

ANALYSING THE IMPACT OF ENERGY STAR REBATE POLICIES IN THE US

September, 2012

Abstract

In this paper we estimate the impact of rebate policies in various US states on the share of sales of ENERGY STAR household appliances between 2001 and 2006. We use a difference-in-difference approach to exploit the variation in the rebate policies over time and across US states to estimate their effect on the share of sales of ENERGY STAR household appliances. To account for the possibility of an endogenous rebate policy we use an instrumental variables approach in a fixed effects panel data regression model. Results suggest that rebate policies increase the share of sales of ENERGY STAR household appliances by around 7.4% and this represents an impact of around 21% on the mean level of the share of sales of ENERGY STAR household appliances in the US between 2001 and 2006.

Keywords: Residential appliances; ENERGY STAR; Rebate policies; Difference-in-difference.

JEL Classification Codes: D, D1, Q, Q4, Q5.

1 Introduction

The generation of electricity from fossil fuels is one of the leading causes of anthropogenic GHG emissions accounting for approximately 65% of our output of GHGs (International Energy Agency, 2009). The total CO₂ emissions from the consumption of electricity was a little over 30,300 million metric tonnes in 2009 of which the United States contributed around 18% (Energy Information Administration, 2012). While the per capita CO₂ emissions from the consumption of electricity in the US remains one of the highest in the world, chiefly due to its reliance on coal-fired power plants, there have been several policy initiatives undertaken at the level of state and federal governments to reduce it. These initiatives include the implementation of appliance standards, financial incentives in the shape of cash rebates, income tax credits and deductions, and the introduction of information and voluntary programmes like Climate Challenge and ENERGY STAR. The energy efficiency policies have been promoted to also reduce air pollution from pollutants such as sulphur dioxide, nitrogen oxides, ozone and particulate matter, to improve energy security and to prevent the need for constructing increasingly expensive new power plants.

In view of these advantages of energy efficiency, policy instruments that promote the increase in energy efficiency of electrical appliances like household appliances play an important role. One such programme, ENERGY STAR, was introduced in 1992 by the United States Environmental Protection Agency (EPA). The ENERGY STAR programme is a voluntary eco-labelling programme designed to promote the use of energy-efficient products and thus help to reduce the emissions of greenhouse gases by consuming less electricity. There is huge potential of CO₂ reductions from increased energy efficiency which is considered “low-hanging fruit” due to its low marginal cost. While computers and monitors were the first labelled products under ENERGY STAR, the scheme was subsequently expanded and now covers over 60 product categories including major appliances, office equipment, lighting, home electronics, and even new homes and commercial and industrial buildings. Appliances with the ENERGY STAR label usually consume about 20 to 30 percent less energy than required by federal standards (Tugend, 2008).¹

Federal and local governments and utility companies across the US promote the adoption of ENERGY STAR-labelled products by offering financial incentives. These incentives are usually in the form of mail-in rebates offered to customers who fill in the rebate form and return it to the respective entity offering the rebate. These financial incentives are offered by utilities in certain states as part of the Energy Efficiency Resource Standard (EERS) programme that require energy efficiency programmes to be implemented. The

¹For a more comprehensive description of the ENERGY STAR programme refer to Brown et al. (2002) and McWhinney et al. (2005).

adoption of energy efficient appliances has public (reduced GHG emissions) and private (savings in utility bills) benefits. According to estimates by the EPA, the ENERGY STAR programme has led to energy and cost savings in the US of about \$18 billion in 2010.² Howarth et al. (2000) state that improvements in energy efficiency in the Green Lights and ENERGY STAR Office Products programmes should lead to reductions in energy use with no significant “rebound effect”.³ Webber et al. (2000) conclude that 740 petajoules⁴ of energy has been saved and 13 million metric tons of carbon avoided due to the ENERGY STAR programme. In a more recent study using a bottom-up approach, Sanchez et al. (2008) estimate that ENERGY STAR-labelled products have saved 4.8EJ⁵ of primary energy and avoided 82Tg C equivalent. Given the importance of the ENERGY STAR programme to the EPA and the US Department of Energy⁶ and the high visibility of ENERGY STAR-labelled products, with public awareness of the label increasing from 56% in 2003 (U.S. Department of Energy, 2004) to more than 80% in 2011⁷, it is important to evaluate the impact of financial incentives provided by utility companies designed to promote the sales of ENERGY STAR household appliances. It is important to note that financial incentives to promote the adoption of ENERGY STAR appliances are not present in all US states. We use this variation in financial incentives to analyse the impact of these policy instruments.

