Electric Utility Demand Side Management in Canada

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Government, utility, and private subsidies for energy efficiency play a prominent role in current efforts to reduce greenhouse gas emissions, yet the effectiveness of this policy approach is in dispute. One opportunity for empirical analysis is provided by the past energy efficiency subsidies, called demand-side management programs, offered by electric utilities in North America over several decades. Between 1990 and 2005, most electric utilities in Canada administered such programs, with total spending of $2.9 billion (CDN$2005). This paper uses the significant inter-annual variation in demand side management spending during this period to econometrically estimate the effectiveness of these subsidies. The resulting estimates indicate that these programs have not had a substantial impact on overall electricity consumption in Canada.

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1. INTRODUCTION

Electric utility demand side management (DSM) programs were conceived following the dramatic energy price increases of the 1970s and early 1980s. Increases in fuel prices during this period were accompanied by high interest rates that significantly increased the cost of building and operating new power plants [Gellings, 1996]. Responding to the increase in energy prices, the US government implemented a wave of new policies aimed at stimulating energy efficiency, including The Energy Policy and Conservation Act (1975), The Energy Conservation and Production Act (1976), The National Energy Conservation Policy Act (1978), and The Public Utilities Regulatory Policy Act (1978) [Gillingham et al., 2006]. Electric utility regulators, especially in the US, were also concerned with

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rising energy prices and with potential misinvestment risks of large-scale generation, and so were persuaded that utilities should be required to foster improved efficiency as well as load shifting by their customers. (By reducing peak demand, load shifting delays the need for new power plants.) Pushed by these interrelated drivers, electric utilities in the US initiated DSM programs that initially focused on load shifting and then increasingly on electric end-use efficiency. Although load shifting programs remain important today, most of the DSM focus throughout North America in the past two decades has been on end-use energy efficiency.

In Canada, DSM developed more slowly [Jaccard, 1993]. First, the electricity industry, being especially based on hydropower and coal, did not experience the financial crisis of its US counterpart, although Ontario Hydro was caught with significant cost overruns in its nuclear investments. Second, most of the electricity industry was (and still is) publicly owned with little oversight by utility regulatory agencies, so there was no external force to require consideration of energy efficiency. Third, authority over the electricity system is more decentralized in Canada than in the US, so there is no equivalent federal act in Canada to those in the US prompting energy efficiency investments. The development of DSM in Canada therefore depended to a significant degree on personalities and political preferences. In 1986, the CEO of BC Hydro took a personal interest in DSM and launched Power Smart, a division that eventually had influence across the country. Similar developments in Ontario and eventually Quebec led to a patchwork of DSM efforts across the country.

The first utility DSM programs were implemented in California and the US northwest, and have since spread throughout the United States and Canada [Nadel and Geller, 1996]. Most large electric distribution utilities in these two countries now have some experience with such programs. Total electric utility spending on DSM in the US between 1990 and 2005 was $36 billion (US$2005), while total spending in Canada over the same period was about $2.9 billion (CAD$2005) (see Figure 1 for sources). Once the relative size of the two countries is accounted for, expenditures are relatively similar, although the US out-spent Canada somewhat: Canada spent about $6.01 (CAD$2005) per person per year on DSM between 1990 and 2005, compared to $9.21 (US$2005) in the US. The most aggressive utilities in both countries spend up to 4 percent of their total revenue on DSM, with most utilities spending less than 1.5 percent of total revenue.

As shown in Figure 1, spending on DSM in both the US and Canada peaked in 1993, with US utilities spending about $3.7 billion (US$2005) and Canadian utilities spending about $550 million (CAD$2005). As electricity market restructuring efforts intensified throughout much of the US in the mid-1990s, spending on DSM by utilities fell significantly [Nadel and Geller, 1996]. Despite the more tentative nature of electricity restructuring in Canada, spending fell even more precipitously than in the US during the latter half of the 1990s. This is particularly as a result of the cessation of all DSM programs by Ontario Hydro (formerly the largest-spending entity in Canada) in the mid-1990s, as government
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Figure 1: Electric Utility Demand Side Management Expenditures in U.S. and Canada, 1990–2005

U.S. data from U.S. Energy Information Administration Electric Power Annual. Canadian data was collected for this study from the sources described herein.

Despite the substantial investment in DSM over the past two decades, the impact of the spending is not possible to discern directly and remains the subject of significant controversy, both in academic literature and in utility regulatory processes. Unlike supply side investments in new generation capacity, DSM investments do not result in tangible, utility-owned assets whose output can be measured directly. Instead, electric utilities must infer the results of DSM programs through program evaluations that seek to estimate the incremental (or...
additional) effect of DSM programs on the underlying natural evolution of energy or electricity efficiency in a given economy. While these have improved over the last two decades, effective evaluation of DSM programs remains a difficult and contentious exercise.

This paper aims to estimate the degree to which utility DSM programs have reduced electricity consumption in Canada over the past two decades using a method significantly different than that used by utilities. Following the example of some studies of the US, we use the significant inter-temporal variation in DSM effort by the utilities in Canada as a quasi-experiment to econometrically infer the effectiveness of these programs. Unlike previous studies, we estimate a partial-adjustment dynamic model of electricity demand, from which both short-run and long-run responses of the economy to DSM expenditure can be predicted. While this method is associated with its own set of challenges, it avoids some of the weaknesses of more common forms of program-focused DSM evaluations.

This type of study can contribute to two related public policy debates. First, because utility DSM spending, by both electricity and natural gas utilities, is projected to increase rapidly in Canada during the coming years, it is important to have an understanding of the potential reduction in energy demand that results from such spending, and the cost of energy efficiency relative to new investments in electricity supply. By using a method that is not normally employed by utilities, this study can provide a confirming or contrasting estimate about the degree to which DSM programs can reduce energy demand in a given region.

Second, and perhaps more importantly, this study can provide an indication of the likely effectiveness of any subsidy program aimed at inducing energy efficiency. With increasing concerns about climate change, subsidy programs for energy efficiency are increasing in scope and magnitude. These may be government subsidy programs, utility DSM subsidy programs or even the increasingly popular carbon offsets programs, in which individuals or firms voluntarily pay offset companies to subsidize actions by third parties that apparently reduce GHG emissions from what they otherwise would be. Energy efficiency is frequently a target of these voluntary subsidies. Since there is little in the way of formal ex poste analysis by governments or independent agencies to measure the effectiveness of these subsidies in inducing energy efficiency and thus reducing GHG emissions, this evaluation can provide an independent indication of their likely effectiveness, with important implications for the choice of policy instrument for achieving provincial, national and global GHG reduction targets.

