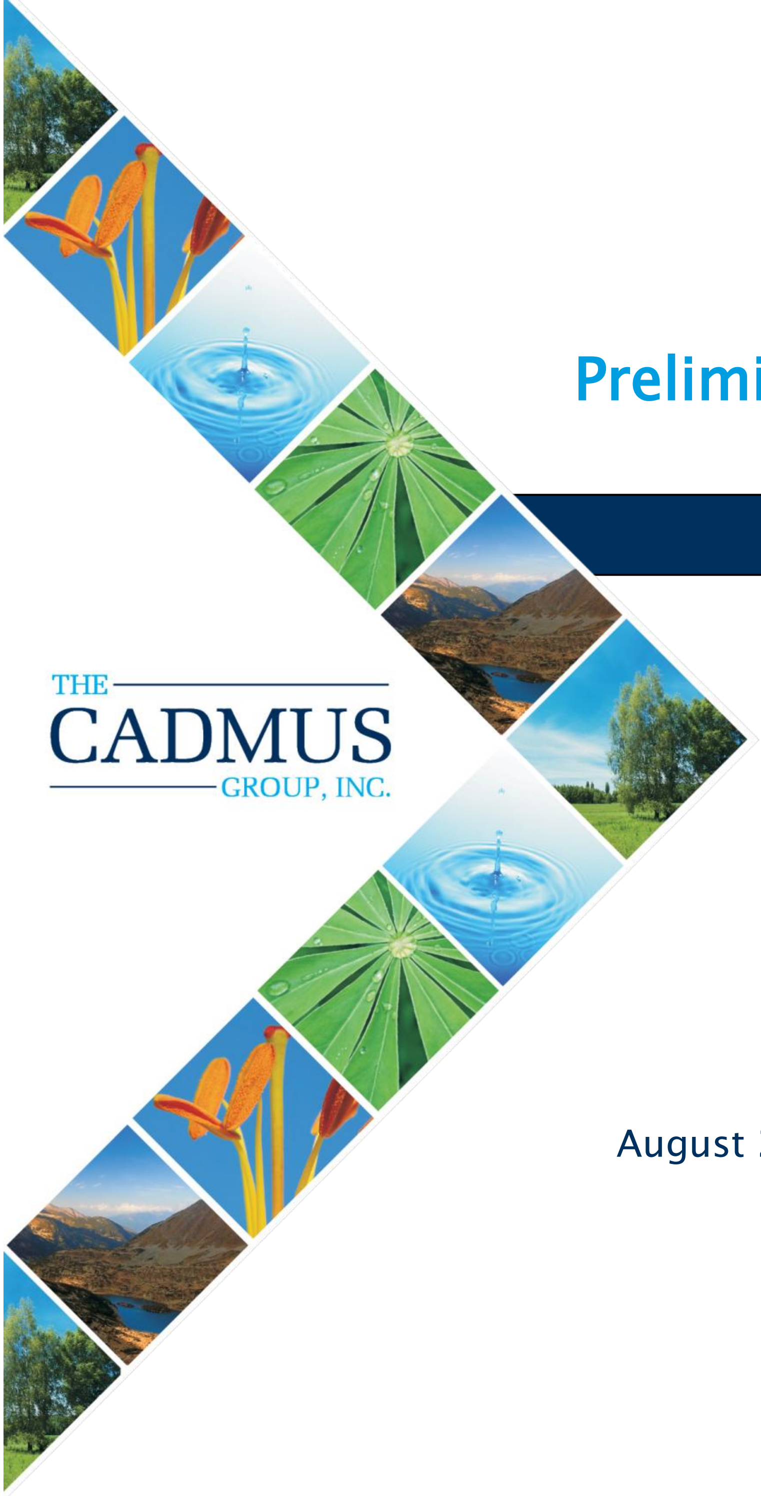

Preliminary Findings Memo

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Executive Summary

The California Public Utilities Commission (CPUC) has expressed interest in potential policy applications of macro-consumption models to estimate energy savings. In contrast to micro-analyses of site energy use, commonly used in energy-efficiency program evaluations, macro-consumption studies use aggregate (e.g., utility service area, county, census block) energy use and energy-use driver (e.g., income, prices) data to measure savings. Macro-consumption models offer a number of potential policy applications, 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 from state policies and utility energy efficiency programs; and
- Incorporating energy efficiency savings in load forecasts.

In spring 2011, CPUC selected Cadmus to participate in its Macro Consumption Pilot Studies project, which involved two parallel macro-consumption studies. The studies sought to:

- Investigate the viability of using macro-consumption approaches to measure reductions in energy consumption from energy-efficiency programs and policies in California;
- 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; and
- Assess the applicability of MCMs to 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 likely success of a macro-consumption study in California; and developed a macro-consumption model research proposal. Much of that work leading up to data collection and preparation was reported in previous CPUC public workshops and in technical memorandums, publicly available at 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; and developed and estimated macro-consumption models.

This memo describes the results from the data collection, database development, and initial modeling efforts, and reports preliminary electricity savings estimates derived from the models.[2] Specifically, Cadmus reports annual electricity savings from utility energy efficiency programs

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

[2] The pilot draft report will include the results of the gas consumption analysis.

between 2008 and 2010 and electricity savings between 2002 and 2010 from the 2001 update to California's Title 24 building codes.

Data collection included energy-use and energy-use driver data for 56 California electric utilities and six gas utilities, including information about energy consumption, population, income, gas and electricity prices, new construction, and weather.

The availability and quality of utility energy-efficiency program expenditures data emerged as the largest obstacle in developing reliable savings estimates. Analysis of expenditures series showed significant discrepancies between sources and suggested the presence of reporting errors in some sources. Recent expenditures data from the California Municipal Utility Association (CMUA) and California's Energy Efficiency Groupware Application (EEGA) appear to be of the highest quality. We provide evidence suggesting significant measurement errors may occur in the Energy Information Administration (EIA) expenditures data.

Using data on California investor- and publicly-owned utilities between 1997 and 2010, Cadmus estimated panel regression models of electricity-use intensity. We modeled:

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

Analysis of utility consumption per capita indicated significant electricity savings from utility energy-efficiency programs and building codes. Analysis of the largest utilities' consumption (PG&E, SDG&E, and SCE) showed a $1.00 increase in current energy-efficiency program expenditures per capita reduced consumption per capita by approximately 0.05%; an equal increase in two-year lagged expenditures reduced energy consumption per capita by 0.2% per year.

Bases on historical expenditures, these results imply total savings from current and past (previous three years) investor-owned utility (IOU) energy-efficiency program expenditures increased from 7,830 GWhs in 2008 to 10,321 GWhs in 2010, reflecting a doubling of energy-efficiency expenditures over this period. Estimated electricity consumption would have been 3.9% higher in 2008 and 5.5% higher in 2010 without the IOU energy-efficiency programs.

The savings estimates imply costs of saved energy from current expenditures (first year savings) of approximately $0.30/kWh. Between 2008 and 2010, the cost of saved energy from current and past (previous three years) energy-efficiency program spending was estimated to be in the range of $0.04–$0.08/kWh, a somewhat higher estimate than costs of saved energy reported in other studies. We hypothesize our results may reflect California's lead in energy efficiency, and the exhaustion of low-cost savings opportunities in the IOU territories. We estimate the cost of first-year savings in other California utility programs at approximately $0.04/kWh, a finding more consistent with those of other studies.

Cadmus had less success detecting savings from utility energy-efficiency programs in the residential and nonresidential sectors. In general, the coefficients on energy-efficiency expenditures did not statistically differ from zero. We believe this may reflect the difficulty of disaggregating expenditures by sector and errors in measurement of energy-efficiency expenditures in the residential and nonresidential sectors.

Cadmus also found that the 2001 update to California's Title 24 building code resulted in significant energy savings. Energy savings in the IOU service territories from the 2001 update increased from 2,700 GWhs in 2002 to 5,200 GWhs in 2008. These savings represented approximately 2.0-2.7% of annual electricity consumption.

Using energy-efficiency program expenditures and building codes as examples, the results of this study demonstrate the potential policy applications of macro-consumption models. Cadmus was able to detect savings from utility energy efficiency programs and building codes, despite using a panel with a small number of utilities and a relatively short time series. One limitation of the study was savings from energy-efficiency programs were not estimated precisely. Future collection of additional data and continued refinement of the models would improve the precision of savings estimates and reduce uncertainty.

Introduction

In the second phase of CPUC's Macro Consumption Pilot Studies project, Cadmus developed a panel database of consumption, prices, incomes, and other economic and demographic variables for California's electric utilities and gas utilities, between 1990 and 2010.[3] In addition, Cadmus completed an initial round of modeling and estimation of utility service area electricity consumption intensities. We modeled utility electricity consumption per capita, residential sector electricity consumption per housing unit, and nonresidential sector electricity consumption per square foot of floor space. This memo describes the results of these recent efforts, including preliminary estimates of electricity savings from utility energy efficiency program and building codes derived from the models.

Database Development

As described in our technical memorandum, Cadmus collected time series data on electricity and gas consumption and variables affecting consumption (such as income, population, new construction, and energy-efficiency expenditures) for the California utilities and counties. Over the previous six months, Cadmus collected and analyzed individual series and merged them into a single database.

This model database covers 1990–2010, and includes data for: 56 electric and 6 natural gas investor-owned, public, and rural cooperative utilities; and 59 California counties. Utility sector and county data include:

3 Cadmus is still working on developing and estimating the gas consumption models. The pilot draft report will include the results of the gas consumption analysis.

- Consumption of electricity and natural gas;
- Personal income;
- Electricity and natural gas prices;
- Residential and commercial new construction, renovations, and total floor space;
- Heating degree days (HDDs) and cooling degree days (CDDs);
- Population;[4]
- Residential and nonresidential new construction and renovations;
- Air conditioning (2000–2010 only) and electric and gas heating saturations; and
- Utility energy-efficiency and demand-side management (DSM) program expenditures

After different variable transformations, which included creating variable lags, natural logs, and energy-use intensities, and converting nominal economic series to real terms, the final electricity database included over 450 series.

Energy-Use Model Specification and Estimation

The final work plan detailed our model specification and approach for estimating energy savings. Briefly, we restate our approach here, but refer interested readers to the work plan for additional information.

We proposed estimating energy savings as a function of utility energy-efficiency program expenditures; building codes (and, data permitting, appliance standards); and changes in energy prices. For each fuel (gas and electricity) and retail sector (all sectors, residential and nonresidential), Cadmus estimated energy-use intensity regressions using the following basic form ('i' indexes a utility service territory and 't' represents time):

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

4 Our technical memorandum about the data neglected to describe how we developed estimates of utility populations between census years. Using census tract populations from the decennial censuses (1990, 2000, 2010) and annual population counts in California counties between 1990 and 2010, we estimated utility population as follows. First, for the census years, we obtained accurate population counts by overlaying utility and census tract boundaries, and counting the population in the utility boundaries. To estimate the utility population in the intervening years, we used county population data, and calculated the population of the smallest area of counties comprising the utility service area in the intra-census years. If the utility was contained in a county, this represented the county population. If a utility covered all or parts of several counties, it represented the sum of the county populations. We then calculated the growth rate between years, and the average annual growth rate of the county area between 1990 and 2000 and between 2000 and 2010. We could then multiply the county area annual growth rates by the ratio of the utility 10-year average annual population growth rate to the 10-year county area average annual population growth rate. Effectively, this made the 10-year county area average growth rate approximately equal the 10-year utility growth rate. The scaled county area annual growth rates could then be applied to utility census population counts.

