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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 ratepayer-funded programs to promote demand-side management (DSM) and energy efficiency (EE) investments. We specify a model that relates electricity demand to previous EE DSM spending, energy prices, income, weather, and other demand factors. In contrast to previous studies, we allow EE DSM spending to have a potential long-term demand effect and explicitly address possible endogeneity in spending. We find that current period EE DSM expenditures reduce electricity demand and that this effect persists for a number of years. Our findings suggest that ratepayer-funded DSM expenditures between 1992 and 2006 produced a central estimate of 0.9 percent savings in electricity consumption over that time period and 1.8 percent savings over all years. These energy savings came at an expected average cost to utilities of roughly 5 cents per kWh saved when future savings are discounted at a 5 percent rate.

Key Words: energy efficiency, demand-side management, electricity demand

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 $2 billion (2007$) on energy efficiency demand-side management (EE 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, often 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 such reductions have been obtained. Estimates of the cost-effectiveness, or cost per kWh

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

saved, of past DSM programs range from just below 1 cent per kWh saved to more 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 2009), 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 2007) suggest 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] Efficiency Vermont reports higher incremental savings from its 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 (EPA) and 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. More than 20 states, including Maryland and New York, have announced specific goals 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

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[2] See Gillingham et al. (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 2009). Reid (2009) breaks down 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 (2007) divided by total 2005 sales reported in Form 1.1 (CEC 2007).

achieved is yet to be determined, but several of the states participating in the Regional Greenhouse Gas Initiative are using a substantial portion of the revenue from carbon dioxide (CO_2) allowance auctions to fund DSM initiatives.[5] Several recent federal legislative proposals to impose a national CO_2 cap-and-trade program also included 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. Stand-alone legislative proposals have also been put forth to create an energy efficiency resource standard or include energy efficiency as part of a clean energy standard that requires a minimum percentage of electricity supply to come from zero- or low-carbon-emitting sources.

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 ratepayer-funded utility and third-party DSM spending on electricity demand at the utility level. There are key differences between our study and previous studies. First, our empirical method deals with the potential endogeneity of DSM spending. We use two political variables—League of Conservation Voters scores and Republican presidential voting percentages in each utility's service territory—as instrumental variables. Second, our model allows for a long-term demand effect from DSM spending. To characterize the time path of the demand effect of DSM spending, we use a flexible function that allows the dynamic effect to increase and then decrease over time. We estimate the model using nonlinear least squares assuming no endogeneity and generalized method of moments with optimal instruments to account for possible endogeneity of DSM spending. We also explore the effects on electricity consumption of decoupling regulation and building energy efficiency codes.

We find that current-period DSM expenditures have a negative effect on electricity demand that persists for a number of years. Based on our results using the largest sample of utilities, our findings, which are robust across different modeling approaches and samples, suggest that ratepayer-funded DSM expenditures between 1992 and 2006 produced a central estimate of 0.9 percent savings in electricity consumption over that time period and a 1.8 percent

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[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 reduce the likelihood that power imports from non-RGGI states will increase under the program (RGGI 2008). As of the end of 2010, the second full year of the RGGI program, more than 50 percent of RGGI CO_2 allowance revenues across the 10 RGGI states collected over the life of the program were used to fund energy efficiency (RGGI Inc. 2011).

savings over all years at an expected average cost to utilities of roughly 5 cents per kWh saved when future savings are discounted at 5 percent. This estimate, which is statistically significant at the 90 percent level, is lower than those of Loughran and Kulick (2004) and at the low end of the range reported by Auffhammer, Blumstein and Fowlie (2008). We also find that for utilities located primarily in states where housing starts are above the mean, the presence of more stringent building costs has a statistically significant negative effect on electricity demand.

The rest of the paper is organized as follows. Section 2 reviews past empirical studies on DSM and energy efficiency. Section 3 examines the effects of electricity sector restructuring on DSM programs and the growing role of 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. Section 6 analyzes the results of the estimation and their implications for cost-effectiveness of energy efficiency expenditures, and Section 7 concludes.

2. Empirical Economic Studies of DSM

Several empirical economic studies have evaluated the effectiveness and cost-effectiveness of utility DSM programs focused on energy efficiency. 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 efficient equipment. Much of this literature was 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. Gillingham et al. (2004) use DSM expenditures by utilities and annual savings reported by utilities to the EIA to derive a cost-effectiveness estimate of 3.9 cents per kWh saved in the year 2000.

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 et al. (2008), which weighted savings and costs by utility size in the construction of a mean cost-effectiveness measure, found a substantially lower estimate of cost per kWh than reported by L&K—a result not disputed by L&K. In their work, Auffhammer et al. found DSM expenditure-weighted average cost estimates ranging 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 Auffhammer et al. found contain the utility-reported estimates. Auffhammer and colleagues pointed out that the

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

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) used 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 employed measures of reported electricity savings attributable to DSM programs to categorize utilities. He found 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 did not look at the question of cost-effectiveness.

Our analysis uses the basic approach of L&K as a starting point. In addition to the key differences between our method and those reported in all previous literature discussed above, our study modifies and augments L&K in several important ways. First, we augment the dataset 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 ratepayers 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 Auffhammer et al., 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 scales. We also carefully lay out the derivation of our estimated cost-effectiveness measures and make a number of other improvements in estimation, as described further below.

3. Evolution of Ratepayer-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, which 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 et al. 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 (ACEEE 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

[7] Note that since 2000, the spread of electricity restructuring has stalled and even been reversed in some states, with the California Public Utility Commission suspending retail competition in March 2002 and the Virginia state legislature rejecting retail competition for 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.

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 York, Ohio, Oregon, Vermont, and Wisconsin—these public benefit efficiency programs are administered by either a state government entity (e.g., a state energy office) or a for-profit or nonprofit 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 ratepayer-funded DSM expenditures.[9] Although these programs have not fully offset the decline in utilities' own spending on DSM, they have partially filled the gap.

4. Empirical Model and Estimation Strategy

Our aim in this paper is to estimate an empirical model of electricity demand change in response to multiple factors, particularly variables related to DSM. Based on the estimated model, we compute estimates of energy savings from DSM, the cost-effectiveness of DSM, and confidence intervals for these measures.

4.1. Empirical Model of Electricity Demand

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

$$Q_{ut} = f(X_{ut}, D_{ut}, \xi_u, \mu_t, \varepsilon_{ut}), \tag{1}$$

where Q_{ut} is aggregate electricity demand. X_{ut} includes a number of demand factors, such as number of customers, level of economic activity, energy prices, weather conditions, and regulatory variables influencing electricity demand. D_{ut} is a vector of DSM spending per customer in current and previous years, $D_{ut} = \{d_{ut}, d_{u,t-1}, d_{u,t-2}, ..., d_{u,t_0}\}$, with t_0 being the year when DSM spending began in utility *u*. This vector is used to capture the fact that the amount of energy efficiency capital owned by customers is a function of all past DSM spending by the utility or other entity charged with implementing DSM programs on behalf of electricity

[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 on EIA Form 861.

customers. ξ_u is a vector of utility-level fixed effects. μ_t is a vector of year fixed effects. And ε_{ut} captures idiosyncratic demand shocks.

Following the literature, we specify the following baseline function for estimation, with the dependent variable being the logarithm of electricity demand:

$$\ln(Q_{ut}) = X_{ut}\alpha + \xi_u + \eta_t + \sum_{j=0}^{t-t_0} \lambda(j)[1 - \exp(\gamma d_{u,t-j})] + \varepsilon_{ut}, \tag{2}$$

where the key variables of interest, past and current DSM spending per customer, are in the fourth term on the right side. Because we ultimately estimate a model to predict percentage changes in demand, we use average DSM spending per customer, rather than simply the level of DSM. Otherwise, the effect on electricity saved of an additional dollar of DSM spending would be larger for larger utilities, which is conceptually incorrect.

Our specification allows DSM spending in all previous years to potentially affect current demand. The exponential function allows the partial effect of DSM spending on electricity demand to vary with DSM spending per customer. $\lambda(j)$ gives the individual effects of current and past DSM expenditures as a function of when they were made relative to year *t*. We use a parametric function for $\lambda(j)$, to be specified below, to capture the time path of the demand effect from previous DSM spending. γ gives the rate of diminishing (or increasing) returns (Jaffe and Stavins 1995). The rate of diminishing returns increases as γ gets large in magnitude, whereas the function becomes linear (i.e., constant returns to DSM) as γ becomes closer to zero. We would expect γ to be negative if increased DSM spending lowers electricity demand. Thus, for example, when λ is positive and γ is negative, the function implies that DSM spending will reduce electricity demand, but at a decreasing rate. In one of the alternative specifications, we use a linear function in DSM spending per customer in the fourth term on the right side of equation (2).[10]

We specify a parametric function for the time effect of DSM spending rather than estimate it nonparametrically for two reasons. First, this parametric function allows DSM spending in all previous years to potentially affect current demand. Our estimation results using

[10] In this research, we initially explored a functional form that was more similar to that used by L&K in that DSM expenditures were entered in a log form, but still using DSM per customer, for the reasons explained. 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 led to very extreme curvature of the percent savings as a function of DSM expenditures and, in turn, of the average cost function described below.

parametric specifications as well as initial estimates using nonparametric specifications suggest that the effect of DSM spending could have long lags. Second, the parametric specification avoids dropping data in the early years as the nonparametric specification does. This is important empirically, given our relatively small sample size.

