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Demand-Side Management and Energy Efficiency Revisited

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Abstract

The key finding of an influential paper that received the International Association for Energy Economists' Best Paper Award (2004) is that utilities have been overstating electricity savings and underestimating costs associated with energy efficiency demand side management (DSM) programs. This claim is based on point estimates of average DSM-related savings and costs implied by an econometric model of residential electricity demand. In this response we first argue that the choice of test statistics, by not weighting estimated savings and costs by utility electricity sales and DSM expenditures respectively, biases results in favor of rejecting the null hypothesis that utility-reported electricity savings reflect true values. We also note that utility estimates of average program savings and costs are rejected based on point estimates alone; no attempt is made to evaluate the uncertainty surrounding these estimates. We use the same data and econometric model to estimate the appropriate test statistics. We then construct nonparametric bootstrap confidence intervals. We fail to reject the average electricity savings and DSM program costs reported by utilities using both the weighted and unweighted test statistics. Our results suggest that the evidence for rejecting utility estimates of DSM savings and costs should be re-interpreted.

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1. Introduction

As public concerns about climate change and air quality escalate, there is increasing political pressure to find ways to reduce the environmental impacts of energy use. One approach currently being pursued by policymakers involves increasing support for "demand-side management" (DSM) programs. Since the 1970s, utilities in the US have been implementing DSM programs designed to reduce residential and commercial electricity demand through information dissemination programs, subsidies, free installation of more efficient technologies, and other conservation related activities. Whereas program evaluations routinely find that these utility-sponsored DSM programs are highly cost effective (EPRI, 1984; Eto et al.,1995; Fickett et al., 1990; Jordan and Nadel, 1993; Nadel, 1992; Nadel and Geller, 1996), in the past some economists have viewed these results with skepticism (Joskow and Marron, 1992; Nichols, 1995).[1] A more recent paper by Loughran and Kulick (2004) has refueled this debate.

The stated objective of the Loughran and Kulick (LK) paper is "to test whether DSM expenditures during the 1990s succeeded in increasing the electricity efficiency of the U.S. economy" (pp 21). LK fail to reject this hypothesis, however they do conclude that "DSM (has) had a much smaller effect on retail electricity sales than estimates reported by utilities themselves" (p. 19). This claim has attracted considerable attention. In the two years since its publication, this paper has been cited in a wide range of contexts, including utility revenue requirement hearings (B.C. Commission, 2005), academic papers (Gillingham et al., 2006; Metcalf, 2006), policy briefs (Geller and Attali, 2005), and partisan position papers (Crane and Boaz, 2005).

Several authors have pointed out shortcomings of methods used to calculate DSM savings and costs, including the potential for free riding, unmeasured positive spillovers, and moral hazard issues.[2] LK derive their result from a novel approach to the problem of free riders (that is, beneficiaries of a utility program who would still have saved energy even if there were no program). While questions could be raised about LK's approach, we do not examine such questions here. Instead, we use a simple hypothesis testing framework to show that DSM savings estimates reported by utilities to the EIA cannot be rejected even when the data and estimation approach used by LK

[1]For an excellent review of energy efficiency policies and their estimated impacts, see Gillingham et al., 2006.

[2]For a comprehensive review of the major criticisms and merits of DSM program evaluations, see Geller and Attali (2005).

are taken at face value.

This response proceeds as follows: Section 2 restates the question addressed by LK in terms of a hypothesis test; Section 3 uses the data and econometric models used by LK to estimate the appropriate test statistics; Section 4 reports the results of hypotheses testing; Section 5 concludes.