The remainder of the paper is structured as follows. In section 2, we summarize estimates made by utilities relating to the effectiveness of DSM programs, and also describe the challenges associated with such evaluations. In section 3, we describe academic studies that have sought to estimate the effectiveness of US DSM programs. In sections 4 and 5, we outline the method and data that are used in this study to assess the effectiveness of Canadian DSM programs. In section 6, we present the results of the model, and in section 7, we conclude.
2. ELECTRIC UTILITY ASSESSMENT OF DSM EFFECTIVENESS

Most utilities that invest significantly in DSM also invest in measurement and verification programs to determine the effectiveness and cost-effectiveness of such spending. Eto et al. [1995], in a survey of commercial sector DSM programs in the US, report that the mean utility-estimated cost for conservation through DSM programs is $0.027/kWh. This is similar to recent estimates in Canada. For example, Manitoba Hydro, in its 2006 DSM plan, estimated a utility cost of $0.019/kWh of avoided demand. BC Hydro, in its 2006 Integrated Electricity Plan, reported costs of $0.032–0.076/kWh. Similarly, the Ontario Power Authority estimated a levelized cost of $0.020/kWh for DSM programs offered by local distribution companies in 2006. In nearly all cases, estimates made by utilities suggest that reducing electricity demand through DSM expenditures is significantly less expensive than investing in new generation.

Utilities use a variety of techniques to estimate the effectiveness and cost-effectiveness of DSM programs, both prior to program implementation and also after the program has been running. While these techniques can be quite sophisticated, and benefit from the detailed micro-data on electricity sales available to the utility, such program level evaluations must make difficult judgements about important factors that are key to program effectiveness: the free ridership rate, the spillover rate, and the rebound effect. Unfortunately, there is no widely accepted method for estimating these factors.

Free Riders

DSM programs are generally targeted at providing incentives for consumers or businesses to adopt more energy efficient equipment. However, adoption of energy efficient equipment also occurs in the absence of DSM programs, as old technologies become obsolete and are replaced with newer and more energy efficient technologies. For example, Natural Resources Canada [2006] estimates that houses built in 2002 are about 35 percent more energy efficient than similar houses built in the 1970s, and that new models of many major household appliances were almost twice as efficient in 2002 compared to 1990. These changes in efficiency can be the result of (1) an evolution toward stricter government efficiency regulations in buildings and equipment, (2) utility and government DSM programs, (3) increases in energy prices and energy price expectations, and (4) natural gains in energy productivity (as well as labour and materials productivity) that occur as firms and households adopt newer technologies.

Given this mix of potential causal factors for improvements in energy efficiency, the main challenge is to estimate how much adoption of energy efficient technologies would have occurred without the DSM program, and thus how much can be attributable to the program [Horowitz, 2004]. There is an important temporal dimension to this challenge: given the general trend towards improved
efficiency of technologies, part of the effect of a DSM program is likely to shift the timing of investments, rather than the overall magnitude. When a DSM program is applied, it cannot normally distinguish between individuals who would have adopted the energy efficient technology anyway, called free riders, and those who required the DSM subsidy to do so [Loughran and Kulick, 2004]. Free riders add to the utility cost of a subsidy program without contributing to its effectiveness.1

Although accounting for free riders was less common when DSM programs were first introduced, most large utilities now attempt to account for them, typically by conducting follow up surveys of program participants asking whether they would have adopted a particular energy efficiency measure in the absence of the DSM program. Those participants who indicate they would have adopted the technology even in the absence of the subsidy are considered free riders. As an alternative, some utilities calculate free riders on a given program by comparison with a group of non-participants, either within the region or in a different region. The percent of non-participants that adopts the energy efficiency measure is considered to be the free rider percentage. Calculations by utilities using these methods often show fairly low free ridership levels. For example, a survey of the 40 largest commercial sector DSM programs in the US by Eto et al. [1995] found an average free ridership rate reported by utilities of 12.2 percent.

However, both of these methods have drawbacks, which result in uncertainty and potential bias in free ridership estimates. In particular, stated preference data can be biased because when answering a survey, consumers do not face real world constraints (e.g., time, budget, or information constraints). Errors or bias may arise if consumers do not understand the survey properly, have difficulty recalling historical decisions, or if they purposefully bias their answers to alter the survey results [Louviere et al., 2000].

Estimating free ridership can equally be a challenge when comparing adoption of energy conservation measures associated with the DSM program with adoption by a control group within or outside the region with the program. Non-participants within a region are by definition those customers who are less likely to undertake conservation activities than program participants, and are therefore an inappropriate control group [Hartman, 1988]. Non-participants outside of the region may not be comparable with participants within the region for reasons that are both observable (income, house size, etc.) as well as unobservable (attitudes towards conservation, willingness to adopt new technologies, etc.). While an inter-region comparison can account for observable differences, it cannot usually account for unobservable differences in the cross-sectional approach that is used in most program evaluations. To the extent that these are important in explaining

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1. Formally, this is an adverse selection problem, created by differences in information between the electric utility and its customers. However, the utility evaluation literature refers to the issue as a free-ridership problem, and we follow this nomenclature here.
technology adoption, inferences made from such comparisons will yield incorrect estimates of free ridership.

The academic literature contains a variety of techniques that attempt to determine the number of free riders on a DSM subsidy program in a way that avoids the issues discussed above. For example, Malm [1996] used a cluster analysis to allocate households from the US Residential Energy Consumption Survey into groups of similar households. With these groups in place, he examined heating system efficiency choice contingent upon the presence and magnitude of DSM programs. This technique aims to correct for some unobserved drivers of energy efficient technology adoption that could be similar between clusters, and results in a free ridership estimate of 89 percent for heating system programs. Train and Atherton [1995] used combined market and survey data in a discrete choice model to find free ridership rates of 36 percent for refrigerator programs and 66 percent for air conditioner programs. Grosche and Vance [2009] use a similar technique and estimate a free ridership rate of about 50 percent for a recent German retrofit program. Loughran and Kulick [2004] estimated a panel model relating electricity sales at all major US electric utilities to spending on DSM programs. The results of this model suggest that DSM expenditures are much less cost effective than claimed by utilities, indicating overall free ridership rates (an average of all utility DSM programs in all sectors) on the order of 50–90 percent.

In general, the free ridership rate calculated by utilities is usually significantly lower than that calculated in independent academic research. By implication, the DSM energy savings estimates of utilities will be higher and their estimated cost of DSM lower.

