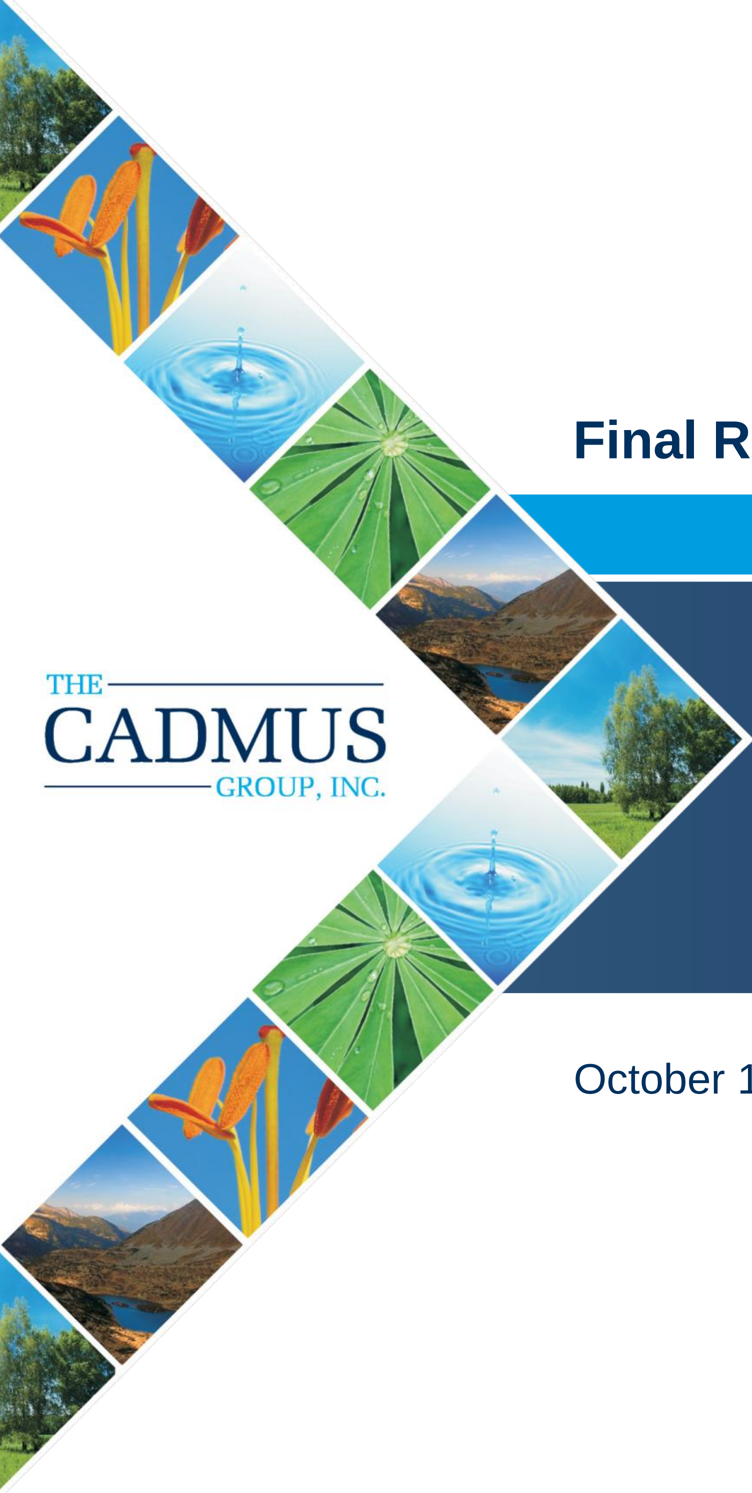
# Final Report



# CPUC Macro Consumption Metric Pilot Study

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***Prepared by:***

The Cadmus Group, Inc.
Energy Services Division
720 SW Washington Street, Suite 400
Portland, OR 97205
503.467.7100

***Prepared for:***

California Public Utilities Commission

Prepared by:
James Stewart, Ph.D.
Hossein Haeri, Ph.D.

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The Cadmus Group, Inc.

720 SW Washington Street
Suite 400
Portland, OR
Tel: 503.467.7100
Fax: 503.228.3696

*An Employee-Owned Company*
www.cadmusgroup.com

Corporate Headquarters:
57 Water Street
Watertown, MA 02472
Tel: 617.673.7000
Fax: 617.673.7001

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# 1. EXECUTIVE SUMMARY

The California Public Utilities Commission (CPUC) commissioned this study to explore the potential policy applications of energy macro-consumption models (MCMs). In contrast to micro-analysis of site energy use, which is commonly used in energy-efficiency program evaluation, macro-consumption analysis uses aggregate (e.g., utility service area, county, census block) energy use and energy-use driver data (e.g., income, prices) to measure savings. MCMs offer a number of potential policy uses, including:

- Estimating savings from utility energy-efficiency programs, building codes or appliance standards, and naturally occurring adoption of energy-efficiency measures;
- Tracking reductions in greenhouse gases (GHGs) from state policies and utility energy-efficiency programs; and
- Incorporating energy-efficiency savings estimates in forecasts of utility or state consumption.

In spring 2011, the CPUC selected The Cadmus Group, Inc. to participate in their Macro Consumption Pilot Study, which involved two parallel macro-consumption projects. The goals of the study were to:

- Investigate the viability of using macro-consumption approaches to measure reductions in energy consumption from utility energy-efficiency programs and policies in California, with the specific aim of estimating savings from the 2006-2008 program cycle;
- Investigate the potential for developing robust methods for measuring and tracking carbon emission reductions resulting from energy-efficiency requirements of the State Assembly Bill 32 (AB32); and
- Assess the applicability of MCMs for forecasting future energy savings from energy-efficiency programs and policies.[1]

For the project's first phase, Cadmus critically reviewed the existing literature; assessed the availability of data for and the likely success of a macro-consumption study in California; and developed a MCM research proposal. We reported much of our work leading up to data collection and preparation in CPUC public workshops and in technical memorandums, which are publicly available on the CPUC's Website.

For the study's second phase, Cadmus followed the tasks described in its research proposal: collected study data; developed a large panel database of gas and electricity consumption and consumption drivers; and developed and estimated gas and electricity MCMs.

This report describes the efforts and results of the second phase of the pilot study, and reports preliminary electricity and gas savings estimates derived from the models. We report estimates

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

of electricity savings from the investor-owned utilities' (IOUs, which are Pacific Gas & Electric (PG&E), San Diego Gas & Electric (SDG&E), and Southern California Edison (SCE)) energy-efficiency programs between 2006 and 2008. We also estimated electricity savings from the 2001 update to California's Title 24 building code. We do not report estimates of gas savings from the IOUs' gas efficiency programs because of limitations with the data.

Cadmus collected energy use and energy-use driver data for 56 California electric utilities and six California gas utilities, including information about energy consumption, population, income, gas and electricity prices, new construction, existing floor space, appliance saturations, and weather. We cleaned the data and merged them into separate electricity and gas databases. The databases covered 1990-2010, although some variables (such as natural gas prices, electricity prices, and energy-efficiency expenditures) were not available for the entire period.

Using the gas and electricity databases, Cadmus estimated panel regression models of electricity- and gas-consumption intensities. Specifically, we modeled:

- Utility consumption per capita;
- Residential sector consumption per housing unit; and
- Nonresidential consumption per square foot of floor space.

In the regressions of utility and nonresidential electricity use intensities, we detected large and statistically significant savings from utility electricity efficiency program spending and building codes. We had less success at detecting savings from utility programs and building codes in the residential sector. We were unable to detect gas savings because of limitations with the gas data.

We illustrated the potential applications of MCMs for policy by using the regression models to estimate electricity savings from IOU electricity efficiency programs and building codes. Our analysis revealed that the IOUs energy-efficiency programs saved substantial amounts of electricity: estimated at approximately 57,000 GWh, or 5% of the total electricity consumption between 2005 and 2010, with a 95% confidence interval for the savings of [19,124 GWh, 95,289 GWh] and relative precision of ±66%.

Also, the IOU energy-efficiency programs appear to have saved energy cheaply. The average cost of electricity savings between 2005 and 2010 from utility spending in these years was estimated to have been $0.058/kWh, with a 95% confidence interval of [$0.035, $0.172].

Cadmus also estimated energy savings from IOU energy-efficiency programs during the 2006-2008 program cycle. The IOUs reported total *ex ante* first-year gross savings of 10,461 GWh, or 1.7% of the consumption between 2006 and 2008. We estimated total first-year net savings from utility program expenditures of 4,357 GWh, or 0.7% of the IOUs' consumption over the same period. Our estimate equals 42% of the IOUs *ex ante* savings claims. However, as the 95% confidence interval for the estimate of first-year net savings includes the IOUs' claims, the claims cannot be rejected.

Finally, we found that building codes resulted in significant electricity savings. We estimated that the 2001 update to California's Title 24 building code saved 5,840 GWh in 2002, with increasing savings over time.

Our MCM estimates demonstrate the promise and limitations of macro-consumption approaches. First on the positive side, macro-consumption methods can yield inexpensive and unbiased estimates of energy savings from utility energy-efficiency programs and building codes. Second, the macro-consumption approach allows for the ability to explicitly quantify uncertainty about energy savings, which is not easily accomplished when aggregating savings from bottom-up evaluations. Third, our research reveals that macro-consumption methods could be used to verify energy-efficiency program savings estimates based on bottom-up evaluation. They could also be applied to future evaluation, measurement, and verification (EM&V) efforts to track the State's progress in reducing GHG emissions, and for use in developing forecasts of energy savings from future utility program spending.

An important limitation of this macro-consumption metric study was data availability and quality. We worked with short time series, 14 or fewer years, for a small number of utilities. We also have concerns about the quality of the energy-efficiency expenditures series, especially when the data are disaggregated at the retail sector level. A second limitation is that the savings estimates are imprecise. The wide confidence intervals we report show there is substantial uncertainty about the true energy savings from utility energy-efficiency programs. The precision of the savings estimates could be improved by collecting additional data or refining the econometric approach.

Despite the limitations, the results of this study are sufficiently promising that Cadmus recommends that the CPUC continue to fund macro-consumption data collection and research. The reliability of the models and savings estimates could be improved with the collection of additional data and refinements to the modeling.

# 2. INTRODUCTION

In 2011, the CPUC commissioned a pilot study to examine the potential application of MCMs to assess California's energy policy. In contrast to micro-analyses of site energy use, which is commonly used in energy-efficiency program evaluations, macro-consumption analysis uses aggregate (e.g., utility service area, county, census block) energy use and energy-use driver data (e.g., income, prices) to measure savings.

MCMs offer a number of potential policy uses, including:

- Estimating aggregate energy savings from utility energy-efficiency programs, building codes or appliance standards, and the naturally occurring adoption of energy-efficiency measures;
- Tracking reductions in GHGs from state policies and utility energy-efficiency programs; and
- Incorporating energy-efficiency savings into load forecasts.

While macro-consumption studies have several potential policy applications, they cannot, in general, be used to evaluate savings from individual energy-efficiency programs.

In spring 2011, the CPUC selected Cadmus to participate in the Macro Consumption Pilot Studies project, which involved two parallel studies. The research objectives of the pilot study were to:

- Assess the ability of top-down, macro-consumption approaches to accurately measure the aggregate impact of the 2006-2008 energy-efficiency programs on energy consumption;
- Assess the ability of these approaches to accurately measure the impact of the CPUC's energy-efficiency efforts on the overall electric energy and natural gas consumption in California in the context of post-2012 EM&V activities;
- Examine the ability of these approaches to improve estimates of aggregate reductions in GHG emissions from efficiency programs as required in AB32;
- Examine the ability of these approaches to more directly align and integrate the study results into the California Energy Commission's (CEC's) demand forecasts, and ultimately into the CPUC's resource procurement process; and
- Provide recommendations as to the specific data needs, analytical frameworks, and systems required to integrate these approaches into the permanent portfolio of post-2012 EM&V activities.

For the project's first phase, Cadmus critically reviewed the existing literature; assessed the availability of data for and likely success of a macro-consumption study in California; and developed a MCM research proposal. We reported much of our work leading up to data collection and preparation in CPUC public workshops and in technical memorandums, which are publicly available on the CPUC's Website.

For the study's second phase, Cadmus followed the tasks described in its research proposal: collected study data; developed large panel gas and electricity databases; and developed and estimated MCMs. This report describes the results of the study's second phase, including data collection, database development, model development and estimation, and the estimation of electricity savings based on the models.

The rest of this report is organized as follows:

- In chapter 3, we briefly review the findings of macro-consumption studies from the last 15 years.
- Next, chapter 4 describes our efforts to develop electricity and gas consumption databases, which was a key research objective. This chapter describes some important limitations of the data as well.
- Chapter 5 of the report describes the econometric modeling. Our approach assumes that annual variation in utility energy-efficiency program spending was exogenous to consumption; however, we also describe a strategy for identifying energy savings if expenditures were determined endogenously.
- Cadmus estimated a large number of electricity use intensity regression models for the utility as a whole, as well as for the residential and nonresidential sectors. Chapter 6 present results from estimating these models. To illustrate the potential policy application of MCMs, we estimated the net electricity savings from California IOU energy-efficiency programs and building codes.
- Chapter 7 present results from estimating gas consumption intensity models for the IOUs and for the residential and nonresidential sectors.
- In the last chapter of this report (chapter 8), Cadmus readdresses the study objectives and assesses what the pilot study has revealed about the potential policy applications of MCMs.

# 3. PREVIOUS MACRO-CONSUMPTION STUDIES

In the last two decades, a number of studies have estimated energy savings from utility energy-efficiency programs using macro-consumption methods. Researchers have largely been motivated by continuing disagreement among academics and policymakers about energy-efficiency program net savings and cost-effectiveness, and about the significance of program freeriding and spillover. Although there has been considerable divergence in macro-consumption estimates of program savings and cost-effectiveness, there is growing macro-consumption-based evidence that these programs save significant energy and are cost-effective relative to traditional supply resources.

An important early contribution was Parfomak and Lave's 1996 paper, *How Many Kilowatts are in a Negawatt*? The authors estimated energy savings in the commercial and industrial sectors using panel regression analysis of 39 U.S. utilities between 1970 and 1993. They found savings from utility program spending to equal 99% of what the utilities claimed.

Additional evidence about savings in the commercial sector came from Horowitz (2004), who analyzed commercial electricity consumption in 42 states between 1989 and 2001. Horowitz estimated that realized savings were 54% of what the utilities claimed. Horowitz speculates that the difference between his estimate and Parfomak and Lave's was due to differences in model specifications, estimation samples, and time periods, or possibly due to changes in the effectiveness of utility energy-efficiency programs.

Loughran and Kulick (2004) took a broader perspective, estimating the impacts of utility program expenditures on total electricity consumption. The authors modeled the first difference of the log of utility 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 that in the Parfomak and Lave (1996) study, including 324 utilities with positive demand-side management (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% of those claimed by utilities, and the cost of saved energy was approximately $0.14/kWh. Loughran and Kulick suggested that utilities have not adequately accounted for freeridership in their savings estimates.

Re-examining Loughran and Kulick's retail electricity savings estimates, Auffhammer, Blumstein, and Fowlie (2008) pointed out two flaws in their analysis. First, in calculating an overall DSM savings rate and the cost of saved energy, Loughran and Kulick did not report utility sales-weighted averages of the percent savings. Instead, they took an unweighted average of the percent savings across 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 found that average utility reported savings (of 2% to 3%) falls within the 95% confidence interval for estimated savings. The cost of saved energy was approximately $0.06 kWh. They concluded they cannot reject the hypothesis that utility reported savings equals actual savings.

In a subsequent paper, 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. Horowitz found that strong commitments to energy efficiency results in decreased energy intensity in the residential sector (by 4.4%), the commercial sector (by 8.1%), and in the industrial sector (by 11.8%).

Arimura, Li, Newell, and Palmer (2011) studied retail electricity consumption in 307 U.S. utilities, and made a number of contributions to macro-consumption modeling and estimation studies, including controlling for building codes, modeling energy prices and utility energy-efficiency program expenditures as endogenous, and allowing consumption to depend on program expenditures in a flexible way. Using utility Energy Information Administration (EIA) data from 1989 to 2006, the authors found electricity savings of 1.8% and cost of saved energy of approximately $0.05/kWh.

Finally, Rivers and Jaccard (2011) conducted macro-consumption analysis of electricity consumption intensities in 10 Canadian provinces between 1990 and 2005 to estimate savings from utility DSM programs. They found that DSM spending had a small and statistically insignificant impact on consumption. However, they also noted their finding comes 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. Reviewers of this Rivers and Jaccard study have also pointed out that their model specification does not adequately control for past energy-efficiency program spending, omits year fixed effects, and imposes strong assumptions about the impacts of past energy-efficiency expenditures on consumption.[2]

This current study makes several additional contributions to our understanding of MCMs and the savings impacts of utility energy efficiency programs. First, Cadmus provides more evidence about the efficacy of utility energy-efficiency programs from a macro perspective. Second, we perform a macro-consumption study for a single state. We are unaware of any other such studies. Third, California is the national leader in energy efficiency and invests significant resources in energy-efficiency program evaluation. Given California's place, it is worth exploring alternative approaches for gauging California's progress in reducing energy use to complement bottom-up evaluations. Fourth, Cadmus has explored modeling the impacts of energy building codes to a more detailed degree than the other studies. We collected data on residential and nonresidential new construction and developed a framework for estimating savings from building codes. Finally, for this study Cadmus estimated gas consumption intensity models. We are unaware of any other macro-consumption studies that attempted to estimate natural gas savings.

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2 Violette, Daniel. *Bottom-Up and Top-Down Approaches For Assessing DSM Program Impacts*. Proceedings, the International Energy Program Evaluation Conference, Rome, Italy. June 12-14, 2012.

# 4. DATA SOURCES AND DATABASE DEVELOPMENT

For this pilot study, Cadmus developed panel databases of 56 California electric utilities and six California gas utilities between 1990 and 2010. For each utility, we collected time-series data on consumption and economic and noneconomic drivers of consumption. We then merged the time series into separate electricity and gas databases.

Table 1 shows the key data we collected, the sources of the data, the reporting units, and the data frequencies. All of these data are publicly available, and all of the data except for new construction and existing floor space were free.

**Table 1. Sources of Key Variables**

| Variable | Source | Reporting Unit | Frequency |
|---|---|---|---|
| Energy consumption (retail sales) | CEC | Utility and county by retail sector | Annual |
| Energy prices | CEC (Gas), EIA (Electricity) | Utility and county by retail sector | Annual |
| Personal income | Bureau of Economic Analysis | County | Annual |
| Population | U.S. Census | Census tract | Annual |
| Cooling degree days and heating degree days | National Climatic Data Center of the National Oceanic and Atmospheric Administration | Weather station | Annual |
| Residential appliance saturations | Residential Appliance Saturation Study, U.S. Census, American Community Survey | Utility, census tract | Annual |
| Energy-efficiency expenditures | Energy Efficiency Groupware Application, California Municipal Utilities Association, EIA | Utility by retail sector | Annual, quarterly |
| New construction floor space | McGraw-Hill Dodge New Construction | Zip code | Annual |
| Existing floor space | McGraw-Hill Dodge New Construction | County | Annual |

Cadmus converted all nominal economic series—including income, prices, and energy-efficiency expenditures—to real terms using the Bureau of Labor Statistics Consumer Price Index (CPI) for California urban areas. Also, we estimated utility energy prices as the average price per kWh or therm with annual utility energy sales and revenues data from the CEC and EIA.[3] We estimated cooling degree days (CDDs) and heating degree days (HDDs) as the population-weighted average of HDDs and CDDs in a utility service area using weather data from dozens of weather stations across California and neighboring states.

[3] With increasing block price schedules, there will be positive correlation between the average price and energy consumption.

When the variable reporting unit was not the utility, such as for personal income or new construction floor space, it was necessary to weight the reporting unit values and aggregate them to derive an estimate for the utility service area. For example, the U.S. Census Bureau reported heating fuel saturations for census tracts. To estimate the utility value, we developed weights for the census tracts by layering a map of the utility service territory over a map of the reporting units using ArcGIS software. The weight for a census tract was the share of the utility service area population in the census tract. (When a census tract comprised parts of two or more utilities, we assumed that the census tract population was distributed uniformly.) We then estimated utility service territory heating fuel saturation as a weighted average of the census tract values.

A key variable in the energy consumption analysis was utility energy-efficiency program expenditures. As Table 2 shows, Cadmus collected energy-efficiency expenditures data from four sources.[4]

**Table 2. Sources of Energy-Efficiency Expenditures Data**

| Source | Reporting Level | Series | Energy | Years | Coverage |
|---|---|---|---|---|---|
| EIA | Utility | DSM, energy efficiency (EE) | kWh | 1990-2010, 2001-2010 | All utilities |
| Energy Efficiency Groupware Application | Utility and retail sectors | EE | kWh, therms | 2006-2010 | PG&E, SDG&E, SCE |
| IOU historical reports | Utility and retail sectors | EE | kWh, therms | 1976-2005 | PG&E, SDG&E, SCE, Los Angeles Department of Water and Power (LADWP), Sacramento Municipal Utility District (SMUD) |
| California Municipal Utilities Association | Utility and retail sectors | EE | kWh | 2006-2010 | LADWP, SMUD, other publicly-owned utilities |

The first source was the EIA of the U.S. Department of Energy. The EIA has made utility DSM (energy efficiency plus demand response) program expenditures since 1990, and utility energy-efficiency program expenditures are available starting in 2001. These expenditures data are not disaggregated by retail sector. Also, the EIA has different reporting requirements depending on a utility's size.[5] Previous researchers have used the EIA data and documented these and other limitations (Arimura, Li, Newell, and Palmer, 2011). We used the EIA data with these limitations in mind.

The Energy Efficiency Groupware Application (EEGA) is the California IOU energy-efficiency reporting database. It contains detailed program expenditures and *ex ante* savings data for IOU gas and electricity efficiency programs between 2006 and 2012. Cadmus used these data to estimate total, residential, and nonresidential gas and electricity program expenditures between

4 The CEC collected much of these data and generously provided them to Cadmus.

5 Since 1998, only utilities with retail sales exceeding 150,000 MWh were required to report their expenditures to the EIA.

2006 and 2010. We allocated the expenditures of programs that served gas and electricity customers using the reported gas and electricity savings. Appendix A describes our procedure in greater detail.