In this paper we focus on rebate policies which are, in general, part of a wider array of programmes labelled demand-side management (DSM) programmes. These DSM programmes are initiatives undertaken by utility companies with regard to the “planning, implementation, and monitoring of utility activities designed to encourage consumers to modify patterns of electricity usage, including the timing and level of electricity demand” (Energy Information Administration, 2009). Initiated primarily to combat rising gas and oil prices in the late 1970s these initiatives have increased from 1.4 billion dollars in 1999 to 4.2 billion dollars in 2010 (Energy Information Administration, 2011) after a dramatic fall in DSM spending in the mid to late 90s due to restructuring of electricity markets.⁸ There was uncertainty about the restructuring efforts and ability to recover spending on energy efficiency through cost recovery mechanisms. As a result, DSM programmes were considered incompatible with competitive retail markets (Molina et al., 2010).

²http://www.energystar.gov/index.cfm?c=about.ab_history, website accessed 17 April, 2012

³The “rebound effect” is a phenomenon, described by Khazzoom (1980), whereby electricity consumption increases due to an increase in energy efficiency. It is caused by the fact that an increase in the level of energy efficiency leads to a decrease in the price of energy services and, via a substitution effect, an increase in demand for these energy services. This, subsequently, causes an increase in the demand for electricity.

⁴1 petajoule = 10^{15} Joules. 740 petajoules is equivalent to 205.5×10^6 MWh. 1 MWh = 3.6×10^9 Joules.

⁵1EJ (Exajoule)= 10^{18} Joules. 4.8EJ is equivalent to 1.3×10^9 MWh. 1Tg (Teragram) = 10^{12} grams

⁶The ENERGY STAR programme has been jointly administered by the EPA and the US Department of Energy (DOE) since 1996.

⁷http://www.energystar.gov/index.cfm?c=about.ab_milestones, website accessed 21 August, 2012

⁸See Eto (1996), Nadel and Geller (1996) and Nadel (2000) for a history of utility DSM programmes in the US.

There is a substantial literature on the evaluation of DSM programmes in general. However, the impact of specific financial incentives on adopting energy efficient products has not been studied as extensively. These incentives can be in the form of tax credits or deductions, loan subsidies and cash rebates. Compared to the studies on over-all DSM initiatives the existing literature on the impact of cash rebate policies on adopting energy efficient appliances is quite limited and even more so at the aggregate level. A recent study by Datta and Gulati (2011) uses aggregated state-level US panel data for some household appliances (clothes washers, refrigerators and dishwashers) and estimates the impact of rebates offered by utility companies on the sales of ENERGY STAR-labelled appliances. In this paper we aggregate the ENERGY STAR appliances that includes air conditioners in addition to clothes washers, refrigerators and dishwashers. Also, more importantly, we use an instrumental variables approach to account for possible endogeneity concerns of rebate policies. At the disaggregate level, the papers by Train and Atherton (1995) and Revelt and Train (1998) are examples of the impact of financial incentives on the choice of efficiency of appliances by residential customers. Revelt and Train (1998) use stated preference data to estimate the impact of rebates and loans on the choice of efficiency of refrigerators and predict that rebates led 8.5% of customers to switch from a standard-efficiency to a high-efficiency refrigerator.

The contribution of this paper is to study the effect of rebate policies on the sales of ENERGY STAR-labelled household appliances using a difference-in-difference framework in a fixed effects panel data model in which we consider the rebate policy to be potentially endogenous. To apply our methodology we use information from 47 US states between 2001 and 2006 and use publicly available data on ENERGY STAR sales share, presence of rebate policies and various socio-economic, weather and price variables. The unobserved state-specific heterogeneity in our panel data set-up is controlled by using fixed effects estimation procedures and we also address potential endogeneity issues in the rebates policy variable with an instrumental variables approach.

The remainder of the paper is organised as follows. In the next section we discuss our empirical specification and follow it up with a description of the data, its sources and limitations in section 3. The econometric results are presented in the penultimate section while the final section has concluding remarks.