Spillover

While free riders can erode the impact of a DSM program, spillover does the opposite. Spillover occurs if a DSM program induces energy efficiency improvements in addition to those directly caused by the program. For example, a participant in an energy efficient lighting program, impressed with energy savings from efficient lighting in a given facility, might decide to install efficient lighting in other facilities. Additionally, a DSM measure could induce non-participants to improve efficiency, for example by changing the market for a given technology. In BC Hydro’s 2002–2005 seasonal light emitting diode (LED) program, the utility estimates that virtually all seasonal LEDs sold in the province were indirectly a result of the utility’s efforts, so that although the utility’s demand side management program was estimated to directly reduce demand by only 0.861 GWh, the overall impact of the program was estimated to be 13.9 GWh [Sampson Research, 2005]. Such impacts are referred to as participant spillover and non-participant spillover respectively, and improve the effectiveness of the program without adding to its costs. Non-participant spillover is not limited to spillover within a jurisdiction. For instance, BC Hydro’s evaluation of its seasonal
LED program attributes increased penetration of seasonal LEDs throughout Canada to the program [Sampson Research, 2005].

Estimation of spillover rates by electric utilities usually follows the same general techniques as estimation of free ridership rates. In this case, both participants and non-participants are surveyed with hypothetical questions about technology adoption with and without the DSM program. As with free ridership estimates, such questions can result in poor estimates of true spillover rates if respondents have difficulty with purchase recollection or are uncomfortable with the hypothetical nature of the questions.

Utilities often correct estimates of DSM effectiveness for estimated spillover. However, we are not aware of any academic studies that attempt to estimate spillover rates empirically in a rigorous way. Largely, this is because it is empirically difficult to distinguish between real spillover effects and autonomous market developments that would have occurred without any program in place. Horowitz [2007] comes closest, conducting a comparative study of energy efficiency trends in each of the US states, and speculating that residential energy efficiency programs in particular have impacts that spread rapidly between states, implying a high spillover rate.

**Rebound Effect**

The potential reduction in energy consumption resulting from adoption of an energy efficiency measure can be eroded as a result of the rebound effect. The rebound effect exists because improving the energy efficiency of a given energy service (while holding real fuel prices constant) reduces the cost of using that energy service, which can increase demand for the service, and therefore erode the net energy savings from the adoption of the energy efficiency measure. With a high enough elasticity of substitution between energy services and other goods, it is theoretically possible that the rebound effect overwhelms energy savings, such that increases in energy efficiency lead to increases in overall energy consumption [Saunders, 1992].

Empirical estimates of the direct rebound effect vary significantly between studies, but Greening et al. [2000] and Sorrell [2007] conclude from a review of several hundred empirical studies that the magnitude of the rebound effect is ‘insignificant to moderate’, but that available studies are associated with significant uncertainty. Specifically, for space heating in the residential sector, they report a rebound effect of 10–30 percent (meaning that this percentage of energy savings from adoption of energy efficiency measures is eroded due to the rebound effect), for space cooling 0–50 percent, for lighting, 5–20 percent, and for water heating, 10–40 percent. Results for firms are less conclusive, but suggest a rebound effect less than 30 percent in the short run, and somewhat larger in the long run.

2. Although the utility claimed these savings were due to its DSM efforts, these savings were not included explicitly in its estimates of savings.
Although the available empirical and theoretical evidence suggests that up to one third of the energy savings due to adoption of energy efficiency measures are eroded due to the rebound effect, utility evaluation protocols often do not include the rebound effect in calculating the effectiveness of DSM programs, in part because of the difficulty of obtaining appropriate estimates at a program level. As a result, it is likely that utility estimates of energy savings overestimate actual energy savings.

Although we will not be able to directly estimate the magnitude of the rebound effect from our data, Sorrell and Dimitropoulos [2007] show that the own price elasticity of energy demand is an upper bound on the direct rebound effect. Specifically, the absolute value of the own price elasticity of energy demand is equal to the direct rebound effect, provided that (among other assumptions) the consumer’s response to increases in energy efficiency is equivalent to reductions in energy price, and that the consumer responds to these changes by altering intensity of equipment use but not equipment efficiency. Since the last of these assumptions is likely to be incorrect, the own price elasticity is likely an overestimate of the direct rebound effect. However, the total rebound effect (including indirect rebound) is likely to be larger than the direct rebound effect for a variety of reasons.

3. AGGREGATE ECONOMETRIC ESTIMATES OF DSM EFFECTIVENESS

Because of these factors that complicate program level analyses of DSM, several studies have attempted to develop and estimate empirical models that indirectly account for these difficulties in a way that avoids making restrictive assumptions. Most of these studies use a time-series cross-section (panel) approach, which greatly increases the number of observations available, allows for a more detailed model specification to be tested with greater reliability, helps to address unobserved heterogeneity, and also enables testing of key time-dependent lags. In particular, these studies have estimated parameters for variants of the following relationship:

\[ EFF_{it} = DSM_{it}\beta + X'_{it}\alpha + e_{it} \]  

where \( EFF_{it} \) is a measure of energy efficiency in region \( i \) at time \( t \), \( DSM_{it} \) is a measure of DSM effort, possibly lagged by one or more years, \( X_{it} \) is a vector of characteristics of the electric utility and customers in the region, \( e_{it} \) is an error term that may be serially correlated and heteroscedastic, and \( \alpha \) and \( \beta \) are parameters to be estimated.

Parfomak and Lave [1996] estimated a variant of equation (1) in which DSM effort is given by utilities’ reported estimates of savings from commercial and industrial DSM programs, and energy efficiency (\( EFF_{it} \)) is proxied by utility electricity sales. They collected data from a sample of 39 utilities in the US.
northeast and California from 1970 to 1993 to estimate the model. This formulation allows them to interpret $\beta$ as a ‘realization rate’: essentially the relationship between utility estimates of conservation and the ‘true’ realized level of conservation. Estimation of the model suggests that the realization rate is very close to 100 percent, with a 95 percent confidence interval of 43 to 156 percent. Provided utility costs for DSM programs are reported accurately, this estimate suggests that utility cost effectiveness estimates should likewise be accurate.

