Efficiency and Distributional Consequences of Subsidies for Energy-Efficient Appliances

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1. Introduction

To promote residential energy efficiency, federal, state, and local governments have relied on an array of fiscal policy instruments to subsidize energy-efficient appliances. The federal government provides tax credits to manufacturers for producing appliances that surpass their minimum efficiency standard by at least 25%. In the 2009 Recovery Act, the federal government appropriated $300 million to finance the state energy-efficiency appliance rebate program ("Cash for Appliances"). Such appliance rebate programs are common in local and utility-operated demand-side management programs. Several state governments also offer occasional sales tax holidays for qualified energy-efficient appliances.

Residential energy efficiency subsidies lower the cost of relatively efficient energy-using capital instead of raising the price of energy to reflect the cost of its externalities. As a result, the net social benefits of such subsidies may be lower than the first-best policy of pricing the externalities. Nevertheless, energy efficiency subsidies could be distributionally progressive if they enable lower-income households to purchase more efficient appliances than they would have otherwise. Our research investigates this trade-off between efficiency losses and distributional benefits of different fiscal policies used to subsidize energy-efficient residential purchases. We are also interested in how the statutory incidence and nature of subsidy implementation impacts economic efficiency and equity in this context. We are exhaustive in our investigation of the different types of subsidies that target residential consumers of energy-intensive durables. In particular, we consider federal manufacturers' tax credit, state sales tax holidays/exemptions, and rebates, both ad valorem and lump-sum. For rebates, we also observe variation in the mechanisms to claim rebates and the entity providing the rebates, i.e., electric utilities and state governments.[1]

Our empirical strategy builds on our previous work (Houde and Aldy 2014, and Houde 2014) and estimates the heterogeneous behavioral responses to different types of energy efficiency subsidies targeting consumers of energy-intensive durables. A single estimation framework is used to identify preference parameters specific to each type of subsidy and different demographic groups. In particular, we estimate discrete choice models for the appliance purchasing decision and exploit rich temporal and regional variation in the features of the various energy efficiency subsidy policies. For instance, the states launched their Cash for Appliances programs at various times during 2010

[1]The only remaining type of subsidy for energy-efficient products available in the U.S. is a federal tax credit offered to consumers for insulation, windows, and other investments. These tax credits do not apply to appliances that we focus in our study.

and state programs varied in terms of rebate amount, appliance coverage, and other characteristics. In 2011, Congress modified the manufacturers' tax credit, which covers only a subset of appliances. Sales tax holidays vary across states and the eligibility criteria vary over time within states. Our data come from a large U.S. retailer over 2008-2012, which includes millions of refrigerator, dishwasher, and clothes washer transactions. About half of the transactions have matched household demographic data and all transactions include store location (for 2000+ stores in our sample). This rich micro-dataset allows us to control for region-specific unobservables and time trends. Our estimation framework also accounts for consumer sorting and more broadly unobserved preference heterogeneity that might be confounded with the behavioral responses to energy efficiency subsidies.

Our preliminary results for the refrigerator market suggest a number of interesting patterns.[2] First, lower income consumers respond less to sales tax and electricity cost relative to higher income households. That is, a dollar increase in tax or net present value of electricity cost has little impact on the purchasing decision of consumers in the lower income group. On the other hand, lower income consumers respond more to rebates, relative to more affluent consumers. Finally, we find that for consumers in all income groups the behavioral responses to energy efficiency subsidies is much less pronounced than the response to retail price. This suggests that intangible decision costs and/or hassle costs to take advantage of the various subsidies play an important role in this context. The above patterns suggest that decision costs might have a larger effect, in relative terms, on the purchasing decision of lower income households, and the opposite for hassle costs. We further investigate this hypothesis by investigating other dimensions of heterogeneity such as age, education, and family structure, and find some support for it.

Our framework permits us to identify the socio-demographic characteristics of the households most likely to be marginal to a particular type of subsidy, as well as the characteristics of those inframarginal to the subsidy. This is important, especially given the findings in several recent papers, including Boomhower and Davis (2014), Davis, Fuchs, and Gertler (2014), and Houde and Aldy (2014), which have shown that appliance efficiency rebate programs have high costs per unit of energy saved due to a large number of inframarginal participants (i.e., large fractions of rebate claimants bought the same appliance they would have bought in the absence of the rebate programs).

[2]Our final empirical analysis intends to focus on three large appliance categories of the U.S. market: refrigerators, clothes washers, and dishwashers.

In addition, our framework provides internally consistent estimates of preference parameters that capture consumer responses to energy operating costs. Our model thus allows us to compare energy efficiency subsidies with cost-minimizing policies that would increase the price of energy. We find that electricity prices do influence the purchase decision. We use these results to simulate the how a carbon price policy (e.g., a carbon tax) affects appliance purchase decisions and compare the cost-effectiveness and distributional impacts to that of an appliance subsidy program.

Finally, our estimated preference parameters can be used to go beyond cost-effectiveness analysis and quantify the welfare effects of different policies across demographic groups. Our framework uses Leggett (2002)'s approach to evaluate welfare in the presence of imperfectly informed consumers. Houde (2014) and Ketcham, Kuminoff, and Powers (2015) are recent examples of studies relying on this framework. We build on these studies to propose a welfare measure that accounts for the fact that some consumers might be imperfectly informed about the existence of energy efficiency subsidies (or energy taxes) at the time they make a purchase decision.

The next section describes how various public policies can promote investment in more energy-efficient appliances. The third section presents our empirical framework. The fourth section describes our data and sources of variation for identifying the impacts of policies and prices on appliance investment decisions. The fifth section presents our primary results and the sixth section discusses robustness checks and extensions. The seventh section describes a policy simulation to compare various energy-efficient appliance subsidies with a carbon tax in terms of efficiency, cost-effectiveness, and distributional consequences. The final section concludes.

2. Policies to Promote Appliance Energy Efficiency

In general, a more energy-efficient appliance will incur greater manufacturing costs than a less-efficient but otherwise equivalent appliance. While this likely results in a higher retail price for the more efficient appliance, the owner of this appliance would likely pay less in electricity bills than an owner of the less-efficient appliance. This trade-off illustrates the margins on which policies could promote investment in energy-efficient appliances. Specifically, policies could subsidize manufacturing, subsidize purchase, or raise energy prices to drive greater investment.

The Energy Star (ES) certification program plays an important role in determining the eligibility criteria of the various subsidies offered for appliances. The ES certification requirement is usually set relative to the federal minimum energy efficiency standard. For instance, for refrigerators all models that are 20% more efficient than than the minimum standard can be ES-certified.

The Federal government subsidizes the manufacture of energy-efficient appliances through the energy efficient appliance tax credit. Initially enacted in the Energy Policy Act of 2005, and modified and extended in the Tax Relief and Job Creation Act of 2010, this policy provides per-unit dollar subsidies for dishwashers, clothes washers, and refrigerators. Eligibility and subsidy amounts are a function of year and the difference between the current minimum efficiency standard and the appliance model's energy efficiency. The ES certification requirement is often used as the eligibility criterion.[3] The manufacturer must demonstrate that production in the current tax year for qualifying appliances exceeds production of qualifying appliances over the average of the previous two years. Except for the most efficient refrigerators and clothes washers, a manufacturer is limited to no more than $25 million in tax credits per year.

The majority of subsidy instruments in the energy-efficient appliance space, however, target retail transactions. Most states apply sales tax to appliance purchase transactions. Some states offer occasional sales tax holidays, with a mix of those that apply across-the-board to all retail transactions and some that apply only to ES-certified appliances.

In the United States, many electric utilities offer rebate programs to encourage the adoption of energy efficient appliances. These rebate programs are all similar in nature. Consumers claim the rebates by filling out a form that must be submitted by mail or online. The purchased appliance must meet a given energy efficiency criterion, which for most programs consists of the ES certification. A complete description of these programs is available in the Database of State Incentives for Renewable and Efficiency (DSIRE). The number of active rebate programs and the amount offered by each program vary over time. For instance, in 2008, 87 utilities offered a rebate program for ES refrigerators, and this number increased to 133 in 2010.

In addition to utility-sponsored rebate programs, the Energy Policy Act of 2005 created the State Energy Efficient Appliance Rebate Program (SEEARP). Through this program, the Federal government provides guidance in the design of and allocates funds in support for state rebate programs for ES-certified (or more efficient) appliances. In 2009, the American Recovery and Reinvestment Act made the initial appropriation to SEEARP, in what became informally known as "Cash for Appliances." This $300 million Cash for Appliances program funded 56 distinct state rebate programs, described in more detail below.