We use a two-parameter function for $\lambda(j)$ to allow a flexible shape for the long-term effect of DSM spending: the effect could be decreasing over time or have a single peak at a point in time. In the baseline specification, we use the probability density function of a gamma distribution:

$$\lambda(j,\eta_1,\eta_2)=\eta_1^{\eta_2}(j+1)^{\eta_1-1}\exp[-\eta_2(j+1)]/\Gamma(\eta_1), \tag{3}$$

where $\Gamma(\eta_1)$ is a gamma function. The two parameters η_1 and η_2 will be estimated together with other parameters in the demand function. In an alternative specification, we use the probability density function of a Weibull distribution and obtain similar results.

The demand model of equation (2) is specified as if EE DSM spending for all previous years were available. As described in Section 5, our data start in 1989, but many utilities engaged in demand-side management programs long before that, and systematic data on DSM spending before 1989 are not available. We modify equation (2) to address this issue. Specifically, we use a flexible function of DSM spending in early years in our data (i.e., 1989–1991) to control for the demand effect of DSM spending that occurred before our data period begins:

$$\ln(Q_{ut})=X_{ut}\alpha+\xi_u+\eta_t+\sum_{j=0}^{t-t_0}\lambda(j)[1-\exp(\gamma d_{u,t-j})]+f(\bar{d}_{u,t_0-1},\tau_t)+\varepsilon_{ut}, \tag{4}$$

where t_0 is chosen to be 1992, implying that equation (4) is estimated for electricity demand beginning from 1992.[11] The control function $f(\bar{d}_{u,t_0-1},\tau_t)$ is a high-order polynomial function of average DSM spending during 1989–1991 and the time trend variable to capture the effect of DSM spending prior to 1989 on electricity demand after 1992. $\bar{d}_{u,t_0-1}$ is the average DSM spending of utility u from 1989 to 1991, and τ_t is the inverse of the number of years since 1991. In the baseline estimation, we include nine interaction terms between the polynomials of $\bar{d}_{u,t_0-1}$ and the polynomials of the time trend variable (both up to the third order). We also conduct

[11] In choosing the number of years for which to construct the proxy for DSM spending before 1989, we face the trade-off between having a good proxy (favoring using a larger number of years) and losing data in demand estimation. Sensitivity analysis shows that setting t_0 to be 1992 or 1993 gives similar results.

robustness checks using different specifications of this control function. Our results show that without controlling for the effect of early DSM expenditures (i.e., not including the control function), the demand effect of recent DSM spending would be substantially overestimated.

4.2. Estimation Strategy

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. Thus, the equation that we bring to the data is given by

$$\ln\left(\frac{Q_{ut}}{Q_{u,t-1}}\right) = \Delta X_{ut}\alpha + \Delta\mu_t + \sum_{j=0}^{t-t_0} \lambda(\eta_1,\eta_2, j)[1-\exp(\gamma d_{u,t-j})] - \sum_{j=0}^{t-t_0-1} \lambda(\eta_1,\eta_2, j)[1-\exp(\gamma d_{u,t-1-j})] + \Delta f(\overline{d}_{u,t_0-1},\tau_t) + \Delta\varepsilon_{ut}, \tag{5}$$

Because η_1,η_2, and γ enter the equation nonlinearly, this equation can be estimated using the nonlinear least squares method. A potential concern in estimating this equation is that DSM spending could be correlated with unobserved demand shocks. For example, utilities may decide to spend more on EE DSM in response to stronger demand coming from shocks that we do not observe (and captured by ε_{ut}). Ignoring this correlation, the nonlinear least squares method would underestimate the effect of DSM spending on demand. On the other hand, the bias could go in the opposite direction if utilities with more effective programs, and thus lower demand, tend to spend more. To our knowledge, the endogeneity issue has not been addressed in previous empirical literature on DSM.

We address the endogeneity concern in two ways, both within the framework of nonlinear generalized method of moments (GMM). First, because we specify the dynamic path of the DSM effect on demand in a parametric form with only two parameters, the third term in equation (5) has only three parameters (η_1,η_2, and γ), but 15 DSM spending variables because we use DSM data from 1992 through 2006. If we assume that current demand shocks are uncorrelated with DSM spending that occurred in the far past, we can employ GMM to estimate the model where lagged DSM spending (as well as their polynomials), denoted by LD_{ut}, can be used as instruments to form moment conditions. Given the nonlinear nature of the model, we construct feasible optimal instruments to improve the efficiency of the GMM estimator. Denoting all the parameters in the model as θ and exogeneous variables as Z, Chamberlain (1987) showed that the optimal instruments in our context are given by $\nabla_\theta E[\log(Q_{ut}/Q_{u,t-1}) \mid z,\theta]$. Following Newey and McFadden (1986), we construct optimal instruments using polynomials of LD_{ut} in an iterative procedure. The procedure starts by using the exogenous variables themselves to obtain initial parameter estimates $\hat{\theta}$ and $\nabla_\theta E[\log(Q_{ut} / Q_{u,t-1}) \mid z, \hat{\theta}]$, which is then regressed on Z including polynomials of LD_{ut}. The fitted values are then used as instruments in the next iteration.

Identification in the previous approach arises from the parametric functional form assumption on $\lambda(j)$, and no excluded exogenous variables are needed. In the second approach, we add additional exclusion restrictions based on two political economy variables: the average League of Conservation Voters (LCV) environmental scores of federal legislators who represent voters in the utility's service territory, and the percentage of voters who voted for the Republican candidate in the last political election. We construct both variables for the area served by each utility. In estimation, these two variables and their polynomials are used to construct optimal instruments in an iterative procedure outlined above. We find that both approaches produce similar results.

4.3. Examining DSM Effectiveness and Cost-Effectiveness

Next we show how equation (4), once the parameters have been estimated, can be transformed to yield expressions to examine both the effectiveness and cost-effectiveness of DSM spending. We measure effectiveness by using two metrics: percentage electricity savings across all utilities from 1992 to 2006 attributable to DSM spending during this period; and electricity savings from 1992 on due to DSM spending during 1992–2006 as a percentage of electricity consumption during 1992–2006.12 Different from the first measure, the second measure also includes the demand effect after the data period as a result of EE DSM spending that occurred during the data period. The first measure can be computed directly from the data based on parameter estimates, whereas the second one necessitates an assumption about the level of electricity demand after 2006.

The estimated percentage change at utility *u* in year *t* (before 2007) due to current and past DSM spending from 1992 on, $\%S_{ut}$, is given:

[12] L&K and Auffhammer et al. report alternative summary statistics for aggregating savings and costs across utilities and time, including unweighted means. We agree with Auffhammer and colleagues that the alternative unweighted measures are misleading and therefore do not report them here.

(6) $$\%S_{ut} = \frac{Q_{ut}^{'}(D_{ut}=0) - Q_{ut}(D_{ut})}{Q_{ut}(D_{ut})} = \frac{1-\exp\left\{\sum_{j=0}^{t-t_0}\lambda(j)[1-\exp(\gamma d_{u,t-j})]\right\}}{\exp\left\{\sum_{j=0}^{t-t_0}\lambda(j)[1-\exp(\gamma d_{u,t-j})]\right\}},$$

where $Q_{ut}(D_{ut})$ is electricity consumption at utility *u* in year *t*. Negative γ implies that the percentage change is negative and that consumption is reduced by DSM spending. Note that the electricity savings in any given year are the result of DSM expenditures from year t_0 to the current year.

To calculate an aggregate estimate of electricity savings from DSM across utilities and time, it is necessary to translate percentage savings into a level of savings (in kWh) by multiplying the percentage savings by total electricity consumption:

(7) $$S_{ut} = \%S_{ut} * Q_{ut}.$$

Equation (7) gives a predicted energy savings from DSM for each observation in the sample. With that, we can compute an overall percentage savings estimate by summing energy savings across all utilities and years (1992–2006) and dividing by the sum of electricity consumption.

(8) $$\%S = \frac{\sum_u \sum_t S_{ut}}{\sum_u \sum_t Q_{ut}}, t \in [1992, 2006].$$

Equation (8) provides the first measure of program effectiveness. The second measure is electricity savings from 1992 on (including savings that persist beyond the data period) due to DSM spending during 1992–2006 as a percentage over electricity consumption during 1992–2006. The difference between these two measures lies in the numerator, and the common denominator permits comparison. We use the estimated γ and the $\lambda(j)$ function to predict the cumulative percentage savings at utility *u* after 2006 attributable to DSM expenditures during 1992–2006 at that utility. The percentage saving at utility *u* in year *k* (*k* > 2006) resulting from DSM spending during the data period is given by

(9) $$\%S_{uk} = \frac{Q_{uk}^{'}(D_{u,2006}=0) - Q_{uk}(D_{u,2006})}{Q_{uk}(D_{u,2006})} = \frac{1-\exp\left\{\sum_{j=0}^{t-t_0}\lambda(k)[1-\exp(\gamma d_{u,t-j})]\right\}}{\exp\left\{\sum_{j=0}^{t-t_0}\lambda(k)[1-\exp(\gamma d_{u,t-j})]\right\}}, \ \forall\ k > 2006.$$

$D_{u,2006}$ is a vector of annual DSM spending from 1992 to 2006. To predict total electricity saved in a future year, we assume that electricity consumption is flat after 2006 for each utility:

(10) $$S_{uk} = \%S_{uk} * Q_{u,2006}.$$

We add these future savings to the numerator in equation (8) and obtain the second measure:

(11) $$\%S' = \frac{\sum_u \sum_{t=1992}^{T} S_{ut}}{\sum_u \sum_{t=1992}^{2006} Q_{ut}},$$

where *T* is the last year when 2006 DSM spending ceases to have any demand effect. Our estimates suggest that the effect is practically zero after 20 years, so we do not add future savings after 2026.

