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Cost-Effectiveness of Electricity Energy Efficiency Programs

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RESOURCES FOR THE FUTURE

Cost-Effectiveness of Electricity Energy Efficiency Programs

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Abstract

We analyze the cost-effectiveness of electric utility rate payer–funded programs to promote demand-side management (DSM) and energy efficiency investments. We develop a conceptual model that relates demand growth rates to accumulated average DSM capital per customer and changes in energy prices, income, and weather. We estimate that model using nonlinear least squares for two different utility samples. Based on the results for the most complete sample, we find that DSM expenditures over the last 18 years have resulted in a central estimate of 1.1 percent electricity savings at a weighted average cost to utilities (or other program funders) of about 6 cents per kWh saved. Econometrically-based policy simulations find that incremental DSM spending by utilities that had no or relatively low levels of average DSM spending per customer in 2006 could produce 14 billion kWh in additional savings at an expected incremental cost to the utilities of about 3 cents per kWh saved.

Key Words: energy efficiency, demand-side management, negawatt cost

JEL Classification Numbers: Q38, Q41

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1. Introduction

Utility programs to reduce demand for electricity have been in existence since the late 1970s following the two energy crises of that decade. Several pieces of federal legislation passed in the late 1970s encouraged utilities to develop programs to promote energy efficiency and reduce demand in peak periods, and the Public Utilities Regulatory Policies Act of 1978 required state Public Utility Commissions to take account of these programs in setting consumer rates for electricity. Programs took off in the early 1990s with U.S. utilities spending a total of nearly $2.0 billion dollars (2007$) on energy efficiency demand-side management (DSM) programs in 1993.[1] After 1993, the peak year of utility spending on DSM according to the Energy Information Administration (EIA), electric utility spending on energy conservation and DSM started to decline as electricity markets were being restructured to introduce more competition, and expenditures on efficiency programs were reduced or eliminated as utilities sought to reduce costs. In some states, the move to competition was accompanied by the establishment of *wires charges*, known as *system benefit charges* or *public benefit charges*, which were used to fund continued investment in energy efficiency.

After nearly three decades of experience with DSM, a good deal of controversy remains over how effective these programs have been in reducing electricity consumption and at what cost those consumption reductions have been obtained. Estimates of the cost-effectiveness, or cost per kWh saved, of past DSM programs range from just below 1 cent per kWh saved to more

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[1] In 1993, total DSM spending, including spending on load management, was about $3.7 billion dollars.

than 20 cents.[2] Estimates of energy savings have been derived using a variety of different methods and are subject to varying degrees of uncertainty, depending on the ability of program evaluators to account for human behavior in engineering models that estimate energy savings, including free-riding participants and countervailing spillovers to nonparticipants. Nationwide, DSM programs have only a modest impact on electricity demand. According to the 2008 *Annual Energy Review (EIA 2008)*, utilities reported that DSM programs produced energy savings in 2007 equal to approximately 1.8 percent of total electricity demand.[3] Savings estimates vary somewhat across the states. Data from the California Energy Commission (CEC 2008) suggests that current and past utility DSM programs across the state saved 1.8 percent of commercial and residential electricity consumption or 1.2 percent of total electricity consumption in 2005.[4] However, Efficiency Vermont reports incremental savings from their efficiency programs in 2008 of 2.5 percent of total electricity sales in the state (Efficiency Vermont 2008).

With increasing electricity prices, concerns about the continued reliability of electricity supply, and growing interest in limiting emissions of greenhouse gases that contribute to climate change, utilities, policymakers, and environmental groups have shown renewed interest in policies and programs to promote energy efficiency. In 2006, a group representing utilities, state regulators, environmentalists, industry, and federal government employees, coordinated by the U.S. Environmental Protection Agency and the U.S. Department of Energy (DOE), published the National Action Plan for Energy Efficiency, which includes a call for more funding of cost-effective energy efficiency. Several states are adopting regulatory rules, including revenue decoupling and financial performance incentives, to reward the utilities in their jurisdictions that invest in cost-effective energy efficiency programs. The governors of some states, including Maryland and New York, have announced specific electricity reduction goals that seek to reduce electricity consumption (or consumption per capita) relative to current levels by a target year in the future. Exactly how these goals will be achieved is yet to be determined, but several of the

[2] See Gillingham, Newell and Palmer (2006) for more information on the ranges of estimates of cost per kWh saved across different studies.

[3] Authors' calculation based on the ratio of total energy savings from DSM programs reported in Table 8.13 and total energy demand reported in Table 8.1 of the Annual Energy Review 2008 (EIA 2008). Reid (2009) breaksdown these numbers by utility and finds that the top 10 utilities in terms of savings all reported cumulative effects of energy efficiency programs in excess of 10 percent.

[4] Calculation based on electricity consumption savings to commercial and residential customers in 2005 attributable to cumulative utility and public agency programs reported in table 6 of CEC (2008) divided by total 2005 sales reported in Form 1.1 (CEC 2008).

states participating in the Regional Greenhouse Gas Initiative are planning to use a substantial portion of the revenue from carbon dioxide (CO_2) allowance auctions to fund DSM initiatives.[5] Several federal legislative proposals to impose a national CO_2 cap-and-trade program also include provisions to encourage utilities and states to adopt energy efficiency resource standards to help increase the role of energy efficiency in meeting emissions reduction goals.

As policymakers try to identify the most effective policies and programs to secure cost-effective energy savings, understanding the effectiveness and cost-effectiveness of past policies and programmatic initiatives becomes particularly important. In this paper, we analyze the effects of rate payer–funded utility and third-party DSM spending on electricity demand growth at the utility level. We also explore the effects on electricity consumption of decoupling regulation and building energy efficiency codes.

Based on our results using the largest sample of utilities, our findings suggest that, over the 18-year period covered by this analysis, rate payer–funded DSM expenditures produced a central estimate of 1.1 percent savings in electricity consumption at an expected average cost to utilities of roughly 6.4 cents per kWh saved. Using a nonparametric bootstrapping approach, we find that the 95 percent confidence interval for savings ranges from 0.6 percent to 1.4 percent, whereas the 95 percent confidence interval for average cost ranges from 4.4 to 10.9 cents per kWh. Our econometric results also allow us to parameterize functional relationships between (a) the percentage savings and the average level of DSM expenditure per customer and (b) the average cost of savings and both the average level of DSM expenditure per customer and the average amount of electricity consumed per customer. These functions suggest that the percentage of electricity savings is an increasing but concave function of average DSM spending per customer, and that the average cost varies roughly linearly with expenditures. Putting these two functions together allows us to trace out an average cost curve for percentage reductions in electricity consumption that is increasing and convex. Focusing on a representative utility with consumption per customer equal to the 2006 average level of 25 MWh, this average cost function suggests that a 1.5 percent electricity savings can be achieved at an expected average cost to the utility of roughly 4.5 cents per kWh saved. Moreover, simulations suggest that increasing utility DSM spending by $440 million at those utilities in our sample that spent less than $10 per

[5] The Regional Greenhouse Gas Initiative (RGGI) states see investment in DSM as a way to help offset the impacts of the regional climate policy on electricity consumers and potentially to reduce the likelihood that power imports from non–RGGI states will increase under the program (RGGI 2008).

customer on average in 2006 would have resulted in 14 billion kWh of additional savings at an expected incremental cost of 3.1 cents per kWh.

The rest of the paper is organized as follows. Section 2 includes a review of past empirical studies on DSM and energy efficiency. Section 3 discusses the effects of electricity sector restructuring on DSM programs and the growing role for programs operated by third parties. Section 4 develops the conceptual model that underlies our calculations of predicted energy savings and their costs, and Section 5 discusses the explanatory variables included in the empirical application of that model. We discuss the results of the estimation and some associated policy simulations in section 6, and section 7 concludes.

2. Empirical Economic Studies of DSM

Several empirical economic studies have evaluated the effectiveness and cost-effectiveness of utility DSM. Utility DSM includes programs such as information programs (e.g. free energy audits), low cost financing and financial incentives or subsidies for purchase of more energy efficiency equipment. Much of this literature is reviewed by Gillingham, Newell and Palmer (2006, 2009), which uncover a range of estimates of both the effectiveness and cost-effectiveness of these programs. The studies that use ex post econometric analysis tend to find higher costs per unit of electricity saved than those that rely largely on ex ante engineering-costing methods. For example, an early study by Joskow and Marron (1992) suggests that failure to account for free riders, overly optimistic estimates of equipment lifetimes, and underreporting of cost lead utilities to tend to overstate the cost-effectiveness of DSM programs by a factor of at least two. However, a subsequent study by Parformak and Lave (1996) using data from a subset of utilities in the Northeast and California finds that 99 percent of utility-reported estimates of savings from DSM are borne out in actual metered data on energy use after controlling for the effects of prices, weather, and economic activity. In a similar vein, Eto et al. (1996) analyze data from 20 large utility-sponsored energy efficiency programs and develop a consistent approach to measuring savings and costs. They conclude that all the programs that they analyze are cost effective conditional on the underlying assumptions about economic lifetimes of the identified energy savings and the level of avoided costs of generation.

Specific estimates of cost-effectiveness from the prior literature range from 0.9 to 25.7 cents per kWh saved. (All cost estimates are reported in 2007$.) The estimate at the low end of this range comes from Fickett et al (1990). Nadel (1992) offers a range of estimates for utility programs of 2.9 – 7.5 cents per kWh saved. Estimates of others tend to fall within this range. Eto et al (2000) report an estimate of 4.2 cents per kWh saved. Nadel and Geller (1996) report both costs to utilities (3.0–4.7 cents per kWh saved) and costs to utilities plus consumers (5.4–8.0 cents per kWh saved). Friedrich et al. (2009) use utility and state evaluations and regulatory reports on energy savings and utility costs for 14 states to develop an average estimate of the average cost to utilities of 2.5 cents per kWh saved.

