Efficiency and Distributional Consequences of Heterogeneous Behavioral Responses to Energy Fiscal Policies

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To promote residential energy efficiency, federal, state, and local governments have relied on an array of fiscal policy instruments to subsidize energy-efficient appliances. Policies could directly subsidize investment in energy-efficient appliances—such as sales tax holidays and purchase rebates for energy-efficient appliances—or raise energy prices to increase the returns to energy-efficient investments—such as a carbon tax or the US Environmental Protection Agency's Clean Power Plan. While the latter policies may deliver greater social welfare as a first-best policy for pricing the externality contributing to climate change, the former subsidies could be distributionally progressive if they enable lower-income households to purchase more energy-efficient appliances. To evaluate this potential trade-off, we estimate a discrete choice model of households' appliance purchase decisions that accounts for the impacts of various types of investment subsidies as well as expected energy operating costs. Drawing from the universe of refrigerator purchase transactions at a national retailer over 2008-2012, we examine how the behavioral response to a subsidy intervention varies with a household's income level. We find evidence of weak salience of sales tax holidays as well as learning and hassle costs associated with claiming rebates for the purchase of energy-efficient refrigerators. Lower-income households have higher implicit discount rates than higher-income households, implying that climate policies that raise electricity prices will induce fewer energy-efficient refrigerator purchases among lower-income households. We use our estimated model to simulate an array of carbon price and energy-efficient appliance subsidy instruments and illustrate how the welfare impacts vary across income groups.

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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. 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 exhaustive in our investigation of the different types of subsidies that target residential consumers of energy-intensive durables. In particular, we consider state sales tax holidays/exemptions and purchase 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. We estimate discrete choice models for the appliance purchasing decision and exploit temporal and regional variation in the features of the various energy efficiency subsidy policies as well as in applicance operating costs (i.e., electricity prices). For instance, the states launched their Cash for Appliances (CFA) program at various times during 2010 and state programs varied in terms of rebate amount, appliance coverage, and other characteristics. Sales tax holidays vary across states and the eligibility criteria vary over time within states. Our analyses focus on refrigertaors, for which we have millions of transactions from a large U.S. retailer over 2008-2012. About half of the

[1]The only remaining type of subsidy for energy-efficient residential appliances in the United States is the federal manufacturers tax credit. Given the complexity of this tax credit–with conditional manufacturer-specific limits, scoring relative to historic production, and other factors–as well as the opacity in public domain tax reporting, this paper focuses on subsidies in retail markets.

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 results for the refrigerator market suggest a number of interesting patterns. First, lower income consumers respond less to sales taxes and electricity prices relative to higher income households; a dollar increase in tax or net present value of electricity expenditure has little impact on the purchasing decision of consumers in the lower income group. In contrast, 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).

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, such as a carbon tax, as well as regulatory approaches that increase electricity prices, such as the Clean Power Plan. We find that electricity prices influence appliance purchase decisions. We use these results to simulate how climate policy (e.g., a carbon tax or the Clean Power Plan) 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. **Fiscal 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 directly subsidize investment (appliance purchase) or raise energy prices to increase the returns to energy-efficiency investment.

The Energy Star (ES) certification program plays an important role in determining the eligibility criteria of various appliance subsidies. The ES-certification requirement is usually set relative to the federal minimum energy efficiency standard. For instance, refrigerator models at least 20% more efficient than than the minimum standard qualify for ES certification.

Most subsidy instruments in the energy-efficient appliance space 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 similar in nature. If an individual purchases a new appliance satisfying a given energy efficiency criterion (typically ES certification), then she may claim a rebate by submitting a form online or through the mail. The Database of State Incentives for Renewable and Efficiency (DSIRE) provides a complete description of these utility rebate programs. 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 (CFA) 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 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.

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

The variable ES takes a value of 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 sales tax using the product's retail price and state-week specific sales tax rates, accounting for sales tax holidays that target ES-certified products. The variables $R_{rt}^{Utility}$ and R_{rt}^{CFA} are rebate amounts offered through utility and CFA programs, respectively. Finally, $Elec$ is the annual electricity cost of operating product j in region r, accounting for manufacturer's expected annual electricity consumption and region-specific electricity prices.

All the preference parameters are interacted with observable demographic information to identify consumer-specific behavioral responses.[2] 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.

The coefficient α_i captures the response to variation in the sales tax rate. If consumers are perfectly informed about the sales tax rate and this information is as salient as the retail price, then the coefficient α_i should exactly match the coefficient η_i. Our prior is that $\alpha_i < \eta_i$, reflecting either 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 represents the combined impact of these two effects.

The coefficients ψ_i and ϕ_i both capture the response to rebates. In most cases, rebate programs require that consumers complete and submit forms (paper or online) to claim their rebates. In addition, consumers must also acquire information about the rebate programs, requiring 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 learn about the existence and key paramters of rebate

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

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 reflect the implicit costs of learning about and claiming rebates. In our analysis, we do not observe whether a consumer claims a rebate, thus we interpret ψ_i and ϕ_i as reduced form intent-to-treat estimators. We show in Appendix A that the ratios ψ_i/η_i and ϕ_i/η_i can represent an approximation of the probabilities to claim a rebate.[3]

Finally, the coefficient on electricity cost, θ_i, reflects how consumers trade-off future energy operating costs with the retail price. Assuming that consumers form time-invariant expectations about the annual operating electricity expenditure and do not account for the effect of depreciation, the lifetime energy operating cost (LC_j) for the durable j is given by:

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

where L is the lifetime of the durable, $\rho_i = 1/(1+r_i)$ is the discount factor, and C_{ij} is the product of the electricity price paid by household i and the manufacturer's expected annual electricity consumption for durable j.[4] 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:

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

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

[3]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.

[4]C_{ij} maps one-to-one to $Elec_{jrt}$ based on the region of residence for household i.

purchased, which is matched to detailed attribute information, including the expected annual electricity consumption 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. 44% of the transactions are matched with household demographics, such as household size, income, education, homeownership, housing type, political orientation, and age of the head of the household. The data aggregator Acxiom collects this transaction-specific demographic information.

The transaction data cover a large number of appliance categories, but we focus on refrigerators. This appliance category is particularly well-suited for the empirical analysis given that refrigerator utilization, and therefore the lifetime energy operating cost, should be relatively constant across households and not correlated with preferences, for a given model. The endogeneity issue raises by correlation in preferences that determine the intensity of utilization and demand for energy-efficient durables (**?**) is not a major concern in this market.

Given the computational demands of our non-linear framework, we draw large random samples ($N \approx 25,000$) of refrigerator purchase transactions from six different income groups. Since the source income data are coded into one of nine annual income ranges, we construct our income groups based on the category thresholds: <$30k, $30k-$50k, $50k-$75k, $75k-$100k, $100k-$150k, and >$150k. Each sample is randomly drawn from the subset of transactions that contains complete demographic information. Moreover, we only consider transactions made by homeowners who bought no more than one refrigerator over 2008-2012. Our estimation samples thus exclude transactions made by contractors making bulk purchases and renters who may not pay for their electricity bills. Renters represent less than 3% of transactions for which demographic is available. Although contractors are not explicitly identified in the data, we observe that about x% of the transactions are made by entities that purchase more than two refrigerators during the period 2008-2012.