With variables defined as follows:

$\ln(e_{it})$ is the natural logarithm of per unit (e.g., capita, housing unit, or square foot) energy use for utility service territory 'i' where i=1, 2, …N, in year 't.' In the residential consumption model, the dependent variable will be energy use per housing unit. In the nonresidential consumption model, the dependent variable will be energy use per area of floor space. The nonresidential model includes consumption in the commercial, industrial, mining, street lighting, and agricultural sectors. In the utility consumption model, the dependent variable will be per capita consumption.

$p_{e,it}$ is the real electricity price for utility service territory 'i' in period 't.'[5] The coefficient γ_e shows the price elasticity of demand. Cadmus used the California Consumer Price Index - All Urban Consumers to put the nominal price series in real terms.

$p_{g,it}$ is the real gas price for utility service territory 'i' in period 't.' The coefficient γ_g shows the price elasticity of demand.

I_{it} is the personal income for utility service territory 'i' in period 't.' The coefficient β is the income elasticity of demand.

HDD_{it} and CDD_{it} are, respectively, annual HDDs and CDDs for utility service territory 'i' in period 't.' Coefficients ω_H and ω_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.' CDD_{it} also interacts with $CACSAT_{it}$, the central air-conditioning saturation in homes within utility service area 'i' in period 't.'

EE_{it-k} is the per capita energy-efficiency expenditure in utility service territory 'i' in period 't-k.' The coefficient δ_j 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 model varies, depending on the length of available data series.

NC_{mit} is cumulative new construction in utility service territory 'i' in year 't' built since the building code m, m=1, 2, …, M. In the residential and nonresidential sector models, this variable will be new construction in the sector. The coefficient η shows the elasticity of current consumption with respect to new construction built under code m, or the incremental effect of building code *m* on consumption. The work plan describes our approach to estimating codes and standards savings more completely.

$TimeTrend_t$ is a time trend variable, equaling one in 1990, and increasing by one unit annually.[6] The time trend accounts for naturally occurring conservation not captured by the energy price and income variables.

[5] Electricity price is the average price per kWh (revenue/sales) and may not reflect the marginal price faced by consumers.

λ_i is a component of the error, reflecting utility-specific, time-invariant characteristics. These unobservable characteristics can be controlled by including utility fixed effects or estimating the first difference of the regression model.

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

In this framework, per-unit (e.g., capita) energy savings in year t from energy-efficiency program expenditures for utility i in year t-k were estimated as: $e_{it} x \delta_k x EE_{it-k}$.[7]

Equation 1 assumes energy-use adjusts instantaneously to changes in independent variables. It is generally accepted, however, that energy use adjusts only partially to market changes (i.e., in incomes and prices) as investments in energy-using equipment and buildings cannot, in general, be adjusted costlessly in the short run.

To capture this costly and gradual adjustment, we also modeled electricity use intensity as a function of lagged use (Houthakker, Verlager, and Sheehan, 1974) using a dynamic demand model. This involved including a lag of the dependent variable as a right-side regressor. In this framework, short- and long-run consumption elasticities could be estimated for each independent variable. In the dynamic demand model, long-run consumption elasticity with respect to an independent variable is determined by dividing the variable's estimated coefficient by one minus the estimate of σ, the coefficient on lagged energy-use intensity.

Model Estimation

We estimated the model with and without the lagged dependent variable, that is, we made different assumptions about the speed with which consumption adjusts to changes in prices, incomes, and other variables. Omitting the lagged dependent variable was equivalent to assuming consumption adjusted fully to market changes in a year.

When we omitted the lagged dependent variable, we estimated the model in two different ways:

- We estimated the models by OLS and calculated utility-clustered standard errors.
- We also estimated the model by Feasible Generalized Least Squares (FGLS), assuming the error followed an order-one autoregressive process.

Both approaches resulted in autocorrelation and heteroskedasticity-robust standard errors.

When we included a lag of the dependent variable in equation 1, we estimated the first difference of the model by General Method of Moments (GMM) using lagged differences of the dependent

[6] Cadmus also considered including utility-specific time trends to capture heterogeneity in naturally occurring trends.

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

variable as instruments for $\Delta\ln(kWh_{it-1})$.[8] Implementation of this approach required a sufficiently large number of cross-sectional units and long time series, so we could implement it only for the utility consumption model.

Estimation Sample

The final electricity consumption estimation sample included data for 39 California utilities for which information about energy-efficiency expenditures was available and that satisfied some simple screening criteria. Our estimation sample includes the largest California utilities (PG&E, SDG&E, SCE, LADWP, and SMUD) and accounts for 99% of retail electricity sales in California in 2010.[9]

We obtained utility energy efficiency program expenditures data from the following sources:[10]

- U.S. Department of Energy EIA;
- California Energy Efficiency Groupware Application (EEGA); or
- California Municipal Utility Association (CMUA).

In addition to information about energy-efficiency expenditures, the utilities in the estimation sample satisfied the following criteria:[11]

- 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.[12] The utility consumption analysis included 34 utilities satisfying these criteria.[13]

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[8] Estimation of equation 1 occurred through general method of moments (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 hence is more efficient. Differencing was necessary, as the time-invariant error component (λ_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 μ_{it-1} are, by definition, correlated.

[9] 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, Los Angeles Department of Water and Power, Merced Irrigation District, Modesto Irrigation District, Pacific Gas and Electric Company, PacifiCorp, Plumas-Sierra Rural Electric Cooperative, Sacramento Municipal Utility District, San Diego Gas and Electric Company, Shasta Dam Area Public Utility District, Sierra Pacific Power Company, Silicon Valley Power, Southern California Edison Company, Surprise Valley Electrical Corporation, Truckee-Donner Public Utility District, and Turlock Irrigation District.

[10] The California Energy Commission has collected much of these data and generously provided them to Cadmus.

[11] Cadmus performed analysis to test the sensitivity of the results to changes in the sample selection criteria and found the results were generally insensitive to significant changes.

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. Analysis of residential sector consumption included 25 utilities.

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

- The difference between maximum and minimum nonresidential consumption between 2006 and 2010 was less than 60%. Analysis of nonresidential sector consumption included 30 utilities.

We imposed the last requirement on the nonresidential sector estimation sample as 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 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 real per capita industrial sector income decreased by 10% over this period.

Table 1 shows summary statistics for the utilities in the estimation sample, including summary statistics for all utilities, the large investor-owned utilities (IOUs) (PG&E, SCE, and SDG&E), and non-IOUs between 1997 and 2010. We limited the estimation period to these years as gas prices were not available before 1997. The IOUs experienced lower per-capita consumption, higher incomes, higher electricity prices, lower air conditioning saturations, and less new construction per capita than the other utilities. According to the EIA, the IOUs had annual per-capita DSM expenditures almost twice as high as the other utilities. The gap narrowed significantly, however, when examining the period from 2006 to 2010.

Table 1. Summary Statistics, 1997-2010

Variable	All utilities	IOUs	Other
Electricity consumption (kWh) per capita	12,510 (20,633)	6,760 (378)	13,030 (21,471)
Residential electricity consumption (kWh) per housing unit	12,866 (21,666)	6,663 (445)	13,427 (22,541)
Nonresidential electricity consumption (kWh) per sq. ft.	46.4 (95.1)	19.6 (2.2)	49 (99.0)
Residential share of electricity consumption	37.2 (15.0)	35.1 (2.0)	37.4 (15.7)
Real income ($) per capita	37,065 (8,814)	43,837 (4,050)	36,485 (8,872)

12 For utilities covering small geographic areas, changes in boundaries of census blocks between decennial censuses can result in large changes in population, and thus skew per-capita variables, such as income and construction.

13 Several utilities were not included in one or more regressions, as information about their energy-efficiency expenditures was available from one source but not another.

Variable	All utilities	IOUs	Other
Annual CDDs	1,213 (833)	1,034 (283)	1,229 (863)
Annual HDDs	2,995 (1,503)	2,088 (500)	3,072 (1,534)
Residential central air conditioning saturation	0.6092 (0.179)	0.4745 (0.082)	0.6207 (0.180)

Variable	All utilities	IOUs	Other
Residential electric heat saturation	0.225 (0.094)	0.243 (0.040)	0.224 (0.097)
Real price of electricity (cents per kWh)	0.124 (0.028)	0.137 (0.009)	0.123 (0.029)
Residential real price of electricity (cents per kWh)	0.135 (0.030)	0.158 (0.012)	0.133 (0.030)
Nonresidential real price of electricity (cents per kWh)	0.121 (0.031)	0.127 (0.012)	0.121 (0.032)
Real price of gas ($ per 000 cf)	9.6 (1.9)	9.8 (1.9)	9.5 (2.0)
Residential real price of gas ($ per 000 cf)	10.8 (2.1)	11.1 (1.9)	10.7 (2.1)
Nonresidential real price of gas ($ per 000 cf)	7.2 (1.9)	7.4 (2.0)	7.1 (1.9)
Per-capita cumulative residential new construction since 1995 code (sq. ft)	76.7 (81.4)	65.2 (31.7)	77.7 (84.3)
Per-capita cumulative nonresidential new construction since 1995 code (sq. ft)	34.3 (31.7)	39.4 (16.9)	33.8 (32.7)
Per-capita cumulative residential new construction since 1998 code (sq. ft)	51.9 (69.2)	39.7 (29.5)	53.0 (71.5)
Per-capita cumulative nonresidential new construction since 1998 code (sq. ft)	21.6 (25.7)	21.2 (15.4)	21.7 (26.4)
Per-capita cumulative residential new construction since 2001 code (sq. ft)	35.3 (51.6)	26.6 (24.3)	36.0 (53.3)
Per-capita cumulative nonresidential new construction since 2001 code (sq. ft)	11.7 (17.6)	12.5 (12.1)	11.6 (18.0)
Per-capita cumulative residential new construction since 2005 code (sq. ft)	6.6 (13.3)	5.1 (7.4)	6.7 (13.7)
Per-capita cumulative nonresidential new construction since 2005 code (sq. ft)	2.9 (5.6)	3.5 (5.2)	2.8 (5.6)
DSM expenditures ($) per capita (Source: EIA)	9.0 (23.6)	19.0 (13.2)	8.1 (24.1)
Energy-efficiency expenditures ($) per capita, 2006–2010 (Source: CEC/EEGA/CMUA)	26.1 (59.5)	28.1 (14.7)	25.9 (62.2)
Residential sector energy-efficiency expenditures ($) per capita, 2006–2010 (Source: CEC/EEGA/CMUA)	10.2 (19.6)	6.2 (4.5)	10.6 (20.5)
Nonresidential sector energy-efficiency expenditures ($) per capita, 2006–2010 (Source: CEC/EEGA/CMUA)	15.9 (48.7)	21.8 (11.9)	15.3 (50.9)

Notes: Unless otherwise noted, all values are: annual averages across 39 utilities, and years between 1997 and 2010. Sample standard deviations are shown in parentheses. IOUs are PG&E, SDG&E, and SCE.