2 Empirical Specification

The policy of utility rebates for ENERGY STAR appliances varies widely across US states and, in some cases, across time within US states. We will use this variation as our identifying strategy to measure the impact

of the rebates. The policy also differs in terms of the coverage among the customers of utility companies that provide electricity. For example, not all utility companies in a state will offer rebates to its customers. Therefore, the coverage of rebates will vary across states and also within states over time.

We use a panel data set of 47 US states over the period from 2001 to 2006 to estimate the impact of a rebates policy on the share of sales of ENERGY STAR-labelled household appliances. The share of sales of ENERGY STAR appliances is assumed to depend on various socio-economic characteristics, weather characteristics and the state-specific rebate policy.

Table 4 in the Appendix shows how such rebates were distributed across the US in the time period 2001 to 2006. We find that there is variation both across states and even within states over time. States like Alabama, Arizona and Florida did not have any utility rebates over the period of six years while California had utility rebates in all years in the same time period. Many states like Colorado, Iowa and Minnesota did not have rebates over the entire period. We will try to use this variation in rebate policies to capture its impact on the adoption of ENERGY STAR appliances. We will be able to estimate the effect of the rebate policy intervention by using a difference-in-differences (DD) approach. The basic idea behind DD is to identify a policy intervention or *treatment* and then compare the difference in the outcomes before and after the intervention for the treated groups with the difference for the untreated or control groups. In our case, the treated groups are the states that had the rebate policy in a particular year while the control groups are the states that had no rebates or states in which the policy was not in effect during a particular year. A typical DD estimation using panel data with more than two time periods will consider individual and year fixed effects. Our DD estimation will, therefore, take into consideration the unobserved time-invariant variables.

We estimate the model using the following specification:

$$ES_{it} = \alpha_i + \beta \text{Rebate Policy}_{it} + \gamma X_{it} + \delta_t + \varepsilon_{it} \quad (1)$$

where subscripts i and t are US state and year indices, respectively. ES_{it} is the share of ENERGY STAR household appliances sold, $\text{Rebate Policy}_{it}$ is the rebates policy variable, X_{it} is a matrix of all other explanatory variables, and ε_{it} is the idiosyncratic error term. The set of covariates in X_{it} are the price of residential electricity, the price of residential gas, the per capita income, the household size, the number of cooling and heating degree days, the percentage of high school graduates and the percentage of males. Unobserved state-specific heterogeneity is captured by the α_i terms and the δ_t terms capture the year-specific

fixed effect. Depending on the assumptions we make about the correlation of the α_i terms with the other explanatory variables in eq. (1) we have either a fixed effects model or a random effects model. The advantage of the fixed effects model is that the individual effects may be correlated with the explanatory variables while in the random effects model this correlation is assumed, by definition, to be zero.

Including both time and state-specific fixed effects in eq. (1) enables us to disentangle the impact of the rebates policy from other determinants related to state characteristics or time effects. Our coefficient of interest is β which provides us with an estimate of the effect of having a rebate policy on the sales share of ENERGY STAR appliances. A positive and significant coefficient would suggest that the rebates policies were effective in increasing the share of ENERGY STAR appliances over the period from 2001 to 2006.

Certain assumptions need to be met by our model to enable us to identify the impact of the rebates policies. First, we need to exclude the presence of unobserved variables affecting ENERGY STAR sales shares that move systematically over time in a different way between the states. In our analysis, the assumption sounds reasonable because all states belong to the US and, therefore, the general trend in ENERGY STAR sales share is expected to be similar. Moreover, the possibility of unobserved heterogeneity should be negligible given that our regressions include all the main socioeconomic determinants of differences in ENERGY STAR sales shares use across the states.