Historic IOU energy-efficiency program reports were the main source of information for gas and electricity program expenditures before 2006. Cadmus merged the EEGA and historic program reports' data to form an electricity efficiency program expenditures series for 1990-2010 and a gas efficiency program expenditures series for 2000-2004 and 2006-2010. IOU gas efficiency expenditures in 2005 were available in EEGA, but were not in a form that could be used in macro-modeling.[6]

The final source of data was the California Municipal Utilities Association (CMUA), which has collected and published data on residential and nonresidential electricity efficiency program expenditures since 2006. California Senate Bill 1037 requires publicly owned utilities (POUs) to report their current and projected electricity efficiency program expenditures to the CEC.[7]

Cadmus compared the different expenditures series. For example, Figure 1, Figure 2, and Figure 3 show plots of the IOUs per-capita energy-efficiency expenditures from EEGA and the historic reports compared to per capita DSM expenditures from the EIA. The series measure slightly different expenditures, as the EIA DSM series includes demand-response expenditures. As expected, for all three IOUs and in most years, energy-efficiency expenditures fell below DSM expenditures. The EEGA and EIA expenditures series for PG&E and SCE track closely, although EIA expenditures are significantly greater after 2006.[8] The expenditures series for SDG&E do not track as well. Between 2001 and 2004, EIA reported zero (not missing values) DSM expenditures for SDG&E.

6 Energy-efficiency program expenditures were available in monthly reports by program. With significant effort, these data could be aggregated to the annual and portfolio or sector levels.

7 The reports for 2006–2011 can be found online at: http://www.ncpa.com/energy-efficiency-reports.html.

8 The expenditures after 2006 are likely cumulative expenditures over the 2006-2009 program cycle, as the sum of annual expenditures in EEGA approximately equal the annual expenditures in EIA. In 2010, which was the beginning of the next program cycle, the EIA and EEGA expenditures are closer or approximately equal.

**Figure 1. PG&E: Comparison of EIA DSM and EEGA Energy-Efficiency Expenditures**

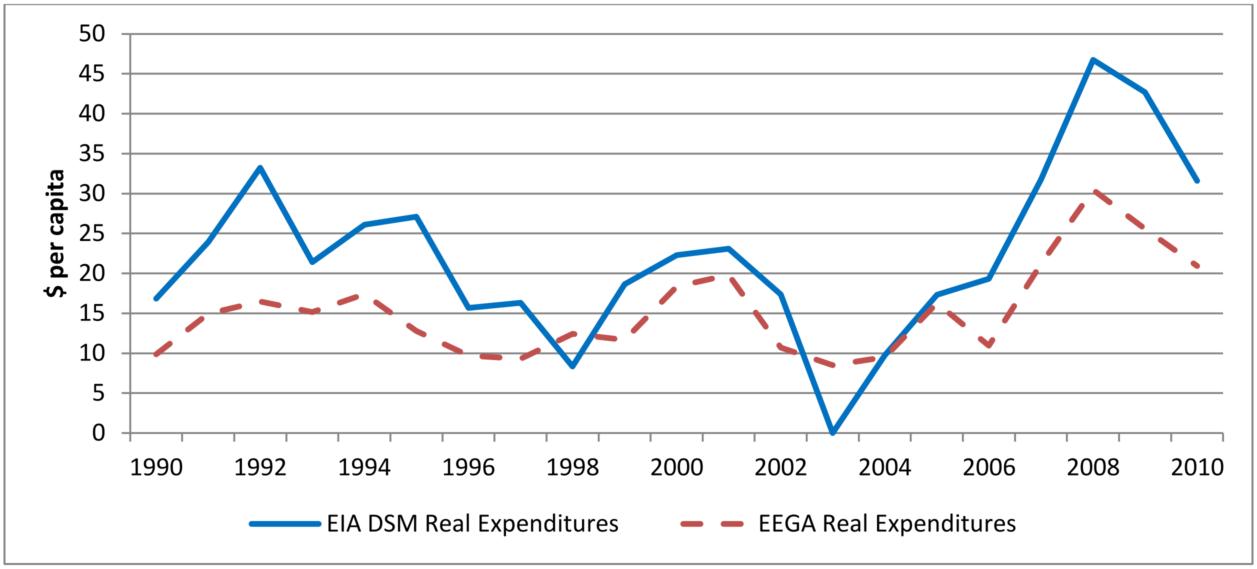



**Figure 2. SCE: Comparison of EIA DSM and EEGA Energy-Efficiency Expenditures**

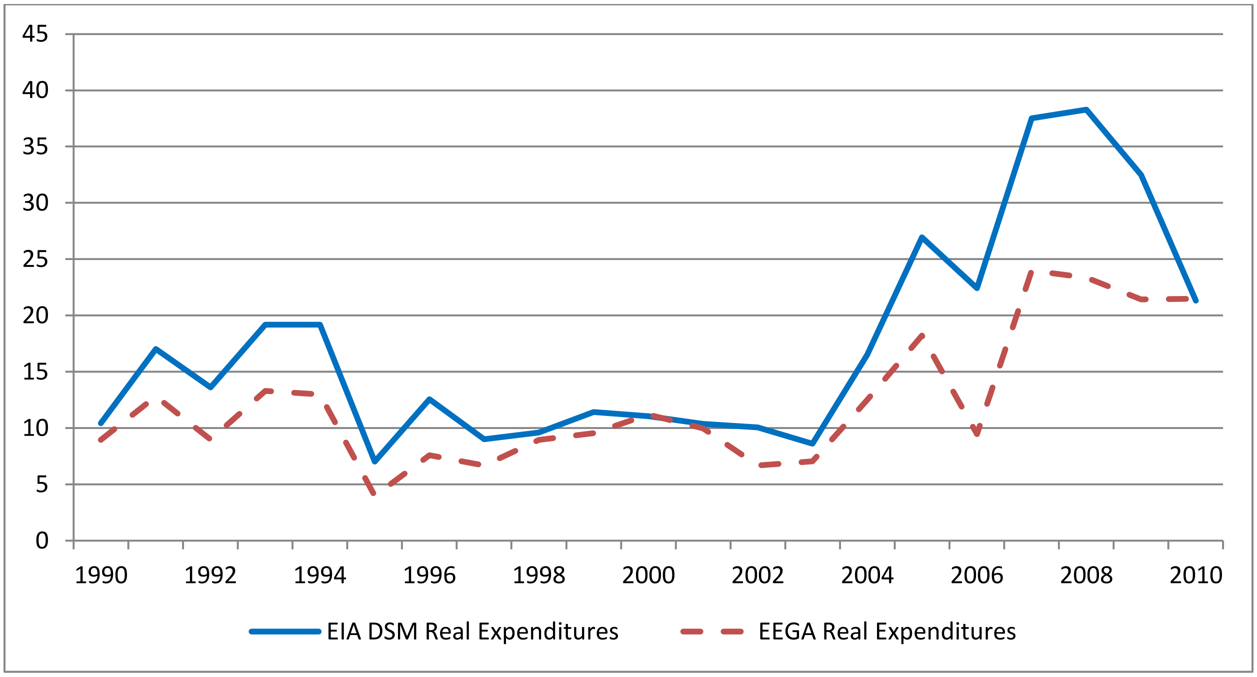
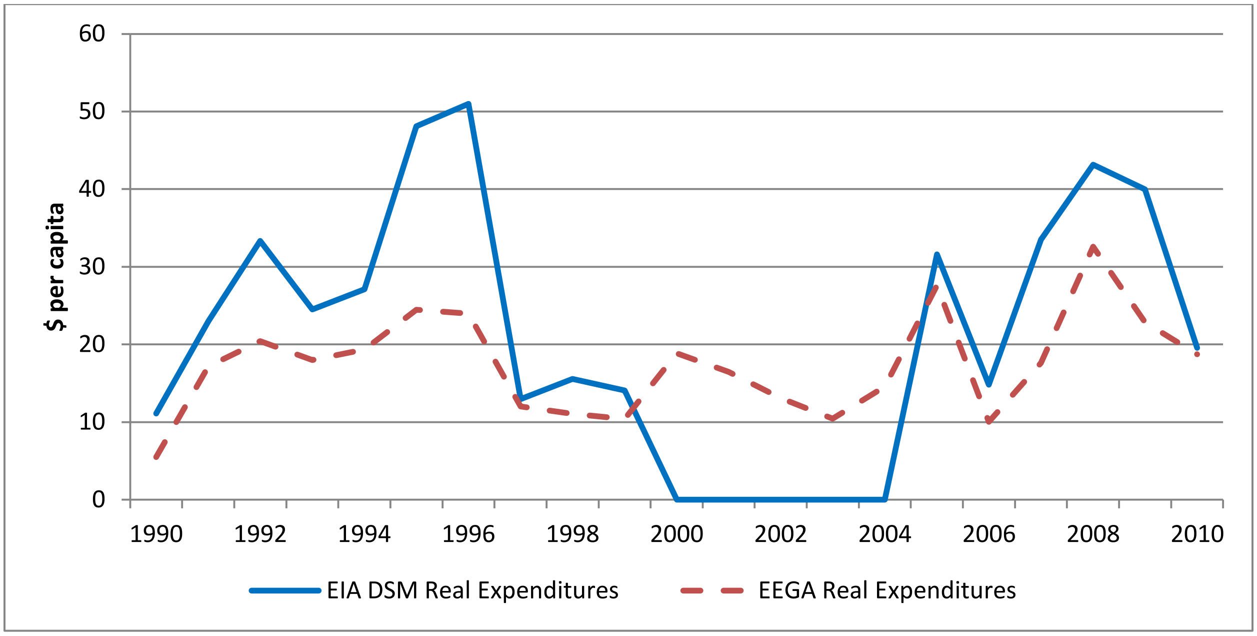


**Figure 3. SDG&E: Comparison of EIA DSM and EEGA Energy-Efficiency Expenditures**




Cadmus found other examples of dubious reports of program expenditures from the EIA for the Los Angeles Department of Water and Power (LADWP), Sacramento Municipal Utility District (SMUD), and other California POUs. However, data issues appear to be severe for small utilities with total sales less than 150,000 MWh, which face less stringent reporting requirements. Generally, the data on IOU energy-efficiency program expenditures from the EEGA and public utility energy-efficiency program expenditures from the CMUA appeared to be of better quality.

# 5. ENERGY USE INTENSITY MODEL SPECIFICATION

Cadmus modeled the intensity of energy use (gas and electricity separately) in a utility service area or a utility retail sector (residential and nonresidential separately) in a regression with the following basic form:

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

(Equation 1)

With variables defined as follows:

| | | |
|---|---|---|
| i | = | Indexes a utility service area. |
| t | = | Represents time. |
| $\ln(e_{it})$ | = | The natural logarithm of energy use per unit (e.g., capita, housing unit, or square foot) for a utility service territory ‘i’ where i=1, 2, …N, in year ‘t.’ In the residential model, the dependent variable was energy use per occupied housing unit. In the nonresidential model, the dependent variable was energy use per square foot of existing floor space.[9] In the utility consumption model, the dependent variable was the per capita consumption. |
| $p_{e,it}$ | = | The real electricity price (in dollars per kWh) for utility service territory ‘i’ in period ‘t.’[10] The coefficient $\gamma_e$ shows the price elasticity of demand. |
| $p_{g,it}$ | = | The real gas price (in dollar per thousand cubic feet) for utility service territory ‘i’ in period ‘t.’ The coefficient $\gamma_g$ shows the price elasticity of demand. |
| $I_{it}$ | = | The real per capita personal income for utility service territory ‘i’ in period ‘t.’ The coefficient β is the income elasticity of demand. |
| $HDD_{it}$ and $CDD_{it}$ | = | Respectively, the annual HDDs and CDDs for utility service territory ‘i’ in period ‘t.’ The coefficients $\omega_h$ and $\omega_C$ indicate the elasticity of consumption with respect to annual degree days. In the residential models, $HDD_{it}$ interacts with $EHSAT_{it}$, which is the electric heating saturation in homes within utility service area ‘i’ in period ‘t.’ |

9 The nonresidential model includes consumption in the commercial, industrial, mining, street lighting, and agricultural sectors. It was not possible to estimate separate commercial and industrial models, because 1) energy-efficiency program expenditures were not disaggregated at this level, and 2) there were concerns about changes in the classification of commercial and industrial loads over time.

10 Electricity price is the average price per kWh and was estimated as revenue/sales. The average price may not reflect the marginal price faced by consumers, and may be endogenous to energy intensity. Increasing block prices will result in a positive correlation between consumption and the average price paid.

| | | |
|---|---|---|
| | | $CDD_{it}$ also interacts with $CACSAT_{it}$, the central air conditioning saturation in homes within utility service area 'i' in period 't.' |
| $EE_{it\text{-}k}$ | = | The per-capita energy-efficiency expenditure in utility service territory 'i' in period 't-k.' The coefficient $\delta_k$ shows the percentage reduction in per-capita consumption in period 't' from a one-dollar increase in energy-efficiency expenditures in period 't-k.' The number of lags in the models varies, depending on the length of the time series. |
| $NC_{mit}$ | = | The cumulative amount of new construction in utility service territory 'i' in year 't' built since the building code 'm' became effective, where m=1, 2, …, M. In the total consumption model, this variable is the per-capita cumulative new construction floor space built since code 'm.' In the residential and nonresidential sector models, this variable was, respectively, new construction floor space per housing unit and new construction floor space per unit of existing floor space. The coefficient $\eta_m$ shows the elasticity of consumption intensity with respect to new construction built under code 'm' using the efficiency of initial building stock (preceding the first building code in the model) as a baseline. Appendix B more completely describes how we estimated savings from building codes. |
| $TimeTrend_t$ | = | A time trend variable, equal to 1 in the first estimation year, and increasing by one unit annually. The time trend accounts for factors such as naturally occurring conservation, the growth of distributed generation, and changes in tastes and attitudes that are not captured by the other model variables. In some models, Cadmus substituted year fixed effects for the time trend. |
| $\lambda_i$ | = | A component of the error, reflecting utility-specific, time-invariant characteristics. These unobservable characteristics were accounted for by including utility fixed effects or estimating the first difference of the regression model. |
| $\mu_{it}$ | = | The error term for utility service territory 'i' in year 't.' |

## 5.1. Energy Savings

Cadmus estimated energy savings as a function of current and past utility energy-efficiency program expenditures and new construction floor space covered by different Title 24 building codes. In utility service area ‘i,’ we estimated the per-unit (e.g., capita) energy savings in year ‘t’ from energy-efficiency program expenditures in years ‘t-k’ as:

$$e_{it} * \delta_k * EE_{it-k}$$

(Equation 2)

where $\delta_k$ is the coefficient on energy-efficiency expenditures ‘k’ years ago.[11]

Total energy savings for utilities ‘i,’ where i=1, 2, …, N, in year ‘t’ from energy-efficiency expenditures in the current and previous k years was estimated as follows:

$$(\Sigma_{k=0}^{K} \delta_k * EE_{it-k}) * \Sigma_{i=1}^{N} (e_{it} * pop_{it})$$

(Equation 3)

The first term in parentheses is the total percent savings from current and past expenditures. The second term is energy consumption in year ‘t.’

Finally, we estimated the total energy savings for the utilities over a particular period (e.g., the 2006-2008 program cycle) from expenditures during the period. The total energy savings over the t=1, 2, …, T years is:

$$S = \Sigma_{i=1}^{N} \Sigma_{t=1}^{T} e_{it} * pop_{it} * [\Sigma_{k=0}^{K} \delta_k * EE_{it-k} * I(t-k>0)]$$

(Equation 4)

Where $pop_{it}$ is the population in period ‘t’ and I(t-k>0)=1 if t-k>0 and = 0, otherwise. The term in brackets is the percent savings in year ‘t’ from current and past expenditures in the period.

Letting ‘$d_{it}$’ denote per-capita utility energy-efficiency program expenditures, and dividing the total expenditures for the ‘N’ utilities in the period by the energy savings from the expenditures, we get the average cost of saved energy:

$$\Sigma_{i=1}^{N} \Sigma_{t=1}^{T} (d_{it} * pop_{it}) / S$$

(Equation 5)

[11] This is an approximation, as energy savings should be estimated as a fraction of counterfactual energy use (without energy-efficiency expenditures) and we observed only actual energy use (net of savings).

Finally, Cadmus measured energy savings from building code ‘m’ in year ‘t’ using the previous building code ‘m-1’ as a baseline.[12] We estimated per capita savings from code update ‘m’ in utility service area ‘i’ in year ‘t’ as:

$$e_{it} * (\eta_m - \eta_{m-1}) * \ln(NC_{mit})$$

(Equation 6)

This expression shows building code ‘m’ will result in energy savings (relative to the preceding code) if $\eta_m - \eta_{m-1} < 0$. It is not necessary that $\eta_m < 0$ for savings.

## 5.2. Model Estimation

Cadmus estimated (Equation 1 in two ways:

1. By ordinary least squares (OLS), with utility-clustered standard errors; and
2. By feasible generalized least squares (FGLS), assuming that the error followed an order-one autoregressive process.

Both approaches address autocorrelation, but FGLS imposes more structure on the error process. As we show below, the FGLS approach usually resulted in more precise savings estimates. Both approaches resulted in autocorrelation- and heteroskedasticity-robust standard errors, however.

(Equation 1 assumes that annual energy use adjusts fully to changes in prices, incomes, and other independent variables. It is widely known, however, that energy use adjusts only partially to market forces, as investments in energy-using equipment and buildings are fixed and cannot, in general, be adjusted without cost in the short term.

To capture this costly and gradual adjustment, we also modeled electricity use intensity as a dynamic process (Houthakker, Verlager, and Sheehan, 1974). This involved including a lag of the dependent variable as a right-side regressor in (Equation 1. In this framework, short- and long-term consumption elasticities can be estimated for each independent variable.[13] However, estimating the model required a sufficiently large number of cross-sectional units and a long time series.

An important assumption of (Equation 1 is that utility energy-efficiency program expenditures and consumption intensity were exogenous. This assumption would be violated if policymakers or utilities adjusted their program expenditures in response to expected consumption. The potential for endogeneity would be minimized to the extent that expenditures depended on exogenous factors.

To control for the potential endogeneity of expenditures and consumption intensities, we attempted to exploit the lag between when a programs’ budget is established and when the

[12] Our approach for estimating energy savings from building codes is explained completely in the Appendix.

[13] The long-term consumption elasticity with respect to an independent variable is the variable’s coefficient divided by $1-\sigma$, which is the coefficient on lagged energy-use intensity. The short-term elasticity is simply the coefficient.

spending actually occurs. We assumed that utility planners set energy-efficiency program budgets one year or more in advance of the actual expenditures. We also assumed they selected expenditure levels endogenously, that is, to achieve a particular growth rate of per-capita consumption (e.g., zero) conditional on expected population growth.

This identification strategy was based on the lag between budget decisions and actual spending, and on the fact that changes in population are partially unpredictable. Specifically, we used deviations from expected population growth to generate the necessary exogenous variation in energy-efficiency spending per capita.[14] The deviation from expected population is correlated negatively with expenditures per capita, but is uncorrelated with consumption per capita (which is conditional on the other independent variables).

We implemented this instrumental variables approach using two-stage least squares, but unfortunately without much success. Our instrument did not generate the necessary variation to identify the impact of utility program spending. It is not clear whether additional observations would improve the outcome or whether unexpected population growth is simply a weak instrument. We will continue to explore this and other identification strategies.

Another important assumption concerns the omission of utility energy-efficiency expenditures more than 'K' years in the past. For example, most of our models included current and the previous five years' expenditures as regressors. Expenditures from more than five years ago are omitted from the models. Thus, it is assumed that the older expenditures are uncorrelated with recent spending. If this assumption does not hold, the coefficients on $EE_{t-k}$, (where k=0, 1, …, K) will reflect a combination of current and previous spending. Cadmus is continuing to explore this issue and to develop a solution to this omitted variable problem.

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[14] We estimated the unexpected component of population change as the difference between the actual population change and the expected population change. Expected population change for a utility was estimated with a regression of the utility population on a time trend. The instrument for year 't' expenditures was the unexpected population growth between years 't' and 't-1,' and potentially in previous years (between year t-1 and year t-2) depending on the length of the lag between the budget decision and spending.

# 6. ELECTRICITY CONSUMPTION INTENSITY MODELS

The final electricity consumption estimation sample included data for 38 California utilities. The estimation sample included the largest California utilities (PG&E, SDG&E, SCE, LADWP, and SMUD) and accounted for 99% of retail electricity sales in California in 2010.[15]

Cadmus imposed some criteria on the estimation sample to remove utilities that we suspected had significant errors in the measurement of key variables. Measurement errors were more likely to arise in utility service areas that covered small land areas or had small populations, because such areas are sensitive to yearly changes in census tract or zip code boundaries used in estimating the utility values.

In the analysis of utility consumption per capita, utilities in the estimation sample satisfied the following criteria:[16]

- Utility per-capita consumption averaged greater than 2,000 kWh per year between 2006 and 2010, and the utility service area population was greater than 5,000 in 2010. The utility consumption analysis included 34 utilities satisfying these criteria.

In the analysis of residential sector consumption, utilities satisfied the following criteria:

- Per-housing unit consumption averaged greater than 4,000 kWh per year between 2006 and 2010, and total housing units exceeded 2,000 in 2010. The analysis of residential sector consumption included 25 utilities.

In the analysis of nonresidential sector consumption, utilities satisfied the following criteria:

- The percentage difference between maximum and minimum nonresidential consumption intensity between 2006 and 2010 was less than 60%. The analysis of nonresidential sector consumption included 30 utilities.[17]

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15 Utilities in the estimation sample included: Anza Electric Cooperative, Azusa Light & Water, Bear Valley Electric Service, City of Alameda, City of Anaheim, City of Banning, City of Biggs, City of Burbank, City of Colton, City of Corona, City of Lodi, City of Lompoc, City of Needles, City of Palo Alto, City of Pasadena, City of Rancho Cucamonga, City of Redding, City of Riverside, City of Roseville, City of Ukiah, Glendale Water and Power, Imperial Irrigation District, Lassen Municipal Utility District, LADWP, Merced Irrigation District, Modesto Irrigation District, PG&E, PacifiCorp, Plumas-Sierra Rural Electric Cooperative, SMUD, SDG&E, Shasta Dam Area Public Utility District, Sierra Pacific Power Company, Silicon Valley Power, SCE, Surprise Valley Electrical Corporation, Truckee-Donner Public Utility District, and Turlock Irrigation District.

16 Cadmus performed analysis to test the sensitivity of the results to changes in the sample selection criteria. We found that the results were generally insensitive to the exclusion or inclusion of specific utilities.

