An Evaluation of the Impact of Demand-Side Management Expenditures on State-Level Electricity Efficiency

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ABSTRACT

Global climate change has become a topic of increasing importance to political leaders, policymakers, and the general public. Roughly one third of US greenhouse gas (GHG) emissions come from electricity generation. Improved energy efficiency in electricity end-uses offers the promise of reductions in GHG emissions and other benefits. Market failures have prompted federal and state governments to intervene to promote energy efficiency. One of the largest interventions has been in the form of demand-side management (DSM) programs run by electric utilities, state agencies, and third parties. Given policymakers' considerations of further investments in energy efficiency through expanded DSM and other programs to help mitigate climate change, it is important to evaluate how effective DSM expenditures have been in improving energy efficiency.

Proponents of expanded energy efficiency programs point to a large "efficiency gap" between the current level of energy efficiency and the socially optimal level while citing market failures and barriers as justification for DSM and other programs to promote greater energy efficiency. Critics point out at least theoretical concerns about the efficacy of DSM. Previous empirical studies have come to divergent conclusions regarding the effectiveness of DSM while also revealing shortcomings in the evaluation methods applied to date. In particular, previous work highlights the need to take into account changes in energy efficiency from market transformation, positive spillover, and shifts in economic activity. This study analyzes a state-level panel data set to estimate the effect of DSM expenditures on state-level electricity efficiency controlling for relevant factors and employing a Fisher Ideal index measure of efficiency that distinguishes changes in electricity usage due to changes in electricity efficiency from those due to changes in economic activity. Regression results do not indicate that DSM expenditures improve efficiency; however, electricity price is found to have a strong impact on electricity efficiency.

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TABLE OF CONTENTS

Chapter 1. Introduction

In recent years, global climate change has become a topic of increasing importance to political leaders, policymakers, and the general public. In its 2007 report, the Intergovernmental Panel on Climate Change states with very high confidence that human activities—primarily the addition of greenhouse gases (GHG) to the atmosphere—have led to a warming of the climate. According to the Energy Information Agency (EIA 2004), carbon dioxide from fossil fuel combustion accounts for roughly 80% of total anthropogenic GHG emissions in the US. The Environmental Protection Agency (2007) estimates that, in 2005, electricity generation accounted for roughly 41% of all US carbon dioxide emissions from fossil fuel combustion. Energy efficiency holds promise as one of several options for reducing GHG emissions from electricity generation in order to avoid dangerous anthropogenic climate change (National Academy of Sciences 1991, Pacala and Socolow 2004, Lovins 2005, Bressand et al. 2007).

In addition to climate change mitigation, proponents of energy efficiency claim that energy efficiency offers other significant benefits. The *National Action Plan for Energy Efficiency* (2006) summarizes these additional benefits: environmental benefits from reduced fossil fuel combustion (fewer emissions of SO_2, NO_X, etc.); cost savings to consumers from lower energy bills; cost savings from avoided or delayed investments in new power generation, transmission, and distribution infrastructure; rapid deployment compared to construction of new infrastructure; economic development (as consumers spend energy savings on other goods and services); and energy security.[1]

[1] While imports of foreign petroleum, which does not play a large role in electricity generation, cause the most concern over energy security, natural gas imports do factor significantly into US electricity production.

Chapter 2. Literature Review

Energy Efficiency Policies

The energy crises of the 1970s spurred the federal and state governments to focus on energy efficiency. The federal government has at times adopted a number of different energy efficiency policies that address electricity usage including minimum energy efficiency standards for a variety of products, tax incentives for energy efficiency investments, and the Energy Star program. States have also undertaken energy efficiency programs and policies including tax incentives, building codes, minimum appliance energy efficiency standards, and demand-side management (DSM). Of the options for promoting energy efficiency, some reports suggest that DSM offers the greatest potential for energy savings (Western Governors Association 2006, Eldridge et al. 2007).

DSM includes several types of programs—including: general information to foster awareness of energy saving opportunities; technical information to identify specific energy saving opportunities (e.g. energy audits); financial assistance to customers (including loans and rebates) to promote investments in energy efficiency; direct or free installation of energy-efficient products; performance contracting; load control and load shifting; and non-traditional tariffs (e.g. time-of-day and real-time pricing) (Nadel 1992). Federal legislation played a role in advancing DSM. The National Energy Conservation Policy Act of 1978 (NECPA) mandated that utilities offer residential customers on-site energy audits (Eto 1996). States' adoption of least-cost planning requirements for regulated electricity providers also bolstered the growth of DSM. By the mid-1980s many states had adopted the least-cost planning paradigm wherein utilities would engage in semi-public planning processes for new resource acquisition to meet expected demand rather than simply recovering costs after investments in new power generation had already been made—a change that spurred interest in DSM as an alternative to investments in new generation assets (Eto 1996). DSM spending reached its peak in 1993 and generally declined thereafter following the states' electricity market restructuring (Gillingham et al. 2004).

As states that restructured their electricity markets saw DSM spending decline, many of these states created public benefit funds (PBF) to pay for DSM and other programs (e.g. renewable energy, low-income bill-payment assistance) where states typically funded PBFs with system (or public) benefit charges applied as per-kilowatt-hour fees for electricity distribution (Gillingham et al. 2004). DSM spending experienced an upswing following the enactment of PBFs, and, while some states passed on PBF monies to utilities to continue administering DSM programs, other states authorized state agencies or third parties to administer DSM programs using funding from PBFs (Eldridge et al. 2007).

In a step beyond DSM, twelve states have implemented energy efficiency resource standards (EERS) that require power suppliers to meet specified percentages of demand via energy efficiency (Eldridge et al. 2007). EERS are too new of a development for evaluation but may prove an important complement to DSM programs.

Rationales for Energy Efficiency Policies

Proponents of energy efficiency policies have put forth a number of arguments to justify government intervention in order to promote more energy efficiency than the market provides and have pointed to the existence of an "efficiency gap" or "efficiency paradox." The difference between actual energy efficiency and the energy efficiency that households and firms would achieve were they to invest in the socially optimal level of energy efficiency constitutes the "efficiency gap." Golove and Eto (1996) disaggregate the "efficiency gap" into the amount of additional energy efficiency households and firms would realize were they to apply the same investment criteria to energy efficiency as they do to other investments (profit maximization) and the additional energy efficiency beyond this amount that households and firms would realize were they to make socially optimal investments (social welfare maximization).

Those who subscribe to the “efficiency paradox” paradigm cite the seemingly excessively high discount rates that households and firms apply to energy efficiency investments as evidence. Engineering studies estimate the cost of investments in energy efficiency and their energy savings. Given such estimates, empirical studies have estimated the effective discount rates that households and firms use when evaluating energy efficiency investments. Train (1985) surveyed a number of such studies of discount rates for household energy efficiency investments and found estimates of discount rates of 39-100% for refrigerators and 3-29% for air conditioning.

Explanations of the “efficiency gap” and the high discount rates used for energy efficiency investments—and justifications for government intervention to promote energy efficiency—fall into the categories of market failures and market barriers. Market failures include: principal-agent slippage; imperfect information and public-good aspects of information; environmental externalities; and regulatory mis-pricing of electricity. Principal-agent slippage occurs when, for example, tenants or home buyers cannot trust the energy efficiency claims of landlords or home owners and, as a result, rents or house prices do not accurately reflect the value of energy efficiency investments (Jaffe and Stavins 1994). In a similar vein, Lovins (1996) writes of “perverse incentives” related to energy efficiency such as those whereby a cost-plus contract rewards a builder for spending more on materials but not for reducing future energy expenditures.

Studies have also examined the informational market failures associated with energy efficiency (Jaffe and Stavins 1994, Golove and Eto 1996). Since information about energy efficiency has some characteristics of a public good, the market may undersupply such information. In addition, the adoption of an energy-efficient technology by one household or firm may produce information that could prove valuable to other entities considering the technology—a positive externality. Eto et al. (2000) define participant and non-participant spillover from government-run energy efficiency programs where a program participant makes energy efficiency investments beyond those subsidized by the program and where a non-participant makes energy efficiency investments after observing the benefits enjoyed by a program participant, respectively.

Studies (Jaffe and Stavins 1994, Golove and Eto 1996, Brennan 1998) also emphasize the environmental externalities that may lead to suboptimal investments in energy efficiency since the market price of electricity does not reflect the true social cost of electricity generation (e.g. SO_2, NO_X, CO_2, and mercury emissions from fossil-fuel combustion at power plants). Because of environmental externalities, consumers face an electricity price lower than the true marginal cost of production and thus over-consume from a social welfare perspective. Cost-of-service regulated pricing may also lead to the under-pricing of electricity compared to its true marginal cost of generation (Jaffe and Stavins 1994, Golove and Eto 1996) and thus to an inefficient consumption level. Brennan (1998) notes, however, that government policies to promote energy efficiency are a second-best tool for addressing such inefficiency compared to policies that force the market price of electricity to accurately reflect its marginal cost of production (e.g. emissions taxes or permit trading).

In addition to market failures, some authors also point to market barriers to energy efficiency as rationales for government intervention. Golove and Eto (1996) list several market barriers: financing or borrowing limitations; market power; "gold plating" and inseparability of product features; and custom.

Critiques of Energy Efficiency Policies

Criticisms of energy efficiency policies and programs fall into two categories. First, critics argue that those who point to a large "efficiency gap" either misunderstand the economics of energy efficiency investments or at least overestimate the size of the "efficiency gap." Second, studies that criticize energy efficiency programs identify reasons that such programs may prove ineffective or have undesirable consequences. Attacking the claim that market barriers represent inefficiencies that warrant policy intervention, Sutherland (2000) argues that so-called market barriers exist in all markets and simply represent the cost of adjusting to market conditions—a claim that calls into question the very existence of an "efficiency gap."

Hassett and Metcalf (1995) suggested that households and firms may apply high discount rates to energy efficiency investments as an economically rational response since such investments are irreversible investments made in the face of uncertainty over future energy prices and energy savings.

Other studies (Joskow and Marron 1992, Jaffe and Stavins 1994) point to two factors often ignored by estimates of the "efficiency gap," namely the private costs of energy efficiency adoption and heterogeneity of consumers and firms. Granting that information about energy efficiency has public-good aspects, households and firms must nonetheless incur private costs to adopt new energy-efficient products or technologies. Households and firms must incur costs both to acquire relevant information and assess energy efficiency options and to actually adopt and adapt to new products and technologies. Moreover, estimates of the "efficiency gap" will overstate its magnitude if they fail to acknowledge the heterogeneity of households and firms insofar as energy efficiency investments might prove profitable for only a subset of all such entities given their different uses of the products and technologies in question.