2. Formulating the null hypothesis

In the past, studies demonstrating the cost effectiveness of DSM programs have relied heavily on cost and savings estimates that the utilities are required to report annually to the Energy Information Administration (EIA). Each year, utilities are not only required to report their annual DSM expenditures (denoted EE) and electricity sales (kWh), but also to estimate the annual savings (s). LK use these data from 324 utilities over the period 1989-1999 to estimate several models of DSM electricity savings.[3]

The first aspect of the LK paper we take issue with is their choice of test statistic to test the stated null hypothesis. In order to test whether DSM expenditure increased the energy efficiency of the US economy, one needs to consider the percent change in *aggregate* US electricity consumption due to *aggregate* expenditure on energy efficiency DSM. LK, however, use the average percent change in electricity consumption due to energy efficiency DSM expenditures across utilities and years as their indicator. As we will show below, this interpretation of the null hypothesis will lead to an underestimation of percent savings and an overestimation of costs if one cares about economy wide savings and costs.

A simple example may illustrate this point. Envision utility A, which spends \$1 on DSM and saves 50 kWh, producing 950 kWh instead of 1,000 kWh in the counterfactual. Now consider utility B, which spends \$10 on DSM and saves 400 kWh, producing 3,600 kWh instead of 4,000 kWh in the counterfactual. Utility A saves 5% at 2 cents per kWh and utility B saves 10% at 2.5 cents per kWh. In order to obtain average savings, LK use the average of the (econometrically estimated) percentage savings across utilities, 7.5% to test their stated hypothesis. We argue that the appropriate savings

[3]The sample used by LK contains only 327 of the 3,254 utilities reporting to the EIA each year. The majority of utilities do not report any DSM expenditures in the period 1992-1999. Only 119 report positive DSM expenditures throughout the study period. The energy efficiency component of DSM expenditures is reported separately by utilities beginning in 1992. LK impute the percentage of total DSM expenditures that a utility allocated to energy efficiency for years 1989-1991 based on the percentage reported by the utility in 1992.

are $450kWh/5{,}000kWh = 9\%$. One special case where the two statistics would be the same is in world of identical utilities with constant returns to scale in percent reductions due to DSM expenditures, which is not supported given the data. LK use their estimate of savings to calculate average costs. For this example, using their approach one would arrive at an average cost of $\frac{(\$1+\$10)}{7.5\%\cdot(1000kWh+4000kWh)} = 2.93$ cents per kWh saved, while we argue that the appropriate number is $\frac{(\$1+\$10)}{(50kWh+400kWh)} = 2.44$ cents per kWh saved.

Some additional notation helps to make these concepts more precise. Let n index utilities: $n = 1...N$. Let t index years. The nth utility reports electricity sales, DSM related expenditures and savings in $t = 1...T_n$ years.[4] The level of electricity consumption reported by utility n in year t after spending EE_{nt} on DSM programs is $kWh(1)_{nt}$. We let $kWh(0)$ represent electricity demand in the counterfactual, unobserved situation where no DSM program is in place: $kWh(1)_{nt} + s_{nt} = kWh(0)_{nt}$, where savings are positive ($s_{nt} \geq 0$). In order to obtain an estimate of s_{nt} one can either rely on the utility reported figures or resort to econometric estimates.

The LK approach to summarizing costs and savings is to take *unweighted* averages across observations. Let S_1 represent the true, unweighted average of percentage savings across all utilities and years. Let C_1 represent the true, unweighted average cost. Utility reported savings percentages and costs can be used to construct estimates of these two population parameters:

$$\hat{S}_1 = \frac{\sum_{n=1}^{N}\sum_{t=1}^{T_n}\left(\frac{kWh(0)_{nt}-kWh(1)_{nt}}{kWh(0)_{nt}}\right)}{\sum_{n=1}^{N} T_n} \tag{1}$$

$$\hat{C}_1 = \frac{\sum_{n=1}^{N}\sum_{t=1}^{T_n}\left(\frac{EE_{nt}}{kWh(0)_{nt}-kWh(1)_{nt}}\right)}{\sum_{n=1}^{N} T_n} \tag{2}$$

In calculations of $\hat{S}_1$ and $\hat{C}_1$, savings and costs reported by utilities who spend relatively small amounts on DSM are weighted the same as savings and costs reported by utilities with very large DSM programs. Utilities who spend more on DSM programs report significantly larger percentage savings on average. If we are interested in the average returns per dollar spent on DSM programs, these measures will be misleading.