To examine the cost-effectiveness of DSM spending, we calculate spending (in cents) per kWh saved. Denoting the number of customers in utility *u* at time *t* by N_{ut}, we divide total DSM spending across all utilities and years by total electricity savings:

(12) $$AC = \frac{\sum_u \sum_{t=1992}^{2006} d_{ut} * N_{ut}}{\sum_u \sum_{t=1992}^{T} S_{ut}}.$$

When the energy savings from DSM spending last a long time, as our empirical results show, one should discount future benefits in order to compare them with upfront DSM spending. Discounting makes a bigger difference in the cost-effectiveness analysis when the energy savings accrue over a longer time period. We calculate average cost per kWh saved (AC) using alternative discount rates: 0, 3, 5, and 7 percent. A higher discount rate implies smaller total discounted electricity savings and hence a larger average cost estimate. We take the estimates based on 5 percent discount rate as the focal point of discussion, as this is in the middle of the 3 and 7 percent rates typically used for government policy analysis.

5. Estimation Variables and Data Sources

Our dataset is a panel of annual utility-level data from Form EIA-861, *Annual Electric Power Industry Report*, and other sources over the 18-year period 1989–2006.[13] The observations in the estimation sample start in 1992 because we use DSM spending in 1989–1991 to control for spending prior to our data period. Thus, our panel covers a period roughly twice as long as that of L&K. Summary statistics appear in Table 1. All dollar values are converted from nominal to real using the gross domestic product (GDP) deflator.

Our main sample has 3,326 observations from 307 utilities. The original dataset from which our main sample is drawn includes all utilities in the Lower 48 states that meet the minimum size criteria for reporting DSM expenditures throughout the sample period. We exclude utilities with no residential customers. The original dataset has many observations with missing values for DSM spending, even after our meticulous efforts to find them from various sources.[14] Because our empirical model allows all previous DSM spending to potentially affect current demand, whenever encountering a missing DSM spending, we have to drop all subsequent observations for the same utility.

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[13] Analysts have raised some concerns about the quality of the utility-level data on energy efficiency collected on Form 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, 2010; Reid 2009; York and Kushler 2005). 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, which 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 (because of mergers, acquisitions, and other factors) and utilities with no residential customers. Also, there appears to be inconsistent reporting of zeros and missing values for DSM energy efficiency expenditures in the EIA-861 data, depending on the year. We do some consistency tests across the different components of DSM expnditures to determine when reported zeros are likely missing values and when reported missing values are likely to be zeros. When energy efficiency expenditure is reported as zero and total DSM expenditures is nonzero, if the sum of the components of DSM, including energy efficiency, load management, load building (for those years when it is reported), and indirect costs, is less than the total DSM, then we convert the zero expenditures to missing. Alternatively, if EE DSM is reported as missing and total DSM is reported as zero, then we treat the energy efficiency component of DSM expenditures as zero. Although measurement error may be associated with the energy efficiency DSM expenditures reported to EIA, we do not believe it introduces a systematic bias to our analysis.

[14] 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.

5.1. Electricity Demand and DSM Expenditures

Data on utility-level electricity sales, DSM spending, and number of customers are from Form EIA-861. Like L&K, we use as our measure of utility spending on energy efficiency 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 ratepayer-funded DSM energy efficiency programs, we also include third-party state-level DSM programs that have come into being postrestructuring.[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 some overlap exists, 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 intrautility 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.

[15] 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; these data are reported in Appendix Table A-1, 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.

5.2. Decoupling Regulation

To test whether state-level revenue decoupling regulation leads to reduced demand, 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 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. Because our data end in 2006, we do not incorporate the recent dramatic increase in the adoption of decoupling regulation at the state level.

5.3. Building Energy Efficiency Codes

Previous studies of DSM have not examined the effects of building codes on electricity demand.[19] As a result, if building code stringency is positively correlated with average DSM expenditures per customer,[20] 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.[21] 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-

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[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.

[19] Jaffe and Stavins (1995) examined the effectiveness of building codes using a cross-sectional dataset, finding no significant effect of building codes on energy demand in their analysis. Aroonruengsawat et al. (2009) reported that building codes decreased per capita residential electricity consumption by 3%–5% in 2006. Jacobsen and Kotchen (2010) noted that the introduction of more stringent building codes in Gainesville, Florida, reduced demand for electricity by about 4%. Costa and Kahn (2009) found that building codes affected residential electricity consumption in California after 1983 but not before.

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

[21] 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.

energy.org) and the DOE Building Energy Codes Program (www.energycodes.gov). See Figure 2 for a map of building code stringency as of 2007, 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. In order of decreasing stringency, these are as follows: (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 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 the state had no significant adoptions of building codes. 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 (f) above.[22] Thus, the variables are structured to indicate the incremental effect of building codes compared with 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.[23] 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

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[22] 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, so we chose to focus on a single measure of stringency.

[23] Electricity prices can vary substantially across utilities within a state, and our price data will not reflect this intrastate variation in price levels where it exists However, given the potential for endogeneity introduced by using utility 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.

summed to construct a single climate variable.[24] Data on state-level housing starts are from the 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 available only at the utility level and are not broken down by state. For variables that are available only at the state level (energy prices, 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.

We obtained the League of Conservation Voters (LCV) scores for each member of the U.S. House of Representatives directly from National Environmental Scorecards for 1991–2006 from the LCV website.[25] The National Environmental Scorecard grades representatives on a scale of 0 to 100 based on how they vote on key environmental legislation, such as legislation related to energy, global warming, environmental health and safety protections, public lands and wildlife conservation, and spending for environmental programs. We matched congressional districts with utility service territories via geographical information systems (GIS), tracking changes in congressional district geography over time. Where a utility service territory overlaps multiple congressional districts, we used area weights to construct a utility service territory–level LCV index for each year.[26] The Republican voting share variable comes from county-level information on the percentage of votes for the Republican candidate in each presidential election from 1988 through 2004. We mapped these county-level data to the utility service territory

[24] 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 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 by region of the country. 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.

[25] See www.lcv.org/scorecard/past-scorecards/.

[26] We chose area weighting because although representatives are elected by the populations of their districts, an LCV score is assigned to a single congressional representative, who is representative of each component of an entire congressional district area equally.

employing GIS information.[27] For years between presidential elections, we used the information from the most recent election.

6. Estimation and Results

We first estimate equation (5) using nonlinear least squares assuming no endogeneity in DSM spending, as has been done in previous studies in this literature. To address the issue of possible endogeneity, we then estimate equation (5) using nonlinear GMM as discussed in Section 4. We conduct a variety of robustness checks on the sensitivity of the findings with respect to assumptions on demand specification, parametric assumptions on the time path of the effects of past DSM spending, and treatment of missing DSM data, as well as controlling for DSM spending before 1992. Based on the estimated parameters, we examine the effectiveness and cost-effectiveness of DSM spending. The results appear in Tables 2–6. In the following discussion, we first present coefficient estimates, and then discuss their implications for program effectiveness and cost-effectiveness.

6.1. Coefficient Estimates

Table 2 presents coefficient estimates and their standard errors from estimating equation (5). The first-difference equation includes year dummies and the control function to capture the demand effect of EE DSM spending before 1992. As discussed in Section 4.1, the control function includes nine interaction terms between the polynomials of the average level of DSM spending during 1989–1991 and the polynomials of the time trend variable.[28] The results under Model 1 are obtained from nonlinear least squares (NLS). The results under Model 2 are from GMM where we use the polynomials (up to the fifth order) of the lagged spending (the fourth lags and those earlier) to construct the optimal instrument $\nabla_\theta E[\log(Q_{ut} / Q_{u,t-1}) \mid z, \theta]$ as described in Section 4.2. Model 3 includes LCV scores and percentage of Republican presidential votes in the last election in each utility service territory as additional variables to construct optimal instruments.

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[27] Where a service territory spans multiple counties, we summed the number of Republican votes cast across the component counties, and then divided this sum by the total number of presidential votes cast across the component counties. Where a county is split among multiple utility service territories, we performed an area weighted calculation, assigned a weight to each utility-county component relative to the total county size, and multiplied that by the number of voters in the county.

[28] These nine interactions are $\bar{d}*\tau, \bar{d}^2*\tau, \bar{d}^3*\tau, \bar{d}*\tau^2, \bar{d}^2*\tau^2, \bar{d}^3*\tau^2, \bar{d}*\tau^3, \bar{d}^2*\tau^3, \bar{d}^3*\tau^3$.