Skeptics of energy efficiency programs highlight four reasons why such programs will prove ineffective or have undesirable effects: the free-rider problem; the rebound effect; perverse regulatory incentives for utilities; and inequitable redistributionary effects. The free-rider problem refers to the ability of households and firms to engage in strategic behavior owing to their private information regarding their own intentions to invest in energy efficiency. Entities that would invest in energy efficiency in the absence of subsidies or other programs will nonetheless accept the subsidies or other inducements for energy efficiency investments. Such free-riding means that some portion of resources devoted to energy efficiency inducements will simply be wealth transfers to free-riders.[2] Gehring (2002) highlights the free-rider problem with both energy efficient appliance rebate programs and time-of-use rates. Wirl (1999) criticizes much of the literature on DSM for overlooking the strategic behavior on the part of consumers that private information allows.

The rebound, or take-back, effect refers to the theoretical prediction that an increase in energy efficiency may actually lead to an increase in electricity consumption by making the corresponding energy service (e.g. air cooling, lighting) less expensive. As the effective price of an energy service decreases, consumers may demand a larger quantity of the energy service. Greening (2000) surveys empirical estimates of rebound effects and finds that increased energy efficiency does generally lead to energy savings; although, the magnitude of the take-back effect is not insubstantial.

[2] Joskow and Marron (1992) note that some portion of DSM expenditures directed toward free riders will be wealth transfers, which raise equity concerns but do not constitute inefficiency, whereas some other portion (e.g. that spent on DSM administration rather than efficient equipment rebates) will constitute actual economic inefficiency.

Wirl (2000) uses a theoretical, economic framework to explain why the regulatory incentives utilities face may lead them to design inefficient DSM programs and raises the issue of distributional equity by suggesting that the optimal DSM program (i.e. one designed to minimize free ridership) will actually subsidize the most efficient consumers, who tend to be the wealthiest, since it is costly to masquerade as high efficiency.[3] Similarly, Sutherland (2000) suggests that efforts to promote energy efficiency may have adverse equity effects since most participants in residential energy conservation programs are from higher income classes; however, all classes bear the cost of such programs thus making such programs redistributions of wealth from lower to higher income classes.

Empirical Studies of Demand-Side Management

Utility-level studies have attempted to empirically evaluate the impact of DSM programs. Joskow and Marron (1992) examined data provided by 10 utilities on their DSM programs and estimated that the actual cost of supplying a kilowatt-hour (kWh) of saved energy was likely twice as high as the costs reported by utilities owing to the utilities' biased estimates of costs and energy savings. Joskow and Marron attributed the biases to utilities' reliance on overly optimistic *ex ante* estimates of energy savings (rather than *ex post* verifications of actual energy savings), lack of adequate adjustments for free riders, and failure to include all relevant costs (e.g. utility administrative costs). Eto et al. (2000) reviewed data from 1992 on the 40 largest commercial-sector DSM programs operated by 23 utilities and found that utilities saved energy at an average cost of 3.2 cents per kWh. Eto et al. took a more positive view of utilities' reported energy savings and costs than Joskow and Marron; Eto et al. did not find a statistically significant difference in the average reported cost of energy savings among utilities employing different

[3] Joskow and Marron (1992) note that free riders are likely to be those for whom energy efficiency investments are most profitable, so the least energy-efficient customers are the ones most likely to be free riders.

energy savings calculation methodologies (i.e. between those utilities relying more heavily on *ex ante* vs. *ex post* estimates of energy savings). Eto et al. did, however, document the extent to which utilities relied on *ex ante* estimates and noted that only half of the DSM programs reviewed employed *ex post* energy savings evaluations that included comparing the electricity consumption of DSM-participating customers with that of a control group of similar customers who did not participate in DSM. Eto et al. pointed out that only two of the 23 utilities surveyed attempted to include estimates of positive spillover into their energy savings calculation.

Parfomak and Lave (1996) took an econometric approach to evaluating the energy savings reported by a sample of 39 utilities in the Northeast and California from program inception through 1993 for commercial and industrial DSM programs. Parfomak and Lave regressed actual utility electricity sales against reported energy savings while controlling for factors such as weather, electricity prices, and sectoral employment levels. From their regression model, the authors found a statistically significant coefficient of -0.994 (95% confidence interval of +/- 0.28) on the estimated energy savings variable (where a coefficient of -1 would indicate no bias in utilities' estimates of energy savings) and noted that utilities had improved their energy savings estimation methodologies over time.

Loughran and Kulick (2004) also conducted an econometric evaluation of DSM programs, examining 324 utilities from 1989 to 1999. Loughran and Kulick regressed actual electricity sales on current-year and lagged DSM expenditures while controlling for other factors such as economic output, number of customers, sectoral sales, weather, and electricity prices to identify the effect of DSM spending on electricity consumption. Loughran and Kulick found a cost per kWh conserved that was 2 to 6 times greater than that estimated by the utilities themselves, which the authors attributed primarily to the utilities' failure to correct for selection bias in DSM program participation (i.e. free riders). Loughran and Kulick note that their approach does not account for positive spillover effects.

Taking a different approach, several investigators have examined the factors driving energy efficiency at a macro-level. In order to account for market transformation effects, Horowitz (2004) examined the effect of DSM programs on commercial-sector electricity intensity (i.e. the ratio of commercial-sector electricity consumption to commercial-sector economic output) at the state level as a proxy for energy efficiency and found that utilities' estimates of electricity conservation overstated actual energy savings by nearly a factor of two. While not examining the effect of DSM programs or limiting themselves to the electricity sector, Bernstein et al. (2003) conducted an econometric analysis to identify factors driving changes in state-level energy intensity (i.e. energy consumption per unit of economic output). Applying a similar approach to the evaluation of DSM spending, Feltes (2003) investigated the effect of utility DSM spending on state-level electricity intensity, defined as electricity sales per unit of Gross State Product (GSP), in an effort to control for the effect of the level of economic activity on electricity use. Feltes found that a 10% increase in DSM expenditures was associated with a roughly 0.09% decrease in electricity intensity.

Metcalf (2008) criticizes the use of energy intensity as a measure of energy efficiency since energy intensity changes both because of changes in energy efficiency and because of changes in economic activity (e.g. a shift from energy-intensive manufacturing to less energy-intensive services), and, to overcome this shortcoming of energy intensity, Metcalf employed a Fisher Ideal index to decompose changes in energy intensity into changes due to energy efficiency and economic activity. Looking at the entire US economy and all energy use—rather than just electricity—Metcalf uses the index methodology to estimate that roughly 2/3 to 3/4 of the decrease in energy intensity of the US economy since 1970 has resulted from increases in energy efficiency with the rest coming from changes in the composition of economic activity.

Chapter 3. Conceptual Model, Analytical Plan, and Data

Conceptual Model and Analytical Plan

The studies reviewed above suggest that one should not rely on simple estimates of energy savings in assessing the impact of DSM programs. In particular, the following factors support the use of a state-level econometric evaluation of DSM programs using Metcalf's Fisher Ideal index: the need to account for free riders; positive spillover effects and market transformation; and changes in energy intensity due to shifts in the composition of economic activity.

This study seeks to gauge the effect of DSM expenditures on aggregate, state-level electricity efficiency using regression models with an electricity efficiency index as the dependent variable on a time-series cross-sectional data set. The independent variable of interest is a continuous variable measuring DSM expenditures. The regression models also incorporate independent variables controlling for other factors that affect electricity efficiency, including electricity price, regulatory environment, per capita income, fuel prices, weather, political environment, state fixed effects, and a time trend.

This study examines independent variables that overlap with those investigated in previous studies; however, this study also controls for changes in electricity intensity that result from different compositions of economic activity rather than from different levels of efficiency. Boyd and Roop (2004) and Metcalf (2008) developed a Fisher Ideal index variable that decomposes changes in energy intensity into those due to changes in energy efficiency and those due to changes in economic activity. This study uses the Fisher Ideal index approach to develop a variable that measures the efficiency with which states use electricity that will serve as the dependent variable in the regression model.

The study employs variants of the regression model illustrated below:

$$eei_{i,t} = ß_0 + eei_{i,t-1} + ß_1 dsm_{i,t} + ß_2 dsm_{i,t-1} + ß_3 dsm_{i,t-2} + ß_4 resdereg_{i,t} + ß_5 resdereg_{i,t-1} + ß_6 resdereg_{i,t-2} + ß_7 commindereg_{i,t} + ß_8 commindereg_{i,t-1} + ß_9 commindereg_{i,t-2} + ß_{10} hdd_{i,t} + ß_{11} cdd_{i,t} + ß_{12} pci_{i,t} + ß_{13} pci_{i,t-1} + ß_{14} pci_{i,t-2} + ß_{15} ep_{i,t} + ß_{16} ep_{i,t-1} + ß_{17} ep_{i,t-2} + ß_{18} ng_{i,t} + ß_{19} ng_{i,t-1} + ß_{20} ng_{i,t-2} + ß_{21} gdp_{i,t} + ß_{22} demgov_{i,t} + ß_{23} state1_t + \cdots + ß_{69} state47_t + ß_{70} year92_t + \cdots + ß_{84} year06_t$$

where $eei_{i,t}$ is the state-level electricity efficiency index for state *i* in year *t* and $dsm_{i,t}$ is a measure of DSM spending in year t and state i.[4]

The remaining variables control for other factors that may affect electricity efficiency in order to isolate the partial effect of DSM programs. The variables *resdereg* and *commindereg* are dichotomous variables that describes the regulatory status of state residential and commercial/industrial electricity markets, respectively. The variables *hdd*, *cdd*, *pci*, *ep*, *ng*, *gsp*, and *demgov* control for heating degree days, cooling degree days, per capita income, electricity prices, natural gas prices, state gross domestic product (GDP), and presence of a Democratic governor respectively. Finally, the regression model includes dichotomous variables controlling for fixed state effects and a time trend.

Theory and prior studies allow one to hypothesize the effects of the independent variables. One might expect that a larger number of heating and cooling degree days would require more air heating and cooling and thus reduce energy efficiency.[5] Previous econometric studies have found mixed results for heating and cooling degree day variables. One would also expect higher electricity prices in the current year and in past years to contribute to greater

[4] Feltes (2003) used the log of DSM expenditures. This study employs a different measure of DSM expenditures, the ratio of DSM expenditures to electricity sales, since one would not expect a dollar of DSM spending to have the same effect on an energy efficiency index in states with economies of different sizes.

electricity efficiency since higher electricity prices would make firms and individuals more likely to invest in energy efficiency. Prior empirical studies have confirmed this effect of electricity prices. The model includes lagged variables for electricity prices and several other variables since one expects energy efficiency to be a function of conditions and investments made in past years as well as the current year. The model includes variables for natural gas prices and absolute GSP because natural gas is the closest substitute for electricity for certain uses and states with larger economies might experience economies of scale in the use of energy to produce output (Horowitz 2004). Finally, the regression model includes a variable denoting the presence of a Democratic governor as a proxy for state political culture and leadership based upon the hypothesis that citizens in more liberal states might be more likely to favor energy conservation and efficiency while such states might also be more likely to spend more on energy efficiency programs. Previous studies have used the presence of a Democratic governor as a proxy variable in their regression models to control for political economy factors, including studies of renewable energy (Okazaki 2006), environmental enforcement (Helland 1998), and state expenditures (Painter and Bae 2001).