Loughran and Kulick [2004] estimated equation (1) using utility-reported expenditures on DSM programs as a measure of effort (DSM$_t$) and electricity sales as a measure of efficiency (EFF$_t$). Their data covers all large electric utilities in the US from 1989 to 1999, and is derived from form EIA-861—a census of electric utilities which includes DSM expenditures and savings that is annually administered by the Energy Information Administration. With this formulation, $\beta$ is interpreted as the elasticity of electricity sales with respect to DSM investments (the equation is estimated in log-log form). From this measure, Loughran and Kulick inferred the cost effectiveness of DSM programs, given as the cost of reducing electricity demand by one kilowatt-hour. To account for the fact that DSM investments may influence electricity sales not just in the year of program implementation, but also in future years, they included DSM expenditure as a stock variable and include DSM expenditures lagged by two years in their effort variable (DSM$_{t-2}$), and tested (but did not report) variations of the model with DSM lagged by as much as four years. Using this formulation, they reported point estimates suggesting that DSM programs have cost between $0.06 and $0.22/kWh of reduced electricity consumption, significantly higher than most utilities themselves reported during this time period. They concluded that utilities’ estimates of ex poste free ridership rates are likely biased downwards.

The Loughran and Kulick study has been controversial, attracting research that counters and supports its findings. Geller and Attali [2005] noted that since the specification estimated by Loughran and Kulick only includes two lags of DSM expenditures, it is likely to underestimate the cost effectiveness of DSM programs, since these are likely to have effects that last longer than 3 years. While Loughran and Kulick discussed model specifications involving as many as four years of lagged DSM expenditures, Geller and Attali claim that even this may be insufficient to fully capture the potentially highly persistent impact of DSM programs. However, this criticism was countered by Gillingham et al. [2006], who suggested that Geller and Attali misunderstood the estimation approach used by Loughran and Kulick. In particular, by treating DSM expenditures as a stock as opposed to a flow in their first differenced model, Loughran and Kulick accounted for the persistence of DSM expenditures, beyond even the two lags explicitly estimated in their model.

Auffhammer et al. [2008] provided two alternative criticisms. First, they suggested that the calculation used by Loughran and Kulick to convert DSM elasticity to DSM cost effectiveness should weight utilities according to size, rather than equally. Correcting for this makes DSM appear more cost effective.
than in the original Loughran and Kulick study. Second, they implemented a bootstrapping procedure to develop confidence intervals around Loughran and Kulick’s point estimates. Since these confidence intervals include the cost effectiveness estimates of utilities, frequently $0.01–0.03/kWh, Auffhammer, Blumstein, and Fowlie concluded that the results from Loughran and Kulick’s study are insufficiently precise to statistically reject utility estimates of DSM effectiveness.

Horowitz [2007] converted DSM energy savings from the EIA-861 database to an ordinal measure of DSM effort at the state level ($DSM_i$) and used state level energy intensity as a measure of energy efficiency ($EFF_i$) to estimate equation (1). He found that states with utilities that have a strong commitment to DSM programs have reduced energy intensity much faster than those with a weak commitment to energy efficiency programs. Although this suggests that DSM programs have been effective at reducing energy intensity, it is not possible to infer either a realization rate or a cost effectiveness estimate from this study.

Horowitz [2004] produced another similar study, but focusing on the commercial sector only, and using continuous, rather than ordinal, values as a measure of DSM effort. This study suggests that DSM expenditures from 1989 to 2001 reduced commercial sector electricity intensity by roughly 1.8 percent, suggesting a realization rate of 54 percent. This is relatively similar to the Loughran and Kulick estimate, again suggesting that utilities have overestimated cost effectiveness of DSM programs. Like Loughran and Kulick, however, Horowitz does not provide confidence intervals around the estimate, making it hard to reject utility estimates of cost effectiveness or realization rate.

Most recently, Arimura et al. [2009] have updated the analysis of Loughran and Kulick as well as Auffhammer, Blumstein, and Fowlie. Starting from the same base data set on utility DSM spending (but with a longer time dimension), they include contemporaneous energy efficiency regulations as an additional explanatory variable, and also include state-level spending on energy efficiency programs that falls outside of utility DSM expenditures. Additionally, they estimate the model in non-linear form, allowing for declining marginal effects of DSM expenditures as the level of expenditures increases. They find an average DSM cost effectiveness of about $0.06/kWh, with a 95 percent confidence interval of about $0.025–0.11/kWh, and they find that the marginal effectiveness of DSM expenditures decreases with additional expenditures, as predicted by theory.

Overall, these aggregate studies suggest that electric utility DSM programs in the US over the past three decades have been between 50 and 100 percent as effective as utilities themselves have estimated. The cost of such programs per unit of electricity consumption reduced would therefore be between equal to and double what utilities have estimated. However, there is significant uncertainty in these estimates, suggesting the value of additional research. This is particularly the case since virtually all studies to date have used the same data set, derived from EIA’s form 861. Given the ongoing nature of this dispute, and its critical importance for future energy efficiency policy, testing of different data sets, model formulations, and jurisdictions may help to clarify some of the key issues.
4. THE MODEL

This section uses an approach similar to those described in the previous section to estimate the impacts of DSM expenditures on energy consumption. The estimates are based on a data set containing electric utility DSM expenditures and electricity sales in Canada from 1990 to 2005. Since DSM programs were initiated only in the late 1980s in Canada, this period covers nearly the entire Canadian experience with such programs up to 2005.

The impact of utility DSM expenditures on electricity sales can be captured in the following equation:

$$\log \frac{kWH^*_i}{kWH_i} = \beta_i + DSM_i + X_i \alpha_i + e_i$$  \hspace{1cm} (2)

Here, $kWH^*_i$ is the consumption of electricity per capita in province $i$ in year $t$, measured in kWh, $DSM_i$ is the per capita expenditure on demand side management, $X_i$ is a vector of length $k$ of observed characteristics of the utility and the customers it serves, $\beta_i$, $\alpha_i$, and $e_i$ are coefficients, and $e_i$ is an error term.

The “*” on the left hand side variable indicates desired, rather than actual, electricity consumption. Because electricity-using capital generally lasts for several years, and because firms and households cannot immediately adjust electricity consumption in response to changes in electricity price, demand side management incentives, or other variables, actual electricity consumption may deviate from desired electricity consumption. We assume a constant-elasticity adjustment process between actual and desired electricity consumption, such that actual electricity consumption can be modeled as:

$$\frac{kWH_i}{kWH_{i,-1}} = \left( \frac{kWH^*_i}{kWH_{i,-1}} \right)^{\nu_i}$$ \hspace{1cm} (3)

where $\nu_i$ is a parameter that can take on values between 0 and 1. A value of 1 indicates that full adjustment to desired energy consumption takes place immediately, and implies that there is no inertia in adjusting energy consumption following an exogenous shock. A value of 0 indicates that no adjustment towards desired energy consumption following a shock is possible. Taking logarithms and substituting (2) into (3) gives:

$$\log kWH^*_i = \nu_i(\phi_i + DSM_i \beta_i + X'_i \alpha_i - \log kWH_{i,-1})$$

$$+ \log kWH_{i,-1} + \nu_i e_{it}$$ \hspace{1cm} (4)

Letting $\omega_i = \nu_i \phi_i$, $\delta_i = \nu_i \beta_i$, $\eta_i = \nu_i \alpha_i$, $\lambda_{it} = 1 - \nu_{it}$, and $\mu_{it} = \nu_i e_{it}$, we obtain:

$$\log kWH^*_i = \omega_i + DSM_i \delta_i + X'_i \eta_i + \log kWH_{i,-1} \lambda_{it} + \mu_{it}$$ \hspace{1cm} (5)

Equation (5) is a partial adjustment model of electricity demand, of the type commonly used in studies of the electricity sector as well as for other energy.
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3. We measure DSM in levels rather than logs because so that we can include utility-year pairs where DSM expenditures are zero. Our results are qualitatively unchanged when we conduct the analysis using logged DSM expenditures.