The cost estimates at the high end of the range come from a more recent study by Loughran and Kulick (2004; hereafter L&K). L&K analyze the effects of changes in DSM expenditures on changes in electricity sales using utility-level panel data over the time period from 1992 through 1999[6]. They find that the DSM programs are less effective and less cost-effective than utility-reported data would suggest, with their estimates of costs ranging from 7.1 to 25.8 cents per kWh saved coming in at between 2 and 6 times as high as utility estimates. These high cost estimates follow primarily from their finding that the savings attributable to DSM programs indicated by the econometrics are substantially smaller than those directly reported by utilities, suggesting a substantial amount of free riding. However, these cost comparisons rely on the application of predicted values of percentage savings to mean levels of electricity demand to calculate average savings; therefore, they do not represent an appropriately weighted national average cost. A reevaluation of the L&K econometric results by Auffhammer, Blumstein and Fowlie (2008; hereafter ABF), which weights savings and costs by utility size in the construction of a mean cost-effectiveness measure, finds a substantially lower estimate of cost per kWh than reported by L&K—a result not disputed by L&K. In their work, ABF find DSM expenditure-weighted average cost estimates that range from 5.1 to 14.6 cents per kWh. Their reevaluation also accounts for the uncertainty surrounding the model predictions to construct confidence intervals for L&K estimates of predicted energy savings from DSM, which ABF find contain the utility-reported estimates. ABF point out that the appropriately weighted L&K findings are not statistically significantly different from those reported by the utilities in their sample.

In another recent study, Horowitz (2007) uses a difference-in-differences approach to determine whether changes in electricity demand and electricity intensity from the pre-1992 (1977 – 1992) to the post-1992 (1992 – 2003) period for residential, commercial, and industrial electricity users were stronger for utilities with a strong commitment to DSM than for those with a less strong or weak commitment. In this analysis, Horowitz uses measures of reported

[6] Some specifications focus on a shorter time period because of the limited availability of certain explanatory variables.

electricity savings attributable to DSM programs to categorize utilities. He finds that utilities with strong DSM programs see a bigger decline in energy intensity among all classes of customers and in total energy demand among industrial and commercial customers. Horowitz does not look at the question of cost-effectiveness.

Our analysis uses the basic approach of L&K as a starting point, but modifies and augments this earlier work in several important ways. First, we augment the data set to include data on utility DSM spending through 2006. Second, we incorporate spending on DSM by "third party" state agencies or independent state-chartered energy efficiency agencies tasked with using revenues collected from utility rate payers to implement energy efficiency programs. Third, we explore the influence of decoupling regulations and the stringency of state-level residential building codes in the region where each utility operates. Fourth, following ABF, we calculate confidence intervals for our estimates of percentage savings and cost effectiveness. Finally, we model percentage electricity savings as a function of average DSM expenditures per customer, rather than the level of DSM expenditures. Normalizing expenditures in this way better represents the relationship of DSM expenditures and associated electricity savings across utilities of widely differing scale. We also tie our empirical specification clearly to a conceptual model of electricity demand, carefully lay out the derivation of our estimated cost-effectiveness measures, and make a number of other improvements in estimation compared to previous studies, as described further below.

3. Evolution of Rate Payer–Funded DSM in an Era of Electricity Restructuring

During the late 1990s, the electric utility industry was in the midst of an important transition to greater competition. The 1992 Energy Policy Act required the Federal Energy Regulatory Commission (FERC) to devise rules for opening the transmission grids to independent power producers to sell electricity in the wholesale markets under its jurisdiction. In 1996, FERC issued Orders 888 and 889 to comply with its mandate (Brennan 1998). In the wake of the opening of transmission, several states began to give customers a choice of electricity suppliers. In 1994, California became the first state to begin restructuring its utility industry, and by 2000, a total of 23 states and the District of Columbia had passed an electric industry restructuring policy and opened up their electricity markets to greater competition.[7]

The prospect of competition and restructuring had a negative impact on utility DSM spending as utilities started to shed all discretionary spending to be better able to compete with new entrants that did not offer such programs. The regulatory environment also became less favorably disposed toward DSM programs as regulators shifted emphasis away from the integrated resource planning approach that often created incentives to invest in DSM rather than in new generation capacity. In the new regulatory environment, price caps and greater reliance on markets for setting electricity prices created strong incentives for utilities to cut costs and seek new opportunities to increase profits by increasing electricity sales, both of which served to diminish incentives for DSM programs (Nadel and Kushler 2000). The resulting effect on DSM expenditures over the course of the 1990s can be seen in Figure 1, which shows a substantial decline in utility DSM spending directed toward energy efficiency between 1993 and 1998.[8]

In anticipation of a decline in utility DSM spending in the wake of electricity restructuring, a number of states established mechanisms to replace utility programs as part of the restructuring process (Eto et al. 1998). The most common approach has been to establish a public benefit fund to pay for DSM and other public benefit programs, such as renewable energy promotion, research and development, and low-income assistance, as a part of restructuring legislation or enabling regulation (Nadel and Kushler 2000). Typically, these programs are funded by a per-kWh wires charge on the state-regulated electricity distribution system (Khawaja, Koss, and Hedman 2001). These wires charges are often referred to as systems benefit charges or public benefit charges.

According to the American Council for an Energy Efficient Economy (2004), 23 states have policies encouraging or requiring public benefit energy efficiency programs that were in effect during some portion of our data sample period. Most of these programs are administered by the distribution utilities and thus presumably are captured in the EIA energy efficiency spending data by utility. However, in nine states — Illinois, Maine, Michigan, New Jersey, New

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[7] Note that since 2000 the spread of electricity restructuring has stalled and even reversed itself with the California Public Utility Comission suspending retail competition in that state in March 2002 and the Virginia state legislature rejecting retail competion for Virginia electricity consumers in 2007.

[8] Note that Figure 1 includes only the portion of DSM spending used for energy efficiency and thus excludes expenditures on load management, load building, and indirect expenditures.

York, Ohio, Oregon, Vermont, and Wisconsin — these public benefit efficiency programs are administered either by a state government entity (e.g., state energy office) or a for-profit or non profit, third party administrator and therefore potentially excluded from the EIA data. We refer to these as third-party DSM programs. The aggregate level of spending by these state-level third-party energy efficiency programs is shown by year in Figure 1, as is their effect on total national rate payer–funded DSM expenditures.[9] Note that, although these programs have not fully offset the decline in utilities' own spending on DSM, they have partially filled the gap.

4. A Conceptual Model of Electricity Demand and Energy Savings from DSM

Our aim in this paper is to estimate an empirical model of electricity demand change in response to multiple factors that is consistent with an underlying conceptual model of electricity demand. This linking of empirics with a clear conceptual model is important both for selecting relevant explanatory variables and for determining how those variables, particularly variables related to DSM, should appear in the empirical model. Based on the estimated model, we compute estimates of energy savings from DSM, the cost-effectiveness of DSM, and confidence intervals for these measures using a nonparametric bootstrap approach.

4.1 Estimating Electricity Demand Growth as a Function of DSM and Other Variables

We begin by specifying an aggregate Cobb–Douglas electricity demand function for the customers of each utility *u* in each year *t*

$$Q_{ut} = p_{f,ut}^{\alpha_f} Y_{ut}^{\lambda} W_{ut}^{\rho} \exp\left(g\left(K_{ut}, R_{ut}, t\right)\right) \tag{1}$$

where Q_{ut} is aggregate electricity demand; $p_{f,ut}$ is a vector of fuel prices for electricity, natural gas, and oil; Y_{ut} is a vector of energy service demand shifters (e.g., level of economic activity and number of customers); W_{ut} is weather; *g* is a function; K_{ut} is the level of DSM energy efficiency capital per customer; R_{ut} is a vector of other regulatory variables influencing

[9] Note that in constructing the total line in this graph, we add third-party expenditures to utility-level expenditures only when there are no reported utility-level expenditures. We can therefore be certain that the utility-reported expenditures do not include money expended by the utility, but obtained from the funds managed by a third-party administrator. To assume otherwise would potentially double-count this DSM spending, and in our data we found evidence that third party spending through utilities is in fact reported by utilities in the EIA form 861.

electricity energy efficiency and demand; and *t* represents a vector of year effects. [10]The key variable of interest in this demand function is K_{ut}. Taking logs of both sides yields the linear function

$$\ln(Q_{ut}) = \sum_f \alpha_f \ln p_{f,ut} + \lambda \ln Y_{ut} + \rho \ln W_{ut} + g\left(K_{ut}, R_{ut}, t\right) \tag{2}$$

Following L&K and many other energy demand studies, we estimate a model in first-difference form, thereby controlling for unobserved utility-specific attributes that could otherwise lead to omitted variable bias

$$\ln\left(\frac{Q_{ut}}{Q_{u,t-1}}\right) = \sum_f \alpha_f \ln\left(\frac{p_{ft}}{p_{f,t-1}}\right) + \lambda \ln\left(\frac{Y_{ut}}{Y_{u,t-1}}\right) + \rho \ln\left(\frac{W_{ut}}{W_{u,t-1}}\right) + f\left(\Delta K_{ut}\right) + \omega R_{ut} + \theta t + \varepsilon_u \tag{3}$$

where *f* is a function, ΔK_{ut} is DSM augmentation of energy efficiency capital, and ε is an error term. We assume that ΔK_{ut} is a function of current and past average rate payer–funded DSM energy efficiency investments per customer, D_{ut}, and we allow for diminishing returns in the relationship between DSM capital and energy demand reductions through an exponential form

$$\ln\left(\frac{Q_{ut}}{Q_{u,t-1}}\right) = \sum_f \alpha_f \ln\left(\frac{p_{ft}}{p_{f,t-1}}\right) + \lambda \ln\left(\frac{Y_{ut}}{Y_{u,t-1}}\right) + \rho \ln\left(\frac{W_{ut}}{W_{u,t-1}}\right) + \sum_{j=0}^{n} \beta_j \left(1 - \exp\left(\gamma D_{u,t-j}\right)\right) + \omega R_{ut} + \theta t + \varepsilon_u \tag{4}$$

where $D_{u,t-j}$ is the average level of DSM expenditure per customer in year *t–j* , *j* indicates lags, and *n* is the maximum number of lags included. Because we are estimating a model to predict percentage changes in demand, we use average DSM spending per customer (as opposed to simply the level of DSM). Otherwise, the effect on kWh saved of an additional dollar of DSM spending would be larger for larger utilities, which is conceptually incorrect. The functional form specification for *D* allows for percentage savings to depend in a flexible manner on average DSM spending per customer, where the β_j give the individual effects of current and past DSM expenditures, and γ gives the rate of diminishing (or increasing) returns (Jaffe and Stavins 1995). The rate of diminishing returns increases as γ gets large, whereas the function becomes linear (i.e., constant returns to DSM) as γ gets small. We would expect both γ and βj to be negative if