Finally, a variety of policies may increase the price of electricity and thus influence the returns on investing in a more energy-efficient appliance. For example, a price on carbon would increase

[3]Dishwashers and clothes washers also have a water usage requirement as a part of its eligibility criteria.

electricity prices, although the impacts would vary geographically given the heterogeneity in carbon intensity of power generation across the country. In addition, more conventional command-and-control regulations on the power sector would likely increase electricity prices. Understanding how consumers respond to idiosyncratic variation in electricity prices may provide some sense of how future carbon dioxide regulations or carbon pricing policies could impact energy-efficient appliance investment.

3. Framework

Our starting point is a discrete choice model for the appliance purchasing decision, where consumer i (household) values product j at time t in region r as follows.

$$(1)\quad U_{ijtr} = \gamma_{ij} + \tau_i ES_{jt} - \eta_i P_{jrt} - \alpha_i Tax_{jrt} + \psi_i R_{rt}^{Utility} \times ES_{jt} + \phi_i R_{rt}^{CFA} \times ES_{jt} - \theta_i Elec_{jrt} + \epsilon_{ijtr}$$

The variable ES takes value 1 if product j is ES certified at time t and zero otherwise. The variable P is the retail price gross of tax and Tax is the sales tax. For each product, we compute the overall sales tax using state-week specific sales tax rates and account for sales tax holidays that target ES certified products. The variables $R_{rt}^{Utility}$ and R_{rt}^{CFA} are rebates offered by utilities and as part of the Cash for Appliance program, respectively. Finally, $Elec$ is the annual electricity cost of operating product j in region r.

All the preference parameters are interacted with observable demographics information to identify consumer-specific behavioral responses.[4] Additional demographic information, such as education, age of the head of household, type of housing, homeownership, and political affiliation, is also available and used to control for preference heterogeneity that may be correlated with our coefficients of interest. In particular, we include the term γ_{ij}, which is a consumer-product-specific fixed effect computed as the sum of a product fixed effect, $\tilde{\gamma}_j$, and interaction terms between product attributes (X_j) and demographics ($Demo_i$), i.e.,: $\gamma_{ij} = \tilde{\gamma}_j + X_j Demo_i$. Below, we further discuss the importance of γ_{ij} for our identification. Finally, ϵ_{ijtr} represent idiosyncratic taste parameters.

3.1. Interpretation of Model Parameters

In this framework, the coefficient on price, η_i, corresponds to the marginal utility of income and is thus crucial to interpret the relative magnitude of the other behavioral parameters. η_i also captures

[4] In the current draft, we focus on income. In future versions, we will also consider education, age, and family structure.

the behavioral response to the manufacturers' tax credit. The manufacturers' tax credit impacts the marginal cost of producing high energy efficient products and will ultimately be reflected in the final retail price of these products. Of course, the incidence of the tax credit on retail prices depends on the market structure and demand elasticity for a specific appliance category. In this project, we will consider different scenarios about the incidence of the manufacturers' tax credit, based on the observe degree of competition and estimated demand elasticities, and adjust the retail prices of the targeted products consequently. In sum, we will then simulate the behavioral response to the manufacturers' tax credit by changing the retail prices directly.

The coefficient α_i captures the response to variation in the sales tax rate. If consumers were perfectly informed about sales tax rate and this information were as salient as the retail price, the coefficient α_i should exactly match the coefficient η_i. Our prior is that $\alpha_i < \eta_i$ either due to the lack of tax salience (Chetty, Looney, and Kroft 2009) or consumers not being fully informed about changes in sales tax rates. The ratio α_i/η_i will thus inform about the combined effect of these two effects.

The coefficients ψ_i and ϕ_i both capture the response to rebates. In most instances, rebate programs require that consumers fill and send some forms (paper or online). Consumers must also collect information to learn about the rebate programs, in the first place. These actions require time and effort. The decision to claim a rebate is then function of the information acquisition costs and hassle costs that consumers must incur to first learn about the existence of rebate programs and then to claim rebates. In the absence of these costs, the coefficients ψ_i and ϕ_i should also exactly match the coefficient on price: η_i. The ratios ψ_i/η_i and ϕ_i/η_i thus inform about the difficulty to learn about and claim rebates. In the present context, we do not observe whether or not a consumer claims a rebate, we can thus informally refer to ψ_i and ϕ_i as reduced form intent-to-treat estimators. Under this interpretation, we show in Appendix A that the ratios ψ_i/η_i and ϕ_i/η_i can be interpreted as an approximation of the probabilities to claim a rebate.[5]

Finally, the coefficient on electricity cost, θ_i, informs about the extent to which consumers trade off future energy operating cost with the retail price. Assuming that consumers form time-invariant expectations about the yearly operating electricity cost and do not account for the effect

[5]This interpretation is only exactly valid in a linear framework. Given that we use a non-linear framework, we rely on a linear approximation of the choice model to make this argument. In particular, in our framework, the interpretation of the ratios ψ_i/η_i and ϕ_i/η_i as probabilities to claim rebates is only valid if we assume that these probabilities are constant as a function of the rebate level.

of depreciation, the lifetime energy operating cost (LC_j) for the durable j is given by:

$$LC_{ij} = \sum_{t=1}^{L} \rho_i^t C_{ij} = \rho_i \cdot \frac{1-\rho_i^L}{1-\rho_i} \cdot C_j,$$

where L is the lifetime of the durable, and $\rho = 1/(1+r)$ is the discount factor. In the choice model specified by Equation 1, the coefficient on electricity cost is then a reduced form parameter that relates to the discount factor and marginal utility of income as follows:

$$\theta_i = \eta_i \cdot \rho \cdot \frac{1-\rho_i^L}{1-\rho_i}. \tag{2}$$

For consumer i, the estimates of η_i and θ_i can then be used to infer a value of an implicit discount rate r_i.

4. Data and Environment

4.1. Data

The main data source for this project is transaction level data from a large U.S. appliance retailer during the period 2008-2012. Each transaction contains information about the manufacturer model purchased, which is matched to detailed attribute information, including the expected annual energy consumption and expenditure based on the appliance's EnergyGuide label. Each transaction also contains information about the date the transaction was made, the exact price paid, the total amount of sales taxes paid, the manufacturer suggested retail price (MSRP) the date the transaction was made, the location of the store. Approximately 44%-49% of the transactions are matched with household demographics, depending of the appliance categories we focus on, such as household size, income, education, homeownership, housing type, political orientation, and age of the head of the household. This demographic information is transaction specific and is collected by the data aggregator Acxiom.

The transaction data cover a large number of appliance categories, but we focus on three particular categories: refrigerators, clothes washers, and dishwashers. For each appliance category, the estimation is carried on large random samples ($N \approx 45,000$) of transactions draw from each income tertile. Note that income information is coded with a nine-value categorical variable. The cut-offs for each income tertile are thus determined based on these categories. For all three appliance categories, the first tertile corresponds to household annual income of less than $50,000. The second tertile corresponds to household income equal to or greater than $50,000, but less than $100,000. The third tertile corresponds to income equals to or greater than $100,000.

Each sample is randomly drawn from the subset of transactions that contain complete demographic information. Moreover, we only consider transactions made by households living in single family housing units, owning their house, and that bought no more than one appliance of a specific appliance category during the period 2008-2012. We consider that these criteria are a conservative way to restrict the set of transactions to households that are the most likely to be homeowners that pay for their electricity bills. Our estimation samples thus exclude transactions made by contractors making bulk purchases and renters who may not pay for their electricity bills.

4.2. **Source of Variation**

Retail Prices and Federal Manufacturers' Tax Credit. Given that the Federal manufacturers' energy-efficient appliance tax credit impacts manufacturers' marginal costs and will ultimately be reflected in the final retail price paid by consumers, our strategy to estimate the behavioral response to the tax credit is to first estimate consumers' price sensitivity to the retail price, i.e., the coefficient: η_i. To identify this parameter, we exploit a number of institutional features of the appliance market.

Our retailer, like most other large US appliance retailers, has a national pricing policy. This implies that a given appliance model has the same retail price across store locations, and the only variation in price is over time. There is, however, substantial temporal variation in prices. This is illustrated on Figures 1-2 that show the median prices of the most popular refrigerator models for two major brands.[6] Each panel plots the weekly variation in price for a specific model of a specific brand. For each brand, we show the weekly variation for the nine most popular models offered by this brand. We use the sales rank during the period 2008-2012 as our measure of popularity. The red line corresponds to the median change in price relative to the average price over the lifetime of the product, where the median is taken across zip codes. That is, we computed week-zip code-specific changes in price for each model and then plotted the median of the weekly changes for a specific model. The grey band identifies the 25^{th} and 75^{th} percentile of these weekly changes in price. The rationale to present various quantiles of the distribution of weekly changes is to show whether the local store managers comply with the national price policy. The answer is yes, for most week the 25^{th} and 75^{th} percentiles coincide with the median.