Following previous studies (Horowitz 2004, Metcalf 2008), this study examines regression models with and without a lagged dependent variable on the right-hand side of the equation above, and this study uses the natural log of continuous independent variables. Previous studies that examined aggregate state-level energy intensity (Bernstein et al. 2003), electricity intensity (Horowitz 2004, Feltes 2003), and energy efficiency (Metcalf 2008) using panel data sets employed regression models with state and year fixed effects. Likewise, this study also

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[5] The electricity efficiency index dependent variable is constructed such that an improvement in energy efficiency from one year to the next manifests as a decline in the value of the energy efficiency index. See the appendix and Metcalf (2008) for details on the index.

employs fixed-effects models. Wooldridge (2005) explains that failure to control for unobserved effects (in this case for states and years) when they are correlated with any of the independent variables leads to heterogeneity bias (a form of omitted variable bias) and notes that the fixed effects approach is superior to the random effects model for policy analysis concerning aggregate entities such as states.

State and year fixed-effects models, however, only control for time-invariant unobserved effects that differ across states and years. Beck and Katz (1995) reviewed the challenges of using OLS with panel data on geographic entities such as states owing to heteroskedasticity and spatially and temporally correlated errors and recommended the use of panel-corrected standard errors (PCSE). When applied to this study's panel data set, the tests described by Wiggins and Poi (2003) found evidence of heteroskedasticity and serial correlation in the errors. As such, this study presents the results of various regression models that control for heteroskedasticity and serial correlation. In addition, models that include a lagged dependent variable as a regressor risk dynamic panel bias (Roodman 2006). This study uses two regression techniques to control for dynamic panel bias. The first is the Arellano-Bond dynamic panel estimators, and the second is the least squares dummy variable with autoregression correction (LSDVC). Bruno (2004) contends that the latter is a superior estimation technique based on evidence from Monte Carlo simulations.

Data

Data were compiled from a number of sources for the 48 contiguous United States for the years 1990 to 2006. Data on utility DSM spending, electricity prices, natural gas prices, electricity usage, and electricity market restructuring status come from the Energy Information Agency (EIA). In particular, data on utility DSM spending and utility electricity sales by state come from the form EIA-861. The availability of data on electric utilities' DSM spending from EIA determined the start year for the dataset. Heating and cooling degree days are from the National Oceanic and Atmospheric Administration (NOAA). State GDP and personal income data come from the Bureau of Economic Analysis (BEA). State GDP values were converted to 2005 dollars using the GDP deflator from the BEA; all other monetary values were converted to 2005 dollars using the CPI as provided by the Federal Reserve Bank of Minneapolis. Data regarding the party affiliation of state governors over time comes from Rulers.org. The tables in Appendix B summarize the dependent and independent variables with descriptive statistics shown for each of the 48 states included in the study.[6]

Since 1989, EIA has required electric utilities to report spending on DSM programs annually in Form EIA-861. This study utilizes data on DSM expenditures at the utility-level from EIA-861 for the years 1990 through 2006. Since EIA-861 contains data reported at the utility-level and this study uses states as its units of observation, in cases where utilities supply electricity across multiple states, these utilities' DSM expenditures were prorated across states served proportionally to utilities' electricity sales in the states. In addition, prior to 1992 form EIA-861 did not require utilities to separately report DSM expenditures on energy efficiency (as opposed to load shifting) programs; as such, this study assumes energy efficiency constituted the same proportion of total DSM spending prior to 1992 as in 1992. Previous studies that utilized EIA-861 data made use of both of the two previous assumptions.

As a measure of spending on energy efficiency programs, form EIA-861 suffers from inaccuracies in reporting and incompleteness of coverage, especially in the most recent years and

[6] Data have also been collected on state electricity market restructuring and the presence of Democratic governors, but these data have been excluded from the summary table since they are dichotomous variables.

in states with restructured electricity markets.[7] To address this issue, data were collected to supplement the DSM expenditure data from form EIA-861. Aggregate state-level DSM expenditures by state summed from the EIA-861 data were compared to the values reported by Eldridge et al (2007) (see Appendix C for details). In states where significant discrepancies were found, additional data were collected on energy efficiency program spending.[8] Nonetheless, discrepancies remain between ACEEE figures and those used in this study even after corrections and measurement error concerns persist.

Of additional concern, data availability may lead to omitted variable bias in the study's regression results. States employ several energy efficiency policies and programs in addition to DSM, such as energy efficiency resource requirements, building codes, appliance standards, and demand-side bidding. One may reasonably assume both that these other factors affect aggregate state-level energy efficiency and that they are correlated with DSM expenditures. For example, California both invests heavily in DSM and has strict building codes to promote energy efficiency. No database exists that tracks the status of a wide-array of state energy efficiency policies and programs across time.[9] Given the lack of readily available data, the inclusion in the study's regression model of variables for energy efficiency policies other than DSM fell outside the scope of this study.

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[7] Based on personal communication from Dr. Dan York of the American Council for an Energy-Efficient Economy (ACEEE).

[8] For example, supplementary data came from the Database of State Incentives for Renewables and Efficiency (DSIRE), annual reports for such agencies as Efficiency Vermont, Oregon Energy Trust, New Jersey Clean Energy Collaborative, and utilities' reports to public utility commissions.

[9] Based on a personal communication from Dr. Dan York of ACEEE (20 November 2007) and the author's extensive search. Some databases (e.g. DSIRE) do have cross-sectional data on energy efficiency policies aside from DSM.

Chapter 4. Results and Discussion

Results

Table 1 below lists the independent variables used in the regression models discussed below.

Table 1 Description of Variables

Variable	Description
DSM_PER_MWH_SALES	Ratio of aggregate state DSM energy efficiency spending in 2005$ to total state electricity sales in MWh
DSM_PERC_OF_TOT_REV	Ratio of aggregate state DSM energy efficiency spending in 2005$ to total state electricity sales in 2005$
HDD	Number of heating degree days
CDD	Number of cooling degree days
PerCapitaIncome	Per capita income (2005$)
EP_CentsKWh	Average state electricity price in cents per kWh (2005$)
NG	Average state natural gas price in dollars per thousand cf city gate (2005$)
GDP	State GDP (2005$)
RestructuringRes	Dichotomous variable equal to 1 where a state had restructured its residential electricity market
RestructuringIndComm	Dichotomous variable equal to 1 where a state had restructured its commercial and/or industrial electricity market
DemGov	Dichotomous variable equal to 1 where a state had a Democratic governor in office
Feff	Energy efficiency component of Fisher Ideal index for energy intensity. Used in level form.
ElectricityIntensity	Alternative regressand used, equal to the ratio of total electricity sales (MWh) to state GDP (2005$). Used in log form in regressions.

Notes: The regression models use the natural logs of all non-dichotomous variables except where otherwise noted. Regression models used either DSM_PER_MWH_SALES or DSM_PERC_OF_TOT_REV but not both as the key independent variable of interest. Regression models also used lagged versions of the variables above where the suffixes _LAG1 and _LAG2 denote the one- and two-period lagged versions respectively.

As a first step, eight fixed-effects OLS models were run to test the sensitivity of regression results to the following factors: choice between using the ratio of DSM expenditures to electricity sales revenue and using the ratio of DSM expenditures to electricity sales measured in MWh as the key independent variable of interest; inclusion of lagged dependent variable; inclusion of lagged independent variables. Table 2 shows the results of these eight regressions.

Table 2: State and Year Fixed-Effects OLS Regression Results

	Model 1: OLS		Model 2: OLS		Model 3: OLS		Model 4: OLS		Model 5: OLS		Model 6: OLS		Model 7: OLS		Model 8: OLS	
Variable	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.
Intercept	4.570 *	1.815	4.575 *	1.816	10.030 **	1.157	10.038 **	1.158	6.814 **	1.103	6.818 **	1.103	10.278 **	0.888	10.282 **	0.888
F_EFF_LAG1	0.494 **	0.119	0.494 **	0.119					0.453 **	0.085	0.453 **	0.085				
DSM_PER_MWH_SALES	0.001	0.001			0.001	0.001			0.002	0.001			0.002	0.001		
DSM_PER_MWH_SALES_LAG1	0.003 *	0.001			0.003 *	0.002										
DSM_PER_MWH_SALES_LAG2	-0.002	0.001			-0.001	0.001										
DSM_PERC_OF_TOT_REV			0.001	0.001			0.001	0.001			0.002	0.001			0.002	0.001
DSM_PERC_OF_TOT_REV_LAG1			0.003 *	0.001			0.003 *	0.002								
DSM_PERC_OF_TOT_REV_LAG2			-0.002	0.001			-0.001	0.001								
HDD	0.057 *	0.029	0.057 *	0.029	0.024	0.034	0.024	0.034	0.049	0.029	0.049	0.029	0.027	0.034	0.027	0.034
CDD	0.041 **	0.008	0.041 **	0.008	0.030 **	0.009	0.030 **	0.009	0.041 **	0.008	0.041 **	0.008	0.024 **	0.009	0.024 **	0.009
PerCapitaIncome	-0.967 **	0.167	-0.967 **	0.167	-0.872 **	0.156	-0.872 **	0.156	-0.530 **	0.096	-0.530 **	0.096	-0.637 **	0.096	-0.637 **	0.096
PerCapitaIncome_LAG1	0.700 **	0.225	0.700 **	0.225	0.254	0.149	0.254	0.149								
PerCapitaIncome_LAG2	-0.038	0.125	-0.038	0.125	0.029	0.138	0.029	0.138								
EP_CentsKWh	-0.190 **	0.055	-0.189 **	0.055	-0.145 *	0.057	-0.144 *	0.057	-0.252 **	0.037	-0.250 **	0.037	-0.381 **	0.033	-0.378 **	0.033
EP_CentsKWh_LAG1	0.014	0.088	0.017	0.088	-0.154 *	0.071	-0.151 *	0.070								
EP_CentsKWh_LAG2	-0.083 *	0.038	-0.084 *	0.037	-0.194 **	0.047	-0.194 **	0.047								
NG	-0.015	0.037	-0.015	0.037	-0.050	0.031	-0.050	0.031	-0.013	0.028	-0.013	0.028	-0.044 *	0.022	-0.044 *	0.022
NG_LAG1	0.023	0.023	0.023	0.023	0.012	0.024	0.012	0.024								
NG_LAG2	-0.004	0.018	-0.004	0.018	0.005	0.015	0.005	0.015								
GDP	-0.139	0.104	-0.139	0.104	-0.149	0.104	-0.149	0.104	-0.113 *	0.046	-0.113 *	0.046	-0.256 **	0.048	-0.256 **	0.048
GDP_LAG1	0.143	0.134	0.143	0.134	0.046	0.141	0.046	0.141								
GDP_LAG2	-0.134	0.111	-0.134	0.111	-0.157	0.113	-0.157	0.113								
RestructuringRes	-0.005	0.027	-0.005	0.027	0.022	0.022	0.022	0.022	0.012	0.015	0.012	0.015	0.029	0.019	0.029	0.019
RestructuringRes_LAG1	0.022	0.026	0.022	0.026	0.000	0.022	0.000	0.022								
RestructuringRes_LAG2	-0.017	0.017	-0.017	0.017	-0.027	0.021	-0.027	0.021								
RestructuringIndComm	-0.025	0.024	-0.025	0.024	-0.064 **	0.018	-0.064 **	0.018	-0.045 **	0.015	-0.045 **	0.015	-0.088 **	0.018	-0.088 **	0.018
RestructuringIndComm_LAG1	-0.012	0.021	-0.012	0.021	-0.007	0.018	-0.007	0.018								
RestructuringIndComm_LAG2	0.004	0.014	0.004	0.014	0.005	0.017	0.005	0.017								
DemGov	-0.004	0.006	-0.004	0.006	-0.002	0.005	-0.002	0.005	-0.004	0.004	-0.004	0.004	-0.006	0.004	-0.006	0.004
DemGov_LAG1	-0.003	0.006	-0.003	0.006	-0.003	0.006	-0.003	0.006								
DemGov_LAG2	0.004	0.004	0.004	0.004	0.000	0.005	0.000	0.005								
# of Observations	701		701		701		701		701		701		701		701	
R-Squared	0.91		0.91		0.88		0.88		0.90		0.90		0.86		0.86	
F-statistic (df)									151 (72)		151 (72)		76 (71)		76 (71)	