[10] In this research we initially explored a functional form that was more similar to that used by L&K in that DSM expenditures entered in a log form, but still using DSM per customer for reasons explained below. However, we found that the results obtained using this specification were highly dependent on the treatment of observations with zero DSM spending. Entering DSM expenditures in log form also lead to very extreme curvature of the percent savings as a function of DSM expenditures and in turn of the average cost function described below.

increased DSM spending lowers energy consumption, but at a diminishing rate. Neither value is imposed, but is rather estimated from the data. We also do not constrain the individual βj coefficients on lagged DSM expenditures to take on any particular form, allowing instead for a flexible depreciation structure. The chosen function therefore balances the need for parsimony, with the desire to allow for both a lasting, flexible DSM effect and the potential for diminishing (or increasing) returns.

4.2 Computing Predicted Energy Savings from DSM

Next we show how equation (4), once estimated, can be transformed to yield expressions for expected percentage electricity savings resulting from different average levels of DSM expenditures per customer as well as the associated average cost of achieving those savings. Because the model is estimated in log differences, which approximate percentage changes,[11] the estimated year *t* percentage energy savings at utility *u* attributable to current and past DSM spending , $\%S_{ut}$,is given by the terms involving *D*

(5) $$\%S_{ut} = -\sum_{j=0}^{n} \beta_j \left(1 - \exp\left(\gamma D_{u,t-j}\right)\right)$$

where the minus sign indicates demand reductions. Note that the electricity savings in any given year are the result of current and previous years' DSM expenditures. We can use the estimated β_j and γ coefficients to predict the cumulative percentage savings at utility *u* in the current and subsequent years attributable to DSM expenditures at that utility in year *T*.

(6) $$\%S_{uT} = -\sum_{j=0}^{n} \beta_j \left(1 - \exp\left(\gamma D_{uT}\right)\right)$$

To calculate an aggregate estimate of electricity savings and cost-effectiveness from DSM across utilities and time, it is necessary to translate percentage savings into a level of savings (in kWh) by multiplying by the level of electricity demand, Q_{ut}

(7) $$S_{uT} = -\sum_{j=0}^{n} \beta_j \left(1 - \exp\left(\gamma D_{u,T}\right)\right) Q_{u,T+j}$$

[11] We found empirically that the predicted changes were sufficiently small that log differences very closely approximated percentage savings. We also found that the Goldberger (1968) correction for the expected level values of log-form equations was extremely close to 1. For simplicity, we therefore do not include these subtleties here.

Equation (7) gives a predicted energy savings from DSM for each observation in the sample. One can also compute an overall percentage savings estimate by summing energy savings across all utilities and years, and dividing by the sum of demand

(8) $$\%S = \frac{\sum_u \sum_T S_{uT}}{\sum_u \sum_T Q_{uT}}$$

Note that L&K and ABF report alternative summary statistics for aggregating savings and costs across utilities and time, including unweighted means. We agree with ABF that the alternative unweighted measures are misleading and we therefore do not report them here.

4.3 Computing DSM Cost-Effectiveness

By dividing total DSM expenditures in year *T* by S_{uT}, one can measure the cost-effectiveness of DSM expenditures, AC_{uT}, for each observation

(9) $$AC_{uT} = \frac{D_{uT} C_{uT}}{S_{uT}}$$

where recall that *D,* average DSM spending per customer, must be multiplied by *C*, the number of customers, to yield total spending.

One can also compute an overall cost-effectiveness estimate by summing DSM expenditures across all utilities and years, and dividing by the sum of energy savings from DSM

(10) $$AC = \frac{\sum_u \sum_T D_{ut} C_{uT}}{\sum_u \sum_T S_{uT}}$$

Finally, using the simplified savings function of equation (6) along with (9), the average cost of energy savings at a utility with DSM expenditures, D_u, and a benchmark level of electricity sales per customer, Q_u / C_u, is

(11) $$AC_u = D_u \Big/ \left[\%S_u \left(Q_u / C_u \right) \right]$$

We use equation (11), along with (6), to illustrate our main findings.

5. Estimation Variables and Data Sources

We estimate the model specified in equation (3) above using a panel of annual utility-level data from EIA Form 861 *Annual Electric Power Industry Report* and other sources over the

18-year period 1989–2006, with the observations in the estimation sample starting in 1994–1995 because of the role of lagged DSM expenditures in the model. Thus, our panel covers a period roughly twice as long as that of L&K. The definitions of the variables are shown in Appendix Table A-1 and are described below. All dollar values are converted from nominal to real using the gross domestic product (GDP) deflator. Summary statistics appear in Table 1.

Our main sample, sample 1, has 3,155 observations (513 utilities), whereas our more constrained sample, sample 2, has 1,614 observations (189 utilities). Sample 1 includes all utilities in the lower 48 states that meet the minimum size criteria for reporting DSM expenditures throughout the sample period and excludes utilities with no residential customers.[12] Sample 2 includes the subset of utilities with at least 10 years of experience with DSM reporting, defined as those utilities that have nonmissing values for DSM expenditures for at least 10 years.[13]

5.1 Electricity Demand and DSM Expenditures

Data on utility-level electricity sales, DSM spending, and number of customers are from Form EIA-861[14]. Like L&K, we use as our measure of utility spending on energy efficiency

[12] Under Form EIA-861, utilities with sales to both ultimate consumers and resale less than 120,000 MWh were not required to report energy efficiency expenditures through 1997. The threshold became 150,000 MWh in 1998; we therefore exclude all utilities with less than 150,000 MWh. Further, following L&K, we do not include utilities in Alaska, the District of Columbia, Hawaii, or the U.S. territories. We also drop observations that have missing values for DSM expenditures during the estimation process.

[13] We also ran the model using two other samples that were substantially smaller: one including all utilities that had at least 10 years of positive DSM expenditures and another including only those utilities that had at least 15 years of positive DSM expenditures. These two samples had substantially fewer significant coefficients and some significant coefficients of the wrong sign, yielding a confidence interval for average percentage savings for the sample that included negative values.

[14] Analysts have raised some concerns about the quality of the utility level data on energy efficiency collected on EIA-861, including missing values for expenditures in some years for large utilities and a lack of consistency across utilities in what gets reported for both expenditures and savings measures, particularly the annual savings (Horowitz 2004, York and Kushler 2005, Reid 2009). Note that we do not use the EIA-861 energy savings data for our econometric analysis. Early in the course of this research, we also attempted to identify and correct shortcomings in the expenditures data, drawing on other sources including ACEEE and the Consortium for Energy Efficiency that have sought to fill in missing expenditures in certain years or collect their own data. However, we were unable to use those data because they did not have a sufficient degree of detail and time coverage necessary for our analysis. So we proceeded solely with the EIA data. Nonetheless, we did carefully check the EIA data and eliminated a number of outliers, including observations with year-to-year growth in demand or total customers in excess of 30 percent (due to mergers, acquisitions, and other factors) and utilities with no residential customers. While we believe there may be measurement error associated with the energy efficiency DSM expenditures reported to EIA, we do not believe it introduces a systematic bias to our analysis.

DSM that portion of DSM expenditures that utilities report as being devoted specifically to energy efficiency, as opposed to load management, load building, or indirect costs.[15] To be as comprehensive as possible in our treatment of rate payer–funded DSM energy efficiency programs, we also include third-party state-level DSM programs that have come into being post-restructuring.[16] We share state-level third-party DSM expenditures to the utility level using each utility's share of total customers within the state. Given that comparisons of third-party DSM expenditure data shared to the utility and utility-reported DSM expenditures suggest that there is some overlap, we only include third-party expenditures in the analysis when the utility-reported DSM expenditures are zero or missing.[17] As noted in section 4, we normalized DSM expenditures by number of customers at the utility in order to control for size. Finally, note that conducting the analysis at the utility level means that we are able to pick up the effects of intra-utility spillovers that would result when customers who do not participate in a program actually make investments in efficient equipment on their own and thus reduce their electricity consumption at no cost to the program.

5.2 Decoupling Regulation

To test whether state-level revenue decoupling regulation leads to reduced demand growth, we include a categorical variable indicating its presence.[18] Because of the way electricity is priced in most places, many of the fixed costs of delivering electricity are recovered in per-kWh charges. This means that programs that are effective at reducing electricity consumption

[15] Note that utilities did not report expenditures for energy efficiency separately until 1992, so we use the energy efficiency share of total DSM expenditures by utility in 1992 to impute values for energy efficiency–related expenditures in prior years to use as lagged measures of energy efficiency DSM expenditures.

[16] From a variety of sources, we were able to collect data on energy efficiency expenditures for third-party programs for only eight states and these data are reported in Appendix Table A-2, which shows the annual DSM expenditures by each program). When constructing these data, we did our best to match the categories of expenditures included in the energy efficiency portion of DSM spending reported by utilities to the expenditures reported by third parties, but such parsing of the third-party data into the portion that is directly comparable to the EIA definition of energy efficiency spending was not always possible. To the extent that we overrepresent the relevant category of energy efficiency spending, that would tend to bias our cost-effectiveness estimates upward.We were unable to obtain data on energy efficiency spending by the public benefit fund administrator in Ohio and thus we exclude the Ohio utilities from our estimation for the years 2000 and beyond.