Finally, the blue dashed line plots the median change in price after removing brand dummies interacted with week-of-sample fixed effects. The goal is to show the remaining weekly variation

[6] Brand names are anonymized to keep the confidentially of the data. Similar patterns are fond for other brands, but not shown here.

in the price of each model after accounting for seasonal as well as contemporaneous brand-specific shocks. The main take away is that after accounting for those temporal shocks, the price time series are smoother, but large and frequent variation persists. This is especially true for weeks where the changes are large relative to the average price. These patterns mean that the weekly variation in prices is weakly correlated between models of the same brand, and large price events are model-specific and tend to be idiosyncratic.[7] In sum, there is significant randomness in how the retailer set prices. These patterns are consistent with Varian (1980)'s classical model of sales where stores play a mixed strategy that consists to randomize prices to screen between loyal/uninformed and non-loyal/informed consumers. In the present case, the variation is also driven by some institutional details of the appliance market. In this market, manufacturers set high MSRPs, and let retailers set promotional prices. To comply with antitrust laws, retailers, however, do not offer products at a constant discount relative to MSRPs, and cycle promotions across similar products.

In our estimation, we rely on this high frequency temporal variation in prices to identify consumers' sensitivity to prices. The identification argument here is similar to Einav, Jenkins, and Levin (2012)–abrupt variation in prices identify price elasticities as long as they are not correlated with slower-moving trends in demand. We show that this exclusion restriction is likely to hold in the present context. For instance, we show that controlling for brand-week-specific fixed effects have little impact on the coefficient on price. Suggesting that the raw variation in price alone is mostly uncorrelated with demand shocks.

State Sales Tax. The coefficient α_i can be identified by three sources of variation in sales tax rates. First, there is substantial cross-sectional variation across states in the level of the sales tax rate, and to a lesser extent within states due to local jurisdictions imposing their own sales taxes. This is shown on Figure 3 from Einav, Knoepfle, Levin, and Sundaresan (2014). Second, state and local sales taxes also vary over time and this variation can be economically important. Tax rates are typically adjusted every year and these changes are usually coordinated with calendar time, i.e., new tax rates usually take effect on January 1^{st}. Finally, sales taxes also vary over time due to tax holidays offered by states. Moreover, in some regions, these tax holidays specifically target ES-qualified products. As shown on Table 1, of the eleven states that offered a sales tax holiday affecting the appliance market during the sample period, nine of them used the ES certification as an eligibility criterion.

[7]These patterns are not restricted to the nine most popular models.

In the present context, these three sources of variation identify three different margins of adjustment to sales tax that are all potentially policy relevant. First, variation in tax rates across states induces some consumers to shop across state lines. This margin is important to capture if we want to simulate a scenario where only a subset of states decide to subsidize energy efficient products via a reduction in their sales tax rates. Second, variation over time induces some consumers to delay or pull-forward their purchase decision, which would arise in a scenario where the tax reduction is temporary. The third and most important variation is across products–whether sales tax induce substitution between ES and non-ES certified products. This margin of adjustment is crucial for our policy scenarios where the sales tax is used as an instrument to subsidize the adoption of energy efficient products.

Utility Rebates. For the current analysis, we collected all information related to utilities rebate programs during the period 2007-2012 from the DSIRE database. We then computed a measure of the average utility rebate offered at the year-county level for each appliance category that we consider. We created county averages by first mapping each utility territory to county information using EIA's form 861. We then averaged rebate amounts for each county. For counties where more that one utility had an active rebate program, we simply computed non-weighted averages of the rebate amounts.

State Rebate. The 2005 Energy Policy Act authorizes SEEARP to allocate federal funds to state programs proportional to each state's share of the national population. In addition, SEEARP requires states to use ES certification or more stringent but similar criteria for rebate eligibility.[8] Table 2 summarizes the eligibility criteria used for the three appliance categories that we study. Most states allocated rebates for products that just met the ES certification, although for clothes washers and dishwashers several states adopted more stringent efficiency criteria.

Under SEEARP, states have sovereignty over the design of several elements of their rebate programs. As a result, the C4A program gave rise to a collection of 56 different programs[9] that differed in the rebate amounts offered, appliances covered, eligibility criteria, timing and duration, and mechanisms to claim the rebates.

[8]The Energy Policy Act of 2005 was amended in 2007 to allow eligibility criteria more stringent than the ES requirements. These more stringent requirements must, however, be based on a formula similar to the one used to determine ES eligibility.

[9]The District of Columbia and territories also received funds, but we focus on the 50 states in our empirical analysis.

Consumers could claim a rebate, typically through online and mail options, by providing proof of purchase and residency. Some states established a reservation system where consumers could reserve rebates prior to going to the store. Most states did not offer rebates for online purchases. Rebates were limited to one for each appliance category, but several states allowed households to claim multiple rebates. New York offered rebates for bundled purchases (i.e., multiple appliances purchased at once). Alaska offered additional incentives to rural residents. Kansas, Ohio, Oregon, and Montana employed means-tested eligibility criteria for their rebate programs. In most states, however, all households were eligible to claim rebates for qualifying appliances. Several states provided additional incentives if the old appliance was hauled away and recycled.

The states offered economically significant rebates, on average 12%-15% of sales prices for refrigerators, dishwashers, and clothes washers, and these varied greatly among states (Figure 4). Most states offered a fixed rebate amount for a qualifying purchase, but four states, Florida, Illinois, North Carolina, and Oregon, offered ad valorem rebates (e.g., 20% of the price paid (FL), or 70% (OR)).[10]

States also varied in the timing of the implementation of their rebate programs. On July 14, 2009, DOE issued a press release announcing the program and allocation of funds to the states. State governments began to draft design and implementation plans for C4A, which they submitted to DOE for review and approval. States began advertising their programs in November and December 2009. The first program started the second week of December 2009 in Kansas. By April 2010, more than 80% of the states had launched their C4A programs. The programs lasted 26 weeks on average, although program duration was quite heterogeneous. Programs in Iowa, Illinois, Massachusetts, and Texas exhausted all rebate funds in only one day,[11] while Alaska's program lasted 91 weeks. Several states offered the rebates in different phases, where the program closed temporarily between phases.[12]

[10]In some cases, the rebates claimed were extremely generous; the maximum rebates often exceed several thousand dollars (Table 3). These numbers are outliers and should be put in the context of the Great Recession. Program administrators were directed to distribute the stimulus funds quickly, which may have led them to distribute unclaimed funds to bundled purchases.

[11]Programs in Illinois, Massachusetts, and Texas, however, reopened for a second phase that lasted longer.

[12]States that interrupted their programs are Arizona, California, Florida, Georgia, Illinois, Massachusetts, Michigan, Minnesota, Montana, North Carolina, New Jersey, Ohio, Oregon, Texas, Vermont, and Washington.

Electricity Operating Costs. We compute the electricity operating cost for each appliance model in the sample using the expected annual electricity consumption reported by the manufacturer multiplied by the average electricity price of the region where each household made a purchase.[13] We assume that consumers form time-invariant expectations about electricity prices using the current local average price. The time-invariant assumption can be justified by two reasons. First, electricity prices, unlike gasoline prices, have been relatively very stable over the sample period. For instance, between 2008 and 2010, the national average electricity price remained virtually unchanged. Second, time-unvarying expectations are consistent with recent evidence in the car market suggesting that consumers' best forecasts of future gasoline prices are simply the current prices (Anderson, Kellogg, Sallee, and Curtin 2011).

Whether consumers respond to marginal or average electricity prices and the appropriate level of spatial aggregation to compute average electricity prices are important elements to consider. We rely on average price based on ITO (2014)'s recent findings that consumers respond to variations in average electricity prices within California. These findings also suggest that fairly local average electricity prices are the most appropriate measure. Houde (2014) has shown that whether one using county versus state average electricity prices has economically important effects on estimates. With county average prices, the implied discount rates are roughly twice as large than with state average prices. He, however, argues that these two measures of electricity prices identify two different policy-relevant estimates. Specifically, when county average prices are used, the choice model identifies the share of consumers that are sophisticated enough to collect and process information about very local electricity prices.

For the present application, we are interested to show how setting the price of electricity closer to its social cost will impact appliance purchasing decisions. Given that each state might adopt different policies to internalize negative externalities in the price of electricity and the interconnected nature of the US electricity markets, the policy-relevant variation should be mostly at the state level. Therefore, for most of our analysis, we will exploit variation in state average electricity prices.

[13]We do not observe the zip code of each household, but the zip code of the store where each transaction was made. Average annual electricity prices for each region (state or county) are computed using the form 861 of the Energy Information Administration.