Table 3 shows summary statistics for the utilities in the estimation sample, including statistics for all utilities, IOUs (PG&E, SCE, and SDG&E), and other utilities (non-IOUs). We limited the analysis to the years between 1997 and 2010 because natural gas prices were unavailable before 1997.

On a per capita basis, the IOUs experienced lower electricity consumption, higher incomes, and less new construction than the other utilities. The IOUs also experienced higher electricity prices and lower air conditioning saturations. According to the EIA, the IOUs also had per-capita DSM expenditures almost twice that of non-IOU utilities between 1997 and 2010. Most of this difference arose before 2006, however. The gap in spending narrowed significantly between 2006 and 2010. After 2006, the IOUs spent more on energy efficiency in the residential sector and less on energy efficiency in the nonresidential sector than the other utilities.

**Table 3. Summary Statistics, 1997-2010**

| Variable | All Utilities | IOUs | Non-IOUs |
|---|---|---|---|
| Electricity consumption (kWh) per capita | 12,510<br>(20,633) | 6,760<br>(378) | 13,030<br>(21,471) |
| Residential electricity consumption (kWh) per housing unit | 12,866<br>(21,666) | 6,663<br>(445) | 13,427<br>(22,541) |
| Nonresidential electricity consumption (kWh) per square foot | 46.4<br>(95.1) | 19.6<br>(2.2) | 49<br>(99.0) |
| Residential share of electricity consumption | 37.2<br>(15.0) | 35.1<br>(2.0) | 37.4<br>(15.7) |
| Real income ($) per capita | 37,065<br>(8,814) | 43,837<br>(4,050) | 36,485<br>(8,872) |
| Annual cooling degree days | 1,213<br>(833) | 1,034<br>(283) | 1,229<br>(863) |
| Annual heating degree days | 2,995<br>(1,503) | 2,088<br>(500) | 3,072<br>(1,534) |
| Residential central air conditioning saturation | 0.6092<br>(0.179) | 0.4745<br>(0.082) | 0.6207<br>(0.180) |
| Residential electric heat saturation | 0.225<br>(0.094) | 0.243<br>(0.040) | 0.224<br>(0.097) |
| Real price of electricity (cents per kWh) | 0.124<br>(0.028) | 0.137<br>(0.009) | 0.123<br>(0.029) |
| Residential real price of electricity (cents per kWh) | 0.135<br>(0.030) | 0.158<br>(0.012) | 0.133<br>(0.030) |
| Nonresidential real price of electricity (cents per kWh) | 0.121<br>(0.031) | 0.127<br>(0.012) | 0.121<br>(0.032) |

[17] We imposed this last requirement on the nonresidential sector estimation sample because a few utilities exhibited very large increases or decreases in nonresidential consumption between 2006 and 2010, and it was unclear whether these changes represented true changes in consumption or inconsistencies in the reporting of nonresidential loads. For example, in 2006, the City of Banning had nonresidential energy intensity of 32 kWh/sq. ft. By 2010, the intensity decreased to 2 kWh/sq. ft. Total floor space increased by 6%, and the real per-capita industrial sector income decreased by 10% over this period.

| Variable | All Utilities | IOUs | Non-IOUs |
|---|---|---|---|
| Real price of gas ($ per 000 cubic feet) | 9.6<br>(1.9) | 9.8<br>(1.9) | 9.5<br>(2.0) |
| Residential real price of gas ($ per 000 cubic feet) | 10.8<br>(2.1) | 11.1<br>(1.9) | 10.7<br>(2.1) |
| Nonresidential real price of gas ($ per 000 cubic feet) | 7.2<br>(1.9) | 7.4<br>(2.0) | 7.1<br>(1.9) |
| Per capita cumulative residential new construction (square feet) since 1995 code | 76.7<br>(81.4) | 65.2<br>(31.7) | 77.7<br>(84.3) |
| Per capita cumulative nonresidential new construction (square feet) since 1995 code | 34.3<br>(31.7) | 39.4<br>(16.9) | 33.8<br>(32.7) |
| Per capita cumulative residential new construction (square feet) since 1998 code | 51.9<br>(69.2) | 39.7<br>(29.5) | 53.0<br>(71.5) |
| Per capita cumulative nonresidential new construction (square feet) since 1998 code | 21.6<br>(25.7) | 21.2<br>(15.4) | 21.7<br>(26.4) |
| Per capita cumulative residential new construction (square feet) since 2001 code | 35.3<br>(51.6) | 26.6<br>(24.3) | 36.0<br>(53.3) |
| Per capita cumulative nonresidential new construction (square feet) since 2001 code | 11.7<br>(17.6) | 12.5<br>(12.1) | 11.6<br>(18.0) |
| Per capita cumulative residential new construction (square feet) since 2005 code | 6.6<br>(13.3) | 5.1<br>(7.4) | 6.7<br>(13.7) |
| Per capita cumulative nonresidential new construction (square feet) since 2005 code | 2.9<br>(5.6) | 3.5<br>(5.2) | 2.8<br>(5.6) |
| DSM expenditures ($) per capita (Source: EIA) | 11.8<br>(13.6) | 20.3<br>(12.6) | 10.4<br>(13.3) |
| Energy-efficiency expenditures ($) per capita, 2006-2010 (Source: CEC/EEGA/CMUA) | 16.8<br>(11.4) | 20.7<br>(6.7) | 16.1<br>(11.9) |
| Residential sector energy-efficiency expenditures ($) per capita, 2006-2010 (Source: CEC/EEGA/CMUA) | 7.6<br>(5.7) | 14.5<br>(6.1) | 6.3<br>(4.7) |
| Nonresidential sector energy-efficiency expenditures ($) per square foot, 2006-2010 (Source: CEC/EEGA/CMUA) | 0.040<br>(0.037) | 0.027<br>(0.012) | 0.042<br>(0.039) |

Notes: All values in this table are annual averages across utilities and represent the years between 1997 and 2010 unless otherwise noted. Sample standard deviations are shown in parentheses. The IOUs are PG&E, SDG&E, and SCE.

Figure 4, Figure 5, Figure 6, Figure 7, and Figure 8 show the following different electricity consumption intensities and energy-efficiency program expenditures for the IOUs, LADWP, and SMUD between 1997 and 2010:[18]

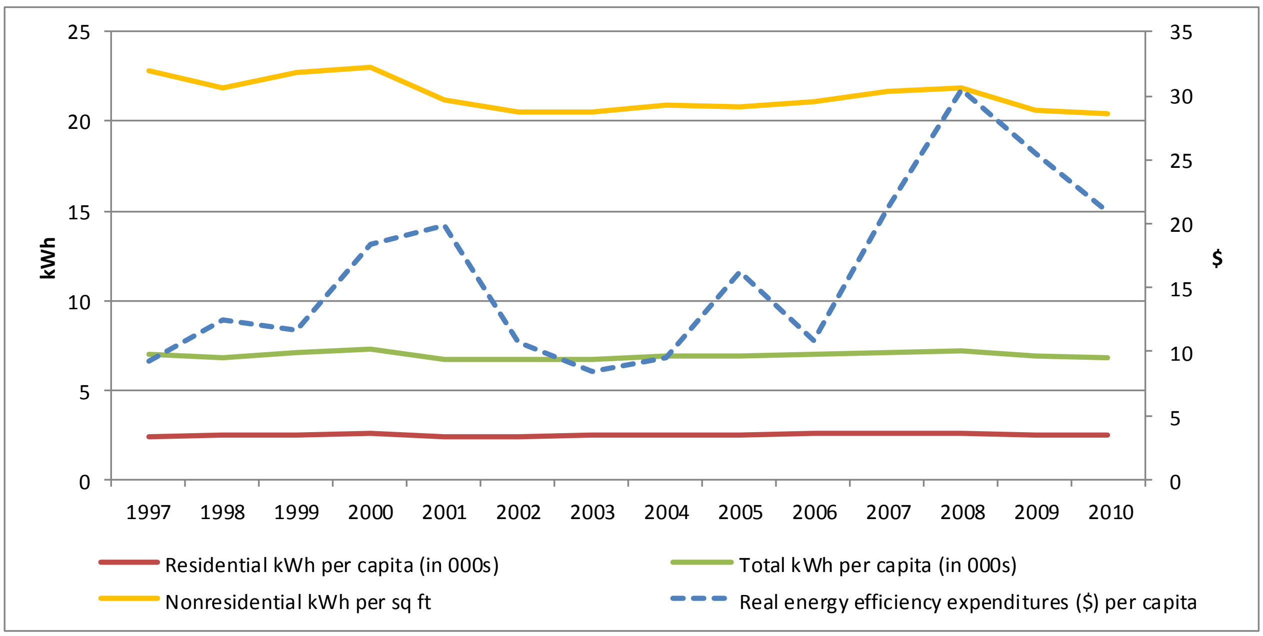
- Utility annual electricity consumption per capita;
- Residential sector annual electricity consumption per capita;
- Nonresidential sector annual electricity consumption per square foot of floor space; and
- Real electricity-efficiency program expenditures per capita.

18 In 2010, these five utilities accounted for 88% of California's electricity consumption.

Although total electricity consumption rose between 1997 and 2010, the figures show that electricity consumption intensities remained roughly constant, a phenomenon known as *The Rosenfeld Curve*.[19] Also, there are noticeable decreases in consumption intensities around 2000-2001 and 2008-2009. These decreases coincided with the IOUs ratcheting up their energy-efficiency expenditures, suggesting the potential influence of their efficiency programs. However, other factors were also possibly involved, as both episodes of decreasing intensities coincided with economic downturns, and the first episode occurred immediately after a significant increase in electricity prices and public appeals for conservation during the California Energy Crisis.

In modeling the consumption intensities and estimating savings, it was important to control for the potential confounding effects of changes in incomes, prices, and the California Energy Crisis. Our models capture the effects of the California Energy Crisis using year dummy variables for 2001 and 2002. They capture other naturally occurring adoption with a time-trend.

**Figure 4. Pacific Gas & Electric Electricity Consumption Intensities and Energy-Efficiency Program Expenditures, 1997-2010**

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

**Figure 5. San Diego Gas and Electric Electricity Consumption Intensities and Energy-Efficiency Program Expenditures, 1997-2010**

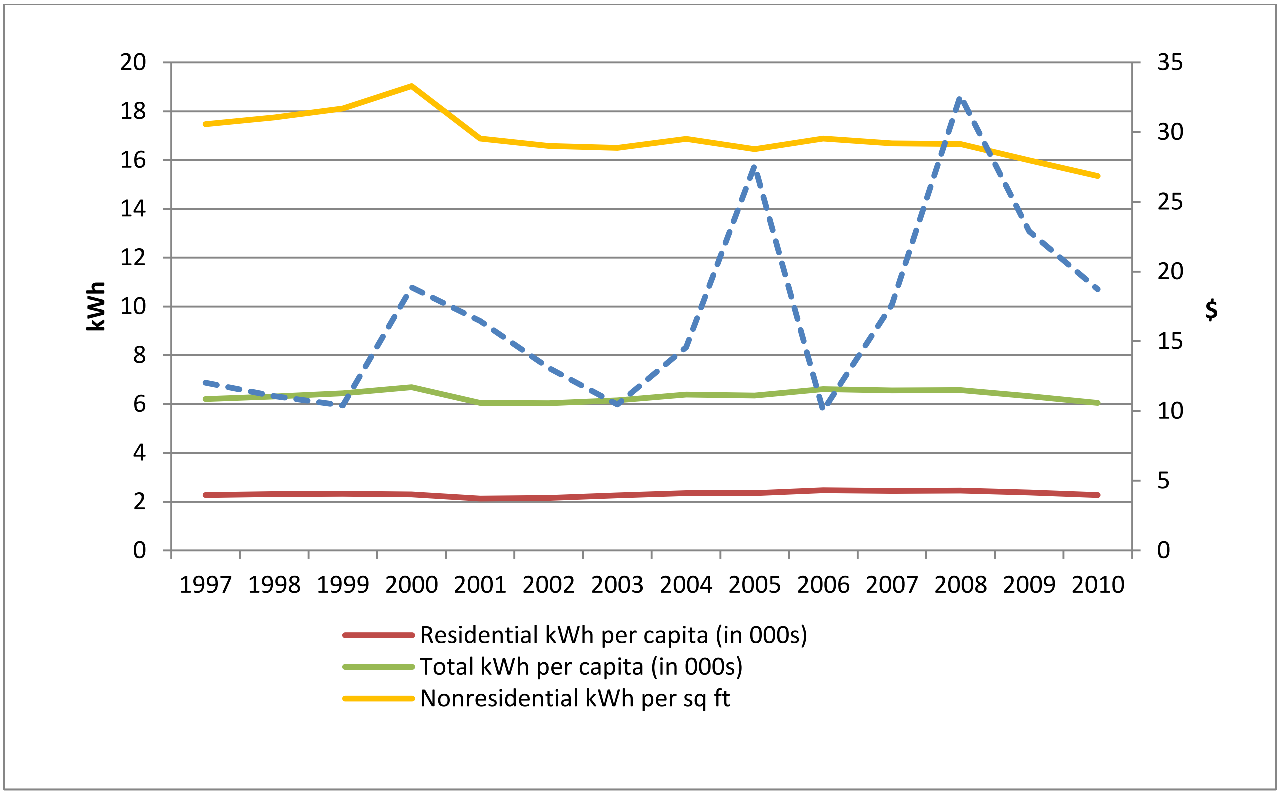


**Figure 6. Southern California Edison Electricity Consumption Intensities and Energy-Efficiency Program Expenditures, 1997-2010**

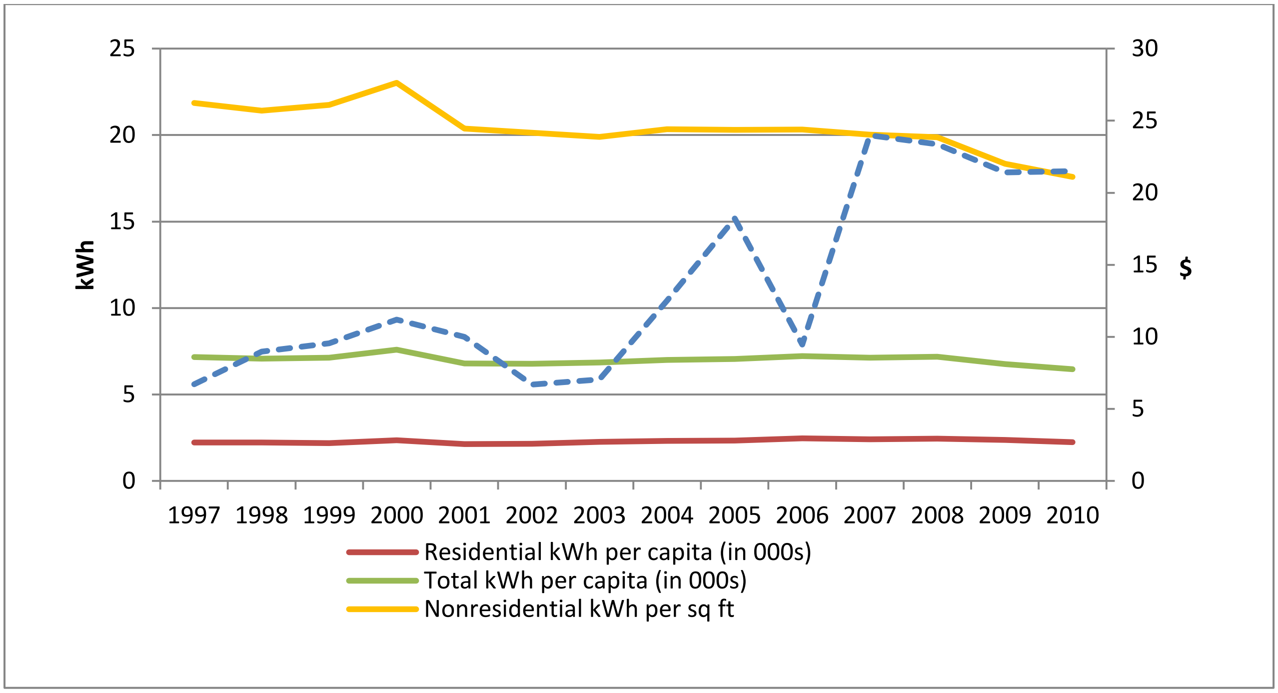



**Figure 7. Los Angeles Department of Water and Power Electricity Consumption Intensities and Energy-Efficiency Program Expenditures, 1997-2010**

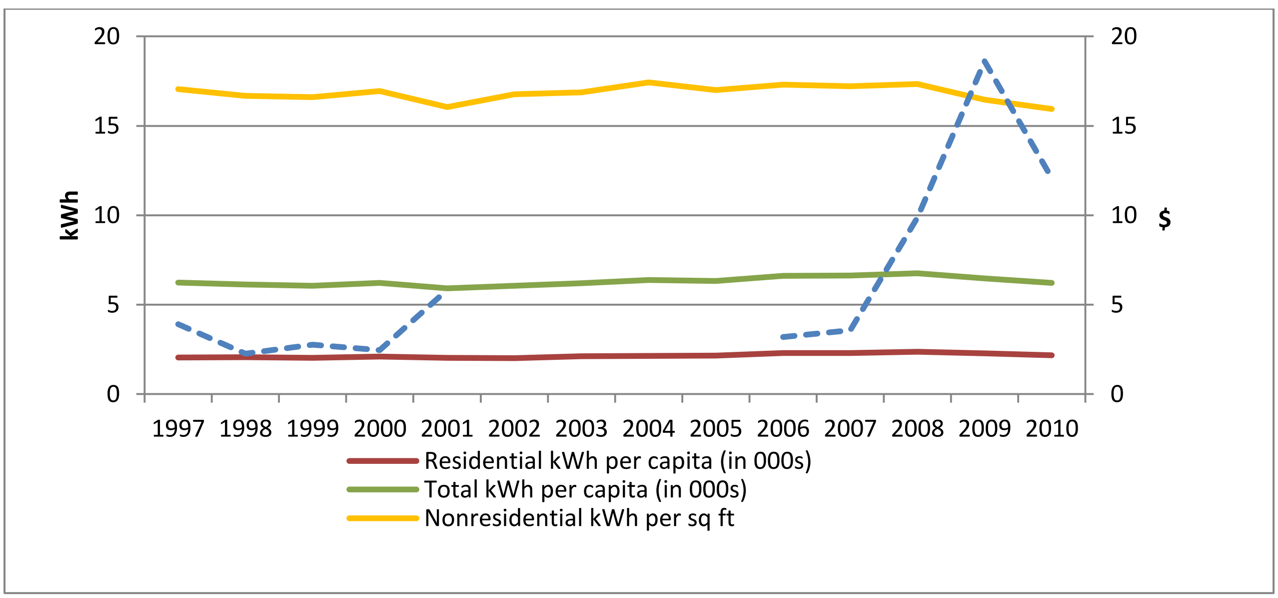
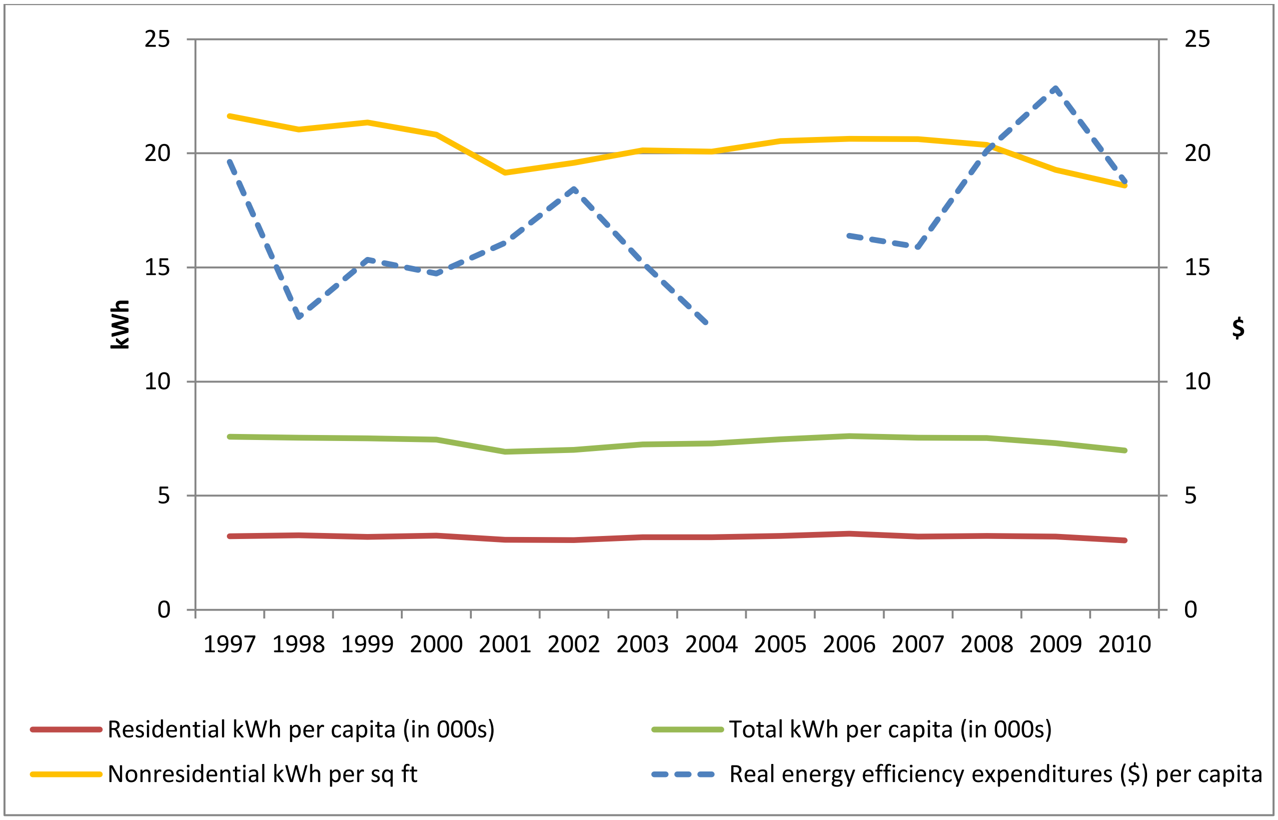


**Figure 8**. **Sacramento Municipal Utility District Electricity Consumption Intensities and Energy-Efficiency Program Expenditures, 1997-2010**




Though difficult to discern in the graphs, total consumption per capita was much more variable than residential consumption per capita. This variability was largely the influence of nonresidential loads. The residential sector has less variable consumption because residential demand is relatively inelastic. Residential customers face high costs when adjusting their energy use in the short run because of fixed capital investments, and households typically attempt to smooth their consumption over time. To control for the volatility of energy use in the nonresidential sector, we included income earned in the industrial sector as explanatory variables in several of our models.