4.2. **Sources of Variation**

Retail Prices. To identify consumers' price sensitivity to the retail price, represented by the parameter η_i, we exploit a number of institutional features of the appliance market. Our retailer, like most other large U.S. 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 in Figures 1-2 that show the median prices of the most popular refrigerator models for two major brands.[5] 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. By presenting various quantiles of the distribution of weekly changes, we show that the local store managers typically comply with the national price policy; for most weeks the 25^{th} and 75^{th} percentiles coincide with the median.

Finally, the blue 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 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. 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.[6] In sum, there is significant randomness in how the retailer sets prices. These patterns are consistent with Varian (1980)'s classical model of sales where stores play a mixed strategy that consists of randomizing prices to screen between loyal/uninformed and non-loyal/informed consumers. In our context, 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 has

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

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

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 in Table 1, of the eleven states that offered an appliance-oriented sales tax holiday over 2008-2012, nine of them used ES certification as an eligibility criterion.

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 exemptions 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 qualifying refrigerators. We created county averages by first mapping each utility territory to county information using EIA's form 861 database. 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.Table

2 summarizes the eligibility criteria established by the states; 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[7] that differed in the rebate amounts offered, appliances covered, eligibility criteria, timing and duration, and mechanisms to claim the rebates.

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% of refrigerators' sales prices, 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)).[8]

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,

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

[8] 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.

and Texas exhausted all rebate funds in only one day,[9] while Alaska's program lasted 91 weeks. Several states offered the rebates in different phases, where the program closed temporarily between phases.[10]

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.[11] 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, are quite stable over our sample period. For instance, between 2008 and 2010, the national average electricity price remained virtually unchanged. Second, time-invariant 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 uses 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.

In this paper, we are interested in illustrating how setting the electricity price closer to its social cost will impact appliance purchasing decisions. Given that each state might adopt different

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

[10]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.

[11]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 Energy Information Administration form 861 database.

policies to internalize negative externalities in the price of electricity (e.g., through Clean Power Plan implementation) 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.

5. Estimation and Results

5.1. Empirical Strategy

To implement our empirical strategy, we estimate a conditional logit without an outside option discrete choice model. We assume that the ϵ's 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 explicitly account for substitution over time or store location, and focuses on substitution across products. This has a number of implications for the interpretation of the behavioral responses to the different subsidies and electricity cost. For instance, the coefficient on sales tax is not explicitly 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 allow us to account for these behaviors.

We estimate the model via maximum likelihood by forming the choice probabilities of each consumer included in the random samples. The consideration set of each consumer consists of all the refrigerator models offered in the zip code where the purchase was made. We use observed sales to impute the choice set for each zip code by trimester (January-April, May-August, and September-December for each year of our sample). That is, if we observe a particular refrigerator 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 model. We also restrict the consideration set of each consumer based on the overall size of the refrigerator that was purchased. Imposing such a restriction reflects the physical constraints to upsize or downsize their refrigerator due to kitchen design for most households. We present results for two specifications. In one specification, we impose a lax restriction and include in the consideration set all refrigerators within 5 cubic feet of the refrigerator volume a consumer purchased. This criterion represents a range of about 30% of an average refrigerator size. In a second specification, we limit the consideration set to refrigerators within 0.5 cubic feet of the refrigerator volume purchased, which almost rules out substitution with respect to size.

For each income group, we draw (with replacement) 100 random samples from the set of original transactions and perform the estimation for each sample. The standard errors are estimated via a bootstrap procedure.

5.2. **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 data 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.

We further control for region-specific unobservables by including state dummies interacted with an ES dummy, which turns one if product j is ES certified at time t. 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 of the 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 mass 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.

In our preferred specification, we also interact the variable for electricity cost with the ES dummy. The coefficient on this interaction term aims to capture that consumers might perceive energy operating costs for ES certified models. As shown by Houde (2014), the ES label and information about energy operating costs appear to be substitutes—consumers that have a high willingness to pay for the label do not value information energy costs and vice-versa. The interaction term between the ES dummy and energy operating cost is a simple way to capture this effect.

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. As we show, these fixed effects have little impact on our coefficients of interest. To alleviate the computational burden of the estimation, our preferred specification excludes these fixed effects.

To distinguish various sources of variation in sales tax, we interact the sales tax variable with a dummy that identify sales tax holidays that target ES models (Table 1). In the presence of state-ES fixed effects, the identifying variation of the coefficients on sales tax comes from the year-to-year variation in both the sales tax and the tax holidays targeting ES products.

Finally, for the estimation of the behavioral response to rebates offered during the CFA program, we include variables that capture the intertemporal substitution in the timing of the purchase the program induced and shown by Houde and Aldy (2014). We add a variable that identifies the two months preceding the start of a rebate program in a given state and that is interacted with a rebate amount. Similarly, we add a variable that identifies the two months following the end of rebate program interacted with the rebate amount. These interactions represent the behavioral response to the CFA program before, during, and after program enactment in a given state.

5.3. **Main Results**

Table 4 reports the results for the six income groups for our preferred specification. This specification includes interaction terms between demographics and attributes, product fixed effects, and state-ES fixed effects. We also form consumer-specific consideration sets assuming that consumers restrict their search to refrigerator models within 5 cubic feet of the size they finally purchased. The interpretation of the coefficients are shown on Figure 6. Several interesting patterns emerge. Panel (a) shows that the response to electricity cost relative to the response to appliance price is increasing with income. That means that the trade-off between lifetime energy operating cost and price is rationalized by a lower discount rate for higher income groups. The magnitude of the implicit discount rates across the six income groups ranges from 10% to 16%, which, overall, suggests a very modest undervaluation of energy operating cost in the purchase decision, if any. For all income groups, we also found that the interaction term between electricity cost and the ES dummy is positive, which suggests that consumers pay less attention to electricity cost for ES certified models. As discussed earlier, this effect is a manifestation of the fact that the ES certification and information about energy operating costs, notably provided by the EnergyGuide label, are substitutes (Houde 2014).

The behavioral responses to the various types of subsidies are systematically less than the response to price (Panels (c)-(f)), with the exception of sales tax holidays for a few income groups (Panel (d)). The fact that the coefficient on sales tax is about half the coefficient on price (Panel (c)) suggests that households do not respond to a change in sales taxes the same way that they do for a change in retail prices. This result is consistent with Chetty, Looney, and Kroft (2009), who found that sales taxes are not as salient as prices. The response to sales tax holidays appears, however, more pronounced, with the caveat that this coefficient is currently imprecisely estimated. Together, these results suggest that a short-lived tax holidays for ES models might induce a larger behavioral response than a permanent tax exemption.

For the coefficients on rebates, lower-income consumers tend to respond more to rebates, and higher-income consumers less. Although, the difference between the estimates is not large. This result is particularly noticeable for state rebates offered during the CFA program. Interpreting, the ratio of the coefficient on rebates on the coefficient on price as the probability to take rebate, this probability is 26% for the lowest income group during the CFA program and decreases to 12%-15% for the two highest income groups. These results are consistent with the notion that hassle costs influence the decision to claim a rebate. 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 various types of tangible hassle costs due to the fact that retail stores were more crowded and consumers had to wait in line longer than usual.

5.4. **Extensions and Additional Robustness Tests–In Progress**

In Table 5, we show the results for a specification similar to Table 4 except that we restrict the consideration set of each consumer to refrigerator models that are within 0.5 cu. ft. of the size actually purchased. This way to define the consideration sets almost completely rules out substitution across size. This restriction mostly impacts the coefficient on electricity costs that becomes larger (in absolute value). This holds for all six income groups. Under this specification, the implicit discount rates decrease and range from

Not shown here are the results with time dummies interacted with brand dummies fixed effects. In previous versions of the estimation (using only three income groups), these fixed effects had little impact on the coefficients. We are planning to show these results again for the six income groups that we now consider.