4. We conduct unit root tests to ensure that the variables of concern are stationary. A Levin-Lin-Chu panel unit root test rejects the null hypothesis of a unit root for the sales variable \((p = 0.0188)\).

3. Commodities [Houthakker et al., 1974]. Although it is an ad hoc model, not directly derived from consumer theory, it is commonly used because it is parsimonious and specifies an explicit dynamic adjustment process. This allows both short-run and long-run responses to exogenous shocks to be determined. In the current context, it allows us to estimate both short- and long-run responses to demand side management expenditures. Assuming the demand side management variable is measured in levels (rather than logs), a $1 expenditure on DSM in province \(i\) at time \(t\) is associated with a \(\delta_i\) percent change in electricity demand in period \(t\). This is the short-run response. In the long-run, the same expenditure is associated with a \(\frac{\delta}{1 - \lambda}\) percent change in electricity demand.

Estimation of (5) in its current form however, is impossible, since the number of coefficients to be estimated exceeds the number of data points. To make estimation possible, some restrictions have to be put on coefficients.

An obvious starting point is to restrict coefficients to be time invariant:

\[
\log kWH_{it} = \omega_i + DSM_i \delta_i + X' \eta_i + \log kWH_{i,t-1} \lambda_i + \mu_{it}
\]  

(6)

In this formulation, coefficients are allowed to vary across utilities, so for example the effectiveness of DSM expenditures is able to vary from one utility to another. Estimation of (6) is possible, provided that \(4 + k < T\). It is exactly equal to estimation of separate time series models for each of the utilities in the sample. This strategy is attractive because it puts a relatively small number of restrictions on the model coefficients. However, in the current sample, which has a relatively short time dimension (16 years), estimation is unlikely to yield precise coefficient estimates. Much more precision could be gained if it were possible to restrict coefficient values (except for intercepts) to the same value for all utilities, as in the following:

\[
\log kWH_{it} = \omega_i + DSM_i \delta + X' \eta_i + \log kWH_{i,t-1} \lambda + \mu_{it}
\]  

(7)

We test whether the joint restrictions imposed by (7) are warranted by using an F-test.

In (7), \(\omega_i\) captures unobserved time-invariant heterogeneity across utilities. Because it is unobserved, we can include it with the error to form a compound error term \(v_i = \mu_i + \omega_i\). Problems can arise in estimation of (7) if \(v_i\) is correlated with the other covariates. Two data transformations are generally employed to deal with this issue: differencing and within-group demeaning. We use the former here:
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\[
\log kWH_t - \log kWH_{t-1} = (DSM_t - DSM_{t-1})\delta + (X'_t - X'_{t-1})\eta \\
+ (\log kWH_{t-1} - \log kWH_{t-1})\lambda + (\mu_t - \mu) \tag{8}
\]

In (8), the overbar denotes a time-average. Both differencing and demeaning eliminate \( \omega \), and should eliminate this source of bias in model coefficients.\(^5\)

It is possible that the idiosyncratic error term is serially correlated, such that \( E(\mu_t|\mu_s) \neq 0 \forall t \neq s \). We therefore estimate the model using generalized least squares, allowing for a first order autoregressive error structure, in addition to the ordinary least squares approach described above.

The presence of the lagged dependent variable introduces additional complication into the model estimation. As Nickell [1981] shows, in the presence of a lagged dependent variable, the demeaning strategy generates correlation between the lagged variable and the error term, which results in biased coefficients. Several strategies have emerged to deal with this problem, mostly involving instrumenting the lagged dependent variable with additional lags that are truly exogenous [Arellano and Bond, 1991, Blundell and Bond, 1998]. However, these general method of moments strategies rely on a large number of cross-sectional observations, and so are inappropriate in the current context where the number of cross-sectional units is small and fixed. Instead, Kiviet [1995] derives a ‘correction’ for the bias present in the demeaned model and adjusts coefficient estimates with this correction. Monte Carlo evidence suggests that this correction is appropriate for the dimensions of data in this study [Judson and Owen, 1999]. As a result, we report coefficient estimates corrected for the bias resulting from the presence of lagged dependent variables.

We include key variables that are expected to influence electricity sales in \( X_t \), with all variables in log form:

1. the number of heating degree days, measured from an 18°C base
2. the number of cooling degree days, measured from an 18°C base
3. the residential retail electricity price, in 2005 Canadian dollars per kWh
4. gross provincial product per capita, in 2005 Canadian dollars
5. the price of the closest substitute energy for electricity (natural gas in all but Atlantic provinces; heating oil in Atlantic provinces, where natural gas is unavailable) in dollars per GJ
6. the percentage of total end-use electricity consumption by the residential sector

Finally, we note that the price variables in the model are not strictly exogenous, since the price and quantity of electricity consumption may be co-

and for the DSM expenditure variable (\( p = 0.0020 \)). Thus we do not transform our variables using differences.\(^5\)

Both first differencing and demeaning should eliminate the problem of correlated errors; the relative desirability of the two depends on error structure. We estimated the model in differences; our conclusions are unchanged by the estimation strategy.
determined. We tried to find appropriate instruments for the electricity price in the model, including the cost of fossil fuels and capital inputs. However, most electricity in Canada is produced from hydro and nuclear sources, so fossil fuel prices are very poorly correlated with electricity prices, and we could not find an appropriate capital cost series that was adequately disaggregated. Consequently, we use electricity prices directly in the model, with the caveat that inferences on coefficients may overlook the interdependence of electricity price and quantity. We think that this problem is less severe than in other markets, however, because electricity prices throughout Canada are generally regulated, with prices set in the year or years prior to the actual year that consumption takes place. To the degree that regulators are not forward-looking, electricity price can therefore be considered relatively exogenous. Paul et al. [2009] use a similar identifying assumption in their recent study of electricity demand in the US.