Alternative measures of average savings and costs weight observations by electricity sales

[4]This is not a balanced sample. 156 utilities report DSM expenditures and savings in all eight years. Others do not report in all years. Several report expenditures in only one year.

and program expenditures, respectively. Let S_2 represent total savings attributable to DSM programs divided by total electricity sales in the absence of DSM programs. Let C_2 represent the total DSM expenditures divided by total electricity savings. Utility reported data can be used to construct the following estimates of these two population parameters:

$$\hat{S}_2 = \frac{\sum_{n=1}^{N}\sum_{t=1}^{T_n}(kWh(0)_{nt} - kWh(1)_{nt})}{\sum_{n=1}^{N}\sum_{t=1}^{T_n} kWh(0)_{nt}} \tag{3}$$

$$\hat{C}_2 = \frac{\sum_{n=1}^{N}\sum_{t=1}^{T_n} EE_{nt}}{\sum_{n=1}^{N}\sum_{t=1}^{T_n}(kWh(0)_{nt} - kWh(1)_{nt})} \tag{4}$$

These measures are more informative summaries of the overall average returns per dollar spent on DSM programs, and the average cost per kWh saved. Using utility reported savings, consumption and DSM expenditures, we construct estimates of these two sets of population parameters using the complete dataset and the five subsets of the data analyzed by LK. These summary statistics are reported in Table 1. Note that estimates of percentage savings averaged across all utility-year observations ($\hat{S}_1$) are consistently smaller than average percentage savings weighted by electricity sales ($\hat{S}_2$). This is because smaller utilities (who tend to spend relatively less on DSM programs and report lower percentage savings) are weighted relatively more heavily in calculations of $\hat{S}_1$ as compared to $\hat{S}_2$.

Estimates of $\hat{C}_1$ are substantially larger than estimates of $\hat{C}_2$. There are two reasons for this. The first has to do with the positive relationship between DSM expenditures and percentage savings. Observations associated with smaller DSM expenditures (and thus higher per kWh costs on average) are weighted relatively more heavily in calculations of $\hat{C}_1$. The second reason has to do with outliers in the reported savings data. There are 1,459 utility-year observations in which utilities report both expenditures and savings, which makes it possible to calculate \$/kWh saved. In a small number of cases, very small reported savings imply extremely high costs (i.e., above \$100/kWh in five cases). A closer look at the data reveals that these unusually small savings (relative to expenditures) are typically associated with the first year of reporting by utilities overseeing relatively small DSM programs.[5] These outliers are discussed in more detail in the following section.

[5]For example, utilities that report costs on the order of \$400/kWh saved in the first year of their DSM program consistently report costs of \$0.02/kWh in subsequent years.

In summarizing these data and formulating a null hypothesis, LK report that average utility-estimated DSM-related electricity savings range between 1.8 and 2.3 percent and that the average per kWh program costs reported by utilities range from $0.02-$0.03/kWh (p.39). Although LK do not explain how they calculate these summary statistics, Table 1 shows that these ranges are more consistent with expenditure weighted averages $\hat{S}_2$ and $\hat{C}_2$ as compared to unweighted averages $\hat{S}_1$ and $\hat{C}_1$.

3. Deriving Average Savings and Costs from Econometric Estimates

When estimating energy savings from DSM programs, we want to know how the level of electricity consumption we observe after implementing a DSM program $kWh(1)$ differs from what electricity consumption would have been in the absence of the program $kWh(0)$. Of course, we can only observe the former, so we are left to construct our best estimate of what demand would have looked like had there been no DSM program in place.