5.4.1. ***Additional Heterogeneity with Respect to Demographics***

The above results suggest that decision costs and hassle costs are important drivers of heterogeneity in the behavioral responses to different types of fiscal instruments. We would like to investigate further this question, by showing 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 experience and knowledge and thus be more likely to account for sales tax and electricity costs. 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 are more likely to be retirees or derive income for non-labor sources. 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.

Tables 7-**??** show results using our old sample. We are planning on updating these results. Overall, we find that family structure has an impact on the coefficient on electricity costs—larger families tend to respond less to electricity costs. Older households tend also to respond more to electricity costs. Education also has an impact for some income groups, where households with at least one member with a graduate degree respond more to electricity costs. Education might also have a similar impact on the probability of taking advantage of CFA rebates. For some income groups, the effect of graduate education is large, but imprecisely estimated.

5.4.2. ***Impact of Rebate Program Features***

State program managers had and exploited their discretion in designing their state's C4A program, subject to the energy-efficiency constraints established in the federal law authorizing the program. Among other aspects, rebate programs varied in terms of the ease in claiming rebates. Some programs opted for an online system, while others favored 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.

5.4.3. ***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.

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.

6. **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 in the first year of a carbon tax of $25 per ton carbon dioxide using the 2013 Annual Energy Outlook published by the Energy Information Administration (Outlook 2013). At the national level, this carbon tax translates in a price increase of $0.02/kWh from an average price of $0.11/kWh. In future version of the paper, we are also planning to carry a similar analysis, but differentiate the impact of a carbon tax by electricity market (comprising 22 regions in the continental United States). Simulations based on a national average allow us to focus on important conceptual issues related to the measurement of consumer welfare, which we discuss below.

Our policy analysis focuses on four different combination of fiscal instruments.

(1) $25 per ton carbon dioxide;
(2) $25 per ton carbon dioxide with revenue recycled in a rebate program run by electric utilities;
(3) $25 per ton carbon dioxide with revenue recycled in a state rebate program similar to CFA;
(4) $25 per ton carbon dioxide with revenue recycled in a sales tax exemption for ES-certified products;

For both rebate programs considered, we assume that the eligibility criterion is the ES certification. The level of the rebate and sales tax exemption is set equal to the expected burden of the carbon tax that households in each income group face. We compute this burden by summing and discounting the expected increase in annual energy operating costs that a given household will face. For instance, assuming that the lifetime of refrigerator is L years, household i's tax burden of a $25 per ton carbon dioxide that translate in an increase in electricity prices of \$0.02/kWh is given by

$$Burden_i = 0.02 \times \sum_{t}^{L} \rho^t \sum_{j}^{J} P_{ij} \times kWh_j, \tag{3}$$

where P_{ij} is the choice probability (given by our discrete choice model), kWh_j is the annual electricity consumption (as reported by the manufacturers) for product j, and ρ is the discount factor. Throughout our policy analysis, we use a discount rate of 7% and a refrigerator lifetime of 18 years. The total revenue collected from the carbon tax is: $\sum_i^N Burden_i$. The average burden that determines the rebate amount is thus: $(1/N)\sum_i^N Burden_i$. For the sales tax, the level of the tax exemption is to: $(1/N)\sum_i^N Burden_i/p_{avg}$, where p_{avg} is the average price of a refrigerator.

Note that because the behavioral responses to rebates and sales tax suggest that not all consumers would take advantage of these subsidies, the revenue recycled in those instruments will always be less than the revenues collected from the carbon tax. This raises the question of how the government will distribute the revenue of the carbon tax that are not distributed through a subsidy program. We will consider two scenarios. One where those revenue are not redistributed to consumers that purchase a refrigerator. Another where the government has the ability to identify consumers that made a purchase and target a lump-sum transfer to those consumers.

6.1. **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 behavioral responses to sales taxes and sales tax holidays should be the same than for prices.*

Assumption 2. *Under perfect information, the coefficient on electricity cost should imply a discount rate in line with other investment/borrowing decisions. We assume* $r = 7\%$.

Assumption 3. *Under perfect information, the ES certification should impact how consumers perceive electricity costs.*

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

(4)
$$U^E_{ijtr} = \gamma_{ij} + \tau_i ES_{jt} - \eta_i P_{jrt} - \eta_i Tax_{jrt} + \psi_i R^{Utility}_{rt} \times ES_{jt} + \phi_i R^{CFA}_{rt} \times ES_{jt} - \eta_i \rho_i \frac{1-\rho_i^L}{1-\rho_i} Elec_{jrt} + \epsilon_{ijtr},$$

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

$$\Delta CS_{itr} = \frac{1}{\eta_i} \cdot \left[ln \sum_j^J exp(\tilde{U}_{ijtr}) + \sum_j^J \tilde{P}_{ijtr}(\tilde{U}^E_{ijtr} - \tilde{U}_{ijtr}) \right] - \frac{1}{\eta_i} \cdot \left[ln \sum_j^J exp(U_{ijtr}) + \sum_j^J P_{ijtr}(U^E_{ijtr} - U_{ijtr}) \right]. \quad (5)$$

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 because of the terms taking the form $\sum_j^J P_{ijtr}(U^E_{ijtr} - U_{ijtr})$, which is the Leggett (2002)'s correction. It has an intuitive interpretation. It represents the expected difference between experienced and decision utility. In the absence of Leggett (2002)'s correction, the formula in 5 takes the usual form given by the log-sum formula. The classic expression for welfare is thus a special case of 5 and can thus be reported.

Whether the effect of the ES label is truly experienced and therefore whether τ_i should be considered in the expression for experienced utility 4 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.

6.2. **Results**

Table presents the results for the four combinations of fiscal instruments we consider. Focusing on the scenario with carbon tax alone, one average, households face a tax burden of about \$100. The tax burden is slightly increasing with income, but the differences across income groups are small, only a few dollars. The expected change in consumer surplus, if we exclude the Leggett's correction, is about \$50 for the lowest income group and increasing with income up to \$73. The Leggett's correction has the opposite pattern and decreases with income due to the fact that lower income groups have higher implicit discount rates. Summing both components of welfare, we find that the expected change in consumer surplus is almost constant across the six income groups. Our interpretation of the behavioral response to electricity costs is thus crucial from both an efficiency and distributional standpoint. If we were to conduct the welfare analysis using the standard approach, we would conclude that the carbon tax is progressive[12] and we would underestimate the welfare impact on consumers by about half.

Under the first scenario, if the government has the ability to make a lump-sum transfer that perfectly targets consumers that purchase a refrigerator, the change in consumer surplus is close to zero. Finally, note that the change in externality cost is small. The carbon tax leads to substitution across products, but the change in market shares appear to not be economically important.

For the three other scenarios, the patterns are similar. That is, if we exclude the Leggett's correction, the policies appear to be progressive. Once we account for it, the welfare effects are much less differentiated across income groups. Regarding the ranking of the policies, if we assume that we cannot make a lump-sum transfer to households, the scenarios where the carbon tax revenues are recycled via a sales tax exemption is the one that benefits the consumers the most. However, the assumption about the ability of the government to make a (frictionless) lump-sum transfer is crucial. If the government can make such transfer, consumers will always be better off in a scenario where they receive a lump-sum transfer approximately equal to the tax burden they face without having to incur various costs, tangible or not, to claim rebates or a sales tax exemption.