5. Model I: Conditional Logit without Outside Option

The first model that we estimate is a conditional logic without an outside option. We assume that the ϵs in Equation 1 follow a Type-1 extreme value distribution and are i.i.d. This leads to a closed-form expression for the choice probabilities corresponding to the conditional logit. By excluding the outside option, we focus on modeling the purchasing decision of consumers that decided to buy a new appliance at a given store in a specific week. Therefore, the model does not account for substitution over time or store location, and solely focuses on substitution across products. This has a number of implications for the interpretation of the behavioral responses to the different subsidies and electricity costs. For instance, the coefficient on sales tax for the choice model without an outside option is not capturing the effect of consumers shopping across jurisdictions to take advantage of lower taxes. Similarly, the model does not account for consumers waiting or pulling forward their purchase decision to take advantage of short-lived rebate programs or tax holidays. We discuss extensions of the model below that will account for these behaviors.

We estimate the model via maximum likelihood by forming the choice probabilities of each consumer included in the random sample. In our base specification, the consideration set of each consumer consists of all the appliance models of a specific appliance category offered in the zip code where the purchase was made. The choice set for each zip code is imputed at the trimester level using observed sales. That is, if we observe an appliance model being sold in a zip code during a given trimester, we assume that all consumers shopping at this location during that trimester could also purchase that appliance model.

5.1. Preferred Specifications and Identification

In our base specification, we control for product fixed effects and include interactions between attribute information and demographics. Product fixed effects are identified using repeated sales of the same product at different points in time and at different locations. They thus capture all time-invariant product attributes for a specific appliance model. Without additional controls, the behavioral responses to subsidies and electricity costs are thus identified by variation across regions in subsidy programs offered and electricity prices, as well as temporal variation. One concern with exploiting cross-sectional variation is that consumers' preferences for specific attributes correlated with energy usage might also be correlated with some policy instruments. For instance, richer households that prefer larger appliances might live disproportionally in regions with low electricity prices and no rebates. In such a scenario, preferences for size, which is strongly correlated with overall appliance energy use, might be confounded with a response to electricity prices and rebates. Including interactions between attribute information and demographics is a first way to control for region specific preferences. In particular, we focus on including attributes that are correlated with energy use such as size, appliance design, and add-on options (e.g., ice-maker for refrigerators). The demographic information that we include is income, education, and family size.

Demographic information also help to control for the effect of consumer sorting due to substitution across locations or time to take advantage of subsidies. For instance, if one particular jurisdiction offers a generous temporary sales tax holiday, some consumers will postpone or pull forward their purchase decisions, and some others will shop across tax jurisdictions to take advantage of this subsidy. If consumers optimizing along those margins are systematically different, the coefficient on sales tax might capture unobserved heterogeneity in preferences due to sorting instead of sensitivity to sales tax, per se. Interacting the coefficients corresponding to the various behavioral responses with demographic information will, however, help to rule out the effect of consumer sorting.

In an alternative specification, we further control for region-specific unobservables by including state dummies interacted with an ES dummy. This set of dummies estimates state-specific effects of the ES certification, which capture both time-invariant-region-specific consumer preferences for energy efficiency and more broadly equilibrium supply-side responses, as well. Controlling for the latter is particularly important given that energy efficiency subsidy programs rely primarily on the ES certification and in regions where those programs are offered, governmental agencies, utilities, and retailers might be more likely to publicize the ES program. As a result, the awareness and understanding of the ES certification might vary systematically across regions due to advertising and be confounded with the responses to various subsidies relying on the ES program. The state-ES fixed effects should, however, control for this, if we assume that publicity intensity and awareness for the ES program is relatively constant across time. Figure 5 shows that this assumption is likely to hold throughout the sample period. In their yearly report of the ES program, the U.S. EPA publishes a publicity "intensity" map. Figure 5 shows that there is substantial variation across designed marketing areas (DMAs), but there is very little variation over time.

In the presence of state-ES fixed effects, the coefficient on electricity cost is still identified using some cross-sectional variation in electricity prices, but we argue that this captures policy-relevant variation. To understand this, suppose that all ES certified models are characterized by the exact same expected annual electricity use and likewise for all of the non-ES certified models. That is, the distribution of electricity use would have only two point masses. In this case, state variation in electricity prices could not identify the coefficient on electricity cost if state-ES fixed effects were included because the difference in electricity costs between certified and non-certified models will be a state specific constant that would be perfectly captured by these fixed effects. Only if there is variation in electricity use within the subset of products that are ES-certified models and/or non-certified models that the coefficient on electricity cost is identified. Formally, the support of the distribution in electricity use must have more that one point masses below and/or above the ES certification requirement. State variation in electricity prices will then scale down or up the distance between products in the energy dimension of the characteristic space. In particular, in regions with high electricity prices, the distance will be the greatest and electricity costs should matter more in the purchasing decision. Note that the state-ES fixed effects will still capture preferences for energy efficiency correlated with high and low electricity prices. This is the variation in the numerical value of the electricity use of each particular model scaled by the level of electricity price that provides the identifying variation. Variation in electricity price over time is another useful source of variation. However, it is not necessary. The coefficient on electricity cost could still be identified using state-year-ES fixed effects, which would then capture time-varying-region-specific preferences for energy efficiency. We will also provide results with that specification.

Time shocks are also a potential source of concerns, especially for the identification of the coefficient on price. As shown earlier, there is substantial variation in price that is model specific, but we also detected correlation within brands. In some periods of the year, brands might also be more likely to offer generous promotions and advertise their products more. We can flexibly account for these effects and other time trends using brand dummies interacted with week-of-sample fixed effects. We will present a specification using these fixed effects. To alleviate the computational burden in the estimation, we will also consider a specification with brand-month-of-sample fixed effects.

5.2. **Preliminary Results**

Table 4 reports the results for the three income groups for our two preferred specifications. Specification I includes product fixed effects, brand dummies interacted with month-of-sample fixed effects, together with state-ES fixed effects. Several interesting patterns emerge. First, both the responses to sales tax and electricity cost are increasing with income. The coefficient on sales tax for the lower income group is economically small, unexpectedly positive, but not statistically significant. For the higher group, it is about half the coefficient on price and significant. This suggests that higher-income households are more responsive to changes in the sales tax than lower-income households. Nonetheless, higher-income households do not respond to a change in the sales tax the same way that they do for retail price changes. There results are consistent with Chetty, Looney, and Kroft (2009) and suggest that sales tax on appliances are not fully salient to consumers. This lack of salience also raises questions about the efficacy of energy-efficiency sales tax holidays in promoting the sale of energy-efficient appliances.

The coefficients on electricity costs are negative and statistically significant for all three income groups. They correspond to implied discount rates of 34.8%, 19.8%, and 12.6% for the first, second, and third income tertile, respectively. As shown by Houde (2014), the main factor causing these high implied discount rates is the presence of consumers that do not pay attention to electricity cost in the purchasing decision and credit constraints play a lesser role. The present estimates imply that lower-income households are more likely to dismiss energy information about electricity costs in their purchasing decision. But across the three income groups, there is, however, a share of consumers that still trade off electricity cost with other attributes.

Taking together, the estimates of the coefficients on sales tax and electricity cost suggest that lower-income consumers have higher costs to collect and process information about local sales tax rates and electricity prices, relative to higher-income consumers. These decision costs might be tangible and correspond to the time spent investigating these issues, or be of a more cognitive nature. No matter the interpretation of these costs, in both cases they imply that what consumers believe at the time of the purchasing decision will differ from what they ultimately pay for sales tax and electricity costs. That is, there is a discrepancy between decision and experienced utility. This has important implications for welfare measurement.

For the coefficients on rebates, we observe the opposite patterns. Lower-income consumers respond to rebates, and higher-income consumers less. This result is particularly striking for state rebates offered during the Cash for Appliances (CFA) program, where the probability that consumers in the third income tertile take advantage of rebates is about half the probabilities in the other two income groups. These results are intuitive if we believe that the decision of taking advantage of rebates are influenced by hassle costs, which are tangible, i.e., truly experienced. This would explain why high-income consumers, who have a higher opportunity cost of time, are less likely to take time to claim a rebate. There is also anecdotal evidence that during the CFA program there were tangible hassle costs to claim rebates due to the fact that retail stores were more crowded and consumers at to wait in line longer than usual.

6. Extensions and Additional Robustness Tests

6.1. Additional Heterogeneity with Respect to Demographics

We are planning on a number of extensions and robustness tests. The above results suggest that decision costs and hassle costs are important drivers of heterogeneity in the behavioral responses to different types of subsidies. We would like to investigate further this question, by investigating how the behavioral responses change across dimension of observable heterogeneity. We are particularly interested to investigate the role of education, age, and family structure. With respect to education, we expect that education should lower decision costs, and thus we should have larger behavioral responses to sales tax and electricity costs for consumers with more education. For age, our prior is that the relationship is non-linear. Older consumers should have more experienced and knowledge and thus be more likely to account for sales tax and electricity cost. Cognitive ability is, however, non-monotonic over the life-cycle, which suggests that toward the upper end of the age distribution decision costs are high. Older consumers should be more likely to be retiree or get their income for other sources that employment. This should lead to lower hassle costs, and thus larger response to rebates. Regarding family structure, our prior is that consumers that are household member of a family with children should have a larger opportunity cost of time. Therefore, hassle costs may be play a more important for that particular group. We do not have a strong prior how family structure impacts decision costs.