LK estimate an econometric model explaining variation in the approximate percent change in observed electricity sales[6], $\Delta kWh_{nt} = \ln kWh(1)_{nt} - \ln kWh(1)_{nt-1}$:

$$\Delta kWh_{nt} = \beta_o \ln EE_{nt} + \beta_1 \ln EE_{nt-1} + \beta_2 \ln EE_{nt-2} + \gamma Z_{nt} + \varepsilon_{nt} \tag{5}$$

Energy efficiency DSM expenditures enter as the current, single and double lag. The vector Z_{nt} contains, depending on the specification, a combination of the change in the number of customers, gross state product (GSP), price of electricity and substitutes, climate, share of electricity sold to different users as well as year fixed effects, state-year fixed effects or a state-specific quadratic time trend. Using results from a least squares regression of equation (5), the difference in log transformed electricity sales attributable to contemporaneous and lagged DSM expenditures

[6] The difference in a log transformed kWh_{nt} is approximately equal to the percentage change in kWh_{nt}, provided this percentage is small.

is estimated as follows:

$$\hat{s}_{nt} = \hat{\beta}_o \ln EE_{nt} + \hat{\beta}_1 \ln EE_{nt-1} + \hat{\beta}_2 \ln EE_{nt-2}. \tag{6}$$

The five different specifications control for variation in different sets of the observed utility characteristics, state characteristics, year effects, and energy prices. The specifications also differ in their susceptibility to the influence of DSM program cost outliers. Table 2 reports the number of utility-year observations associated with reported costs that exceed \$10/kWh and \$100/kWh, respectively. The subset of the data used to estimate Model 4 contains the fewest outliers. It is also the specification that controls for the most confounding factors (including energy prices and GSP). Subsequent analysis will emphasize the sample and specification used for model 4.

Estimated regression coefficients, together with reported DSM expenditures, are used to generate estimates of electricity savings attributable to DSM expenditures. LK use these utility-year specific estimates of percentage electricity savings $\hat{s}_{nt}$ to generate an estimate of the population parameter S_1. For each regression model, LK report the average percent savings across utilities:

$$\hat{S}_1 = \frac{\sum_{n=1}^{N} \sum_{t=1}^{T_n} \hat{s}_{nt}}{\sum_{n=1}^{N} T_n}, \tag{7}$$

This econometrically estimated *average* is used to compute an estimate of average costs per kWh saved at the mean of the data, which uses $\hat{S}_1$ above to obtain the predicted kWh saved for the cost calculation:

$$\hat{C}_1 = \frac{\frac{\sum_{n=1}^{N} \sum_{t=1}^{T_n} EE_{nt}}{\sum_{n=1}^{N} T_n}}{\hat{S}_1 \left(\frac{\sum_{n=1}^{N} \sum_{t=1}^{T_n} kWh(0)_{nt}}{\sum_{n=1}^{N} T_n} \right)} \tag{8}$$

The second and fourth columns of Table 3 present the estimates of S_1 and C_1 that LK report in the paper.

We have argued that the weighted averages S_2 and C_2 are the preferred test statistics, since they more closely reflect the stated null hypothesis. We construct estimates of these parameters using LK's econometric estimates of $\hat{s}_{nt}$. The point estimates of S_2 and C_2 are reported in the third and fifth column of Table 3 respectively.

The sales-weighted savings implied by the econometric estimates are consistently larger than the unweighted average $\hat{S}_1$. Figure 1 helps to illustrate why this is so. The percentage savings estimates $\hat{s}_{nt}$ constructed by using estimated regression coefficients from Model 4 are plotted against reported expenditures EE_{nt}[7]. The DSM-related energy savings implied by the regression model are larger among utilities that spend more on DSM programs. The solid line corresponds to the unweighted average ($\hat{S}_1 = 1.2\%$). The broken line corresponds to the DSM-expenditure weighted average ($\hat{S}_2 = 1.7\%$). Because of the strong positive relationship between DSM expenditures and electricity savings, $\hat{S}_1 < \hat{S}_2$.

4. Hypothesis Testing

LK correctly note that the effects of DSM program expenditures implied by their regression coefficient point estimates are small relative to the estimate of average utility-reported savings. They reach similar conclusions with regard to average program costs per kWh saved.