The parameter estimates across the three models are very close, suggesting that current DSM spending is not correlated with current demand shocks. This similarity may reflect that DSM spending is determined before the current demand shocks are realized. If utilities base their DSM spending on (projected) future demand conditions, their predictions of future demand conditions can be captured well by the observed demand factors used in our model. Basing current DSM spending on expectations regarding future demand growth is consistent with an integrated planning model approach in which utilities see energy efficiency investments as an alternative to building new power plants in order to balance demand and supply in the future (Gillingham et al. 2006). This finding also holds in other demand specifications to be discussed in the next section. In all of the models, we find a negative estimate for the γ coefficient. Given that $\lambda(j)$ in equation (4) is always positive, a negative γ implies a negative relationship between electricity demand and DSM spending per customer. The magnitude of the γ coefficient, which gives the rate at which diminishing returns set in, is quite small, implying that the diminishing return is not strong at least for the spending levels observed in the data.

The next two parameters (η_1, η_2) characterize the function (pdf of a gamma distribution) used to capture the long-term effect of DSM spending. Depending on parameter values, the function could be strictly decreasing or nonmonotonic with a single peak. The top panel of Figure 3 plots the function itself and 95% confidence intervals based on estimates of (η_1, η_2) from Model 1 (NLS); the bottom panel is based on results from Model 3 (GMM with exclusion restrictions).We also plot an arbitrary path within the 95% confidence band in each plot to illustrate one alternative time path that is consistent with the confidence interval around the estimated function. For example, the function itself in both plots peaks around $t = 9$ ($t = 1$ for current year), and based on the function itself, one might conclude that DSM spending has the strongest demand effect after eight years. However, this interpretation ignores the fact that the confidence band around the function is quite wide, especially around the peak point, suggesting that the peak point may be hard to isolate based on the data and model we have. In fact, the confidence bands suggest that the alternative path given in the plots could also be a potential time path for the demand effect of DSM spending.

We believe that the plots give us two important messages. First, DSM spending has a long-lasting demand effect. The plots suggest that the demand effect in year 15 is still statistically different from zero at the 5 percent confidence level. This is in contrast to the modeling assumption used in previous studies: that DSM spending affects demand only within the first few years. Many DSM programs promote energy-efficient investments by customers (including residential, commercial, and industrial users). These investments are often in the form of subsidies for the purchase of energy-efficient durable (consumption or capital) goods or for building retrofits such as insulation or new windows. The reduction in electricity demand resulting from these types of long-lived investments could last a long time.

Second, the demand effect of DSM spending could be small initially and not achieve its maximum until a few years later. For example, we may not see immediate results from programs that subsidize energy audits, as customers may need time to take up all the recommendations from these programs (e.g., making energy-efficient investments). To the extent that these recommendations could require large financial commitments, consumers may not act on them immediately. This may be especially true for industrial and commercial customers if the investment involves significant capital turnover. Also, according to Gillingham and colleagues (2004), by the 1990s utilities increasingly focused their DSM spending on programs that sought to transform markets for energy using equipment such that the efficient option would become the norm. These types of programs involved coordinated information, training, demonstrations, and financing campaigns, and their effectiveness could very well build over time, as suggested by our results. Although it is impossible to know from our EE DSM expenditure data exactly what types of programs utilities were funding during the years for which we have data, our results are consistent with some of the general trends in program evolution identified by Gillingham et al. (2004).

The remaining parameter estimates are intuitively signed and in most cases are statistically significant. The relationships between electricity demand and indicators of the size of the market (number of customers and population) and overall economic condition (gross state product and housing starts) are positive and significant across the different models. We include prices of electricity, natural gas, and fuel oil (in logarithm) and their quadratic terms to allow for more flexible elasticity patterns. Electricity demand is significantly negatively associated with the price of electricity (elasticity of –0.27 at the mean level of electricity price) and is positively associated with the prices of natural gas and fuel oil (elasticity of 0.04 and 0.18 at the mean level of prices).[29] Electricity demand is also positively associated with increases in the climate variable (i.e., heating or cooling degree days), and the size of this effect is fairly consistent across the different models at an elasticity of about 0.1. In all models, we also include building code stringency dummies (base group: no building codes) and their interactions with housing starts.

[29] The parameter estimates on electricity price suffer from the potential endogeneity problem and are better interpreted as an indication of association rather than causation.

As per Section 5.3, the dummy for having building codes is one if the area has any type of building codes, regardless of stringency, whereas the two dummies for more stringent building codes are one for all areas that have building codes above a certain threshold. The coefficient estimates suggest that having the most stringent building codes reduces electricity demand and that the reduction effect is stronger in areas with more housing starts.[30]

6.2. Percentage Savings and Average Cost-Effectiveness

We use the estimated coefficients in Table 2 to examine the effectiveness and cost-effectiveness of DSM spending. We use equation (8) to calculate the percentage electricity savings that occurred from 1992 to 2006 from DSM spending in the same period. We present the results for the three models in Table 3, based on the corresponding parameter estimates in Table 2. Noting that the results are very close across models, we focus on the results from NLS in our discussion.

We find that DSM expenditures in the data period, from 1992 through 2006, produce weighted average energy savings during the data period of just below 1 percent. When savings in future years are taken into account and divided by demand during the data period (when the DSM expenditures were incurred), the total effect is a 1.8 percent reduction in demand. Assuming a discount rate of 5 percent, the cost of these energy savings is estimated at 5 cents per kWh saved, with a 90 percent confidence interval that goes from nearly 0.3 to 9.8 cents per kWh. Because our demand estimation suggests that the demand effect from DSM spending lasts a long time, the average cost estimates can be quite different under various discount rates: the cost is estimated to be 3 cents per kWh under no discounting and 6 cents per kWh when future savings are discounted using a 7 percent discount rate.

We can use our model to compare predictions of savings with the actual savings data reported by the utilities to EIA in the 861 database. Utilities report to EIA the cumulative savings in each year that result from all current and past spending. Given our model's reliance on EE DSM spending data that start in 1992 and our finding that savings persist for several years, the most reasonable comparison is one for a later year in the database. In 2006, only 50 utilities had nonmissing values of energy savings for all relevant categories of customers, and for those 50

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[30] The partial effect of having the most stringent building codes on electricity demand is given by $(0.1061 - 0.0953 + 0.1981) + (-0.0091 + 0.0102 - 0.0203) * \log(\text{housing starts})$. It is equal to –0.0184 at the mean value of housing starts (138,340) in the areas with most stringent building codes.

utilities, the total reported savings in 2006 was 4.2 percent of total sales in the same year. Our model predicts total savings for those same 50 utilities of 2.6 percent with a standard error of 1.4 percent, and thus the reported savings are within the 90 percent confidence interval of our estimate. Note that these 50 utilities appear to be slightly more successful at producing savings, as the average cumulative savings in 2006 for all 126 utilities in our dataset is only 2.1 percent with a standard error of 1.1 percent.

The expected average cost estimate of 5 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). These are costs only for the utility itself, however. The fact that the average electricity price is higher than the estimated utility cost per kWh saved 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 to 27 cents per kWh, depending on location and time of day (PJM ISO 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, range from roughly 8 to 9 cents per kWh for new baseload fossil capacity to a little over 13 cents per kWh for a new gas turbine peaker (NAS 2009).

Accounting for customer costs is also challenging. Earlier research (Joskow and Marron 1992; Nadel and Geller 1996) has suggested 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 it to estimate customer costs for our results. Nonetheless, it suggests that the total average cost of a kWh saved is still below the price of electricity, indicating that energy efficiency programs can be a cost-effective way to reduce CO_2 emissions.

Our estimate is in the range of some more recent estimates of the cost-effectiveness of energy efficiency programs. For example, Pacific Gas and Electric finds that its energy efficiency programs in 2009 produced savings at an average cost to the utility of 4.5 cents per kWh saved (PG&E 2010).

6.3. Robustness Analysis

To check the sensitivity of our findings to modeling assumptions, we conduct a variety of robustness checks. The first robustness check is with respect to the specification of the model. The baseline specification given by equation (4) assumes that DSM spending enters the demand equation nonlinearly, which is to capture the possibility that the demand reduction effect could have a diminishing return. In an alternative specification, we let the DSM spending variable enter the demand equation linearly:

$$\ln(Q_{ut}) = X_{ut}\alpha + \xi_u + \eta_t + \gamma\sum_{j=0}^{t-t_0}\lambda(j)d_{u,t-j} + f(\overline{d}_{u,t_0-1}, \tau_t) + \varepsilon_{ut}. \tag{13}$$

The estimation results based on NLS and GMM with exclusion restrictions for this specification are presented in Table 4. NLS and GMM results are very similar to the baseline specification, again suggesting that DSM spending is not correlated with idiosyncratic demand shocks. The parameter estimates from this alternative specification are very close to those from the baseline specification shown in Table 2. This is consistent with the fact that γ is estimated to be very close to zero in the baseline specification, implying a near linear relationship between DSM variables and the dependent variable. The percentage electricity savings and average cost estimates from the alternative specification, shown in Panel 1 of Table 6, are also similar to those in the baseline specification. The average cost per kWh saved is estimated to be 4.8 cents with a discount rate of 5 percent, compared with 5.0 cents in the baseline specification.