[17] A linear regression of utility-reported DSM expenditures on third-party DSM expenditures shared to the utility level yields a coefficient of 1, suggesting that these third-party expenditures may be incorporated into utility reports.

[18] Another approach is lost revenue recovery, which allows utilities to raise prices to compensate them for revenues from sales that utilities can show were lost as a result of DSM programs. Unfortunately, data on the presence and form of state rules governing lost revenue recovery are not available for several of the years in our sample.

could also reduce revenues that are used to recover fixed costs, potentially creating losses for the utilities that offer DSM programs. In some states, regulators have allowed the utilities that they regulate to recover the relevant portion of lost revenues to eliminate disincentives for offering DSM programs. One such approach is revenue decoupling, so named because it decouples the portion of utility revenues dedicated to recovering fixed distribution costs from the amount of electricity that the utility sells. Note that because our data end in 2006, we do not incorporate the recent dramatic increase in the adoption of decoupling regulation at the state level.[19]

5.3 Building Energy Efficiency Codes

Previous studies of DSM have not examined the effects of building codes on electricity demand.[20] As a result, if building code stringency is positively correlated with average DSM expenditures per customer,[21] a portion of the energy savings caused by building codes may be attributed to DSM spending, which would result in an underestimate of the cost per kWh savings.[22] We address this issue by including a series of categorical variables to characterize the stringency of building codes within each state during each year. We obtained data on the evolution of energy building codes from the Building Codes Assistance Project (www.bcap-energy.org) and the DOE Building Energy Codes Program (www.energycodes.gov). See Figure 2 for a map of current building code stringency, which shows the western states, such as California and Washington, with the most stringent building codes and Midwestern states with typically less stringent codes.

We began by creating six categories of building code stringency, which, in order of decreasing stringency, are: (a) code met or exceeded the 2006 International Energy Conservation Code (IECC) or equivalent and was mandatory statewide; (b) code met 2003 IECC or equivalent

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[19] The decoupling indicator that we use is for the state where the utility has the majority of its sales. We also estimated an alternative model that used a weighted average of the decoupling indicator across all the states where a utility does business. We found no statistically significant effect for that weighted decoupling variable.

[20] Jaffe and Stavins (1995) examined the effectiveness of building codes using a cross-sectional data set, finding no significant effect of building codes on energy demand in their analysis.

[21] In our sample, we find a small positive correlation of building code stringency and DSM expenditures per customer.

[22] In some cases, however, such attribution may not be so far off. A significant issue with building codes is compliance, and for some utilities in some years, a portion of DSM expenditures may be devoted to improving compliance with residential building codes. In these cases DSM could increase the potential for building codes to yield savings.

and was mandatory statewide; (c) code met the 1998–2001 IECC or equivalent and was mandatory statewide; (d) code preceded the 1998 IECC or equivalent and was mandatory statewide; (e) significant adoptions in jurisdictions, but not mandatory statewide; and (f) none of the aforementioned conditions hold and no significant adoptions of building codes in the state. After speaking with a building codes expert, we further consolidated these into four categories to represent more substantial differences in stringency: BC1 indicates the stringency is (a) above; BC2 indicates the stringency is (a)–(d) above; BC3 indicates the stringency is (a)–(e) above; the fourth (excluded) category is category (f).[23] Thus, the variables are structured to indicate the incremental effect of building codes compared to the next most-stringent category.

5.4 Energy Prices and Other Variables

The annual average price of electricity by state also comes from Form EIA-861.[24] Residential natural gas and fuel oil prices by state also come from EIA. We compiled state-level data on several other variables from a variety of sources. Annual state-level GDP comes from the Bureau of Economic Analysis. Data on population-weighted heating and cooling degree days by state are from the National Oceanic and Atmospheric Administration (NOAA). These data are summed to construct a single climate variable.[25] Data on state-level housing starts are from Mitsubishi Bank (Bank of Tokyo-Mitsubishi UFJ, Ltd.). Some utilities operate in multiple states and separately report sales of electricity for each of the states in which they operate. We sum these sales to a utility-level total for our dependent variable. This is necessary because the energy efficiency DSM expenditures from Form EIA 861 are only available at the utility level and not broken down by state. For variables that are only available at the state level (i.e., energy prices,

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[23] We also obtained data on energy efficiency codes for commercial buildings. However, we found a high correlation between the residential and commercial building code stringency, and so chose to focus on a single measure of stringency.

[24] Electricity prices can vary substantially across utlities within a state and our price data will not reflect this intra-state variation in price levels where it exists However, given the potential for endogeneity introduced by using utlity level price data, and the fact that our analysis focuses on changes in price and not price levels, we believe that using state level prices for electricity and other fuels is appropriate.

[25] Although more than 99 percent of building air cooling is powered by electricity, the role of electricity in space heating is much smaller (between 2 percent and 18 percent) and varies substantially across regions of the country. To better represent the limited role of electricity in delivering space heating, we weight our heating degree day variable by the share of electricity in space heating for residential and commercial buildings. The shares are from the Residential Energy Consumption survey and Commercial Building Energy Consumption survey for available years, and are interpolated for intervening years. We found this adjustment to be important empirically.

GDP, and heating and cooling degree days), we use the value associated with the state in which the utility does the majority of its business.

6. Estimation and Results

Estimation employed a nonlinear least squares estimator using Newton's method (as implemented in Stata). We also use robust errors, clustered by utility, in order to account for heteroskedasticity. Estimation results for equation (4) appear in Table 2, where the dependent variable is the first difference in log electricity demand (approximately equal to the rate of change). The table includes two different specifications and two different samples, for a total of four models. The primary focus of our analysis is on the relationship between electricity demand growth and contemporaneous and lagged rate payer–funded energy efficiency DSM spending.[26] We considered a variety of lag structures and chose to include contemporaneous and six prior year lags for average DSM expenditures per customer, based on the Schwarz–Bayes and Akaike information criteria. Including additional lags also led to no increase in the total percentage savings attributable to current and past DSM spending.

6.1 Coefficient Estimates

In all of the models, we find a significant negative relationship between annual growth in electricity demand and the collection of variables representing average DSM spending per customer in current and past years.[27] The magnitude of the γ coefficient, which gives the rate at which diminishing returns set in, is always highly significant and slightly larger in absolute value with the smaller sample 2.

The results reveal that the relationship between electricity demand growth and indicators of growth in the size of the market (number of customers and population) and overall economic growth (gross state product) is generally positive and significant across the different models. The additional effect of growth in per capita housing starts is significant and positive in models 1 and 2, but not significant in models 3 or 4. The coefficient on population growth is positive and

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[26] As noted in section 4 above, we use DSM spending per customer (as opposed to simply the level of DSM) to ensure that the effect on kWh saved of an additional dollar of DSM spending will not be larger for larger utilities; this would be conceptually incorrect.

[27] An F-test on the group of DSM (β) coefficients is significant at the 5 percent level for models 3 and 4, and at the 1 percent level for models 1 and 2. Although some of the individual coefficients on DSM are positive, none of the models has a significant positive value for a coefficent on DSM.

significant in all 4 models. Electricity demand is also positively associated with increases in the climate variable (i.e., heating/cooling degree days) and the size of this effect is fairly consistent across the different models at an elasticity of about 0.1. Electricity demand is significantly negatively associated with the price of electricity (elasticity of –0.05 in model 1), as expected, as well as the price of natural gas (although the latter coefficient is quite small).[28] The price of oil has a positive and significant coefficient in models 1 and 2, but is insignificant in the other models.

In models 2 and 4 we also include the effect of decoupling regulation and building codes on electricity demand growth. Decoupling has a negative but statistically insignificant effect on demand growth in both models. We find no statistically significant effect of building codes on electricity demand growth in model 2, and in model 4 we actually find a counterintuitive positive and statistically significant effect. Although the model 2 finding is consistent with Jaffe and Stavins (1995), it is perhaps surprising and could suggest that these codes have not been particularly binding in the past. However, it seems more likely that our admittedly blunt measure of code stringency is insufficient to detect any effect.

The results of models 3 and 4 and other models run with smaller samples not presented suggest that limiting the analysis to the smaller samples tends to decrease the number of significant variables. For example, housing starts are not significant in models 3 or 4 and the overall effect of DSM expenditures is less significant in models 3 and 4 than in models 1 and 2.[29] Given the insignificance of the decoupling and building code variables in model 2, this leads us to focus on model 1 as our preferred specification.

6.2 Percentage Savings and Average Cost-Effectiveness

We use the estimated coefficients from each model and equations (8) and (10) to solve for the weighted average percentage savings and average cost according to each model. To

[28] The electricity price coefficient interpretation as a demand elasticity suffers from the potential endogeneity of electricity price. To assess the potential effects of simultaneity bias, we also estimated a two-stage model with an initial regression of electricity price on all of the economic variables included in our demand regression and input prices of natural gas and coal to electric utilities and year dummies. We then substituted the predicted values of price from this regression into model 1. Using this two-stage model, we find that the coefficient on the predicted electricity price is larger in absolute value (–0.14 versus –0.04), but not statistically significant. None of the other coefficients changes.

[29] The same is true for other models run with smaller samples that are not presented here.

associate savings with energy efficiency expenditures in years 2000 and later, we require predictions of electricity sales for 2007 through 2012 and we assume that the level of electricity sales at each utility remains at 2006 levels through 2012.[30] Table 3 reports predictions of the percentage electricity savings and the weighted average cost along with 95 percent confidence intervals for each of the four models.[31] The mean predicted percentage electricity savings from DSM is 1.1–1.4 percent, and the mean predicted cost-effectiveness for models 1 to 4 is 5.5–6.4 cents per kWh.