Figure 1, Figure 2, Figure 3, Figure 4, and Figure 5 show different electricity consumption intensities and energy efficiency program expenditures for the IOUs, LADWP, and SMUD, which together account for approximately 90% of California utility consumption:[14]

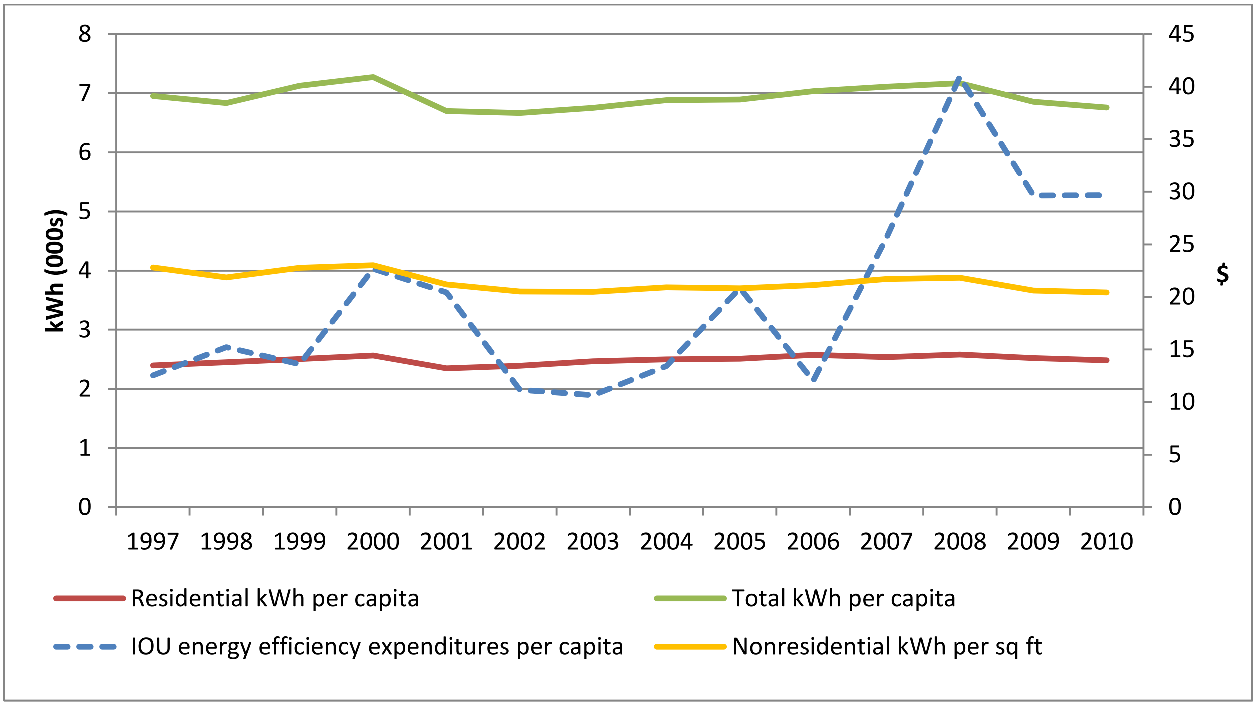
- Utility annual electricity consumption per capita;
- Residential sector annual electricity consumption per capita;

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

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

The figures show total, residential, and nonresidential electricity consumption intensities remained roughly constant between 1997 and 2010. Consumption decreased after the 2001 and 2008 recessions, suggesting the important influence of income changes. High electricity prices and public appeals for conservation during the California Energy Crisis also may have reduced consumption in 2001 and 2002.[15] For each of the utilities, significant ratcheting up of energy-efficiency expenditures occurred, beginning in 2006. Per-capita consumption decreased simultaneously, but, without additional analysis, it is difficult to determine whether this reflected the influence of DSM, changes in income, or other factors.