6.2. Impact of Rebate Program Features

One particular feature of the C4A program, is that state program managers were sovereign to design various feature of their rebate programs. Among other aspects, rebate programs varied in terms of ease to claim rebates. Some programs opted for an online system, while others favor a system where customers had to file a paper-claim and mail the rebate. Online reservation systems were also allowed in some states. The duration of the rebate programs should also have had an impact on the ease with which consumers could take advantage of rebates. As discussed above, it appears that long waiting lines might have formed in some retail stores, especially in states with short-lived programs. We are planning to investigate how these various program features impact the coefficients on rebates.

6.3. Substitution Across Time and Location

In Houde and Aldy (2014), we shown that under the C4A program some consumers delayed their purchasing decision by a few weeks to take advantage of the rebates. We conjecture that similar behavior might be induced by the sales tax holidays, which last only a few days on average. Our current choice model does not explicitly account for such dynamic effects, but we are planning to do so in a future version of the model. A simple approach would be to define a period window that includes the rebate period and some weeks in the pre-period and post-period as well. The coefficient on rebates will then capture the net effect of rebates accounting for short-term substitution.

In future work, we also want to account for substitution across locations induce by some of the subsidies. Einav, Knoepfle, Levin, and Sundaresan (2014) show that internet shoppers respond to sales tax and substitute to take advantage of difference in sales tax across jurisdictions. For brick-and-mortar stores, we expect that consumers might also substitute across tax jurisdictions, and this effect should be the most pronounced for stores located to state boundaries. In one specification, we are thus planning to create a measure of distance of stores from state boundaries and interact this measure with the coefficient on sales tax. We are also plan on distinguishing the effect of variation in sales tax induced by tax holidays versus yearly change and/or cross sectional variation.

7. Policy Analysis

The most cost-effective way to reduce carbon dioxide emissions is through policies that price carbon, such as a carbon tax or cap-and-trade program (Aldy, Krupnick, Newell, Parry, and Pizer 2010). The distributional consequences of carbon pricing, however, are ambiguous, depending on program design (Metcalf (2007); Burtraw, Sweeney, and Walls (2009)). Nonetheless, the existence of national, state, and local appliance subsidy programs and the dearth of U.S. carbon pricing policies suggest greater political interest and support for appliance subsidies (as well as other efficiency and renewable policies). To illustrate the potential efficiency and distributional implications of this political preference for appliance subsidies, we use a carbon pricing policy as a benchmark.

To simulate the effect of carbon pricing, we first estimate percentage changes in electricity prices by electricity market module (comprising 22 regions in the continental United States) in the first year of a carbon tax based on each of three carbon tax scenarios – \$10, \$15, and \$25 per ton carbon dioxide – in the 2013 Annual Energy Outlook published by the Energy Information Administration

(Outlook 2013). We then map these percentage changes on state level electricity prices[14] and use our empirical framework to simulate appliance purchase decisions.

7.1. **Quantifying Consumer Welfare**

In the discrete choice modeling literature, Kenneth A. Small (1981) first developed the standard measure of welfare using the concept of compensating variation, which takes a well-known expression for the multinomial logit model. The implicit assumption under the standard approach is that the choice model identifies the utility that a consumer would actually experience for choosing a specific alternative. The behavioral parameters of our discrete choice model violate this assumption because it implicitly captures consumers that do not fully process subsidies or electricity cost information. For instance, because all consumers ultimately pay the sales tax and future electricity cost, there is a discrepancy between the sales tax and electricity cost consumers believe they would pay and what they effectively pay. The model thus captures decision utility, which may differ from experienced utility. This gap between decision and experience utility raises several issues. Recently, (Allcott, Mullainathan, and Taubinsky 2014) discussed the policy implications of this gap for energy-intensive durables, and Houde (2014); Ketcham, Kuminoff, and Powers (2015) specifically addressed welfare measurement in part using the work of Leggett (2002). For the present application, Leggett (2002)'s work is also particularly important as it adapts Kenneth A. Small (1981)'s expression for the case where consumers are not perfectly informed. Our proposed welfare measure is directly derived from Leggett (2002)'s formula using the following assumptions.

Assumption 1. *Under perfect information, the coefficient on sales tax is equal to the coefficient on price.*

Assumption 2. *Under perfect information, the coefficient on electricity cost implied a discount rate in line with other investment/borrowing decisions. We assume* $r = 12\%$ *for consumers in the first income tertile (<$50,000), and* $r = 5\%$ *for other consumers.*

[14] To implement this mapping, evaluations, we begin by mapping the percentage changes in electricity prices for each of the 22 electricity markets to zip codes, based on an EPA crosswalk, which was accessed on April 1, 2016 at: `http://www2.epa.gov/sites/production/files/2015-10/power_profiler_zipcode_tool_2012_v6-0.xlsx`, which permits us to match to each of the consumers in our appliance transaction dataset. Thanks to John Conti of EIA for suggesting this approach.

Under these assumptions, the utility that consumers experience ex-post, i.e., once the purchase decision is made, is given by

(3)

$$U^E_{ijtr} = \gamma_{ij} + \tau_i ES_{jt} - \eta_i P_{jrt} - \eta_i Tax_{jrt} + \psi_i R^{Utility}_{rt} \times ES_{jt} + \phi_i R^{CFA}_{rt} \times ES_{jt} - \eta_i \rho_i \frac{1-\rho_i^L}{1-\rho_i} Elec_{jrt} + \epsilon_{ijtr},$$

where ρ_i is the discount factor for a given discount rate r_i. In the Appendix, we show that for a policy change $\mathcal{P} \to \tilde{\mathcal{P}}$, the (expected) compensating variation for a specific income group is given by

$$CV_{itr} = \frac{1}{\eta_i} \cdot \left[ln \sum_j^J exp(\tilde{U}_{ijtr}) + \sum_j^J \tilde{P}_{ijtr}(\tilde{U}^E_{ijtr} - \tilde{U}_{ijtr}) \right] - \left[ln \sum_j^J exp(U_{ijtr}) + \sum_j^J P_{ijtr}(U^E_{ijtr} - U_{ijtr}) \right]. \tag{4}$$

where the terms with a tilde are evaluated at the post-policy change, U^E_{ijtr} denotes experienced utility and U_{ijtr} corresponds to decision utility given by Equation 1. The above expression differs from the standard expression for the multinomial logit in two ways. First, the terms taking the form $\sum_j^J P_{ijtr}(U^E_{ijtr} - U_{ijtr})$ is the Leggett (2002)'s correction. It has an intuitive interpretation. It represents the expected difference between experienced and decision utility.

Whether the effect of the ES label is truly experienced and therefore whether τ_i should be considered in the expression for experienced utility 3 can be debated. A key insight from Houde (2014) is that consumers that rely on ES value certified products well beyond purely energy savings. Whether this high willingness to pay for the label itself reflects a behavioral bias or corresponds to preferences has important welfare implications. In the present application, we consider that τ_i capture preferences and thus should be accounted for in experienced utility.