The second robustness check is with respect to missing data in the sample. Because we have to drop all the observations subsequent to a missing one for the same utility, this implies that the number of utilities used in the analysis is smaller over time. To check how this could affect estimation results, we use the same demand function specification as the baseline but focus on utilities that have at least 10 observations in the data, and this gives rise to 3,014 instead of 3,326 observations. The parameter estimates are close to those in the baseline model. Panel 2 of Table 6 provides the estimates of percentage electricity savings and average cost, all of which are similar to the baseline estimates as well.

In the third robustness check, we investigate the sensitivity of the findings to the control function used to capture the demand effect of DSM spending that occurred before 1989, the first year of our data. We use a polynomial function of average DSM spending between 1989 and 1991 and the time trend as the control function. The baseline specification includes interaction terms between third-order polynomials of the average annual level of DSM spending during 1989–1991 and those of the time trend variable (9 interactions in total), whereas this robustness check includes interaction terms of fourth-order polynomials of each of the two variables (16 interactions). Estimation results from this specification, shown in the first part of Table 5 and Panel 3 of Table 6, are still in line with those in the baseline model.[31]

The fourth alternative specification employs a different parameter function to capture the long-term demand effect of DSM spending. Instead of the probability density function of the gamma distribution in the baseline model, we use a Weibull distribution, which is also a two-parameter function and allows a flexible pattern of the time path. The parameter estimates are presented in Table 5. Based on the estimates for η_1, η_2, we plot the function and the 95% confidence interval in Figure 4. The two plots correspond to estimation results from NLS and GMM with exclusion restriction. The two salient features observed in Figure 3 for the baseline specification are still present in Figure 4: DSM spending could have a long-lasting effect, and the effect could be small initially and reach its maximal strength a few years later. Panel 4 of Table 6 shows the percentage saving and average cost estimates. The average cost decreases from 5 cents in the baseline to 4 cents in this specification. Nevertheless, given the standard errors for these two estimates, the difference would not be statistically significant.

To investigate whether revenue decoupling strengthens the demand-reducing effect of DSM spending, we add an interaction term between DSM spending and the decoupling dummy in the baseline specification. The demand equation becomes

$$(15) \quad \ln(Q_{ut}) = X_{ut}\alpha + \xi_u + \eta_t + \sum_{j=0}^{t-t_0} \lambda(j)[1-\exp(\gamma_1 d_{u,t-j} + \gamma_2 \text{decoup}_{u,t-j} d_{u,t-j})] + f(\bar{d}_{u,t_0-1}, \tau_t) + \varepsilon_{ut}.$$

In the equation, decoup is a dummy variable equal to 1 if revenue decoupling policy is in effect for the utility. The estimates for γ_1 and γ_2 from NLS are –0.0006 (0.0007) and –0.0034 (0.0029), with standard errors in parenthesis. The γ_2 estimate suggests that the demand reduction effect is stronger among utilities that have revenue decoupling regulation. However, it is not statistically significant, likely because only 7 percent of the observations are affected by this policy and the policy status does not change often over time for the same utility during our data period (more and more utilities are subject to this policy after 2006, the end of our data period). All the other

[31] We also estimate the model without including the control function. Because this approach would attribute the demand effect of DSM spending that occurred before 1992 to expenditures in later years, the results show that the demand effect would be substantially overestimated: the estimated percentage savings during 1992–2006 is 3.2 percent and the cost per kWh saved is less than 1 cent, compared with 0.9 percent and 5 cents in the baseline model.

parameter estimates (not reported to save space) are close to those in the baseline model. Moreover, NLS and GMM give similar results as well. The percentage savings estimates based on equations (8) and (11) are 0.9 percent (0.5) and 1.5 percent (1.0) from NLS. The average cost per kWh saved is 6 cents with a standard error of 4 with a discount rate of 5 percent.

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 have taken 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, however, we use a different approach that relies on econometric techniques to estimate how DSM expenditures affect electricity demand, controlling for other demand drivers, such as changes in price, income, and weather. We build on earlier work by expanding the dataset and including additional important explanatory variables. More important, we develop a carefully motivated empirical model to capture the long-term demand effect of DSM expenditure. We explicitly address the potential endogeneity problem of DSM expenditure using nonlinear GMM, which has not been done previously.

Our main results suggest that over the 15-year period covered by this analysis, ratepayer-funded DSM expenditures produced a central estimate of 0.9 percent savings in electricity consumption within the data period, and 1.8 percent when including savings that occur beyond the data period. The average cost to utilities of electricity savings achieved under these programs depends importantly on the discount rate employed to calculate the present discounted value of future electricity savings. With a discount rate of 5 percent, the average cost is 5 cents per kWh saved, with a 90 percent confidence interval that goes from 0.3 to nearly 10 cents per kWh saved. Higher discount rates yield higher mean estimates of average cost. Our findings are robust to many alternative assumptions about model structure and the structural model used to incorporate the effects of lagged DSM spending. Our model suggests that over the range of DSM spending data in our sample, returns to increased EE DSM spending are roughly constant. Decoupling regulation appears to strengthen the demand-reducing effects of EE DSM spending. Our results provide evidence that for utilities located primarily in states where housing starts are above the mean, the presence of more stringent building costs has a statistically significant negative effect on electricity demand.

In future work, it would be useful to discern lessons about the relative effectiveness of different types of energy efficiency programs (e.g., information programs versus rebate programs versus loan programs) and of programs targeted at different classes of customers (residential, commercial, industrial), both of which would require more detailed data on EE DSM spending by program type and type of customer. In recent years, energy efficiency regulatory policy has focused on questions of who is best suited to deliver energy savings through efficiency investments at the point of use and what types of regulatory incentives are necessary to encourage utilities to embrace end-use energy efficiency. States have opted either to charge the electric utilities with promoting energy efficiency or to establish separate state-run or state-chartered entities (e.g., Efficiency Maine Trust, Efficiency Vermont, and New York State Energy Research and Development Authority) to operate their ratepayer-funded energy efficiency programs.

On the regulatory side, state utility regulators have had renewed interest in developing regulatory mechanisms such as revenue decoupling and incentive mechanisms to reward successful energy efficiency programs to help overcome utility incentives to maximize revenues and profits through greater electricity sales. As experience with these different structural and regulatory institutions accumulates, we hope the necessary data will be collected to enable us and other researchers to identify the implications of these different institutional arrangements and regulatory approaches for the performance of programs that use ratepayer funds and other public dollars to invest in greater end-use energy efficiency.

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

Variables	Mean	Median	Std. dev.	Min.	Max.
First difference of log(electricity demand)	0.031	0.028	0.045	–0.290	0.297
Electricity demand (billion kWh)	7.98	1.08	16.02	0.16	103.65
Electricity demand per customer (MWh)	24.02	21.49	10.75	8.21	96.52
DSM spending (million $)	4.71	0.06	16.82	0.00	230.20
DSM spending per customer ($)	9.41	1.19	18.08	0.00	191.85
Number of customers (thousands)	325	53	678	4	5,121
Population (thousands)	9,139	6,452	8,072	574	36,200
State GDP (billion $)	362	256	346	18	1,788
Housing starts (thousands)	48	31	52	2	265
Electricity price (cents per kWh)	8.80	8.12	2.37	4.90	15.87
Natural gas price (cents per Mcf)	10.30	9.79	2.91	5.35	22.12
Fuel oil price (cents per gallon)	130.43	119.49	35.84	73.40	275.31
Climate	1,647	1,454	825	369	3,937
Indicator: most stringent building codes	0.028	0.000	0.165	0.000	1.000
Indicator: more stringent building codes	0.797	1.000	0.402	0.000	1.000
Indicator: building codes exist	0.852	1.000	0.355	0.000	1.000
Mean DSM spending per customer, 1989–1991 ($)	7.40	0.81	13.18	0.00	64.82
Number of observations	3,326				
Number of utilities	307				

Notes: Dollars are inflation-adjusted to 2007$. Mcf = thousand cubic feet.