Figure 1. Pacific Gas & Electric



15 Our models capture the effects of the California Energy Crisis using year dummy variables for 2001 and 2002.

Figure 2. San Diego Gas and Electric

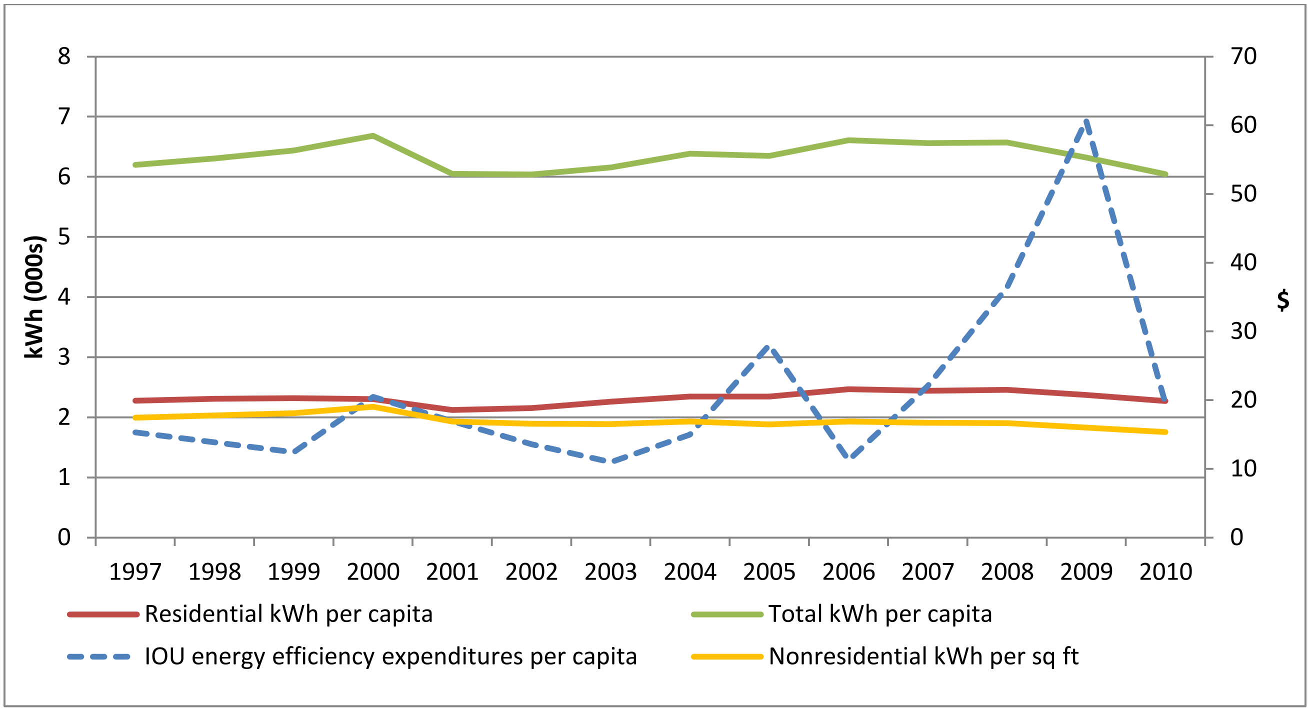


Figure 3. Southern California Edison

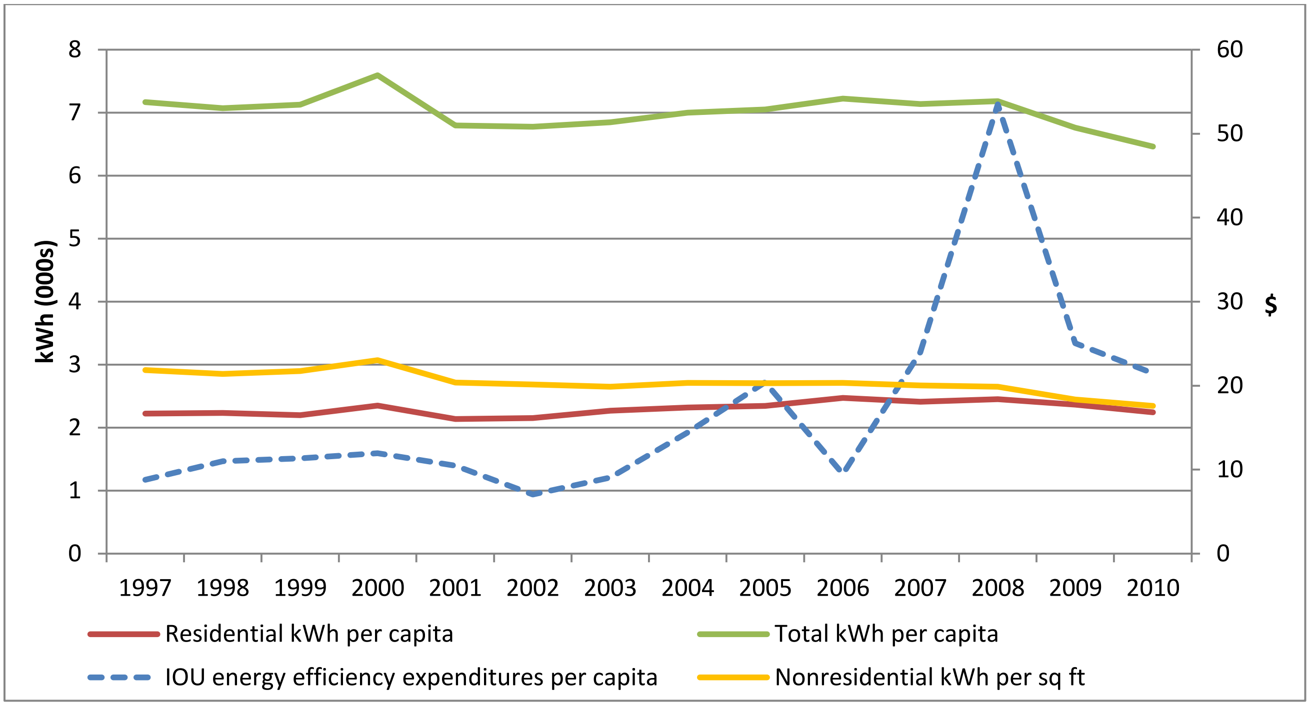


Figure 4. Los Angeles Department of Water and Power

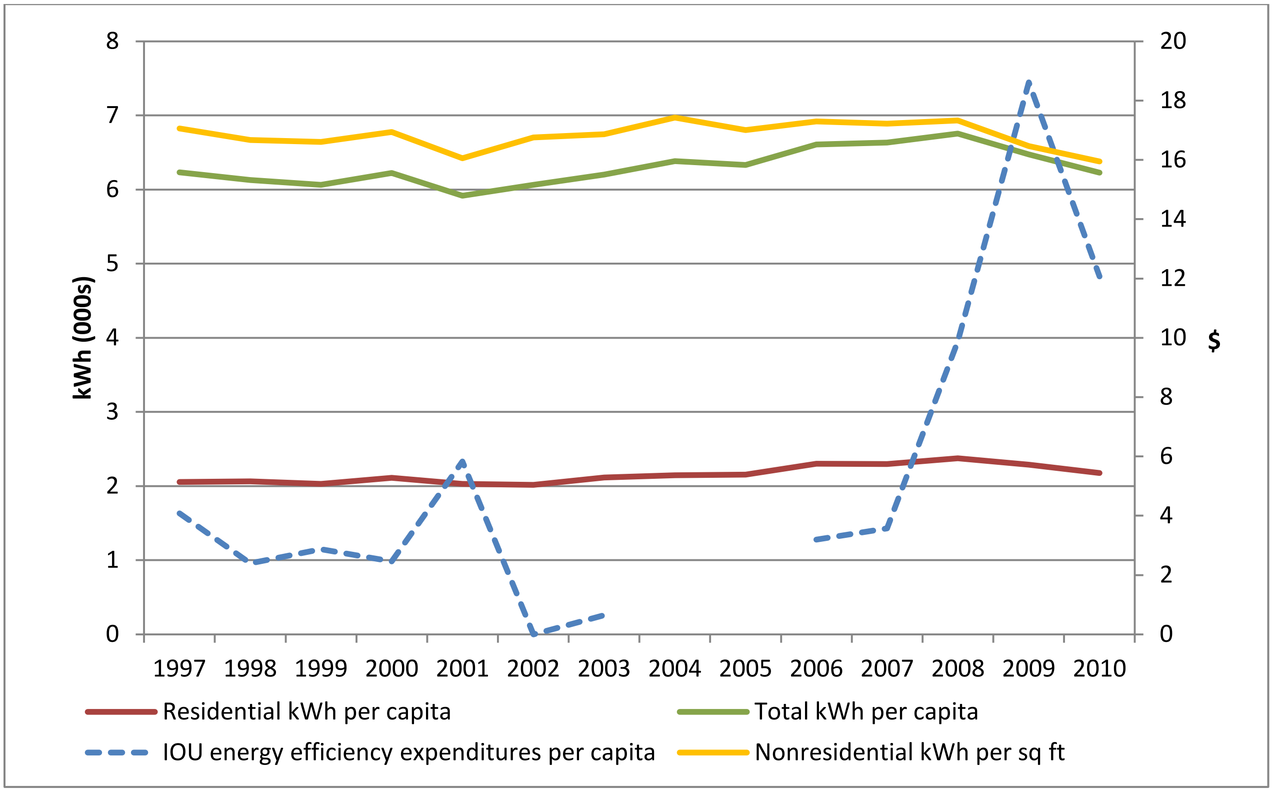
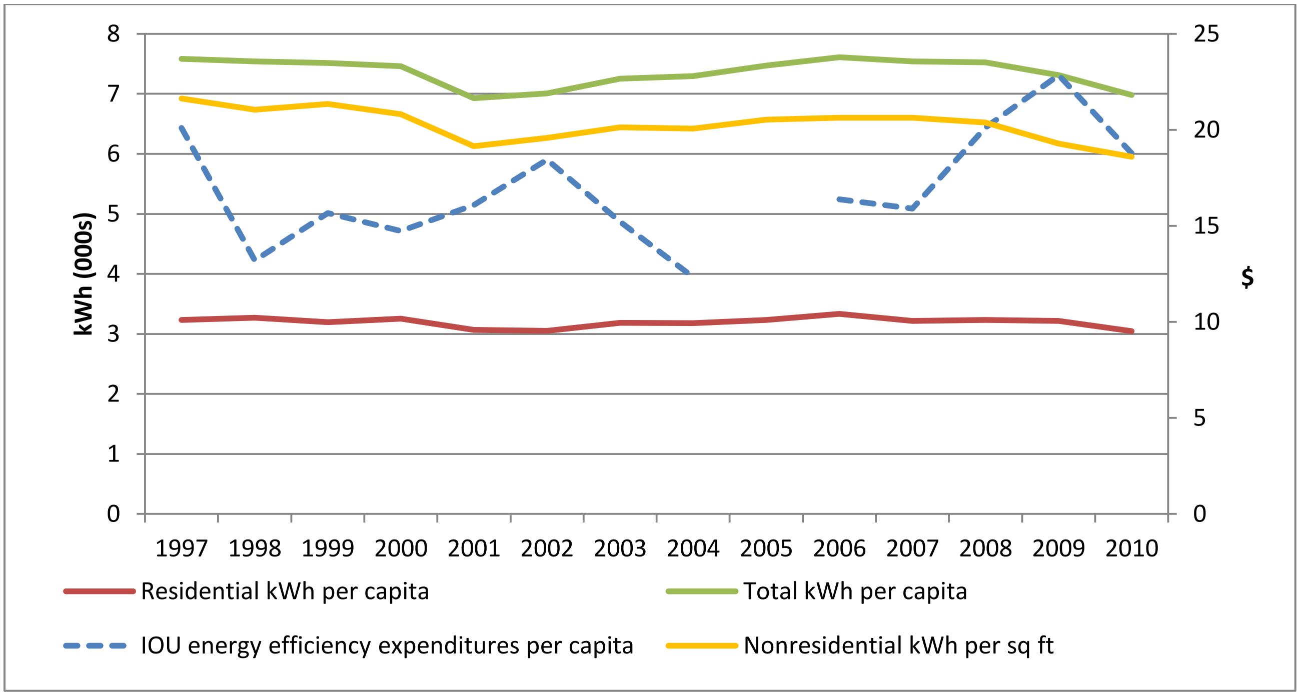


Figure 5. Sacramento Municipal Utility District



Based on analysis of utility consumption intensities and DSM expenditures data, we determined the following, which informed the regression analysis of consumption and the savings estimation:

- Based on visual inspection of the data, per-capita consumption series for the large IOUs, LADWP, and SMUD appear stationary, a necessary condition for regression inference procedures to be valid. 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.[16] 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 ((ρ=0.330, Z=-3.73, p<0.0001) and without (ρ=0.5669, Z=-5.84, p<0.0001) a time trend.
- Though difficult to discern in the graphs, total consumption proved much more variable over time than residential consumption. The residential sector is expected to have the least variable consumption as residential customers have relatively inelastic demands, face high costs of adjusting their energy use because of fixed capital investments, and typically attempt to smooth their consumption. Most variance in total consumption arose from changes in industrial electricity use. This is evident in the nonresidential consumption series. To control for volatility of industrial consumption, several of our models included income earned in the industrial sector as an explanatory variable.
- Significant variance occurred between utilities in relative contributions of residential and nonresidential loads to total consumption (as shown in Table 1). To control for these differences, we included utility fixed effects.[17]
- Based on plots of sales by retail sector for individual utilities, it became clear 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 in industrial sales, suggesting utilities reported sales as industrial in the previous year and as commercial in the current year. Given this inconsistency, we thought it prudent not to estimate models at the industrial and commercial sector levels. Rather, we aggregated all nonresidential loads (commercial, industrial, mining, street lighting, and agricultural) into

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16 Analysis includes 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 (-23.79, p<0.0001); SDG&E (-17.43, 0.0009); SCE (-16.43, 0.0017); LADWP (-4.34, p=0.435); and SMUD (-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).

17 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 pointed out, however, including this variable as a regressor changed the interpretation of model coefficients from total consumption elasticities to residential sector consumption elasticities. The authors can provide details showing this. We thank Nahid Movassagh of the CEC for bringing this to our attention.

a single class, and estimated a nonresidential model. Thus, the nonresidential models used different specifications than the residential ones.

- Omissions and errors appeared to occur in reporting of utility energy-efficiency program expenditures. In addition, there are significant inconsistencies occurred between sources.

  For example, Figure 6 and Figure 7 compare: energy-efficiency expenditures from EEGA; and historical IOU sources with DSM expenditures from EIA for PG&E and SDG&E. For both utilities, in most years, energy-efficiency expenditures fell below DSM expenditures (which included demand response program expenditures), as expected. While the two data sources matched well for PG&E, this was not so for SDG&E. Between 2001 and 2004, EIA reported zero (not missing values) DSM expenditures for SDG&E.

  We found many other examples of implausible expenditure reports in EIA, or inconsistencies between EIA and other sources. The problems appeared most severe for small utilities having total sales less than 150,000 MWh, which face less stringent requirements for reporting to the EIA. Generally, data on IOU energy-efficiency program expenditures from EEGA and public utility energy-efficiency program expenditures from the CMUA appeared to be of better quality.[18]

  Errors in the reporting of utility energy efficiency program expenditures have the potential to attenuate (bias down) estimates of program effects in the energy use regression models. We are exploring potential solutions to this problem including the use of instrumental variables. The estimates of energy savings in this memo are based on energy efficiency expenditures data expected to have the least amount of error.

[18] California Senate Bill 1037 requires all public utilities to report their annual energy-efficiency expenditures to the CEC. Reports for 2006–2011 can be found at: http://www.ncpa.com/energy-efficiency-reports.html

Figure 6. PG&E Comparison of EIA and EEGA Energy-Efficiency Expenditures

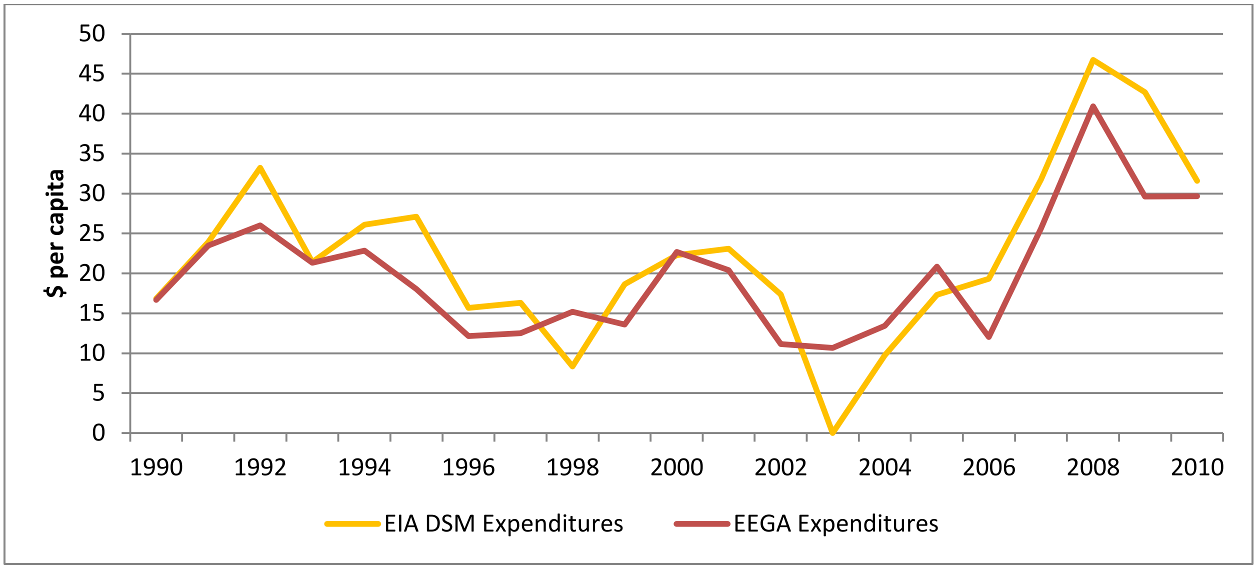
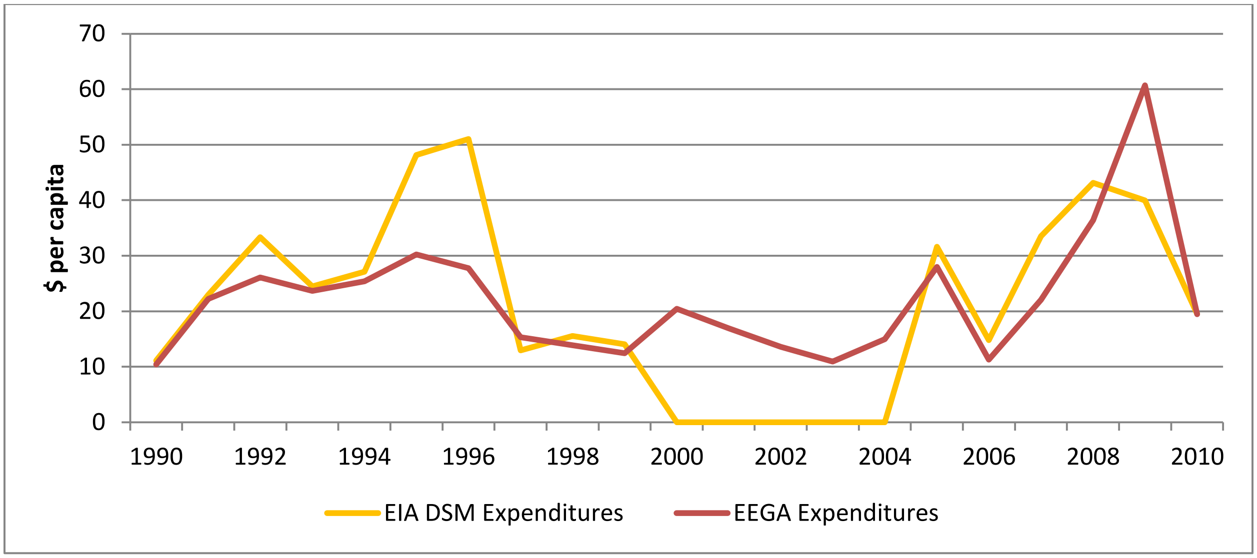


Figure 7. SDG&E Comparison of EIA and EEGA Energy-Efficiency Expenditures



Results

This memo reports results from regressions of utility, residential, and nonresidential sector consumption intensities with different sources of utility energy-efficiency program expenditures and covering different time periods:

- Regression of electricity consumption intensity (per capita, per housing unit, per square foot, depending on the sector) between 2006 and 2010, using CMUA and EEGA data on energy-efficiency expenditures. These regressions included data from investor-owned and public California utilities.

