Belt and Suspenders and More: The Incremental Impact of Energy Efficiency Subsidies in the Presence of Existing Policy Instruments

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We investigate the incremental impact of energy efficiency rebates in the context of regulatory and information mandates by evaluating the State Energy Efficient Appliance Rebate Program. We show that 70% of consumers claiming a rebate were inframarginal and an additional 15%-20% of consumers simply delayed their purchases by a few weeks. We also find evidence that rebates led consumers to upgrade toward higher quality, but less energy-efficient models. Overall the impact of the program on long-term energy demand is likely to be small. Our measures of cost-effectiveness are an order of magnitude higher than estimates for other energy efficiency programs.

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I. Introduction

Over the past 40 years, policymakers have implemented an array of instruments – regulatory mandates, information campaigns, and technology subsidies – to promote energy efficiency. For energy-consuming durables, it is quite common that an

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individual consumer purchases a product designed under an energy efficiency standard, marketed subject to government-required information disclosure, and eligible for a subsidy. For example, an individual buying a Toyota Prius in 2006 contributed to Toyota's compliance with Department of Transportation Corporate Average Fuel Economy standards, likely learned of the fuel savings of the hybrid from the vehicle's Environmental Protection Agency (EPA) fuel economy label, and benefited from a Federal tax credit administered by the Internal Revenue Service. Likewise, large appliances are subject to Federal minimum energy efficiency standards, information disclosure on typical annual energy usage, and occasionally various kinds of local, state, and Federal rebates and tax credits. Given scarce resources and the existing overlay of policy instruments, what is the incremental impact of energy efficiency subsidies on energy outcomes?

To address this question, we evaluate the State Energy Efficient Appliance Rebate Program (SEEARP) implemented through the 2009 American Recovery and Reinvestment Act. The program, informally known as the "Cash for Appliances" (C4A) program, disbursed to state governments $300 million proportional to each state's share of the national population. In order to receive their respective allocations, state governments had to design and secure approval of their rebate program from the Department of Energy. The 2005 law authorizing SEEARP established several criteria for state programs, such as requiring that qualifying appliances met or exceeded the ENERGY STAR (ES) certification. States had substantial discretion regarding other program design parameters, such as the choice of eligible appliance types, rebate amounts, the use of advance reservation systems, online rebate claims, program start dates, etc. Upon taking delivery of an eligible appliance, a household could then apply for the rebate so long as the purchase occurred when its state program was open.

Using transaction-level data from a large national retailer, we first estimate the energy savings, based on manufacturers' reported expected energy use, for the three major appliance categories that attracted the most rebate funds: refrigerators, clothes washers, and dishwashers. We find that the program did not have a meaningful impact on aggregate electricity consumption. For example, across an array of specifications, the highest reduction in expected refrigerator energy use under the rebate programs was a statistically significant, but economically minuscule 0.35% (or less than 2 kilowatt-hours per year). Our preferred estimator suggests that the rebate programs had very little impact on long-term energy demand for all three appliance categories. We then investigate the mechanisms explaining these results. We quantify the behavioral response to rebates along three dimensions: (1) substitution from non-eligible products toward eligible products, (2) intertemporal substitution, and (3) upgrading toward higher quality products. We find that about 70% of consumers that claimed a rebate would have bought an ES-rated appliance during the period of the C4A program in the absence of the rebates. An additional 15% to 20% of consumers changed the timing of their purchase of an ES-rated appliance by a few weeks. Altogether, about 90% of consumers that claimed a rebates do not contribute to a long-term reduction in energy demand. Finally, we also find that rebates led consumers to upgrade toward higher quality, but less energy-efficient models. Upgrading is partly driven by the design of the rebate program – in particular the eligibility premised on the ES program, which is in turn a function of minimum energy efficiency standards. The minimum efficiency standards vary by size and style for a given category of appliance, which results in ES certification and hence SEEARP eligibility varying as a function of product attributes. For example, a consumer may buy an ES-certified refrigerator with a bottom-mounted freezer and through-the-door ice service that requires more electricity annually than a non-certified top-mounted freezer with an icemaker but without through-the-door ice service. In the present case, we show that holding utilization constant, the interaction between subsidies and minimum energy efficiency standards, a particular case of attribute-based regulation (Ito and Sallee, 2014), induces perverse upgrading. Finally, we also find some evidence that the generous rebates may have induced an income effect that led consumers to upgrade toward higher quality, but larger size models.

The design and implementation of the C4A program facilitate our empirical analysis. First, the Federal government allocated funds to the states on a per capita basis; thus the "size" of this stimulus program, at the state level, is exogenous of the state's economic condition in 2009 and 2010. Our identification strategy is similar to that of other papers that have estimated the economic impacts of Recovery Act programs implemented through formula-based allocations (e.g., Wilson (2012) and Chodorow-Reich, Feiveson, Liscow, and Woolston (2012)). Second, the state discretion in program design resulted in significant heterogeneity in terms of start dates, eligible appliance categories, rebate amounts, and other characteristics. We combine this rich source of variation with unique micro-data on individual appliance sales aggregated to the week-state level. Our main estimators rely on a difference-in-differences strategy and accounts for state-year unobservables. We also provide extensive robustness tests that show that pre-existing time trends and sorting into the program are not a threat to the internal validity of our main estimates.

Our results can inform the emerging empirical literature on the use of multiple policy instruments to address a single societal objective. Several recent papers have highlighted the potential interactive impacts of overlapping greenhouse gas mitigation policies, such as a cap-and-trade program and renewable portfolio standards (Goulder and Stavins, 2011; Levinson, 2012). In the context of biofuels policy, scholars have also illustrated the potential welfare losses and unintentional incentives associated with the historically complicated overlay of policies to support ethanol, including the ethanol blenders tax credit, the Clean Air Act oxygenate mandate, an import tariff, and some state-specific ethanol mandates (de Gorter and Just, 2010). While this previous work focuses on multiple instruments faced by firms, and in many cases the unique impacts of policies overlaying cap-and-trade, our research highlights the impact of a fiscal instrument (appliance rebates) in the presence of information and minimum standards all focused on individual consumer behavior.

In terms of energy demand policies, subsidies are the marginal policy lever on the extensive margin. As a result, state governments and utilities currently rely heavily on subsidies and are likely to further increase their use in the future. In October 2015, there were nearly 500 active utility rebate programs for ES-rated clothes washers, dishwashers, and refrigerators according to www.energystar.gov. In 2010, utility consumer-funded energy efficiency programs amounted to about $5 billion and such expenditures could double by 2025 (Barbose, Goldda, Hoffa, and Billingsley, 2013). Appliance rebates have traditionally been a significant component of such programs.

At the federal level, appliance rebate programs may also play an important role in the implementation of the EPA's Clean Power Plan. In its regulatory impact analysis, the EPA notes that rebates for high-efficiency appliances could represent one approach for reducing power sector emissions (EPA, 2014).

Our findings offer a cautionary tale to federal, state, and local program managers designing energy efficiency programs to promote cost-effectiveness and maximize their net social benefit. We show that for C4A, the cost per kilowatt-hour saved is on the order of about \$0.21 to \$1.10, depending on assumptions and appliance category. The low end of this range is four times the average cost-effectiveness of utility-sponsored energy efficiency programs (Arimura, Li, Newell, and Palmer, 2012). The fact that we find a very large proportion of inframarginal participants first explains this result. Our estimates of "freeriders" are similar to Boomhower and Davis (2014), who find that for a large-scale rebate program in Mexico for energy-efficient air conditioners (ACs) and refrigerators, more that 65% of the participants would have purchased a similar appliance in the absence of rebates. Our estimates are also on par with other recent studies in the United States. For instance, Alberini, Gans, and Towe (2014) find evidence that rebate programs in Maryland for energy-efficient heat pumps had a proportion of inframarginal participants ranging from 50% to 89%.

We also find that short-term intertemporal substitution considerably reduces the cost-effectiveness of the C4A program. Several recent papers have also looked at the importance of intertemporal substitution for a similar Recovery Act program: Cash for Clunkers.[1] Mian and Sufi (2012); Li, Linn, and Spiller (2013); and Hoekstra, Puller, and West (2014) all found significant intertemporal shifting under Cash for Clunkers as a large share of the participants took advantage of the rebates by pulling forward their car purchase decision by a few months. For a different type of subsidy, Sallee (2011) also found that consumers shifted the timing of the purchase of the Toyota Prius to maximize their tax benefits. We find some evidence, for one out of three of the appliance categories that we study, that consumers pulled forward their appliance purchase decision by a few months. However, most consumers that

[1]Technically, Cash for Clunkers was not part of the American Recovery and Reinvestment Act. Nonetheless, Cash for Clunkers was intended to stimulate investment in new, energy-efficient vehicles and thus was similar to various Recovery Act clean energy programs (Aldy, 2013).

substituted over time appear to have simply delayed their purchases by a few weeks until the start of their state's C4A program.

Our results pertaining to upgrading shows an important unintended consequence of using the ES certification requirement as a rebate eligibility criterion under SEEARP. The fact that the ES certification relies on minimum efficiency standards – an attribute-based regulation – implies that rebates may act as implicit subsidies for non-energy attributes, such as size. These results are related, but differ from the concept of the rebound effect (Gillingham, Rapson, and Wagner, 2014), which has also been found to be important for other energy-efficiency subsidy programs. Davis (2008) shows that subsidizing energy-efficient clothes washers induce people to use them more. Davis, Fuchs, and Gertler (2014) find that the large-scale rebate program in Mexico may have actually increased (ACs) or led to modest reduction (refrigerators) in electricity consumption. They argue that the fact that consumers may have replaced an old non-functioning appliance, have been prone to a rebound effect, or have upgraded to an appliance with more features could explain these results. Our contribution to this debate is to show that upgrading is present, likely to be economically important, and caused by the design of the eligibility criterion combined with an income effect. Our policy simulations show that if SEEARP were to rely on eligibility criteria based on percentiles of energy use alone, the cost-effectiveness of the program could be significantly enhanced.

We should also note that the constraints on the subsidy instrument could affect the extent to which consumers upgrade on product quality. In our context, the fact that higher-quality appliances along multiple dimensions are correlated with the ES certification, suggests that consumers are not constrained to move along the quality dimension in order to claim the subsidy. In contrast, the Cash for Clunkers program imposed a requirement on the fuel economy of the new car purchased that may have limited consumers' vehicle options. In Hoekstra, Puller, and West (2014)'s assessment, they found that the Cash for Clunkers subsidy program induced consumers to purchase cheaper cars than they would have otherwise bought. Again, this illustrates the importance of evaluating the subsidy instrument in light of its design parameters, especially as they are correlated with existing policies.

Finally, our findings add to the growing body of evidence (e.g., Boomhower and Davis (2014); Alberini, Gans, and Towe (2014); and Fowlie, Greenstone, and Wolfram (2015)) showing that the econometric estimates of the expected energy use reductions in energy efficiency programs are much less favorable than engineering estimates. This reinforces the role of using credible research designs to estimate the returns to energy efficiency programs (Allcott and Greenstone, 2012).

The remainder of the paper proceeds as follows. Section 2 describes the appliance efficiency policy landscape. Section 3 presents a framework for evaluating multiple, overlapping energy efficiency policy instruments. Section 4 presents the data. Section 5 presents our empirical strategy. Section 6 describes our results. Section 7 investigates whether the program induces an income effect and upgrading. Section 8 presents a policy analysis of the cost-effectiveness of C4A and counterfactual policy scenarios. Conclusions follow.

II. Appliance Efficiency Policy Landscape

Since the oil shocks of the 1970s, local, state, and federal governments have employed an array of policy instruments to promote the energy efficiency of appliances (and energy efficiency more generally). The 1975 Energy Policy and Conservation Act established a national energy conservation program, including EnergyGuide labels for residential appliances. These labels provide a common set of information on all appliances within a product category, including expected annual energy use and operating cost and a comparison to the range of operating costs of similar models. The Federal Trade Commission (FTC) implements the EnergyGuide label program and undertakes occasional revisions of the program, including expansion to new products, updates of energy use and cost information, and modifications of the label format.

The 1987 National Appliance Energy Conservation Act created minimum efficiency standards for appliances. The act established the initial Federal standards and delegated authority to the Department of Energy (DOE) to administer and periodically update the standards. These national standards preempt state efficiency standards. For example, refrigerators have been subject to California standards promulgated in 1978, 1980, and 1987 and national standards promulgated in 1990, 1993, and 2001.