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8. Tables and Figures

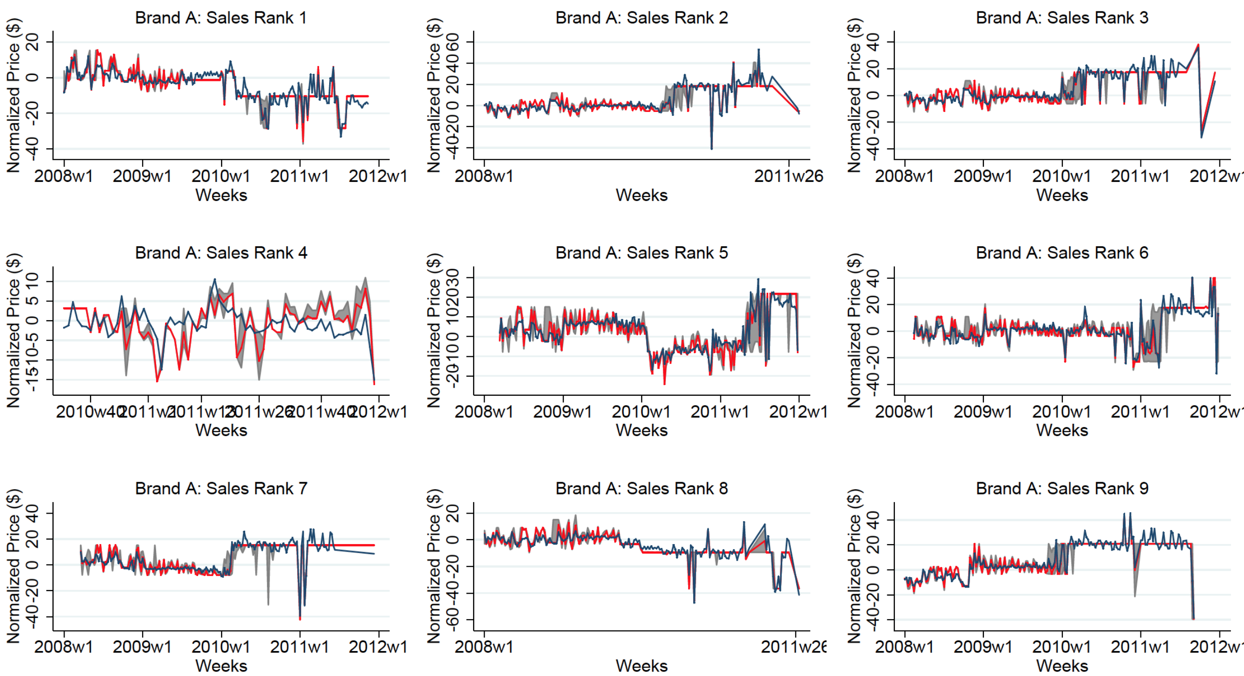

FIGURE 1. Temporal and Cross Strore Variation in Promotional Price, Brand A

Notes: The red line shows the normalized prices of the nine most popular models offered by Brand A. The normalized price was first computed for each store. The median across stores is depicted by the red line. The 25^{th} and 75^{th} correspond to the gray shaded area. The fact that median and lower and upper percentiles coincide in most weeks show that the national price policy is respected. The blue if the median price after controlling for brand-week-of-sample fixed effects. Substantial within model variation remains after controlling for temporal shocks.

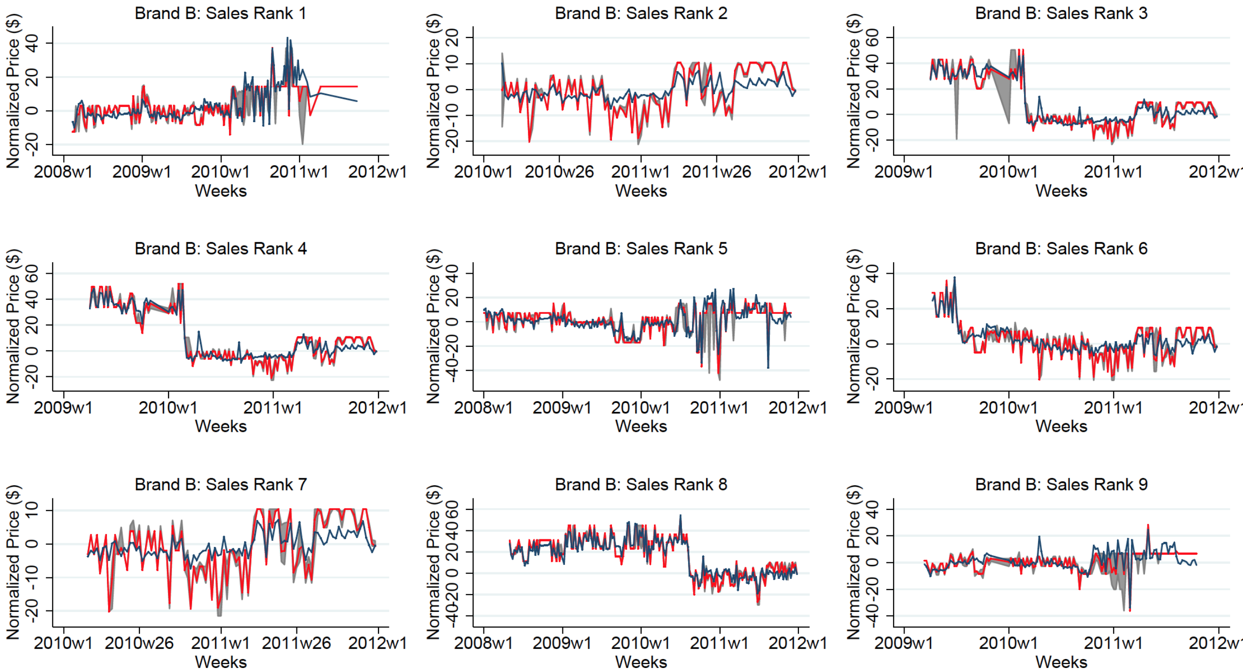

FIGURE 2. Temporal and Cross Store Variation in Promotional Price, Brand A

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Table 1. State Sales Tax Holidays for Appliances: 2008-2012

State	Year	Start Date	End Date	ES Requirement	Price Cap	Sales Tax Rate
GA	2008	10/2/08	10/5/08	Energy Star Qualified	1500	4.00%
GA	2009	10/1/09	10/4/09	Energy Star Qualified	1500	4.00%
GA	2012	10/5/12	10/7/12	Energy Star & Water Sense Qualified	1500	4.00%
LA	2008	8/1/08	8/2/08	none	2500	4.00%
LA	2009	8/7/09	8/8/09	none	2500	4.00%
LA	2010	8/6/10	8/7/10	none	2500	4.00%
LA	2011	8/5/11	8/6/11	none	2500	4.00%
LA	2012	8/3/12	8/4/12	none	2500	4.00%
MA	2008	8/16/08	8/17/08	none	2500	5.00%
MA	2010	8/14/10	8/15/10	none	2500	6.25%
MA	2011	8/13/11	8/14/11	none	2500	6.25%
MA	2012	8/11/12	8/12/12	none	2500	6.25%
MD	2011	2/19/11	2/21/11	Energy Star Products	none	6.00%
MD	2012	2/18/12	2/20/12	Energy Star Qualified	none	6.00%
MO	2009	4/19/09	4/25/09	Energy Star Qualified	1500	4.23%
MO	2010	4/19/10	4/25/10	Energy Star Qualified	1500	4.23%
MO	2011	4/19/11	4/25/11	Energy Star Certified	1500	4.23%
MO	2012	4/19/12	4/25/12	Energy Star Qualified	1500	4.23%
NC	2008	11/7/08	11/9/08	Energy Star Qualified	none	4.50%
NC	2009	11/6/09	11/8/09	Energy Star Qualified	none	5.75%
NC	2010	11/5/10	11/7/10	Energy Star Qualified	none	5.75%
NC	2011	11/4/11	11/6/11	Energy Star Qualified	none	5.75%
NC	2012	11/2/12	11/4/12	Energy Star Qualified	none	4.75%
SC	2008	10/1/08	10/31/08	Energy Star Qualified	2500	6.00%
TX	2009	5/23/09	5/25/09	Energy Star Qualified	6000/2000	6.25%
TX	2010	5/29/10	5/31/10	Energy Star Qualified	6000/2000	6.25%
TX	2011	5/28/11	5/30/11	Energy Star Qualified	6000/2000	6.25%
TX	2012	5/26/12	5/28/12	Energy Star Qualified	6000/2000	6.25%
VA	2008	10/10/08	10/13/08	Energy Star Qualified	2500	5.00%
VA	2009	10/9/09	10/12/09	Energy Star & Water Sense Qualified	2500	5.00%
VA	2010	10/8/10	10/11/10	Energy Star & Water Sense Qualified	2500	5.00%
VA	2011	10/7/11	10/10/11	Energy Star Qualified	2500	5.00%
VA	2012	10/5/12	10/8/12	Energy Star & Water Sense Qualified	2500	5.00%
VT	2008	7/12/08	7/18/08	Energy Star Qualified	2000	6.00%
VT	2009	8/22/09	8/22/09	none	2000	6.00%
VT	2010	3/6/10	3/6/10	none	2000	6.00%
WV	2008	9/1/08	9/7/08	Energy Star Qualified	2500	6.00%
WV	2009	9/1/09	11/30/09	Energy Star Qualified	2500	6.00%
WV	2010	9/1/10	11/30/10	Energy Star Qualified	2500	6.00%

Notes: Missouri restricted its tax holiday to the following appliance categories: clothes washers, water heaters, dishwashers, air conditioners, furnaces, refrigerators, and freezers. Maryland restricted its tax holiday to air conditioners, clothes washers and dryers, furnaces, heat pumps, boilers, solar water heaters, standard size refrigerators, dehumidifiers, programmable thermostats, and compact fluorescent light bulbs. Texas restricted its tax holiday to air conditioners, clothes washers, ceiling fans, dehumidifiers, dishwashers, incandescent or fluorescent light bulbs, programmable thermostats, and refrigerators.