Table 2. Estimation Results from the Baseline Model

Variables	Model 1: NLS		Model 2: GMM		Model 3: GMM	
	Para.	S.E.	Para.	S.E.	Para.	S.E.
DSM spending per customer (γ)	–0.0016	0.0010	–0.0015	0.0010	–0.0016	0.0010
η_1 in gamma probability density function	8.4155	5.7705	8.8819	6.1876	8.3271	5.7275
η_2 in gamma probability density function	0.7768	0.5972	0.8282	0.6409	0.7672	0.5930
Log(number of customers)	0.3617	0.0453	0.3617	0.0454	0.3617	0.0454
Log(population)	0.4573	0.0921	0.4574	0.0921	0.4573	0.0921
Log(gross state product)	0.2003	0.0436	0.2004	0.0436	0.2002	0.0436
Log(house starts)	0.0381	0.0080	0.0381	0.0080	0.0381	0.0080
Log(electricity price)	–0.4660	0.1905	–0.4655	0.1908	–0.4661	0.1909
Log(electricity price) squared	0.0911	0.0406	0.0910	0.0407	0.0911	0.0407
Log(natural gas price)	0.1229	0.0589	0.1228	0.0588	0.1229	0.0589
Log(natural gas price) squared	–0.0349	0.0143	–0.0349	0.0143	–0.0349	0.0143
Log(fuel oil price)	0.3451	0.2213	0.3460	0.2213	0.3449	0.2212
Log(fuel oil price) squared	–0.0344	0.0232	–0.0345	0.0232	–0.0344	0.0232
Log(climate)	0.0962	0.0066	0.0962	0.0066	0.0962	0.0066
Dummy for most stringent bldg. codes	0.1061	0.0586	0.1054	0.0586	0.1062	0.0586
Dummy for more stringent bldg. codes	–0.0953	0.0928	–0.0953	0.0928	–0.0953	0.0928
Dummy for bldg. codes exist	0.1981	0.0861	0.1982	0.0861	0.1981	0.0861
Log(house starts)*most stringent codes	–0.0091	0.0050	–0.0091	0.0050	–0.0091	0.0050
Log(house starts)*more stringent codes	0.0102	0.0093	0.0102	0.0093	0.0102	0.0093
Log(house start)*existing codes	–0.0203	0.0086	–0.0203	0.0086	–0.0203	0.0086
Year dummies (14)	Yes		Yes		Yes	
Control function for early DSM	Yes		Yes		Yes	

Notes: The number of observations is 3,326. Results are for equation (4). The dependent variable is log (electricity demand). The first set of results is from NLS; the second and third sets are from GMM using optimal instruments in an iterative procedure. Model 2 does not include exclusion restrictions in constructing optimal instruments, whereas Model 3 includes LCV scores as well as the percentage of Republican votes in each utility's service area in the last presidential election.

Table 3. Effectiveness and Cost-Effectiveness from Baseline Model

	Model 1: NSL		Model 2: GMM		Model 3: GMM	
	Est.	**S.E.**	**Est.**	**S.E.**	**Est.**	**S.E.**
Demand effect of DSM spending (data period)	–0.009	0.005	–0.009	0.005	–0.009	0.005
Demand effect of DSM spending (total effect)	–0.018	0.011	–0.017	0.011	–0.018	0.011
Cost-effectiveness (no discounting) (cents per kWh saved)	–3.0	1.8	–3.2	1.9	–3.0	1.8
Cost-effectiveness using 3% discount rate	–4.1	2.4	–4.3	2.6	–4.1	2.4
Cost-effectiveness using 5% discount rate	–5.0	2.9	–5.2	3.1	–5.0	2.9
Cost-effectiveness using 7% discount rate	–6.1	3.5	–6.3	3.7	–6.0	3.5

Notes: The first row, the demand effect of DSM spending during the data period, shows the effect of DSM spending from 1992 to 2006 on total electricity demand during the same period. The second row gives the effect of DSM spending from 1992 to 2006 on total electricity demand over all future periods (up to 20 years after the spending), assuming the annual demand after 2007 to be the same as in 2006. The cost-effectiveness is calculated based on total DSM spending from 1992 and 2006 and total electricity saving resulted from it. The four sets of cost-effectiveness estimates are based on four different discount rates: 0%, 3%, 5%, and 7%. All standard errors are obtained using the delta method.

Table 4. Robustness Checks: First Two Sets

	Robustness 1: Log-linear specification				Robustness 2: A subsample			
	NSL		GMM		NLS		GMM	
Variables	Para.	S.E.	Para.	S.E.	Para.	S.E.	Para.	S.E.
DSM spending per customer (γ)	–0.0016	0.0009	–0.0016	0.0009	–0.0015	0.0010	–0.0014	0.0010
η_1 in gamma pdf	7.7790	5.0811	7.7955	5.1572	8.5685	6.0393	8.9962	6.4233
η_2 in gamma pdf	0.7000	0.5244	0.7019	0.5325	0.8000	0.6290	0.8473	0.6695
Log(number of customers)	0.3617	0.0454	0.3617	0.0454	0.3916	0.0519	0.3916	0.0519
Log(population)	0.4571	0.0920	0.4571	0.0920	0.4435	0.0964	0.4436	0.0964
Log(gross state product)	0.2001	0.0436	0.2001	0.0436	0.1991	0.0463	0.1993	0.0462
Log(house starts)	0.0381	0.0080	0.0381	0.0081	0.0330	0.0086	0.0330	0.0086
Log(electricity price)	–0.4665	0.1905	–0.4665	0.1909	–0.4896	0.1937	–0.4893	0.1940
Log(electricity price) squared	0.0912	0.0406	0.0912	0.0407	0.0953	0.0413	0.0952	0.0413
Log(natural gas price)	0.1231	0.0589	0.1231	0.0589	0.1134	0.0603	0.1133	0.0603
Log(natural gas price) squared	–0.0350	0.0143	–0.0350	0.0143	–0.0318	0.0147	–0.0317	0.0147
Log(fuel oil price)	0.3430	0.2212	0.3430	0.2212	0.3303	0.2260	0.3312	0.2260
Log(fuel oil price) squared	–0.0342	0.0232	–0.0342	0.0232	–0.0332	0.0237	–0.0333	0.0237
Log(climate)	0.0962	0.0066	0.0962	0.0066	0.1031	0.0069	0.1031	0.0069
Dummy for most stringent bldg. codes	0.1076	0.0585	0.1075	0.0585	0.1000	0.0590	0.0994	0.0590
Dummy for more stringent bldg. codes	–0.0952	0.0929	–0.0952	0.0929	–0.0891	0.0927	–0.0891	0.0926
Dummy for bldg. codes exist	0.1981	0.0862	0.1981	0.0861	0.1961	0.0859	0.1962	0.0859
Log(house starts)*most stringent codes	–0.0093	0.0050	–0.0093	0.0050	–0.0085	0.0050	–0.0085	0.0050
Log(house starts)*more stringent codes	0.0102	0.0093	0.0102	0.0093	0.0097	0.0093	0.0097	0.0093
Log(house start)*existing codes	–0.0203	0.0086	–0.0203	0.0086	–0.0201	0.0086	–0.0201	0.0086
Year dummies (14)	Yes		Yes		Yes		Yes	
Control function for early DSM	Yes		Yes		Yes		Yes	

Notes: The first set of robustness checks is based on equation (13), which assumes that DSM spending enters the demand equation linearly. The second set of estimations is based on utilities that have at least 10 observations in the data (3,014 observations in total). GMM estimations in both sets include exclusion restrictions (LCV and percentage Republican votes) in constructing the optimal instruments.

Table 5. Additional Robustness Checks

	Robustness 3: Different control function				Robustness 4: Weibull distribution			
	NSL		GMM		NLS		GMM	
Variables	**Para.**	**S.E.**	**Para.**	**S.E.**	**Para.**	**S.E.**	**Para.**	**S.E.**
DSM spending per customer (γ)	–0.0018	0.0012	–0.0018	0.0011	–0.002	0.0012	–0.002	0.0014
η_1 in pdf	7.8165	5.1638	8.2783	5.3018	12.3169	2.3712	12.3756	2.4461
η_2 in pdf	0.6926	0.5245	0.7449	0.5398	2.8819	1.1952	2.8605	1.3109
Log(number of customers)	0.3615	0.0455	0.3591	0.0454	0.3617	0.0455	0.3617	0.0455
Log(population)	0.4626	0.0928	0.4589	0.0929	0.4576	0.0919	0.4575	0.092
Log(gross state product)	0.2019	0.0438	0.2022	0.0438	0.198	0.0435	0.198	0.0434
Log(house starts)	0.0385	0.0081	0.0382	0.0081	0.0382	0.0081	0.0383	0.0081
Log(electricity price)	–0.4658	0.1915	–0.4492	0.1919	–0.4647	0.1912	–0.4647	0.1919
Log(electricity price) squared	0.0912	0.0408	0.0873	0.0409	0.091	0.0408	0.0911	0.041
Log(natural gas price)	0.1248	0.0589	0.128	0.0588	0.1245	0.0589	0.1246	0.0589
Log(natural gas price) squared	–0.0354	0.0143	–0.0362	0.0143	–0.0353	0.0143	–0.0354	0.0143
Log(fuel oil price)	0.3359	0.2212	0.3227	0.2214	0.3332	0.2208	0.3325	0.2208
Log(fuel oil price) squared	–0.0334	0.0232	–0.032	0.0232	–0.0331	0.0231	–0.033	0.0231
Log(climate)	0.0961	0.0066	0.0954	0.0066	0.0962	0.0066	0.0962	0.0066
Dummy for most stringent bldg. codes	0.1071	0.0578	0.1111	0.0579	0.1124	0.0582	0.1127	0.0581
Dummy for more stringent bldg. codes	–0.0925	0.0933	–0.0931	0.0931	–0.0951	0.0934	–0.0951	0.0935
Dummy for bldg. codes exist	0.1964	0.0863	0.1979	0.0862	0.1982	0.0864	0.1982	0.0864
Log(house starts)*most stringent codes	–0.0092	0.0049	–0.0096	0.0049	–0.0097	0.0049	–0.0097	0.0049
Log(house starts)*more stringent codes	0.01	0.0094	0.01	0.0094	0.0102	0.0094	0.0102	0.0094
Log(house start)*existing codes	–0.0202	0.0087	–0.0203	0.0087	–0.0204	0.0087	–0.0204	0.0087
Year dummies (14)	Yes		Yes		Yes		Yes	
Control function for early DSM	Yes		Yes		Yes		Yes	

Notes: The third set of robustness checks includes 16 variables (instead of 9), which are interactions of (up to) fourth-order polynomials of the time trend variable and those of early DSM spending variable, to control for the effect from DSM spending prior to 1992. The fourth set of estimations uses the Weibull distribution (instead of gamma distribution) to parameterize the long-term effect from DSM spending.