The Environmental Protection Agency (EPA) launched in 1992 the ENERGY STAR (ES) program, a voluntary initiative for appliance manufacturers (and others) to demonstrate the energy efficiency of their products. An appliance model can earn the ES label, a simple brand-like logo, if its efficiency exceeds by a certain percentage the minimum standard for that appliance category. For most appliances, the certification is binary, i.e., a product either meets the requirement, or does not.[2] A number of appliance rebate programs (including the SEEARP discussed below) employ the ES certification requirement as the basis for appliance eligibility.

State and local governments as well as utilities also implement a wide array of efficiency policies. These include tax credits, tax deductions, and rebates;[3] mandates to utilities to improve the efficiency and conservation by its customer base through so-called Energy Efficiency Resource Standards;[4] rebates to customers for reductions in electricity consumption (Ito, 2014); and norm-motivated information provision (Allcott, 2011).

The Energy Policy Act of 2005 created the State Energy Efficient Appliance Rebate Program (SEEARP) to provide guidance in the design of and federal support for state rebate programs. In 2009, the American Recovery and Reinvestment Act made the initial appropriation to SEEARP, in what became informally known as "Cash for Appliances."

The 2005 law stipulates that SEEARP 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 1 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

[2]The EPA has recently experimented with a multi-tiered system.

[3]Examples of state and local governments (and quasi-governmental entities) providing ES-based appliance rebates and tax benefits include the following. The New Jersey Office of Clean Energy offers rebates for ES-certified refrigerators and clothes washers. Oregon Trust, a non-profit created by the Oregon state legislature and funded through utility-assessed consumer charges, implements rebates for ES-certified clothes washers, refrigerators, and freezers. The city of Fort Collins (Colorado) offers clothes washer and dishwasher rebates based on ES ratings. The state of Missouri implements a "Show-Me Green Sales Tax Holiday" that exempts ES-rated appliances from the state sales tax for one week each year. As noted above, there are also hundreds of utility operated rebate programs for energy-efficient appliances.

[4]American Council for an Energy-Efficient Economy (2012) notes that 24 states representing approximately two-thirds of U.S. electricity sales have implemented long-term energy efficiency resource standards.

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 50 unique state programs 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%-15% of sales prices for refrigerators, dishwashers, and clothes washers, and these varied greatly among states. 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)).

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. According to Google Trends, consumers first started to search for the program in June 2009. In August 2009, search queries rapidly increased and appear to be correlated with ABC News's national story comparing the program with Cash for Clunkers (August 20, 2009). 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, with some programs open less than a week (Iowa), while Alaska's program lasted 91 weeks. Some states had "1-day programs" that reflect the fact that all appliance rebates had been reserved through advanced reservation systems by the end of the first day. Actual purchase dates occurred over longer periods of time. Programs in Illinois, Massachusetts, and Texas reopened for a second phase when some reserved rebates went unclaimed. In addition, Arizona, California, Florida, Georgia, Michigan, Minnesota, Montana, North Carolina, New Jersey, Ohio, Oregon, Vermont, and Washington offered the rebates in mulitple phases, where the program closed temporarily between phases.

III. The Simple Economics of Energy Efficiency Rebates

The previous section describes the extensive, overlapping, and complicated set of policy instruments focused on residential energy efficiency. We now present a simple economic framework for evaluating this policy space, with a focus on minimum efficiency standards, certification, and rebates for energy-efficient appliances. This will motivate our empirical analysis of the incremental impact of C4A.

Consider that energy efficiency is simply measured as the absolute amount of energy saved. The Federal minimum energy efficiency standards and ES certification are examples of attribute-based regulation (Ito and Sallee, 2014) where the maximum amount of energy a given appliance model can consume is a function of size and other attributes. In the size/energy efficiency space, a minimum efficiency standard (MEF) and ES requirement can be represented by two downward sloping parallel lines (Figure 1), where only bundles above the minimum standard are allowed to be present on the market, and certified products are all bundles above the ES requirement. Consumers can spend their disposable income on appliances or other goods. When purchasing an appliance, each consumer values both size and efficiency. A consumer's optimal bundle thus corresponds to the point where the indifference curve (U) is tangent to the budget constraint (W). Regulations requiring information disclosure about energy efficiency, such as EnergyGuide, aim to induce movements along the efficiency dimension. Minimum standards, the ES certification, and subsidies, however, may induce movements in both the size and efficiency dimensions. Their impact on energy savings is thus ambiguous.

To illustrate, consider Panel A of Figure 1, which depicts the case where the appliance model purchased in equilibrium just meets the ES requirement, as is often the case in several markets (Houde, 2014). Offering a rebate R for purchasing an ES product may first induce the so-called freerider problem, a well-known source of economic inefficiency in this context (Joskow and Marron, 1992). Because program administrators cannot restrict the access to a rebate program, consumers that would have purchased an ES product absent rebates can simply claim the rebate, make the exact same purchase, and spend the windfall income on other goods. It is also possible that the rebate induces a small income effect, which can be represented by an outward movement of the budget constraint. As a result, a consumer may purchase a more efficient, but also larger appliance (Panel B). Depending on consumers' preferences over size and efficiency, it is possible that the income effect induces the purchase of a larger (smaller), but less (more) efficient appliance. Only in the case where firms offer products that bunch exclusively at the ES requirement will the income effect unambiguously lead to more efficient purchases (Panel C).

Even for consumers who could not afford ES products in the first place, offering a rebate R does not ensure that a more efficient appliance will be purchased. Panel D illustrates the case where the rebate leads to the adoption of a more efficient and larger appliance. It is, however, easy to construct an example (Panel E) where the rebate has a perverse effect and leads to the adoption of a less efficient product. In this example, this perverse effect can be ruled out only if the minimum standard and ES requirement are set independently of size and solely lie in the energy efficiency space (Panel F).[5] More generally, rebates could yield perverse outcomes when energy efficiency and the attributes used to set the regulation are inversely correlated. In such case, rebates become implicit subsidies for specific attributes other than energy efficiency.

[5]Ito and Sallee (2014) show that the optimal externality-correcting tax/subsidy can be adjusted to account for the existence of attribute-based standards. Gillingham (2013) discuss similar issues in the design of a feebate policy in the presence of a fuel economy standard.

IV. Data and Preliminary Evidence

The DOE required state program administrators to collect detailed data on their programs. The DOE compiled these data and provided us a dataset that includes all rebate claims, approximately 1.8 million made in the 50 U.S. states. For each rebate claim, we observe the characteristics of the products purchased, such as the manufacturer model number, brand, and price paid. In addition, we observe the amount of the rebate, the dates of the purchase and rebate application, and zip code of the household. Some states also collected information about the appliance that was replaced, whether the old appliance was hauled away, and the retailer where the purchase was made.

One limitation of the DOE data is that they only contain information about C4A participants and do not provide information to construct a valid counterfactual of participants' behavior in the absence of rebates. Thus, for our primary analyses, we rely on transaction-level data that were provided by a large retailer with non-negligible market shares (>5%) in the appliance market. The retailer has brick-and-mortar stores in every state and an online store. The data cover the period from January 2008 to November 2012. For each transaction, we observe the manufacturer model number of the product purchased, the location of the store, the price paid, taxes, and a unique household identifier. For a large number of households, consumer-specific demographic data, including income, education level, housing type, age of head of the household, political orientation, home ownership, and family size, are matched to appliance purchase data by household identifier. The demographic data are collected by a third party (Acxiom) and the match is performed by the retailer. About half the transactions in our dataset (ranging over 44%-49% across the three appliance categories we focus on) include matched demographic information. We do not observe the exact address of each household, but we know the location of the store where the household purchased its appliance(s); we assume that households lived in the same state where they made their purchase(s). In addition to the prices paid, we also observe the manufacturers' suggested retail prices. The retailer has a national price policy, which store managers tend to follow closely. Retail prices are thus set at the national level with little idiosyncratic variation across stores. For each appliance, we observe attribute information such as expected electricity consumption, size, the ES certification, and numerous other features.

A possible limitation of our analysis is that the retailer might not be fully representative of the appliance market. We can address this concern using the DOE data, which recorded the retailer where each participant made a purchase.[6] In the Online Appendix, Table A.1 compares prices, rebates claimed, the expected energy consumption and the size of the products purchased under C4A at our retailer versus all other retailers observed in the DOE data. We found that on average prices tend to be slightly higher, especially for refrigerators, at our retailer relative to other retailers. Except for refrigerators, there are no statistically significant differences in size. For expected energy consumption, there is no clear pattern. Overall, we found that the differences among retailers to be modest. We also examine whether the consumers who shop at our retailer are representative of the consumers participating more broadly in C4A. We map the zip code of delivered appliances for C4A rebate claimants for our retailer and for all other retailers in those states that report retailer information to zip code socioeconomic and demographic data from the 2010 Census. Table A.2 compares median household income, average age, average household size, as well as population shares by gender, ethnicity, homeownership, educational attainment, and poverty line status. While the differences in means for the sociodemographic characteristics of shoppers at our retailer to those of shoppers at other retailers are statistically different for all but one measure (given the large sample size), these differences in magnitudes are not economically meaningful; for nine of the eleven measures, the differences in magnitudes are less than 2%. We believe that these provide good support for external validity.

We collected information about state programs – including appliances covered, rebate amount, eligibility criteria, and start and end dates – from each state's program website. We also conducted interviews with program administrators in several states to learn more about the implementation of their programs.

Table 2 provides summary statistics of the program. Refrigerators, clothes washers, and dishwashers were the most common products covered by the programs. These

[6] Not all states recorded this information.

three appliances attracted 85% of the claims, and 65% of the funds distributed nationwide. For our analysis, we focus on in-store purchases of these three appliances. Kansas, Oregon, Alaska, and Iowa offered the most generous rebates. Rebate amounts in other states were, nevertheless, economically significant.[7]

The ES program covers all three appliance categories evaluated in our study. Over January-June 2009, national ES market shares were 46% for refrigerators, 53% for clothes washers, and 75% for dishwashers (Table 3). Figure 2 plots the first evidence of the impact of rebates on sales, manufacturers' reported appliance energy use, and ES market shares. For ES market shares, all certified appliance models as of January 2010 are included in the market shares. For dishwashers, the certification requirement changed in August 2009, July 2011, and January 2012. For clothes washers, the certification requirement changed in July 2009 and January 2011. For refrigerators, the requirement did not change during the 2009-2012 time period.

For refrigerators and clothes washers, we observe short-lived increases in ES market shares when most rebate programs were enacted. We observe similar increases in sales for all three appliance categories, which further suggests that intertemporal substitution was important. Finally, as a preview of our main results – the correlation between the number of active programs and appliance energy use appears to be weak, especially for dishwashers and refrigerators.

V. Empirical Strategy

We model the decision to replace an appliance as a two-step decision where consumers first decide when to replace and then what new model to purchase. The market for an appliance consists of a population of consumers that can make a purchase at different points in time t over a time horizon starting at $t = 0$ and ending at $t = T$. The market share of a particular product j over the entire time horizon T is then the (weighted) sum of the market shares at different times t. In particular, if we define the market share of product j over T by $\mathcal{M}_j$, by the law of iterated

[7]Figure A.1 in the Appendix plots the average price paid along with the average rebate amount claimed across states for these different appliances.

expectations we have:

$$\mathcal{M}_j = \sum_t \sigma_{j|t}(\Omega_t) \cdot \delta_t(\mathcal{I}_t), \tag{1}$$

where $\sigma_{j|t}(\Omega_t)$ represents the market share of product j conditional on the fact that consumers make a purchase at time t, and $\delta_t(\mathcal{I}_t)$ is the fraction of consumers that decide to replace their appliance at time t. Ω_t represents the characteristics of the products and consumers present on the market at time t. $\mathcal{I}_t$ represents the information set and the characteristics that consumers have at t, which both determine whether consumers make a purchase at this particular time. This may include expectations about current and future prices, product availability, expected remaining lifetime of their appliance, the cost of going to the store, and, crucially, rebates.

Because rebates enter both Ω_t and $\mathcal{I}_t$, they impact decisions on two margins. First, consumers who want to take advantage of a rebate program can do so by waiting for the start of the program or pulling forward their decision to replace their appliance during the program window. We label these consumers the *movers*. Second, when the rebate program is active, consumers can substitute among products. We define as *switchers* the consumers that substitute away from non-rebate-eligible products toward eligible products. *Non-switchers* are the consumers that claim a rebate, although they would have purchased an eligible product even in the absence of a rebate program. Some of these consumers may take advantage of rebates to substitute among eligible products and upgrade toward higher quality models. Rebates lead to expected energy savings via two mechanisms. First, consumers who pull forward their purchases accelerate the replacement of older and less efficient appliances. Note that consumers waiting for the start of a program have the opposite effect and contribute to an overall increase in energy demand by holding on to their old appliances longer.[8] Second, consumers may substitute toward more energy-efficient products.