Our predictions of percentage savings and average cost stand somewhat in contrast to those reported by the utilities in response to EIA Form 861. On that form, utilities report incremental energy savings associated with current efficiency programs and total annual energy savings (from current and past DSM expenditures) as well as annual expenditures on energy efficiency DSM. For purposes of comparison to the average predictions from our model, we use these self-reported total annual savings to calculate an aggregate savings across all of the observations from the EIA data set that are included in our percentage savings and average cost calculations. This aggregate savings number represents the sum across all utilities and all years. We calculate utility-reported average percentage savings by dividing this aggregate savings value by aggregate MWh sold for the same set of utility-level annual observations. We similarly aggregate the reported DSM energy efficiency spending for these observations and calculate a weighted average reported cost by taking the ratio of aggregate cost to total reported savings.[32] These calculations yield a weighted average electricity savings of 2.0 percent, or roughly 80 percent higher than our estimate based on the econometric analysis. The utility reports imply that

[30] Predicting flat levels of electricity sales beyond 2006 may be overly pessimistic. According to EIA, annual average electricity sales growth during 2000-2006 in our sample was 1.2 percent. If we were to assume that electricity sales grew at 1.2 percent per year on after 2006, this would tend to adjust our estimate of total savings up by roughly 1.2 percent, and lead to a neglible reduction in cost of about 0.1 cents per kWh.

[31] We estimate standard errors (using the nonparametric bootstrap, as implemented in Stata) around predicted values of weighted average percentage savings and weighted average cost resulting from each model specification.

[32] Note that these calculated savings and related average cost measures do not include the effects of third-party programs. We are unable to evaluate the cost effectiveness of percentage savings from third-party programs because we were not able to obtain the necessary data. Note also that we may be under counting the cost of annual savings reported in early years by the utilities and under counting the savings of expenditures in later years, because we only have reported savings measures through 2006. The net effect of these two omissions on the implied weighted average cost estimate is difficult to know, but if savings were high during the high expenditure years of the early 1990s relative to what they might be for the lower aggregate expenditures in the early 2000's then our estimate of average cost according to the utility reports is probably biased upwards.

these savings are achieved at an average cost of 2.9 cents per kWh (2007$), which is outside the confidence interval for model 1 but inside the confidence intervals for models 3 and 4.

The expected average cost estimate of 6.4 cents per kWh for utility costs is less than the national average retail price of electricity in 2006 of 9.1 cents per kWh across all sectors (EIA 2009). Recall that these are costs only for the utility itself. This difference suggests that these programs may have produced zero-cost or low-cost CO_2 emissions reductions, depending on the magnitude of the costs to utility customers of implementing energy efficiency measures. Although the marginal cost of electricity—which is not generally equal to the electricity price—is perhaps a better estimate of the benefits of energy savings from DSM, estimates of marginal cost can vary substantially depending on what margin is being considered. In the short run, the marginal cost of generation can vary substantially by time of day. For example, in December 2006, the hourly marginal cost of generation ranged from roughly 2 cents per kWh to 27 cents per kWh depending on location and time of day (PJM 2006). In the longer run, marginal generation costs are given by the levelized cost of new investments, which vary by technology and fuel and, according to the National Academy of Sciences (2009), range from roughly 8–9 cents per kWh for new base load fossil capacity to a little over 13 cents per kWh for a new gas turbine peaker.

Accounting for customer costs is also challenging. Earlier research (Nadel and Geller 1996; Joskow and Marron 1992) suggests that the sum of customer costs and utility costs is roughly 1.7 times utility costs alone. Because this ratio is based on such a small number of somewhat dated studies, we do not think it is appropriate to use this ratio to estimate customer costs for our results. Nonetheless, it suggests that the total average cost of a kWh saved may exceed the retail electricity price, which could raise our estimates of the implied cost of any associated CO_2 emissions reductions into positive territory. However, targeting incremental energy efficiency investments at certain utilities, and in turn certain households, could result in lower-cost energy savings and potentially zero-cost CO_2 emissions reductions, as explored in section 6.4 below.

6.3 Percentage Savings and Cost-Effectiveness Functions

To develop a picture of the effectiveness of DSM spending at a hypothetical utility and of the relationship between DSM spending and the average cost of energy savings, we use our estimated parameter values and equations (6) and (11) to construct Figures 3, 4, and 5 for a representative utility with a 2006 average level of electricity sales per customer (25 MWh). Figure 3 shows that percentage savings is an increasing but concave function of average DSM expenditures per customer on average. Note that spending per customer here is total spending averaged over all customers. The level of spending per customer for DSM program *participants* will be many times higher than the average over all utility customers. Harvesting additional savings tends to become increasingly challenging as the low-cost opportunities are used up. Thus, increased DSM spending has diminishing returns, which can occur due to both increasing the level of spending per participating customer, as well as increasing the number of customers participating in programs. Figure 4 illustrates how the average cost of electricity savings increases with the average level of expenditure per customer in a roughly linear fashion.[33] Both figures (4) and (5) include 95 percent confidence intervals calculated using the delta method with the estimated parameters and variance-covariance matrices for equations (6) and (11).

Figure 5 combines Figures 3 and 4 to provide an average cost curve for different percentages of electricity savings. The average cost curve is convex, indicating that costs rise at an increasing rate as average expenditures per customer increase. Note that this figure suggests that, for a utility with 25 MWh per customer in annual sales, a 1.1 percent savings in electricity can be achieved at an expected average cost of roughly 3 cents per kWh, a much lower average cost than the sample-weighted expected average cost estimate of 6.4 cents per kWh. This difference is attributable to the fact that much of historic DSM spending occurred at utilities with a lower-than-average level of sales per customer and thus a higher cost of achieving reductions than a utility with the average level of sales per customer. Average costs rise with the percentage savings and the function suggests that, to achieve 1.5 percent savings, the utility would have to spend an average of $18 per customer, yielding a central estimate of average cost to the representative utility of roughly 4.5 cents per kWh saved.

6.4 Policy Scenario

The estimated relationships between increased average DSM spending per customer and percentage savings (Eq. 6) and between average DSM spending per customer and average cost of

[33] A recent study by Synapse Energy Economics (Takahashi and Nichols 2008) of a number of different programs uses simple linear regressions of average cost-effectiveness on percentage of incremental electricity savings in the initial year, finding that average costs are flat or slightly decreasing in the level of incremental savings at the utility or program administrator level. They also study the relationship between avearge cost-effectiveness and lifetime energy savings and find similar negative coefficients. In both cases, these linear regressions are typically estimated with a small number of data points, the equations do not control for any other factors that might affect energy savings or costs over time, and they assume utility reports of savings are accurate. For these reasons, that study does not provide reliable information on economies of scale.

energy savings (Eq. 11) can be used to explore the implications of counterfactual energy efficiency investment scenarios. For example, the data suggest that the utilities that invested in energy efficiency in 2006 had a lower level of average consumption per customer (23.9 MWh per customer) than those that did not (30.3 MWh per customer) and that the consumption per customer was even smaller for those that invested at higher than average levels (21.8 MWh per customer for utilities that invested at least $10 per customer, on average, in DSM in 2006). Our model suggests that those utilities with high levels of DSM spending may be facing diminishing returns and thus, ceteris paribus, face high incremental costs of achieving additional energy savings through investments in energy efficiency programs. Equation (11) shows that the average cost of achieving reductions at a utility is inversely related to the level of electricity consumption per customer. This relationship suggests that opportunities for lower-cost electricity savings are available from investing more in energy efficiency DSM at utilities that either currently do not invest in DSM or currently invest at lower levels.

We use the estimated parameters for model 1 to simulate the effects of two counterfactual policies in 2006 in addition to a baseline scenario. In the baseline scenario, we solve equations (6) and (11) using the average level of DSM expenditures per customer reported in the data in 2006 (including the DSM expenditures by third parties that have been allocated to the utility) to find the predicted levels of current and future energy savings for the 410 utilities that are included in our largest, model 1, sample.[34] In the first policy scenario, we increase the average level of DSM spending per customer at all utilities that spent less than $5 per customer to $5 per customer and leave the other, higher-spending, utilities at their reported levels. In the second scenario, we increase the average level of DSM spending per customer at all utilities that spent less than $10 per customer in 2006 up to that level and leave the other spending the same.

The results are displayed in Table 4. The first policy scenario suggests that spending an additional $185 million on energy efficiency DSM in 2006 at the 244 utilities that spent less than $5 per customer, on average, in 2006 would have resulted in 8.3 billion kWh of additional electricity savings at an incremental cost of 2.2 cents per kWh. Under the second scenario, spending an additional $440 million on DSM at the 270 utilities that spent less than $10 per customer, on average, in 2006 would have produced an additional 14 billion kWh of additional

[34] In these simulations, we assume that the future demand for each utility stays at 2006 levels into the future. On balance, this probably provides a conservative estimate of future electricity savings attributable to DSM expenditures today and thus may bias estimates upwards.

electricity savings at an expected incremental cost of 3.1 cents per additional kWh saved relative to the baseline.[35] These scenarios suggest that potential opportunities for cost-effective incremental electricity savings are probably available at those utilities that are not currently making substantial investments in energy efficiency. Thus, the most efficient allocation of demand reductions would not seem to be one that imposes the same reduction requirements on all utilities.

Furthermore, under both scenarios, the expected incremental cost per kWh saved is less than half the retail price of electricity in almost all of the lower 48 states in 2006 and generally lower than wholesale electricity prices as well.[36] This difference suggests that, even if costs to consumers of DSM programs are equal to utility costs, the targeting of incremental DSM expenditures at certain types of utilities could result in zero-cost reductions in CO_2 emissions, although assessing the magnitude of these potential reductions is beyond the scope of this paper.