- Regression of electricity consumption intensity between 1997 and 2010, using EEGA and IOU historical energy-efficiency expenditures data. These regressions included data from PG&E, SDG&E, and SCE.
- Regression of electricity consumption intensity between 1997 and 2010, using annual EIA DSM expenditures data. These regressions included data from investor-owned and public California utilities. We estimate this regression only for utility per-capita consumption, as EIA does not report expenditures disaggregated by retail sector.

We emphasize that in estimating models, we were significantly constrained by the availability and quality of energy efficiency expenditures data. In particular, we were constrained by one or more of the following:

- A small number of time periods (small t);
- A small number of cross-sections (small n); or
- Energy-efficiency expenditures data of questionable quality.

These constraints limited the model specifications and reduced both our ability to detect utility energy efficiency program savings. Although the second set of regressions covered only three IOUs, we believe they include the most reliable data and therefore provide the most robust macro-consumption estimates of savings from utility energy-efficiency programs.

Utility Consumption Models

Table 2 shows results from the estimation of equation 1, where the dependent variable was the natural logarithm of per-capita annual electricity consumption in a utility service area (total kWh consumption per capita). The first five models were estimated by Ordinary Least Squares (OLS) or Feasible Generalized Least Squares (FGLS), include utility fixed effects and a time trend or year fixed effects, and omit the lag of the dependent variable. The final model is the dynamic demand model, estimated by General Method of Moments (GMM) after differencing the equation to remove unobserved time-invariant effects.

The first model was estimated using consumption data between 2006 and 2010 and energy-efficiency expenditures from EEGA and the CMUA. (Due to the inclusion of one lag of energy-efficiency expenditures, there were a maximum of four observations for each utility.) Many model coefficients were estimated imprecisely or had the wrong signs. The elasticity of per-capita consumption with respect to income was 0.51 but not statistically significant. Neither HDDs nor CDDs were statistically significant. Also, the elasticity of consumption with respect to average price paid for electricity (-0.06) was significantly smaller than elasticities estimated in other studies. The insignificance of many independent variables likely resulted from the short time 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.

In Model 1, both the residential and nonresidential new construction variables, which show impacts of 2005 building codes on consumption, and the energy-efficiency expenditures variables were statistically significant. The elasticity of consumption with respect to residential new construction was -0.63: a 1% increase in residential new construction decreased energy consumption by two-thirds of a percent, relative to what consumption would have been under the building codes covering the existing building stock. The consumption elasticity for commercial new construction was -0.20.

Energy-efficiency expenditures were negatively correlated with consumption. Though the variables were not jointly significant at the 10% level (F(2, 25)=1.33, p=0.28), the year one lagged expenditures were almost significant at the 10% level (t=1.62, p=0.11). Also, the magnitude of current expenditures coefficient was less than the lagged expenditures coefficient, as expected.

If expenditures were distributed uniformly over a year, we would expect each dollar of current year expenditures to affect only half of annual consumption on average, and for the coefficient on previous year expenditures to be approximately twice the coefficient on current expenditures. As shown in Table 2, a one-dollar increase in per capita expenditures in the preceding year reduced per-capita consumption by 0.21%. For current year expenditures, the effect was about two-thirds of that amount (0.14%).

Table 2. Utility Consumption Models

	(1) IOUs and Publics 2006-2010	(2) PG&E, SDG&E, SCE 1997-2010	(3) IOUs and Publics 1997-2010	(4) PG&E, SDG&E, SCE 1997-2010	(5) IOUs and Publics 1997-2010	(6) IOUs and Publics 1997-2010, Dynamic Demand
Constant	9.77232*** (2.08536)	7.01042*** (1.39394)	-0.3661 (3.18158)	7.11060*** (1.02971)	3.30467 (2.75378)	
Real income per capita		0.13518 (0.12271)		0.12863 (0.09283)		
Non-industrial real income per capita			0.76303*** (0.27356)		0.33015 (0.23852)	0.61454* (0.36152)
Industrial real income per capita	0.50922* (0.25825)		0.25180* (0.14655)		0.10947* (0.06418)	0.21378 (0.16664)
Annual CDDs	-0.04445 (0.06769)	0.03651* (0.02100)	-0.00874 (0.01533)	0.03705** (0.01690)	-0.07622 (0.05211)	-0.07165 (0.06210)
Annual HDDs	-0.32296* (0.17514)	-0.00053 (0.02208)	-0.09400** (0.03942)	-0.00376 (0.01562)	0.05645 (0.06856)	-0.11199** (0.05168)
Real price of electricity (cents per kWh)	-0.06755 (0.22591)	0.00278 (0.04457)	-0.12162 (0.19201)	0.00604 (0.03780)	-0.80878*** (0.11229)	0.09869 (0.18226)
Residential real price of gas ($ per 000 cf)	-0.01473 (0.24443)	0.03121 (0.02961)	-0.02099 (0.06711)	0.03743* (0.02043)	0.09119 (0.06907)	0.029 (0.04987)
Per-capita cumulative new construction since 1998 code		0.00126 (0.00121)		0.00104 (0.00075)		

	(1) IOUs and Publics 2006-2010	(2) PG&E, SDG&E, SCE 1997-2010	(3) IOUs and Publics 1997-2010	(4) PG&E, SDG&E, SCE 1997-2010	(5) IOUs and Publics 1997-2010	(6) IOUs and Publics 1997-2010, Dynamic Demand
Per-capita cumulative new construction since 2001 code		-0.00576*** (0.00161)		-0.00595*** (0.00099)		
Per-capita cumulative new construction since 2005 code		0.00116 (0.00116)		0.001 (0.00087)		
Per-capita cumulative residential new construction since 1998 code			0.03602 (0.09663)		-0.30409*** (0.06501)	0.03694 (0.06644)

	(1) IOUs and Publics 2006-2010	(2) PG&E, SDG&E, SCE 1997-2010	(3) IOUs and Publics 1997-2010	(4) PG&E, SDG&E, SCE 1997-2010	(5) IOUs and Publics 1997-2010	(6) IOUs and Publics 1997-2010, Dynamic Demand
Per-capita cumulative residential new construction since 2001 code			0.05118*** (0.01074)		0.11588*** (0.02556)	0.06015*** (0.01856)
Per-capita cumulative residential new construction since 2005 code	-0.63744* (0.33008)		-0.01853 (0.01344)		-0.04035* (0.02073)	-0.01383 (0.01165)
Per-capita cumulative nonresidential new construction since 1995 code			-0.1576 (0.09682)		0.24468*** (0.05506)	-0.09314 (0.08013)
Per-capita cumulative nonresidential new construction since 2001 code			-0.05321*** (0.01205)		-0.11241*** (0.02197)	-0.06769*** (0.01891)
Per-capita cumulative nonresidential new construction since 2005 code	-0.20740* (0.11661)		0.0248 (0.01516)		0.05165** (0.02333)	0.02055 (0.01409)
Energy-efficiency expenditures per capita (Source: EEGA/CMUA)	-0.00149 (0.00146)	-0.00046 (0.00038)		-0.00050* (0.00029)		
Energy-efficiency expenditures per capita year t-1 (Source: EEGA/CMUA)	-0.0021 (0.00130)	-0.00078** (0.00030)		-0.00077*** (0.00027)		
Energy-efficiency expenditures per capita year t-2 (Source: EEGA/CMUA)		-0.00196*** (0.00051)		-0.00195*** (0.00033)		
Energy-efficiency expenditures per capita year t-3 (Source: EEGA/CMUA)		-0.00007 (0.00040)		-0.00012 (0.00035)		
DSM expenditures per capita (Source: EIA)			0.00034 (0.00050)		-0.00088 (0.00107)	-0.00015 (0.00077)
DSM expenditures per capita year t-1 (Source: EIA)			0.00051 (0.00044)		-0.00057 (0.00098)	0.0003 (0.00055)

	(1) IOUs and Publics 2006-2010	(2) PG&E, SDG&E, SCE 1997-2010	(3) IOUs and Publics 1997-2010	(4) PG&E, SDG&E, SCE 1997-2010	(5) IOUs and Publics 1997-2010	(6) IOUs and Publics 1997-2010, Dynamic Demand
DSM expenditures per capita year t-2 (Source: EIA)			-0.00068 (0.00076)		-0.00134 (0.00108)	-0.00134* (0.00074)
DSM expenditures per capita year t-3 (Source: EIA)			0.00032 (0.00081)		-0.00076 (0.00106)	0.00017 (0.00097)
Time trend		0.0075 (0.00560)	0.01332 (0.01677)	0.00849** (0.00406)	0.00234 (0.01178)	
Year2001		-0.10951*** (0.02114)	0.00538 (0.18457)	-0.11133*** (0.01185)	0.08139 (0.17386)	-0.05769 (0.18484)
Year2002		0.00538 (0.01834)	0.00912 (0.03441)	0.00971 (0.01253)	-0.02472 (0.04492)	0.00542 (0.03532)
Year2007	-0.41654 (0.25356)					
Year2008	-0.17094 (0.14713)					
Year2009	-0.06921 (0.04843)					
Lagged electricity consumption per capita (kWh)						0.33737** (0.16093)
Utility fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Estimation method	OLS	OLS	OLS	FGLS	FGLS	GMM
R-squared	0.51	0.90	0.23			
Observations	104	42	299	42	280	280
Number of utilities	26	3	30	3	28	28

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

The second model was estimated using 14 years of consumption data (1997–2010) for PG&E, SDG&E, and SCE.[19] Most variables in this model were not precisely estimated. Elasticities of consumption with respect to per-capita income and CDDs were, respectively, 0.13 and 0.04, but neither was statistically significant.

Only one new construction elasticity (the variables as the natural logarithm of per capita cumulative total new construction floor space built since the code) was negative and individually significant. A 1% increase in total new construction under the 2001 building code decreased

19 We did not include LADWP and SMUD due to gaps in their energy-efficiency expenditures data before 2005.

consumption by about 0.1% relative to consumption would have been under the building codes covering existing building stock.