In this framework, the expected energy use of the stock of appliances purchased

[8]In the present context, the C4A program was first mentioned in the new media in the summer of 2009 and most programs started less than a year after. Thus, the effect of delayed replacement is likely limited.

over a time horizon T is given by:

$$E[e|R] = \sum_j \mathcal{M}_j e_j = \sum_j \sum_{t=0}^{T} \sigma_{j|t}(\Omega_j) \cdot \delta_t(\mathcal{I}_t) \cdot e_j = \sum_{t=0}^{T} \delta_t(\mathcal{I}_t) \cdot \bar{e}_t, \tag{2}$$

where e_j is the energy use of product j, and $\sum_j \sigma_{j|t}(\Omega_t) \cdot e_j = \bar{e}_t$ is the energy use of all products purchased at time t, and the rebate amount R enters Ω_t and $\mathcal{I}_t$, for each t. Throughout the paper, the energy use of an appliance model j, i.e., e_j, is the expected annual energy use reported by appliance manufacturers and that appears on the EnergyGuide label. Our analysis does not consider how a particular household idiosyncratically uses energy-intensive durables and thus abstracts from potential rebound effects.

The energy savings associated with a program offering a rebate amount r is the quantity $E[e|R = r] - E[e|R = 0]$, where $E[e|R = r]$ is the expected energy use of all appliances purchased over the entire time horizon for which rebates impacted consumers' decisions, and $E[e|R = 0]$ is the counterfactual quantity where rebates do not impact decisions. The main challenge in estimating the quantity $E[e|R = r]$ is to define the appropriate time horizon over which a rebate program had an impact. To obtain an internally valid estimate of the quantity $E[e|R = r] - E[e|R = 0]$, we need to estimate $E[e|R = r]$ over a time horizon where the distribution of consumer characteristics is exactly the same as for $E[e|R = 0]$.

We distinguish among four distinct time periods of a rebate program: the pre-announcement period, the period between the announcement and the start of a rebate program (the pre-rebate period), the rebate period, and the post-rebate period. Rebates enter consumers' information set, $\mathcal{I}_t$, following the announcement of the program, which leads consumers to substitute intertemporally. The quantity $E[e|R = r]$ needs to be estimated from the beginning of the pre-rebate period to the end of the post-rebate period. The pre-rebate period should begin at the exact time the consumer who first learned about rebates decided to wait for the start of the program. Presumably, this may have happened following the announcement of the program. Similarly, the end of the post-rebate period should be defined as the purchase date that the last consumer who decided to pull forward his purchase would have chosen if rebates had not been offered. These two consumers are not observed. Our strategy to define the beginning of the pre-rebate period and the end of the post-rebate period will then consist of conducting sensitivity analysis. If we were to define the pre-period and post-period accurately, the overall size of the market over which $E[e|R=r]$ is estimated should remain constant because an increase in sales in the rebate period should be canceled by the decreases in the pre-rebate and post-rebate periods.[9] Therefore, the impact of a rebate program on sales over the entire time horizon for which rebates impacted consumers should be zero.

Our empirical strategy consists of looking at three outcome variables: total sales, manufacturers' reported appliance energy use, and ES market shares. The effect of rebates on total sales, $\frac{\partial \delta_t(\mathcal{I}_t)}{\partial R}$, informs us about the extent of the intertemporal substitution and how long the effects of the program lasted. The effect of rebates on expected appliance energy use, $\frac{\partial \bar{e}_t}{\partial R}$, determines the change in energy use of the stock of appliances purchased at the time rebates impacted consumers. Finally, looking at ES market shares allows us to distintguish movers from switchers, and quantifying the number of program participants that were truly marginal to the rebate programs. In Section VII, we also use the estimates for ES market shares to determine the magnitude of the quality effects.

To determine the causal effect of rebates on each of these three outcome variables, we rely on difference-in-differences (DD) estimators that exploit variation across states in program coverage for a specific appliance category, timing of implementation, and rebate amount. To illustrate, the effect of rebates on weekly sales, for a given appliance category, in state s is estimated with the following model:

$$log(sales_{s,t}) = \alpha_{sy} + \gamma_t + \sum_{l=t}^{T} \rho_l \cdot DPeriod_{s,lt} \cdot R_s + \epsilon_{s,t} \tag{3}$$

where $DPeriod_{s,lt}$ is a dummy variable that takes the value one if week t falls in the period l of a rebate program. In all our regressions, we will omit the dummy variable that identifies the pre-announcement period. The rebate amount offered in state s is

[9] This is only true if we assume that the rebate program induces consumers to replace an existing appliance. Note that a dozen states required the recycling of an existing appliance in order to receive a rebate for a new appliance.

given by R_s, and corresponds to the rebate amount reported on the program websites. We use the same specification for the two other outcome variables: expected appliance energy use and ES market shares, which are both aggregated at the state-week level.

In the base specification, we assume that the marginal impact of rebates is the same across all states. We do not account for differences in eligibility criteria, mechanisms to claim rebates, or other factors that may have impacted the behavioral response to the rebates. We address program heterogeneity later. For programs that provided ad valorem rebates, we compute an average rebate amount by multiplying the percentage incentive by the average price specific to each appliance category. By interacting $DPeriod_{s,lt}$ and R_s, ρ_l measures the effect of a rebate in a particular period of the program. For instance, we can estimate the impact of rebates in the first week where rebates are offered, the week just before the start, and the week just after the end. We can also define $DPeriod_{s,lt}$ to cover the whole rebate period, and include some weeks in the pre-rebate and post-rebate periods.

The DD estimator is implemented by adding two sets of fixed effects: α_{sy} and γ_t, which are respectively state-year and week-year fixed effects. The week-year fixed effects take out the effects of promotions and advertising campaigns implemented by the retailer, seasonality, and other shocks that impact the market of each appliance type. The fact that the retailer has a national price policy implies that the week-year fixed effects capture the effect of the retailer's national pricing strategy. The dummy variables $DPeriod_{s,lt}$ are not perfectly correlated with week-year fixed effects because only a subset of states implemented rebate programs for a particular appliance category and the timing of the programs varied across states. The state-year fixed effects control for time varying state-specific unobservables that may be correlated with the design and implementation of rebate programs. They also control for rebate programs offered by state governments and/or energy utilities, which may vary from year to year and have been found to impact the ES market shares for some appliances (Datta and Gulati, 2014). With state-year fixed effects, the coefficients on $DPeriod_{s,lt}$ are identified using variation in the timing of implementation of each state rebate program within the calendar year (see Figure A.2 in the Online Appendix). We are thus comparing weeks in a given year where a rebate program was active to weeks, in the same year, where the program was inactive. For the few states where the rebate programs covered the entire 2011 year (e.g., Alaska), identification is coming from variation in program coverage within the years 2010 and 2012 only.

The main threat to internal validity in our empirical strategy is that the features of state rebate programs could be correlated with the impacts of the Great Recession or other time-varying shocks in each state. Previous Recovery Act program evaluations have used allocation formulas exogenous to economic conditions and state fixed effects and year fixed effects to address such concerns (Wilson (2012) and Chodorow-Reich, Feiveson, Liscow, and Woolston (2012)). In our work, we use of state-year fixed effects, which provide even further controls for possible unobserved economic factors influencing our results, and exploits the fact that the allocation of funds was predetermined by the formula set in the Energy Policy Act of 2005. States had the sovereignty to determine several other features of their programs, which could have been influenced by the local economic conditions at that time. Through our interviews with the various program administrators, however, we concluded that it is unlikely that the program features adopted in each state were systematically correlated with the Great Recession. For all state program administrators, C4A represented their first experience with a large-scale rebate program. Moreover, there was no precedent at the federal level. We argue that the inexperience of the state program administrators, the absence of past examples, and the difficulty to forecast the effects of the recession as it was unfolding make the features of each state program idiosyncratic. The relative timing of a state's initial plan submission, DOE feedback, negotiation over modifications, and final plan approval also appeared to be idiosyncratic. In addition, we present regressions in the Online Appendix where we regress program features on state unemployment rates in 2009 as well as the change in state unemployment rates over 2008-2009 (Tables A.11-A.14). The unemployment rate variables do not statistically explain the variation in most of the fourteen program design characteristics, including rebate amounts. States with higher unemployment rates in 2009 and had experienced larger increases in unemployment rates over 2008-2009 started their programs slightly earlier, with a one standard deviation increase in either unemployment rate measure associated with a start date of about 12 days earlier.

VI. Results

We first present the main results graphically. Figure 3 presents non-parametric estimates of the dynamic effect of rebates on sales, appliance energy use, and ES market shares. To construct these estimates, each outcome variable was first normalized with a regression with state-year and week-year fixed effects. The residuals of this regression, which we refer as the outcome variable normalized, were then regressed on flexible regression splines counting the number of weeks since the start of a rebate program. Each panel plots the estimated splines–smoothed time-varying estimates of the effect of rebates as a function of time.

The first row of Figure 3 shows the effect of rebates on sales for all three appliance categories. We observe a very large, but short-lived impact concentrated in the first two weeks after the start of the rebate programs. The estimates show that this increase is largely driven by consumers delaying their purchase decisions by a few weeks. We observe statistically significant reductions in sales beginning approximately one to two months before the start of the programs. In the Online Appendix (Figure A.3), we show that the impact on sales in the post-rebate period is modest and not statistically significant for all three appliance categories. The regression results from equation 3 (Table A.3) are consistent with the graphical evidence. For refrigerators, a \$100 rebate leads to an increase in sales of 14% in the first week of a program, relative to the pre-announcement period, but this increase is offset by statistically significant reductions that range from 2.2% to 3.9% up to nine weeks preceding the start of the program. For clothes washers, a \$100 rebate leads to a 10% increase in sales in the first week, which is offset by a decrease of 4.9% in the week just prior. The results are qualitatively similar for dishwashers. We detect a statistically significant increase in sales only in the first week of a rebate program, but decreases in the pre-rebate period are found up to nine weeks before the start of a program. In the post-rebate period, the estimates are not statistically significant for all three appliance categories, except for dishwashers, where we detect a decrease in sales several weeks (more than 10) after the program ended. Our results contrast with the findings of Mian and Sufi (2012) who found that the Cash for Clunkers program led to a significant decrease in sales in the post-rebate period. In the present case, we also find evidence of an important short-term intertemporal substitution, but most consumers waited a few weeks to replace their current appliance instead of pulling forward their purchase decisions.

Table 4 further quantifies the importance of short-term intertemporal substitution in the present context. If we estimate the effect of rebates on sales during the whole rebate period, we find increases, relative to the pre-announcement period, of 10%, 6.7%, and 9.6% for refrigerators, clothes washers, and dishwashers, respectively. If we estimate the impact during the rebate period plus two months of the pre-rebate period and two weeks of the post-rebate period, the increases in sales range from only 1% to 2%. Once we include more time in the pre-rebate and post-rebate periods, for instance three months before and after the start of the programs, the effects quickly disappear. This suggests that most consumers who participated in the rebate programs would have still replaced their appliances in the year that the rebates were offered. The overall stimulus effect of the program was then modest: it leveraged little incremental private investment, although it did provide a means for transferring resources to households who participated in the program. It is beyond the scope of this paper to assess the marginal impact of these transfers on non-appliance consumption and subsequent measures of economic activity.

Turning to the effect of rebates on expected appliance energy use, the graphical results (second row, Figure 3) mirror the effect on sales. The appliances purchased during the rebate programs have lower energy use, on average, but statistically significant effects are only found in the first week of the programs. For dishwashers, the rebates had very small effects on energy use, no greater than 1 kWh/yr savings even in the first week of the program. For refrigerators and clothes washers, there is a more substantial short-term effect, on the order of 5-7 kWh/yr, but this effect rapidly fades off. Table 4 (section I.) shows that over the entire rebate period, the reduction for refrigerator is statistically significant but economically small (about 0.35%, or less than 2 kWh/year). For clothes washers, there is a statistically significant reduction of 1.7%, and for dishwashers the estimate is close to zero and not statistically significant. Once we include the pre-rebate and post-rebate periods, the estimates converge to zero and are not statistically significant for all three appliance categories.

The estimates for ES market shares show that most program participants did not substitute from non-ES to ES models, but simply substitute the timing of their purchase of an ES model. Although we find large increases in ES market shares in the first week of the programs (third row, Figure 3), we find no effect once we account for the pre-rebate and post-rebate periods (Table 4, sections II. and III.).