Notes: Dichotomous variables for the state and year fixed effects are not shown above. Reported standard errors are Huber-White standard errors. State and year fixed effect dichotomous variables were jointly statistically significant in all models.
* $p<0.05$ ** $p<0.01$

One can see from Table 2 that the results are insensitive to the choice of DSM variable definition. Moreover, the inclusion of lagged regressors does identify lagged effects. As such, the additional regressions discussed below used lagged regressors and one definition of the DSM regressor (ratio of DSM expenditures to electricity sales measured in MWh). Table 3 presents the results of regressions using different estimation techniques and standard error corrections for models with and without lagged dependent variables. One can see from Table 3 how sensitive the study's findings are to different regression techniques and assumptions.

Table 3: Regression Results for Different Estimators and Models

Variable	Model 9: OLS		Model 10: Prais-Winsten PCSE		Model 11: OLS		Model 12: Prais-Winsten PCSE		Model 13: LSDVC		Model 14: Arellano-Bond	
	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.
Intercept	10.030 **	1.157	10.072 **	1.863	4.570 *	1.815	5.148 **	1.538			10.402 **	2.136
F_EFF_LAG1					0.494 **	0.119	0.439 **	0.070	0.721 **	0.084	0.138	0.127
DSM_PER_MWH_SALES	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.000	0.002	0.000	0.001
DSM_PER_MWH_SALES_LAG1	0.003 *	0.002	0.003 *	0.001	0.003 *	0.001	0.003	0.002	0.003	0.002	0.005 *	0.002
DSM_PER_MWH_SALES_LAG2	-0.001	0.001	0.001	0.001	-0.002	0.001	-0.001	0.001	-0.003	0.002	0.002	0.002
HDD	0.024	0.034	0.064 **	0.023	0.057 *	0.029	0.059 *	0.025	0.045	0.028	0.057 *	0.026
CDD	0.030 **	0.009	0.033 **	0.009	0.041 **	0.008	0.040 **	0.010	0.043 **	0.010	0.033 *	0.014
PerCapitaIncome	-0.872 **	0.156	-0.892 **	0.115	-0.967 **	0.167	-0.960 **	0.118	-0.956 **	0.096	-0.981 **	0.204
PerCapitaIncome_LAG1	0.254	0.149	0.304 *	0.120	0.700 **	0.225	0.667 **	0.147	0.915 **	0.136	0.319	0.235
PerCapitaIncome_LAG2	0.029	0.138	-0.050	0.137	-0.038	0.125	-0.047	0.132	-0.172	0.126	0.054	0.112
EP_CentsKWh	-0.145 *	0.057	-0.202 **	0.035	-0.190 **	0.055	-0.187 **	0.035	-0.186 **	0.042	-0.259 **	0.078
EP_CentsKWh_LAG1	-0.154 *	0.071	-0.140 **	0.042	0.014	0.088	-0.004	0.055	0.071	0.070	-0.076	0.102
EP_CentsKWh_LAG2	-0.194 **	0.047	-0.130 **	0.036	-0.083 *	0.038	-0.093 *	0.038	-0.007	0.055	-0.054	0.052
NG	-0.050	0.031	-0.018	0.021	-0.015	0.037	-0.015	0.020	-0.020	0.016	0.006	0.012
NG_LAG1	0.012	0.024	0.017	0.021	0.023	0.023	0.020	0.024	0.018	0.021	0.033	0.023
NG_LAG2	0.005	0.015	-0.002	0.021	-0.004	0.018	-0.004	0.020	-0.019	0.020	0.011	0.013
GDP	-0.149	0.104	-0.191	0.101	-0.139	0.104	-0.147	0.103	-0.143	0.086	-0.225	0.150
GDP_LAG1	0.046	0.141	0.074	0.112	0.143	0.134	0.141	0.135	0.258 *	0.128	0.207	0.167
GDP_LAG2	-0.157	0.113	-0.142	0.106	-0.134	0.111	-0.138	0.102	-0.165	0.093	-0.260 **	0.096
RestructuringRes	0.022	0.022	-0.003	0.030	-0.005	0.027	-0.004	0.028	-0.005	0.041	-0.026	0.030
RestructuringRes_LAG1	0.000	0.022	0.019	0.032	0.022	0.026	0.022	0.037	0.033	0.055	0.021	0.021
RestructuringRes_LAG2	-0.027	0.021	-0.015	0.032	-0.017	0.017	-0.018	0.031	-0.014	0.042	0.019	0.034
RestructuringIndComm	-0.064 **	0.018	-0.032	0.028	-0.025	0.024	-0.026	0.027	-0.023	0.039	-0.009	0.026
RestructuringIndComm_LAG1	-0.007	0.018	-0.029	0.031	-0.012	0.021	-0.014	0.035	-0.014	0.051	-0.022	0.017
RestructuringIndComm_LAG2	0.005	0.017	-0.003	0.030	0.004	0.014	0.004	0.029	0.006	0.042	-0.026	0.034
DemGov	-0.002	0.005	-0.005	0.004	-0.004	0.006	-0.004	0.004	-0.006	0.005	-0.007	0.008
DemGov_LAG1	-0.003	0.006	-0.002	0.004	-0.003	0.006	-0.003	0.005	0.002	0.006	-0.001	0.003
DemGov_LAG2	0.000	0.005	0.002	0.004	0.004	0.004	0.004	0.004	0.001	0.005	0.002	0.004
# of Observations	701		701		701		701				554	
R-Squared	0.88		0.93		0.91		0.90					
F-statistic (df)												
Wald Chi-Square (df)			2724 (87) **				8385 (88) **				1911 (38) **	

Notes: Results for dichotomous variables for the state and year fixed effects are not shown above.
* $p<0.05$ ** $p<0.01$

The only DSM variable that the models found to be statistically significant was the one-year lag version of the log of the ratio of total state DSM expenditures to total electricity sales measured in MWh. This variable was statistically significant ($p < 0.05$) in Models 9, 10, 11, and 14. However, this variable had a positive coefficient in all models with a value of 0.003 in most models. As such, the regression models indicate that, for example, a 10% increase in DSM expenditures relative to electricity sales would, on average and ceteris paribus, lead to an increase in energy intensity of 0.03% in the following year.[10]

[10] The on average and ceteris paribus conditions are implicitly assumed by all subsequent regression coefficient interpretations.

Turning to the other independent variables, one can see that increases in the need for air cooling and heating lead to an increase in energy intensity. Cooling degree days (CDD) are statistically significant in all six models, and heating degree days (HDD) are statistically significant in four of the six. All coefficients for CDD and HDD are positive and range from 0.030 to 0.041 and 0.057 to 0.064 respectively. The results indicate that, for example, a 10% increase in the number of CDD in a given year would increase that year's electricity intensity by roughly 0.35% while a similar increase in HDD would increase electricity intensity by roughly 0.6%.

Present-year per capita income proved to be statistically significant in all models while one-year lagged per capita income was statistically significant in four of the models. Surprisingly, while present-year per capita income is associated with an improvement in electricity efficiency, prior-year per capita income is associated with an increase in electricity intensity. The coefficients on present-year per capita income suggest that a 10% increase in per capita income decreases electricity intensity by between 8.7% and 9.8%. However, such an increase in per capita income increases the following year's electricity intensity by between 3% and 9.2%.

As expected, present-year electricity prices were statistically significant in all models and lagged versions of this variable were statistically significant in Models 9-12. All statistically significant coefficients were negative, in keeping with the expected improvement in electricity efficiency and resultant decrease in electricity intensity that one would expect from rising electricity prices. Model 10, for instance, indicates that a permanent 10% increase in electricity prices would lead to a roughly 4.7% decrease in energy intensity after three years.

Unlike electricity prices, natural gas price variables were not individually statistically significant in any of the regression models nor were the present-year and lagged variables jointly statistically significant in any of the models.

Results for the state GDP variables provided weak evidence that larger absolute state GDP leads to lower electricity intensity. Lagged GDP variables were individually statistically significant in Models 13 and 14 while the present-year and lagged variables were jointly statistically significant in Models 9, 10, and 12. Most of the coefficients on the GDP variables are negative.

The indicator variables for residential electricity market restructuring were not statistically significant (individually or jointly) in any of the models. The indicator variables for industrial and/or commercial sector electricity market restructuring were jointly statistically significant in Models 9 and 11. The coefficients on the industrial/commercial indicator variables suggest that electricity market restructuring may lead to greater electricity efficiency and lower electricity intensity.

The coefficients on the indicator variables for Democratic governors were not individually or jointly statistically significant in any of the models. Table 4 shows the results of joint significance tests on groups of present-year variables and their lagged versions for the different regression models.

Table 4: Joint Significance Tests for Independent Variables

Variable	Model 9: OLS	Model 10: Prais-Winsten PCSE	Model 11: OLS	Model 12: Prais-Winsten PCSE	Model 13: LSDVC
DSM_PER_MWH_SALES	*		*		
PerCapitaIncome	**	**	**	**	**
EP_CentsKWh	**	**	**	**	**
NG					
GDP	**	**		*	
RestructuringRes					
RestructuringIndComm	**		*		
DemGov					

Notes: The table above shows the results of joint significance tests for each of the listed regressors and its lagged versions. Joint significance tests were not available for the Arellano-Bond estimates.
* $p<0.05$ ** $p<0.01$

In light of the unexpected positive coefficient estimates for the DSM independent variables, additional models were run using electricity intensity (rather than the electricity intensity index value used in the models discussed above).[11] Table 5 presents the results from the regressions using electricity intensity.