In addition, there were significant differences between utilities in their relative contributions of residential and nonresidential loads to total consumption (as shown by the standard deviation of the share of residential consumption in Table 3).[20] These differences can have two effects. First, they have the potential to confound the identification of the impacts of other explanatory

[20] Based on plots of sales by retail sector for individual utilities, it became clear that utilities change the classification of nonresidential loads (plots not shown). Many examples of year-to-year changes occurred in commercial sales, and an equal and opposite change occurred in industrial sales, suggesting that utilities reported sales as industrial in the previous year and as commercial in the current year. Given this inconsistency, we did not estimate models at the industrial and commercial sector levels. Rather, we aggregated all nonresidential loads (commercial, industrial, mining, street lighting, and agricultural) into a single class, which we estimated as a nonresidential model.

variables on per-capita consumption. To control for them, we included utility fixed effects in our specifications.[21] Second, to the extent there remains unexplained variation in nonresidential loads after controlling for income, the model error term will be heteroskedastic. The log-log model specification will minimize the potential for heteroskedasticity, but, as noted above, we also report heteroskedasticity-robust standard errors.

Finally, Cadmus tested the per-capita consumption series for stationarity, a necessary condition for inference procedures in time series estimation to be valid. (We estimated and reported below the results from a dynamic demand regression model.) Visual inspection of the data suggested that per-capita consumption series for the large IOUs, LADWP, and SMUD are stationary. We also performed augmented Dickey Fuller (ADF) unit tests to test the stationarity of the series. In most cases, we could reject the hypothesis of non-stationarity of the level series.[22] In addition, we ran Harris-Tzavalis panel unit root tests to determine the stationarity of the consumption panel, and rejected the null hypothesis that the panel contains unit roots with ($\rho$=0.330, Z=-3.73, p<0.0001) and without ($\rho$=0.5669, Z=-5.84, p<0.0001) a time trend.

## 6.1. Overview of Electricity Consumption Models

We report results from regressions of utility, residential, and nonresidential consumption intensities employing different sources of utility energy-efficiency program expenditures data and covering different time periods. The regressions are summarized in Table 4.

**Table 4. Summary of Regressions**

| Specification | Sectors Covered | Years | Source of EE Expenditures | Utilities |
|---|---|---|---|---|
| Regressions 1 | Utility (kWh per capita)<br>Residential (kWh housing unit)<br>Nonresidential (kWh/square foot) | 2006-2010 | CMUA and EEGA | PG&E, SDG&E, SCE, and POUs |
| Regressions 2 | Utility (kWh per capita)<br>Residential (kWh housing unit)<br>Nonresidential (kWh/square foot) | 1997-2010<br>2000-2010<br>2000-2010 | EEGA and IOU historical energy-efficiency reports | PG&E, SDG&E, SCE |
| Regressions 3 | Utility (kWh per capita) | 2001-2010 | EIA | IOUs and POUs |

21 Originally, in regressions of total consumption per capita, we included the percentage of total consumption in the residential sector as an explanatory variable. Other studies have employed a similar strategy (Arimura, Newell, and Powell, 2009; Rivers and Jaccard, 2011). As a reviewer of an earlier draft of this report pointed out, however, including this variable as a regressor changed the interpretation of model coefficients from total consumption elasticities to residential sector consumption elasticities. Cadmus can provide details showing this result. We thank Nahid Movassagh of the CEC for bringing this point to our attention.

22 Our analysis included data from 1997–2010. Based on the ADF unit root test statistics, we could reject the hypothesis of non-stationary per capita kWh series under the hypothesis of a single mean for most utilities: PG&E (Z=-23.79, p<0.0001); SDG&E (Z=-17.43, p<0.0009); SCE (Z=-16.43, p<0.0017); LADWP (Z=-4.34, p=0.435); and SMUD (Z=-15.195, p=0.0038). For LADWP, we could almost reject the null hypothesis of non-stationary series with a time trend at the 90% confidence level (-12.13, p=0.121). Based on ADF statistics, we could not reject the hypothesis of non-stationary residential per capita kWh with a single mean, but could reject the hypothesis with a time trend: PG&E (-27.44, p<0.001); SDG&E (-17.39, 0.338); SCE (-13.85, 0.114); LADWP (-10.98, p=0.256); and SMUD (-16.29, p=0.050).

The first set of regressions covered the years from 2006-2010 and used energy-efficiency expenditures data from EEGA and the CMUA. These regressions included investor-owned and publicly-owned California utilities. The second set of regressions covered the IOUs between 1997 and 2010 or 2000 and 2010 (sector models) and used data from EEGA and historical IOU reports. The third set covered California utilities between 2001 and 2010 and used the EIA data.

## 6.2. Utility Models

Table 5 shows the results from estimating (Equation 1, where the dependent variable was the natural logarithm of utility annual electricity consumption per capita. We estimated the first five models by OLS or FGLS, and included utility fixed effects and a time trend or year fixed effects. The sixth model is the dynamic demand model, which includes a lag of the dependent variable and was estimated by General Method of Moments (GMM) after differencing the equation to remove unobserved time-invariant effects.

We estimated the first model using consumption and energy-efficiency program expenditures data for 26 utilities between 2006 and 2010. Due to including the lag of energy-efficiency expenditures as an independent variable, there were a maximum of four observations per utility. The residential and nonresidential new construction variables, which show the impacts of the 2005 building codes, had statistically significant effects on consumption. The elasticity of consumption with respect to residential new construction was -0.62: a 1% increase in residential new construction under the 2005 code led to decreased energy consumption by two-thirds of a percent relative to what consumption would have been if the new construction had only satisfied the average efficiency of the existing building stock. The consumption elasticity for nonresidential new construction was -0.21.

Current and lagged energy-efficiency expenditures were negatively correlated with consumption, and were jointly significant at the 15% level ($F(2, 25)=2.14$, $p=0.14$). A one-dollar increase in per-capita expenditures in the preceding year reduced per-capita consumption by 0.34%. The impact of current expenditures on consumption was significantly less, which is expected if program expenditures were distributed over the year. For example, if expenditures were distributed uniformly, we would expect each dollar of current year expenditures to affect only half of current year consumption on average, and we would expect for the coefficient on previous year expenditures to be approximately twice the coefficient on current expenditures.

Other variables also affected consumption. The elasticity of per-capita consumption with respect to industrial sector income was 0.5 with statistically significant at the 10% level. The coefficients on HDDs and CDDs have the wrong signs, however. Also, the elasticity of consumption with respect to average price paid for electricity (-0.05) was not significant, and is smaller than elasticities estimated in other studies.[23] The insignificance of many independent variables likely resulted from the short estimation period. There simply was not enough within-utility variation in prices, incomes, and weather to estimate the coefficients precisely. A longer time series might provide the necessary variation.

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[23] See, for example: Bernstein, Mark A. and J. Griffin. *Regional Differences in the Price-Elasticity of Demand for Energy*. Rand Technical Report. Prepared for National Renewable Energy Laboratory. 2005.

**Table 5. Utility Consumption Intensity Models**

| | (1) IOUs and POUs 2006-2010 | (2) PG&E, SDG&E, SCE 1997-2010 | (3) IOUs and POUs 2001-2010 | (4) PG&E, SDG&E, SCE 1997-2010 | (5) IOUs and POUs 2001-2010 | (6) IOUs and POUs 2001-2010, Dynamic Demand |
|---|---|---|---|---|---|---|
| Constant | 9.36616*** (2.0584) | 7.11247*** (1.1168) | -2.21621 (3.5254) | 7.11344*** (0.9090) | 1.30237 (2.4817) | |
| Real income ($) per capita | | 0.11589 (0.1014) | | 0.12004 (0.0883) | | |
| Nonindustrial real income ($) per capita | | | 0.90293*** (0.2961) | | 0.42513* (0.2282) | 0.78096* (0.4065) |
| Industrial real income ($) per capita | 0.50159* (0.2514) | | 0.25391 (0.1495) | | 0.12912** (0.0620) | 0.21562 (0.1578) |
| Annual cooling degree days | -0.03859 (0.0668) | 0.03463 (0.0267) | 0.00238 (0.0166) | 0.03421* (0.0206) | -0.04872 (0.0462) | -0.06643 (0.0580) |
| Annual heating degree days | -0.32358* (0.1725) | 0.01887 (0.0194) | -0.08017** (0.0374) | 0.01705 (0.0174) | 0.09435 (0.0651) | -0.09905** (0.0431) |
| Real price of electricity ($/kWh) | -0.05436 (0.2237) | 0.06047 (0.0577) | -0.15241 (0.1953) | 0.06101 (0.0459) | -0.88743*** (0.1143) | 0.06285 (0.1902) |
| Residential real price of gas ($ per 000 cubic feet) | -0.00843 (0.2455) | 0.10245** (0.0482) | -0.02346 (0.0722) | 0.10160*** (0.0261) | 0.11612* (0.0706) | 0.02985 (0.0511) |
| Per capita cumulative new construction since 1998 code | | -0.0036 (0.0077) | | -0.00379 (0.0057) | | |
| Per capita cumulative new construction since 2001 code | | -0.02752*** (0.0074) | | -0.02743*** (0.0049) | | |
| Per capita cumulative new construction since 2005 code | | 0.00335 (0.0078) | | 0.00339 (0.0058) | | |
| Per capita cumulative residential new construction since 1998 code | | | 0.03029 (0.1036) | | -0.31689*** (0.0654) | 0.0262 (0.0683) |
| Per capita cumulative residential new construction since 2001 code | | | 0.06228** (0.0273) | | 0.11081*** (0.0298) | 0.05978 (0.0326) |
| Per capita cumulative residential new construction since 2005 code | -0.62124* (0.3116) | | 0.00218 (0.0143) | | 0.01288 (0.0243) | 0.01863 (0.0146) |
| Per capita cumulative nonresidential new construction since 1998 code | | | -0.14425 (0.0940) | | 0.25855*** (0.0535) | -0.06637 (0.0756) |
| Per capita cumulative nonresidential new construction since 2001 code | | | -0.05171*** (0.0157) | | -0.11184*** (0.0221) | -0.07110*** (0.0205) |
| Per capita cumulative nonresidential new construction since 2005 code | -0.21485* (0.1207) | | 0.01961 (0.0160) | | 0.03376 (0.0227) | 0.01325 (0.0141) |
| Energy-efficiency (EE) expenditures ($) per capita (Source: EEGA/CMUA) | -0.00061 (0.0016) | -0.00039 (0.0006) | | -0.00038 (0.0005) | | |
| EE expenditures ($) per capita year t-1 (Source: EEGA/CMUA) | -0.00345 (0.0021) | -0.0007 (0.0005) | | -0.00069 (0.0005) | | |

| | (1) IOUs and POUs 2006-2010 | (2) PG&E, SDG&E, SCE 1997-2010 | (3) IOUs and POUs 2001-2010 | (4) PG&E, SDG&E, SCE 1997-2010 | (5) IOUs and POUs 2001-2010 | (6) IOUs and POUs 2001-2010, Dynamic Demand |
|---|---|---|---|---|---|---|
| EE expenditures ($) per capita year t-2 (Source: EEGA/CMUA) | | -0.00107* (0.0006) | | -0.00109** (0.0005) | | |
| EE expenditures ($) per capita year t-3 (Source: EEGA/CMUA) | | -0.00124* (0.0006) | | -0.00122*** (0.0005) | | |
| EE expenditures ($) per capita year t-4 (Source: EEGA/CMUA) | | -0.00026 (0.0008) | | -0.00028 (0.0007) | | |
| EE expenditures ($) per capita year t-5 (Source: EEGA/CMUA) | | -0.00296*** (0.0009) | | -0.00292*** (0.0006) | | |
| DSM expenditures ($) per capita (Source: EIA) | | | 0.00025 (0.0005) | | -0.00098 (0.0011) | -0.00029 (0.0009) |
| DSM expenditures ($) per capita year t-1 (Source: EIA) | | | 0.00042 (0.0005) | | -0.00055 (0.0010) | 0.00028 (0.0006) |
| DSM expenditures ($) per capita year t-2 (Source: EIA) | | | -0.00076 (0.0007) | | -0.00134 (0.0011) | -0.00139* (0.0007) |
| DSM expenditures ($) per capita year t-3 (Source: EIA) | | | 0.00039 (0.0007) | | -0.00089 (0.0011) | 0.00035 (0.0008) |
| DSM expenditures ($) per capita year t-4 (Source: EIA) | | | -0.00024 (0.0005) | | -0.0016 (0.0011) | -0.00066* (0.0004) |
| DSM expenditures ($) per capita year t-5 (Source: EIA) | | | -0.00109* (0.0006) | | -0.00211* (0.0011) | -0.00096** (0.0005) |
| Time trend | | 0.01029 (0.0077) | 0.0145 (0.0160) | 0.01029* (0.0054) | 0.00731 (0.0116) | |
| Year 2001 | | -0.12918*** (0.0276) | 0.03026 (0.0875) | -0.12864*** (0.0141) | -0.05934 (0.0867) | -0.02066 (0.0833) |
| Year 2002 | | -0.02068 (0.0199) | 0.02331 (0.0319) | -0.01968 (0.0123) | -0.02576 (0.0454) | |
| Lagged electricity consumption per capita (kWh) | | | | | | 0.34061** (0.1587) |
| Utility fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Estimation method | OLS | OLS | OLS | FGLS | FGLS | GMM |
| R-squared | 0.52 | 0.89 | 0.23 | | | |
| Observations | 104 | 42 | 299 | 42 | 280 | 280 |
| Number of utilities | 26 | 3 | 30 | 3 | 28 | 28 |

Notes: In models 1-3, the dependent variable is the natural logarithm of utility electricity consumption per capita. All independent variables are represented in natural logs, except energy-efficiency expenditures. Autocorrelation and heteroskedasticity robust standard errors are shown in parentheses in models 1-3. *=significant at 10%; **=significant at 5%; ***=significant at 1%. See text for data definitions and sources.

Cadmus estimated the second model with 14 years of consumption data (1997–2010) for PG&E, SDG&E, and SCE. It includes current and five lags of annual utility energy-efficiency program expenditures. Current and lagged per-capita energy-efficiency expenditures were negatively correlated with consumption, and the effects were jointly significant at the 1% level ($F(6, 22)=3.54$, $p=0.01$). Two-, three-, and five-year lagged expenditures were also individually significant at the 10% level. For example, a $1 increase in two-year lag expenditures decreased the current consumption by approximately 0.1% ($p=0.07$). The coefficient on one-year lagged expenditures was approximately twice the magnitude of the coefficient of current expenditures.

With regard to the impacts of building codes on consumption intensity, only the 2001 new construction elasticity was negative and statistically significant. A 1% increase in new construction built under the 2001 code decreased consumption by approximately 0.24% (-0.027-(-0.004)) relative to what consumption would have been under the preceding building code. We could not detect statistically significant impacts from the 1998 or 2005 building code updates.

Many other variables in this model were not precisely estimated. The elasticities of consumption with respect to per-capita income and CDDs were, respectively, 0.11 and 0.04, but neither was statistically significant. The gas price of elasticity of consumption was 0.10 and significant at the 5% level.

Cadmus estimated the third model using 10 years of data (2001–2010) for a larger number of IOUs and POUs ($n=30$). The model also includes current plus-five lags of utility energy-efficiency program expenditures per capita as regressors. Energy-efficiency expenditures were obtained from the EIA. Current and one- and three-year lagged energy-efficiency expenditures had the wrong (positive) signs. The expenditures' coefficients are jointly insignificant ($F(6,29)=0.91$, $p=0.4983$). Only five-year lagged expenditures was individually significant. We interpret this result as likely reflecting misreporting of expenditures in the EIA data, rather than the ineffectiveness of energy-efficiency programs for the 30 utilities. Residential and nonresidential new construction elasticities were jointly significant at the 1% level ($F(6,29)=4.43$, $p=0.0027$).

In the fourth and fifth specifications, Cadmus modeled the error term as following a common AR(1) process, then estimated the models by FGLS. Lagrange multiplier tests (Breusch-Godfrey) revealed evidence of auto-correlation (Model 4: $F(1,2)=1.61$, $p=0.33$; Model 5: $F(1,3)=5.52$, $p=0.03$). Model 4 was estimated using 14 years of consumption data for the three IOUs. Model 5 was estimated with 14 years of data for 28 California utilities. Both models include current and plus-five lags of energy-efficiency expenditures per capita.

In Model 4, current and lagged energy-efficiency expenditures decreased consumption. All expenditure coefficients were negative, and all but three-year lag expenditures were statistically significant. Expenditures were jointly significant at less than the 1% level ($\chi^2(6)=41.5$, $p<0.01$). The elasticity of consumption with respect to new construction built under the 2001 codes is negative and statistically significant. The coefficients on real income, CDDs, HDDs, and gas prices had the expected signs.

Model 5 was estimated with data for 28 utilities between 2001 and 2010. All coefficients on current and lagged expenditures were negative, although only the five-year lagged expenditures was individually significant. The expenditures' coefficients were not jointly significant at the

10% level ($\chi^2(6)=9.4$, p=0.15), although their magnitudes were similar to those estimated in Models 2 and 4. Income, electricity prices, and HDDs had the anticipated signs, were statistically significant, or both. The new construction variables were jointly significant at the 1% level ($\chi^2(6)=74.3$, $p<0.001$). The 1998 and 2005 residential building codes and 2001 nonresidential building codes reduced consumption using the preceding building code as a baseline.

Model 6, the dynamic demand model, was estimated with 10 years of data for 28 utilities. Energy-efficiency expenditures were obtained from the EIA, as that source had the longest continuous series of data for the largest number of utilities. We estimated the first difference of the model by GMM using lagged differences of the dependent variable as instruments for $\Delta\ln(kWh_{it-1})$.[24]

The results of Model 6 were generally consistent with those for Model 5. Four of the six energy-efficiency expenditures' coefficients were negative, although they were not jointly significant ($\chi^2(6)=7.76$, $p<0.256$) at the 10% level. The coefficient on the lagged dependent variable was positive and statistically significant at the 5% level, suggesting, as hypothesized, that electricity consumption adjusted gradually to changes in prices, incomes, etc. The coefficient on the 2005 nonresidential new construction suggests that the 2005 Title 24 update reduced consumption, using the 1998 or 2001 building code as a baseline.

Summary of Utility Consumption Intensity Analysis Findings

In summary, based on Cadmus' analysis of utility consumption intensities, we determined the following findings:

- In most of the models, the coefficients on current and lagged utility energy-efficiency program expenditures were negative and individually or jointly significant. This suggests that utility programs saved energy, although we have not yet reported estimates of those savings.
- There is evidence that updates to the building codes saved energy, although interpretation of the individual new construction floor space coefficients is less straightforward. A coefficient on new construction floor space must be interpreted relative to the coefficient on new construction floor space built under the preceding code. In several models, building codes reduced energy use and were jointly significant at the 10% level.
- Cadmus tried different approaches to account for autocorrelation in utility consumption, but found that imposing additional structure on the model by modeling the error as an autoregressive process resulted in the most precise estimates of the coefficients.

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24 The estimation of (Equation 1 occurred through GMM estimation of the first difference of (Equation 1 (Arellano and Bond, 1991; Ahn and Schmidt, 1993; Greene, 1997). GMM uses more information about the relationships between the model error and lagged levels or differences of the dependent variable, and is therefore more efficient. Differencing was necessary, as the time-invariant error component ($\lambda_i$) was assumed to correlate with one or more of the other explanatory variables. However, differencing introduced correlation between the first difference of the lagged dependent variable and the first difference of the error term, as $kWh_{t-1}$ and $\mu_{it-1}$ are, by definition, correlated.

## 6.3. Residential Sector Models

Table 6 shows the results from regressions of residential consumption per occupied housing unit on residential new construction floor space per occupied housing unit, utility residential energy-efficiency program expenditures per housing unit, and other energy-use drivers. Note that, in general, utility energy-efficiency program expenditures are measured with greater error at the residential sector than the utility level. Many utility energy-efficiency programs served multiple retail sectors, and it was necessary to disaggregate expenditures by sector for these programs.[25] Any error in the disaggregation can lead to error in the expenditures, and attenuates estimates of the program savings.

Model 1 was estimated by OLS with utility and year fixed effects, using four years of data for 25 utilities. The model did not perform as expected. None of the independent variables were statistically significant, and the hypothesis that variables were jointly insignificant could not be rejected ($F(11, 24)=0.93$, $p=0.53$). The coefficients on the energy-efficiency expenditures variables had the correct signs, but were estimated imprecisely. The point estimates imply that the effect of a $1 increase in current energy-efficiency expenditures per housing unit decreased consumption by 0.02%. The effect of previous year expenditures on consumption was approximately three times as large (0.06%). The residential new construction elasticity suggests that a 1% increase in new residential construction resulted in an approximately 0.16% decrease in electricity consumption relative to what consumption would have been under previous building codes.