A. Robustness Tests

Our empirical strategy exploits variations across time and regions to isolate the effects of rebates. The time fixed effects are then crucial for controlling the effects of the retailer's pricing and advertising strategies. Although the retailer employed a national pricing strategy, one concern is that store managers in some states systematically deviated from the national strategy such that promotions and marketing efforts are correlated with the implementation of the rebate programs. Our empirical strategy cannot rule out these unobservables. We, however, find that the week-year fixed effects do well in controlling for the retailer's strategies. In the Appendix (Figure A.4), we compare the ES market shares with normalized market shares, which are the residuals of a regression of market shares on week-year and state fixed effects. If the week-year fixed effects were to capture most of the temporal variations that are not attributable to rebates, we should expect that the normalized market shares in states that did not offer rebates for a given appliance category would be tightly concentrated around zero. This is exactly what we observe.

The Online Appendix presents alternative specifications that further validate the difference-in-differences strategy. First, we use the micro-data directly and control for demographics. Adding demographics allows us to account for changes in the composition of consumers going to the retailer's stores caused by the recession, which program administrators may have forecasted. For instance, program administrators in states where low-income households were hard hit by the recession may have decided to offer more generous rebates to attract these consumers to appliance stores. By controlling for demographics, income for instance, we are estimating the effect of rebates holding household composition fixed. To implement this estimator, we add to Equation 3 a vector of household-specific demographics that includes income, education, age of the head of the household, family size, political orientation, type of housing, and a home ownership dummy. Table A.4 shows the results where the dependent variable is the log of the expected energy use of the appliance purchased by each household. Overall, the results are similar to the main results relying on week-state averages. This suggests that changes in household composition are not an important source of endogeneity.

Second, Table A.5 presents results where we include state-specific pre-announcement linear time trends in addition of the state-year fixed effects. This has little impact on the estimates. In general, we find little evidence that time-varying unobservables at the state level are an important concern in this context. As shown on Table A.6, using state fixed effects, instead of state-year fixed effects, leads to similar results.

In the last specification test that we present (Table A.7), we exclude five states from the analysis: Florida, Iowa, Illinois, North Carolina, and Oregon. Iowa was excluded because the DOE data revealed that several claims differed drastically from the program guidelines. We found 375 instances of rebate claims covering 90% of the appliance cost and exceeding $1,000. Other states were excluded because they offered ad valorem rebates. For these states, using the average rebate amount then leads to measurement error. Performing the estimation without these five states leads to qualitatively similar results for all three appliance categories.

B. Heterogeneity by State

One important feature of the legislation establishing SEEARP is that it provides sovereignty to states over the design of their rebate programs. Our empirical strategy has so far exploited variation in coverage, timing, and rebate amount across states to estimate the average treatment effect of a rebate on sales and electricity consumption, where the average was taken over all state programs. State programs under C4A, however, differed with respect to other dimensions, such as the mechanisms to claim rebates, eligibility criteria, reservation system, additional incentives for hauling away the old appliances, and expected program length. In this section, we seek to investigate heterogeneity in the effects of rebate programs across states.

Our empirical strategy is similar as before. We rely on a DD estimator to estimate a treatment effect in each state. In this specification, we use within year and across states variation in program coverage to control for state and time specific effects. Variation in rebate amounts is not a source of identification anymore given that it is confounded with other program features. Our identification then relies on the difference in the timing of the program and the fact that only a subset of states offers rebates for particular appliance categories. The model that we estimate is:

$$log(kWh_{s,t}) = \alpha_{sy} + \gamma_t + \sum_{l=t}^{T} \lambda_{l,s} \cdot Tw_{s,lt} \cdot Dstate_s + \epsilon_{s,t} \tag{4}$$

Figure 4 presents the estimation results graphically by illustrating the effects of rebate programs on energy consumption. Each estimate represents a percentage change in the reported energy use of the appliances purchased relative to the pre-announcement period. We present two estimates for each state. The first estimate reflects the effect of rebate programs during the rebate period only. The second estimate accounts for the effect of intertemporal substitution. For this second estimate, the time horizon considered includes two months of the pre-rebate period and two weeks of the post-rebate period.

Overall, these findings mirror the previous results: the largest reductions in expected energy consumption are observed for clothes washers, and accounting for intertemporal substitution reduces the magnitude of the estimated energy savings. For each appliance category, a few states have large reductions, but for most states the estimates are close to zero.

We also investigate how program design could explain the variation among states by regressing the mean estimate for each state on a vector of program characteristics, such as the average rebate amount, program duration, whether the rebates were ad valorem or not, whether rebates could be claimed online, the existence of a reservation system, incentive or requirement for hauling away the old appliance, and the eligibility criteria. The results are presented in the Online Appendix (Table A.8). More generous rebates tend to lead to larger energy savings for all appliances, except refrigerators, where the effect is not statistically significant. Offering an ad valorem rebate has the opposite effect. Having an eligibility criterion stricter than ES contributed to larger savings for dishwashers, but not for clothes washers. Recycling incentives also had an impact for dishwashers, but not for clothes washers. We do not find statistically significant effects for other program features.

VII. Upgrading

As illustrated by our theoretical framework, rebates for ES-certified appliances can induce an income effect and act as implicit subsidies for non-energy attributes used to establish minimum standards. These two effects combined imply that consumers taking advantage of rebates may substitute toward ES-certified models that differ along several dimensions of quality relative to non-ES-certified models. In this section, we quantify the importance of these upgrading effects. We also show whether they are mainly driven by an income effect or the fact that the ES certification requirement is attribute-based.

To determine the magnitude of the upgrading effects, we compute the average treatment effect on the treated (ATET) for various dimensions of quality. In addition to expected energy use, we report results for size, product design, and manufacturer's suggested retail price, which we consider a proxy of overall quality. In the present context, the ATET estimates the difference, in a specific dimension of quality, between the ES products purchased by program participants and the non-ES products that they would have purchased in the absence of rebates. To determine if the income effect is important, we then compare the ATET estimates to the corresponding differences in quality observed in the choice set. We argue that a large discrepancy between those two quantities suggests the existence of an important income effect. The intuition is the following. If there were no income effect, consumers taking advantage of rebates should substitute toward ES products that are the closest substitutes to the non-ES products that they would have otherwise considered. Therefore, the changes in quality induced by rebates should closely match the model-weighted differences in quality between non-ES and ES products offered by manufacturers. To illustrate, consider this simple example where manufacturers make product lines such that for each non-ES product on the market there is a corresponding ES product offered that is identical along all dimensions of quality except energy use. In the absence of an income effect, a consumer taking advantage of rebates would then purchase a ES product that is identical to the non-ES product he would have purchased without rebates. In this scenario, the effect of rebates on dimensions of quality other than expected energy use should be exactly zero.

The ATET estimates can be readily obtained using the estimates presented in Section VI. For instance, consider the non-parametric DD estimates of Figure 3 for refrigerators. In the first week of the rebate programs, we find an increase in the ES market share of 6% and a decrease in energy use of 4 kWh/yr. The ATET is the implied difference in energy use between ES and non-ES products for program participants. This can thus be computed by dividing the change in energy use in the overall population of consumers by the change in ES market share: 4/0.06=67 kWh/yr. The ATET for other dimensions of quality are computed similarly.

How should we interpret this difference of 67 kWh/yr? In relative terms, it means that ES refrigerators purchased by program participants had 12% lower energy use than non-ES models (547 kWh/yr, Table 3). This reduction is much smaller than implied by the 2010 ES certification requirement for refrigerators. In that year, ES refrigerators had to use at least 20% less energy than their corresponding minimum standards. Given that most refrigerators that are non-ES certified tend to meet exactly the minimum standard (Houde, 2014), switching from a non-ES to a ES refrigerator of similar size and style should lead to a reduction in energy use close to 20%. Therefore, the fact that we find that the reduction in expected energy use is 60% of the certification requirement implies that consumers substituted toward ES refrigerators that differ along key dimensions of quality that impact overall energy use. Figure 5 confirms this. On the first row, we show the effect of rebates on MSRP. In the second and third rows, the dependent variables are overall size and door design style, respectively. For refrigerators, we observe that rebates induce consumers to purchase larger models. In the first week of the program, we detect a statistically significant increase of 0.5%. Given the increase of 6% in ES market share in that week, the implied difference in size between non-ES and ES models purchased under a rebate program is 0.05/0.06=8.3%. Table 3 shows that manufacturers meet the ES certification by offering larger refrigerators–ES refrigerators are on average 5.3%

larger than non-ES models. Upsizing is, therefore, likely to be driven by both the certification requirement and the income effect. If there were no income effect, the adoption of ES certified models should lead to an increase in size that closely matches the model-weighted difference (i.e., 5.3%). But, the fact that we observe upsizing that goes beyond what is induced by the choice set alone, suggests that the income effect plays a role here. We also find that program participants substituted away from top-freezer refrigerators to bottom-freezer or side-by-side, which both tend to use more energy. More precisely, consumers that switched toward ES-certified models in the first week of the programs were 25% (0.015/0.06) less likely to purchase a top-freezer model.

For clothes washers, the upgrading effects are also economically important, but we find little evidence of an income effect. We observe a statistically significant increase in MSRP of the order of 2% in the first week (Figure 5). If we divide this percentage by the change in ES market share, we find that program participants purchased ES clothes washers that were 40% (0.02/0.05) more expensive than non-ES models, on average. This is a large increase, but less than the 60% difference in MSRPs between non-ES and ES clothes washers offered on the market at that time (Table 3). This suggests that program participants purchased more expensive clothes washers simply because ES models have higher MSRPs. That is, upgrading was induced by the choice set, not by the income effect. Results for size and door design (top-load versus front-load) are consistent with this interpretation. The 0.5% increase in size in the first week implied that program participants upsized their clothes washers by 10%, which is very close of the 9.4% difference between certified and non-certified models that were offered on the market at this time (Table 3). Regarding the door design, the ATET suggests that program participants were 40% less likely to purchase a top-load washer. Considering that only 30% of ES-certified clothes washers are top-load, but that 63% of non-ES models are, the higher propensity to purchase front load models during the rebate program can also be explained by the choice set offered to consumers.

Finally, for dishwashers we find that upgrading is also present and that the income effect is likely to be particularly important. Again, focusing on the estimates for the first week of the programs (Figure 5), the 2% increase in MSRP along with the 2% increase in the ES market share implies that participants bought ES dishwashers twice as expensive relative to non-ES dishwashers. It is unlikely that this large difference is entirely driven by manufacturers setting higher prices for ES-certified dishwashers– during that period, the MSRPs of ES dishwashers were only 22% higher, on average, relative to non-ES models (Table 3). Consumers that took advantage of rebates purchased dishwashers of much higher quality than they would have done in the absence of the programs. Figure 5 also shows evidence of upsizing. In the first week, the probability of upgrading from a standard size model to a larger increase by 2%. This translates to an ATET of 100%, which means that program participants were twice as likely to upsize their dishwashers under the rebate programs.

Overall, upgrading effects are important for all three appliance categories. The set of overlapping policy instruments used to establish the rebate criteria appears to be an important driver of these effects. Manufacturers offer ES models that differ systematically from non-ES models partly because the certification requirement is set as a function of non-energy attributes. As a result, we find that program participants purchased ES models that differ from non-ES along these dimensions of quality. In addition, the results for refrigerators and dishwashers reveal an income effect.

Our findings on upgrading on quality dimensions fit within a broader literature that has investigated how capital subsidies affect the quality as well as the quantity of capital purchased. For example, Bils and Klenow (2001) estimate so-called quality Engel curves that reveal substantial quality upgrading across an array of consumer durable goods categories with household income. Goolsbee (1998) finds that capital subsidies are associated with higher equipment prices, although House and Shapiro (2008) do not find price impacts from short-lived bonus depreciation policies. Since our retailer sets a national pricing policy, the changes in the prices of the appliances purchased by the consumers in our dataset reflects changes in bundle of attributes that they are effectively purchasing in an appliance transaction. As indicated our findings, the quality upgrading along non-energy attributes likely explains any price effects.