A similar problem may exist for the variable of interest—demand side management expenditures. In particular, it is possible that demand side management expenditures are influenced by electricity sales, perhaps because jurisdictions with robust growth in electricity are more likely to implement DSM programs. If this is the case, estimation of the current model will result in biased coefficient estimates. We discuss the implications of such endogeneity further below.

5. DATA SOURCES

Although Statistics Canada requires regular reporting by utilities on electricity generation capacity, electricity sales and revenues, and other information, it does not make this data public, except as provincial aggregates. Additionally, neither Statistics Canada nor any other federal department maintains data on DSM expenditures or energy savings from these programs. As a result, we conduct our analysis at a provincial level, and like Parfomak and Lave [1996], we gathered our data on DSM effort from individual electric utilities.

We gathered data on electric utility DSM spending between 1990 and 2005 from electricity distribution utilities in each Canadian province. Data were gathered mostly from utility, utility regulator, and government publications and were supplemented with a structured spreadsheet survey and unstructured interviews of electric utility staff. For most utilities, data were not available to show the breakdown of historical DSM spending between sectors or by activity type. Additionally, we were not able to collect data on utility estimates of energy savings from DSM programs, but only on DSM expenditures. Finally, we were not always able to distinguish between DSM spending aimed at load shifting and DSM spending aimed at energy efficiency, but where such disaggregation was
available, the majority of expenditures (about 75 percent) were directed towards energy efficiency programs. Thus, we include all demand side management expenditures in our DSM variable. We aggregate the data on DSM spending to a provincial level to match the dimensions of the rest of the data in our set.

Other data are sourced from Statistics Canada and Natural Resources Canada. In particular, the volume of electricity sales is derived from Statistics Canada Table 127-0001, and is given by ‘Total available’ electricity minus ‘Total industrial generation’. Sales are broken down by end user based on data from Statistics Canada Tables 128-0002 and 128-0009. Population is from Table 051-0001, gross domestic product is from Table 384-0001, heating and cooling degree days are by request from Natural Resources Canada. Natural gas and heating oil prices are from Tables 129-0003 and 326-0009, respectively, and electricity price is by request from Natural Resources Canada.

In total, our data set forms a balanced panel consisting of 160 observations from 10 provinces over 16 years. A summary of the data is provided in Figure 2 and Table 1. Several trends are obvious in the data. First, in most provinces, electricity consumption is increasing gradually throughout the 16-year pe-
Table 1: Summary of Data

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min.</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sales per capita (GWh)</td>
<td>0.015</td>
<td>0.005</td>
<td>0.006</td>
<td>0.025</td>
</tr>
<tr>
<td>DSM expenditure per capita (2005$)</td>
<td>3.51</td>
<td>5.57</td>
<td>0</td>
<td>33.13</td>
</tr>
<tr>
<td>GDP per capita (2005$ millions)</td>
<td>0.031</td>
<td>0.007</td>
<td>0.019</td>
<td>0.061</td>
</tr>
<tr>
<td>Electricity price (2005c/kWh)</td>
<td>9.37</td>
<td>1.87</td>
<td>6.09</td>
<td>14.56</td>
</tr>
<tr>
<td>Price of electricity substitute (2005c/kWh)</td>
<td>3.20</td>
<td>1.43</td>
<td>0.81</td>
<td>7.21</td>
</tr>
<tr>
<td>Heating degree days</td>
<td>4615</td>
<td>852</td>
<td>2627</td>
<td>6773</td>
</tr>
<tr>
<td>Cooling degree days</td>
<td>123</td>
<td>99</td>
<td>10</td>
<td>493</td>
</tr>
<tr>
<td>Fraction of sales to residential/agricultural</td>
<td>0.328</td>
<td>0.073</td>
<td>0.163</td>
<td>0.474</td>
</tr>
</tbody>
</table>

period of observation. However, in most provinces electricity consumption has fallen for at least part of the period under observation. Second, prices in most provinces are very stable over time since utility prices were regulated, suggesting that it will probably be difficult to obtain precise estimates of price elasticity. Third, most utilities have engaged in demand side management spending during the sample period (Alberta was the only province with no DSM spending at all during the period), and there is substantial intertemporal variation in DSM spending in most provinces, suggesting that if DSM has an effect on electricity sales, it should be possible to identify it in the data.

6. RESULTS

We begin our analysis by testing whether model coefficients for different provinces can be pooled together (i.e., is (7) appropriate, or is it necessary to work with (6)?). An F-test on the joint coefficient restrictions implied by (7) suggests that these are appropriate, so we work with the pooled models (with fixed effects) only in this section.

The first column of Table 2 reports coefficient estimates for the fixed effect (8) model, with standard errors robust to heteroscedasticity. Most coefficients are generally of the expected sign, and all except the coefficient on demand side management expenditures and on cooling degree days are significant at standard levels. The results suggest a short run price elasticity of –0.06 and a long run price elasticity of –0.2. These estimates are fairly consistent with other recent work. For example, in a recent study of US electricity demand Alberini and Fillipini [2010] find a price elasticity of –0.09 to –0.15 in the short run and –0.43 to –0.73 in the long-run. In a meta-analysis, Espey and Espey [2004]

7. Although, as discussed earlier, it is stationary.
8. $F = 0.5563$, df1 = 85, df2 = 50, $p = 0.991$. 
Table 2: Results of Regression Analysis