**Table 6. Residential Consumption Intensity Models**

| | (1) IOUs and POUs 2006-2010 OLS | (2) PG&E, SDG&E, SCE 2000-2010 OLS | (3) PG&E, SDG&E, SCE 1995-2010 OLS | (4) PG&E, SDG&E, SCE 2000-2010 FGLS | (5) PG&E, SDG&E, SCE 1995-2010 FGLS |
|---|---|---|---|---|---|
| Constant | 10.29086<br>(11.0358) | 2.58625**<br>(0.4206) | 2.26784<br>(1.6801) | 2.63191***<br>(0.7267) | 3.45086***<br>(1.2549) |
| Real income per occupied housing unit | 0.05218<br>(0.8644) | 0.50023***<br>(0.0157) | 0.49312*<br>(0.1441) | 0.50096***<br>(0.0584) | 0.40828***<br>(0.1095) |
| CDD * central air conditioning saturation | 0.00348<br>(0.0514) | 0.03729<br>(0.0227) | | 0.03740***<br>(0.0142) | |
| CDDs | | | 0.06914**<br>(0.0103) | | 0.05419***<br>(0.0139) |
| HDD * electric heat saturation | -0.0866<br>(0.0774) | 0.03871*<br>(0.0111) | 0.052<br>(0.0190) | 0.03932**<br>(0.0157) | 0.04005**<br>(0.0161) |
| Residential real price of electricity (cents per kWh) | 0.14849<br>(0.2691) | 0.0227<br>(0.0096) | | 0.02291*<br>(0.0139) | |
| Residential real price of gas ($ per 000 cubic feet) | -0.23507<br>(0.3146) | 0.0192<br>(0.0223) | | 0.01873<br>(0.0207) | |

25 We describe the procedure for disaggregating expenditures in Appendix B.

| | (1) IOUs and POUs 2006-2010 OLS | (2) PG&E, SDG&E, SCE 2000-2010 OLS | (3) PG&E, SDG&E, SCE 1995-2010 OLS | (4) PG&E, SDG&E, SCE 2000-2010 FGLS | (5) PG&E, SDG&E, SCE 1995-2010 FGLS |
|---|---|---|---|---|---|
| Cumulative residential new construction per housing unit since 1998 code | | 0.00672<br>(0.0157) | -0.00067<br>(0.0096) | 0.00735<br>(0.0226) | -0.00009<br>(0.0035) |
| Cumulative residential new construction per housing unit since 2001 code | | 0.00908<br>(0.0058) | 0.00531<br>(0.0047) | 0.00903<br>(0.0086) | 0.00116<br>(0.0047) |
| Cumulative residential new construction per housing unit since 2005 code | -0.16287<br>(0.2080) | 0.00271<br>(0.0076) | -0.00091<br>(0.0012) | 0.00266<br>(0.0038) | 0.0014<br>(0.0040) |
| Residential energy-efficiency (EE) expenditures per square foot for year 't' (Source: EEGA/CMUA) | -0.00027<br>(0.0008) | | | | |
| Residential EE expenditures per housing unit for year 't-1' (Source: EEGA/CMUA) | -0.00067<br>(0.0008) | | | | |
| EE expenditures per capita for year 't' (Source: EEGA/CMUA) | | 0.00049**<br>(0.0001) | 0.00007<br>(0.0001) | 0.00050**<br>(0.0002) | -0.00013<br>(0.0003) |
| EE expenditures per housing unit for year 't-1' (Source: EEGA/CMUA) | | 0.00088<br>(0.0004) | 0.00063<br>(0.0004) | 0.00088***<br>(0.0003) | 0.00048<br>(0.0003) |
| EE expenditures per housing unit for year 't-2' (Source: EEGA/CMUA) | | 0.0004<br>(0.0003) | 0.00017<br>(0.0003) | 0.00041<br>(0.0003) | -0.00015<br>(0.0004) |
| EE expenditures per housing unit for year 't-3' (Source: EEGA/CMUA) | | -0.00067<br>(0.0005) | -0.0002<br>(0.0004) | -0.00067**<br>(0.0003) | -0.00024<br>(0.0004) |
| EE expenditures per housing unit for year 't-4' (Source: EEGA/CMUA) | | | 0.00078<br>(0.0003) | | 0.00064<br>(0.0007) |
| EE expenditures per housing unit for year 't-5' (Source: EEGA/CMUA) | | | -0.00091<br>(0.0006) | | -0.00100*<br>(0.0006) |
| Time trend | | -0.01322<br>(0.0049) | -0.00407<br>(0.0046) | -0.01338***<br>(0.0051) | -0.00059<br>(0.0040) |
| Year 2001 | | -0.07598*<br>(0.0182) | -0.06944*<br>(0.0187) | -0.07618***<br>(0.0170) | -0.07375***<br>(0.0117) |
| Year 2002 | | -0.05677*<br>(0.0160) | -0.05839**<br>(0.0087) | -0.05726***<br>(0.0095) | -0.05317***<br>(0.0090) |
| Utility fixed effects | yes | yes | yes | yes | yes |
| 2007-2009 year dummy variables | yes | no | no | no | no |
| R-squared | 0.10 | 0.97 | 0.90 | 1. | 2. |
| Observations | 100 | 33 | 48 | 33 | 48 |

| | (1) IOUs and POUs 2006-2010 OLS | (2) PG&E, SDG&E, SCE 2000-2010 OLS | (3) PG&E, SDG&E, SCE 1995-2010 OLS | (4) PG&E, SDG&E, SCE 2000-2010 FGLS | (5) PG&E, SDG&E, SCE 1995-2010 FGLS |
|---|---|---|---|---|---|
| Number of Utilities | 25 | 3 | 3 | 3 | 3 |

Notes: In Models 1-5, the dependent variable is the natural logarithm of per-housing-unit residential electricity consumption. All independent variables are in natural logs, except for energy-efficiency expenditures. Autocorrelation and heteroskedasticity robust standard errors are shown in parentheses.
*-significant at 10%;
**-significant at 5%.
***-significant at 1%. See text for data definitions and sources.

The second residential model included three lags of energy-efficiency expenditures and was estimated with 11 years of data for PG&E, SG&E, and SCE.[26] This model performed more in line with expectation, as the longer time series provided enough variation to identify the effects of some independent variables. Real income, residential heating demand, and residential cooling demand were positively correlated with electricity consumption. The elasticity of electricity consumption with respect to income was approximately 0.50. However, neither the building code variables nor the energy-efficiency expenditures variables were individually or jointly significant. In fact, most energy-efficiency and building code coefficients had the wrong signs.

The third model dropped electricity and natural gas prices, and was estimated with a longer time series: 16 years between 1995 and 2010. It also included a larger number (n=5) of lags of annual energy-efficiency expenditures per housing unit. This model yielded results similar to those for Model 2.

The fourth model was estimated using the same data as for Model 2, but assumed that the error followed an AR(1) process. The coefficients had similar magnitudes and signs as those in Model 2, but were estimated more precisely. Three-year lagged energy-efficiency expenditures per housing unit reduced consumption, but current, one-, and two-year lagged expenditures were positively correlated with consumption, which was the opposite of expected.

The fifth model drops gas prices and was estimated by FGLS with a larger number of observations (n=48). The energy-efficiency expenditures variables are jointly significant at the 5% level ($\chi^2(6)=14.73$, $p<0.02$), and four of six coefficients are negative. None of the building code variables had statistically significant effects on consumption.

26 Information about revenues in retail sectors from EIA became available beginning in 2000.

### 6.3.1. Summary of Residential Sector Consumption Intensity Analysis Findings

In summary, based on Cadmus' analysis of residential sector consumption intensities, we determined the following:

- In general, the residential sector model coefficients were not estimated precisely. The residential sector models were estimated with a small number of years or utilities, which reduced precision.
- In most of the models, the coefficients on current and lagged IOU energy-efficiency programs were not individually or jointly significant. The exception was Model 5, estimated with 16 years of data for the IOUs. The insignificance of residential sector expenditures may be the result of measurement error in disaggregating expenditures between the residential and nonresidential sectors.
- There was not much evidence that updates to the residential building codes saved energy.

## 6.4. Nonresidential Sector Models

Table 7 reports results from regressions of nonresidential electricity consumption intensity. We modeled energy use per square foot of floor space in the nonresidential sector as a function of nonresidential new construction, utility nonresidential energy-efficiency program expenditures, and other energy-use drivers , including income, weather, and prices. As with the residential sector, utility energy-efficiency program expenditures were generally measured with greater relative error at the sector level than the utility level.

Model 1 was estimated by OLS using data for 30 utilities between 2006 and 2010. This model, like the corresponding residential one, did not yield the expected results. Many variables were statistically insignificant or had the wrong signs. The coefficient on current energy-efficiency expenditures had a negative sign but was not statistically significant. The coefficient on previous year expenditures was significant at the 10% level but had the wrong (positive) sign. The coefficient on cumulative nonresidential new construction since the 2005 code had the right sign but was not statistically significant.

**Table 7. Nonresidential Consumption Intensity Models**

| | (1) IOUs and POUs 2006-2010 OLS | (2) PG&E, SDG&E, SCE 2000-2010 OLS | (3) PG&E, SDG&E, SCE 1995-2010 OLS | (4) PG&E, SDG&E, SCE 2000-2010 FGLS | (5) PG&E, SDG&E, SCE 1995-2010 FGLS |
|---|---|---|---|---|---|
| Constant | 4.84357***<br>(1.6086) | -0.07337<br>(1.4147) | -0.54865<br>(1.2531) | -1.52117***<br>(0.5044) | -3.06762***<br>(0.4175) |
| Industrial real income per square foot of floor space | 0.31316<br>(0.2586) | 0.56230*<br>(0.1449) | | 0.25991***<br>(0.0489) | |
| Real income per square foot of floor space | | | 0.56062<br>(0.2848) | | 0.49497***<br>(0.0830) |

| | (1) IOUs and POUs 2006-2010 OLS | (2) PG&E, SDG&E, SCE 2000-2010 OLS | (3) PG&E, SDG&E, SCE 1995-2010 OLS | (4) PG&E, SDG&E, SCE 2000-2010 FGLS | (5) PG&E, SDG&E, SCE 1995-2010 FGLS |
|---|---|---|---|---|---|
| Annual CDDs | -0.08896* (0.0452) | 0.08825* (0.0255) | 0.08233** (0.0157) | 0.16381*** (0.0200) | 0.25814*** (0.0255) |
| Annual HDDs | -0.1561 (0.1289) | 0.09084 (0.0675) | 0.0271 (0.0171) | 0.16299*** (0.0363) | 0.25310*** (0.0298) |
| Nonresidential real price of electricity (cents per kWh) | -0.06439 (0.1652) | -0.11763 (0.1782) | | 0.05069 (0.0905) | |
| Nonresidential real price of gas ($ per 000 cubic foot) | -0.19223** (0.0848) | -0.01782 (0.0238) | | 0.07370* (0.0440) | |
| Cumulative nonresidential new construction since 1998 code as a fraction of existing floor space | | | | -1.06759*** (0.3157) | 0.00689 (0.0075) |
| Cumulative nonresidential new construction since 2001 code as a fraction of existing floor space | | 0.02707 (0.1023) | 0.02222** (0.0033) | 0.50047*** (0.1308) | 0.02252*** (0.0084) |
| Cumulative nonresidential new construction since 2005 code as a fraction of existing floor space | -0.00966 (0.0187) | -0.00048 (0.0051) | 0.00679* (0.0017) | 0.00658 (0.0078) | 0.02941*** (0.0074) |
| Nonresidential energy-efficiency (EE) expenditures per square foot of floor space for year t (Source: EEGA/CMUA) | -0.00253 (0.0020) | 0.26111* (0.0867) | -0.09295 (0.1787) | 0.62225 (0.3943) | 0.47905 (0.3911) |
| Nonresidential EE expenditures per square foot of floor space for year 't-1' (Source: EEGA/CMUA) | 0.00416* (0.0022) | -0.68442* (0.1766) | -0.29388* (0.0807) | -0.52786 (0.3892) | -0.43788 (0.4112) |
| Nonresidential EE expenditures per square foot of floor space for year 't-2' (Source: EEGA/CMUA) | | -0.19295 (0.1567) | -0.60106* (0.1971) | 0.36167 (0.3873) | -0.89776** (0.4090) |
| Nonresidential EE expenditures per square foot of floor space for year 't-3' (Source: EEGA/CMUA) | | -0.02141 (0.4783) | -0.20808 (0.2621) | -0.09996 (0.4324) | -1.27050*** (0.4040) |
| Nonresidential EE expenditures per square foot of floor space for year 't-4' (Source: EEGA/CMUA) | | | -0.36889 (0.3897) | | -1.43900*** (0.4164) |
| Nonresidential EE expenditures per square foot of floor space for year 't-5' (Source: EEGA/CMUA) | | | -0.48815 (0.8516) | | -0.87033** (0.4288) |
| Time trend | | 0.00144 (0.0133) | -0.00649* (0.0020) | 0.02545** (0.0128) | -0.0025 (0.0034) |
| Year 2001 | | -0.11345 (0.3441) | -0.07479** (0.0098) | -2.16583*** (0.5660) | -0.12309*** (0.0271) |
| Year 2002 | | 0.02084 (0.0646) | 0.02256 (0.0108) | 0.14746*** (0.0433) | -0.00502 (0.0294) |
| Utility fixed effects | Yes | Yes | Yes | Yes | Yes |
| 2007-2009 year fixed effects | Yes | No | No | No | No |
| R-squared | 0.24 | 0.86 | 0.85 | | |
| Number of utilities | 30 | 3 | 3 | 3 | 3 |

| | (1) IOUs and POUs 2006-2010 OLS | (2) PG&E, SDG&E, SCE 2000-2010 OLS | (3) PG&E, SDG&E, SCE 1995-2010 OLS | (4) PG&E, SDG&E, SCE 2000-2010 FGLS | (5) PG&E, SDG&E, SCE 1995-2010 FGLS |
|---|---|---|---|---|---|
| Observations | 117 | 30 | 48 | 30 | 48 |

Notes: In Models 1-5, the dependent variable is natural logarithm of nonresidential electricity consumption per square foot of floor space. All independent variables are in natural logs, except energy-efficiency expenditures. Autocorrelation and heteroskedasticity robust standard errors are shown in parentheses. *=significant at 10%; **=significant at 5%; ***=significant at 1%. See text for data definitions and sources.

Model 2 was estimated with fewer utilities (PG&E, SDG&E, and SCE) and more years (2001-2010) and yielded results more consistent with expectations. The coefficient on the log industrial income per square foot implies that a 1% increase in industrial income per square foot increased electricity use by 0.56%. A 1% increase in HDDs increased energy-use intensity by approximately 0.1%. The own-price elasticity of nonresidential electricity consumption intensity was -0.11. The energy-efficiency expenditures' intensity coefficients were negative, except for the coefficient on current expenditures, and one-year lagged expenditures were statistically significant. The coefficient on one-year lagged expenditures implies that a $0.10 increase in expenditures per square foot of floor space would result in approximately a 2.6% reduction in energy-use intensity.

Model 3 drops electricity and natural gas prices as independent variables and was estimated with 16 years of data, between 1995 and 2010. The model includes five lags of energy-efficiency expenditures per square foot of floor space. All of the coefficients on energy-efficiency expenditures are negative, and one- and two-year lagged expenditures are statistically significant at the 1% level.

Cadmus estimated Model 4 by FGLS, with the error term following an AR(1) process. The coefficients were more precisely estimated than those in Model 2 and Model 3. Elasticities of energy-use intensity were positive and statistically significant with respect to income, CDDs, and HDDs. For example, a 1% increase in CDDs caused energy use to increase by 0.16%. The elasticity of energy use with respect to industrial income was approximately 0.25. However, the coefficients on current and lagged energy-efficiency expenditure intensities were not individually or jointly significant at the 10% level ($\chi 2(4)=7.39$, $p=0.12$).

Model 5 omits electricity and gas prices and was estimated with 16 years of IOU data. It also includes current and five lags of energy-efficiency expenditures per square foot of floor space. All of the coefficients on expenditures except the coefficient on current expenditures are negative, and the coefficients on year 2 five lagged expenditures are individually significant at the 5% or 1% levels. The coefficients are jointly significant at less than the 1% level ($\chi 2(6)=42.39$, $p<0.01$).

### 6.4.1. Summary of Nonresidential Sector Consumption Intensity Analysis Findings

In summary, based on Cadmus' analysis of nonresidential sector consumption intensities, we determined the following findings:

- In most models, the coefficients on current and lagged utility energy-efficiency program expenditures were negative and individually or jointly significant. This suggests that nonresidential utility programs saved energy.
- The new construction floor space coefficients must be evaluated relative to the coefficients for the previous building code, but there is also evidence that updates to the nonresidential building codes saved energy. The coefficients on new construction floor space were also jointly significant in several models.
- Modeling the error as an autoregressive process resulted in more precise coefficient estimates.

## 6.5. Electricity Savings Estimates

Using the estimates from utility consumption intensity Model 4 in Table 5, we estimated the electricity savings from the IOUs' energy-efficiency programs and the 2001update to California's building codes. We selected Model 4 because the coefficients have the expected signs and pertain to the IOUs.[27] As the model was estimated with IOU data, the model coefficients reflect the average impact of the independent variables on consumption in the IOU service territories between 1997 and 2010. The coefficients in Model 4 are very similar to those in Models 2, which was also estimated with IOU data.

### 6.5.1. Utility Energy-Efficiency Program Savings

Table 8 reports estimates of savings between 2005 and 2010 for the combined energy-efficiency programs of the three IOUs.[28] (Appendix C includes a separate table for each IOUs.) Panel A of the table shows the key inputs used in the calculations, including electricity consumption, energy-efficiency program expenditures, and utility service area population. Panel B shows estimates of IOU electricity savings in each year from current year and previous year program expenditures. For example, Panel A shows that in 2008, the IOUs spent a combined $762 million on energy-efficiency programs. These expenditures were estimated to result in savings of 2,077 GWh in 2008; 3,565 GWh in 2009; and 5,447 GWh in 2010. Panel C shows these savings represented 1.0% of 2008 consumption; 1.8% of 2009 consumption; and 2.6% of 2010 consumption. Total electricity savings in 2008 from current and past (three years in 2005, 2006,

27 The coefficients from this model best reflect the actual effects of IOU program expenditures on consumption for several reasons. First, the model was estimated using data for just the three IOUs; therefore, the estimated coefficients pertained to IOU program impacts. Second, most coefficients had the expected signs or significance. Third, IOU energy-efficiency expenditures data appeared to be measured with a minimum amount of error. As a robustness check of the results, we dropped natural gas prices from the model, which allowed us to estimate the model with 17 years of data for each IOU. This modeling obtained very similar results. (These results are available from Cadmus upon request.)

28 In calculating the energy-efficiency program savings, we used the consumption-weighted approach of Auffhammer, Blumstein, and Fowlie (2008, p. 94).

and 2007) energy-efficiency expenditures was estimated at 10,819 GWh, or 5.4% of consumption. Panel D shows the estimated costs of first-year saved energy. The average cost of current (first) year savings was estimated at $0.37/kWh in 2008.

Panel B shows that between 2005 and 2010, first year savings increased from 1,178 GWh, or 0.6% of consumption in 2005, to 2,077 GWh, or 1.0% of consumption in 2008, reflecting an increase in IOU energy-efficiency program expenditures. First-year savings then decreased to 1,494 GWh, or 0.7% of consumption in 2010, as program expenditures declined.

**Table 8. Estimates of IOU Energy-Efficiency Program Savings and First Year Cost of Conserved Energy**

| | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 |
|---|---|---|---|---|---|---|
| **Panel A: Inputs** | | | | | | |
| Consumption (GWh) | 186,888 | 193,263 | 195,195 | 198,777 | 190,465 | 186,207 |
| Energy-efficiency program expenditures ($) | 444,919,481 | 257,955,388 | 583,784,374 | 762,178,780 | 651,734,803 | 595,297,560 |
| Expenditures per capita ($) | 16.43 | 9.44 | 21.11 | 27.26 | 23.11 | 20.93 |
| Population | 27,072,291 | 27,332,409 | 27,648,206 | 27,963,216 | 28,197,531 | 28,448,916 |
| **Panel B: Savings Estimates** | | | | | | |
| Savings from current expenditures (GWh) | 1,178 | 699 | 1,580 | 2,077 | 1,688 | 1,494 |
| Savings from one-year lagged expenditures (GWh) | | 2,178 | 1,261 | 2,873 | 3,565 | 2,954 |
| Savings from two-year lagged expenditures (GWh) | | | 3,429 | 2,002 | 4,305 | 5,447 |
| Savings from three-year lagged expenditures (GWh) | | | | 3,866 | 2,130 | 4,671 |
| Savings from four-year lagged expenditures (GWh) | | | | | 827 | 465 |
| Savings from five-year lagged expenditures (GWh) | | | | | | 8,517 |
| Total savings from current and previous year expenditures (GWh) | 1,178 | 2,878 | 6,271 | 10,819 | 12,515 | 23,547 |
| **Panel C: Percent Savings** | | | | | | |
| Percent savings from current year expenditures | 0.6% | 0.4% | 0.8% | 1.0% | 0.8% | 0.7% |
| Percent savings from one year lagged expenditures | | 1.1% | 0.6% | 1.4% | 1.8% | 1.4% |
| Percent savings from two year lagged expenditures | | | 1.7% | 1.0% | 2.1% | 2.6% |
| Percent savings from three year lagged expenditures | | | | 1.8% | 1.0% | 2.2% |
| Percent savings from four year lagged expenditures | | | | | 0.4% | 0.2% |
| Percent savings from five year lagged expenditures | | | | | | 4.1% |
| Total percent savings from current and previous year expenditures | 0.6% | 1.5% | 3.2% | 5.4% | 6.6% | 12.6% |
| **Panel D: Cost of Saved Energy** | | | | | | |
| Cost per kWh saved from current expenditures | $0.378 | $0.369 | $0.369 | $0.367 | $0.386 | $0.398 |

Sources: Savings estimates are based on coefficients from FGLS estimation of kWh per-capita regression with data from IOUs between 1997 and 2010. See text for sources of utility energy-efficiency program expenditures, population, and consumption.

By cumulating savings and expenditures, we also estimated the average cost of energy savings between 2005 and 2010. Table 9 shows the estimates of savings, percent savings, and cost of saved energy for these years with 95% confidence intervals.

**Table 9. IOU Electricity Savings and Costs of Saved Electricity, 2005-2010**

| | | 95% Confidence Interval | |
|---|---|---|---|
| | 2005-2010 | Lower Bound | Upper Bound |
| Energy savings (GWh) | 57,207 | 19,124 | 95,289 |
| Percent savings | 5.0% | 1.7% | 8.3% |
| Cost of saved energy ($/kWh) | $0.058 | $0.172 | $0.035 |

We estimated that the IOUs saved 57,207 GWh, equivalent to about 5.0% of total consumption, from utility energy-efficiency program spending between 2005 and 2010.[29] The 95% confidence interval and relative precision for percent savings are, respectively, [1.7%, 8.3%] and ±66%. The average cost of saved energy was approximately $0.06/kWh with a 95% confidence interval of [$0.035, $0.172].

Our estimate of the cost of saved energy of approximately $0.06/kWh is higher than other estimates. For example, in recent studies of the U.S. utility program spending, Auffhammer, Blumstein, and Fowlie (2008) estimated average costs of saved energy of $0.046/kWh, while Arimura, Li, Newell, and Palmer (2011) estimated average program costs of $0.041/kWh.