This raises our second criticism of the LK paper. In order to formally reject a null hypothesis, it is not sufficient to establish that the point estimate of a test statistic is not equal to the value of the statistic under the null hypothesis. A null hypothesis can only be rejected if we are sufficiently certain that the observed value of the test statistic would not occur if the null hypothesis were true. In this section, we estimate confidence intervals around the point estimates of average savings and costs in order to explicitly account for the variance of the estimated regression coefficients.

In the simplest of cases, the standard error of an estimate of a population parameter can be calculated analytically based on standard assumptions about the distribution of the observed data in the population. In this context, however, analytical approaches to constructing confidence intervals are very complex because the predicted savings (i.e., the $\hat{s}_{nt}$) are not independent within utilities. We thus use a nonparametric residual bootstrap. We first estimate Model (4) and record residuals for each utility.[8] We resample from the residuals by utility and with replacement. The

[7]Model 4 controls for most confounding factors. Other specifications use longer time series, but omit significant variables such as energy prices and GSP.

[8]We focus on model (4) because it has the fewest outliers and controls for the most confounding variables, including energy prices and GSP.

model is then re-estimated with 100,000 bootstrap replications. For each replication, the unweighted average $\hat{S}_1$ and the weighted average $\hat{S}_2$ are estimated and recorded for the entire sample and for the subsample that accounts for 90% of total DSM expenditures[9]. Figure 2 represents these four bootstrap distributions. The shaded histogram in each panel corresponds to the full sample, the clear framed histogram corresponds to using only observations responsible for 90% of total program expenditures. The shaded distribution in the left panel is the one underlying the LK results. For the S_1 measure, the distributions for the full and 90% sample are quite different. For the S_2 measure, as expected, the two distributions are quite similar since the large spenders are weighted more heavily.

Quantiles of these bootstrap distributions can be used to construct percentile confidence intervals when the underlying distributions of the test statistics are symmetric, as is roughly the case for the savings distributions. If the underlying distributions are asymmetric, as is the case for the average costs distribution, these percentile intervals can perform poorly. Hansen (2007) suggests an alternative approach to constructing confidence intervals that have proper coverage probability when test statistic distributions are not symmetric. These two types of 90% and 95% confidence intervals are constructed for the point estimates of S_1, S_2, C_1 and C_2. Results are reported in Table 4. To check for robustness of our findings, we also report the savings confidence intervals from two alternate specifications (models 3 and 5 in the LK paper) using the same sample as in model 4.

Based on their point estimates of S_1, LK conclude that the true average electricity savings attributable to DSM are less than 1.8%. As Table 4 shows, the 90% and 95% confidence intervals based on model 4 include savings of 1.8% for both statistics and sets of utilities considered. For the statistic preferred by us, the 90% confidence interval includes savings up to 2.57% for the full set of utility years and up to 2.83% for the top DSM spenders. This finding is also robust for S_2 for both alternate specifications.

Similarly, LK note that their estimates of costs per saved kWh are higher than the average costs reported by utilities ($0.02-$0.03/kWh). Due to the asymmetry of the cost distribution, the appropriate confidence interval is given by Hansen (2007) and we cannot reject costs per saved

[9]The findings are robust to specifying the cutoff at 80% and 95% as well. At 90% this accounts for 205 utility/year observations or roughly 26.5% of the observations used to estimate Model 4.

kWh of 2.3 cents and greater for C_1 and 1.8 cents for our preferred statistic C_2.

5. Conclusions

DSM programs have the potential to play an important role in mitigating the environmental impacts associated with meeting increasing demand for electricity end-uses. Past program evaluations and utility-reported data have indicated that these programs are highly cost effective. In some respects, Loughran and Kulick (2004) offer empirical evidence that is broadly consistent with the earlier literature. They find that DSM expenditures during the 1990s succeeded in increasing the electricity efficiency of the U.S. economy. The finding that has attracted the most attention since this paper was published is that the effects of DSM are "small relative to what the utilities themselves report" (p. 38), implying that programs are not as cost effective as previously thought.