[11] Electricity intensity is defined as the ratio of total state electricity sales (MWh) to state GDP. Note that there is a discontinuity in the GDP by state time series at 1997, where the data change from SIC industry definitions to NAICS industry definitions. As such, BEA recommends against constructing a continuous time-series as done here.

Table 5: Regression Results for Models with Electricity Intensity Regressand

Variable	Model 15: OLS Coeff.	s.e.	Model 16: Prais-Winsten PCSE Coeff.	s.e.	Model 17: OLS Coeff.	s.e.	Model 18: Prais-Winsten PCSE Coeff.	s.e.	Model 19: LSDVC Coeff.	s.e.	Model 20: Arellano-Bond Coeff.	s.e.
Intercept	13.234 **	1.096	12.429 **	1.054	1.724 *	0.867	1.044	0.971			6.199 **	1.667
ELECTRICITY_INTENSITY_LAG1					0.757 **	0.033	0.813 **	0.044	1.135 **	0.348	0.452 **	0.107
DSM_PER_MWH_SALES	0.003 *	0.001	0.002	0.001	0.001	0.001	0.001	0.001	0.001	0.002	0.001	0.001
DSM_PER_MWH_SALES_LAG1	0.003 *	0.001	0.002 **	0.001	0.002	0.001	0.002	0.001	0.001	0.003	0.003 **	0.001
DSM_PER_MWH_SALES_LAG2	-0.001	0.001	-0.001	0.001	-0.001	0.001	-0.001	0.001	-0.003	0.002	0.000	0.001
HDD	0.019	0.031	0.059 **	0.018	0.058 **	0.020	0.043	0.022	0.062	0.040	0.071 **	0.021
CDD	0.021 *	0.010	0.031 **	0.005	0.038 **	0.007	0.035 **	0.006	0.047 **	0.017	0.053 **	0.008
PerCapitaIncome	-0.030	0.141	-0.063	0.074	-0.021	0.090	-0.012	0.059	-0.011	0.152	0.011	0.101
PerCapitaIncome_LAG1	0.176	0.151	0.112	0.084	0.153	0.082	0.145	0.078	0.162	0.180	0.143 *	0.059
PerCapitaIncome_LAG2	-0.362 **	0.138	-0.207 **	0.076	-0.106	0.085	-0.087	0.072	-0.182	0.205	-0.028	0.110
EP_CentsKWh	-0.199 **	0.060	-0.268 **	0.029	-0.271 **	0.054	-0.272 **	0.027	-0.278 **	0.078	-0.268 **	0.090
EP_CentsKWh_LAG1	-0.115	0.064	-0.090 **	0.033	0.160 **	0.057	0.175 **	0.039	0.285 *	0.134	0.105	0.079
EP_CentsKWh_LAG2	-0.226 **	0.051	-0.141 **	0.028	-0.038	0.033	-0.020	0.032	0.031	0.075	-0.059	0.050
NG	-0.017	0.015	-0.007	0.010	-0.007	0.012	-0.009	0.010	-0.010	0.020	-0.005	0.014
NG_LAG1	-0.016	0.014	-0.009	0.010	0.001	0.011	0.004	0.010	0.002	0.024	-0.002	0.012
NG_LAG2	-0.006	0.013	-0.003	0.010	-0.001	0.009	-0.002	0.009	-0.002	0.024	-0.007	0.009
GDP	-0.634 **	0.081	-0.701 **	0.049	-0.784 **	0.055	-0.794 **	0.045	-0.817 **	0.090	-0.796 **	0.085
GDP_LAG1	0.022	0.086	0.138 **	0.049	0.702 **	0.067	0.737 **	0.074	1.045 **	0.355	0.494 **	0.104
GDP_LAG2	0.223 **	0.069	0.143 **	0.054	-0.008	0.045	-0.011	0.047	-0.106	0.170	-0.101	0.068
RestructuringRes	0.044	0.023	0.002	0.032	-0.029	0.016	-0.026	0.029	-0.037	0.065	-0.007	0.046
RestructuringRes_LAG1	-0.015	0.022	0.021	0.033	0.048 **	0.018	0.046	0.041	0.067	0.048	0.049 *	0.021
RestructuringRes_LAG2	0.007	0.021	0.022	0.032	-0.010	0.015	-0.012	0.031	-0.027	0.043	0.007	0.018
RestructuringIndComm	-0.081 **	0.021	-0.035	0.032	0.005	0.014	0.004	0.028	0.020	0.062	-0.020	0.046
RestructuringIndComm_LAG1	0.008	0.018	-0.030	0.032	-0.031 *	0.013	-0.027	0.039	-0.037	0.043	-0.040 *	0.016
RestructuringIndComm_LAG2	-0.021	0.017	-0.034	0.031	0.007	0.012	0.010	0.030	0.025	0.042	-0.005	0.015
DemGov	-0.004	0.004	-0.002	0.003	0.002	0.003	0.003	0.003	0.002	0.008	-0.002	0.004
DemGov_LAG1	-0.007	0.005	-0.007 *	0.003	-0.010 *	0.004	-0.011 **	0.004	-0.006	0.005	-0.003	0.003
DemGov_LAG2	-0.003	0.004	-0.003	0.003	0.005	0.003	0.006 *	0.003	0.006	0.007	-0.004	0.004
# of Observations	701		701		701		701				554	
R-Squared	0.99		1.00		1.00		1.00					
F-statistic (df)												
Wald Chi-Square (df)			44,200,000 (50) **				1.6 x 10^12 (51) **					

Notes: The models above use the natural log of the electricity intensity variable as their regressand. Results for dichotomous variables for the state and year fixed effects are not shown above. OLS models report White-Huber heteroskedasticity-robust standard errors.
* p<0.05 ** p<0.01

In particular, the author hoped to determine whether the positive coefficients for the DSM regressors resulted from the novel application of the Fisher Ideal index regressands. The results for Models 15-20 show that DSM regressors were only statistically significant in three of the six models. In all cases of statistical significance the DSM regressor estimates were positive. Moreover, the magnitudes of the estimates in Models 15-20 closely follow those in Models 9-14.[12] As in Models 9-14, the only DSM regressor estimates found to be negative were the two-

[12] Note that the use of a level-log specification in Models 9-14 and a log-log specification in Models 15-20 allow for a roughly direct comparison of regressor estimates since their interpretations are nearly identical between the two specifications.

year lagged variable (in four of the six models). However, none of the negative estimate were found to be statistically significant.

Discussion

Some of the regression results discussed above fit neatly with theory and expectations. This analysis of the efficiency component of electricity intensity found a long-run price elasticity for electricity intensity of roughly -0.47. This is similar to the long-run price elasticity for overall energy intensity found by Metcalf (2008) of -0.299 using the Fisher Ideal index approach. Metcalf (2008) also cites a survey by Atkinson and Manning (1995) that found median price elasticities of -0.5 for studies of energy demand; this study's results closely match this median estimate. The results for CDD and HDD fit with expectations since the need for additional air cooling and heating requires more energy input without resulting in additional economic output, thus worsening electricity efficiency.

The study did not find evidence to support certain hypothesized determinants of electricity efficiency. Controlling for electricity prices, the study did not find evidence that natural gas prices affect electricity efficiency. One might have expected that natural gas prices would have a positive coefficient in the study's regression models based on the theory that lower natural gas prices would lead some firms or households to substitute natural gas for electricity for certain applications thus lowering the electricity input for a given level of economic activity and seemingly improving electricity efficiency. The regression results, however, provide no support for this theory. Likewise, the results do not support the hypothesis that states with liberal political cultures, which one may assume to be more conducive to energy conservation and associated with Democratic governors, have better electricity efficiency.

The study results provide at least weak support for some theories regarding the determinants of electricity efficiency. The results provide some weak support for the theory suggested by Horowitz (2004) that states with larger GDPs would have lower ratios of electricity usage to economic output based on economies of scale in transforming electricity inputs into economic outputs. Similarly, the results provide some evidence that restructuring of a state's industrial and commercial electricity markets improves the state's electricity efficiency; however, the study does not offer evidence to suggest why this may be the case.

In applying the same index number approach, Metcalf (2008) also found that increases in present-year per capita income tend to lower energy intensity; however, he did not include lagged regressors with which to compare this study's findings. Why might present-year per capita income increases lead to improved electricity efficiency in the current year and worsened electricity efficiency in the following year? This study provides no support for any explanation, but one might theorize that increases in per capita income will lead to improved residential electricity efficiency in the current year and worsened residential electricity efficiency in the following year since an increase in per capita income may lead households to purchase larger homes (requiring more air heating and cooling) and more electrical appliances. These hypothesized effects might not all manifest in the first year of increased per capita income.

The aim of this study was to measure the effect of DSM expenditures, and the estimates for the DSM regressors did not match expectations. This study is the first to explore the effects of DSM expenditures using the Fisher Ideal index number approach to separating changes in electricity intensity into those due to efficiency changes and those due to activity changes. As such, the results for the DSM regressors cannot be directly compared to other studies. Before concluding that DSM expenditures have no effect or the opposite from the expected effect on electricity efficiency and intensity based on this study's findings one should consider factors that may explain the unexpected findings. First, the study's regression models likely suffer from omitted variable bias. In particular, one would expect that policies and programs other than DSM expenditures, such as building codes and appliance standards that vary by state, would affect electricity efficiency; however, this study does not control for these policies and programs because of data availability. If these variables tend to be correlated with DSM expenditures, then one would expect their omission to lead to bias in estimating the DSM regressors' coefficients.[13] Second, it has already been shown that the DSM regressors suffer from measurement error. Too little is known about the degree or nature of measurement error, however, to estimate the magnitude or direction of resultant bias in the regression estimates.

Finally, the regression results that find little to no evidence in support of energy savings from DSM via improvements in energy efficiency might be taken as reflective of the truth. Some prior studies have found utilities' estimates of energy savings from DSM to be wildly optimistic. For example, Gillingham et al. (2004) note that the findings of Loughran and Kulick (2004) suggest that 50% to 90% of reported energy savings from DSM programs are not actual savings.

The results from this study suggest several avenues for future research efforts. The sections above have already detailed the problems with measurement error in the key regressors. Future studies might benefit from investments in compiling better data than are available from Form EIA-861. Furthermore, additional data collection could ameliorate the problem of omitted variable bias. Subsequent research on this topic could attempt to obtain data regarding other energy efficiency policies besides DSM, such as building codes, appliance standards, energy

[13] One might expect, however, that these omitted variables would be positively correlated with DSM expenditures and would thus bias estimates of DSM expenditures' effect away from zero in the negative direction by their omission.

efficiency resource requirements, and demand-side bidding in electricity markets. Future studies could also attempt to better understand the effect of rising incomes on electricity efficiency.