The results of this historical simulation exercise should be interpreted with care. The demand function parameters that we estimate are based on the collection of energy efficiency programs that were in existence over the 18-year sample period from 1989 through 2006. Thus, changes in the composition of measures included in energy efficiency programs, such as the recent increase in savings attributable to compact fluorescent light bulbs, are not reflected in the simulation analysis. Moreover, the data set that we use for the estimation incorporates all DSM spending included in the EIA-861 database plus incremental state-level spending, and no attempt is made to distinguish highly cost-effective programs from those that performed less well on cost-effectiveness grounds. Thus, the model is limited in its ability to provide predictions about the performance of any particular DSM program or insights into how a "state-of-the-art" energy efficiency DSM program is likely to perform. However, it does provide insight into how programs performed on average over this time period and what types of opportunities might exist if future programs were to perform similarly (no better and no worse), on average.

[35] A large portion of the energy savings from existing programs over this time period have come from programs that invest in energy efficient lighting. To the extent that recently legislated lighting efficiency standards will lower the energy consumption associated with lighting in the future, this could lower the potential savings from future DSM lighting programs and raise their costs. Alternatively, there may be future improvements in utility's and other program administrator's ability to deliver savings that are not captured here and could contribute to lowering incremental costs of future energy savings relative to what is reported here.

[36] According to EIA, however, the incremental cost of the energy savings under policy scenario 2 is more than 50 percent of the average retail price of electricity in Idaho, Kentucky, West Virginia, and Wyoming in 2006.

7. Conclusions

The cost-effectiveness of utility DSM programs is a subject of considerable interest and study. Most of the past efforts to study cost-effectiveness generally take utility reports of electricity savings attributable to DSM programs as given, often adjusting by a preestablished net-to-gross factor to account for free riders net of spillover effects. In this analysis, we take a different approach that relies on econometric techniques to estimate how DSM expenditures affect actual growth in electricity demand, controlling for other demand drivers, such as changes in price and income. We build on earlier work by expanding the data set, including additional important explanatory variables, and developing a carefully motivated flexible functional form to describe the accumulation of past and current DSM expenditures per customer into a DSM capital variable. By focusing on average DSM per customer, we control for the scale of a utility's operation in a way that we believe is an improvement on the specification used in L&K. We also find that the sensitivity of L&K results to the estimation sample was probably due to limitations in functional form, rather than the sample per se.

Our main model results suggest that, over the 18-year period covered by this analysis, rate payer–funded DSM expenditures produced a central estimate of 1.1 percent savings in electricity consumption at an average cost to utilities of roughly 6.4 cents per kWh saved. Using a nonparametric bootstrapping approach, we find that the 95 percent confidence interval for savings ranges from 0.6 percent to 1.4 percent, whereas the confidence interval for average cost spans values from 4.4 to 10.9 cents per kWh.

We also used our econometric results to parameterize functional relationships between (a) the percentage savings and the average level of DSM expenditure per customer and between (b) the average cost of savings and both the average level of DSM expenditure per customer and the amount of electricity consumed per customer. These functions suggest that percentage savings is an increasing but concave function of the average level of DSM spending per customer and that average cost varies linearly with expenditures. Putting these two functions together allows us to trace out an average cost curve for percentage reductions in electricity consumption that is increasing and convex. We can also use these functions to simulate the effects of policies that increase energy efficiency spending by utilities that had no or low levels of spending in the past. We find that increasing energy efficiency DSM program spending at the 270 utilities in our sample in 2006 that had expenditures of less than $10 per customer, on average, by a total of $440 million could result in a central estimate of 14 billion kWh in incremental electricity savings at an expected incremental cost of about 3.1 cents per kWh.

Utility energy efficiency programs are taking center stage in ongoing discussions about U.S. energy policy and how best to combat climate change. Studies such as the recent McKinsey Study (Granade et al. 2009) on the potential for saving energy at low or negative cost are part of this debate. However, missing from studies like McKinsey's are the specific policy measures that would be required to bring about the investments and behavioral changes necessary to realize these energy savings and estimates of the extent to which the costs of implementing these policies might differ from the engineering costs. The present study offers additional evidence about how effective past utility and third-party state-level programs have been in reducing electricity demand, and how much they have cost per unit of electricity saved.

Tables and Figures

Table 1. Summary Statistics

	Sample 1					Sample 2				
Number of observations	3,155					1,614				
Number of utilities	513					189				
Variable	mean	median	std dev	min	max	mean	median	std dev	min	Max
D.LN.Electricity demand	0.027	0.025	0.045	–0.290	0.285	0.022	0.021	0.044	–0.289	0.285
Electricity demand (billion kWh)	6.86	0.89	14.90	0.16	104.00	9.07	2.16	16.70	0.17	104.00
Electricity demand per cust (MWh)	27.9	22.7	45.5	6.8	782.3	26.1	23.3	17.9	8.4	251.1
DSM spending ($ millions)	3.50	0.03	14.16	0	230.20	6.53	0.58	19.16	0.00	230.20
DSM spending per customer ($)	8.08	0.88	15.16	0	162.90	14.57	7.49	18.18	0.00	162.90
Number of customers (thousands)	277	41	626	1	4,782	394	93	774	1	4,782
Population (thousands)	8,827	5,991	7,926	480	36,200	10,000	5,991	9,353	583	36,200
State GDP ($ billions)	361	253	347	18	1788	422	253	411	18	1788
Housing starts per capita	0.008	0.005	0.012	0.000	0.095	0.009	0.005	0.015	0.000	0.095
Electricity price (cents per kWh)	8.44	7.72	2.34	4.76	15.87	9.12	8.03	2.73	4.76	15.87
Natural gas price (cents per Mcf)	10.65	10.38	2.99	5.35	22.12	11.05	10.79	3.12	5.35	22.12
Fuel oil price (cents per gallon)	136.46	124.19	41.55	73.40	275.31	144.65	133.73	43.72	73.40	275.31
Climate	1,634	1,424	817	369	3,937	1,490	1,154	880	369	3,937
Indicator for decoupling	0.042	0	0.202	0	1	0.066	0	0.249	0	1
Indicator: most stringent bldg codes	0.033	0	0.178	0	1	0.055	0	0.228	0	1
Indicator: more stringent bldg codes	0.796	1	0.403	0	1	0.812	1	0.391	0	1
Indicator: building codes	0.872	1	0.334	0	1	0.885	1	0.319	0	1

Notes: Dollars are inflation-adjusted to 2007. LN denotes variable is logged. D denotes first-difference of variable. Mcf denotes thousand cubic feet.

Table 2. Estimation Results

Explanatory variables	Coefficient	Model 1 Sample 1	Model 2 Sample 1	Model 3 Sample 2	Model 4 Sample 2
DSM expenditure and all lags	γ	–140***	–120***	–170**	–170**
		53.0827	48.3672	83.6770	78.5208
1-exp(gamma*DSM expenditure)	β_0	0.0024	0.002	–0.0041	–0.0051
		0.0046	0.0047	0.0049	0.0050
1-exp(gamma*L1.DSM expenditure)	β_1	–0.0038	–0.0038	0.0076	0.0077
		0.0067	0.0068	0.0058	0.0059
1-exp(gamma*L2.DSM expenditure)	β_2	0.0023	0.0026	–0.0016	–0.0011
		0.0053	0.0054	0.0061	0.0062
1-exp(gamma*L3.DSM expenditure)	β_3	–0.0076	–0.0074	–0.0153**	–0.0154**
		0.0066	0.0068	0.0070	0.0070
1-exp(gamma*L4.DSM expenditure)	β_4	0.0064	0.0064	0.0070	0.0072
		0.0057	0.0059	0.0071	0.0072
1-exp(gamma*L5.DSM expenditure)	β_5	–0.0088*	–0.0091*	–0.0058	–0.0066
		0.0049	0.005	0.0060	0.0061
1-exp(gamma*L6.DSM expenditure)	β_6	–0.0076*	–0.0081*	–0.0061	–0.0066
		0.0042	0.0044	0.0049	0.0049
F-statistic for joint DSM		8.018***	8.074***	3.450**	4.128**
D.LN.Number of customers	λ_1	0.3238***	0.3232***	0.3739***	0.3731***
		0.05	0.0501	0.0674	0.0669
D.LN.Population	λ_2	0.4616***	0.4329***	0.4409***	0.4443***
		0.0916	0.093	0.1592	0.1617
D.LN.Gross state product	λ_3	0.1349***	0.1317***	0.2347***	0.2329***
		0.0366	0.0369	0.0586	0.0592
D.LN.Housing starts per capita	λ_4	0.0158*	0.0152*	0.0138	0.0103
		0.0084	0.0084	0.0119	0.0123
D.LN.Price of electricity	α_1	–0.0467**	–0.0469**	–0.0483*	–0.0507*
		0.0214	0.0213	0.0279	0.0280
D.LN.Price of natural gas	α_2	–0.0144*	–0.015*	–0.0115	–0.0122
		0.0079	0.0079	0.0117	0.0118
D.LN.Price of fuel oil	α_3	0.0394**	0.0388**	0.0278	0.0287
		0.017	0.017	0.0272	0.0263
D.LN.Climate	ρ	0.1056***	0.1058***	0.1023***	0.1032***
		0.0077	0.0077	0.0094	0.0095
Indicator for decoupling regulation	ν		-0.0045		–0.0060
			0.0034		0.0039
Indicator: Most stringent bldg codes	ϕ_1		0.0056		0.0053
			0.0038		0.0045
Indicator: More stringent bldg codes	ϕ_2		0.0000		0.0057**
			0.0023		0.0025
Indicator: Building codes	ϕ_3		0.0034		0.0006
			0.0026		0.0034
F-statistic for joint building codes			1.444		3.208**
Adjusted R^2		0.45	0.45	0.40	0.40
Number of observations		3,155	3,155	1,614	1,614

Notes: The dependent variable is change in the log of electricity demand. LN denotes variable is logged. L1 and L2 denote 1-year and 2-year lags of variable. D denotes first-difference of variable. Standard errors below coefficient estimates. * indicates statistical significance at 10%, ** at 5%, and *** at 1% level. See text and Table A-2 for further detail on variable construction.