We contend that LK's choice of test statistic biases results in favor of rejecting the null hypothesis that utility-reported electricity savings reflect true values. Utilities who spend more on DSM programs report significantly larger percentage savings on average. An unweighted average of reported savings weights smaller utilities with small DSM program expenditures and large utilities with significant program expenditures equally. This summary statistic underestimates the electricity savings per dollar spent on DSM programs.

A null hypothesis can only be rejected if we are sufficiently certain that the observed value of the test statistic would not occur if the null hypothesis were true. We estimate confidence intervals around the point estimates of average savings and costs implied by LK's regression coefficient estimates. Using both the weighted and unweighted measure of savings, we fail to reject the null of savings greater than or equal to 1.8%, which LK rejected based on a point estimate alone. Further, the appropriate bootstrapped confidence interval for costs per kWh saved contains costs of \$0.018, which is even lower than the \$0.02 - \$0.03 range rejected by LK.

This analysis, which uses the same data and the same econometric models used by these authors, implies that utility-reported savings and costs can not be rejected on the basis of these econometric results. The estimates of average savings and costs implied by the regression coefficient estimates are consistent with the average effects reported by the utilities themselves over the same study period.

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Figure 1: Energy Efficiency DSM Expenditures and Predicted Savings

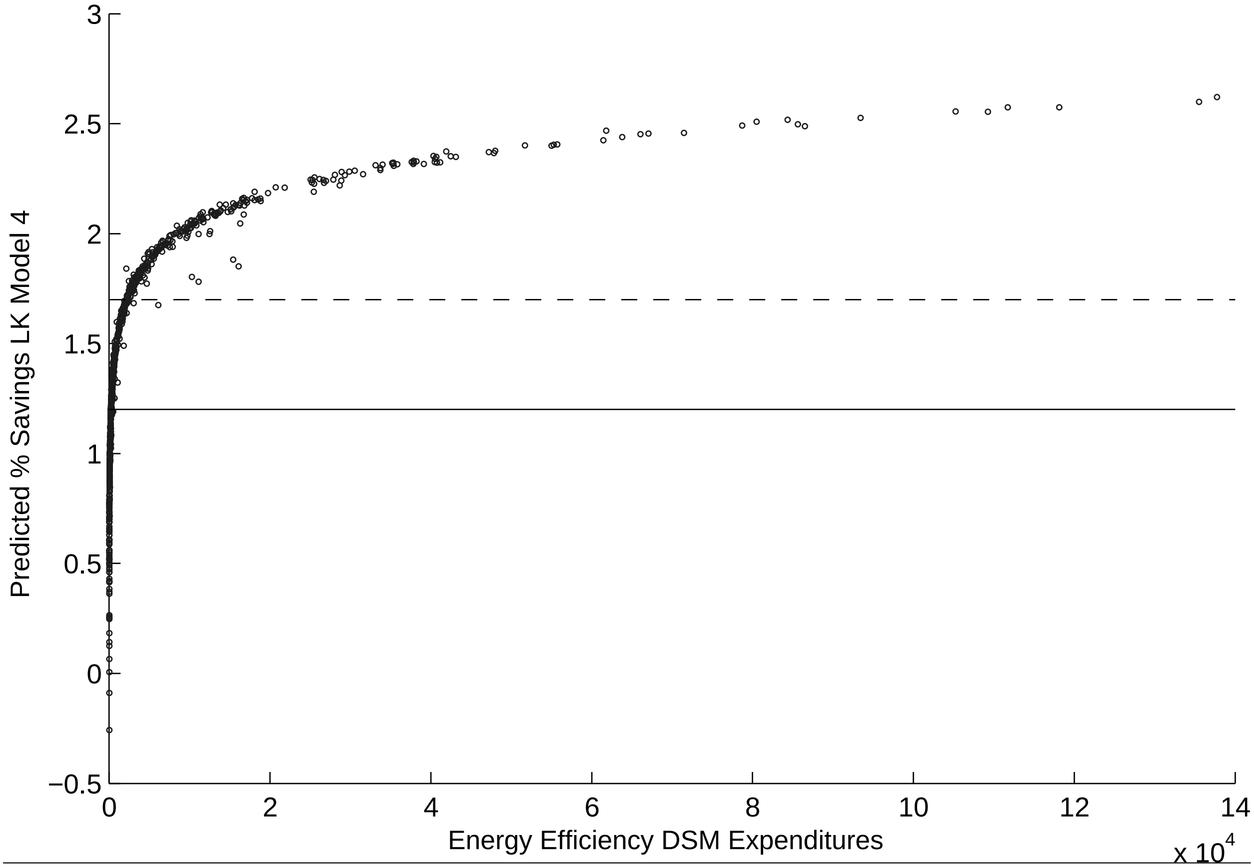

Figure 2: Bootstrap Distribution of Average Savings

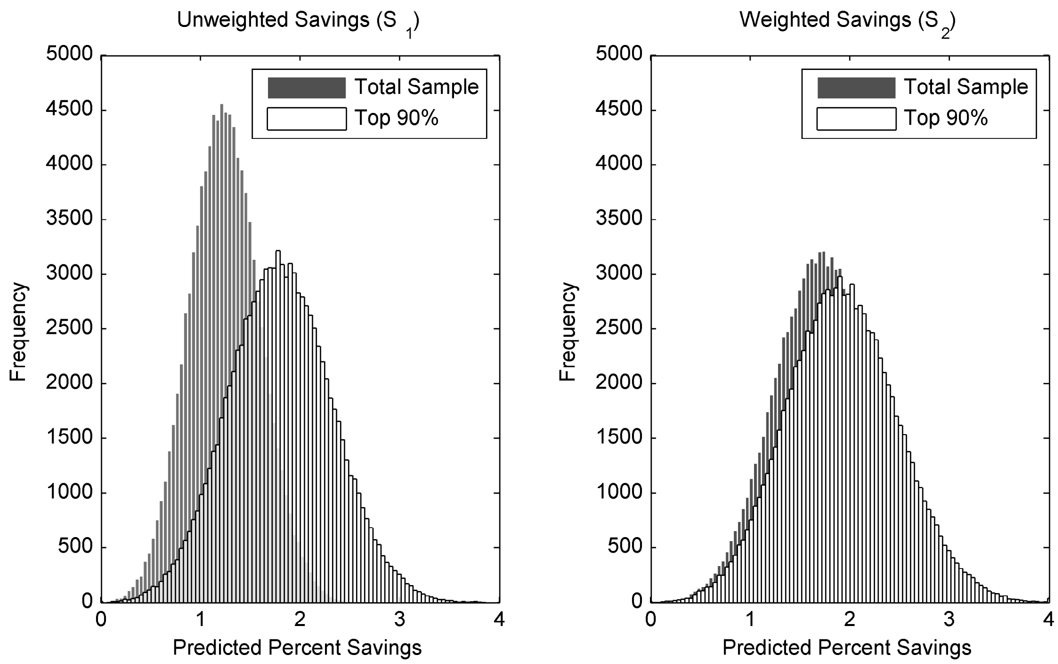

Table 1: Summarizing utility reported data

			Sales		Expenditure
		Unweighted Average Electricity Savings (%)	Weighted Average Electricity Savings (%)	Unweighted Average Costs ($\$/kWh$)	Weighted Average Costs ($\$/kWh$)
Sample	N	$\hat{S}_1$	$\hat{S}_2$	$\hat{C}_1$	$\hat{C}_2$
Full	3597	1.45%	1.46%	1.72	0.024
Model 1	1815	1.51%	1.82%	1.69	0.026
Model 2	1815	1.51%	1.82%	1.69	0.026
Model 3	2,373	1.53%	1.86%	1.75	0.023
Model 4	774	1.99%	2.58%	1.09	0.024
Model 5	998	2.13%	2.79%	0.84	0.021