A further assumption is that the decision to have a rebate policy is independent of the ENERGY STAR sales share in a state, i.e. policies are exogenous. However, this assumption may be debatable because it is possible that rebate policies in a state may be driven by the penetration of ENERGY STAR sales share. It is entirely plausible that states with a low ENERGY STAR sales share have rebate policies in place. As noted by Besley and Case (2000) there is a literature in political economy in which state policies may be taken to be endogenous and therefore there is a need to obtain unbiased estimates of the impact of a policy. We therefore seek to improve on our initial results by endogenizing the policy variable using a couple of two step instrumental variables approaches. Firstly, we use a standard two stage least squares linear model with instruments in the first stage. Secondly, we use a two stage instrumental variables approach with a probit regression of the endogenous policy variable in the first step and an instrumental variables approach in the second step (Heckman, 1978). We use a political variable as one our instruments, namely, the share of Democratic House members in a state. The political variables are missing for the state of Nebraska due to the unusual nature of its legislature. The Nebraska legislature is unicameral and non-partisan and therefore, we do not have any information on the division of the legislature on party lines. The second instrument we use is the percentage of Sierra Club members in a state. We will describe the rationale for considering these

two instruments in section 4.

A final issue is the possibility of positive serial correlation in the outcomes causing standard errors to be inconsistent (Bertrand et al., 2004). To deal with this problem we report the standard errors clustered by state. The remainder of the paper deals with estimating the coefficient β in eq. (1) where we model unobserved heterogeneity using fixed and random effects and use instrumental variables estimation procedures to correct for potential endogeneity problems.

As mentioned previously, the coverage of rebates varies within states and also across the four different appliances under consideration, viz. clothes washers, dishwashers, refrigerators and air conditioners. Also, rebate policies are not present in all US states. To solve this we use the fraction of people that are covered by rebates. This is calculated by using the number of customers that would be covered under the rebate policy and then using the distribution of the fraction of customers covered to define a cut-off for defining a policy dummy. It should be noted that the rebate policies under consideration apply only to four major household appliances, viz. clothes washers, refrigerators, dishwashers and air conditioners. In many cases, the policies apply to a subset of this group. For example, there could be a cash rebate for clothes washers and not for the other three appliances. All the possible combinations need to be accounted for. The way we have proceeded in this case is to consider the number of appliances that are covered by the rebate. If, as in our previous example, there is a cash rebate for only clothes washers and not for the other three appliances then the coverage will be 25%. Since all the customers in a state are unlikely to be covered by the same rebate policy, if that is the only rebate policy in place, the coverage for the entire state will be less than 25%. Figure 1 provides an indication of the distribution of the extent, in the presence of a rebate policy, of the rebate policy covering the population. Table 3 in the Appendix provides a summary of the average coverage in each state over the six years from 2001 to 2006.

We consider a coverage of 6.7% as our critical value which turns out to be the median. In our framework, a state is considered to have a value of one for the rebate policy variable if the coverage of the rebates exceeds the cut-off value. In all our subsequent discussions, states that are less than the 6.7% coverage are categorised as those states with no rebate policies while those with a coverage of greater than or equal to 6.7% are considered states that have rebate policies. We have also considered a range of coverage values from 1% up to 45% coverage as the cut-off value. The results are fairly similar in magnitude up to a certain stage but the precision of the policy variable in our preferred specification decreases as the cut-off value is increased while the magnitude of the coefficient of interest also declines as the cut-off value is made more stringent.

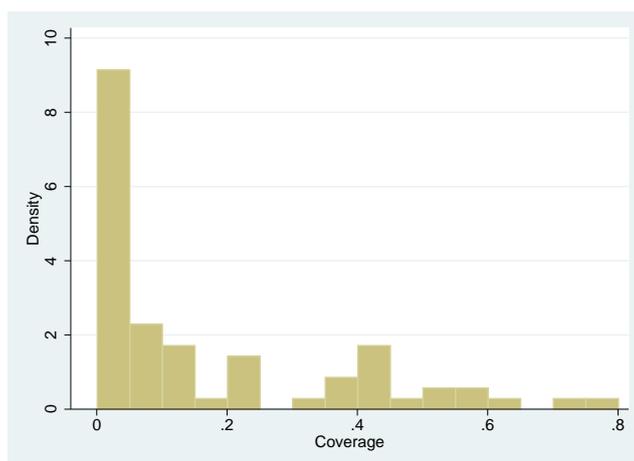


Figure 1: Histogram of Rebate Policy Coverage

3 Data Description

Annual data of US states between 2001 and 2006 have been compiled from a number of sources. We restrict our analysis to the contiguous US states and exclude the District of Columbia and the states of Alaska and Hawaii from our analysis while the state of Rhode Island is excluded due to incomplete information. The share of ENERGY STAR appliances sold are from the US Department of Energy (DOE). The price of residential electricity and the price of gas, a substitute of electricity, are obtained from the Energy Information Administration (EIA) of the US Department of Energy. The price of residential electricity is an average price calculated by the EIA from dividing the revenue of the utility companies coming from the residential sector with the volume of electricity sales to the residential sector. The gas price, also an average, is calculated similarly by the EIA by dividing total revenue from the residential sector with the total volume of sales to it.