Some of the difference between the literature estimates and ours may have resulted from California's lead in energy efficiency. California may have already exhausted much of the low-cost potential for savings, whereas utilities in other states have more recently started their programs and therefore have more abundant low-cost savings opportunities. Consistent with our hypothesis, when we estimated Model 1 of Table 5 (utility consumption, 2006–2010) and omitted IOUs from the estimation sample, the coefficients on current and previous year energy-efficiency expenditures significantly decreased (i.e., became more negative). These estimates imply costs of first-year savings of $0.07/kWh. First-year costs of this magnitude are more consistent with those found in previous studies of U.S. utilities.

Other potential explanations for the relatively low estimated cost-effectiveness of the IOU programs include:

- Utility energy-efficiency program expenditures are measured with significant error, which could bias down the savings estimates. This possibility is not likely, however, given that IOU expenditures data appeared to be of high quality.
- There is more energy-efficiency program freeriding and less program spillover in California than in the rest of the United States. California energy consumers may be more likely to invest in energy-efficiency measures without utility financial incentives or other assistance than consumers in other states. We expect freeriding to be greater and spillover to be lower in markets with high awareness of energy efficiency, such as California.

[29] As the analysis does not account for program expenditures before 2005, the savings estimates represent a lower bound of total savings from current and past expenditures.

#### 6.5.1.1. Savings from 2006-2008 Utility Energy-Efficiency Program Cycle

A main research objective of the study was to estimate energy savings from utility energy-efficiency program spending between 2006 and 2008. We used the results from Model 4 to estimate the electricity savings from utility programs during this period. Table 10 shows the savings from expenditures and the average cost of saved energy in this period.

**Table 10. IOU Electricity Savings in the 2006-2008 Program Cycle**

| | | 95% Confidence Interval | |
|---|---|---|---|
| | 2006-2008 | Lower Bound | Upper Bound |
| Energy savings (GWh) | 10,493 | -3,019 | 24,005 |
| Percent savings | 1.8% | -0.5% | 4.2% |
| Cost of saved energy ($/kWh) | $0.153 | | $0.067 |

The point estimate of IOU savings between 2006 and 2008 is 10,493 GWh. This represents approximately 1.8% of total consumption in these years. The average cost of saved energy during this period was approximately $0.15/kWh. There is, however, significant uncertainty about the utility energy-efficiency program savings between 2006 and 2008. The 95% confidence interval for the savings, [-3,019 GWh, 24,005 GWh], is very wide, reflecting the fact that the regression coefficients on current and previous year expenditures were estimated imprecisely. The relative precision of the savings estimate is ±129%.

We compared our estimate of savings for the 2006-2008 program years with the IOUs' reports of savings. The annual reports filed by the IOUs about their energy-efficiency programs include *ex ante* estimates of first-year savings adjusted for the rate of measure installations. The IOUs claimed credit for savings for only the portion of the year that measures were installed. As our savings estimates also reflect the average installation rate of measures, it is possible to compare the savings estimates. An important difference between the estimates is that ours are *net* savings, which excludes savings from freeriding and includes spillover and other utility program market effects. The IOU savings are *gross* estimates and do not reflect adjustments for these factors.

Table 11 shows the IOUs' claim and our estimate of first-year savings between 2006 and 2008. The IOUs claimed savings of 10,461 GWh during these years. We estimated total first-year savings of 4,357 GWh, which equals 42% of the IOUs' claim. However, our point estimate has a large error bound. The 95% confidence interval for electricity savings between 2006 and 2008 includes the IOUs' claim, so we cannot reject it.

**Table 11. IOU First-Year Savings Claims, 2006-2008 Program Cycle**

| | 2006 | 2007 | 2008 | 2006-2008 |
|---|---|---|---|---|
| IOU ex ante claimed savings (GWh) | 1,751 | 3,826 | 4,884 | 10,461 |
| Estimated savings (GWh) | 699 | 1,580 | 2,077 | 4,357 |
| Lower bound 95% confidence interval (GWh) | (1,195) | (2,701) | (3,551) | (7,543) |
| Upper bound 95% confidence interval (GWh) | 2,594 | 5,862 | 7,705 | 16,256 |

The imprecision of savings estimates suggests the need to collect additional data and refine the econometric models.

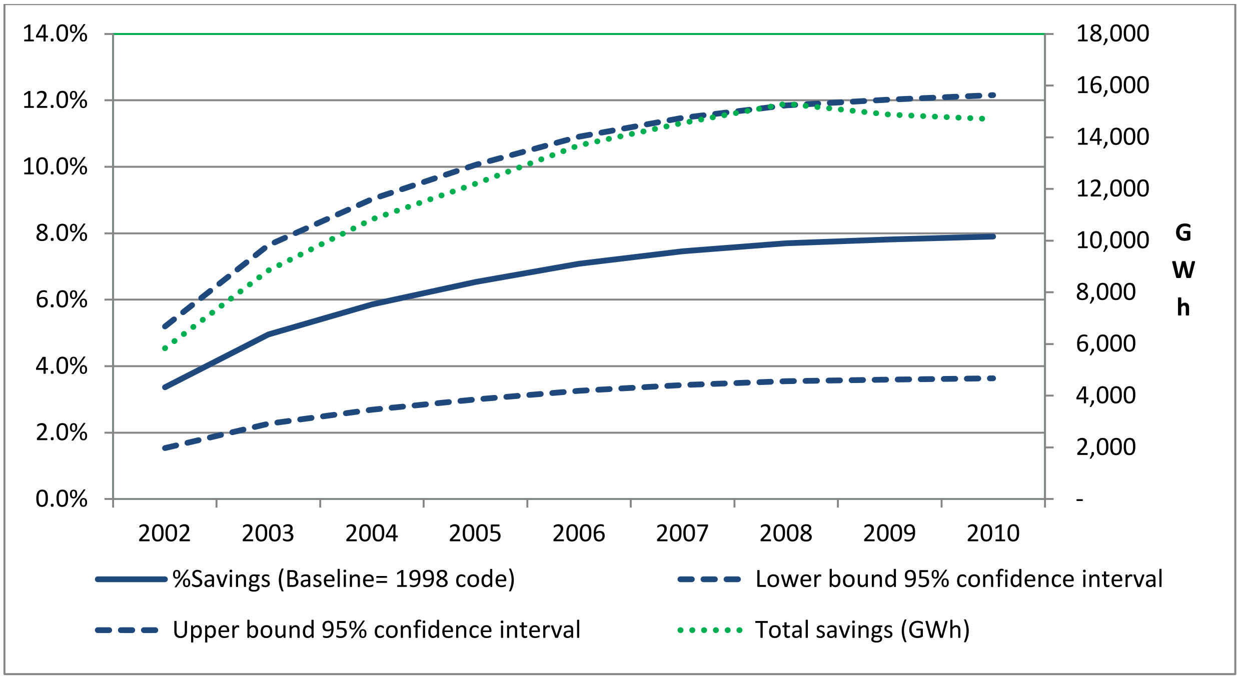
### 6.5.1.2. Savings from Building Codes Updates

We used the coefficients on 1998 and 2001 new construction from Model 4 of Table 5 to estimate the savings from the 2001 update to Title 24. Figure 9 shows an estimate of per-capita percent electricity savings and total GWh savings in the IOU service areas in each year between 2002 and 2010. The savings were measured relative to the average efficiency of residential and nonresidential buildings constructed under the 1998 building code.[30] In each year, the savings reflect the higher efficiency of all buildings constructed since the 2001 code update.

Per-capita savings from the 2001 Title 24 update increased from approximately 2.5% in 2002 to 8% in 2010. The 95% confidence interval for the percent savings estimate is fairly wide but does not include zero, ranging between 1.5% and 5.2% of 2002 consumption.[31] The relative precision of the 2002 percent savings estimate is ±54%. The percent savings increases over time because new construction in each year increases the total building stock affected by the 2001 code.

We estimate that the electricity savings from the 2001 code update increased from approximately 6,000 GWhs in 2002 to 15,000 GWhs in 2008. Savings decreased slightly in 2009 and 2010, as overall energy use decreased in the aftermath of the economic downturn of 2007-2008.

**Figure 9. Electricity Savings from the 2001 Title 24 Building Code Update***




*In PG&E, SDG&E, and SCE service territories. Savings were calculated using the 1998 Title 24 code update as a baseline.

30 The incremental effect of the 2001 Title 24 building code update was estimated as the difference between the 2001 and 1998 building code coefficients.

31 Our savings estimates for building codes are in the range of those in previous studies. See: Aroonruengsawat, Anin, M. Auffhammer, and A. Sanstad. *The Impact of State Level Building Codes on Residential Electricity Consumption*. University of California, Berkeley working paper. 2009.

# 7. GAS CONSUMPTION INTENSITY MODELS

This chapter reports results from analysis of natural gas consumption intensities. The final gas consumption estimation sample included data for the California IOUs (PG&E, SDG&E, and Southern California Gas (SCG)), as gas efficiency expenditures were not available for other California gas utilities. The IOUs accounted for nearly all (98%) of retail gas consumption in California in 2010.

Table 12 shows summary statistics for the IOUs. Columns 1 and 2 show the sample mean and standard deviation for all IOUs and all years between 2000 and 2010. Columns 3-5 show the sample means for each IOU. The estimation sample was limited to the previous decade because utility gas program energy-efficiency expenditures were not available before 2000. Also, energy-efficiency expenditures data for 2005 were not available in a form that could be used in macro-modeling.

There were significant differences between the IOUs in gas consumption intensity, which appears to be largely reflecting differences in climate and heating fuel saturations. SDG&E had the lowest average consumption intensity, approximately half of PG&E's and 65% of SCG's. PG&E's service area averaged just over 2,600 HDDs between 2000 and 2010, whereas SDG&E's area averaged 1,640 HDDs. There were also significant differences between utilities in the percent of homes using gas as a heating fuel. SDG&E had the lowest residential gas heating fuel saturation among the IOUs. Nevertheless, SDG&E's residential sector accounted for the highest share of gas consumption (60% vs. 45% for PG&E and 47% for SCG), perhaps reflecting the low daytime heating requirements of commercial and industrial buildings in SDG&E's service area.

**Table 12. Summary Statistics, 1997-2010**

| Variable | (1) Mean | (2) Standard Deviation | (3) PG&E | (4) SDG&E | (5) SCG |
|---|---|---|---|---|---|
| Natural gas consumption (therms) per capita | 274 | 71 | 349 | 184 | 290 |
| Residential natural gas consumption (therms) per capita | 134 | 20 | 156 | 112 | 136 |
| Nonresidential natural gas consumption (therms) per square foot of floor space | 4.9 | 5.4 | 12.4 | 0.3 | 2.1 |
| Residential share of natural gas consumption | 50.7 | 7.3 | 44.6 | 60.6 | 47.0 |
| Real price of electricity ($ per kWh) | 0.13 | 0.01 | 0.13 | 0.14 | 0.13 |
| Residential real price of electricity ($ per kWh) | 0.15 | 0.01 | 0.14 | 0.17 | 0.15 |
| Real price of gas ($ per 000 cubic feet) | 10.3 | 1.9 | 10.3 | 11.0 | 9.6 |
| Residential real price of gas ($ per 000 cubic feet) | 11.6 | 1.9 | 11.7 | 12.2 | 10.9 |
| Nonresidential real price of gas ($ per 000 cubic feet) | 7.8 | 2.1 | 7.6 | 8.8 | 7.1 |
| Real income ($) per capita | 44,363 | 3,721 | 47,715 | 45,564 | 39,811 |
| Annual HDDs | 2,071 | 455 | 2,618 | 1,640 | 1,956 |
| Percent of households using natural gas as heating fuel | 65.6 | 4.7 | 64.3 | 60.6 | 71.7 |

| Variable | (1) Mean | (2) Standard Deviation | (3) PG&E | (4) SDG&E | (5) SCG |
|---|---|---|---|---|---|
| Per capita cumulative residential new construction (square feet) since 1995 code | 77.6 | 24.9 | 88.4 | 79.9 | 64.7 |
| Per capita cumulative residential new construction (square feet) since 1998 code | 51.1 | 24.1 | 56.8 | 51.1 | 45.4 |
| Per capita cumulative residential new construction (square feet) since 2001 code | 34.2 | 22.9 | 38.9 | 30.7 | 32.9 |
| Per capita cumulative residential new construction (square feet) since 2005 code | 6.6 | 7.9 | 7.3 | 5.3 | 7.1 |
| Per capita cumulative nonresidential new construction (square feet) since 1995 code | 45.4 | 12.0 | 42.4 | 51.9 | 41.9 |
| Per capita cumulative nonresidential new construction (square feet) since 1998 code | 26.6 | 11.9 | 23.9 | 30.1 | 25.8 |
| Per capita cumulative nonresidential new construction (square feet) since 2001 code | 15.9 | 11.2 | 13.3 | 18.2 | 16.0 |
| Per-capita cumulative nonresidential new construction (square feet) since 2005 code | 4.04 | 2.27 | 5.04 | 4.15 | 2.93 |
| Energy efficiency expenditures ($) per capita (Source: CEC/EEGA) | 4.48 | 5.51 | 3.90 | 4.78 | 4.74 |
| Residential energy efficiency expenditures ($) per capita (Source: CEC/EEGA) | 1.67 | 1.06 | 1.98 | 2.04 | 0.98 |
| Nonresidential energy efficiency expenditures ($) per square foot of floor space (Source: CEC/EEGA) | 0.08 | 0.11 | 0.19 | 0.01 | 0.03 |
| Number of observations | 33 | 33 | 11 | 11 | 11 |

In addition, there were differences between IOUs in per-capita gas-efficiency program expenditures. The largest per capita spender was SDG&E at $4.78, although PG&E spent the most in total. PG&E spends significantly more on gas efficiency in the nonresidential sector ($0.19 per square foot of floor space) than SDG&E ($0.01/square foot) or SCG ($0.03/square foot).

Figure 10, Figure 11, and Figure 12 show the following gas consumption intensities and energy-efficiency program spending for the IOUs between 2000 and 2010:

- Utility annual gas consumption per capita;
- Residential sector annual gas consumption per capita;
- Nonresidential sector annual gas consumption per square foot of floor space; and
- Real utility gas-efficiency program expenditures per capita.

The figures show that gas-consumption intensities decreased between 2000 and 2010, although total consumption trended upward in the PG&E and SCG service territories (not shown). The decreasing gas intensities could be reflecting utility energy-efficiency program efforts, fuel switching by existing gas customers, or increasing use of electricity for heating in the residential sector and nonresidential new construction.

As with electricity, there were noticeable decreases in gas consumption intensities around 2000-2001 and 2008-2009. These decreases coincided with SDG&E and SCG ratcheting up their energy-efficiency expenditures, indicating the possible influence of utility programs. However, both episodes also coincide with economic downturns, and winter temperatures during 2009 were relatively mild.

In modeling gas consumption intensities, it was important to control for the simultaneous influences of weather, incomes, and gas-efficiency expenditures. We use utility fixed effects to capture differences between IOUs in average heating demands, separately from differences in fuel saturations, climate, and HDDs. This will capture year-to-year variation in heating demand within a utility.

**Figure 10. Pacific Gas & Electric Gas Consumption Intensities and Energy-Efficiency Program Spending, 2000-2010**

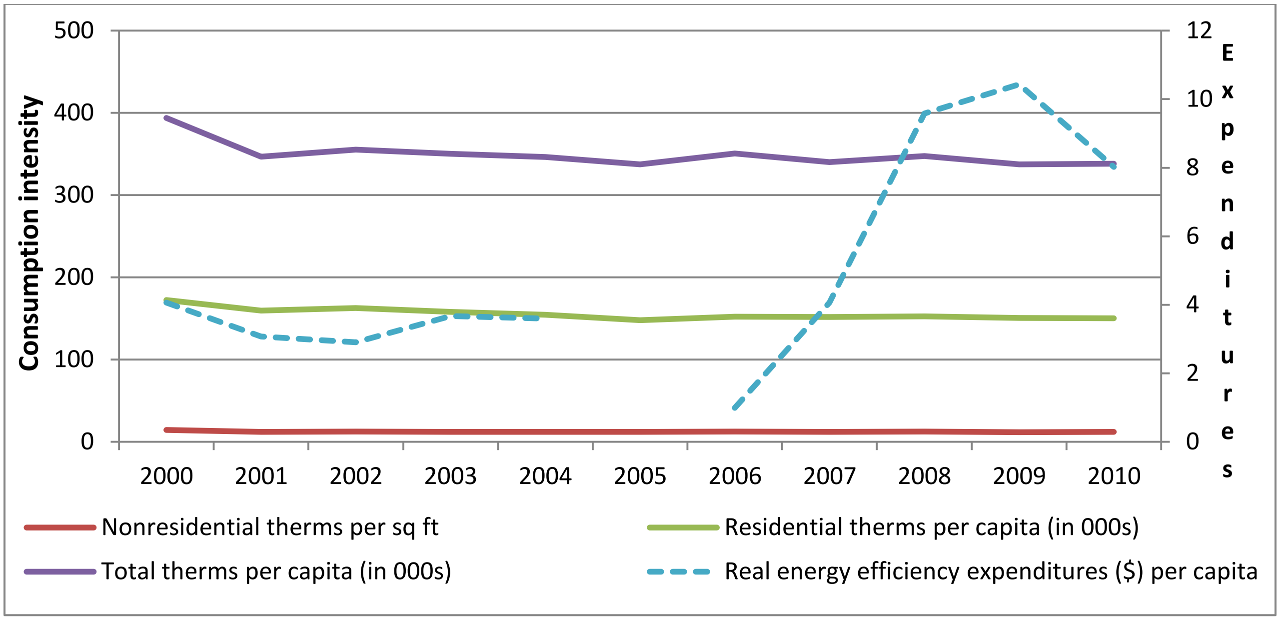


**Figure 11. San Diego Gas & Electric Gas Consumption Intensities and Energy-Efficiency Program Spending, 2000-2010**

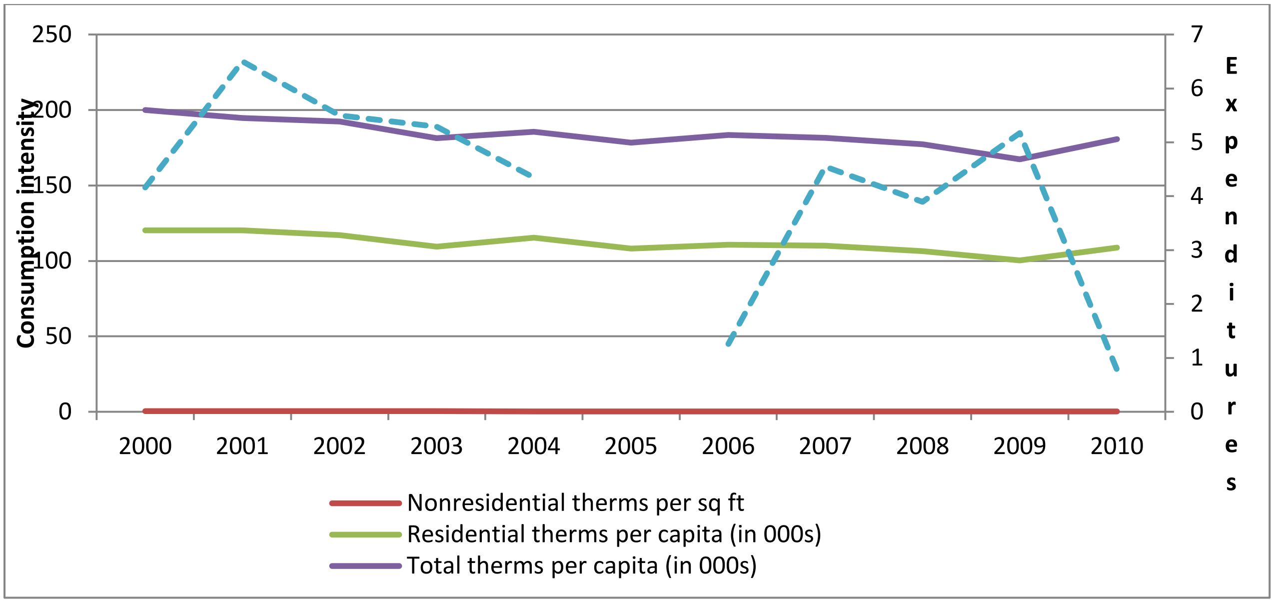
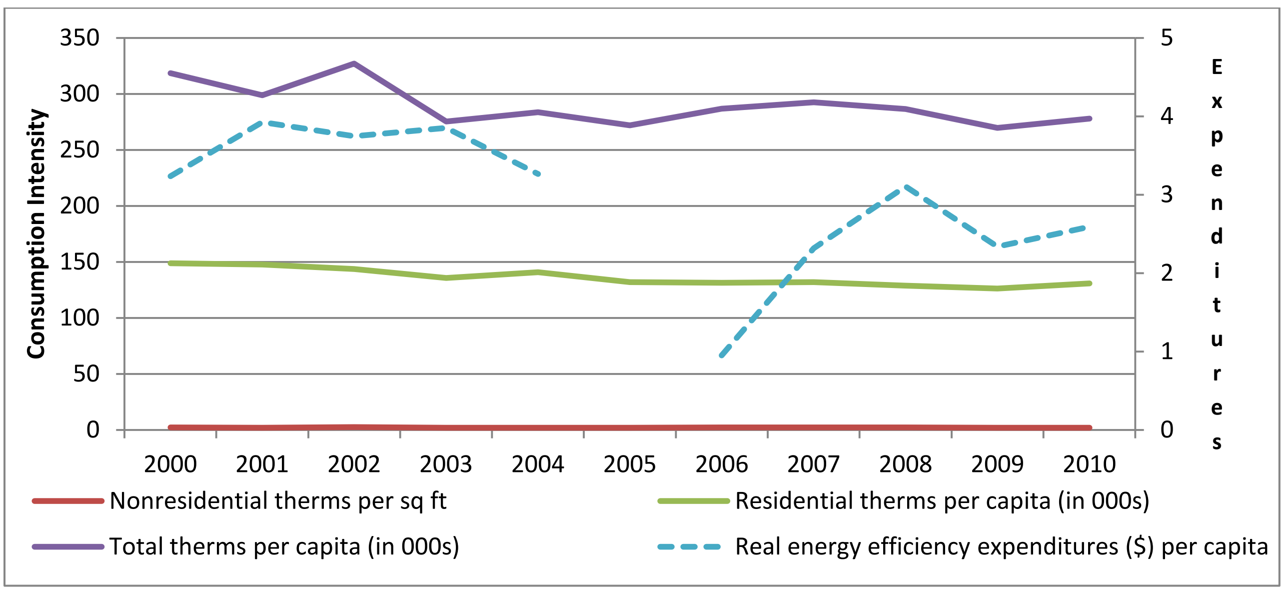



**Figure 12. Southern California Edison Gas Consumption Intensities and Energy-Efficiency Program Spending, 2000-2010**




## 7.1. Overview of Gas Models

We report results from separate regressions of utility, residential, and nonresidential sector consumption intensities. The regressions use utility energy-efficiency program expenditures data from EEGA and historical IOU energy-efficiency reports, and cover the period from 2000-2004 and 2005-2010. The regressions are summarized in Table 13.