Table 3. Estimated Average Cost-Effectiveness and Percentage DSM Energy Savings

	Model 1	Model 2	Model 3	Model 4
Average cost-effectiveness (2007 cents per kWh)	6.4	6.4	5.9	5.5
95% confidence interval	(4.4–10.9)	(4.5–10.9)	(2.6–15.7)	(2.5–13.7)
% average DSM energy savings	1.1	1.1	1.3	1.4
95% confidence interval	(0.6–1.4)	(0.6–1.3)	(0.4–2.7)	(0.5–2.8)

Note: The confidence intervals reported here are based on approximately 1,000 replications of a nonparametric bootstrap.

Table 4. Estimated Incremental Savings and Cost-effectiveness of Greater DSM Spending at Utilities with Low Spending in 2006 (2007$)

	Total DSM expenditures (million $)	Total electricity savings (BkWh)	Average Cost (cents per kWh)	Incremental expenditures (million $)	Incremental savings (BkWh)	Incremental cost (cents per kWh
Baseline	1,249	18.6	6.7	—	—	—
Scenario 1	1,434	26.9	5.3	185	8.3	2.2
Scenario 2	1,689	32.6	5.2	440	14.0	3.1

Note: BkWh denotes billion kilowatt hours. Emdash — denotes not relevant.

Figure 1. Rate Payer–Funded Energy Efficiency Expenditures

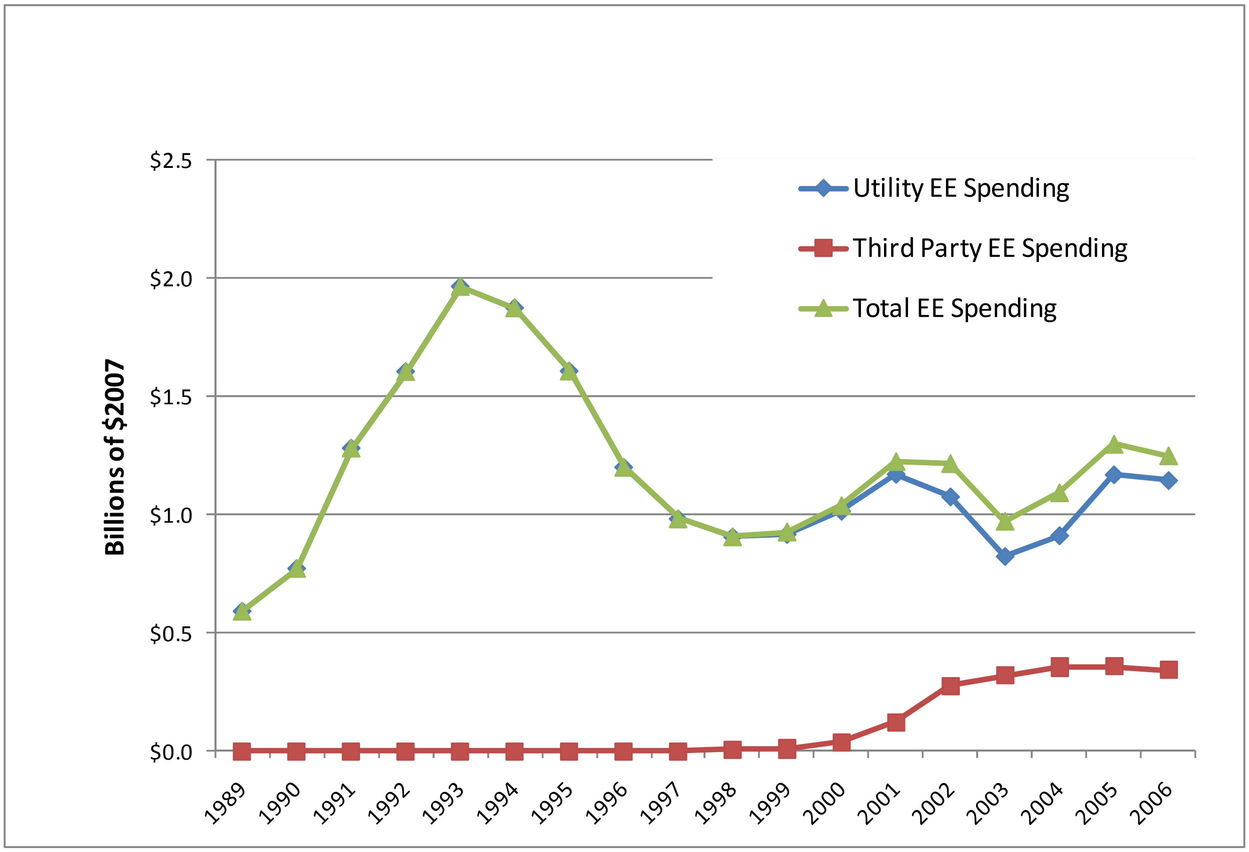


Figure 2. Stringency of Building Codes in 2007

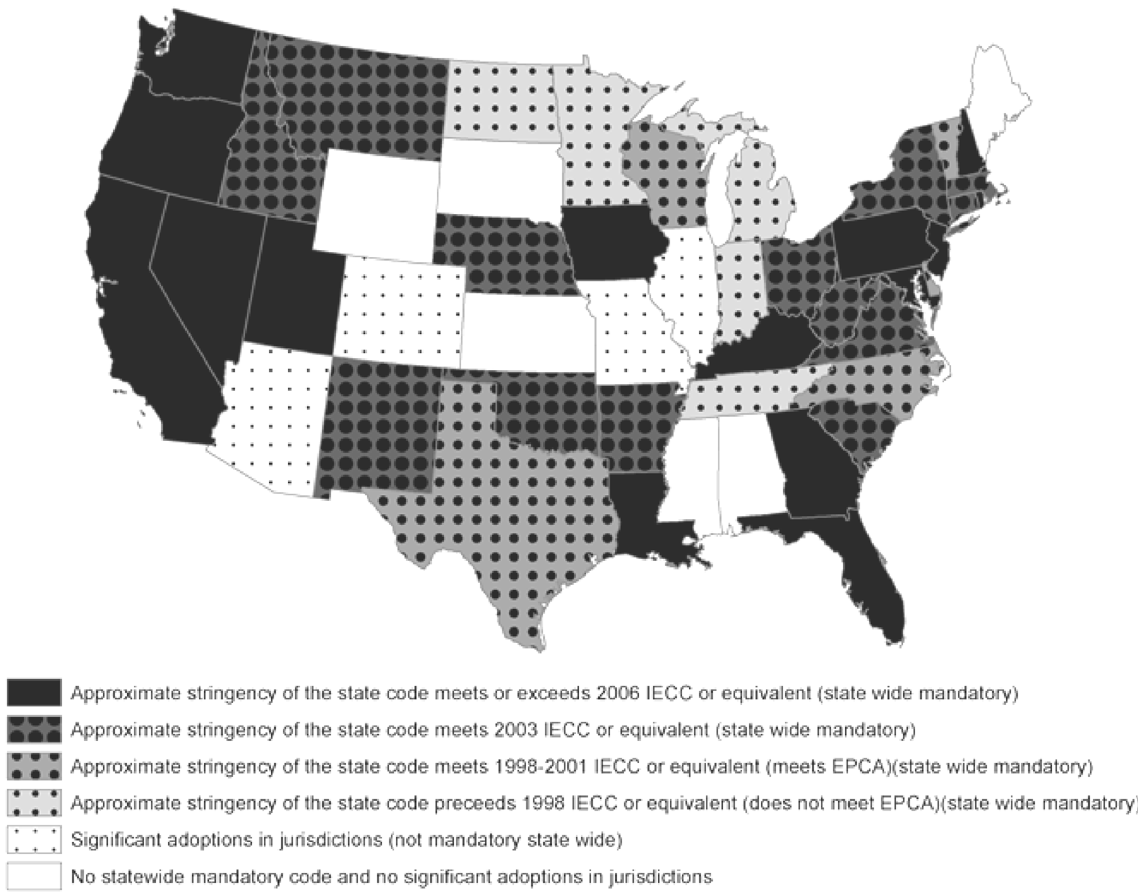
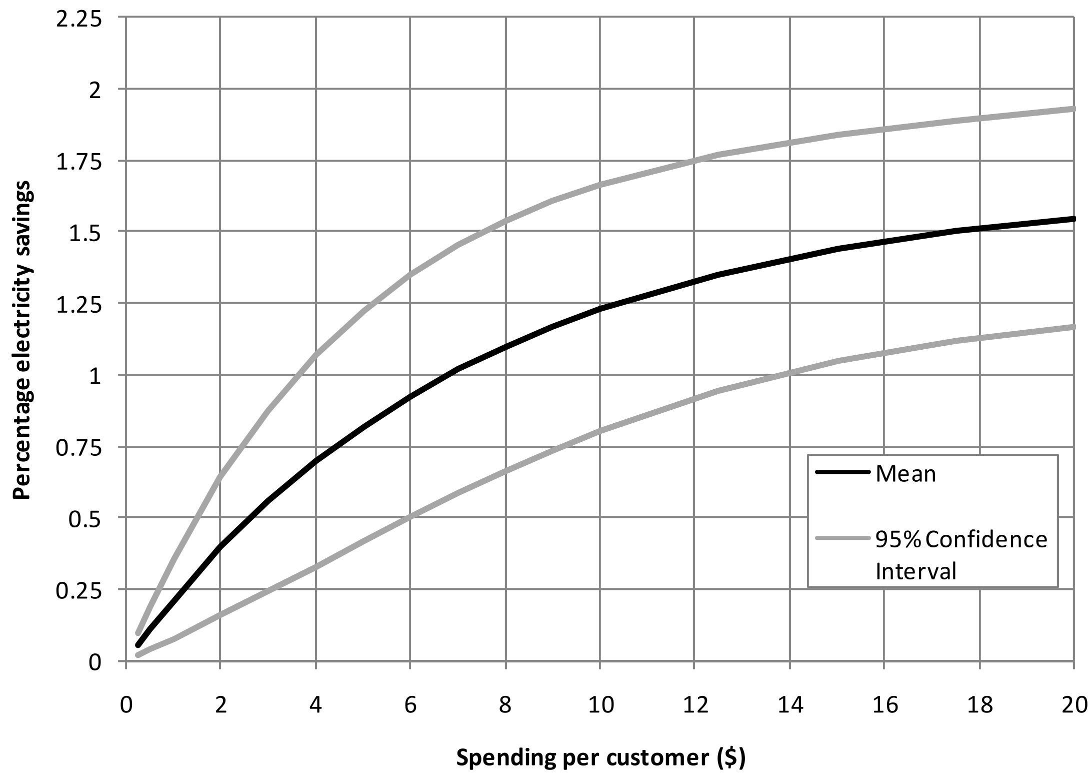
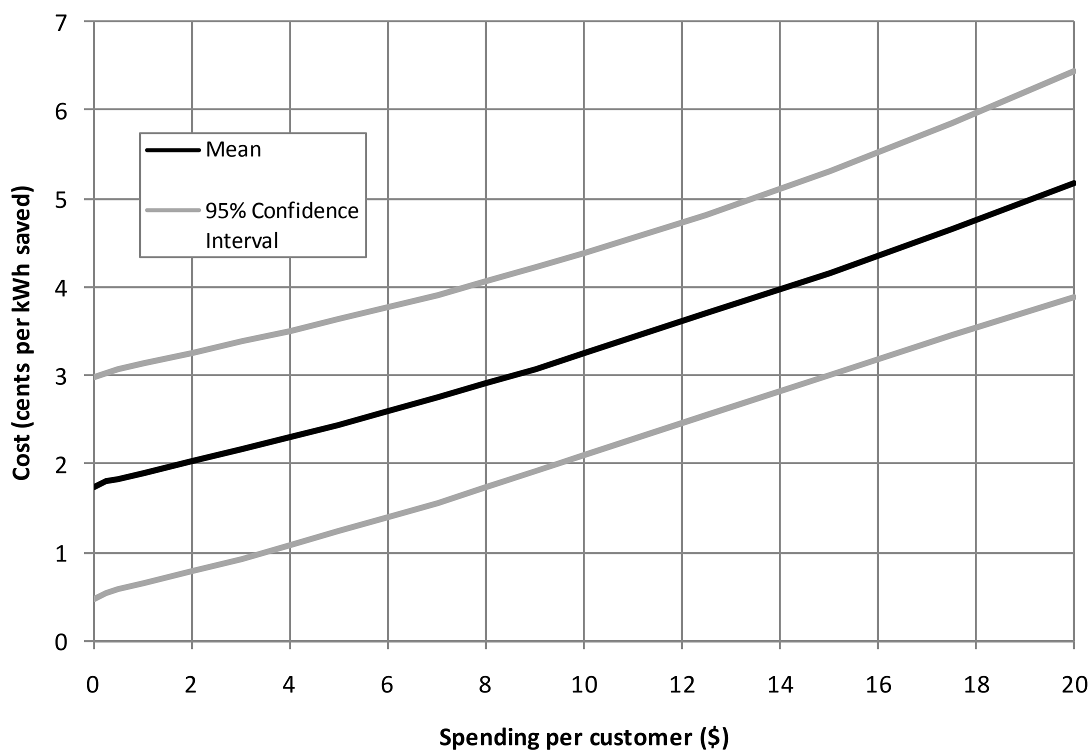