The socioeconomic data used in our estimation, viz. population, the number of housing units, per capita income, percentage of people who are at least high school graduates and percentage of males are obtained from the Bureau of Economic Analysis of the US Census Bureau. The nominal values are converted to real values by dividing them with the consumer price index obtained from the U.S. Bureau of Labor Statistics (2010) so that the prices of electricity and gas and per capita income are all in real terms. Information on heating and cooling degree days (HDD and CDD, respectively) is from the National Climatic Data Center at the National Oceanic and Atmospheric Administration (NOAA). We also use instrumental variables to solve for possible simultaneity bias in the regression. The instruments are the fraction of House members in a state

Table 1: Summary Statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Rebate Policy	0.124	0.330	0	1	282
Fraction of ENERGY STAR Appliances	0.348	0.137	0.091	0.636	282
Log Per Capita Electricity Demand	8.427	0.277	7.701	8.859	282
Log Price of Electricity	-3.091	0.222	-3.480	-2.479	282
Log Price of Gas	-5.162	0.235	-5.881	-4.562	282
Log Per Capita Income	9.627	0.127	9.365	9.968	282
Log Household Size	0.839	0.070	0.642	1.068	282
Log Cooling Degree Days	6.816	0.709	5.112	8.207	282
Log Heating Degree Days	8.422	0.509	6.404	9.138	282
Percentage of High School Graduates	86.101	3.798	77.200	93	282
Percentage of Males	49.211	0.629	48.230	50.860	282
Percentage of Sierra Club members	0.238	0.143	0.036	0.673	282
Fraction of Democratic House members	0.498	0.145	0.130	0.880	276

who belong to the Democratic party and the percentage of Sierra Club members in a state. The number of Sierra Club members in a state has been obtained directly from Sierra Club upon request. The Sierra Club is an environmental organisation in the US.⁹ We calculate the percentage of Sierra Club members in a US state to construct a measure of the environmental pressure. Summary statistics of all the variables are presented in Table 1.

Calculating the share of ENERGY STAR appliances sold is not very straightforward. The sales data on ENERGY STAR covers only four major household appliances, viz. clothes washers, dishwashers, refrigerators and air conditioners. All other household products that may fall under the ENERGY STAR label, e.g. computers and light bulbs, are not captured by the sales figures. Given the sales shares of each of the four household appliances, we calculate an aggregate sales share of those ENERGY STAR appliances by adding up the total ENERGY STAR units sold and dividing that number by the total appliances sold. In essence, we are capturing the penetration of ENERGY STAR appliances in households. We have to complement the ENERGY STAR data on units sold with figures from Appliance Design magazine (various years) in a few years as well as the units of air conditioners sold.

The rebate policy dummy variable $\text{Rebate Policy}_{it}$ is constructed using data about rebates obtained from D&R International Ltd. The dummy is assigned a value of one when a state has a rebate programme in place in a year that covers more than 6.7% of the population while it is zero otherwise. Table 4 provides an overview of all the US states we have considered and their corresponding rebate policies between 2001 and

⁹ “[...] America’s largest and most influential grassroots environmental organization”, <http://www.sierraclub.org/>, website accessed 25 April 2012.

2006. States which had rebates offered by any utility company in a particular year are marked with a “■” in the table.

4 Estimation and Results

We now describe the methods used to estimate eq.(1) and present the results. The dependent variable in all our specifications is the sales share of ENERGY STAR appliances. There are several approaches to estimating the equation which include the pooled ordinary least squares model (POLS), the random effects model (RE) and the fixed effects model (FE). Our objective is to estimate the effect of the rebate policies using a DD framework and we employ some standard tests to choose the most appropriate method to estimate the effect of the policy variable.