**Table 13. Gas Regression Models**

| Specification | Sectors | Years | Source of Expenditures | Utilities |
|---|---|---|---|---|
| Regressions | Utility (therms per capita)<br>Residential (therms per housing unit)<br>Nonresidential (therms/square foot) | 2000-2004,<br>2006-2010 | EEGA and IOU historical energy-efficiency reports | PG&E, SDG&E, SCG |

Cadmus estimated the consumption intensity models by OLS, with utility-clustered standard errors. The missing 2005 energy-efficiency program expenditures yielded a total of 10 observations per utility. The inclusion of the lag of energy-efficiency program expenditures reduced the number of observations per utility to eight.

## 7.2. Gas Consumption Models

Table 14 shows results from the OLS estimation of regressions of utility, residential, and nonresidential gas-consumption intensities. The results were disappointing in that we were unable to detect savings from utility gas-efficiency programs in any of the models.

**Table 14. Gas Consumption Intensity Models Regression**

| | (1)<br>Utility Model<br>2000-2010 | (2)<br>Residential Sector Model<br>2000-2010 | (3)<br>Nonresidential Sector Model<br>2000-2010 |
|---|---|---|---|
| Constant | -3.77399<br>(7.3015) | -0.72757<br>(4.3978) | -10.9324<br>(7.6788) |
| Real income per capita | 0.77225<br>(0.6557) | | |
| Real income per occupied housing unit | | 0.49234<br>(0.3683) | |
| Industrial real income per square foot of floor space | | | 1.78655<br>(1.2624) |
| Annual HDDs | 0.26506*<br>(0.1534) | | 0.22144*<br>(0.1172) |
| Annual HDDs * gas heat saturation | | 0.14112<br>(0.0932) | |
| Real price of electricity (cents per kWh) | 0.3779<br>(0.3663) | -0.08669<br>(0.3445) | 0.75288<br>(0.5473) |
| Real price of gas ($ per 000 cubic feet) | -0.07842<br>(0.0724) | -0.09059<br>(0.0614) | -0.09254<br>(0.0792) |
| Per capita cumulative new construction since 2001 code | -0.0062<br>(0.0149) | | |
| Per capita cumulative new construction since 2005 code | -0.0299<br>(0.0333) | | |
| Cumulative residential new construction per housing unit since 2001 code | | -0.01284<br>(0.0102) | |
| Cumulative residential new construction per housing unit since 2005 code | | -0.01955<br>(0.0187) | |

| | (1) Utility Model 2000-2010 | (2) Residential Sector Model 2000-2010 | (3) Nonresidential Sector Model 2000-2010 |
|---|---|---|---|
| Cumulative nonresidential new construction since 2001 code as a fraction of existing building stock | | | -0.01121 (0.0083) |
| Cumulative nonresidential new construction since 2005 code as a fraction of existing building stock | | | 0.01077 (0.0066) |
| Energy-efficiency (EE) expenditures intensity for year 't' (Source: EEGA/CMUA) | 0.01485 (0.0101) | 0.00411 (0.0041) | 0.49386** (0.2224) |
| Energy-efficiency expenditures intensity for year 't-1' (Source: EEGA/CMUA) | -0.00744 (0.0055) | -0.00025 (0.0005) | -0.12327** (0.0539) |
| Time trend | 0.00722 (0.0189) | 0.00026 (0.0091) | -0.00289 (0.0032) |
| Utility fixed effects | Yes | Yes | Yes |
| R-squared | 0.72 | 0.90 | 0.68 |
| Number of observations | 24 | 24 | 24 |

Notes: In Model 1, the dependent variable is natural logarithm of electricity consumption per capita. In Model 2, the dependent variable is the natural logarithm of electricity consumption per housing unit. In Model 3, the dependent variable is the natural logarithm of electricity consumption per square foot of floor space. All independent variables in natural logs except energy efficiency expenditures and time trend. Autocorrelation and heteroskedasticity robust standard errors are shown in parentheses.
*-significant at 10%.
**-significant at 5%.
***-significant at 1%.
See text for data definitions and sources.

In Model 1, we regressed total gas consumption per capita on current and lagged energy-efficiency expenditures per capita and other drivers of gas use. Income and HDDs were positively correlated with gas consumption per capita. For example, a 1% increase in HDDs resulted in a 0.26% increase in gas consumption per capita. The coefficients on current gas-efficiency expenditures per capita has the wrong sign, and neither current nor lagged gas-efficiency expenditures had statistically significant effects on consumption.

The second column of Table 14 shows the results for the residential gas sector. We regressed gas consumption per housing unit on utility gas-efficiency expenditures per housing unit and other gas use drivers. In the residential sector, gas use was correlated positively with income and HDDs interacted with gas heat saturation, and correlated negatively with the price of natural gas. The own-price elasticity of gas consumption indicated that a 1% increase in natural gas prices resulted in a 0.09% reduction in consumption. The coefficients on 2001 and 2005 residential new construction were negative but not statistically significant at the 10% level. The coefficient on current energy-efficiency expenditures was positive, while the coefficient on previous year expenditures was negative, but neither gas-efficiency spending coefficient was statistically significant.

Model 3 shows results for nonresidential sector gas-consumption intensity. We regressed nonresidential consumption per square foot of existing nonresidential floor space on energy-efficiency expenditures per square foot and other gas consumption drivers. Gas use intensity was correlated positively with real income per unit of floor space and negatively with natural gas prices. The energy-efficiency expenditure intensity variables were jointly significant at the 10% level ($F(2,2)=11.32$, $p=0.08$), but the coefficient on current expenditures had a positive sign.

## 7.3. Gas Savings Estimates

Cadmus was unable to detect savings from utility gas-efficiency programs in the utility, residential, and nonresidential sector models. As a consequence, we did not attempt to estimate the gas savings of the IOUs.

This inability to detect gas savings stems from three factors. First, the length of the time series, covering just 11 years, is inadequate. There is not enough variation over time in consumption to precisely estimate the impacts of time varying factors like income, prices, and gas-efficiency expenditures. Second, there is a gap in our utility gas-efficiency program expenditures time series. This limited our ability to model the error as dependent on previous error values. Third, it is possible that utility gas-efficiency program expenditures were endogenous to consumption. Unfortunately, there are not enough observations to estimate the gas-consumption models by instrumental variables.

# 8. CONCLUSIONS

The objective of the CPUC Macro Consumption Metric Pilot Study was to investigate the potential policy applications of macro-consumption metrics. In this study, Cadmus demonstrated the macro-consumption concept. We collected data series on electricity and gas consumption series and drivers of consumption for a large number of California utilities between 1990 and 2000. We then merged the data into gas and electricity databases. Then, using regression analysis of consumption intensities of California utilities, we estimated electricity savings from utility energy-efficiency programs and updates to the state building codes. Due to data limitations, we were unable to estimate utility gas efficiency program savings.

Based on our research and analysis of the data, we made the following key findings:

- There were differences in the reliability of utility energy-efficiency program spending data depending on the source, the level of aggregation (utility vs. utility retail sector), and the time period. Researchers should be aware of these considerations.
- The amount of gas utility data was insufficient to estimate utility gas efficiency program savings. We were also unable to detect gas savings from building codes because of data limitations.
- In regressions of utility and nonresidential sectors' electricity use intensities, we detected large and statistically significant savings from utility energy-efficiency program spending and building codes. We had less success at detecting savings from utility programs and building codes in the residential sector.
- The IOU energy-efficiency programs saved substantial amounts of electricity. We estimated these savings as approximately 57,000 GWh, or 5% of the total electricity consumption between 2005 and 2010, with a 95% confidence interval of [19,124 GWh, 95,289 GWh] and relative precision of ±66%.
- IOU energy-efficiency programs appear to save energy cheaply relative to most supply-side resources. The average cost of cumulative electricity savings from utility spending between 2005 and 2008 was estimated to have been $0.058/kWh, with a 95% confidence interval of [$0.035, $0.172].
- For the 2006-2008 program cycle, we estimated that the IOUs savings equaled 42% of their *ex ante* savings claims. The IOUs reported *ex ante* total first-year gross savings of 10,461 GWh, or 1.7% of consumption between 2006 and 2008. Cadmus estimated total first-year net savings from utility program expenditures of 4,357 GWh, or 0.7% of IOU consumption between 2006 and 2008. However, as the 95% confidence interval for the first-year savings included the IOUs' claim, it is not possible to reject it.
- Building codes resulted in significant electricity savings. We estimated that the energy savings from the 2001 update to California's Title 24 building code equaled 5,840 GWh in 2002 and increased over time.
- Cadmus tried different approaches to account for autocorrelation in utility consumption, but found that modeling the error as an autoregressive process resulted in the most precise estimates of the savings.

- There was substantial uncertainty about the true energy savings from utility energy-efficiency programs and building codes, as demonstrated by the wide confidence intervals we estimated. The precision of the savings estimates could be improved by collecting additional data or refining the econometric approach. In particular, the precision of the savings estimates could be improved by increasing the estimation sample size, along the following data collection activities:
  - **Collect data for additional California utilities.** These would include large municipal utilities (such as LADWP, SMUD, Burbank, Glendale, etc.) for which it will be possible to develop reliable historical data. However, including non-IOUs in the estimation sample may affect the internal validity of the saving estimates if the goal is to measure IOU energy-efficiency program effects. With a larger number of utilities, the regression model coefficient estimates will not reflect the variables' average effects in the IOU service territories, but rather reflect the average effects in the IOU ***and*** non-IOU service territories. It may not be appropriate to measure the energy savings of IOU programs using models that include data from publicly-owned utilities.
  - **Collect additional data for the IOUs in past and future years**. For this pilot study, Cadmus collected data on the IOUs between 1990 and 2010. It is possible to collect IOU data before 1990 to improve the precision of the savings estimates; however, this data could also affect the study's internal validity. To the extent that the focus or efficiency of utility energy-efficiency programs has changed since the 1980s, the impacts of IOU programs in the past may not be representative of their impacts today. For example, savings per dollar of expenditures during the 2006-2008 program cycle may be very different from the savings per dollar of expenditures in the 1970s and 1980s.

    Looking forward, it is also possible to collect data on the IOUs after 2010. Enlarging the estimation sample this way will result in greater precision, but is a slow and gradual process. For example, the year of income data for California counties in 2011 will not be available until April 2013.
  - **Collect time-series data for smaller geographic units of analysis**. For this study, Cadmus collected data for California utilities, but an alternative approach would be to collect data for U.S. Census tracts. This approach was taken by Demand Research in its pilot study. The advantage of this approach is the ability to observe consumption in a significantly larger number of geographic units. The disadvantages are that some explanatory variables may not be available annually at the census tract level, and the difficulty of accounting for energy-efficiency program expenditures that are not tracked at the customer level. In the residential sector, utility program expenditures on CFLs are tracked at the point of sale (in stores), so it would not be possible to match purchases to specific census tracts. As CFLs have recently accounted for over 50% of IOU savings claims in the residential sector, the inability to track CFL purchases at the census track would be a significant limitation of this approach.

- The precision of the savings estimates may also be improved by collecting time-series data on the following additional variables and including them in the macro-consumption models:
  - **Education**. College education correlates to energy-efficiency awareness and knowledge, and is a driver of energy use. It is expected that after controlling for income, energy use would be negatively correlated with education. Information about educational attainment is available from the decennial censuses and the American Community Survey.
  - **Appliance Standards.** Since the 1970s, California has adopted standards to regulate the energy use of appliances. In the macro-consumption model, an appliance standards series would measure the purchase and installation of regulated appliances in homes and businesses over time. The series would be interpreted similarly to the new construction variables. It is worth exploring whether a series for California utilities could be constructed from consumer credit data.
- Finally, it would be worthwhile to investigate potential refinements to the utility energy-efficiency program expenditures series. As expenditures were the most important policy variable in the macro-consumption models, Cadmus invested significant effort in developing the expenditures series, especially for the years 2005-2010 using EEGA data. Nevertheless, it may be possible to improve the accuracy of the series by collecting additional data from the IOUs, and refining Cadmus' methods for allocating program expenditures between the gas and electricity markets and between the residential and nonresidential sectors.

These findings lead to the following conclusions about the potential application of macro-consumption methods to California policy:

- This study's estimates of electricity savings from utility efficiency programs and building codes in this study illustrate the kinds of analysis that CPUC could perform with macro-consumption metrics.
- Macro-consumption methods could yield inexpensive estimates of energy savings from utility energy-efficiency programs and building codes.
- MCMs are attractive because it is possible to explicitly quantify uncertainty about energy savings, something that is not easily accomplished in aggregating the savings of bottom-up evaluation studies.
- MCMs can be used to verify energy-efficiency program savings estimates based on bottom-up evaluation. They could also be applied to future EM&V efforts, to track the State's progress in reducing greenhouse gas emissions, and for use in developing forecasts of energy savings from future program spending.

- An important limitation of macro-consumption studies is data availability and quality. Cadmus worked with short time series, 14 or fewer years, and for a small number of utilities. We also identified concerns about the quality of some energy-efficiency expenditures series, especially when the data were disaggregated to the retail sector level.
- Macro-consumption metrics may be too imprecise for some policy applications. Policy makers must decide what level of uncertainty is tolerable before applying these methods.

In summary, this study demonstrates that macro-consumption methods have substantial promise for California policy, notwithstanding the limitations we described. Cadmus recommends that the CPUC continue to fund research on MCMs. In particular, the CPUC should continue to support the following:

- **Data collection**. As most required data are publicly available for free, it would be inexpensive to update annually this study's database. Continued funding would also enable the collection of data on additional energy use drivers, such as average education levels or the market penetration of efficient appliances that influence energy use. It would also be inexpensive to re-estimate the models annually with updated data. Additional data would improve the precision of the savings estimates.
- **Public access to the MCM electricity and gas databases**. Access to the database would stimulate additional research about MCMs, and potentially increase their acceptance and ability to accurately estimate savings.
- **Refinement of the macro-consumption models specifications and estimation**. This study identified many issues in modeling energy consumption intensities, including the potential endogeneity of consumption and energy-efficiency expenditures, but it did not address all of the issues. Future research should address all the issues.

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# 10. APPENDIX A. DATA SOURCES AND COLLECTION METHODS

## 10.1. Energy Consumption

Energy sales or energy sales intensity will be the dependent variable in the MCM models. Cadmus obtained annual electricity retail sales data for 51 investor-owned or publicly owned utilities or rural electric cooperatives (EDCs) in California between 1990 and 2010 from the CEC Website.[32] The sales data are reported for seven retail sectors: Agricultural and Water Pumping, Commercial Building, Commercial Other, Industry, Mining and Construction, Residential, and Street Lighting. In addition, we obtained annual electricity sales for the residential and nonresidential sectors in 58 California counties from the CEC Website.

We also obtained annual sales data for eight California investor-owned or publicly owned gas utilities over the same period from the CEC Website.[33] Sales were reported for all of the sectors except street lighting. We also obtained annual gas sales for the residential and nonresidential sectors in 58 California counties from the CEC Website.

To construct gas and electricity commercial sales series, Cadmus combined the Commercial Building and Commercial Other series. To construct industrial series, Cadmus combined Industry and Mining and Construction. To construct a nonresidential series, Cadmus summed the non-residential sector sales.

## 10.2. Population

Cadmus acquired population data at the census tract level from the U.S. Census Bureau, using values from three decadal surveys: 1990, 2000, and 2010. We used population to normalize the dependent variable (per capita consumption) and many of the right-side explanatory variables. In addition, we used population, population density, or percent population as a weighting variable in estimating utility values for some variables that were not reported at the utility service territory or county level. For example, Cadmus used census tract population to develop population weighted heating degree days (HDDs) and cooling degree days (CDDs). The weights are dynamic in that we interpolated them over the intra-decadal years.

For the county energy use models, Cadmus used the county populations reported in the U.S. Census. For the utility service area models, Cadmus estimated the utility service area population by summing over the census tract populations in the utility service area. This required using GIS software, census tract and utility service area shape files, and calculations about the percentage of a census tract area contained in the utility service territory.

32 http://ecdms.energy.ca.gov/.

33 These utilities are Avista Energy (1990-2005), PG&E, SDG&E, SCG, Southwest Gas Corporation, City of Coalinga, City of Palo Alto, and Long Beach Gas Department.

## 10.3. Electricity and Natural Gas Retail Prices

We expect energy prices to explain variation over time and between counties or utility service areas in electricity and gas consumption. Cadmus estimated the average retail sector price for electricity or natural gas as retail sector energy revenues ($000) divided by retail sector energy sales (MWh). As many California gas utilities used tiered rate schedules, the average price is only an approximation of the marginal rate facing consumers. There are complications to the econometric analysis from using average instead of marginal rates, which the Cadmus white paper discusses addresses.

Cadmus obtained California utility electricity revenues and sales by sector between 2001 and 2010 from the EIA. Since 2001, the annual survey asked utilities to "Enter the reporting year revenue (thousand dollars), megawatthours, and number of customers for sales of electricity to ultimate customers by state and customer class category for whom your company provides both energy and delivery service." Before 2001, EIA did not ask utilities to disaggregate revenues or sales by retail sector. Cadmus also obtained total electricity revenues and sales from EIA for all years between 1990 and 2010.

In addition, Cadmus obtained average retail electricity rates by sector (residential, commercial, and industrial) for the IOUs, LADWP, SMUD, and for the combined Burbank, Glendale, and Pasadena municipal utilities between 1982 and 2010 from the CEC. Cadmus also received electricity revenue and sales by sector for all California utilities between 2008 and 2010.

We compared average retail rates calculated from the CEC and EIA data and found only small differences.

We obtained natural gas revenues and sales by retail sector for California utilities between 2001 and 2010 from the CEC Website.

## 10.4. Personal Income

Cadmus obtained estimates of personal income and personal income per capita in California counties between 1990 and 2010 from the U.S. Bureau of Labor Statistics.[34] The Bureau defines personal income as the sum of compensation of employees (wages, salary, and wage and salary supplements), proprietor's income, rental income, personal income on assets (interest and dividends), and personal current transfer receipts (federal, state, and local social benefits reports) minus social insurance contributions. It is a place-of-residence measure of income earned by residents of an area.[35] Real personal income (personal income adjusted for changes in the consumer price index) will be a right-side variable in the electricity and gas consumption

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[34] Bureau of Economic Analysis Series CA1-3 Personal income summary. Available at http://www.bea.gov/regional/downloadzip.cfm.

[35] There is a residence adjustment for the net flow of compensation of inter-county commuters. This residence adjustment makes personal income an ideal variable for the residential sector model, as it includes all income of residents. The adjustment is less than ideal for the commercial sector. Commercial-sector income should measure the demand for goods and services in the commercial sector in the county. To the extent county income is earned by nonresidents or residents of the county earn income in other counties, personal income could overstate or understate county economic activity.

models. As electricity and gas consumption are normal goods, it is expected there will be a positive relationship between income and energy consumption.

Cadmus mapped county personal income to utility service territories as follows. We developed weights for each county indicating the county's share of the utility service territory population in each year. These weights were dynamic, in that they accounted for changes in the utility service territory's population over time.[36] We then estimated utility service territory personal income per capita as a weighted average of the county personal incomes per capita. Total personal income was obtained by multiplying by the population of the utility service area.

## 10.5. Industrial-sector Income

Cadmus obtained personal income by North American Industry Classification System (NAICS) industry in California counties between 2001 and 2010 from the Bureau of Economic Analysis.[37] Income in a NAICS industry is the income earned in the industry as salary and wage income, proprietor income, interest and dividends, and rental income. It excludes earnings retained by corporations and companies.

We estimated personal income in the industrial sector as personal income earned in the manufacturing sector.[38] Industrial-sector income should be positively correlated with energy consumption as higher income corresponds to greater demand for industrial output. To the extent retained earnings are significant in the industrial sector, the series would understate the amount of economic activity in the sector.

We mapped county manufacturing income to utility service territories using the approach for mapping county personal income. Census tract population counts were used to construct dynamic weights for the county manufacturing income values.[39]

## 10.6. Existing Residential Floor Space

Cadmus obtained annual existing floor space data for single family and multifamily residential buildings in California counties between 1990 and 2011 from McGraw-Hill Dodge Construction. The county was the smallest geographic unit of analysis residential floor space at which data were available. Cadmus used these variables in the residential sector model to control for changes in the composition of housing over time or differences between geographic areas that affect energy use.

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36 We used census block populations from the 1990, 2000, and 2010 censuses to create county weights for those years. We then used a linear interpolation to estimate the weights for the other years.

37 Bureau of Economic Analysis Series CA05N Personal income by major source and earnings by NAICS industry. Available at: http://www.bea.gov/regional/downloadzip.cfm.

38 These industries were wholesale trade; retail trade; transportation and warehousing; finance and insurance; real estate and rental and leasing; professional, scientific, and technical services; management; administration and waste management; education services; health care and social assistance; arts, entertainment, and recreation; accommodation and food services; other services except public administration; government; and information.

39 An alternative weight would use ZIP code commercial new construction (floor space) to estimate the county's share of the utility service territory floor space. We will explore this alternative.

The historical residential existing floor space data are estimates and generally not known quantities. They are based on U.S. Census counts of dwellings in counties. McGraw Hill Dodge Construction constructed the data in three steps:

1. Established a benchmark year (a point-in-time) estimates;
2. Updated benchmarks for subsequently completed square footage;
3. Updated benchmarks for removals and conversions.

Cadmus mapped the county floor space data to utility service areas using information about the spatial distribution of population in utility service areas from the U.S. Census. The mapping process is described above. To estimate residential floor space in a utility service area comprising all or parts of several counties, we did the following:

1. Estimate floor space per person in each county;
2. Calculate the share of utility service territory population in each county;
3. Calculate a weighted average per capita floor space per person using the county population shares as weights;
4. Multiply the weighted average by the utility service area population.