Table 6. Effectiveness and Cost-Effectiveness from Alternative Specifications

	NSL		GMM	
	Est.	S.E.	Est.	S.E.
Panel 1. Robustness check 1: Log-linear specification				
Demand effect of DSM spending (data period)	–0.010	0.005	–0.010	0.005
Demand effect of DSM spending (total effect)	–0.019	0.010	–0.019	0.010
Cost-effectiveness no discounting (cents per kWh saved)	–2.9	1.5	–2.9	1.6
Cost-effectiveness using 3% discount rate	–3.9	2.1	–3.9	2.1
Cost-effectiveness using 5% discount rate	–4.8	2.5	–4.8	2.5
Cost-effectiveness using 7% discount rate	–5.8	3.1	–5.8	3.1
Panel 2. Robustness check 2: A subsample				
Demand effect of DSM spending (data period)	–0.009	0.005	–0.009	0.005
Demand effect of DSM spending (total effect)	–0.017	0.011	–0.016	0.011
Cost-effectiveness no discounting (cents per kWh saved)	–3.2	2.0	–3.3	2.1
Cost-effectiveness using 3% discount rate	–4.4	2.7	–4.5	2.8
Cost-effectiveness using 5% discount rate	–5.3	3.2	–5.4	3.4
Cost-effectiveness using 7% discount rate	–6.4	3.9	–6.6	4.1
Panel 3. Robustness check 3: Different control function				
Demand effect of DSM spending (data period)	–0.010	0.005	–0.010	0.005
Demand effect of DSM spending (total effect)	–0.021	0.012	–0.021	0.012
Cost-effectiveness no discounting (cents per kWh saved)	–2.6	1.6	–2.7	1.5
Cost-effectiveness using 3% discount rate	–3.7	2.1	–3.7	2.1
Cost-effectiveness using 5% discount rate	–4.5	2.6	–4.5	2.6
Cost-effectiveness using 7% discount rate	–5.4	3.1	–5.5	3.1
Panel 4. Robustness check 4: Weibull distribution				
Demand effect of DSM spending (data period)	–0.011	0.006	–0.011	0.007
Demand effect of DSM spending (total effect)	–0.022	0.012	–0.023	0.014
Cost-effectiveness no discounting (cents per kWh saved)	–2.5	1.4	–2.4	1.5
Cost-effectiveness using 3% discount rate	–3.4	1.8	–3.1	1.5
Cost-effectiveness using 5% discount rate	–4.1	2.2	–3.8	1.8
Cost-effectiveness using 7% discount rate	–4.9	2.7	–4.6	2.1