Chapter 5. Policy Implications and Conclusion

Policy Implications

This study's findings lend further support for skepticism of optimistic claims about the ability to generate "negawatts" at very low or no cost. Furthermore, this study highlights the need for improved government-financed electricity efficiency data collection and research in order to better understand the drivers of electricity efficiency. Lastly, the regression results underscore the potential gains in electricity efficiency and subsequent carbon emission reductions from policies that put a price on carbon emissions and thus increase electricity prices.

As detailed above, previous studies have called into question the energy savings reported by utilities for their DSM programs and, consequently, have cast doubt upon the claims by some energy efficiency proponents that society can generate "negawatts" at little or no cost. This study's regression analyses did not find evidence that DSM expenditures improve state-level aggregate electricity efficiency. While the analyses herein suffer from shortcomings noted above, the regression results with respect to DSM expenditures were insensitive to various changes in model specification and variable definition. Since utilities and state agencies responsible for DSM programs continue to report large energy savings, this study's results suggest that policymakers view such estimates with skepticism and that entities responsible for DSM programs strive to engage in more rigorous program evaluations.

This study's shortcomings related to omitted variables and measurement error in the key independent variables of interest suggest a need for improved data collection with respect to energy efficiency policies and programs. Horowitz (2006) explains the data quality problems with EIA-861, the lack of a consolidated national data collection effort for energy efficiency comparable to the rigorous data collection efforts devoted to other sources of energy, and the public-good aspects of data collection. Form EIA-861 has proven particularly inadequate for accurate DSM evaluations in the years following electricity market restructuring as utilities are no longer the sole entities responsible for DSM programs. As states and the federal government enact new policies to reduce carbon emissions, they will face challenges in optimally designing policies for and allocating resources to energy efficiency if they lack rigorous and accurate assessments of the impacts of existing energy efficiency policies and programs.

Finally, one can see from the regression results above that electricity prices have an unmistakable and large effect on electricity efficiency. For example, the results from regression Model 10 indicate that, focusing solely on the effect of price on efficiency, a permanent 10% increase in electricity prices would lead to a nearly 5% decrease in electricity intensity, holding all else constant. This result points to the powerful effect that a price on carbon emissions would have on reducing the quantity of electricity demanded and thus reducing carbon emissions from electricity generation. A carbon tax or a cap-and-trade program would lead to higher electricity prices and thus improvements in electricity efficiency and reduced carbon emissions. Several states have already implemented regional cap-and-trade programs focused on the electricity market such as the Northeastern states' Regional Greenhouse Gas Initiative. At the federal level, Rep. John Dingell (D-MI) is drafting legislation for a carbon tax that would start at $50 per ton of carbon (roughly $12 per metric ton of CO_2) and rise with inflation (Dingell 2007). Moreover, several cap-and-trade bills are active in the 110th Congress (Pew Center 2008).

Conclusion

Concern over the dangers of anthropogenic climate change has sparked interest in energy efficiency as one cost-effective way to mitigate GHG emissions. In order to properly prioritize energy efficiency policies, policymakers need accurate information on the effectiveness of various policy options. This study sought to evaluate the effectiveness of DSM expenditures for improving efficiency in the use of electricity since electricity generation accounts for roughly a third of US GHG emissions.

Previous studies suggested the need to account for free riders, positive spillover effects and market transformation, and changes in energy intensity due to shifts in the composition of economic activity in evaluating the effect of DSM expenditures on electricity consumption. As such, this study examined state-level aggregate electricity efficiency and took the novel approach of using an index number to decompose electricity intensity changes into those due to shifting economic activity and those due to changes in electricity efficiency.

The regression results discussed above did not find evidence that DSM expenditures improve electricity efficiency controlling for other factors. This study did reaffirm the findings of previous studies that electricity prices do influence electricity efficiency. In interpreting this study, one must keep in mind several potential weaknesses, including relevant variables omitted due to a lack of data availability and error in measuring DSM expenditures. However, the study's findings do bolster previous empirical work that cast suspicion on energy efficiency proponents' claims for low- or no-cost "negawatts." The results provide empirical support for policies that seek to control GHG emission via price mechanisms and warrant caution and skepticism in evaluating optimistic claims for negative marginal cost climate change mitigation options.

This study suggests several avenues for future research. Efforts to improve the measurement of DSM expenditures as well as to quantify related energy efficiency variables (e.g. building codes and appliance standards) would allow for more accurate analysis. In addition, this study does not shed light upon the reason that DSM expenditures seemingly fail to improve efficiency. Further research could explore whether the lack of efficacy stems from poor program design or from a smaller than expected "efficiency gap."

This study's shortcomings also underscore the need for expanded publicly funded data collection on energy efficiency policies and programs. Without rigorous evaluations of the effectiveness of energy efficiency programs such as DSM, policymakers cannot optimally allocate resources to promote energy efficiency nor can they improve the design and operation of energy efficiency programs.

Appendix A: Electricity Efficiency Index

Many studies, such as Bernstein et al. (2003), that have sought to examine energy efficiency have used energy intensity as their measure of energy efficiency where energy intensity is the ratio of energy usage to the value of economic output (e.g. Btu per dollar of GDP). In his study of the effect of DSM on energy usage, Horowitz (2004) calculated commercial electricity intensity, defined as the ratio of electricity consumption by the commercial sector to the economic output of the commercial sector (i.e. MWh per dollar of commercial sector output). Metcalf (2008) noted that energy intensity is a poor measure of energy efficiency because energy intensity does not allow one to identify whether changes in energy usage per unit of economic output result from changes in energy efficiency or from changes in the composition of economic activity (e.g. a shift from energy-intensive manufacturing to services). Drawing on the work of Boyd and Roop (2004), Metcalf developed a Fisher Ideal index that allowed for the perfect decomposition of an energy intensity index into economic activity and energy efficiency indexes.

Define energy intensity in time t (e_t) as:

(1) $e_t = E_t / Y_t = S\ (E_{i,t} / Y_{i,t})*(Y_{i,t} / Y_t) = S\ e_{i,t}s_{i,t}$

where E_t is the total energy usage in the economy, Y_t is the total economic output, $E_{i,t}$ is the energy usage in sector i of the economy, $Y_{i,t}$ is the economic output of sector i, $e_{i,t}$ is the energy intensity of sector i, and $s_{i,t}$ is the sectoral activity for sector i. Given the sectoral decomposition of energy intensity shown above, one can create the Fisher Ideal index described above such that:

$$\frac{e_t}{e_0} = F_t^{act} F_t^{eff}$$

where F_t^{eff} is the electricity efficiency index used as the regressand in this study (see Metcalf 2008 for details on the index decomposition).

This study has adapted Metcalf's Fisher Ideal index to electricity (rather than energy) intensity. For this study, the sectoral electricity intensity values at the state level (i.e. $e_{i,t}s_{i,t}$) are defined in Table A.1 below.

Table A.1: Sectoral Decomposition for Electricity Intensity Index

Sector	**Economic Activity Measure**	**Sectoral Energy Efficiency Measure**
Residential	Personal Income	MWh / ('000 $2005)
Commercial	Earnings by place of work in commercial sector	MWh / ('000 $2005)
Industrial	Earnings by place of work in industrial sector	MWh / ('000 $2005)
Transportation	Earnings by place of work in transportation	MWh / ('000 $2005)
Total	Personal Income	MWh / ('000 $2005)

Notes: The industrial sector includes manufacturing, agriculture, forestry, fishing, mining, and construction. The commercial sector includes transportation (minus rail and transit and ground transportation subsectors), communication, wholesale and retail trade, finance, services, and government. The transportation sector includes the rail and transit and ground transportation subsectors.

Appendix B: Data Set Descriptive Statistics

Table B1: Regressand and Independent Variable Summary Statistics[14]