[12]Here, the progressivity of the policy comes from the fact that lower income households are more likely to purchase smaller refrigerators that consume less electricity.

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7. Tables and Figures

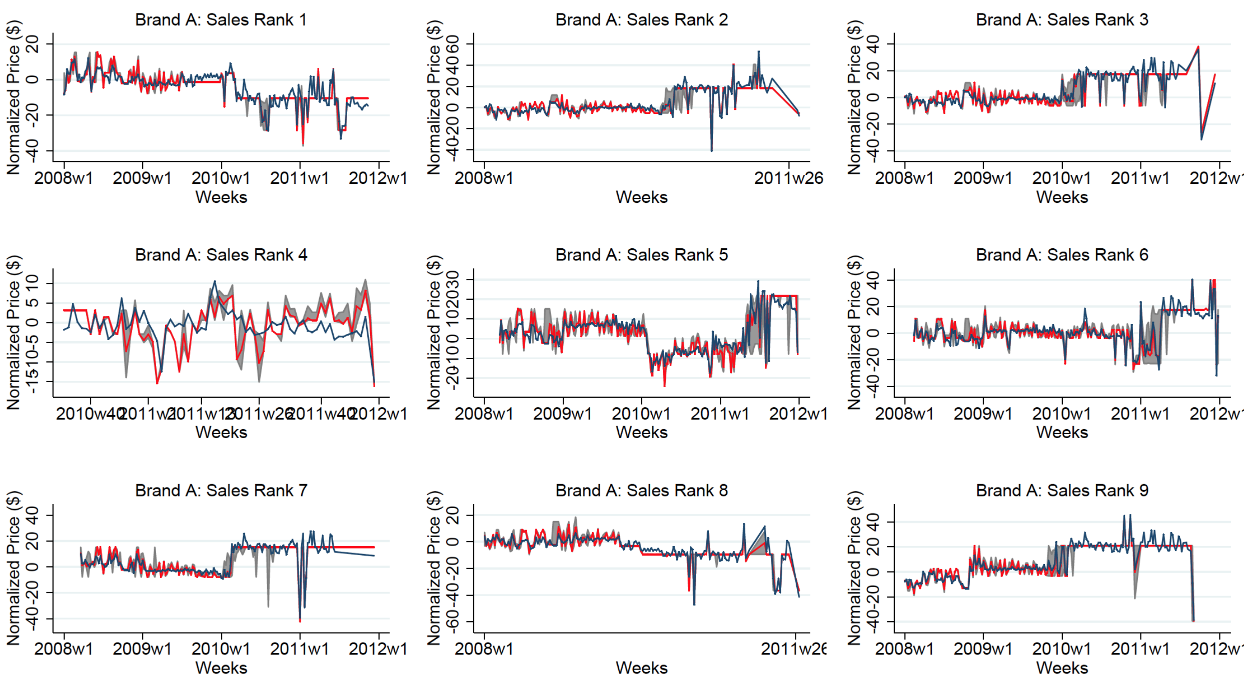


FIGURE 1. Temporal and Cross Strore Variation in Promotional Price, Brand A

Notes: The red line shows the normalized prices of the nine most popular models offered by Brand A. The gray shaded are corresponds to the 25^{th} and 75^{th} percentile of the normalized price distribution. The blue line is the median price after controlling for brand-week-of-sample fixed effects.

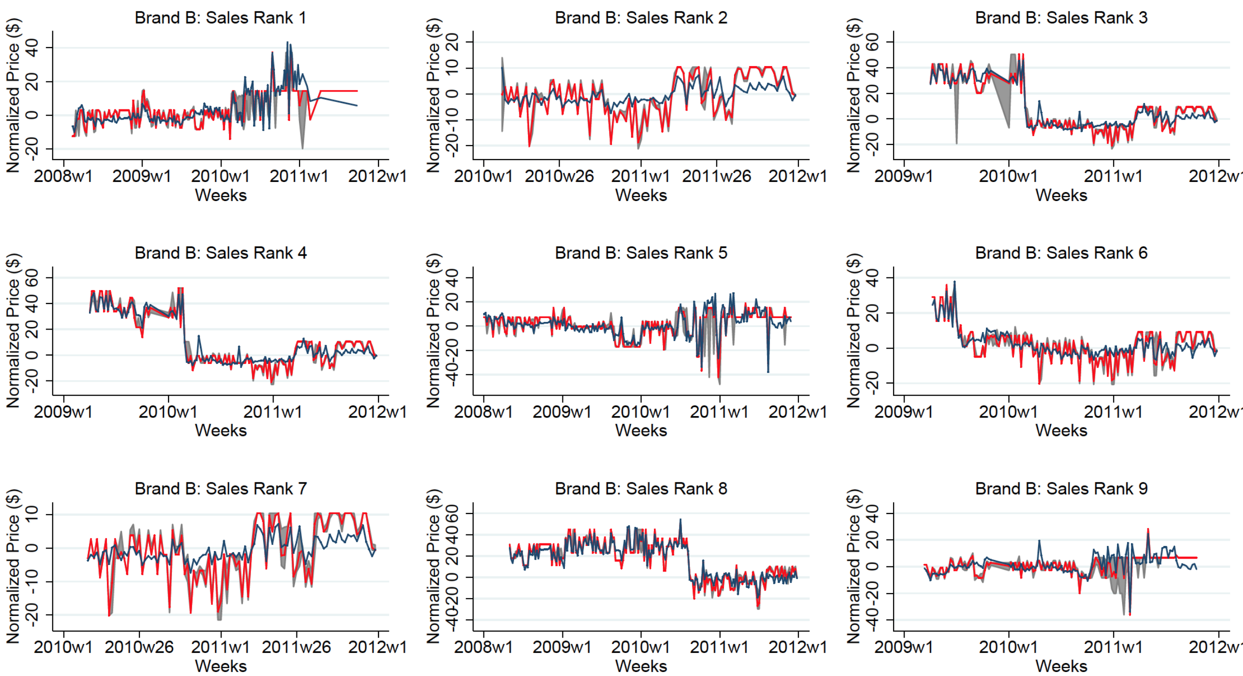


Figure 2. Temporal and Cross Strore Variation in Promotional Price, Brand B

Notes: The red line shows the normalized prices of the nine most popular models offered by Brand B. The gray shaded are corresponds to the 25^{th} and 75^{th} percentile of the normalized price distribution. The blue line is the median price after controlling for brand-week-of-sample fixed effects.

