is almost instantaneous and consumers can freely adjust their consumption. A value close to 0 indicates that consumers are significantly constrained in their ability to change consumption and that adjustment is a slow process.

Taking the natural logarithm of both sides and rearranging terms, we get:

$$\ln E_{it} = \ln E_{it-1} + \sigma \ln E_{it}^* - \sigma \ln E_{it-1}$$
$$= \ln E_{it-1} + \sigma \ln E_{it}^* - \sigma \ln E_{it-1}$$
$$= \sigma \ln E_{it}^* + (1- \sigma) \ln E_{it-1} \qquad \text{(Equation A.1)}$$

If we substitute a linear function of drivers of energy consumption in natural logarithmic form for desired energy consumption in year ‘t,’ we get:

$$\ln E_{it} = \sigma g(p_{e,it}, I_{it}, W_{it}, EE_{it}, P_{it}) + (1-\sigma)\ln E_{it-1}$$

$$\ln E_{it} = \sigma\xi \ln(p_{e,it}) + \sigma\nu \ln(I_{it}) + \sigma\alpha \ln(W_{it}) + \sigma\varphi \ln(EE_{it}) + \sigma\phi \ln(P_{it}) + (1-\sigma)\ln(E_{it-1})$$

In the above equation, the coefficients ξ, ν, α, φ, and ϕ are long-term consumption elasticities.

Making the substitutions $\sigma\xi = \gamma_e$, $\sigma\nu = \beta$, $\sigma\alpha = \omega$, and $\sigma\varphi_k = \delta$ and adding an error term to the model provides our main estimating equation:

$$\ln(E_{it}) = \gamma_e \ln(p_{e,it}) + \beta\ln(I_{it}) + \omega\ln(W_{it}) + \delta \ln(EE_{it}) + (1-\sigma)\ln(E_{it-1}) + \lambda_i + \mu_{it} \quad \text{(Equation A.2)}$$

The long-term consumption elasticities can be recovered by dividing the estimated coefficients γ, β, ω, and δ by one minus the estimate of $(1-\sigma)$.

Estimating Market Gross Savings

We now use the regression framework and results to estimate first year total market gross savings, which reflect long-term changes in consumption from energy saving activities. First, note that for utility service territory ‘i’ in year ‘t,’ long-term consumption is:

$$E_{it}^* = g(p_{e,it}, I_{it}, W_{it}, EE_{it}, P_{it})$$

$$= e^{\varphi EE_{it}} * p_{e,it}^{\ \xi} I_{it}^{\ \nu} W_{it}^{\ \alpha} P_{it}^{\ \lambda}$$

Taking natural logarithms yields:

$$\ln(E_{it}^*) = \xi\ln(p_{e,it}) + \nu\ln(I_{it}) + \alpha\ln(W_{it}) + \varphi EE_{it} + \lambda\ln(P_{it})$$

Totally differentiating both sides of this equation to express the percentage change in consumption as a function of the percentage changes in the independent variables becomes:

$$d\ln(E_{it}^*) = \xi d(\ln(p_{e,it}))/dp_{e,it} + \nu d(\ln(I_{it})/dI_{it}) + \alpha d(\ln(W_{it})/dW_{it}) + \varphi dEE_{it} + \lambda d(\ln(P_{it})/dP_{it})$$

$$= \xi(dp_{e,it}/p_{e,it}) + \nu(dI_{it}/I_{it}) + \alpha(dW_{it}/W_{it}) + \varphi dEE_{it} + \phi(dP_{it}/P_{it})$$

And putting the equation in discrete “delta” form yields:

$$\Delta\ln(E_{it}^*) = \xi(\Delta p_{e,it}/p_{e,it}) + \nu(\Delta I_{it}/I_{it}) + \alpha(\Delta W_{it}/W_{it}) + \varphi\Delta EE_{it} + \phi(\Delta P_{it}/P_{it})$$

This equation outlines how small changes in the independent variables change the percentage of long-term consumption as a function of the percentage changes in prices, incomes, weather, and population, as well as the absolute change in energy-efficiency expenditures. With estimates of the long-term consumption elasticities, we can use the equation to predict the percentage change in long-term consumption as a function of the percentage and absolute changes in the independent variables. Specifically, we can multiply the percentage change in long-term consumption due to naturally occurring savings and energy-efficiency expenditures by an estimate of long-term consumption to estimate market gross savings.

From Equation A.1, long-term consumption can be estimated as:

$$E_{it}^{*} = \exp((\ln E_{it} - (1- \sigma)\ln E_{it-1})/\sigma)$$

where σ would be obtained from the regression estimate of σ in Equation A.2.

In our simplified model, market gross savings for utility 'i' in year 't' would arise from changes in energy prices and energy-efficiency expenditures, and would be estimated as:

$$\text{Market gross savings}_{it} = \text{Naturally occurring savings from price changes}_{it} + \text{energy-efficiency savings}_{it}$$

$$= E^{*}_{it} *(\xi(\Delta p_{e,it}/p_{e,it}) + E^{*}_{it} *(\varphi\Delta EE_{it}))$$

$$= e^{(\ln(Eit) - (1- \sigma) \ln(Eit-1))/\sigma} * (\xi(\Delta p_{e,it}/p_{e,it}) + \varphi\Delta EE_{it})$$

We would obtain an estimate of ξ and φ by dividing the regression estimates of γ and δ by one minus the regression estimate of $1-\sigma$.

If variables for codes and standards and changes in attitudes and awareness are included in the model (see the main text), market gross savings for utility 'i' in year 't' would be:

$$\text{Market gross savings}_{it} = E^{*}_{it} *[(\gamma_e /(1-\sigma)*(\Delta p_{e,it}/p_{e,it}) + \tau/(1-\sigma) + (\delta_t/(1-\sigma))*\Delta EE_{it}) + (\mu/(1-\sigma))* NC_{it}*\Delta Code_{it}]$$

$$= e^{(\ln(Eit) - (1- \sigma)\ln(Eit-1))/\sigma} * [((\gamma_e /(1-\sigma))*(\Delta p_{e,it}/p_{e,it}) + \tau/(1-\sigma) + (\delta_t/(1-\sigma))*\Delta EE_{it}) + (\mu/(1-\sigma))* NC_{it}*\Delta Code_{it}]$$

To estimate market gross savings in the state in year 't,' we would sum the market gross savings over all utilities in the state.