Also, Model 2 included current and three lags of annual energy-efficiency expenditures. Current and lagged per-capita energy-efficiency expenditures negatively correlated with consumption, the effects were jointly significant ($F(4, 24)=5.34$, $p=0.003$), and one- and two-year lagged expenditures were individually significant. A $1.00 increase in two year lag expenditures decreased current consumption by about 0.2% ($p=0.001$). Energy-efficiency expenditures had impact magnitudes similar to those shown $1.00 in Model 1.

The third model was estimated using 14 years of data (1997–2010) for a larger number of IOUs and public utilities (N=30). Energy-efficiency expenditures were obtained from the EIA. Residential and nonresidential new construction elasticities were jointly significant at the 1% level, but elasticities for the 1998 and 2001 residential and 2005 nonresidential codes had the wrong (positive) sign. Current and lagged energy-efficiency expenditures also had the wrong (positive) signs, except for two-year lagged expenditures, and were statistically insignificant. We suspect this reflects error in EIA expenditures data rather than the ineffectiveness of energy-efficiency programs for the 30 utilities.

In the fourth and fifth specifications, we modeled the error term as following a common AR(1) process and estimated the models by FGLS. Lagrange multiplier (Breusch-Godfrey) tests find evidence of auto-correlation (Model 4: $F(1,2)=1.76$, $p=0.32$; Model 5: $F(1,3)=5.02$, $p=0.03$). Model 4 was estimated using 14 years of sales data for the IOUs. Model 5 was estimated with 14 years of data for 28 utilities. In Model 4, current and lagged energy-efficiency expenditures decreased consumption. All expenditure coefficients were negative, and all but three year lag expenditures are statistically significant. A $1.00 increase in two-years lagged per capita expenditures reduced consumption by approximately 0.2 %; previous year's expenditures reduced consumption by 0.07%, and current expenditures reduced consumption by -0.05%. The elasticity of consumption with respect to the 2001 building codes is negative and statistically significant; neither, the 1998 nor the 2005 codes reduced consumption.

In Model 5, more independent variables, including income and electricity prices, had the anticipated signs or were statistically significant. Also, the 1998 and 2005 residential new construction and 2001 nonresidential new construction elasticities reduced consumption. New construction variables were jointly significant at the 1% level ($\chi^2(6)=68.5$, $p<0.001$). All coefficients on current and lagged expenditures variables (source: EIA) were negative, but not statistically significant individually or jointly (($\chi^2(4)=3.2$, $p=0.52$). Their magnitudes, however, were similar to those estimated in the other models.

Model 6 is the dynamic demand model, estimated with 14 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. Results were consistent with those for Model 5. The coefficient on the lagged dependent variable was 0.33, and statistically significant at the 5% level, suggesting electricity consumption adjusts with a lag to changes in prices, incomes, etc. (See the work plan for a discussion regarding interpretation of the coefficient on the lagged dependent variable.) The short-run elasticity of electricity consumption with respect to industrial income was 0.61%. None of the coefficients on the energy-efficiency expenditures variables were statistically significant.

Residential Sector Models

Table 3 shows results from regressions of residential consumption per housing unit on residential new construction, utility residential energy-efficiency program expenditures, and other energy-use drivers. Note that, in general, utility energy-efficiency program expenditures can be measured with greater relative error at the sector than the utility level. Many utility energy-efficiency programs served multiple retail sectors, and expenditures for these programs could not be easily disaggregated. This measurement error can attenuate estimates of program savings.

Model 1 was estimated by OLS with utility and year fixed effects, using four years of data for 25 utilities. The model performed poorly. None of the independent variables was statistically significant, and the hypothesis that variables were jointly insignificant could not be rejected ($F(11, 24)=1.09$, $p=0.41$). Many coefficients also had the wrong signs. Both residential new construction and energy-efficiency expenditures coefficients had the correct signs, but were estimated imprecisely. The residential new construction elasticity, showing the savings from the 2005 building code, suggested a 1% increase in new residential construction resulted in an approximately 0.15% decrease in electricity consumption, relative to what consumption would have been under previous building codes. The effect of a $1.00 increase in current per-capita, energy-efficiency expenditures decreased current per-capita consumption by 0.07 %. The effect of previous year expenditures on current consumption was about the same (0.08%), but also not statistically significant.

Table 3. Residential Consumption Models

	(1) IOUs and Publics 2006-2010	(2) PG&E, SDG&E, SCE 1997-2010	(3) PG&E, SDG&E, SCE 1997-2010
Constant	11.34516 (11.22381)	3.38971** (0.72280)	3.56665*** (0.70171)
Real income per occupied housing unit	-0.03312 (0.87530)	0.40206** (0.07850)	0.39348*** (0.05597)
CDD * CAC saturation	0.00022 (0.05016)	0.06318* (0.01520)	0.06132*** (0.01209)
HDD * Electric heat saturation	-0.08529 (0.07554)	0.0518 (0.01874)	0.04672*** (0.01456)
Residential real price of electricity (cents per kWh)	0.16799 (0.27542)	0.0206 (0.01671)	0.02045 (0.01250)
Residential real price of gas ($ per 000 cf)	-0.26065 (0.31866)	0.01493 (0.00805)	0.01664 (0.01591)
Cumulative residential new construction per housing unit since 1998 code		0.01408 (0.03073)	0.01556 (0.01804)

	(1) IOUs and Publics 2006-2010	(2) PG&E, SDG&E, SCE 1997-2010	(3) PG&E, SDG&E, SCE 1997-2010
Cumulative residential new construction per housing unit since 2001 code		-0.00071 (0.00264)	-0.00084 (0.00146)
Cumulative residential new construction per housing unit since 2005 code	-0.14559 (0.19867)	0.00016 (0.00057)	0.00023 (0.00061)
Energy-efficiency expenditures per housing unit year t (Source: EEGA/CMUA)	-0.00072 (0.00095)	0.00048 (0.00025)	0.00044** (0.00020)
Energy-efficiency expenditures per housing unit year t-1 (Source: EEGA/CMUA)	-0.00086 (0.00094)	0.00041 (0.00020)	0.00043** (0.00020)
Energy-efficiency expenditures per housing unit year t-2 (Source: EEGA/CMUA)		-0.00072** (0.00016)	-0.00078*** (0.00025)
Energy-efficiency expenditures per housing unit year t-3 (Source: EEGA/CMUA)		-0.00059 (0.00063)	-0.00053 (0.00039)
Time trend		-0.00358 (0.00283)	-0.00371 (0.00229)
Year 2001		-0.09218* (0.02898)	-0.09323*** (0.01260)
Year 2002		-0.04002** (0.00470)	-0.03875*** (0.00899)
Utility fixed effects	Yes	Yes	Yes
2007-2009 year dummy variables	Yes	No	No
R-squared	0.10	0.97	
Observations	100	33	33
Number of utilities	25	3	3
Estimation method	OLS	OLS	FGLS

Notes: In Models 1-3, dependent variables were the natural logarithm of per-housing unit residential electricity consumption. All independent variables in natural logs, except energy-efficiency expenditures. Autocorrelation and heteroskedasticity robust standard errors in parentheses in Models 1-2.* significant at 10%; ** significant at 5%; *** significant at 1%. See text for data definitions and sources.

The second model was estimated using 11 years of residential consumption data for PG&E, SG&E, and SCE.[20] This model performed significantly better than Model 1, as the longer time series provided the necessary variation to identify effects of the independent variables. The model showed real income, residential heating demand, and residential cooling demand associated positively with residential electricity consumption. A 1% increase in annual CDDs increased per capita electricity consumption by about 0.06%. The elasticity of electricity consumption with respect to income was about 0.40. Building code variables were individually and jointly insignificant. Current and lagged energy-efficiency expenditures were jointly

[20] Information about revenues in retail sectors from EIA became available, beginning in 2000.

significant, but only two-year lagged and three-year lagged expenditures reduced consumption. A $1.00 increase in two-year lagged, per-capita energy-efficiency expenditures reduced per-capita consumption by 0.07%.

The third model was estimated using the same data as Model 2, but assumed the error followed an AR(1) process. The coefficients had similar magnitudes and signs as those in Model 2, but were estimated more precisely. Again, two- and three-year lagged, energy-efficiency expenditures reduced consumption, but current and one-year lagged expenditures were positively correlated with consumption.

Nonresidential Sector Models

Table 4 reports results from regressions of nonresidential electricity consumption intensity. We modeled energy use per square foot of floor space 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, it should be noted that utility energy-efficiency program expenditures generally will be measured with greater relative error at the sector than utility level. This measurement error can attenuate estimates of program effects.

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

Table 4. Nonresidential Consumption Models

	(1) IOUs and Publics 2006-2010	(2) PG&E, SDG&E, SCE 1997-2010	(3) PG&E, SDG&E, SCE 1997-2010
Constant	4.82444*** (1.53050)	1.03671 (0.50653)	-0.05369 (0.57793)
Industrial real income per square foot of floor space	0.29892 (0.24487)	0.46863** (0.08692)	0.36093*** (0.06921)
Annual CDDs	-0.08351* (0.04258)	0.01378 (0.02027)	0.13674*** (0.02380)
Annual HDDs	-0.14886 (0.12359)	0.10864 (0.04655)	0.18461*** (0.04913)
Nonresidential real price of electricity (cents per kWh)	-0.05947 (0.15840)	-0.06365 (0.02693)	0.02844 (0.08972)
Nonresidential real price of gas ($ per 000 cf)	-0.18810** (0.08270)	-0.07380*** (0.00535)	-0.11250** (0.05186)
Cumulative nonresidential new construction since 1998 code as a fraction of existing floor space			0.08415 (0.15019)
Cumulative nonresidential new construction since 2001 code as a fraction of existing floor space		0.03587 (0.01258)	0.0344 (0.02940)

	(1) IOUs and Publics 2006-2010	(2) PG&E, SDG&E, SCE 1997-2010	(3) PG&E, SDG&E, SCE 1997-2010
Cumulative nonresidential new construction since 2005 code as a fraction of existing floor space	-0.01002 (0.02137)	0.00099 (0.00088)	-0.00551*** (0.00171)
Nonresidential energy-efficiency expenditures per square foot of floor space (Source: EEGA/CMUA)	-0.00246 (0.00204)	0.38079 (0.13126)	-0.07017 (0.21433)
Nonresidential energy-efficiency expenditures per square foot of floor space year t-1 (Source: EEGA/CMUA)	0.00387* (0.00216)	-0.18855* (0.06010)	-0.65870*** (0.15499)
Nonresidential energy-efficiency expenditures per square foot of floor space year t-2 (Source: EEGA/CMUA		-0.10766 (0.14836)	-0.54167* (0.30106)
Nonresidential energy-efficiency expenditures per square foot of floor space year t-3 (Source: EEGA/CMUA)		-0.20333 (0.09652)	-0.18909 (0.34258)
Time trend		-0.00884 (0.00394)	0.01594 (0.01643)
Year 2001		0.56911 (0.22201)	0.67336 (0.49658)
Year 2002		-0.02665** (0.00591)	0.02957 (0.03136)
Utility fixed effects	Yes	Yes	Yes
2007–2009 Year fixed effects	Yes	No	No
R-squared	0.25	0.94	
Observations	117	30	30
Number of utilities	30	3	3
Estimation method	OLS	OLS	FGLS

Notes: In Models 1-3, the dependent variable is the natural logarithm of per square foot of nonresidential electricity consumption. All independent variables in natural logs except energy-efficiency expenditures. Autocorrelation and heteroskedasticity robust standard errors in parentheses in Models 1-2.* significant at 10%; ** significant at 5%; *** significant at 1%. See text for data definitions and sources.