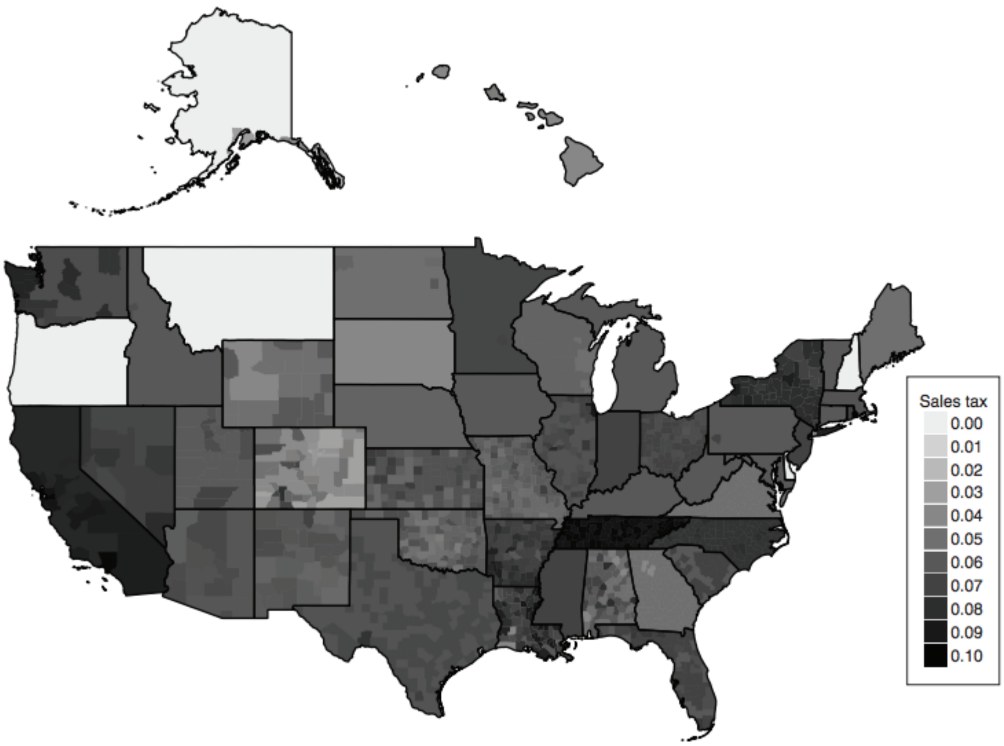
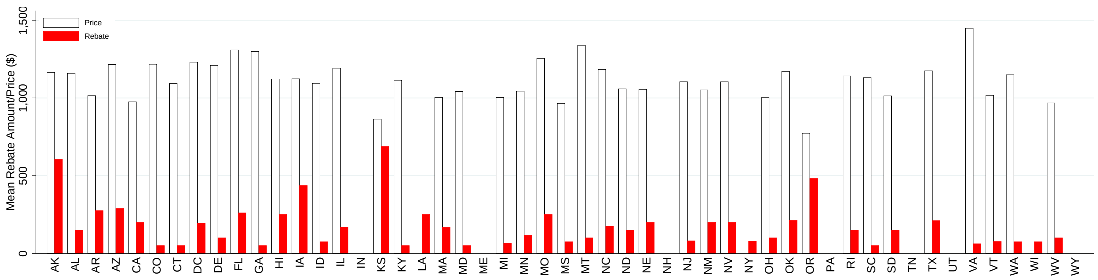
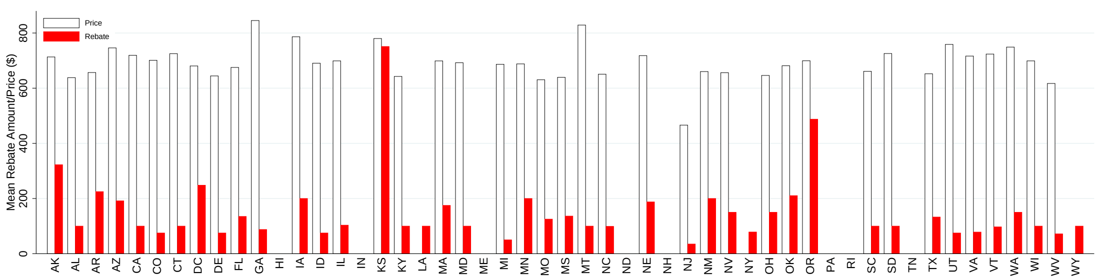


Figure 3. Cross Section Variation in Sales Tax Rates (Source: Einav et al., 2014)

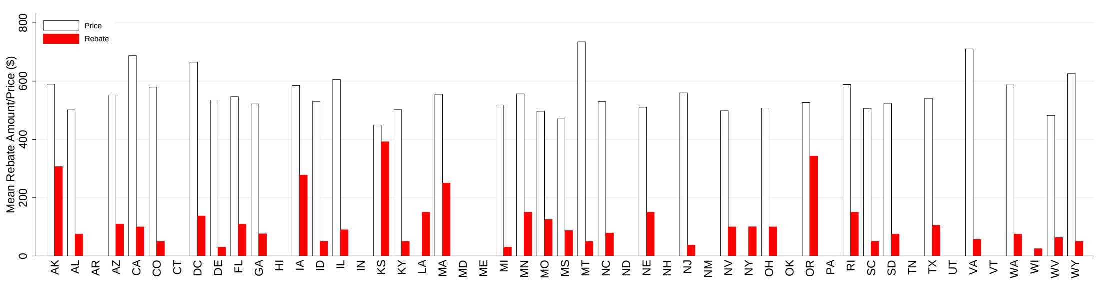
Notes: This map is from Einav et al. (2014) and shows the (population weighted) average sales tax rate in the United States as of January 1, 2010.



(a) Refrigerators



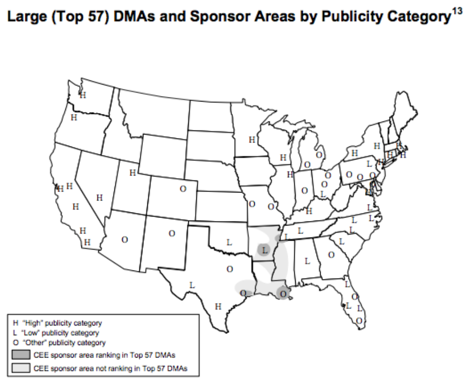
(b) Clothes Washers



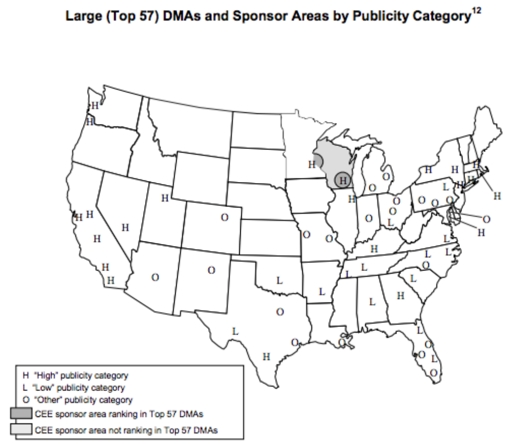
(c) Dishwashers

FIGURE 4. Average Price vs. Rebate Amount

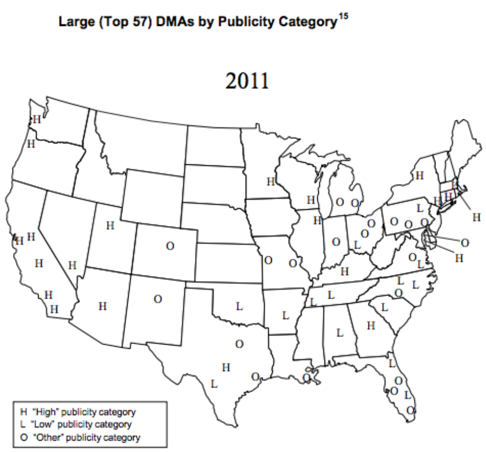
Each panel shows the average price of the appliance purchased (in white) and the average rebate amount claimed (in red). States with no average price but a positive rebate amount are states where program managers did not collect price information. States where both price and rebate information are missing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



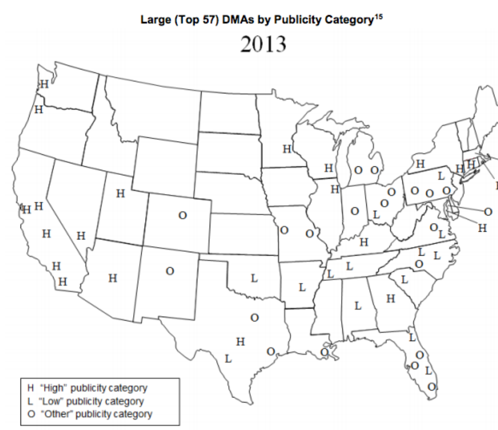
(a) 2007



(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.