	Efficiency Index				DSM $THD				DSM $/MWh				DSM % of Sales			
State	Min	Max	Avg	StdDev	Min	Max	Avg	StdDev	Min	Max	Avg	StdDev	Min	Max	Avg	StdDev
AL	1.00	1.16	1.09	0.05	738	50,134	6,571	11,599	0.01	0.62	0.09	0.15	0.01%	0.96%	0.13%	0.22%
AR	0.96	1.22	1.12	0.08	149	648	299	129	0.00	0.01	0.01	0.00	0.01%	0.02%	0.01%	0.00%
AZ	0.85	1.02	0.93	0.06	1,071	26,103	8,076	6,134	0.02	0.36	0.15	0.10	0.02%	0.45%	0.16%	0.11%
CA	0.87	1.05	0.96	0.07	183,279	422,811	318,033	82,579	0.78	1.98	1.38	0.36	0.59%	1.54%	1.13%	0.28%
CO	0.81	1.01	0.90	0.07	725	19,434	8,128	5,238	0.02	0.52	0.20	0.13	0.03%	0.70%	0.27%	0.17%
CT	0.89	1.04	0.97	0.05	32,792	119,853	60,067	20,997	1.10	4.41	2.06	0.78	0.94%	3.20%	1.65%	0.58%
DE	0.99	1.24	1.09	0.07	-	3,003	1,061	1,153	-	0.31	0.11	0.12	0.00%	0.36%	0.13%	0.14%
FL	0.93	1.05	1.01	0.03	57,817	117,494	77,606	18,167	0.26	0.68	0.44	0.14	0.26%	0.76%	0.49%	0.15%
GA	0.97	1.04	1.01	0.02	808	56,786	11,538	18,395	0.01	0.64	0.13	0.21	0.01%	0.70%	0.14%	0.23%
IA	1.00	1.16	1.09	0.05	4,337	38,875	25,102	9,526	0.15	1.13	0.67	0.23	0.17%	1.47%	0.94%	0.34%
ID	0.76	1.03	0.89	0.09	2,277	25,441	8,050	6,086	0.10	1.36	0.40	0.32	0.21%	2.51%	0.76%	0.60%
IL	0.98	1.08	1.02	0.03	1,034	8,457	3,663	2,254	0.01	0.06	0.03	0.02	0.01%	0.08%	0.03%	0.02%
IN	1.00	1.11	1.06	0.03	676	57,214	14,118	19,167	0.01	0.68	0.17	0.23	0.01%	0.99%	0.24%	0.33%
KS	0.96	1.06	1.03	0.03	3	5,009	521	1,242	0.00	0.15	0.02	0.04	0.00%	0.19%	0.02%	0.05%
KY	1.00	1.16	1.09	0.05	64	11,664	5,767	3,095	0.00	0.13	0.07	0.03	0.00%	0.29%	0.14%	0.08%
LA	0.90	1.07	1.01	0.04	229	2,490	1,259	872	0.00	0.03	0.02	0.01	0.00%	0.04%	0.02%	0.01%
MA	0.86	1.03	0.95	0.05	90,155	192,189	145,675	27,093	1.91	3.95	2.94	0.60	1.50%	3.45%	2.39%	0.58%
MD	0.90	1.14	1.06	0.07	52	129,233	36,562	43,748	0.00	2.36	0.67	0.79	0.00%	2.55%	0.74%	0.87%
ME	0.91	1.12	1.01	0.07	258	35,061	16,597	6,943	0.02	3.04	1.41	0.61	0.02%	2.66%	1.22%	0.52%
MI	0.99	1.10	1.03	0.03	30	72,553	15,551	17,917	0.00	0.83	0.17	0.21	0.00%	0.86%	0.19%	0.21%
MN	0.95	1.08	1.01	0.04	14,029	74,959	40,348	14,561	0.30	1.39	0.71	0.27	0.37%	1.94%	1.03%	0.38%
MO	0.98	1.13	1.06	0.04	284	14,177	1,867	3,282	0.00	0.21	0.03	0.05	0.01%	0.28%	0.04%	0.07%
MS	0.98	1.11	1.04	0.04	-	2,718	1,232	806	-	0.06	0.03	0.02	0.00%	0.09%	0.04%	0.03%
MT	0.67	1.00	0.84	0.11	3,646	127,623	33,123	40,646	0.31	9.68	2.51	3.09	0.48%	16.30%	4.19%	5.26%
NC	0.94	1.04	0.99	0.03	44	43,567	14,514	16,645	0.00	0.42	0.14	0.16	0.00%	0.49%	0.17%	0.19%
ND	0.95	1.22	1.08	0.07	1,137	4,379	3,003	916	0.16	0.56	0.34	0.12	0.19%	0.76%	0.51%	0.17%
NE	0.98	1.17	1.08	0.05	9	4,499	654	1,217	0.00	0.17	0.03	0.05	0.00%	0.29%	0.04%	0.08%
NH	0.83	1.02	0.91	0.07	2,410	22,674	8,346	6,034	0.27	2.07	0.82	0.52	0.20%	1.80%	0.63%	0.45%
NJ	0.89	1.06	0.98	0.05	15,119	188,154	98,337	63,703	0.24	2.48	1.34	0.80	0.18%	2.46%	1.20%	0.81%
NM	0.95	1.04	0.99	0.03	17	2,112	898	580	0.00	0.11	0.05	0.03	0.00%	0.14%	0.06%	0.04%
NV	0.85	1.02	0.95	0.05	2	20,456	7,570	6,566	0.00	1.02	0.33	0.31	0.00%	1.29%	0.40%	0.39%
NY	0.87	1.05	0.98	0.05	13,624	313,838	114,221	95,298	0.10	2.42	0.86	0.75	0.08%	1.70%	0.62%	0.51%
OH	0.96	1.07	1.02	0.04	1,222	47,626	17,907	12,867	0.01	0.32	0.12	0.08	0.01%	0.38%	0.15%	0.10%
OK	0.87	1.00	0.93	0.04	47	1,509	507	485	0.00	0.04	0.01	0.01	0.00%	0.05%	0.02%	0.01%
OR	0.73	1.02	0.86	0.10	16,609	171,779	68,985	54,009	0.35	3.82	1.52	1.22	0.62%	6.30%	2.50%	2.04%
PA	1.00	1.10	1.05	0.03	416	35,520	12,380	12,722	0.00	0.28	0.10	0.11	0.00%	0.28%	0.10%	0.10%
RI	0.96	1.08	1.02	0.03	-	22,888	14,434	4,767	-	3.57	2.06	0.73	0.00%	2.45%	1.64%	0.55%
SC	1.00	1.12	1.08	0.03	4,595	25,998	11,284	7,365	0.06	0.40	0.17	0.13	0.09%	0.55%	0.24%	0.16%
SD	0.97	1.12	1.03	0.04	810	3,613	2,101	699	0.13	0.49	0.26	0.09	0.14%	0.61%	0.35%	0.12%
TN	0.91	1.01	0.94	0.03	151	6,106	2,849	1,916	0.00	0.06	0.03	0.02	0.00%	0.10%	0.05%	0.03%
TX	0.79	1.01	0.92	0.07	16,268	58,953	39,948	12,876	0.05	0.22	0.14	0.05	0.06%	0.26%	0.17%	0.06%
UT	0.89	1.01	0.95	0.04	731	27,841	9,994	6,574	0.03	1.51	0.51	0.38	0.06%	2.22%	0.76%	0.53%
VA	0.96	1.11	1.03	0.04	3	22,111	4,786	6,688	0.00	0.27	0.06	0.08	0.00%	0.33%	0.07%	0.10%
VT	0.89	1.06	0.99	0.06	3,931	16,075	9,780	4,504	0.84	3.03	1.82	0.79	0.68%	2.50%	1.54%	0.70%
WA	0.60	1.01	0.80	0.15	49,969	370,943	156,099	94,611	0.52	4.10	1.78	1.05	1.05%	8.32%	3.40%	2.17%
WI	1.00	1.06	1.03	0.02	21,898	100,822	54,004	20,100	0.36	1.98	0.92	0.43	0.57%	2.59%	1.27%	0.53%
WV	1.00	1.20	1.10	0.05	-	3,770	719	1,135	-	0.15	0.03	0.04	0.00%	0.22%	0.04%	0.07%
WY	0.75	1.33	0.93	0.13	19	9,747	3,494	2,527	0.00	0.87	0.29	0.22	0.00%	1.57%	0.52%	0.39%

[14] All dollar values in $2005.

Table B2: Independent Variable Summary Statistics (continued)

	Per Capita Income				Electricity Price (cents/kWh)				Natural Gas Price ($ / thd cf City Gate)				State GDP			
State	Min	Max	Avg	StdDev	Min	Max	Avg	StdDev	Min	Max	Avg	StdDev	Min	Max	Avg	StdDev
AL	23,494	29,877	26,228	2,049	6.2	8.3	6.9	0.7	3.70	9.94	5.42	1.78	98,451	155,656	124,533	17,307
AR	21,607	27,555	24,338	1,822	5.9	10.0	7.5	1.3	2.97	8.83	4.84	1.88	52,780	89,027	71,193	11,110
AZ	24,724	30,951	27,377	2,118	7.7	11.6	9.2	1.4	2.69	7.43	4.40	1.47	96,009	225,350	155,997	42,100
CA	30,577	38,128	33,868	2,650	10.3	13.5	12.2	1.0	2.60	7.88	4.51	1.62	1,065,875	1,674,497	1,305,041	214,013
CO	28,908	38,350	33,840	3,570	6.5	8.8	7.5	0.7	2.71	7.37	4.20	1.18	102,773	223,425	163,002	41,437
CT	38,016	49,200	43,315	3,782	10.5	14.4	12.5	1.4	5.02	9.67	6.63	1.45	134,123	197,887	164,437	22,554
DE	31,008	37,766	33,747	2,307	6.9	9.8	8.5	0.9	3.46	8.56	4.99	1.60	27,863	58,514	41,999	10,419
FL	28,363	35,519	30,995	2,299	7.8	10.5	9.0	0.8	3.51	9.30	5.07	1.71	356,273	691,671	495,330	108,638
GA	25,911	31,742	29,208	2,064	6.7	9.8	7.9	1.0	3.46	9.85	5.57	1.75	193,240	367,936	285,348	60,849
IA	25,296	31,985	28,725	2,247	6.5	8.9	7.3	0.8	3.61	8.88	5.24	1.58	77,181	120,176	96,925	13,914
ID	22,986	29,012	26,015	1,837	4.6	6.1	5.2	0.4	2.34	7.95	3.99	1.67	24,610	48,380	35,716	7,109
IL	30,421	37,100	34,030	2,322	6.8	11.2	8.8	1.5	3.32	8.38	5.00	1.57	383,494	571,556	481,341	64,371
IN	25,623	31,219	28,877	1,953	5.7	8.0	6.5	0.7	2.88	8.83	4.85	1.73	152,325	241,298	200,172	30,410
KS	26,708	33,658	29,827	2,255	6.5	9.8	7.8	1.1	3.02	9.08	4.96	1.90	71,013	108,281	87,865	12,370
KY	23,067	28,790	25,908	1,977	4.6	6.7	5.2	0.6	3.59	9.69	5.38	1.85	93,497	141,493	120,066	15,709
LA	22,672	30,389	25,544	2,087	6.5	9.0	7.7	0.7	2.79	8.56	4.69	1.73	116,306	187,228	143,534	19,952
MA	33,600	44,810	38,784	4,051	10.5	15.0	12.4	1.2	4.38	10.66	6.19	2.06	214,365	327,240	272,627	42,231
MD	33,410	42,406	36,889	3,243	6.7	9.8	8.5	1.0	3.68	10.29	5.87	2.02	155,530	249,926	194,125	32,861
ME	25,131	31,090	28,025	2,310	10.0	12.7	11.5	0.8	3.93	11.78	6.04	2.37	31,310	45,536	37,730	5,049
MI	27,709	33,515	31,160	2,024	7.2	10.6	8.6	1.1	3.32	8.44	4.67	1.60	259,943	381,286	337,130	45,905
MN	29,077	37,540	33,567	3,194	6.3	8.0	7.0	0.5	3.23	8.52	5.00	1.67	138,889	237,063	187,668	34,691
MO	26,317	31,768	29,182	1,958	6.1	9.7	7.5	1.1	3.50	8.67	5.26	1.64	144,172	218,964	184,123	25,833
MS	19,558	26,067	22,826	2,038	6.6	9.1	7.6	0.8	3.24	8.85	5.01	1.84	53,693	81,648	68,873	8,715
MT	23,083	29,921	25,642	2,314	5.6	7.2	6.2	0.4	2.91	7.62	4.69	1.37	18,582	31,333	23,704	3,801
NC	25,347	31,327	28,653	1,981	7.2	9.5	8.0	0.8	3.78	10.11	5.55	2.00	194,273	363,064	276,082	56,770
ND	23,347	32,053	27,148	2,913	5.8	8.6	6.9	0.9	3.31	8.54	4.99	1.54	15,608	25,578	19,832	3,057
NE	26,562	33,309	29,923	2,464	5.9	8.3	6.6	0.8	3.19	8.21	5.06	1.58	46,779	73,384	59,912	8,522
NH	30,242	38,416	34,330	3,094	11.5	15.0	13.4	1.2	4.34	9.97	5.77	1.76	32,940	54,554	44,191	7,608
NJ	35,629	44,880	40,036	3,192	10.1	13.6	12.0	1.4	4.28	10.51	5.99	1.94	296,642	439,310	364,400	49,163
NM	22,300	28,796	24,853	2,025	7.1	10.6	8.4	1.1	1.87	7.04	3.84	1.49	37,216	73,587	54,705	9,712
NV	29,770	37,796	33,196	2,323	6.8	9.3	8.1	0.8	3.04	8.50	4.87	1.71	44,070	114,776	74,813	22,554
NY	33,980	42,588	37,261	2,660	11.7	14.8	13.5	0.9	3.17	8.93	5.00	1.64	680,977	990,672	815,029	103,904
OH	27,388	32,179	30,174	1,766	7.1	8.8	7.8	0.6	4.37	10.66	6.28	1.94	314,115	447,186	387,876	46,816
OK	23,737	31,386	26,478	2,454	6.1	8.3	7.1	0.7	2.93	8.84	4.60	1.98	79,578	130,531	97,210	15,384
OR	26,566	32,213	29,742	2,054	5.5	6.9	6.1	0.3	3.01	7.85	4.44	1.54	79,324	146,671	112,900	22,065
PA	29,058	35,542	31,921	2,258	7.9	11.5	9.5	1.2	3.34	9.98	5.80	1.97	343,899	494,678	417,869	50,808
RI	28,749	36,097	31,980	2,603	10.0	14.6	12.5	1.4	4.53	9.65	6.08	1.48	28,914	44,263	35,683	5,477
SC	23,288	28,760	26,033	1,917	6.3	8.4	7.0	0.6	4.06	10.00	5.70	1.85	91,007	144,648	117,307	18,291
SD	24,053	32,058	27,837	2,831	6.5	9.2	7.6	0.8	3.69	8.48	5.23	1.47	17,762	31,341	24,568	4,381
TN	24,804	31,295	28,257	2,125	6.2	7.9	6.7	0.5	3.47	9.08	5.18	1.76	130,953	230,745	183,680	31,510
TX	25,709	33,962	29,456	2,806	7.1	10.0	8.1	0.8	3.15	8.09	4.86	1.37	532,018	1,033,274	743,779	162,854
UT	22,214	28,839	25,324	2,243	5.5	8.2	6.4	0.8	2.80	8.16	4.92	1.51	43,549	94,758	67,448	16,123
VA	30,018	38,328	33,525	2,961	6.6	9.0	7.5	0.9	3.74	10.18	5.89	2.08	203,627	357,960	270,111	53,451
VT	25,789	33,541	29,438	2,762	10.9	12.4	11.9	0.4	2.84	8.34	4.60	1.43	15,686	23,472	19,184	2,594
WA	29,666	36,877	33,170	2,767	4.7	6.4	5.4	0.6	2.64	7.95	4.23	1.78	160,172	284,549	220,516	41,378
WI	26,609	33,399	30,376	2,457	6.4	8.0	7.1	0.5	3.61	8.35	5.30	1.49	138,931	220,277	182,511	27,746
WV	21,645	27,190	24,141	1,805	4.9	7.1	6.1	0.7	3.65	9.69	5.25	1.74	39,245	53,955	46,166	4,468
WY	26,786	39,301	30,886	4,221	4.9	6.3	5.4	0.4	2.67	8.04	4.60	1.63	17,405	28,656	20,261	3,584