The following tests performed indicate that the POLS model can be rejected in favour of panel data methods of estimation. The Breusch and Pagan lagrange multiplier test rejects the null hypothesis that there is no individual heterogeneity present and therefore we prefer the RE model over the OLS. We also perform the F -test of the null hypothesis that the constant terms are equal across all the states and this is also rejected. This means that there are significant state-level effects and the POLS model is inappropriate when compared to the FE model. We, therefore, restrict our subsequent analysis to fixed and random effects panel data estimation methods.

Now we need to make the choice between the fixed effects model and the random effects model. The random effects model assumes exogeneity of all the explanatory variables with the individual effects which is a strong assumption that may not be realistic in our case. We use a test for overidentifying restrictions to test for fixed versus random effects and find that the hypothesis of the explanatory variables being orthogonal to the state-level fixed effects is rejected.¹⁰ We, therefore, consider a DD estimator with fixed individual effects from now. The results from estimating eq.(1) using fixed effects are presented in column FE1.

As discussed previously, a potential problem with a straightforward application of fixed effects models is the possible endogeneity problem when estimating the coefficient of Rebate Policy_{*it*} in eq.(1). The policy variable may be endogenous due to simultaneous causality that runs from the adoption of ENERGY STAR appliances to the rebate policy. It is possible that rebate policy is influenced by the penetration of ENERGY STAR appliances and we deal with this by considering two instrumental variables approaches. In the first

¹⁰We use the `xtoverid` command (Schaffer and Stillman, 2006) in `STATA`. Fixed effects estimators use the orthogonality conditions that the explanatory variables are not correlated with the error term. Random effects estimators, in addition, use the orthogonality conditions that the explanatory variables are uncorrelated with the group-level individual effects. These additional orthogonality conditions are the overidentifying restrictions we are testing.

Table 2: Fixed Effects Models of ENERGY STAR share

	FE1	FE2	FE3
Rebate Policy	0.028 ^a (0.016)	0.053 (0.058)	0.074 ^c (0.026)
Log Price of Electricity	0.022 (0.056)	0.004 (0.067)	-0.008 (0.063)
Log Price of Gas	0.070 ^a (0.036)	0.080 ^a (0.042)	0.089 ^b (0.040)
Log Per Capita Income	0.077 (0.125)	0.056 (0.126)	0.053 (0.131)
Log Household Size	0.183 (0.154)	0.181 (0.143)	0.184 (0.142)
Log Cooling Degree Days	-0.017 (0.019)	-0.024 (0.023)	-0.030 (0.020)
Log Heating Degree Days	-0.067 (0.052)	-0.074 (0.050)	-0.077 (0.049)
Percentage of High School Graduates	0.002 (0.003)	0.002 (0.003)	0.003 (0.003)
Percentage of Males	0.088 ^b (0.040)	0.104 ^a (0.058)	0.116 ^b (0.051)
Year Dummies	Yes	Yes	Yes
Observations	282	276	276
Adjusted R^2	0.932	0.915	0.910
Overidentification Test (p -value)		0.482	

Standard errors, in parentheses, are clustered at the state level

^a: Significance level at 10%

^b: Significance level at 5%

^c: Significance level at 1%

Dependent variable is share of ENERGY STAR appliances sold

approach we predict the policy dummy variable in the first stage by using a linear probability model while in the second approach we use a probit model in the first stage. As discussed later, the first stage probit model seems to be more appropriate for our model due to the binary nature of our policy variable. The instruments we use are the fraction of Democratic members in the House of each US state and the percentage of people in the state that belong to the Sierra Club, an environmental organisation. The rationale behind using these variables as instruments is that we expect the composition of the legislature to be correlated with the policy in a state but uncorrelated with the adoption of energy efficient appliances. We also assume that the membership in an environmental organisation will affect rebate policy through possible political pressure but will not affect the adoption of ENERGY STAR appliances. While this second assumption may appear tenuous there are some who have argued that environmentally conscious consumers save energy through reducing activity and not by aiming to improving energy efficiency (Faiers and Neame, 2006).