VIII. Cost-Effectiveness

How much is society paying to reduce a unit of (expected) electricity consumption? Understanding the cost per kilowatt-hour avoided can also inform consideration of pollution externalities, such as the carbon intensity of electricity (CO_2/kWh) that serves as the basis for state targets under the Environmental Protection Agency's Clean Power Plan. This would also permit a comparison of C4A's cost-effectiveness with other energy-efficiency programs? To investigate this issue, we propose a simple approach to measure cost-effectiveness. The first step consists of estimating the proportion of rebate takers that does not contribute to expected energy savings. Takers fall into four categories: (1) switchers/non-movers–the consumers who substituted away from a non-ES product, and purchased an ES product because of the existence of rebates, but did not delay or accelerate their purchase decision; (2) switchers/movers–the consumers who switched and substituted over time; (3) non-switchers/non-movers–the consumers who would have bought an ES product during the rebate program even in the absence of rebates; and (4) non-switchers/movers–the consumers who did not switch, but substituted over time to take advantage of rebates. Non-switchers/non movers are commonly referred as the freeriders. They are non-marginal program participants that do not contribute to expected energy savings. In the present context, non-switchers/movers contribution to expected energy savings is small and possibly negative given that most simply delayed their purchase decision by a few months. To illustrate the importance of intertemporal substitution we present next two estimates of cost-effectiveness. One that only considers the proportion of freeriders and the other that considers the overall proportion of non-switchers, whether or not they are movers.

A unique feature of our data is that we observe the number of rebate participants shopping at our retailer in a number of states. This allows us to quantify the take-up rate, and quantify the proportion of takers that fall in each of the four categories described above.

We integrate our national retailer data with the DOE data for the 13 states that identify the retailer in their C4A reporting. For these states, the proportion of takers is simply the total number of rebate claims divided by total sales at our retailer. The average proportion of takers across these 13 states is 11.3%, 14.3%, and 10.7% for refrigerator, clothes washer, and dishwasher, respectively.

To estimate the freeriders' share of rebate claims, we employ a state-specific estimator where our dependent variable is the log of total sales of ES products:

$$log(SalesES_{s,t}) = \alpha_{sy} + \gamma_t + \sum_{s=1}^{S} \lambda_s \cdot TRebate_{s,lt} \cdot Dstate_s + \epsilon_{s,t} \tag{5}$$

As before, the index s denotes state and t denotes week. We define the dummy variable $TRebate_{s,t}$ to take a value of one during the rebate period and zero otherwise. We use this model to estimate the increase in ES sales during the rebate period only, which is attributable to both types of switchers (i.e., movers and non-movers) and to non-switchers/movers. We then divide this estimate by the number of takers that we observe. The freeriders' share is simply one minus this share. We find that the freeriders' share is about 70% for all three appliance categories (Table 5). The proportion of non-switchers can be estimated following a similar approach. The difference is that we define a dummy variable in Equation 5 that includes both the pre-rebate and post-rebate periods, in addition of the rebate period, which allows us to detect the increase in ES sales that are due to switchers irrespective of the fact they substituted over time or not. The switchers' share is obtained by dividing this estimate by the number of takers, and the non-switchers' share is one minus this estimate. If we include two months of the pre-rebate period and two weeks of the post-rebate period, the non-switchers' share is 92.0%, 90.5%, and 85.9% for refrigerators, clothes washers, and dishwashers.

The second step to perform the cost-effectiveness analysis consists of computing the expected energy saved by switchers for a given rebate eligibility criterion. We consider that for switchers the savings correspond to the difference in the model-weighted energy use between rebate-eligible products and non-rebate-eligible products offered on the market. This approach has a number of implicit assumptions. First, it rules out income effects that would lead to upgrading, but accounts for upgrading due to the nature of the ES certification requirement, i.e., the fact that eligible-products differ from non-eligible products in various dimension of quality, in addition of energy use. Second, it does not account for equilibrium effects and how manufacturers' product lines would respond to a rebate program. Finally, it abstracts from consumers' utilization decisions.

Using the estimated share of freeriders or non-switchers and the average energy saved by switchers, the energy saved by the overall population of takers is given by:

$$\Delta kWh_{Takers} = (1 - \pi) \cdot \Delta kWh_{Switchers} \cdot Lifetime \tag{6}$$

where π is the proportion of consumers that does not contribute to expected energy savings. Depending on whether one wants to account for intertemporal substitution, π corresponds to the share of freeriders or non-switchers, respectively. $\Delta kWh_{Switchers}$ is the difference in average annual energy use between rebate-eligible and non-rebate-eligible products. This difference is then multiplied by the average lifetime of the appliance. The cost-effectiveness measure that we report is the dollar amount spent for each kWh saved, which is the ratio of the rebate offered over the average lifetime energy savings achieved for the rebate eligibility criterion selected.

In our calculations, we assume a 15-year lifetime.[10] For all three appliance categories, we use data from NPD Group, a market research company, to characterize the choice set of the U.S. appliance market for the years 2010-2011. We then use this choice set to compute the model-weighted average energy use corresponding to different rebate eligibility criteria. The NPD data have been used in several recent studies of the appliance market (Houde, 2014; Spurlock, 2013; Ashenfelter, Hosken, and Weinberg, 2013). They provide monthly sales at the model level from the year 2001 to 2011 and were collected from various retailers. The NPD Group reports that their data covered approximately 40% of the U.S. appliance market.

Finally, we also adjust our estimated energy savings to account for accelerated replacement of existing appliances. We first assume that all switchers replaced their old appliances five years earlier than they would have in the absence of the program. We selected five years after inspecting the manufacturing year for a subset of refrigerators

[10]The DOE assumes a lifetime of 18 years in its regulatory impact analysis of minimum efficiency standards for refrigerators. According to a study of the National Association of Home Builders (NAHB, 2007), the average life expectancy of refrigerators is 13 years.

that were scrapped under C4A.[11] For these replaced refrigerators, we found that the average manufacturing year was 2001 and the average electricity consumption was 639 kWh/y. Again, assuming that the average life expectancy of a refrigerator is 15 years implies that switchers may have pulled forward their replacement decision by five years under C4A, on average. We then compute the total amount of energy saved by taking the difference in electricity consumption of an ES-rated appliance purchased in 2010 and an appliance purchased 10 years before (in 2001). We then sum this difference over 5 years. For the remaining, 10 years of the appliance lifetime, the average savings are simply the difference between an ES and non ES-rated appliance purchased in 2010.

Table 6 compares our cost-effectiveness measure for different proportions of freeriders and non-switchers, including our preferred estimates. At the average rebate amount offered for all three appliance categories, the C4A did not perform well. The dollar amount spent for each kWh saved is \$1.10 for refrigerators, \$0.21 for clothes washers, and \$0.46 for dishwashers. This well exceeds the cost found for other utility-funded programs, which is \$0.06, on average (Arimura, Li, Newell, and Palmer, 2012; Gillingham, Newell, and Palmer, 2009; Auffhammer, Blumstein, and Fowlie, 2008). Table 6 also shows that C4A would have cost more than \$0.07 per kWh saved for refrigerators and dishwashers even if there is zero freeriding. Due to the much larger difference between ES and non-ES clothes washers' energy consumption, lower-freeriding proportions of 50% or less would have delivered cost-effectiveness on par with other utility-funded programs.

Would it have been possible to achieve better cost-effectiveness using alternative eligibility criteria? One limitation of ES-based rebates is that they provide an implicit subsidy for other attributes. To avoid these perverse incentives, we consider criteria solely based on electricity consumption. In other words, we construct a rebate that is not a function of the existing information (ENERGY STAR) and regula-

[11] To identify the manufacturing year of the refrigerators replaced, we matched the DOE data with data from the California Energy Commission, which provides historical attribute data for refrigerators dating back to 1978. Our matching procedure can only recover detailed attribute information for a subset of refrigerators that were replaced under C4A (approximately 10,000) because not all states recorded the manufacturer appliance numbers of the replaced appliances. There were also some inconsistencies in the way the manufacturer numbers for replaced appliances were recorded in the C4A database. For clothes washers and dishwashers, we could not recover attribute information on the replaced appliances, because we do not have historical attribute data.

tory (minimum efficiency standards) programs. For instance, we consider offering rebates only for products in the lower 5th, 10th, or 20th percentiles of electricity consumption. Of course, products that consume less electricity in absolute terms tend be smaller, and may have fewer features. Eligible products are thus most likely inferior in the non-energy dimension, which is at the source of welfare losses. The cost-effectiveness metric does not account for these losses. The estimates reported in Table 6 should then be interpreted as an upper bound for the potential benefits of using a particular criterion. We find that using non-attribute based rebates improves the cost-effectiveness for refrigerators and dishwashers, only. However, the cost per unit energy saved is still high for these two appliance categories. For instance, the cost is above $0.08 for each kWh saved if the proportion of freeriders is at least 70%.

In the Online Appendix, we also present cost-effectiveness estimates that assume zero accelerated replacement. If consumers are purchasing new appliances and claiming rebates at the time that they planned to replace their existing appliances anyway, then there would be no benefit from prematurely scrapping an older, less-efficient appliance. As Table A.10 shows, the cost-effectiveness measures increase to as much as $1.64 per kWh of expected energy saved.

A. Comparison with Other Estimates

The DOE contracted the consulting group D&R International to evaluate the impact of the C4A program. According to D&R, C4A had a large impact and led to important energy savings (D&R, 2013). Their estimate of the overall savings is 2 trillion BTU per year, and the major appliances contributed to savings of 815 billion of BTU per year.

To put these aggregate energy savings in perspective, D&R estimated average savings per rebate claim of 116 kWh/year, 257 kWh/year, and 57 kWh/year for refrigerators, clothes washers, and dishwashers, respectively.[12] We cannot reconcile these large energy savings with our estimated free-riding behavior. We cannot even reconcile the refrigerator savings of 116 kWh/year with assumptions of 0% freeriding and 5-year accelerated replacement. The proportion of freeriders would have to be

[12] Table A.9 reports their estimates for the three appliances that we study.

no more than 25%-30% for clothes washers and dishwashers, respectively, well below the 92% and 73% estimated free-riding rates in our analysis. These differences illustrate the importance of explicitly accounting for free-riding behavior, including through intertemporal substitution beyond the time horizon of program operation, in assessing the impact of energy efficiency subsidies on investment decisions and energy outcomes.

IX. Conclusions

In this paper, we investigate the incremental impact of a nationwide energy efficient appliance rebate program, Cash for Appliances, in light of existing regulatory standards and information disclosure programs. We find a short-term boost in appliance sales and ES-rated appliance market share, but much smaller improvements in the expected energy use of appliances purchased during the C4A program. For example, we find that refrigerator sales increase 10%, ES market share increases 2%, but the expected energy use declines by about 1/3 of 1% during the rebate period.

We estimate that about 70% of the consumers claiming a rebate would have bought an ES-rated appliance during the period of the C4A program in the absence of the rebates. An additional 15% to 20% of the rebate takers changed the timing of the ES-rated appliance that they planned to buy anyway. We find economically meaningful evidence of upgrading, where consumers claimed rebates to purchase higher quality, but less energy-efficient models. We show that by making the rebates a function of ES certification, which is in turn a function of attribute-based energy efficiency standards, C4A acts as an implicit subsidy for non-energy attributes. Income effects also appear to play a role in upgrading.

Such high freeriding rates coupled with short-term intertemporal substitution and perverse upgrading translate into high costs per expected kilowatt-hour saved. With refrigerator rebate programs spending about $1.10 for every expected kilowatt-hour saved, C4A cost an order of magnitude more than typical energy efficiency and conservation programs. Rebate programs for clothes washers and dishwashers, with cost-effectiveness ranging from $0.21 to $0.46 per kilowatt-hour saved, were more cost-effective than refrigerators, but still relatively expensive per unit of energy saved.

This empirical analysis of the Recovery Act's Cash for Appliances program has potentially important implications for future energy and climate change policies. As noted at the start, there are nearly 500 utility appliance rebate programs operating in 2015, and many of these programs have similar design attributes as the state C4A programs. Moreover, state governments are increasing their funding of energy efficiency programs as a result of revenues raised through the auctions of greenhouse gas cap-and-trade program allowances. The U.S. Environmental Protection Agency has also finalized its Clean Power Plan, which sets power sector carbon dioxide emission targets for each of the states. While U.S. EPA provides states with discretion on how to design and implement policies to attain the targets, the agency has noted the potential role that rebates for energy efficient appliances could play. Given the expanding set of overlapping energy and climate policies, this work informs the design of future rebate programs and highlight potential considerations in choosing to subsidize energy efficient appliances.