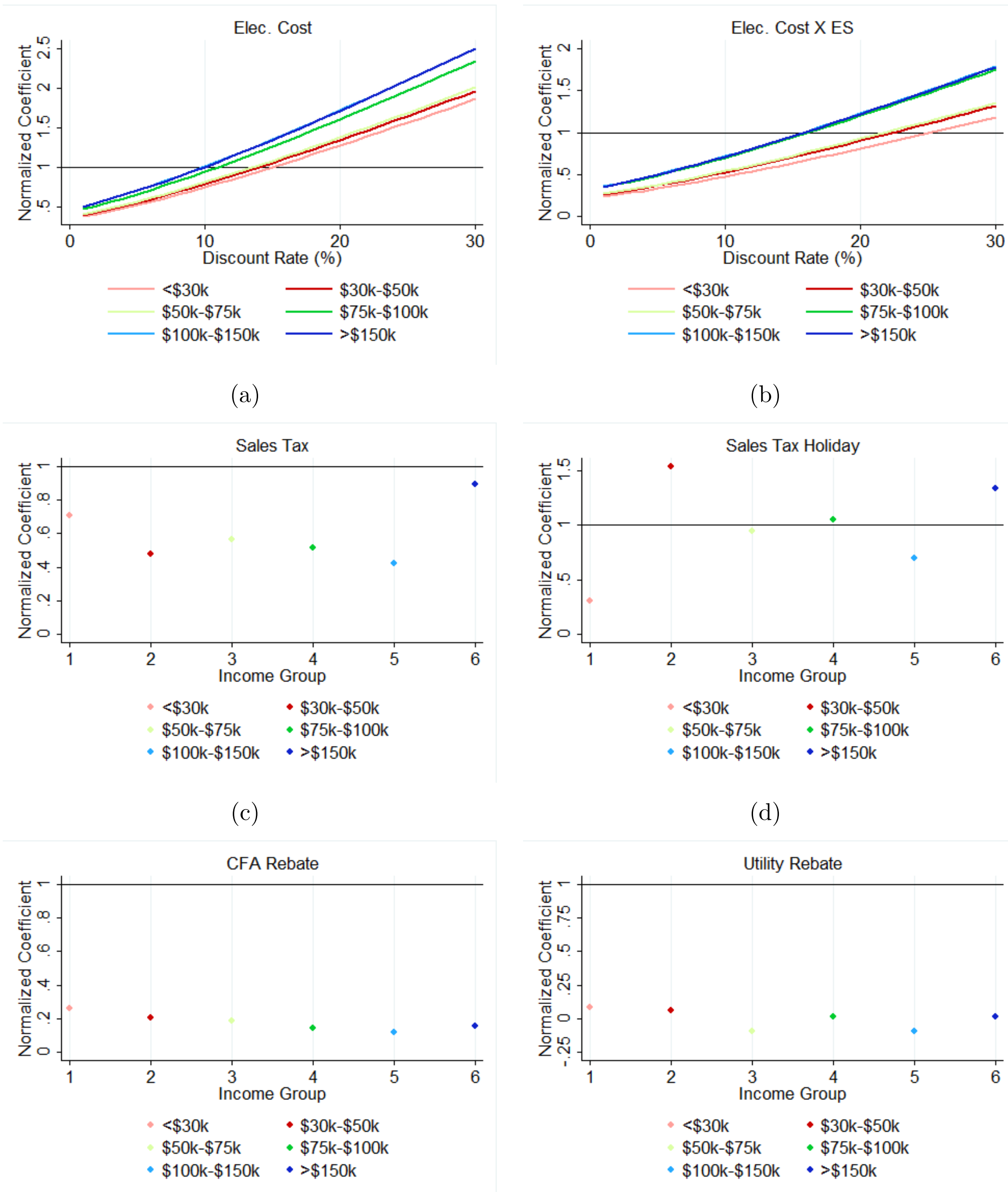
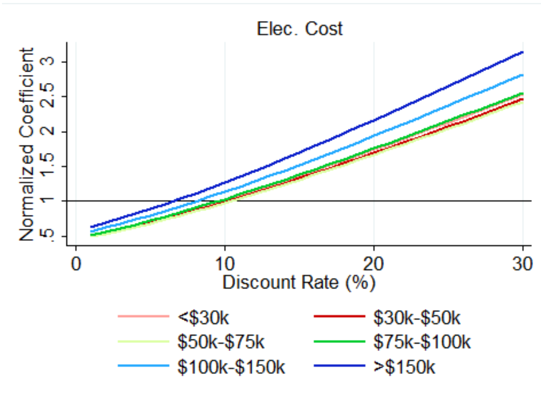
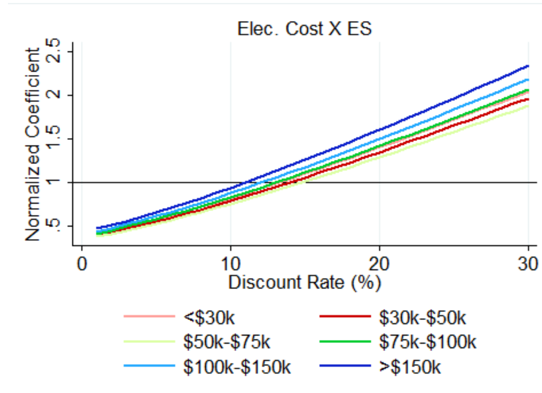


Figure 6. Interpretation of Behavioral Responses to Electricity Cost, Rebates, and Sales Tax, Table 4

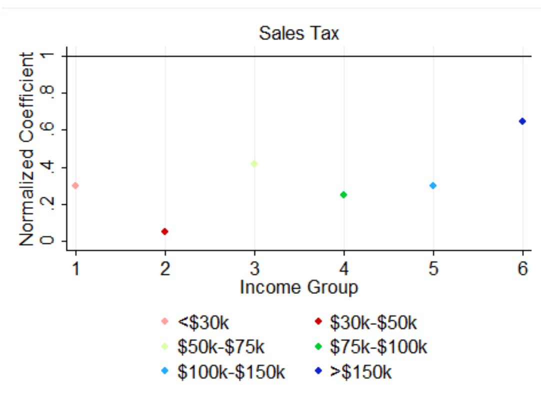
Notes: Panels (a) and (b) plot the ratio $\theta_i / \left(\eta_i \cdot \rho_i \cdot \frac{1-\rho_i^L}{1-\rho_i}\right)$ for different values of the discount rate r. The implicit discount rate corresponding to each income group is the value of r that sets this ratio to one. Panels (c)-(f) show the ratio of the coefficient for a given type of fiscal instrument divided by the marginal value of income (i.e., absolute value of the coefficient on price). A ratio that takes a value of one means that the behavioral response to the fiscal instrument is the same than the response to the price.