The results obtained from a two-stage least squares model (2SLS) are presented in column FE2. The high p -value obtained from calculating the Hansen J-statistic in the overidentification test suggests that the share of Democratic party members in state Houses and the percentage of Sierra Club members are uncorrelated with the error term and that their exclusion from the estimated equation is valid. This means that our instruments are valid. Observations are also allowed to be correlated within groups. The presence of a possible endogenous dummy policy variable indicates a situation as described in Heckman (1978). Using the procedure described by Wooldridge (2002) we perform another instrumental variables estimation which exploits the binary nature of our policy variable by fitting a probit in the first stage model. We first fit a probit model of the rebate policy variable using the instruments and all the other exogenous variables by maximum likelihood. We then obtain the fitted probabilities of the response variable and finally estimate eq.(1) using the fitted probabilities as instruments and the other explanatory variables. The advantage of using this latter approach is that the standard errors are smaller and we can obtain a more precise estimate. Another advantage is that the probit model in the first stage does not need to be correctly specified (Wooldridge, 2002).

The effects of rebate policies on ENERGY STAR sales share are reported in Table 2. All regression results reported in Table 2 include state-level fixed effects and year dummy variables. The results are stable and no structural differences are observed across the models. In all the fixed effects models the relatively low number of statistically significant coefficients of socioeconomic variables could be explained, as suggested by Cameron and Trivedi (2005), by the low within variation of these variables. The number of significant coefficients increases in the two-stage least squares model FE3. However our main goal in this paper is to estimate the coefficient of the rebate policy dummy variable using a DD framework. The coefficient for the “Rebate Policy” variable in model FE2 is similar to the OLS estimation, FE1, but loses its significance. The estimate for “Rebate Policy” in FE3 using the Heckman-type estimator is also significantly different from zero and larger in magnitude than the estimate in FE2. We believe that the FE3 specification is a better model compared to FE2 because of the probit model estimated in the first stage to obtain the predicted probabilities of the policy dummy.

As explained previously, the control group consists of all the states that did not have a sufficiently large coverage of a rebates policy in a year to increase ENERGY STAR household appliances share between 2001 and 2006. Thus, when we study the effects of the rebate policies, the controls are the states that either do not have a policy in a year or the coverage was less than 6.7% of the customers. The variable “Rebate Policy” is a dummy variable equal to 1 when the rebate covers 6.7% or more of the customers and 0 otherwise for

the treated state only. Its estimated coefficient captures the average effect of the policy. In line with our expectations, policy coefficients are significant in all the models apart from FE2. The policy dummy variable shows a positive sign, which suggests that the implementation of rebates leads to an increase in the sales of ENERGY STAR appliances. Using the estimated coefficient of “Rebate Policy” in FE3, we observe that adopting rebates may increase the sales share of ENERGY STAR appliances by around 7.4%. This roughly represents an impact of around 21% on the mean level of ENERGY STAR sales share in US states between 2001 and 2006.

5 Conclusion

There are not many studies that have shown the impact of having state-wide rebate policies on the sales of ENERGY STAR household appliances. Some areas within a few US states have adopted this policy while those in most of the other US states have not. It is, therefore, important to make an analysis of the impact of such policies to have a good understanding of this particular aspect of DSM initiatives.

In this paper we estimate the impact of such rebate policies in US states by using a difference-in-difference approach. This approach allows us to identify the effect of rebate policies by relating differential changes in the sales of ENERGY STAR appliances across US states and over time to changes in the rebate policy variable. The crucial contribution of this paper is to use an instrumental variables approach to solve for the potential endogeneity of our rebate policy variable. Using this approach our results show that the use of rebates are an effective tool to increase the penetration of ENERGY STAR household appliances. However, the paucity of studies in this area suggests that it is necessary to conduct further research.