Model 2, which was estimated by OLS using many fewer utilities (N=3) but more years (T=10), yielded results more consistent with expectations. The coefficient on the log industrial income per square foot was 0.46, implying a 1% increase in income per square foot increased electricity use by 0.46%. A 1% increase in HDDs increased energy use intensity by 0.1%. The price elasticity of consumption was estimated as -0.06. All energy-efficiency expenditures intensity variable coefficients, except those on current expenditures, were negative, and lagged year-one and lagged year-three expenditures coefficients were statistically significant. The coefficient on year-one lagged expenditures implied a $1.00 increase in expenditures per foot of floor space would result in approximately a 20% reduction in energy-use intensity.

Model 3, which was estimated by GLS, had coefficients similar to but more precisely estimated than those in Model 2. Elasticities of energy-use intensity, with respect to income, CDDs, and HDDs, were positive and statistically significant. For example, a 1% increase in CDDs caused energy use to increase by 0.13%. The coefficient on cumulative nonresidential new construction since 2005 was negative and statistically significant. It implied a 1% increase in the share of existing floor space built since 2005 reduced consumption by 0.005%. The other nonresidential new construction variables were statistically insignificant. Also, coefficients on the current and lagged energy-efficiency expenditure intensity variables were large, negative, and jointly significant at the 1% level ($\chi 2(4)=19.2$, $p<0.001$).

County Consumption Models

The relatively small number of cross-sectional units (no more than 30, and often a smaller number of utilities) in our panel data limited our ability to detect energy savings. To increase the number of cross-sectional units and the ability to detect savings, we collected data on electricity use intensities in 58 California counties.

We obtained data on county electricity consumption between 2006 and 2010 from the CEC. We obtained data on county populations, incomes, and residential and nonresidential new construction from, respectively: the U.S. Census, the Bureau of Economic Analysis, and McGraw-Hill Dodge Construction.

As data on utility energy-efficiency program expenditures or gas and electricity prices (revenues from retail sales) in California counties were not available, it was necessary to map utility expenditures and prices to counties using information about the share of a county's population in each utility service area. For example, if two utilities served a county, the per-capita, energy-efficiency expenditures for the county were estimated as a weighted average of the utilities' expenditures per capita, with population shares as weights.[21]

As PG&E comprises parts of (or the entirety of) many California counties, relatively little variation existed between counties to identify effects of expenditures or energy prices on consumption. Most variation came from changes in utility prices over time, or from the relatively few counties served by more than one utility.

We estimated county models of total electricity consumption, residential sector electricity consumption, and nonresidential sector consumption. This memo, however, does not report results from these regressions as they did not yield the expected results, and remain a work in progress. The largest problem we encountered was, while we found evidence of energy savings from utility energy-efficiency programs, many other model coefficients had the wrong signs. Again, the problem may be the time period was too short (five years) to detect impacts of most independent variables on consumption.

Savings Estimates

Using the estimated coefficients on utility energy-efficiency program expenditures in Model 4 (Table 2), we estimated energy savings from the IOUs' energy-efficiency programs and the 2001 update to California's building codes. We selected Model 4 to estimate IOU program and

[21] Our mapping procedure made the strong assumption that expenditures and average unit revenues (average price per kWh) were distributed uniformly across the utility service area. This necessarily introduced error in our variables, which would attenuate effects of expenditures and prices in the regression models.

building code savings because the coefficients had the expected signs and the model was estimated using 14 years of data for the IOUs.[22])

Table 5 shows savings estimates between 2008 and 2010 for the combined energy efficiency program expenditures of the three IOUs.[23] (The appendix includes tables with separate estimates for each of the IOUs.) Panel A 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 from the current year's and previous three years' expenditures. For example, Panel A shows, in 2008, the IOUs spent a combined $340 million on energy efficiency. These expenditures were estimated to result in savings of 1,206 GWhs in 2008; 1,765 GWhs in 2009; and 4,331 GWhs in 2010.[24] Panel C shows these savings represented 0.6% of 2008 consumption; 0.9% of 2009 consumption; and 2.3% of 2010 consumption. Total electricity savings in 2008 from current and past (three years) energy-efficiency expenditures was estimated at 7,830 GWhs. Panel D shows estimated costs of conserved energy. The average cost of current (first) year savings was estimated at: $0.28/kWh in 2008; $0.30/kWh in 2009; and $0.31/kWh in 2010. Costs per kWh saved from current and previous year expenditures were about: $0.043/kWh in 2008; $0.086/kWh in 2009; and $0.068/kWh in 2010. In estimating the cost of saved energy, we assumed current costs of savings from previous year expenditures were zero. Table 6 shows 95% confidence intervals for IOU program savings and program costs of saved energy between 2008 and 2010. Dividing the sum of all expenditures in years 2005–2010 by energy savings during these years produced overall cost per kWh saved of $0.068.

[22] We believe the coefficients from this model best reflect the actual effects of program expenditures on consumption for several reasons. First, the model was estimated using data for just the three IOUs; so the estimated coefficients pertained to IOU program impacts. Second, most coefficients had the expected signs or significance. Third, 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. We obtained very similar results. (Results are available from the authors.)

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

[24] As this analysis did not account for program expenditures occurring more than three years in the past, our savings estimates represent a lower bound of total savings from current and past expenditures.

Table 5. IOU Energy-Efficiency Program Savings and Cost of Conserved Energy Estimates

	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 ($)	518,481,240	307,405,693	350,768,323	339,355,140	676,311,064	704,521,516
Expenditures per capita ($)	19	11	13	12	24	25
Population (estimate)	27,072,291	27,332,409	27,648,206	27,963,216	28,197,531	28,448,916
Panel B: Savings Estimates						
Model predicted savings from current expenditures (GWh)	1,790	1,087	1,238	1,206	2,284	2,306
Model predicted savings from one-year lag expenditures (GWh)		2,823	1,671	1,920	1,765	3,409
Model predicted savings from two-year lag expenditures (GWh)			7,138	4,261	4,620	4,331
Model predicted savings from three-year lag expenditures (GWh)				442	249	276
Model predicted total savings from current and three previous year expenditures (GWh)				7,830	8,919	10,321
Panel C: Percent Savings						
Model predicted savings from current year expenditures as % of current consumption	0.9%	0.6%	0.6%	0.6%	1.2%	1.2%
Model predicted savings from one-year lag expenditures as % of current consumption		1.5%	0.9%	1.0%	0.9%	1.8%
Model predicted savings from two-year lag expenditures as % of current consumption			3.6%	2.1%	2.4%	2.3%
Model predicted savings from three-year lag expenditures as % of current consumption				0.2%	0.1%	0.1%
Model predicted total savings from current and three previous year expenditures as a % of current consumption				3.9%	4.7%	5.5%
Panel D: Cost of Conserved Energy						
Model predicted cost per kWh saved from current expenditures	$0.290	$0.283	$0.283	$0.281	$0.296	$0.306
Model predicted cost per kWh saved from one-year lag expenditures		$0.000	$0.000	$0.000	$0.000	$0.000
Model predicted cost per kWh saved from two-year lag expenditures			$0.000	$0.000	$0.000	$0.000
Model predicted cost per kWh saved from three-year lag expenditures				$0.000	$0.000	$0.000
Model predicted cost total per kWh saved from current expenditures and three previous year expenditures				$0.043	$0.076	$0.068

Table 6. Estimated Confidence Intervals for IOU Savings and Program Costs of Conserved Energy

	2008	2009	2010
	Annual savings (GWhs)		
95% CI Lower Bound	4,883	3,338	4,688
95% CI Upper Bound	10,776	14,499	15,954
	Cost-effectiveness ($/kWh)		
95% CI Lower Bound	$0.031	$0.047	$0.044
95% CI Upper Bound	$0.069	$0.203	$0.150

Our estimates indicated the IOU's current and past energy-efficiency expenditures saved 7,830 GWhs, or 3.9% of consumption, in 2008; 8,919 GWhs, or 4.7% of consumption, in 2009; and 10,321 GWhs, or 5.5% of consumption, in 2010. Increased annual savings reflected an approximate doubling of energy-efficiency expenditures over this period. Our cost estimates of saved energy of $0.04//kWh-$0.08/kWh are slightly higher that reported in the literature. For example, in recent studies of U.S. utilities, Aufhammer, Blumstein, and Fowlie (2008) estimated average costs of saved energy of $0.046/kWh, and Arimura, Li, Newell, and Palmer (2011) estimated average program costs of $0.041/kWh.

Some of the difference between the literature's estimates and ours may have resulted from California's lead in energy efficiency. California may have exhausted much low-cost potential for savings (i.e., "the low hanging fruit"), whereas utilities in other states have only recently started their programs, and have more abundant low-cost opportunities. Consistent with hypothesis, when we estimated Model 1 of Table 2 (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 larger in absolute values). This implies costs of first-year savings of $0.07/kWh, as opposed to IOU costs of first-year savings of $0.30/kWh. Such first-year costs estimates were more consistent with those found by Aufhammer, Blumstein, and Fowlie (2008) and Arimura, Li, Newell, and Palmer (2011). Another possible explanation for the low cost-effectiveness of IOU savings was that our expenditures data were measured with significant error, which could have biased down the savings estimates. We think this explanation less likely, however, as IOU expenditures data appeared to be of high quality.

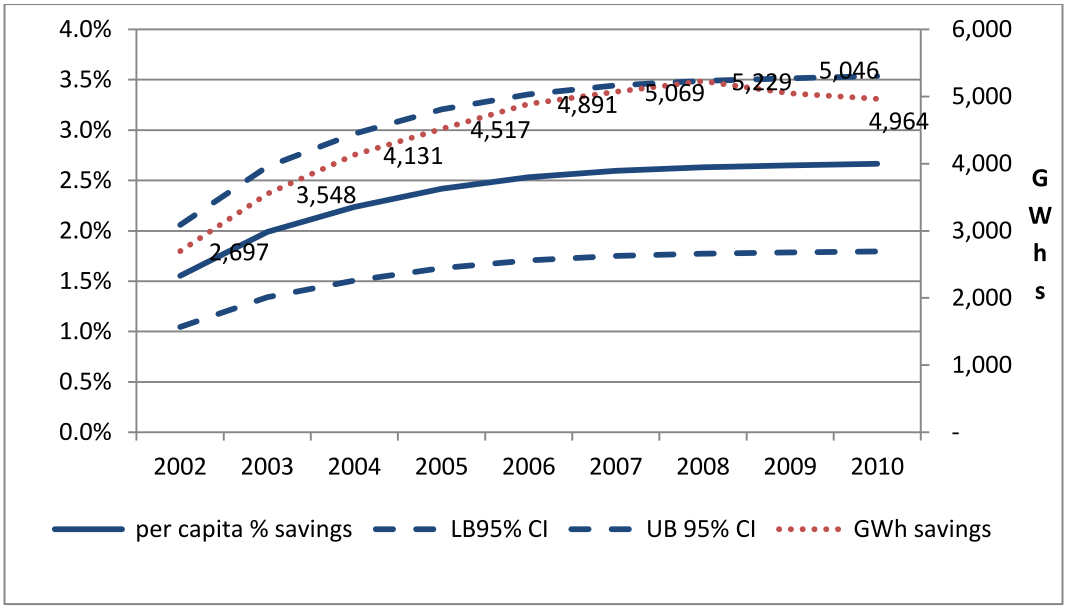
Figure 8 shows estimates of per capita percent electricity savings and total electricity savings in the IOU service territories from the 2001 update to California's Title 24 building codes.[25] The savings are measured relative to the average efficiency of residential and nonresidential buildings constructed under previous codes.