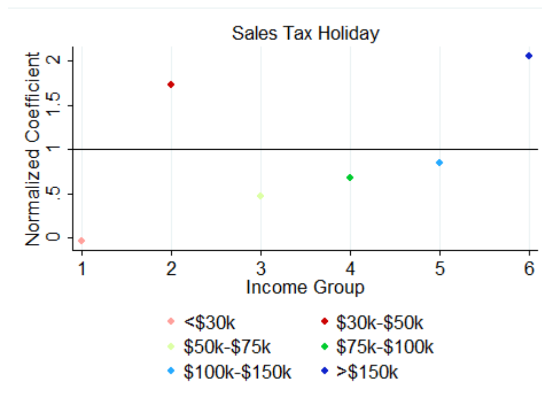
(a)



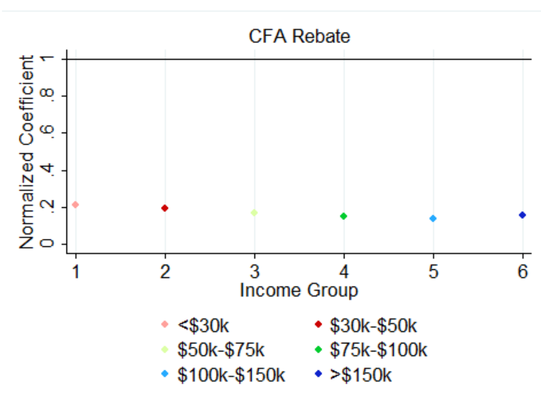
(b)



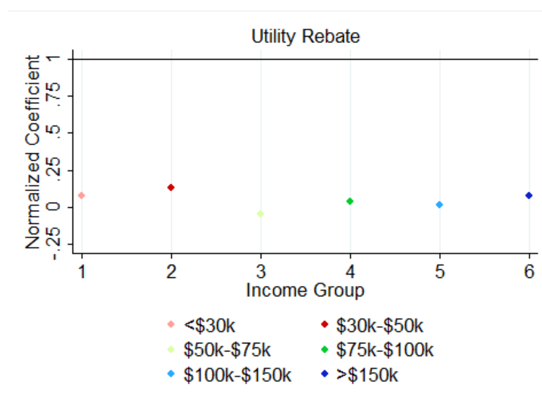
(c)



(d)



(e)



(f)

FIGURE 7. Interpretation of Behavioral Responses to Electricity Cost, Rebates, and Sales Tax, Table 5

Notes: Panels (a) and (b) plot the ratio $\theta_i / \left(\eta_i \cdot \rho_i \cdot \frac{1-\rho_i^L}{1-\rho_i} \right)$ for different values of the discount rate r. The implicit discount rate corresponding to each income group is the value of r that sets this ratio to one. Panels (c)-(f) show the ratio of the coefficient for a given type of fiscal instrument divided by the marginal value of income (i.e., absolute value of the coefficient on price). A ratio that takes a value of one means that the behavioral response to the fiscal instrument is the same than the response to the price.

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.

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
WI	75	ES	100	ES	25	ES
WV	100	ES	50-75	Above ES	50-75	ES & Above ES
WY	-		100	ES	50	ES

Notes: Criteria using ENERGY STAR have the acronym ES. Above ES means that a criteria more stringent than ES was used. Alaska offered different rebate amounts for rural and non-rural residents.

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. Preferred Specification Conditional Logit

	<$30,000	≥$30,000, <$50,000	≥$50,000 <$75,000	≥$75,000 <$100,000	≥$100,000 <$150,000	≥$150,000
Price	-0.41	-0.42	-0.39	-0.35	-0.34	-0.29
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Elec. Cost	-2.54	-2.71	-2.57	-2.75	-2.82	-2.43
	(0.41)	(0.52)	(0.52)	(0.41)	(0.45)	(0.52)
Elec. Cost X ES	0.93	0.90	0.84	0.70	0.81	0.70
	(0.29)	(0.37)	(0.32)	(0.33)	(0.37)	(0.32)
Sales Tax	-0.29	-0.20	-0.22	-0.18	-0.14	-0.26
	(0.16)	(0.14)	(0.13)	(0.11)	(0.10)	(0.09)
Sales Tax X	0.05	-0.41	-0.13	-0.14	-0.28	-0.03
Tax Holiday	(0.47)	(0.98)	(0.43)	(0.38)	(0.43)	(0.42)
Utility Rebate	0.03	0.02	-0.04	0.00	-0.03	0.00
	(0.05)	(0.06)	(0.05)	(0.05)	(0.05)	(0.04)
CFA Rebate:	0.11	0.09	0.07	0.05	0.04	0.05
During Program	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)
CFA Rebate:	0.09	0.04	0.02	0.05	0.05	0.03
2 Months After	(0.05)	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)
CFA Rebate:	0.00	-0.04	-0.01	-0.01	-0.01	-0.02
2 Months Before	(0.06)	(0.06)	(0.06)	(0.06)	(0.04)	(0.06)

Notes: All variables are measures in hundreds of dollars. The model includes product fixed effects, state-ES fixed effects, and interaction terms between demographics and attributes. The consideration set for each consumer is restricted to refrigerator models that are within 5 cu. ft of the size purchased and offered in the same zip code than the purchase was made. Bootstrapped standard errors in parentheses. The number of bootstrap iterations vary from 22 to 75 (to be fixed, eventually it will be 100 for each income group). The number of observations for each bootstrap iteration is approximately 25,000.

Table 5. Robustness Check: Conditional Logit with Restricted Consideration Set +/10.5 cu. ft.

	<\$30,000	≥\$30,000, <\$50,000	≥\$50,000 <\$75,000	≥\$75,000 <\$100,000	≥\$100,000 <\$150,000	≥\$150,000
Price	-0.45	-0.45	-0.41	-0.38	-0.36	-0.32
	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
Elec. Cost	-3.76	-3.66	-3.28	-3.21	-3.35	-3.32
	(0.62)	(1.13)	(0.69)	(0.62)	(0.65)	(0.61)
Elec. Cost X ES	0.73	0.75	0.75	0.62	0.77	0.86
	(0.36)	(0.52)	(0.47)	(0.39)	(0.45)	(0.45)
Sales Tax	-0.14	-0.02	-0.17	-0.09	-0.11	-0.21
	(0.22)	(0.23)	(0.21)	(0.18)	(0.14)	(0.11)
Sales Tax X	-0.16	-0.62	-0.01	-0.21	-0.35	-0.11
Tax Holiday	(0.59)	(1.25)	(0.55)	(0.43)	(0.47)	(0.56)
Utility Rebate	0.04	0.06	-0.02	0.02	0.00	0.02
	(0.07)	(0.08)	(0.07)	(0.06)	(0.08)	(0.06)
CFA Rebate:	0.06	0.03	-0.01	0.05	0.05	0.04
During Program	(0.07)	(0.04)	(0.05)	(0.06)	(0.05)	(0.05)
CFA Rebate:	-0.04	-0.08	-0.07	-0.06	-0.05	-0.06
2 Months After	(0.06)	(0.07)	(0.08)	(0.08)	(0.06)	(0.06)
CFA Rebate:	0.10	0.09	0.07	0.06	0.05	0.05
2 Months Before	(0.03)	(0.04)	(0.04)	(0.03)	(0.03)	(0.04)

Notes: All variables are measures in hundreds of dollars. The model includes product fixed effects, state-ES fixed effects, and interaction terms between demographics and attributes. The consideration set for each consumer is restricted to refrigerator models that are within 0.5 cu. ft of the size purchased and offered in the same zip code than the purchase was made. Bootstrapped standard errors in parentheses. The number of bootstrap iterations vary from 22 to 75 (to be fixed, eventually it will be 100 for each income group). The number of observations for each bootstrap iteration is approximately 25,000.