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Appendix

Table 3: Coverage of Rebate Policy by US State and Year

State	2001	2002	2003	2004	2005	2006
Alabama	0	0	0	0	0	0
Arkansas	0	0	0	0	0	0
Arizona	0	0	0	0	0	0
California	0.0248	0.0391	0.0525	0.5551	0.6112	0.7519
Colorado	0	0	0.0034	0.0099	0.0108	0.0386
Connecticut	0	0	0.75	0	0.4395	0.4093
Delaware	0	0	0	0	0	0.2500
Florida	0	0	0	0	0	0
Georgia	0	0	0	0	0	0
Iowa	0	0	0	0.0036	0.0008	0.0401
Idaho	0	0.0095	0.0146	0.0209	0.0014	0.0214
Illinois	0	0	0	0.0372	0	0
Indiana	0	0	0	0	0	0
Kansas	0	0	0	0	0	0
Kentucky	0	0	0	0	0	0
Louisiana	0	0	0	0	0	0
Massachusetts	0	0	0.0426	0.1164	0.2070	0.2051
Maryland	0	0	0	0	0	0
Maine	0	0	0	0	0	0
Michigan	0	0	0	0	0	0
Minnesota	0	0	0.0284	0.0678	0.0912	0.1248
Missouri	0	0	0	0	0	0
Mississippi	0	0	0	0	0	0
Montana	0	0	0.0584	0.0055	0.0110	0.0740
North Carolina	0	0	0	0	0	0
North Dakota	0	0	0	0	0	0
Nebraska	0	0	0	0	0	0
New Hampshire	0	0.0743	0.0991	0.1250	0.2500	0.1250
New Jersey	0	0	0	0	0	0
New Mexico	0	0	0	0	0	0
Nevada	0	0	0.3125	0.3750	0.3750	0.3750
New York	0	0	0	0	0.0363	0.0363
Ohio	0	0	0	0	0	0
Oklahoma	0	0	0	0	0	0
Oregon	0.0039	0.0452	0.1826	0.2061	0.1273	0.5778
Pennsylvania	0	0	0	0	0	0
South Carolina	0	0	0	0	0	0
South Dakota	0	0	0	0.0018	0	0
Tennessee	0	0	0	0	0	0
Texas	0	0	0	0	0	0
Utah	0	0	0	0	0	0
Virginia	0	0	0	0	0	0
Vermont	0	0	0.1250	0.4375	0.4375	0.4375
Washington	0.0049	0.0661	0.4356	0.4585	0.5020	0.5448
Wisconsin	0	0	0	0.0412	0	0.0420
West Virginia	0	0	0	0	0	0
Wyoming	0	0.0048	0.0095	0.0095	0.0095	0.0143

Table 4: Implementation of Rebate Policy by US State and Year

State	2001	2002	2003	2004	2005	2006
Alabama						
Arkansas						
Arizona						
California				■	■	■
Colorado						
Connecticut			■		■	■
Delaware						■
Florida						
Georgia						
Iowa						
Idaho						
Illinois						
Indiana						
Kansas						
Kentucky						
Louisiana						
Massachusetts				■	■	■
Maryland						
Maine						
Michigan						
Minnesota				■	■	■
Missouri						
Mississippi						
Montana						■
North Carolina						
North Dakota						
Nebraska						
New Hampshire		■	■	■	■	■
New Jersey						
New Mexico						
Nevada			■	■	■	■
New York						
Ohio						
Oklahoma						
Oregon			■	■	■	■
Pennsylvania						
South Carolina						
South Dakota						
Tennessee						
Texas						
Utah						
Virginia						
Vermont			■	■	■	■
Washington			■	■	■	■
Wisconsin						
West Virginia						
Wyoming						

■: States with rebate policy coverage ≥ 0.067 in Table 3

Table 5: Fixed Effects Models of ENERGY STAR share

	FE1	FE2	FE3
Rebate Policy	0.033 ^b (0.013)	0.050 (0.050)	0.086 ^c (0.026)
Log Price of Electricity	0.009 (0.054)	-0.010 (0.072)	-0.042 (0.065)
Log Price of Gas	0.065 ^a (0.034)	0.068 ^a (0.035)	0.076 ^b (0.037)
Log Per Capita Income	0.071 (0.119)	0.049 (0.118)	0.038 (0.121)
Log Household Size	0.177 (0.152)	0.171 (0.143)	0.169 (0.146)
Log Cooling Degree Days	-0.020 (0.019)	-0.025 (0.025)	-0.036 ^a (0.020)
Log Heating Degree Days	-0.081 (0.050)	-0.093 ^a (0.051)	-0.113 ^b (0.050)
Percentage of High School Graduates	0.002 (0.003)	0.002 (0.003)	0.001 (0.003)
Percentage of Males	0.080 ^a (0.040)	0.086 ^a (0.046)	0.093 ^a (0.053)
Year Dummies	Yes	Yes	Yes
Observations	282	276	276
Adjusted R^2	0.934	0.917	0.907
Overidentification Test (p -value)		0.760	

Standard errors, in parentheses, are clustered at the state level

^a: Significance level at 10%

^b: Significance level at 5%

^c: Significance level at 1%

Dependent variable is share of ENERGY STAR appliances sold