Per capita savings from the 2001 code update increased from approximately 1.5% of consumption in 2002 to 2.7% in 2010. The 95% confidence interval for percent savings ranges

[25] We focus on the 2001 update to Title 24 as Model 4 in Table 2 did not detect savings from the 1998 and 2005 building code updates.

between 1.8% and 3.5% of 2008 consumption.[26] Percent savings increased over time because new construction increased the total amount of floor space built under to the 2001 code. Total electricity savings from the 2001 code increased from approximately 2,700 GWhs in 2002 to 5,200 GWhs in 2008 as both new construction and the population increased. Savings from the 2001 code update decreased in 2009 and 2010 as overall energy use decreased in the wake of the Great Recession.

Figure 8. Electricity Savings from the 2001 Title 24 Building Code Update*



*In PG&E, SDG&E, and SCE service territories.

Preliminary Findings

Based on our analysis of California utility consumption data, we can make the following, preliminary findings:

- The availability and quality of the utility energy-efficiency program expenditures data varies, presenting the largest obstacle to developing reliable savings estimates. In particular, EIA data appear to be of relatively poor quality, with a great deal of missing and erroneous values. Measurement errors in expenditures can attenuate the estimated effects of energy-efficiency programs. As predicted, when we used EIA expenditures data in our regressions, we generally experienced less success in detecting program savings. EEGA and CMUA data collected by the CEC and Cadmus appear to be of better

[26] Our savings estimates for building codes are in the range of others in previous studies. See Aroonruengsawat, Anin, Maximilian Auffhammer, and Alan Sanstad. The Impact of State Level Building Codes on Residential Electricity Consumption. University of California, Berkeley working paper, 2009.

quality. These sources cover a fairly large number of investor-owned and public utilities, but have relatively short histories, dating back only as far as 2004 and 2006, respectively.

- Energy-efficiency expenditures data can be measured with least the least error at the utility level. Retail sector expenditures will be measured with more error due to the difficulty of disaggregating expenditures of programs serving more than one sector. This may explain why we had less success in detecting savings in the residential and nonresidential sector analyses.
- When we used higher-quality data from EEGA, CMUA, and the IOUs, we found evidence of savings from utility energy-efficiency programs. Based on a model of per-capita consumption in the IOU service territories (Table 2, Model 4), we found a $1.00 increase in current energy-efficiency program expenditures per capita reduced consumption per capita by approximately 0.05%. This implies cost of first year saving of approximately $0.30/kWh. A $1.00 increase in two-year lagged expenditures increased expenditures by 0.2% per year.
- Annual savings from IOU energy-efficiency program expenditures in the current and previous three years increased from 7,830 GWhs in 2008 to 10,321 GWhs in 2010, reflecting a doubling of energy-efficiency expenditures over this period. Estimated electricity consumption would have been 3.9% higher in 2008 and 5.5% higher in 2010 without the utility energy-efficiency programs.
- Our estimates imply somewhat higher costs of conserved energy for IOU energy-efficiency programs than estimated in the literature. Between 2008 and 2010, IOU costs of conserved energy of current and past spending were estimated in the range of $0.04 to $0.08/kWh. Other studies of U.S. utilities have found costs 50% lower than this. Our result may reflect California's lead in energy efficiency, and the exhaustion of low-cost savings opportunities in the IOU territories. Our estimates of costs of first-year savings of other California utility programs are approximately $0.04/kWh, which are more consistent with the findings from other studies.
- Electricity savings from the 2001 Title 24 building code update in the IOU service territories increased from approximately 2,700 GWhs in 2002 to 5,200 GWhs in 2008. After 2005, savings from the 2001 update equaled approximately 2.5% of the IOUs' annual electricity consumption.

Future Work and Refinements

Cadmus continues to work on the following issues in developing the macro-consumption savings estimates:

- We will continue to explore additional model specifications, including those addressing additional lags of dependent variables and lags of some independent variables.
- We will pay additional consideration to the functional forms of energy-efficiency expenditures, and of residential and commercial new construction in the regression models. As Arimura, Newell, and Palmer (2011) observe, log-log and semi-log

specifications impose somewhat strong assumptions about relationships between expenditures and consumption.

- We will pay additional consideration to exogenous treatment of electricity prices in the models. Electricity price enters the models as the average price per kWh. With increasing use of block rates, utilities with high consumption will tend to have higher average prices. This positive correlation between sales and prices will bias downward the estimated price elasticity of consumption. Most coefficients on electricity prices in our study present positive signs. Following previous studies, it may be possible to instrument for electricity prices using lagged values of average price.
- We will explore the potential application of instrumental variables estimation to account for error in the measurement of utility energy efficiency program expenditures. A candidate instrument would be whether the utility's total sales exceed

Conclusions

While our findings are preliminary, they suggest the potential value of applying macro-consumption methods to estimate energy savings in California. Cadmus detected savings from energy efficiency programs and state building codes, despite using a panel with a small number of utilities and relatively short time series. Our study also points out an obvious limitation of macro-consumption methods: while we were able to detect energy savings, the savings were not estimated precisely. Policy makers must decide what level of uncertainty is tolerable before these methods can be applied. Collection of additional data and continued refinement of the models has the potential to increase the precision of the savings estimates and reduce uncertainty.

Appendix: IOU Savings Estimates

Table A.1 PG&E Savings Estimates

	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 ($)	$220,515,000	$142,232,412	$155,833,067	$183,688,891	$360,222,645	$370,371,323
Expenditures per capita ($)	$19	$12	$13	$15	$29	$30
Population (estimate)	11,852,896	11,977,193	12,137,844	12,292,971	12,402,367	12,506,697
Panel B: Savings Estimates						
Model predicted savings from current expenditures (GWh)	760	500	554	658	1,235	1,252
Model predicted savings from one year lag expenditures (GWh)		1,194	779	860	970	1,875
Model predicted savings from two year lag expenditures (GWh)			3,058	1,988	2,084	2,421
Model predicted savings from three year lag expenditures (GWh)				190	117	126
Model predicted total savings from current and three previous year expenditures (GWh)				3,697	4,406	5,673
Panel C: Percent Savings						
Model predicted savings from current year expenditures as % of current consumption	0.9%	0.6%	0.6%	0.7%	1.4%	1.5%
Model predicted savings from one-year lag expenditures as % of current consumption		1.4%	0.9%	1.0%	1.1%	2.2%
Model predicted savings from two-year lag expenditures as % of current consumption			3.5%	2.2%	2.4%	2.8%
Model predicted savings from three-year lag expenditures as % of current consumption				0.2%	0.1%	0.1%
Model predicted total savings from current and three previous year expenditures as a % of current consumption				4.2%	5.2%	6.7%
Panel D: Cost of Conserved Energy						
Model predicted cost per kWh saved from current expenditures	$0.290	$0.284	$0.281	$0.279	$0.292	$0.296
Model predicted cost per kWh saved from one-year lag expenditures		$0.000	$0.000	$0.000	$0.000	$0.000
Model predicted cost per kWh saved from two-year lag expenditures			$0.000	$0.000	$0.000	$0.000
Model predicted cost per kWh saved from three-year lag expenditures				$0.000	$0.000	$0.000
Model predicted cost per kWh saved from current expenditures and three previous year expenditures				$0.050	$0.082	$0.065

Table A2. SDG&E Savings Estimates

	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 ($)	$75,708,302	$33,982,873	$70,517,334	$110,659,276	$90,313,867	$63,018,198
Expenditures per capita ($)	$25	$11	$23	$35	$28	$20
Population (estimate)	3,027,213	3,047,107	3,090,723	3,142,350	3,181,631	3,222,404
Panel B: Savings Estimates						
Model predicted savings from current expenditures (GWh)	240	112.31	231.31	363.50	285.46	190.53
Model predicted savings from one-year lag expenditures (GWh)		385	172	357	539	421
Model predicted savings from two-year lag expenditures (GWh)			968	435	869	1,305
Model predicted savings from three-year lag expenditures (GWh)				60	26	51
Model predicted total savings from current and three previous year expenditures (GWh)				1,215	1,719	1,967
Panel C: Percent Savings						
Model predicted savings from current year expenditures as % of current consumption	1.2%	0.6%	1.1%	1.7%	1.4%	1.0%
Model predicted savings from one-year lag expenditures as % of current consumption		1.9%	0.8%	1.7%	2.6%	2.1%
Model predicted savings from two-year lag expenditures as % of current consumption			4.7%	2.1%	4.3%	6.6%
Model predicted savings from three-year lag expenditures as % of current consumption				0.3%	0.1%	0.3%
Model predicted total savings from current and three previous year expenditures as a % of current consumption				5.9%	8.5%	10.1%
Panel D: Cost of Conserved Energy						
Model predicted cost per kWh saved from current expenditures	$0.32	$0.30	$0.30	$0.30	$0.32	$0.33
Model predicted cost per kWh saved from one-year lag expenditures		$0.00	$0.00	$0.00	$0.00	$0.00
Model predicted cost per kWh saved from two-year lag expenditures			$0.00	$0.00	$0.00	$0.00
Model predicted cost per kWh saved from three-year lag expenditures				$0.00	$0.00	$0.00
Model predicted cost per kWh saved from current expenditures and three previous year expenditures				$0.09	$0.05	$0.03

Table A3. SCE Savings Estimates

	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 ($)	222,257,938	131,190,408	124,417,922	45,006,974	225,774,551	271,131,995
Expenditures per capita ($)	18	11	10	4	18	21
Population (estimate)	12,192,182	12,308,110	12,419,638	12,527,895	12,613,533	12,719,815
Panel B: Savings Estimates						
Model predicted savings from current expenditures (GWh)	783	473.83	443.82	161.68	763.42	876.05
Model predicted savings from one-year lag expenditures (GWh)		1,236	721	688	234	1,123
Model predicted savings from two-year lag expenditures (GWh)			3,092	1,838	1,641	567
Model predicted savings from three-year lag expenditures (GWh)				192	106	96
Model predicted total savings from current and three previous year expenditures (GWh)				2,880	2,745	2,663
Panel C: Percent Savings						
Model predicted savings from current year expenditures as % of current consumption	0.9%	0.5%	0.5%	0.2%	0.9%	1.1%
Model predicted savings from one-year lag expenditures as % of current consumption		1.4%	0.8%	0.8%	0.3%	1.4%
Model predicted savings from two-year lag expenditures as % of current consumption			3.5%	2.0%	1.9%	0.7%
Model predicted savings from three-year lag expenditures as % of current consumption				0.2%	0.1%	0.1%
Model predicted total savings from current and three previous year expenditures as a % of current consumption				3.2%	3.2%	3.2%
Panel D: Cost of Conserved Energy						
Model predicted cost per kWh saved from current expenditures	$0.28	$0.28	$0.28	$0.28	$0.30	$0.31
Model predicted cost per kWh saved from one-year lag expenditures		$0.00	$0.00	$0.00	$0.00	$0.00
Model predicted cost per kWh saved from two-year lag expenditures			$0.00	$0.00	$0.00	$0.00
Model predicted cost per kWh saved from three-year lag expenditures				$0.00	$0.00	$0.00
Model predicted cost per kWh saved from current expenditures and three previous year expenditures				$0.02	$0.08	$0.10