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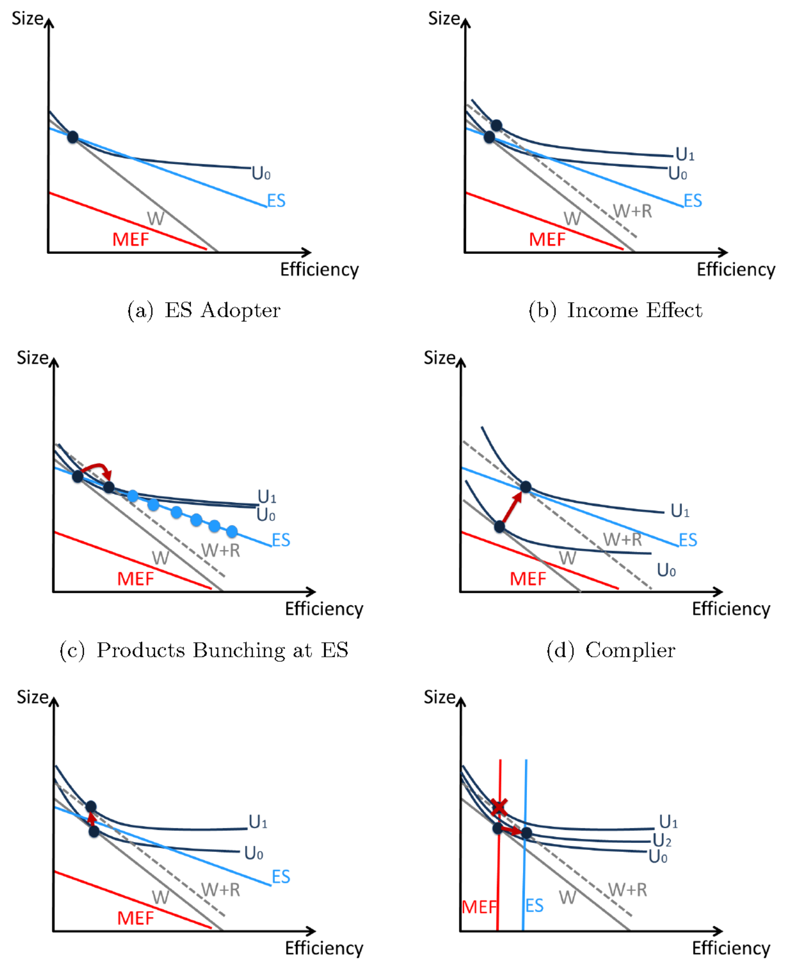
X. Figures and Tables



(a) ES Adopter

(b) Income Effect

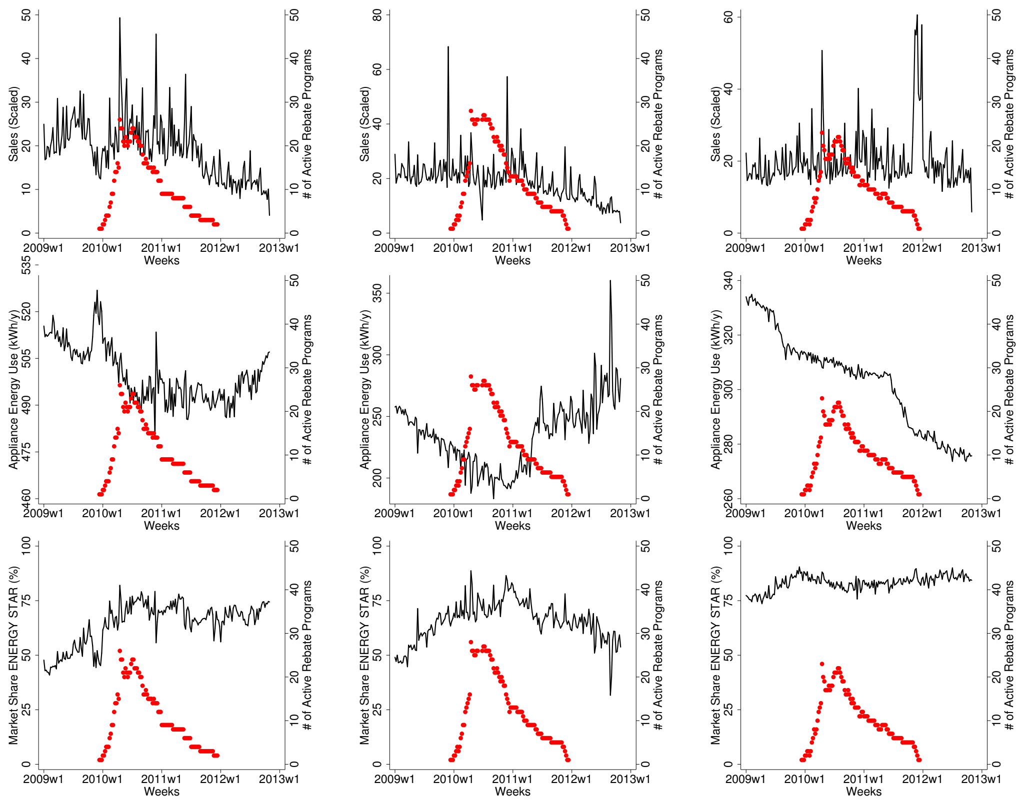
(c) Products Bunching at ES

(d) Complier

(e) Perverse Rebate

(f) Comparative Statics: Non-Attribute-Based Standard

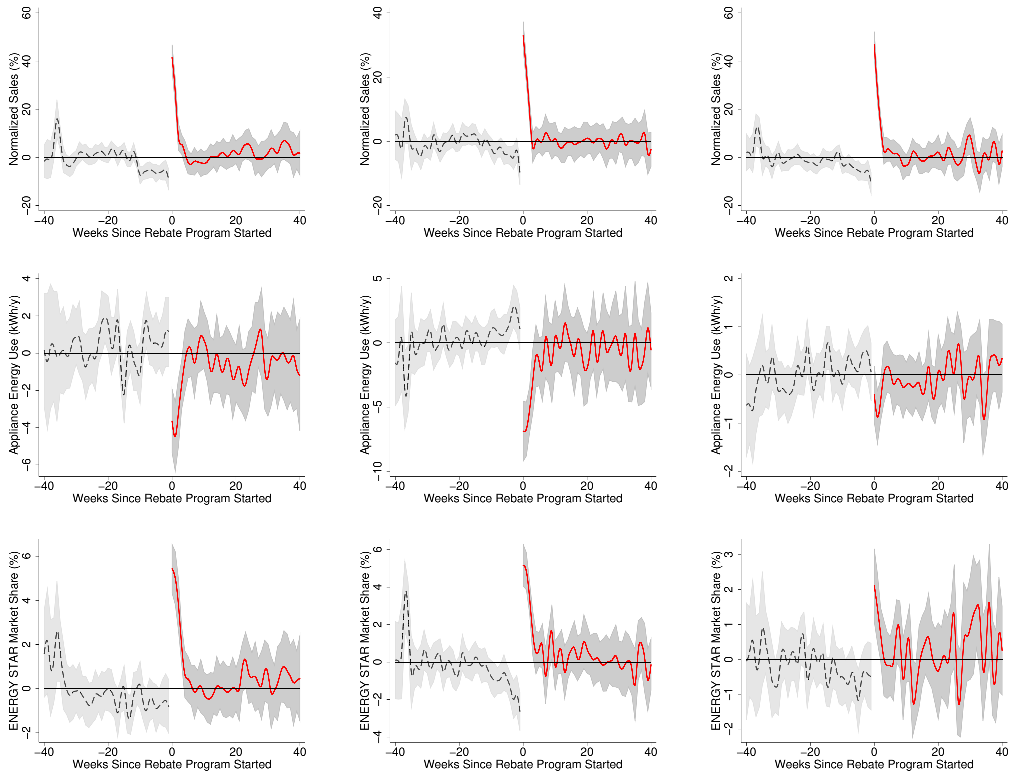
Figure 1. : The Simple Economics of Energy Efficiency Rebates



(a) Refrigerators (b) Clothes Washers (c) Dishwashers

Figure 2. : Number of Active Rebate Programs vs. National Averages: Sales, Expected Appliance Energy Use, and ENERGY STAR Market Shares

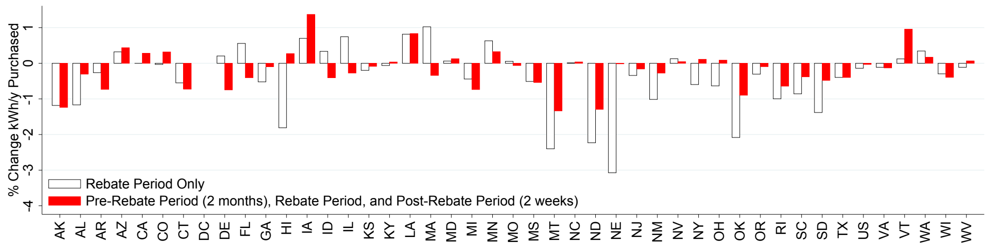
Each panel shows a weekly national average compared to the number of active state rebate programs. Total weekly sales are scaled by a factor such that levels are not disclosed. Appliance models that were ES certified as of January 1, 2010 are included in the ES market share for the whole time horizon.



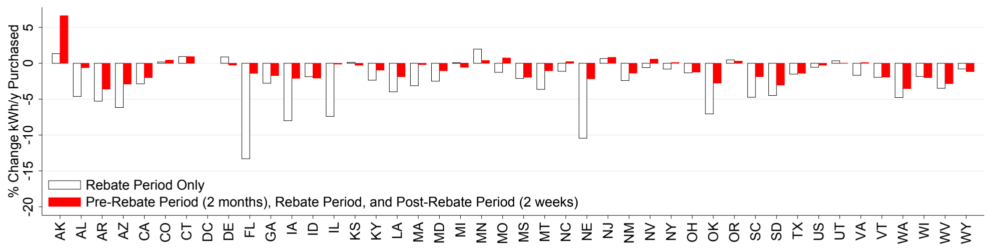
(a) Refrigerators (b) Clothes Washers (c) Dishwashers

Figure 3. : Sales, Expected Appliance Energy Use, and ENERGY STAR Market Share Since Program Start Date

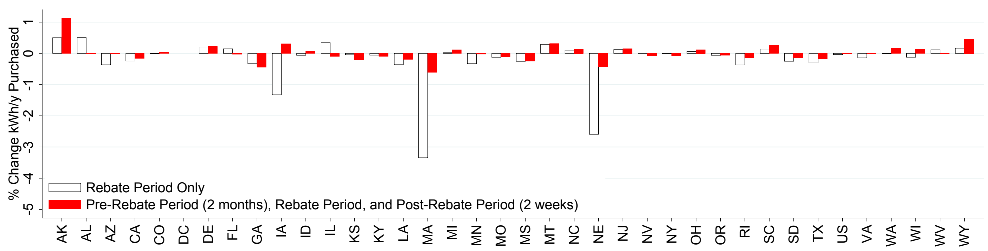
The figure shows normalized sales, appliance energy use (kWh/y), and ES market share. All three outcome variables are normalized using a regression that removes week-of-sample and state-year fixed effects. The figure presents a fitted spline and the 95% confidence interval. The positive part of the X-axis corresponds to the number of weeks since a rebate program started.



(a) Refrigerators



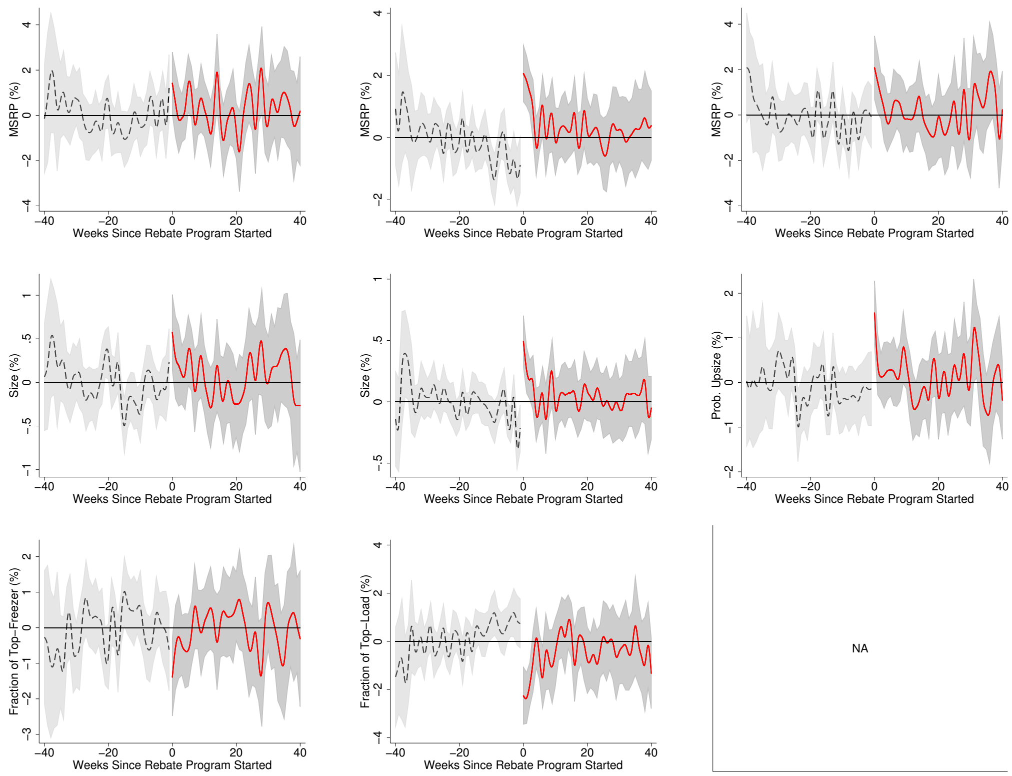
(b) Clothes Washers



(c) Dishwashers

Figure 4. : Impact of State Rebate Programs on Expected Appliance Energy Use by State

Each panel shows the average percentage change in expected energy use (kWh/y) of the appliances purchased during state rebate programs. For each state, two estimates are shown: the change during the rebate period only, and the change during the period that includes two months before the rebate period, the rebate period, and two weeks after the rebate period.