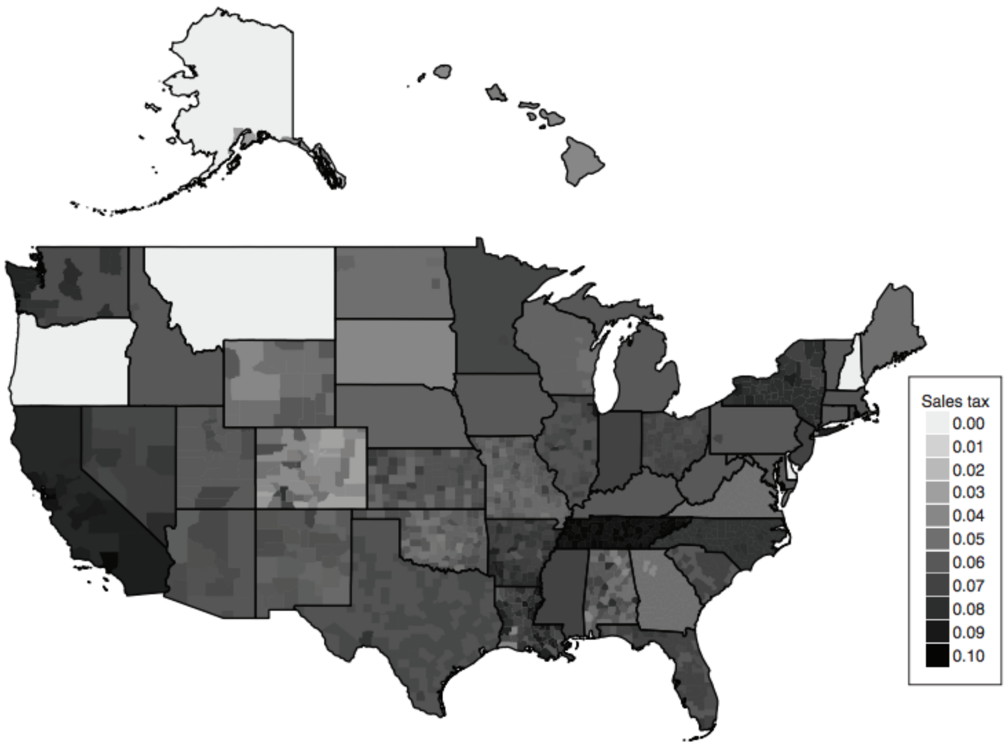
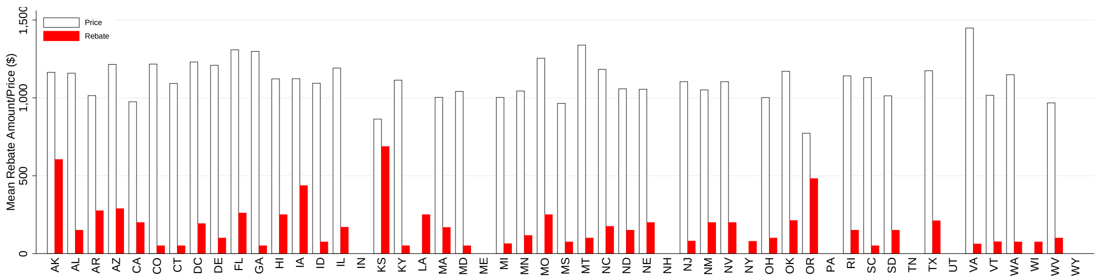
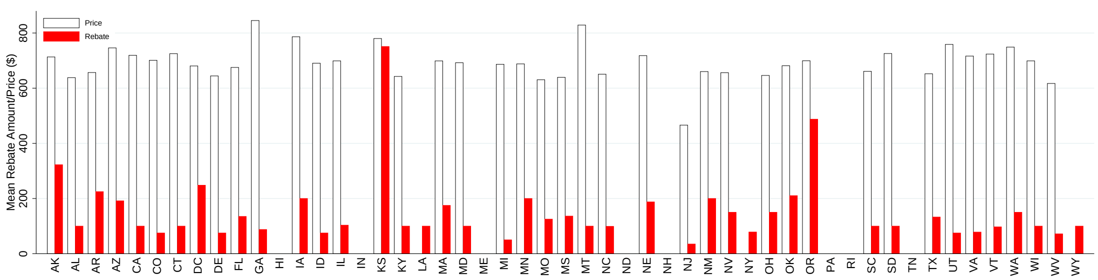


FIGURE 3. Cross Section Variation in Sales Tax Rates (Source: Einav et al., 2014)

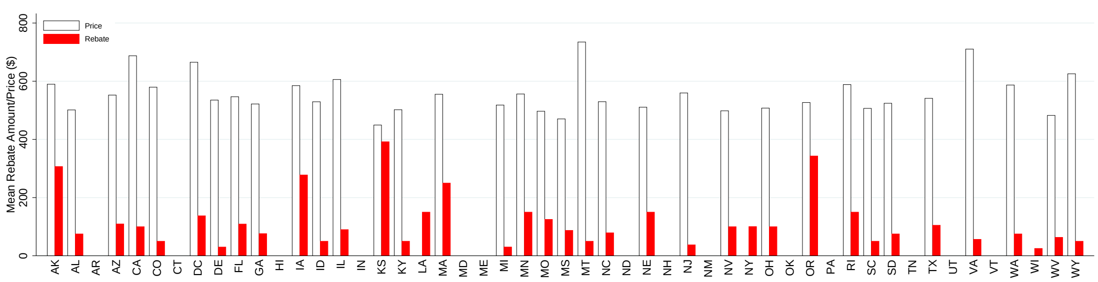
Notes: This map is from Einav et al. (2014) and shows the (population weighted) average sales tax rate in the United States as of January 1, 2010.



(a) Refrigerators



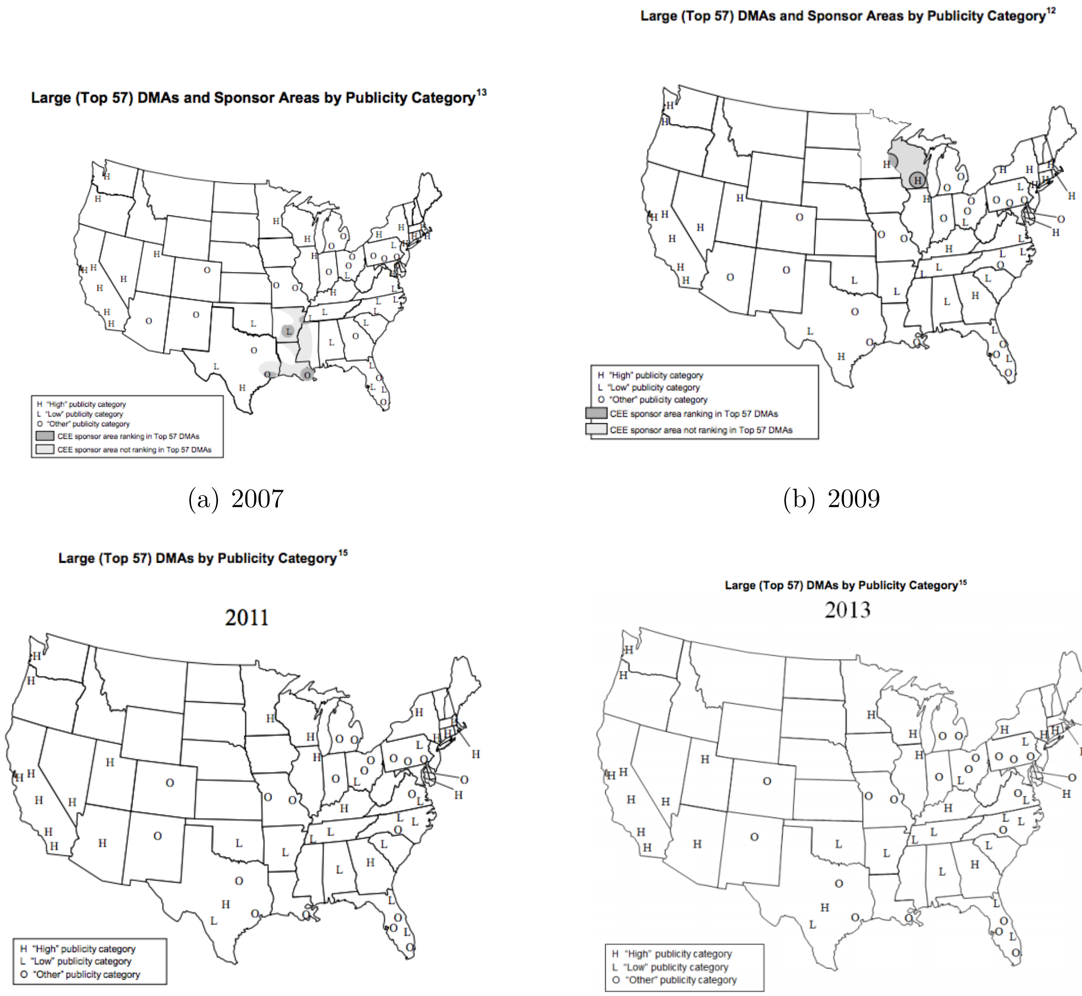
(b) Clothes Washers



(c) Dishwashers

FIGURE 4. Average Price vs. Rebate Amount

Each panel shows the average price of the appliance purchased (in white) and the average rebate amount claimed (in red). States with no average price but a positive rebate amount are states where program managers did not collect price information. States where both price and rebate information are missing did not offer rebates for this particular appliance.