Source: EIA Form 861, 1989:1999

Table 2: Reported Costs per kWh Saved Outliers

Model	# Observations	# Observations above \$10/kWh	# Observations above \$100/kWh
1	1815	24	3
2	1815	24	3
3	2373	26	3
4	774	7	0
5	998	26	3

Table 3: Point Estimates Implied by Regression Coefficient Estimates

	Reported Average Savings Estimates(%) $(\hat{S}_1)$	Sales Weighted Average Electricity Savings (%) $(\hat{S}_2)$	Reported Average Cost Estimates ($/kWh saved) $(C(\hat{S}_1))$	Expenditure Weighted Average Costs* ($/kWh saved) $(\hat{C}_2)$
Model 1	0.4%	0.7%	0.14	0.079
Model 2	0.3%	0.4%	0.22	0.130
Model 3	0.3%	0.5%	0.17	0.096
Model 4	1.2%	1.7%	0.06	0.046
Model 5	0.6%	0.9%	0.12	0.078

*These cost estimates are obtained by dividing the total costs (summed across all utility-year observations) by the total savings implied by the econometric estimates (i.e. $\sum_{i=1}^{N}\sum_{t=1}^{T_n}\frac{pc_{it}}{1-pc_{it}} * kWh(1)_{it}$).

Table 4: Confidence Intervals for Point Estimates of Average Savings and Costs (n=774)

	Specification	All utility years	90% of total DSM expenditures
Savings (S_1) in %			
90% Percentile interval	Model 4	[0.661 : 1.833]	[0.963: 2.667]
	Model 3	[0.181 : 1.452]	[0.233: 2.081]
	Model 5	[0.456 : 1.816]	[0.608: 2.583]
95% Percentile interval	Model 4	[0.554 : 1.954]	[0.809: 2.841]
	Model 3	[0.062 : 1.581]	[0.060: 2.265]
	Model 5	[0.329 : 1.950]	[0.424: 2.779]
90% Hansen interval	Model 4	[0.646 : 1.818]	[0.940 : 2.645]
95% Hansen interval	Model 4	[0.525 : 1.924]	[0.767 : 2.800]
Savings (S_2) in %			
90% Percentile interval	Model 4	[0.932 : 2.601]	[1.023 : 2.864]
	Model 3	[0.171 : 1.442]	[0.219 : 2.066]
	Model 5	[0.553 : 2.471]	[0.600 : 2.717]
95% Percentile interval	Model 4	[0.783 : 2.774]	[0.600 : 3.056]
	Model 3	[0.056 : 2.184]	[0.053 : 2.399]
	Model 5	[0.378 : 2.663]	[0.408 : 2.931]
90% Hansen interval	Model 4	[0.900 : 2.568]	[0.987 : 2.828]
95% Hansen interval	Model 4	[0.726 : 2.717]	[0.795 : 2.991]
Costs ($C(S_1)$) in ($/kWh)			
90% Percentile interval	Model 4	[0.042 : 0.117]	[0.037 : 0.104]
95% Percentile interval	Model 4	[0.039 : 0.140]	[0.035 : 0.124]
90%Hansen interval	Model 4	[0.023 : 0.098]	[0.020 : 0.087]
95% Hansen interval	Model 4	[0.000 : 0.101]	[0.000 : 0.090]
Costs (C_2) in ($/kWh)			
90% Percentile interval	Model 4	[0.032 : 0.084]	[0.037 : 0.100]
95% Percentile interval	Model 4	[0.030 : 0.010]	[0.035 : 0.118]
90% Hansen interval	Model 4	[0.018 : 0.071]	[0.021 : 0.084]
95% Hansen interval	Model 4	[0.003 : 0.073]	[0.003 : 0.086]