## 10.7. Commercial Floor Space

Cadmus obtained annual existing floor space data for 13 commercial building segments in California counties between 1990 and 2011 from McGraw-Hill Dodge Construction.[40] Cadmus summed the annual commercial-building segment estimates to obtain total commercial floor in a year.[41]

McGraw-Hill Dodge Construction estimated commercial floor space using a methodology similar to that for residential floor space.[42]

We mapped county commercial floor space to utility service territories using the same mapping procedure for residential floor space. We estimated the population-weighted average of the commercial floor space per capita and multiplied this estimate by the total population in the utility service territory.

## 10.8. New Construction Floor Space

Cadmus obtained estimates of new construction building floor space, building units, and building value (in current year dollars) for two residential, 12 commercial building, and one industrial

40 The commercial building segments are Amusement, Social, and Recreation; Dormitories; Government Service Buildings; Hospitals and Other Health Treatment; Hotels and Motels; Miscellaneous Nonresidential Buildings; Office and Bank Buildings; Parking Garages and Automotive Services; Religious Buildings; Schools, Libraries, and Labs; Stores and Restaurants; and Warehouses.

41 McGraw-Hill also provided data on existing floor space in Manufacturing Plants, Warehouses, and Labs. These were used to construct annual estimates of industrial floor space.

42 See the McGraw-Hill data description for more detail.

building segment in each California ZIP code between 1990 and 2011.[43] We used the new construction data to estimate residential and non-residential new floor space construction in each county and utility service territory. In the econometric models, these variables will capture the impacts of new building and new building codes on electricity and natural gas consumption.

We estimated residential, commercial, and industrial new construction in California counties by summing the new construction in each ZIP code in the county. This was straightforward as ZIP codes and county boundaries are coterminous.

Utility service territory and ZIP code boundaries are not always coterminous, however, so it was not possible to sum the ZIP codes to estimate utility service territory new construction. Using California ZIP code and utility service area GIS shape files, we estimated the percentage of each ZIP code land area in each utility service territory. Under the assumption that new construction was uniformly distributed over each ZIP code area, we allocated the ZIP code new construction between the utility service territories. We then summed the ZIP codes in each utility service area to estimate utility service area new construction.

## 10.9. Weather

Cadmus calculated a population-density-weighted average HDD and CDD for each year and each utility service territory and county. Weather is a significant driver of electricity and gas demand for space heating and cooling and will be included as right side variables in the residential and nonresidential models.

To develop the weather series, we downloaded annual HDD and CDD data for 391 weather stations in California from NOAA for each year between 1990 and 2010. In any given year, approximately 55% of the stations had complete records. Consequently, Cadmus was able to use approximately 220 data points across California in each year. Most of these data points were concentrated in major population areas.

Cadmus used GIS software to spatially interpolate HDDs and CDDs in each year across the whole state. Our interpolation was based on a simple distance algorithm, which did not take into account elevation or other geophysical factors affecting temperature. The interpolation was used to determine annual CDDs and HDDs for each census tract. We then calculated HDDs and CDDs for the California counties and service territories as a population-weighted average of the census tract degree days.

While some degree day interpolations may be inaccurate because our method does not account for physical geography such as mountains, their impact will be minimal. First, in each year, there were a large number of stations (more than 200) with available data, yielding wide and dense coverage of the state. This minimizes the likelihood that any census tract would be very distant from a weather station. Second, most of the weather stations are located near population centers, which means degree day values for most of the California population are likely to be very accurate. Any erroneous interpolations are likely to be associated with census tracts that have small populations.

[43] These are the same building segments reported for existing floor space.

## 10.10. Energy-Efficiency Expenditures

Cadmus obtained annual DSM program expenditures for California utilities between 1990 and 2010. Expenditures measure utility investments in energy efficiency, and we expect them to be negatively correlated with consumption. Expenditures will be a key variable in the analysis, and we dedicated significant resources to develop these series.

The utility energy-efficiency program expenditure series were developed from the following sources:

- **U.S. Department of Energy's Energy Information Administration (EIA)**. The annual electric utility survey (Form 861) collects data from California utilities about utility DSM program expenditures. Since 2001, EIA has collected and reported information about utility energy-efficiency and load-management program expenditures separately; however, the data are not disaggregated by sector.
- **CPUC Energy Efficiency Groupware Application (EEGA)**. EEGA contains implementation plans; monthly, quarterly, and annual reports; evaluations; and monthly data on program gas and electricity savings and efficiency expenditures for California investor-owned utilities' energy-efficiency programs between 2004 and 2011. Cadmus used the monthly and quarterly reports to develop annual electricity and gas efficiency program expenditure series between 2006 and 2010 for the IOUs.
- **California Energy Commission.** The California Energy Commission provided Cadmus with the most comprehensive existing data on utility DSM and energy efficiency program expenditures. The CEC collected data from four sources:
  - EIA
  - IOU historical energy efficiency program reports
  - California Municipal Utility Association reports on public utility energy efficiency program spending
  - EEGA annual energy-efficiency program reports

The CEC data contain the following expenditures series: (1) annual expenditures on electricity DSM programs by IOU and program between 1990 and 1999; (2) annual expenditures on electricity DSM programs by IOU and target market (EE residential, EE non-residential, new construction, cross-cutting, IOU partnership programs, non-utility programs, summer initiative, and other[44]) between 1990 and 2005; (3) annual expenditures on electricity and gas efficiency programs by IOU between 2006 and 2009; (4) annual expenditures on electricity DSM programs by SMUD and LADWP and target market between 1990 and 2004; and (6) annual expenditures on electricity efficiency programs by 40 California public utilities by sector (residential, non-residential) between 2006 and 2010; and (7) annual expenditures on gas efficiency programs by PG&E, SCG, and SDG&E and target market (residential, non-residential, new construction, crosscutting, third party provider, low income, and summer initiative) between 2000 and 2005.

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[44] Other DSM includes the following energy-efficiency and load-management program types: information and general, load management, A/C cycling, pool pump timer, time of use rates, interruptible/curtailable, thermal storage, fuel substitution, load building, load retention, and miscellaneous.

We encountered several challenges in constructing continuous energy efficiency expenditures series. First, none of the sources reported energy-efficiency program expenditures by utility, retail sector, or subsector for all electric or gas utilities over the whole time period, 1990-2010. To construct a continuous series, it was necessary to rely on two or more sources. For example, to construct energy efficiency program expenditures series for the IOUs, we used data from historical IOU energy efficiency program reports between 1990 and 2005 and monthly and quarterly energy efficiency program reports from EEGA between 2006 and 2010.

Another challenge was that the sources used different reporting conventions, and some sources had changed their conventions. For example, EIA reported total utility DSM expenditures (the sum of energy-efficiency and load-management expenditures), while the CMUA reported energy-efficiency expenditures. Furthermore, some sources reported expenditures by retail sector (residential, non-residential), while others reported expenditures by retail subsector (residential, commercial, industrial, agriculture) or by energy-efficiency target market (energy efficiency residential, energy efficiency non-residential, new construction, low income.) Inconsistencies in reporting complicated the development of continuous expenditures series for all California utilities and years.

Yet another challenge was that some energy efficiency programs served the retail gas and electricity markets but program expenditures were not broken out by fuel. Thus, in building the IOU expenditures series between 2006 and 2010, it was necessary to disaggregate expenditures between gas and electricity. We did this by converting the reported ex-ante gas and electricity savings to BTUs and apportioning the expenditures according to each fuel's share of the savings. We recognize the deficiencies of this approach and explored alternatives but concluded that it was the best one.

Here, we briefly list the energy-efficiency series that we constructed:

- Electricity
  - Annual DSM program (sum of energy-efficiency and load-management program) expenditures for California utilities (IOUs, POUs, and rural cooperatives) between 1990 and 2010 (Source: EIA)[45]
  - Annual energy-efficiency program expenditures for California utilities between 2001 and 2010 (Source: EIA)
  - Annual DSM program expenditures and annual energy-efficiency program expenditures by retail sector (residential, non-residential) for IOUs, SMUD, and LADWP between 1990 and 2010 (Sources: CEC, EEGA)[46]

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[45] After 2001, it is possible to disaggregate DSM expenditures into energy-efficiency and load-management program expenditures.

[46] The allocation of new construction and other DSM expenditures between the residential and nonresidential sectors between 2000 and 2005 was not reported. We allocated these expenditures in proportion to the relative values of residential and commercial new construction in the service territory. This expenditure series will omit spending on information and fuel substitution programs as these programs were categorized as "Other" and included with load management programs.

- Annual energy-efficiency program expenditures by retail sector (residential, non-residential) for California utilities between 2006 and 2010 (Sources: CEC, EEGA)
- Annual energy-efficiency program expenditures by retail sector (residential, non-residential) and program type (resource, non-resource) for IOUs between 2006 and 2010. (Source: EEGA)

- Gas
  - Annual energy-efficiency program expenditures by retail sector (residential, nonresidential) for California IOUs between 2000 and 2010. (Source: CEC)

## 10.11. Appliance Saturations

Cadmus estimated residential heating fuel and central air conditioning saturations for California utility service areas and counties. Energy demand for space heating and cooling is expected to be higher in areas with greater saturations of residential central air conditioning. The saturation variables were interacted with heating degree days or cooling degree days in the residential regression models.

We obtained the numbers of homes heating with utility gas and electricity and the total number of homes in each census tract from the 2000 U.S. Census and the American Community Survey five-year average for 2005-2009. We then summed the census tracts to estimate heating fuel saturations for utility service areas or counties.

Cadmus obtained estimates of air conditioning saturations for 13 CEC forecast climate zones in 2003 and 2009 from the California Residential Appliance Saturation Survey.[47] Using GIS shape files, we assigned the RASS air conditioning saturation in each climate zone to every census tract in the climate zone. Then, using GIS utility service area and county shape files, we estimated utility service area and county air conditioning saturations as a census tract population weighted average of the census tract saturations.

## 10.12. Price Indices

Cadmus obtained the annual consumer price index (CPI) for California between 1990 and 2010 from the Bureau of Labor Statistics. The CPI is a measure of the average change over time in the prices paid by urban consumers for a market basket of consumer goods and services. Cadmus obtained the CPI for three California metropolitan areas—Los Angeles-Anaheim-Riverside, San Francisco-Oakland-San Jose, and San Diego—and for all California urban consumers.

The consumer price index will be used to adjust nominal expenditures, income, and price series for changes in the purchasing power of the dollar over time.[48] All economic series in the models were put in real terms using 2010 as the base year.

47 See Table 2-9 (p. 15) of 2009 California Residential Appliance Saturation Survey, Volume 2: Results; and Table 2-7 (p. 15) of 2003 California Statewide Residential Appliance Saturation Study, Volume 2, Study Result Final Report.

48 Urban consumers represent about 87% of the U.S. population.

# 11. APPENDIX B. MODELING CODES AND APPLIANCE STANDARDS SAVINGS IMPACTS

Consider the impact of a new building code that became effective one year ago.[49] In the current year, there would be two types of buildings: New and Old. New buildings are built according to the most recent code, and old ones are built according to the original code. We ignore retired buildings, those that left the building stock and are likely to have been built under very old codes.

Under the new building code, new construction will have two, partially offsetting effects on energy use. New construction will increase energy consumption because there are now more buildings than before; but energy consumption will not go up by as much as if the construction had occurred under the original code. We assume the energy consumption of old buildings does not change from year-to-year, holding prices, incomes, and energy efficiency investments, and other variables constant.

We can formalize these ideas algebraically, which will lead to a strategy for estimating savings from building codes.

Let $E_t$ be building energy use in year t in a utility service area. Also, let $e^N$ and $e^O$ be the per unit average consumption in new and old buildings and $N^N$ and $N^O$ be the number of new and old buildings. Finally, let $\eta = e^N - e^O$, the difference in per unit consumption between old and new building.

Then building energy use in year t is:

$$E_t = e^O N_t^O + e^N N_t^N$$

$$= e^O N_t^O + e^O N_t^N + (e^N - e^O) N_t^N$$

$$= e^O N_t^O + e^O N_t^N + \eta N_t^N$$

Total energy use is the sum of energy use in old buildings, energy use in new buildings if the new buildings had been built under the old code, and the number of new buildings times the energy use impacts of the new code. The last two terms of equation shows the dual impact of new construction: to increase consumption but by a lesser amount than if the new code had not been adopted. The coefficient $\eta$ is the per-building impact of the new building code on consumption and reflects the extent of code compliance.

Letting $N_t = N_t^O + N_t^N$, total energy use can be rewritten as:

$$E_t = e^O N_t + \eta N_t^N$$

49 The Cadmus Group gratefully acknowledges helpful suggestions about the modeling of codes and standards impacts from external reviewers of our proposal.

If we let $g(X_t) = e^O N_t$, where $X_t$ is a vector of time-varying covariates affecting energy consumption in the existing building stock, and we add an error term to capture uncertainty about our model specification, the estimating equation would be:

$$E_t = g(X_t) + \eta N_t^N + \varepsilon_t$$

This specification does not capture the fact that buildings constructed under the new code will continue to save energy in future years. In the kth, k=1, 2, … year after the new code, the number of buildings built since the code would be $\sum_{y=0}^{k} N_{t+y}^N$. New construction since the new code will enter the regression equation cumulatively. The estimating equation becomes:

$$E_{t+k} = g(X_{t+k}) + \eta(\sum_{y=0}^{k} N_{t+y}^N) + \varepsilon_t$$

While this equation captures future savings impacts of new homes, it does not account for future code updates that have different savings impacts. Suppose the building code is updated for a second time m years after the first update. Then to measure the savings impact of the second code update relative to the original code, we must add another term to the model. Let $j \varepsilon \{1,2\}$ denote the first or second code update. Let $N_{tj}^N$ be the number of new buildings constructed *since* and *under* the jth code update in year t. Then the estimating equation would become:

$$E_{t+k} = g(X_{t+k}) + \eta_1(\sum_{y=0}^{k} N_{t+y,1}^N) + \eta_2(\sum_{y=0}^{k} N_{t+y,2}^N) + \varepsilon_t$$

The coefficient $\eta_1$ is the per building savings from the first code update relative to buildings constructed under the original code and $\eta_2$ is the per building savings from the second code update relative to buildings constructed under the original code. The difference $\eta_2$-$\eta_1$ would be an estimate of building savings from the second code update using the first code update as a baseline. Total *first year* savings from the second code update in year t+k would then be $(\eta_2-\eta_1)*N_{t+k,2}^N$. Total savings in year t+k would equal $(\eta_2-\eta_1)*(\sum_{y=m}^{k} N_{t+k,2}^N)$.

# 12. APPENDIX C: ENERGY-EFFICIENCY PROGRAM SAVINGS ESTIMATES FOR PG&E, SDG&E, AND SCE

**Appendix Table C-1. Estimates of PG&E Energy-Efficiency Program Savings and First Year Cost of Conserved Energy**

| | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 |
|---|---|---|---|---|---|---|
| **Panel A: Inputs** | | | | | | |
| Consumption (GWh) | 81,718 | 84,214 | 86,313 | 88,124 | 85,051 | 84,524 |
| Energy efficiency program expenditures ($) | 172,045,000 | 121,420,300 | 246,185,318 | 370,824,002 | 313,017,804 | 261,589,971 |
| Expenditures per capita ($) | 14.52 | 10.14 | 20.28 | 30.17 | 25.24 | 20.92 |
| Population | 11,852,896 | 11,977,193 | 12,137,844 | 12,292,971 | 12,402,367 | 12,506,697 |
| **Panel B: Savings Estimates** | | | | | | |
| Savings from current expenditures (GWh) | 451 | 324 | 665 | 1,010 | 816 | 672 |
| Savings from one year lagged expenditures (GWh) | | 835 | 596 | 1,218 | 1,755 | 1,460 |
| Savings from two year lagged expenditures (GWh) | | | 1,334 | 949 | 1,840 | 2,732 |
| Savings from three year lagged expenditures (GWh) | | | | 1,505 | 1,016 | 2,030 |
| Savings from four lagged expenditures (GWh) | | | | | 330 | 230 |
| Savings from five year lagged expenditures (GWh) | | | | | | 3,395 |
| Total savings from current and previous year expenditures (GWh) | 451 | 1,159 | 2,595 | 4,681 | 5,757 | 10,518 |
| **Panel C: Percent Savings** | | | | | | |
| Percent savings from current year expenditures | 0.5% | 0.4% | 0.7% | 1.1% | 0.9% | 0.7% |
| Percent savings from one year lagged expenditures | | 1.0% | 0.7% | 1.3% | 1.9% | 1.5% |
| Percent savings from two year lagged expenditures | | | 1.5% | 1.0% | 2.0% | 2.9% |
| Percent savings from three year lagged expenditures | | | | 1.6% | 1.1% | 2.1% |
| Percent savings from four year lagged expenditures | | | | | 0.4% | 0.2% |
| Percent savings from five year lagged expenditures | | | | | | 3.6% |
| Total percent savings from current and three previous year expenditures | 0.6% | 1.4% | 3.0% | 5.3% | 6.8% | 12.4% |
| **Panel D: Cost of Saved Energy** | | | | | | |
| Cost per kWh saved from current expenditures | $0.382 | $0.374 | $0.370 | $0.367 | $0.384 | $0.389 |

Sources: Savings estimates based on coefficients from FGLS estimation of kWh per capita regression with data from IOUs between 1997 and 2010. See text for sources of utility energy-efficiency program expenditures, population, and consumption.

**Appendix Table C-2. Estimates of SDG&E Energy-Efficiency Program Savings and First Year Cost of Conserved Energy**

| | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 |
|---|---|---|---|---|---|---|
| **Panel A: Inputs** | | | | | | |
| Consumption (GWh) | 19,213 | 20,141 | 20,276 | 20,644 | 20,113 | 19,485 |
| Energy efficiency program expenditures ($) | 74,622,727 | 28,369,439 | 52,229,933 | 101,500,905 | 71,875,244 | 60,340,084 |
| Expenditures per capita ($) | 24.65 | 9.31 | 16.90 | 32.30 | 22.59 | 18.73 |
| Population | 3,027,213 | 3,047,107 | 3,090,723 | 3,142,350 | 3,181,631 | 3,222,404 |
| **Panel B: Savings Estimates** | | | | | | |
| Savings from current expenditures (GWh) | 180 | 71 | 130 | 253 | 173 | 139 |
| Savings from one year lagged expenditures (GWh) | | 340 | 128 | 237 | 443 | 300 |
| Savings from two year lagged expenditures (GWh) | | | 534 | 203 | 360 | 669 |
| Savings from three year lagged expenditures (GWh) | | | | 598 | 219 | 385 |
| Savings from four lagged expenditures (GWh) | | | | | 132 | 48 |
| Savings from five year lagged expenditures (GWh) | | | | | | 1,318 |
| Total savings from current and previous year expenditures (GWh) | 180 | 412 | 792 | 1,291 | 1,326 | 2,858 |
| **Panel C: Percent Savings** | | | | | | |
| Percent savings from current year expenditures | 0.9% | 0.3% | 0.6% | 1.2% | 0.8% | 0.6% |
| Percent savings from one year lagged expenditures | | 1.7% | 0.6% | 1.1% | 2.1% | 1.3% |
| Percent savings from two year lagged expenditures | | | 2.5% | 0.9% | 1.7% | 3.0% |
| Percent savings from three year lagged expenditures | | | | 2.7% | 1.0% | 1.7% |
| Percent savings from four year lagged expenditures | | | | | 0.6% | 0.2% |
| Percent savings from five year lagged expenditures | | | | | | 5.9% |
| Total percent savings from current and three previous year expenditures | 0.9% | 2.0% | 3.9% | 6.3% | 6.6% | 14.7% |
| **Panel D: Cost of Saved Energy** | | | | | | |
| Cost per kWh saved from current expenditures | $0.415 | $0.398 | $0.401 | $0.401 | $0.416 | $0.435 |

Sources: Savings estimates based on coefficients from FGLS estimation of kWh per capita regression with data from IOUs between 1997 and 2010. See text for sources of utility energy-efficiency program expenditures, population, and consumption.

**Appendix Table C-3. Estimates of SCE Energy-Efficiency Program Savings and First Year Cost of Conserved Energy**

| | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 |
|---|---|---|---|---|---|---|
| **Panel A: Inputs** | | | | | | |
| Consumption (GWh) | 85,956 | 88,908 | 88,605 | 90,009 | 85,301 | 82,198 |
| Energy efficiency program expenditures ($) | 198,251,754 | 108,165,649 | 285,369,123 | 289,853,873 | 266,841,755 | 273,367,505 |
| Expenditures per capita ($) | 16.26 | 8.79 | 22.98 | 23.14 | 21.16 | 21.49 |
| Population | 12,192,182 | 12,308,110 | 12,419,638 | 12,527,895 | 12,613,533 | 12,719,815 |
| **Panel B: Savings Estimates** | | | | | | |
| Savings from current expenditures (GWh) | 531 | 297 | 774 | 791 | 686 | 671 |
| Savings from one year lagged expenditures (GWh) | | 988 | 532 | 1,415 | 1,353 | 1,190 |
| Savings from two year lagged expenditures (GWh) | | | 1,542 | 847 | 2,104 | 2,042 |
| Savings from three year lagged expenditures (GWh) | | | | 1,738 | 892 | 2,250 |
| Savings from four lagged expenditures (GWh) | | | | | 375 | 196 |
| Savings from five year lagged expenditures (GWh) | | | | | | 3,741 |
| Total savings from current and previous year expenditures (GWh) | 531 | 1,285 | 2,848 | 4,791 | 5,410 | 10,089 |
| **Panel C: Percent Savings** | | | | | | |
| Percent savings from current year expenditures | 0.6% | 0.3% | 0.8% | 0.8% | 0.8% | 0.7% |
| Percent savings from one year lagged expenditures | | 1.1% | 0.6% | 1.5% | 1.5% | 1.3% |
| Percent savings from two year lagged expenditures | | | 1.7% | 0.9% | 2.3% | 2.2% |
| Percent savings from three year lagged expenditures | | | | 1.8% | 1.0% | 2.4% |
| Percent savings from four year lagged expenditures | | | | | 0.4% | 0.2% |
| Percent savings from five year lagged expenditures | | | | | | 4.1% |
| Total percent savings from current and three previous year expenditures | 0.6% | 1.4% | 3.2% | 5.3% | 6.3% | 12.3% |
| **Panel D: Cost of Saved Energy** | | | | | | |
| Cost per kWh saved from current expenditures | $0.373 | $0.364 | $0.369 | $0.366 | $0.389 | $0.407 |

Sources: Savings estimates based on coefficients from FGLS estimation of kWh per capita regression with data from IOUs between 1997 and 2010. See text for sources of utility energy-efficiency program expenditures, population, and consumption.