(a) 2007 (b) 2009

(c) 2011 (d) 2013

Figure 5. Energy Star and Publicity Intensity

Notes: Each panel shows the publicity intensity of the Energy Star program as classified by the US EPA. All maps and analysis are taken from the "National Awareness of Energy Star" yearly reports published by the EPA. The main take away of the above figure is that there is little variation over time in publicity intensity.

Table 2. Rebates and Eligibility Criteria for Each State

	Refrigerators		Clothes Washers		Dishwashers	
	Rebate	Criteria	Rebate	Criteria	Rebate	Criteria
AK	300-600	ES rural/non-rural	300-600	ES	300-600	ES rural/non-rural
AL	150	ES	100	ES	75	ES
AR	275	ES	225	ES	-	
AZ	200-300	ES	125-200	ES & Above ES	75-125	ES & Above ES
CA	200	ES	100	Above ES	100	Above ES
CO	50-100	ES	75	ES	50	Above ES
CT	50	ES	100	Above ES	-	
DE	100	ES	75	ES	75	ES
FL	20%	ES	20%	ES	20%	ES
GA	50	ES	50-99	ES & Above ES	50-99	ES & Above ES
HI	250	ES	-		-	
IA	200-500	ES	200	ES	200-250	ES & Above ES
ID	75	ES	75	ES	50	ES
IL	15%	ES	15%	ES	15%	ES
IN	-		-		-	
KS	700	ES	800	Above ES	400	Above ES
KY	50	ES	100	ES	50	ES
LA	250	ES	100	ES	150	ES
MA	200	ES & Above ES	175	ES	250	ES & Above ES
MD	50	ES & Above ES	100	ES	-	
ME	-		-		-	
MI	50-100	ES & Above ES	50	ES	25-50	ES & Above ES
MN	100	ES	200	ES	150	ES
MO	250	ES	125	ES	125	ES
MS	75	ES	100-150	ES & Above ES	75-100	ES & Above ES
MT	100	ES	100	ES	50	ES
NC	15%	ES	100	ES	75 or 15%	ES
ND	150	ES	-		-	
NE	200	ES	100-200	ES & Above ES	150	Above ES
NJ	75-100		35	ES	25-50	ES & Above ES
NM	200	ES	200	ES	-	
NV	200	ES	150	ES	100	ES
NY	75-105		75-100	ES & Above ES	165	ES
OH	100	ES	150	ES	100	ES
OK	200	ES	200	ES	-	
OR	70%	ES	70%	ES	70%	ES
RI	150	ES	-		150	ES
SC	50	ES	100	ES	50	ES
SD	150	ES	100	ES	75	ES
TX	175-315	ES	100-225	ES & Above ES	85-185	ES
UT	-		75	ES		
VA	60	ES	75-350	ES & Above ES	50-275	ES & Above ES
VT	75	ES	150	ES	-	
WA	75	ES	150	ES	75	ES

Table 3. Summary Statistics: Cash for Appliances

Product	# of States Offering Rebates	# of Claims	Amount Distributed ($M)	Average Price Paid ($)	Average Rebate Claimed ($)	Max Rebate Claimed ($)
Air Conditioners	30	70,781	25.6	4,511	361	3,812
Boilers	18	7,678	4.0	5,516	518	4,036
Clothes Washers	43	580,863	62.1	698	107	1,034
Dishwashers	37	316,117	26.6	543	84	47,751
Electric Water Heaters	25	3,267	1.0	1,636	307	1,816
Freezers	26	24,312	2.5	579	103	1,500
Furnaces	34	76,469	30.9	5,772	404	3,227
Gas/Propane Water Heaters	30	15,766	2.1	703	130	1,742
Gas/Propane Water Heaters (Tankless)	31	11,140	3.0	2,266	267	1,223
Heat Pumps	26	47,470	23.6	6,403	497	4,400
Refrigerators	44	613,561	78.8	1,112	128	7,085
Solar Water Heaters	15	634	0.8	7,961	1,308	2,500
Total		1,768,058	260.9			

Notes: Data collected by program administrators and provided to the Department of Energy. Excludes U.S. territories.

Table 4. Conditional Logit with No Outside Option

	Specification I			Specification II		
	<\$50,000	≥\$50,000, <\$100,000	≥\$100,000	<\$50,000	≥\$50,000, <\$100,000	≥\$100,000
Price	-0.430	-0.369	-0.317	-0.445	Computing...	Computing...
	(0.009)	(0.007)	(0.007)	(0.009)		
Sales Tax	0.024	-0.056	-0.142	0.049		
	(0.058)	(0.052)	(0.044)	(0.062)		
Elec. Cost	-1.229	-1.792	-2.221	-1.334		
	(0.249)	(0.257)	(0.272)	(0.248)		
Utility Rebates	0.057	0.045	0.031	0.063		
	(0.043)	(0.030)	(0.029)	(0.044)		
State Rebates	0.095	0.082	0.030	0.121		
	(0.025)	(0.021)	(0.022)	(0.031)		
Interpretation						
Own-Price Elasticity	-5.587	-4.801	-4.116	-5.785		
Sales Tax/Price	-0.055	0.152	0.449	-0.111		
Implied Discount Rate	0.348	0.198	0.126	0.332		
Prob. Take Utility Rebates	0.132	0.123	0.096	0.142		
Prob. Take State Rebates	0.222	0.221	0.096	0.272		
Model FE	Yes	Yes	Yes	Yes	Yes	Yes
Brand-Month-of-Sample FE	Yes	Yes	Yes	Yes	Yes	Yes
State-ES FE	Yes	Yes	Yes	No	No	No
State-Year-ES FE	No	No	No	Yes	Yes	Yes
# Obs	46,097	45,487	45,249	46,097	45,487	45,249

Notes: All variables are measures in hundreds of dollars. The implied discount rates are computed assuming an appliance lifetime of 18 years. Standard errors in parentheses clustered at the zip code level.

Appendix A. Interpretation of Coefficients on Rebates

We interpret each of the coefficient on rebates (utility or states), as the probability to claim rebates times the marginal utility of income. In a linear model for the choice probabilities, this interpretation is fully consistent with a structural model where the decision to claim rebates is explicitly modeled. We show this below. With a non-linear model such as the conditional logit, this interpretation of the coefficient on rebates is not fully consistent with the structural model. However, this interpretation holds locally around the estimates, as we also show below.

Consider the following general choice model that explicitly models the decision to claim rebates. Suppose again that this decision is not observed, and α_i denotes the probability that consumer i claims a rebate. The observable choice probabilities for consumer i for product j thus correspond to a latent choice model taking the following form:

$$F_{ij} = \alpha_i F_{ij}^R + (1 - \alpha_i) F_{ij}^{NR}, \tag{5}$$

where F_{ij}^R is the choice probability when consumer i claims a rebate, and F_{ij}^{NR} is the choice probability when consumer i does not claim a rebate. If the functions F_{ij}^R and F_{ij}^{NR} are linear, we can readily see that the structural model corresponds to a reduced-form model where the coefficient on rebates, say ψ_i, is interpreted as the product of α_i and the behavioral response to rebates η_i. Without loss of generality, suppose that we are in a choice environment where only prices and rebates matter. We then have $F_{ij}^R = -\eta_i \cdot Price_j + \eta_i \cdot Rebate_j$, and $F_{ij}^{NR} = -\eta_i \cdot Price_j$. Therefore, we have:

$$\begin{aligned} F_{ij} &= \alpha_i \cdot (-\eta_i \cdot Price_j + \eta_i \cdot Rebate_j) + (1 - \alpha_i) \cdot (-\eta_i \cdot Price_j) \\ &= -\eta_i \cdot Price_j + \alpha_i \cdot \eta_i \cdot Rebate_j \\ &= -\eta_i \cdot Price_j + \psi_i \cdot Rebate_j. \end{aligned} \tag{6}$$

In a non-linear model, the above holds only for a local linear approximation of the structural model F_{ij} around the parameter on rebates at its estimated value.