<table>
<thead>
<tr>
<th></th>
<th>LSDV</th>
<th>LSDVAR1</th>
<th>LSDVc</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lagged log of per capita sales</td>
<td>0.7005***</td>
<td>0.6329***</td>
<td>0.7722***</td>
</tr>
<tr>
<td></td>
<td>(–0.0949)</td>
<td>(–0.0622)</td>
<td>(–0.0631)</td>
</tr>
<tr>
<td>Log of GDP per capita</td>
<td>0.1362**</td>
<td>0.1433***</td>
<td>0.1110***</td>
</tr>
<tr>
<td></td>
<td>(–0.0441)</td>
<td>(–0.0411)</td>
<td>(–0.0405)</td>
</tr>
<tr>
<td>Log of electricity price</td>
<td>–0.0637*</td>
<td>–0.0820*</td>
<td>–0.0664</td>
</tr>
<tr>
<td></td>
<td>(–0.0306)</td>
<td>(–0.0444)</td>
<td>(–0.0455)</td>
</tr>
<tr>
<td>Log of substitute energy price</td>
<td>–0.0358**</td>
<td>–0.0349**</td>
<td>–0.0345**</td>
</tr>
<tr>
<td></td>
<td>(–0.0144)</td>
<td>(–0.0145)</td>
<td>(–0.0144)</td>
</tr>
<tr>
<td>Log of heating degree days</td>
<td>0.1128*</td>
<td>0.1245**</td>
<td>0.1115**</td>
</tr>
<tr>
<td></td>
<td>(–0.0594)</td>
<td>(–0.048)</td>
<td>(–0.0509)</td>
</tr>
<tr>
<td>Log of cooling degree days</td>
<td>0.0031</td>
<td>0.0061</td>
<td>0.003</td>
</tr>
<tr>
<td></td>
<td>(–0.0045)</td>
<td>(–0.0069)</td>
<td>(–0.0059)</td>
</tr>
<tr>
<td>Log of percent sales to residential sector</td>
<td>–0.0864*</td>
<td>–0.0969***</td>
<td>–0.0705**</td>
</tr>
<tr>
<td></td>
<td>(–0.0409)</td>
<td>(–0.0301)</td>
<td>(–0.0287)</td>
</tr>
<tr>
<td>Per capita demand side management</td>
<td>0.0001</td>
<td>0.0002</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>(–0.0003)</td>
<td>(–0.0007)</td>
<td>(–0.0007)</td>
</tr>
<tr>
<td>N</td>
<td>150</td>
<td>140</td>
<td>150</td>
</tr>
</tbody>
</table>

* p<0.1; ** p<0.05; *** p<0.01

This finding is potentially caused by mis-specification of the model. If electricity and other fuels are actually substitutes, an upward shock to fuel demand would increase fuel price (provided fuel supply is not perfectly elastic) and reduce electricity demand (since fuel and electricity are substitutes). However, our single-stage model will report a negative correlation between fuel price and electricity demand, suggesting the two are complements.

Our estimated income elasticity is likewise somewhat below published results, at 0.14 in the short run and 0.47 in the long run. For example, in the same meta-analysis, Espey and Espey [2004] report a mean short-run income elasticity of 0.28 and a long-run elasticity of 0.97. Counter intuitively, the sign on the substitute energy price is negative and significant, implying that increases in the price of substitute fuels are associated with reductions in the consumption of electricity. This contradicts other studies, which typically find that electricity and other heating fuels are substitutes rather than complements [Serletis et al., 2010].

More heating degree days are associated with larger electricity sales in the model, which
Electric Utility Demand Side Management in Canada

10. The confidence interval of the long-run response to demand side management expenditure is the ratio of two random variables, and so was determined by bootstrapping with 1000 replications. This implies that a $6 per capita DSM expenditure, which was the sample mean during 1990–2005, is estimated to increase electricity consumption in the short run by 0.00075 percent (with a 95 percent confidence interval of [–0.0032, 0.0047]). In the long run, the same expenditure is estimated to increase electricity consumption by 0.0025 percent (with a 95 percent confidence interval of [–0.018, 0.023]).

11. This estimate is based on the weighting scheme proposed by Auffhammer et al. [2008] and implemented by Arimura et al. [2009]. Formally, cumulative per capita savings in kWh $S$ are calculated for each utility in each year based on model parameters: $S_p = \frac{\delta}{1-\delta}kWH_pDSM_p$. Makes sense: a one percent increase in the number of heating degree days is associated with about a 0.1 percent increase in electricity sales. In contrast, the coefficient on cooling degree days is not significant (although it is of the correct sign). Finally, the coefficient on the percent of sales going to the residential sector is significant and of the correct sign, and suggests that as the residential sector makes up a larger share of total sales, the utility’s sales fall.

The coefficient on the demand side management variable is close to zero and statistically insignificant. Despite the fact that the variable is not precisely estimated, it is possible to estimate confidence bounds on the effectiveness of DSM over the period analyzed. In the short run, the standard error on the coefficient suggests a 95 percent confidence bound of [–0.00054, 0.00079]. This implies that a $6 per capita DSM expenditure, which was the sample mean during 1990–2005, is estimated to increase electricity consumption in the short run by 0.00075 percent (with a 95 percent confidence interval of [–0.0032, 0.0047]). In the long run, the same expenditure is estimated to increase electricity consumption by 0.0025 percent (with a 95 percent confidence interval of [–0.018, 0.023]).

It is useful to consider the economic implications of these findings. By weighting the estimated long-run (cumulative) percentage savings resulting from demand side management expenditures by the quantity of electricity sales at each utility in each year, we obtain an estimate of the total reduction in electricity sales resulting from DSM. When this estimate is divided by the total expenditures on demand side management, we obtain an estimate of the cost of reducing electricity demand through DSM expenditures. Because the parameter on DSM is not estimated precisely in the model, we apply these calculations to the 95 percent confidence bounds suggested by the estimate, which allow us to identify a range of DSM savings and cost effectiveness that are consistent with our data and model. Based on these calculations, we find that DSM expenditures from 1990 to 2005 have resulted in changes in electricity sales between –1186 GWh (a saving) and +1519 GWh (an increase). Both of these are trivial in size compared to total Canadian domestic utility sales of over 500 TWh (roughly one quarter of a percent of total Canadian electricity consumption). The lower 95 percent confidence interval implies a cost effectiveness of reducing electricity demand through demand side management of over $2/kWh, much higher than other sources of supply (we do not calculate a cost-effectiveness for the upper end of the confidence interval, since this estimate suggests that DSM expenditures are associated with electricity demand increases, rendering a cost-effectiveness calculation meaningless).

The second two columns of Table 2 implement alternative estimation strategies described earlier, designed to correct for serial correlation in the model...

10. The confidence interval of the long-run response to demand side management expenditure is the ratio of two random variables, and so was determined by bootstrapping with 1000 replications.