TABLE 6. Welfare Results:

	<\$30,000	≥\$30,000, <\$50,000	≥\$50,000 <\$75,000	≥\$75,000 <\$100,000	≥\$100,000 <\$150,000	≥\$150,000
I. \$25 Carbon Tax						
Avg Burden	100.2	99.4	103.3	103.7	103.0	102.9
Classic CS	-51.0	-50.6	-57.4	-69.3	-70.8	-72.8
Leggett's Correction	-51.2	-50.4	-48.0	-36.3	-34.8	-32.5
Δ CS no Lump-Sum	-102.1	-101.0	-105.4	-105.6	-105.6	-105.3
Δ CS with Lump-Sum	-2.0	-1.6	-2.1	-1.8	-2.6	-2.4
Δ Externality	-0.4	-0.4	-0.5	-0.4	-0.4	-0.4
IVI. \$25 Carbon Tax, Revenue Recycled in a Utility Rebate Program						
Rebate Amount	100.2	99.4	103.3	103.7	103.0	102.9
Lump-Sum Transfer	50.8	34.0	51.1	46.8	42.1	50.8
Classic CS	-46.9	-46.7	-62.4	-68.5	-76.5	-72.0
Leggett's Correction	-51.9	-50.9	-47.1	-36.4	-33.9	-32.6
Δ CS no Lump-Sum	-98.8	-97.6	-109.5	-104.9	-110.4	-104.6
Δ CS with Lump-Sum	-48.0	-63.6	-58.4	-58.1	-68.3	-53.8
Δ Externality	-0.5	-0.5	-0.4	-0.5	-0.4	-0.4
III. \$25 Carbon Tax, Revenue Recycled in a state-CFA Rebate Program						
Rebate Amount	100.2	99.4	103.3	103.7	103.0	102.9
Lump-Sum Transfer	47.8	32.9	48.6	45.1	39.7	49.7
Classic CS	-26.9	-36.2	-45.9	-55.2	-55.3	-62.7
Leggett's Correction	-55.2	-52.0	-50.0	-38.3	-37.2	-34.2
Δ CS no Lump-Sum	-82.1	-88.2	-95.8	-93.5	-92.5	-96.9
Δ CS with Lump-Sum	-34.3	-55.3	-47.3	-48.4	-52.8	-47.2
Δ Externality	-0.8	-0.6	-0.7	-0.6	-0.6	-0.5
IV. \$25 Carbon Tax, Revenue Recycled in a Permanent Sales Tax Exemption						
Avg. Exemption	100.2	99.4	103.3	103.7	103.0	102.9
Lump-Sum Transfer	47.2	36.0	47.6	45.0	38.5	43.9
Classic CS	-15.8	-21.3	-27.4	-40.3	-44.4	-23.4
Leggett's Correction	-41.5	-20.5	-28.9	-11.8	-1.6	-34.0
Δ CS no Lump-Sum	-57.3	-41.8	-56.3	-52.1	-46.0	-57.5
Δ CS with Lump-Sum	-10.1	-5.8	-8.7	-7.1	-7.5	-13.5
Δ Externality	-0.9	-0.7	-0.9	-0.7	-0.6	-0.8

Notes: All numbers are in 2015 U.S. dollar. "Classic CS" refers to the measure of welfare that relies only on the log-sum formula and excludes the Leggett's correction.

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:

$$F_{ij} = \alpha_i F_{ij}^R + (1 - \alpha_i) F_{ij}^{NR}, \tag{6}$$

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:

$$\begin{aligned} F_{ij} &= \alpha_i \cdot (-\eta_i \cdot Price_j + \eta_i \cdot Rebate_j) + (1 - \alpha_i) \cdot (-\eta_i \cdot Price_j) \\ &= -\eta_i \cdot Price_j + \alpha_i \cdot \eta_i \cdot Rebate_j \\ &= -\eta_i \cdot Price_j + \psi_i \cdot Rebate_j. \end{aligned} \tag{7}$$

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.

Appendix B. Additional Heterogeneity with Respect to Demographics

Table 7. Heterogeneity with Respect to Demographics: Households Income<$50,000

	Price	Sales Tax	Elec. Cost	Utility Rebates	C4A Rebates
Omitted	-0.431***	-0.02	-1.039**	-0.056	0.092
Educ. College	-0.004	0.111	0.117	0.047	0.014
Educ. Grad. School	0.032**	-0.147	-0.271	-0.063	0.01
Age 35-50	0.006	-0.093	0.478*	0.087	0.054
Age 50-65	0.004	-0.143	-0.418*	0.124	0.104
Age 65+	-0.019	0.089	-1.018***	0.243	0.067
Family w. Children	-0.018*	0.101	0.925***	-0.034	-0.072
Income: [$30,000; $50,000]	0.015	0.028	-0.631***	-0.043	-0.031

Notes: The omitted category corresponds to households where the head of the household has a high school diploma or less and is less than 35 years old, and where there is no children and household income is less than $35,000.

Table 8. Heterogeneity with Respect to Demographics: Households Income$[\$50,000; \$100,000)$

	Price	Sales Tax	Elec. Cost	Utility Rebates	C4A Rebates
Omitted	-0.379***	-0.151	-1.935***	0.127	0.008
Educ. College	0.009	0.009	-0.133	-0.038	0.056
Educ. Grad. School	0.023*	0.031	-0.795**	-0.08	0.12*
Age 35-50	-0.002	0.094	0.301	0.023	0.064
Age 50-65	-0.011	0.089	-0.417	0.019	0.056
Age 65+	-0.017	0.139	-0.629*	0.014	0.094
Family w. Children	-0.002	-0.043	0.91***	-0.069	0.024
Income: [$75,000; $100,000)	0.014*	0.034	-0.21	-0.002	-0.07 *

Notes: The omitted category corresponds to households where the head of the household has a high school diploma or less and is less than 35 years old, and where there is no children and household income is [$50,000; $75,000) .

Table 9. Heterogeneity with Respect to Demographics: Households Income$\geq$ \$100,000

	Price	Sales Tax	Elec. Cost	Utility Rebates	C4A Rebates
Omitted	-0.353***	-0.195	-2.543***	-0.211	0.043
Educ. College	0.023	-0.059	0.127	0.063	0.008
Educ. Grad. School	0.028***	-0.091	-0.303	0.044	0.05
Age 35-50	0.004	0.159	0.092	0.265	-0.069
Age 50-65	-0.004	0.178	-0.418	0.252	0.008
Age 65+	-0.032	0.411	-0.598	0.254	-0.034
Family w. Children	-0.001	0.046	0.542***	-0.045	-0.017
Income: $\geq$\$150,000)	0.026***	-0.16	0.278	0.011	0.057

Notes: The omitted category corresponds to households where the head of the household has a high school diploma or less and is less than 35 years old, and where there is no children and household income is [\$100,000; \$150,000).