(a) Refrigerators (b) Clothes Washers (c) Dishwashers

Figure 5. : MSRP, Size, and Appliance Type Since Program Start Date

The figure shows normalized manufacturers' suggested retail prices, appliance size, and appliance type. For refrigerators, appliance type is dummy variable that takes a value of one if this is a top-freezer and zero otherwise. For clothes washers, appliance type distinguishes among top-load and front-load washers. For dishwashers, size is a categorical variable that takes four values, where 1 = standard, 2 = tall, 3 = giant, and 4 = super capacity. All three outcome variables are normalized using a regression that removes week-of-sample and state-year fixed effects. The figure presents a fitted spline and the 95% confidence interval. The positive part of the X-axis corresponds to the number of weeks since a rebate program started.

Table 1—: Rebates and Eligibility Criteria for Each State

	Refrigerators		Clothes Washers		Dishwashers	
	Rebate	Criteria	Rebate	Criteria	Rebate	Criteria
AK	300-600	ES (rural)	300-600	ES	300-600	ES (rural)
AL	150	ES	100	ES	75	ES
AR	275	ES	225	ES	-	
AZ	200-300	ES	125-200	ES & Above	75-125	ES & Above
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	50-99	ES & Above
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	175	ES	250	ES & Above
MD	50	ES & Above	100	ES	-	
ME	-		-		-	
MI	50-100	ES & Above	50	ES	25-50	ES & Above
MN	100	ES	200	ES	150	ES
MO	250	ES	125	ES	125	ES
MS	75	ES	100-150	ES & Above	75-100	ES & Above
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	150	Above ES
NJ	75-100		35	ES	25-50	ES & Above
NM	200	ES	200	ES	-	
NV	200	ES	150	ES	100	ES
NY	75-105		75-100	ES & Above	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	85-185	ES
UT	-		75	ES		
VA	60	ES	75-350	ES & Above	50-275	ES & Above
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
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 2—: 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 Water Heaters	30	15,766	2.1	703	130	1,742
Tankless Water Heaters	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 3—: Summary Statistics: Retailer's Choice Set

	Appliances		
	Refrigerators	Clothes Washers	Dishwashers
ES Market Share Pre-Announcement Period (January-July 2009)			
Mean	46%	53%	75%
SD (across states)	8%	10%	12%
Number of Models Offered in 2010-2011			
ES	1,470	488	889
Non-ES	1,527	226	87
Average Electricity Consumption (kWh/year), 2010-2011 Models			
ES	498	205	305
Non-ES	549	502	338
Average Size, 2010-2011 Models			
ES	27.7	3.5	2.0
Non-ES	26.6	3.2	1.4
Average Promotional Price ($), 2010-2011 Models			
ES	1,642	954	697
Non-ES	1,859	610	573
Average Manufacturer's Suggested Retail Price ($), 2010-2011 Models			
ES	1,778	1,033	764
Non-ES	1,938	643	624
Style, 2010-2011 Models			
	% Top-freezer	% Top-load	
ES	18	30	-
Non-ES	27	63	-

Notes: Summary statistics for number of models, electricity consumption, size, price, and style are non-sales weighted. The metric "size" is measured in cubic feet for clothes washers and refrigerators. For dishwashers, size is defined with a categorical variable, where 1 = standard, 2 = tall, 3 = giant, and 4 = super capacity. The price corresponds to the retail price.

Table 4—: Impact of Rebates on Sales, Appliance Energy Use, and ES Market Share

	I. Rebate Period Only			**II. Rebate Period, 2 Months Pre, 2 Weeks Post**			**III. Rebate Period, 3 Months Pre, 3 Months Post**		
Dep. Var.:	log(sales)	log(kWh)	ES	log(sales)	log(kWh)	ES	log(sales)	log(kWh)	ES
Refrigerators									
Est.	0.10***	-0.0035**	0.021***	0.012	-0.00018	0.0024	0.0085	0.00013	-0.00031
s.e.	(0.021)	(0.001)	(0.005)	(0.006)	(0.0003)	(0.002)	(0.005)	(0.0005)	(0.001)
# Obs	12450	12450	12450	12450	12450	12450	12450	12450	12450
R^2	0.995	0.901	0.915	0.995	0.901	0.914	0.995	0.901	0.914
Clothes Washers									
Est.	0.067***	-0.017***	0.021***	0.0097**	-0.0017	0.00087	0.007	-0.00029	-0.00063
s.e.	(0.016)	(0.004)	(0.005)	(0.003)	(0.001)	(0.001)	(0.004)	(0.001)	(0.001)
# Obs	12100	12100	12100	12100	12100	12100	12100	12100	12100
R^2	0.996	0.936	0.917	0.996	0.936	0.916	0.996	0.936	0.916
Dishwashers									
Est.	0.096***	-0.00056	0.0073**	0.021**	-0.00015	-0.00026	0.0024	-0.00014	-0.0007
s.e.	(0.018)	(0.000)	(0.003)	(0.007)	(0.0003)	(0.001)	(0.005)	(0.0003)	(0.002)
# Obs	12600	12600	12600	12600	12600	12600	12600	12600	12600
R^2	0.995	0.989	0.766	0.995	0.989	0.765	0.995	0.989	0.766

Notes: The dummy variable for the pre-announcement period is omitted. Standard errors (in parentheses) clustered at the state level. * ($p < 0.05$), ** ($p < 0.01$), *** ($p < 0.001$). All specifications have week-of-sample and state fixed effects.

Table 5—: Takers, Non-Switchers, and Non-Movers

	Takers (%)	**Freeriders: Non-Switchers & Non-Movers (%)**	**Non-Switchers (%)**
Refrigerators	11.3	71.5	92.0
Clothes Washers	14.2	69.3	90.5
Dishwashers	10.7	70.6	85.9

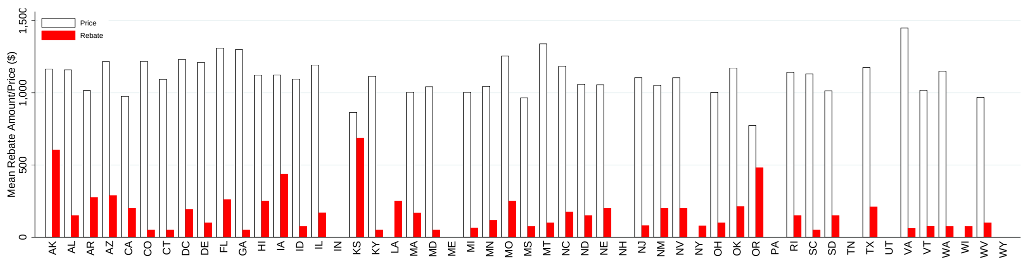
Notes: The first column shows the proportion of rebate takers among all consumers that purchase an appliance of a given category during the rebate period, two months prior, or two weeks after the rebate ended. The second column shows the proportion of takers that are non-switchers and non-movers. Those are the inframarginal consumers (freeriders). The third column shows the proportion of takers that are non-switchers, which includes movers and non-movers.

Table 6—: Cost-Effectiveness Analysis: With Adjustment for Accelerate Replacement

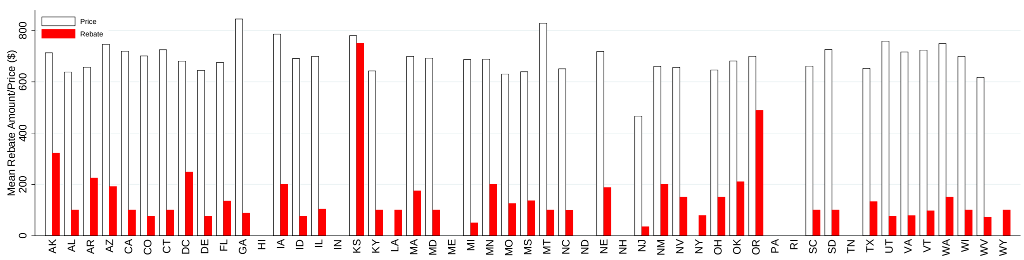
	Δ kWh/y	Rebate ($)	Cost-Effectiveness ($/kWh saved) Proportion of Freeriders/Non-Switchers						
			0%	25%	50%	70%	85%	90%	92%
Refrigerators									
ES vs. Non-ES	-65	128	0.09	0.12	0.18	**0.29**	0.59	0.88	**1.10**
Top 5% vs. Bottom 95%	-183	128	0.04	0.05	0.08	**0.13**	0.26	0.39	**0.48**
Top 10% vs. Bottom 90%	-165	128	0.04	0.06	0.09	**0.14**	0.28	0.43	**0.53**
Top 20% vs. Bottom 80%	-142	128	0.05	0.07	0.10	**0.16**	0.33	0.49	**0.62**
Clothes Washers									
ES vs. Non-ES	-201	107	0.02	0.03	0.04	**0.07**	0.14	**0.21**	0.26
Top 5% vs. Bottom 95%	-115	107	0.02	0.03	0.05	**0.08**	0.15	**0.23**	0.29
Top 10% vs. Bottom 90%	-116	107	0.02	0.03	0.05	**0.08**	0.15	**0.23**	0.29
Top 20% vs. Bottom 80%	-121	107	0.02	0.03	0.05	**0.08**	0.16	**0.23**	0.29
Dishwashers									
ES vs. Non-ES	-34	84	0.07	0.09	0.14	**0.23**	**0.46**	0.68	0.85
Top 5% vs. Bottom 95%	-108	84	0.03	0.05	0.07	**0.11**	**0.23**	0.34	0.43
Top 10% vs. Bottom 90%	-83	84	0.00	0.05	0.08	**0.14**	**0.27**	0.41	0.51
Top 20% vs. Bottom 80%	-57	84	0.00	0.07	0.10	**0.17**	**0.35**	0.52	0.65

Notes: The rebate amount for each appliance category is the non-weighted average of the rebate amount offered by each state. The estimates in bold correspond to the proportions of freeriders and non-switchers estimated (Table 5). For all appliances, we assume a lifetime of 15 years.