Table B3: Independent Variable Summary Statistics (continued)

	HDD				CDD			
State	Min	Max	Avg	StdDev	Min	Max	Avg	StdDev
AL	2,240.00	3,037.00	2,694.59	214.80	1,565.00	2,263.00	1,923.29	184.42
AR	2,985.00	3,887.00	3,338.53	258.92	1,411.00	2,290.00	1,792.00	195.34
AZ	1,759.00	2,289.00	1,983.41	156.87	2,752.00	3,357.00	3,092.65	189.00
CA	2,243.00	2,904.00	2,506.41	181.58	787.00	1,121.00	959.06	105.61
CO	6,716.00	7,866.00	7,090.94	331.67	144.00	462.00	308.24	100.32
CT	5,224.00	6,351.00	5,862.18	405.04	377.00	829.00	622.53	123.47
DE	3,882.00	5,021.00	4,539.35	373.47	825.00	1,317.00	1,105.59	138.42
FL	422.00	797.00	642.24	97.80	3,275.00	3,845.00	3,528.76	163.52
GA	2,233.00	3,166.00	2,783.06	236.60	1,457.00	2,091.00	1,722.53	167.05
IA	6,047.00	7,798.00	6,802.76	474.94	496.00	969.00	802.18	138.37
ID	6,029.00	7,482.00	6,607.18	312.43	203.00	740.00	522.53	124.33
IL	5,176.00	6,969.00	6,062.94	447.53	543.00	1,137.00	876.00	173.53
IN	4,814.00	6,337.00	5,643.94	414.07	570.00	1,139.00	886.29	164.23
KS	4,358.00	5,661.00	4,875.65	340.07	1,036.00	1,712.00	1,445.47	192.74
KY	3,861.00	4,907.00	4,374.71	323.71	869.00	1,463.00	1,197.94	166.00
LA	1,396.00	1,937.00	1,664.12	146.98	2,327.00	3,111.00	2,679.41	181.26
MA	5,533.00	6,735.00	6,184.59	404.72	285.00	655.00	498.53	101.14
MD	3,957.00	5,169.00	4,619.35	363.31	790.00	1,316.00	1,091.94	155.69
ME	7,046.00	8,355.00	7,860.24	428.55	123.00	351.00	238.18	60.64
MI	5,721.00	7,412.00	6,705.71	457.66	284.00	790.00	572.35	141.90
MN	7,303.00	9,713.00	8,336.71	606.90	242.00	702.00	501.18	120.49
MO	4,457.00	5,653.00	4,967.59	373.34	905.00	1,482.00	1,245.41	162.09
MS	2,065.00	2,755.00	2,448.41	188.50	1,785.00	2,541.00	2,120.65	178.90
MT	7,500.00	9,114.00	8,003.24	454.02	73.00	436.00	274.59	92.64
NC	2,729.00	3,805.00	3,368.41	277.45	1,193.00	1,651.00	1,427.76	141.80
ND	8,302.00	10,840.00	9,158.59	627.76	216.00	616.00	442.18	118.40
NE	5,708.00	7,234.00	6,284.53	431.97	608.00	1,231.00	989.35	165.99
NH	6,595.00	7,862.00	7,328.12	414.92	171.00	495.00	347.35	90.39
NJ	4,512.00	5,652.00	5,197.29	391.31	545.00	1,181.00	831.94	153.01
NM	4,247.00	5,025.00	4,633.76	228.54	741.00	1,168.00	979.82	138.76
NV	3,285.00	3,898.00	3,561.24	192.36	1,859.00	2,488.00	2,161.59	181.81
NY	5,134.00	6,341.00	5,859.35	433.23	407.00	944.00	673.06	134.30
OH	4,873.00	6,326.00	5,724.59	419.29	492.00	1,005.00	765.24	157.17
OK	3,078.00	4,164.00	3,550.88	277.15	1,457.00	2,476.00	1,886.71	226.98
OR	4,366.00	5,298.00	4,911.59	237.77	164.00	378.00	284.71	59.19
PA	4,882.00	6,168.00	5,701.24	396.26	438.00	929.00	704.71	132.41
RI	5,103.00	6,269.00	5,693.00	398.87	287.00	738.00	547.24	114.00
SC	2,102.00	3,052.00	2,684.00	248.24	1,558.00	2,140.00	1,848.29	163.47
SD	6,885.00	8,975.00	7,558.65	568.86	379.00	925.00	716.88	155.73
TN	3,347.00	4,287.00	3,813.18	266.58	1,071.00	1,655.00	1,371.29	157.45
TX	1,526.00	2,174.00	1,864.06	168.53	2,415.00	3,218.00	2,744.00	196.58
UT	5,683.00	7,064.00	6,227.47	353.36	388.00	1,013.00	774.24	160.12
VA	3,600.00	4,831.00	4,296.18	329.23	842.00	1,265.00	1,082.24	140.58
VT	7,110.00	8,557.00	7,960.47	486.77	133.00	465.00	280.76	83.19
WA	4,870.00	5,728.00	5,261.82	264.50	141.00	323.00	231.18	53.78
WI	6,413.00	8,527.00	7,473.29	504.02	237.00	718.00	504.41	132.67
WV	4,475.00	5,595.00	5,117.29	325.39	583.00	1,000.00	795.76	134.57
WY	7,624.00	9,014.00	8,025.65	365.69	122.00	467.00	321.41	96.36

Appendix C: Comparison of ACEEE and EIA Energy Efficiency Spending Data

Table C1: Differences between ACEEE Reported Energy Efficiency Spending and Form EIA-861

State	1. ACEEE EE Spending ($THD)	2. EIA DSM Spending ($THD)	3. Diff ([2]-[1])	% Diff ([3]/[1])
AL	438	2,766	2,328	532%
AR	231	238	7	3%
AZ	4,000	2,643	(1,357)	-34%
CA	380,009	196,322	(183,687)	-48%
CO	13,715	13,737	22	0%
CT	58,098	58,098	-	0%
DE		-	-	-
FL	72,014	57,763	(14,251)	-20%
GA	1,356	1,368	12	1%
IA	28,833	31,094	2,261	8%
ID	7,023	4,533	(2,490)	-35%
IL	3,000	2,423	(577)	-19%
IN	2,062	2,062	-	0%
KS	-	33	33	-
KY	4,146	9,082	4,936	119%
LA	324	1,918	1,594	492%
MA	133,326	66,978	(66,348)	-50%
MD	50	50	-	0%
ME	13,118	6,365	(6,753)	-51%
MI	8,000	40	(7,960)	-100%
MN	55,784	43,715	(12,069)	-22%
MO	928	878	(50)	-5%
MS	497	1,628	1,131	228%
MT	8,002	4,082	(3,920)	-49%
NC	3,722	125	(3,597)	-97%
ND	465	2,809	2,344	504%
NE	4,348	4,351	3	0%
NH	15,120	15,120	-	0%
NJ	92,753	168,344	75,591	81%
NM	2,000	2,043	43	2%
NV	8,473	8,358	(115)	-1%
NY	147,193	53,202	(93,991)	-64%
OH	16,195	2,630	(13,565)	-84%

State	1. ACEEE EE Spending ($THD)	2. EIA DSM Spending ($THD)	3. Diff ([2]-[1])	% Diff ([3]/[1])
OK	316	398	82	26%
OR	62,888	11,283	(51,605)	-82%
PA	3,446	3,437	(9)	0%
RI	13,990	13,990	-	0%
SC	4,920	4,920	-	0%
SD	542	2,380	1,838	339%
TN	10,937	3,323	(7,614)	-70%
TX	80,000	16,971	(63,029)	-79%
UT	16,450	8,946	(7,504)	-46%
VA	-	67	67	-
VT	14,000	1,060	(12,940)	-92%
WA	88,522	45,673	(42,849)	-48%
WI	53,734	15,837	(37,897)	-71%
WV	992	-	(992)	-100%
WY	-	2,862	2,862	-

Notes: Spending data are for 2004. EIA data from form EIA-861. ACEEE data are energy efficiency spending data reported in Eldridge et al. (2007).

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