Figure 1. Ratepayer-Funded Energy Efficiency Expenditures

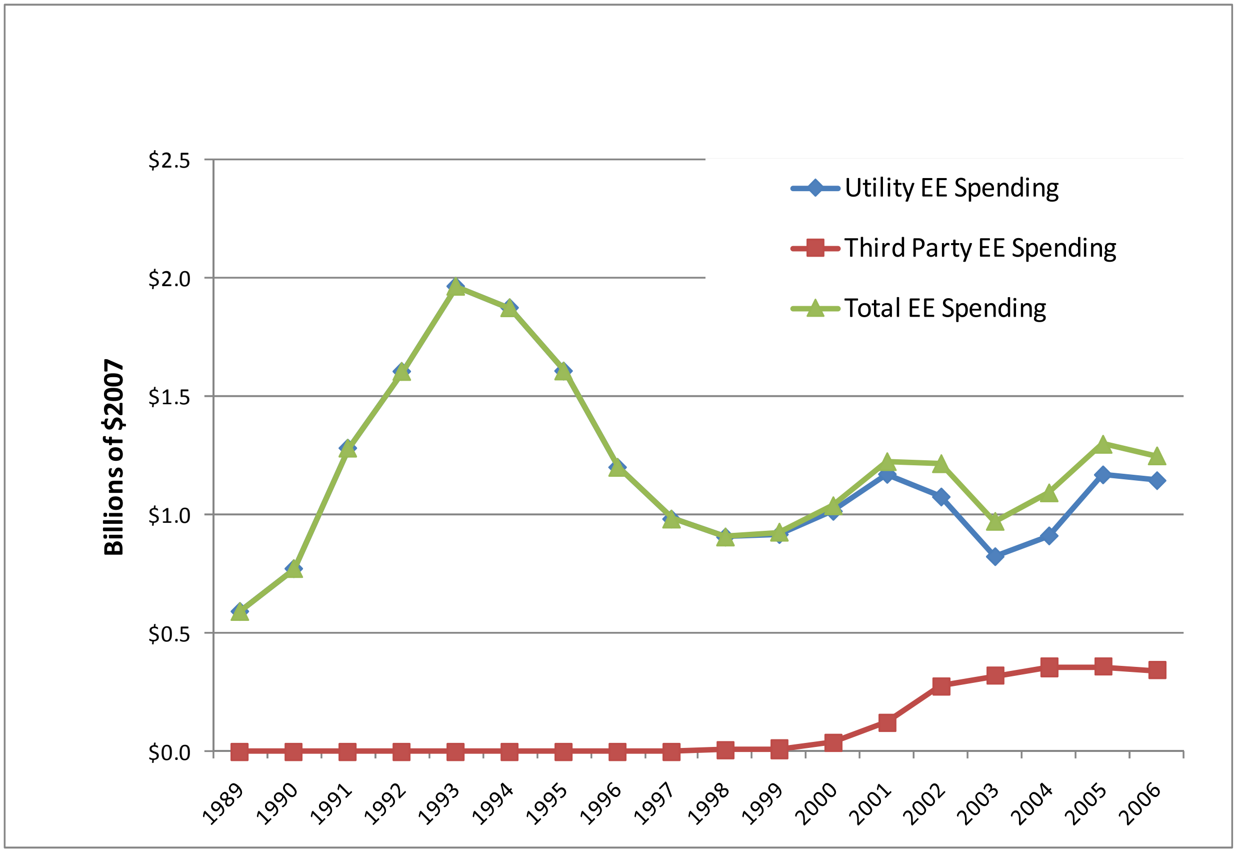


Figure 2. Stringency of Building Codes in 2007

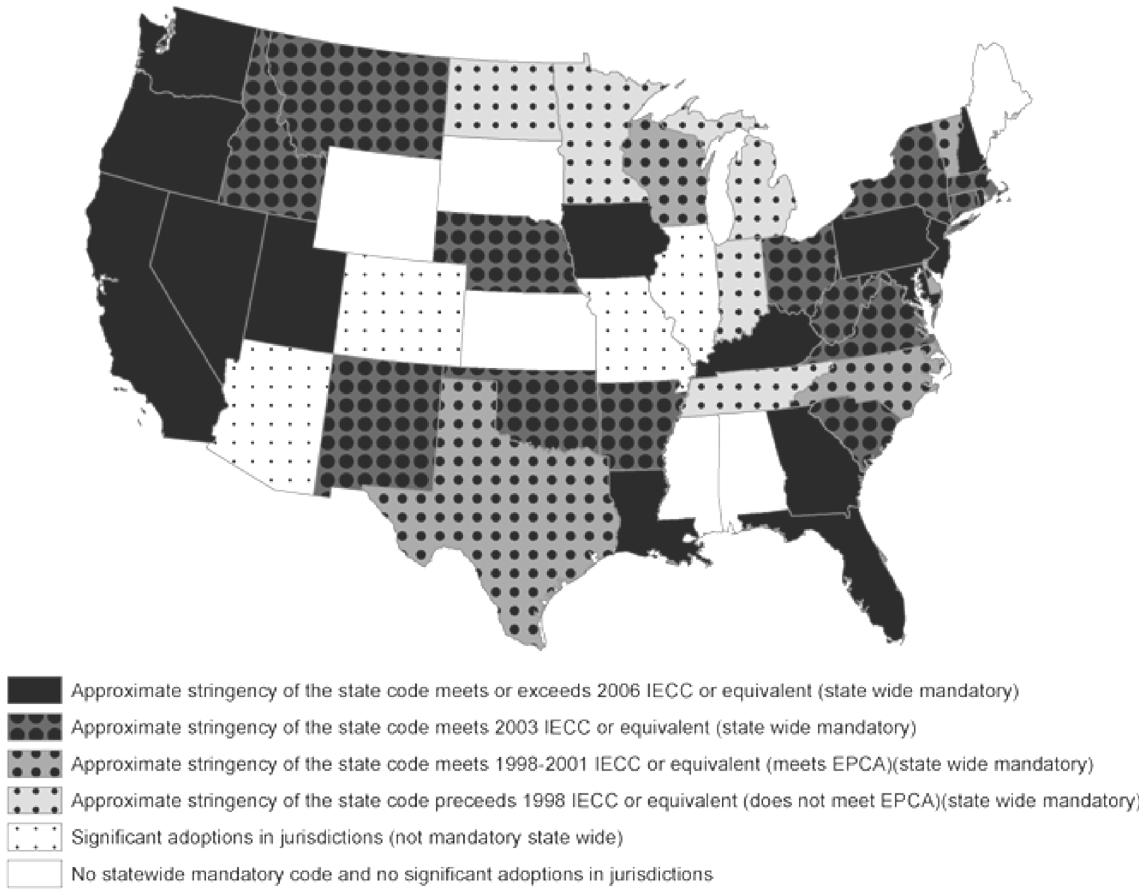
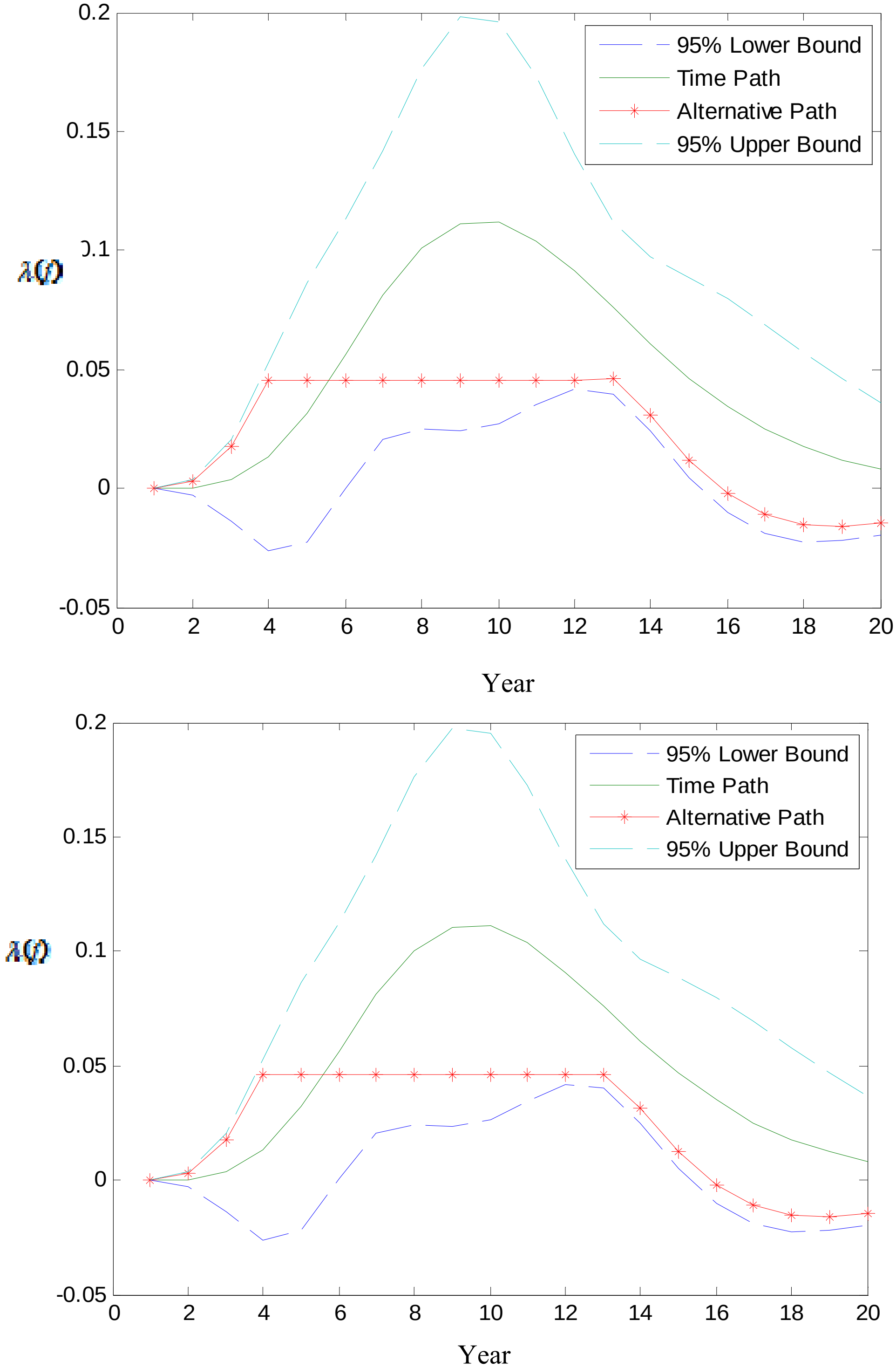
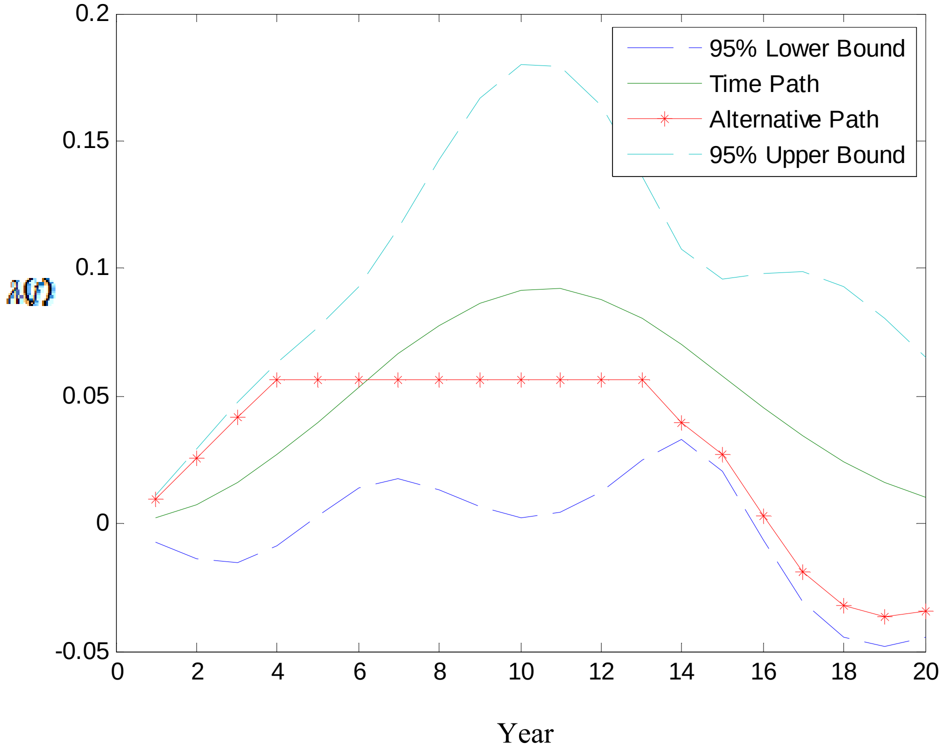


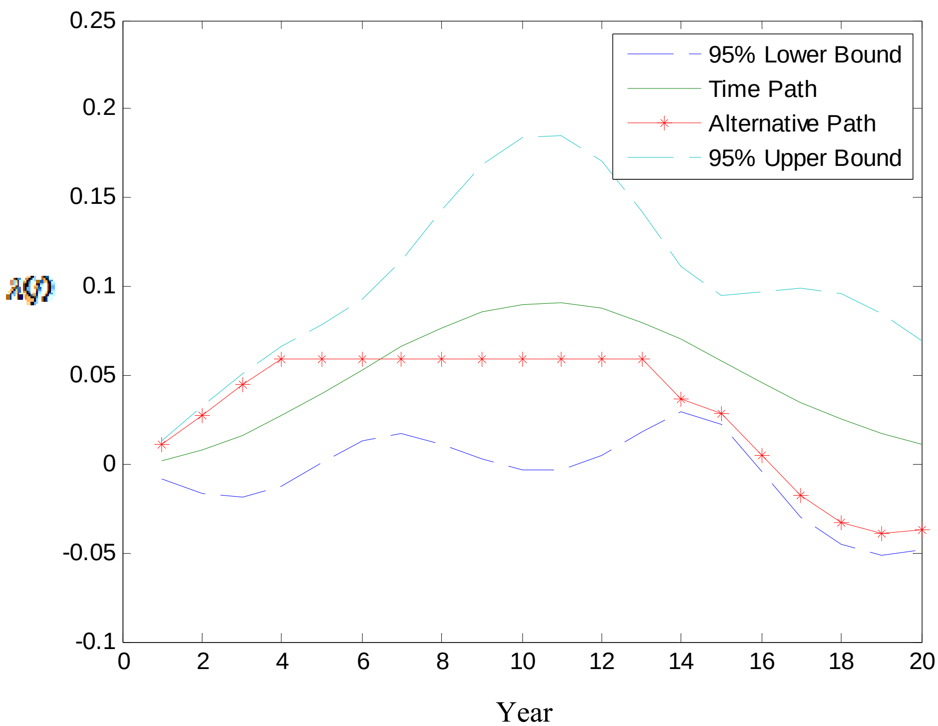
Figure 3. Long-Term Effects of DSM Spending from the Baseline Model



Notes: The top graph is based on results from NLS (Model 1 in Table 2), and the bottom graph is based on results from GMM (Model 3 in Table 2).

Figure 4. Long-Term Effects of DSM Spending Using Weibull Distribution





Notes: The top graph is based on results from NLS, and the bottom graph on results from GMM (both Robustness 4 in Table 5).

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Appendix

Table A-1. 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 (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	