11. This estimate is based on the weighting scheme proposed by Auffhammer et al. [2008] and implemented by Arimura et al. [2009]. Formally, cumulative per capita savings in kWh $S$ are calculated for each utility in each year based on model parameters: $S_p = \frac{\delta}{1-\delta}kWH_pDSM_p$. 
residuals and to deal with bias introduced as a result of the lagged dependent variable. Accounting for serial correlation using a first-order autoregressive error term does not substantially change parameter estimates (see the second column of the table). The coefficient for demand side management is actually reduced in absolute value in this approach, and the confidence interval is somewhat widened. These changes do not affect the conclusions drawn above. Correcting for the bias caused by inclusion of the lagged dependent variable using the method proposed by Kiviet [1995] does affect parameter estimates somewhat. In particular, the coefficient on the lagged dependent variable increases substantially, implying that electricity consumption is more persistent than suggested in previous models.\textsuperscript{12} The long-run price and income elasticities in this new model are 0.29 and 0.48 respectively, somewhat higher than in the uncorrected models, and more consistent with the evidence from other studies described above. However, the coefficient on demand side management expenditures remains statistically insignificant and economically small (even when evaluated at the bounds of the confidence interval), again suggesting that demand side management expenditures have not played a substantial role in influencing electricity demand in Canada and that the cost of reducing demand through demand side management programs has been high.\textsuperscript{13}

In sum, all of the models that were estimated suggest that demand side management expenditures have had minimal impact on electricity demand. Our best estimate, from our preferred model, is that demand side management expenditures in Canada, which averaged roughly $6 per person per year across all utilities during our sample timeframe, have resulted in an increase of electricity demand of about one hundredth of a percentage point, an economically very small amount. As a result, we estimate that reductions of electricity consumption using demand side management have cost significantly more than estimated by utilities. Although coefficients on DSM expenditure are estimated imprecisely, standard confidence bounds around the estimates do not include low-cost estimates of demand side management that are estimated by utilities themselves. Our data do not allow us to suggest why this is the case, but we speculate that a combination of underestimating free-ridership rates and neglecting to account for rebound effects are the likely reasons. In particular, the estimates from our model suggest an upper bound for the direct rebound effect of about 30 percent, and other studies cited in this paper have shown that free ridership rates are often 50 percent or higher. The combination of these two effects could worsen the cost-effectiveness of a utility DSM program to the degree that we have reported here.

\textsuperscript{12} To determine cost effectiveness, total expenditures on DSM across the sample are divided by the sum of total savings: \[ CE = \frac{\sum \sum DSM_i \cdot POP_j}{\sum \sum S_i \cdot POP_j}. \]

\textsuperscript{13} As briefly noted above, we tested a specification of the model using logged DSM spending as the explanatory variable, and also tested a differencing strategy. Neither of these variations produced meaningful differences in the coefficient on the demand side management variable.
Several potential problems may contaminate our findings. First, although demand side management expenditures are treated as an exogenous variable here, it is possible that they could be endogenous. A possibility is that jurisdictions with high electricity sales are more likely to implement DSM programs, or else that in years when electricity sales are high, DSM programs are more likely to be implemented. If either of these is the case, our estimates of the impact of DSM are likely to be biased towards zero. In theory it is possible to find an instrument to account for this source of endogeneity, but in practice, especially given our small sample, we could not find an appropriate one. However, we feel that it is unlikely that DSM is endogenous in our formulation. DSM effort in Canada has been driven especially by the regulatory environment and by personalities, and anecdotal evidence as well as our experience in the industry suggests that causality in the relationship runs from DSM expenditures to electricity sales, and not the reverse.

A second problem that our study could suffer from is that it does not account for regulations, standards, and policies that affect electricity sales other than utility demand side management. For example, both provincial and federal governments offer tax credits to encourage energy efficiency, as well as implement standards and regulations that affect energy sales. Local and provincial governments also regulate land use and building codes, each of which can affect energy consumption. If changes in these variables are correlated with demand side management expenditures, then omitting them from the model will cause the coefficient on the DSM variable to be biased. In particular, if other policies are implemented simultaneously with DSM expenditures, then the (absolute value of) the DSM coefficient will be biased upwards. On the other hand, if government regulations are used as a substitute for DSM expenditures, such that they increase in intensity when DSM intensity is reduced, then the DSM coefficient will be biased towards zero. We have no reason to suspect either case. The federal government regulates appliances and industrial equipment on a regular cycle in Canada, with new regulations issued every year and existing regulations updated every several years.

Third, we note that our data on demand side management expenditures include all demand side management—in particular it includes both load management expenditures as well as energy efficiency expenditures. Since load management expenditures are not aimed at curtailing electricity demand explicitly, including these could lead us to suggest that demand side management is more costly than is really the case. However, in utilities that were able to provide us with data (as well as in US utilities), load management expenditures amounted to less than 25 percent of the total, so error in our estimates should not be too severe, and in particular should not change the nature of our conclusions.

7. CONCLUSIONS

The estimates from our analysis indicate that in aggregate DSM expenditures by Canadian electric utilities have had only a marginal effect on electricity
sales. Thus, our mean estimates for the cost effectiveness of DSM spending, for the period covered by our study, suggest that the costs for reducing overall electricity demand through DSM subsidies are high in comparison to the values estimated by utilities themselves. Additionally, although the coefficient on DSM spending in our estimated models is not estimated precisely, at conventional levels of statistical significance we are able to reject the DSM cost effectiveness values that have been estimated by the utilities.

The method we use, which because of its aggregate nature directly accounts for the net effect of free ridership, rebound effect, and within-jurisdiction spillover, provides a useful comparison to utility estimates of DSM effectiveness. However, because of the aggregate nature of our approach, we are not able to determine if the cost effectiveness of DSM has changed over time, or whether DSM expenditures in some utilities or sectors are more effective than those in others. Indeed, our data set almost surely includes some DSM programs that are very cost effective, as well as others which are not. Our analysis is only able to estimate the aggregate effectiveness and cost effectiveness of all DSM programs in Canada over a 16-year period.

It is important to emphasize that the cost effectiveness estimates generated by this research do not indicate the full technico-economic cost of improving energy efficiency, but rather reveal the cost of pursuing energy efficiency by a utility, which is typically conducted with subsidies. Subsidies are less effective than often assumed because they cannot avoid distributing the subsidy to those who would have undertaken the energy efficiency measure in the absence of the subsidy. These free riders weaken the effectiveness of the subsidy. Additionally, the rebound effect, which occurs as consumers adjust purchases in response to changes in relative prices, further erodes the effectiveness of an energy efficiency subsidy. Our analysis is suggestive that free ridership and rebound may have been substantial during the period of electric utility DSM subsidies covered by this study. This suggests that policy initiatives that rely on subsidies to promote energy efficiency may be much less effective than their supporters claim. This holds equally for government subsidy programs and for private subsidy programs, such as offset programs currently associated with efforts to reduce GHG emissions via subsidy.

The results should not be taken, however, to imply that investments in energy efficiency are undesirable from a social perspective. In estimating the cost-effectiveness of DSM programs, electric utilities are confined to a narrow definition of cost effectiveness that typically excludes environmental and social externalities. If these are taken into account, there is considerable research indicating that energy efficiency remains cost effective relative to new conventional generation from a social perspective. The challenge for utilities, governments and concerned individuals is to find policies that will actually ensure greater energy efficiency than that which naturally occurs as the capital stock evolves.
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REFERENCES