Figure 3. Percentage Electricity Savings as a Function of DSM Spending per Customer



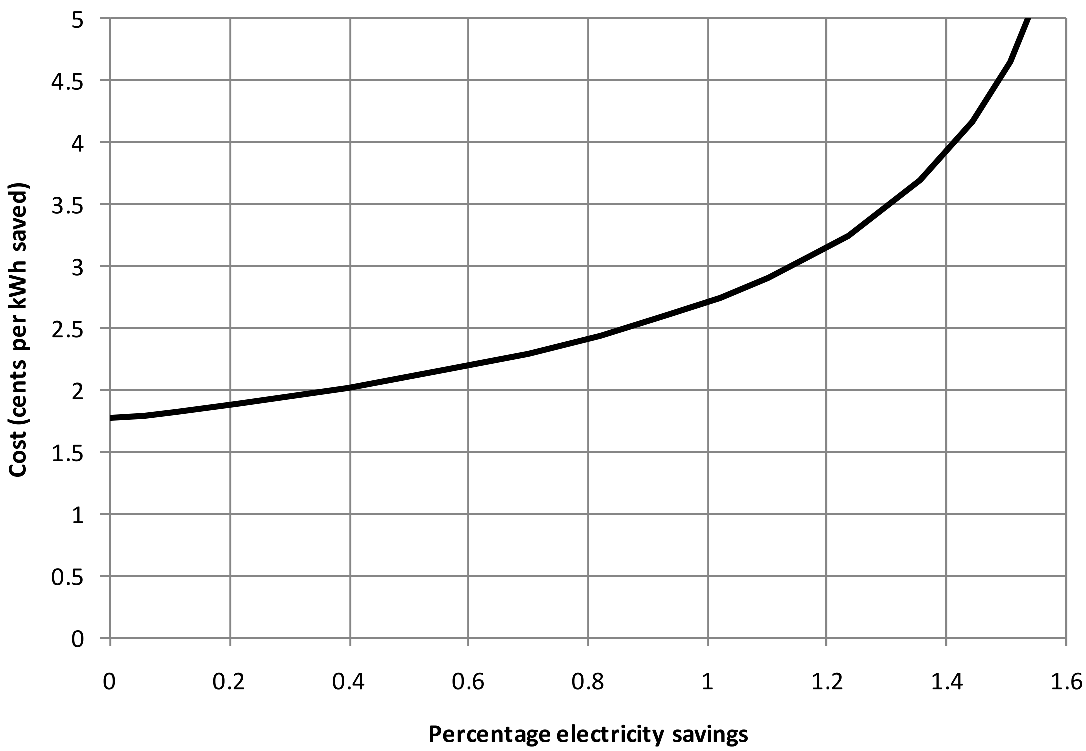
Note: Real 2007$. Predictions based on eq. (6) using model 1 estimates.

Figure 4. Average Cost per kWh as a Function of DSM Spending per Customer



Note: Real 2007$. Based on eq. (11), using model 1 estimates for a utility with mean 2006 electricity sales per customer of 25 MWh.

Figure 5. Cost per kWh as a Function of Percentage Savings from DSM



Note: Real 2007$. Based on eq. (6) and (11), using model 1 estimates for a utility with mean 2006 electricity sales per customer of 25 MWh.

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Appendix

Table A-1. Variable Definitions and Data Sources

Variable	Definition	Data source
DSM expenditure	DSM spending per 1,000 customers	EIA-861
D.LN.Number of customers	First difference of log of total number of customers served by utility	EIA-861
D_LN.Population	First difference of log of population in state in which utility has most of its sales	Census
D_LN.Gross state product	First difference of log of gross state product	Bureau of Economic Analysis
D_LN.Housing starts per capita	Log of annual housing starts per capita by state	Mitsubishi Bank
D.LN.Price of electricity	First difference of log of average annual state-level price of electricity to final consumers in $ per kWh	EIA
D.LN.Prce of natural gas	First difference of log of residential natural gas price by state in $ per trillion cubic feet	EIA
D.LN.Price of fuel oil	First difference of log of price of fuel oil number two in $ per gallon	EIA
D.LN.Climate	First difference of log of the sum of population-weighted heating degree days also weighted by electricity share of heating consumption in million BTUs and population-weighted cooling degree days	NOAA and EIA
Indicator for decoupling	Dummy variable set equal to one if utility operates in state that has decoupling	American Council for an Energy Efficient Economy, National Association of Regulatory Utility Commissions
Indicator: Most stringent bldg codes	State building code meets or exceeds 2006 IECC standard	Building Codes Assistance Project, DOE
Indicator: More stringent bldg codes	State building code meets or exceeds 1998 IECC standard or more recent ones	Building Codes Assistance Project, DOE
Indicator: bldg codes	State building codes are significantly adopted in most jurisdictions or they meet or exceed 1998 IECC standard or more recent ones	Building Codes Assistance Project, DOE

Table A-2. Third-Party DSM Expenditures: State, Year, and Data Source (millions of 2007$)

State	1998	1999	2000	2001	2002	2003	2004	2005	2006	Administrator
Illinois	0.00	0.00	0.00	0.00	0.00	3.21	3.12	0.93	1.06	Department of Commerce and Economic Opportunity (Energy Efficiency Trust Fund)
Maine	0.00	0.00	0.00	0.00	0.00	2.80	5.11	8.26	9.33	Efficiency Maine
Michigan	0.00	0.00	0.00	0.00	1.12	2.51	3.66	3.70	2.89	Michigan Public Service Commission (The Low-Income and Energy Efficiency Fund)
New Jersey	0.00	0.00	0.00	66.19	107.25	99.44	101.52	90.53	81.78	New Jersey Board of Public Utilities (New Jersey Clean Energy Collaborative)
New York	7.86	12.05	30.54	80.34	137.77	160.32	152.87	150.86	155.01	New York State Energy Research and Development Authority
Oregon	0.00	0.00	0.00	0.00	8.41	27.46	43.89	54.49	46.69	Energy Trust of Oregon
Vermont	0.00	0.00	6.71	10.30	12.63	14.59	15.31	16.01	15.24	Efficiency Vermont
Wisconsin	0.00	0.00	0.00	0.00	29.07	50.65	42.62	41.48	40.84	Focus on Energy
Total	7.86	12.05	37.25	156.83	296.24	360.98	368.11	366.26	352.84	