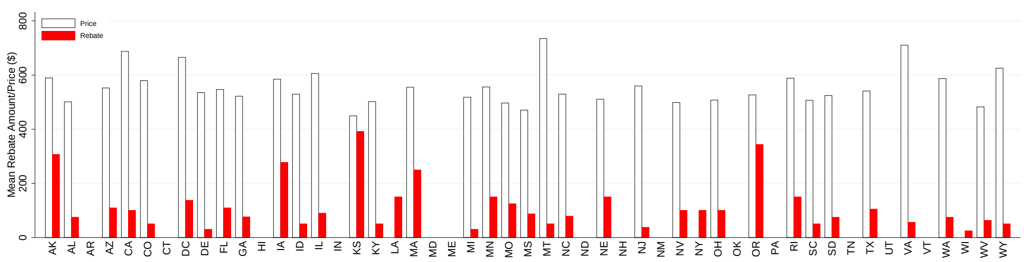
Online Appendix



(a) Refrigerators



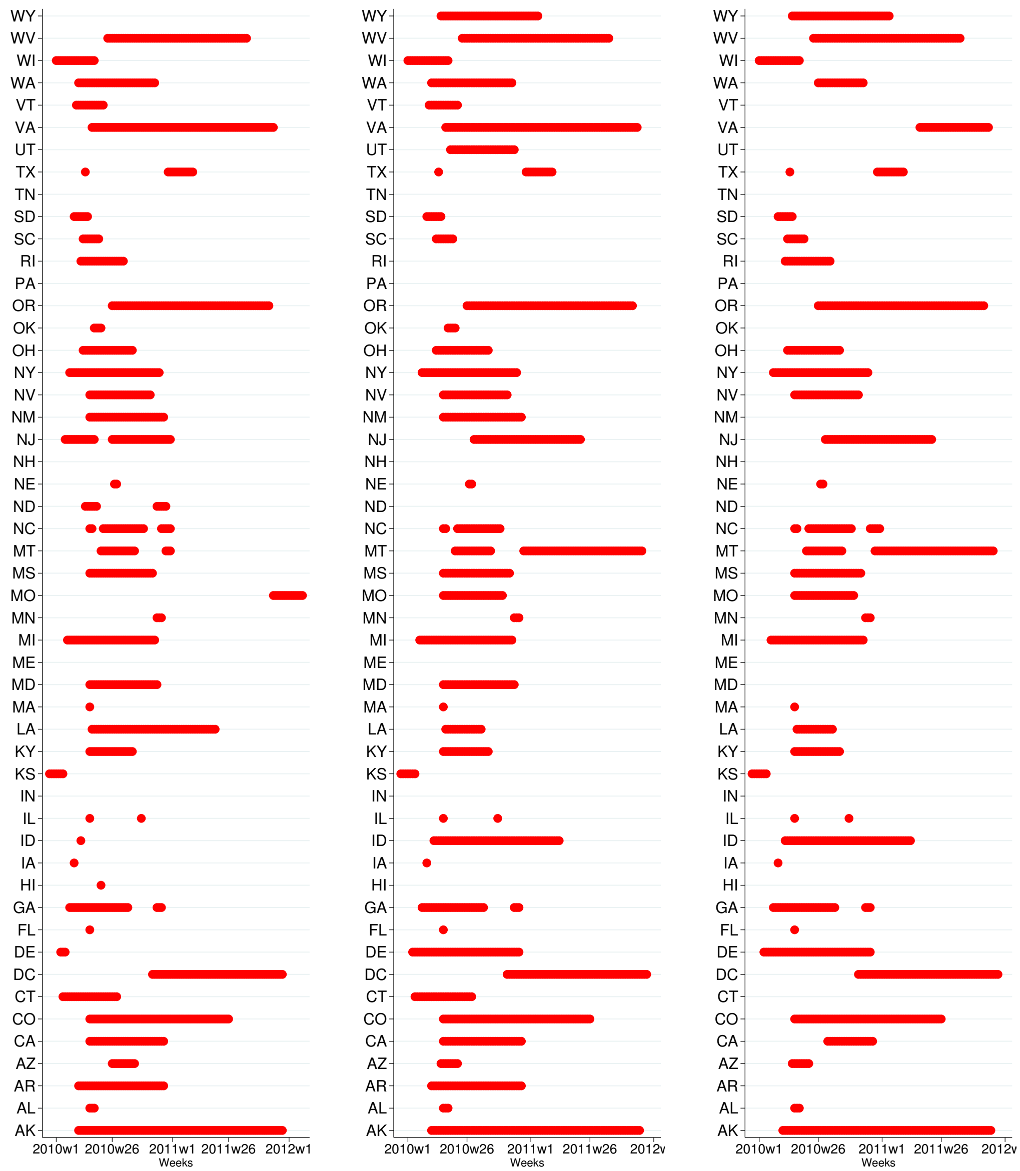
(b) Clothes Washers



(c) Dishwashers

Figure A.1. : Average Price vs. Rebate Amount

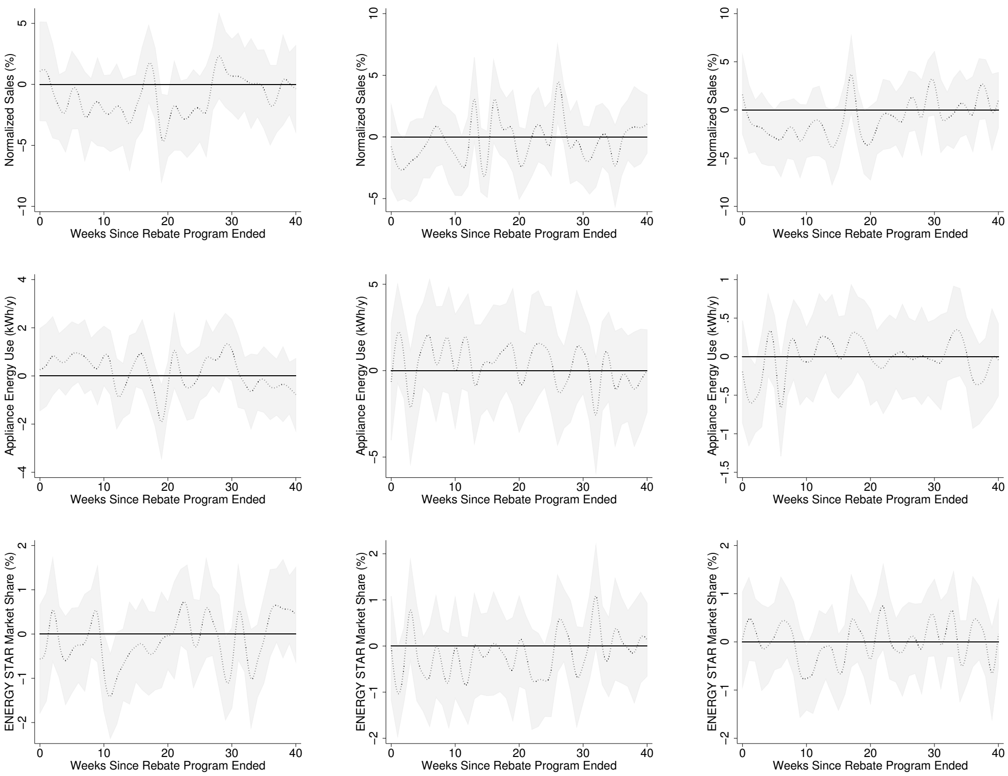
Each panel shows the average price of the appliance purchased (in white) and the average rebate amount claimed (in red). States with no average price but a positive rebate amount are states where program managers did not collect price information. States where both price and rebate information are missing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



(a) Refrigerators (b) Clothes Washers (c) Dishwashers

Figure A.2. : Timing of Active Rebate Programs

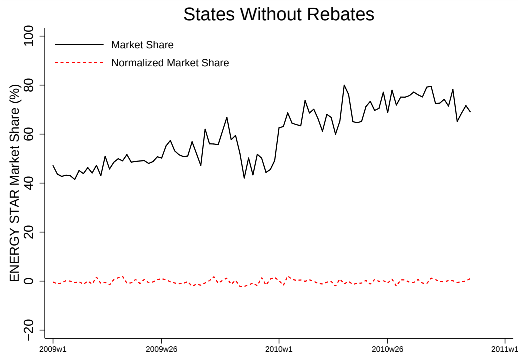
Each panel identifies the weeks that a state rebate program was active for specific appliance category.



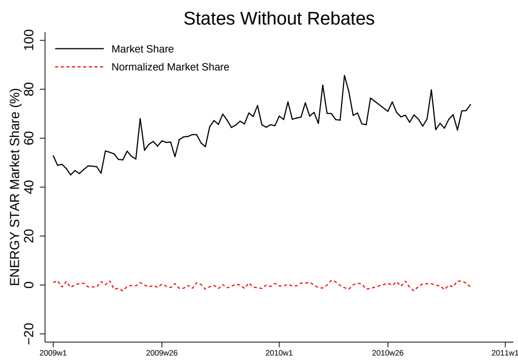
(a) Refrigerators (b) Clothes Washers (c) Dishwashers

Figure A.3. : Sales, Expected Appliance Energy Use, and ENERGY STAR Market Share: Post-Rebate Period

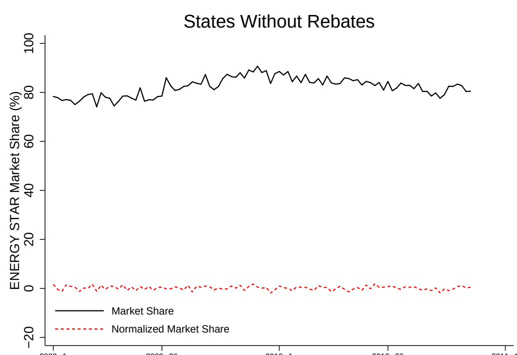
The figure shows normalized sales, expected appliance energy use (kWh/y), and ES market share. All three outcome variables are normalized using a regression that removes week-of-sample and state-year fixed effects. The figure presents a fitted spline and the 95% confidence interval. The X-axis corresponds to the number of weeks after a rebate program ended.



(a) Refrigerators



(b) Clothes Washers



(c) Dishwashers

Figure A.4. : ES Market Shares vs. Normalized Market Shares, States Without Rebates

Each panel shows the weekly ES market share for all states that did not offer rebates and the corresponding normalized market shares. Normalized market shares are the residuals of a regression of market shares on state and week-year fixed effects. The figure shows that, for states without rebates, the fixed effects capture most of the variations in market shares.

Table A.1—: External Validity

	Retailer	Other Retailers	t-statistics
Refrigerators			
Price	1154	1083	25.17
Rebate	180	135	98.84
kWh	480	456	60.92
Size	22	20	14.46
Clothes Washers			
Price	699	674	24.41
Rebate	114	113	4.66
kWh	160	175	-48.92
Size	4	4	0.63
Dishwashers			
Price	554	543	7.64
Rebate	116	85	86.97
kWh	160	174	-1.54
Size	4	4	0.05

Notes: Using the DOE data alone, this table compares the average price, rebate amount, kWh purchased, and size of the appliances purchased at our retailer (retailer from which we collected transaction level data) versus all other retailers. Note that some states did not record the retailer where the purchase was made.

Table A.2—: External Validity: Consumers

	Retailer	Others
Median Household Income	68089	66701
	(26118.0)	(25308.2)
Median Age in Years	39.2	39.4
	(6.359)	(6.249)
Average Household Size	2.7	2.7
	(0.444)	(0.420)
Female Population Share	50.9	51.0
	(2.390)	(2.390)
White Population Share	75.3	77.0
	(19.16)	(19.22)
Black Population Share	7.8	7.7
	(11.77)	(11.98)
Hispanic Population Share	18.6	14.9
	(19.03)	(16.83)
Homeowner Share	67.4	68.0
	(15.38)	(16.00)
Below Poverty Line Share	11.9	12.0
	(7.497)	(7.634)
High School Graduate Share	29.0	29.1
	(9.641)	(9.806)
College Graduate or Above	11.6	12.1
	(8.899)	(9.106)
Observations	135678	450581

Table A.3—: The Dynamic Effect of Rebates

	Refrigerators			Clothes Washers			Dishwashers		
Dep. Var.:	log(sales)	log(kWh)	ES	log(sales)	log(kWh)	ES	log(sales)	log(kWh)	ES
Rebate Period									
Rebate×Wk. 1	0.14*	-0.0025**	0.018*	0.10*	-0.01	0.011	0.21**	-0.00096	0.01
	(0.053)	(0.001)	(0.008)	(0.048)	(0.006)	(0.008)	(0.076)	(0.001)	(0.007)
Rebate×Wks. 2-3	0.059*	-0.0020*	0.012	0.049*	-0.0069	0.01	0.065	-0.00093	0.0057
	(0.024)	(0.001)	(0.007)	(0.021)	(0.004)	(0.006)	(0.036)	(0.001)	(0.004)
Rebate×Wks. 4-6	-0.0055	-0.00079	-0.00045	-0.0033	-0.00025	-0.002	0.006	0.00082	0.0017
	(0.018)	(0.001)	(0.004)	(0.016)	(0.002)	(0.003)	(0.013)	(0.001)	(0.004)
Rebate×Wks. 7-9	-0.012	0.00022	-0.0015	0.0055	0.000071	-0.0022	-0.008	0.000027	0.0031
	(0.018)	(0.001)	(0.003)	(0.019)	(0.002)	(0.003)	(0.011)	(0.000)	(0.006)
Rebate×Wks. 10+	0.0038	-0.00076	0.0024	0.0075	0.002	-0.0018	0.0027	0.0002	-0.0011
	(0.014)	(0.001)	(0.003)	(0.016)	(0.002)	(0.002)	(0.011)	(0.001)	(0.005)
Pre-Rebate Period									
Rebate×1 Wk. Pre	-0.039*	0.001	-0.0031	-0.049**	0.0027	-0.013*	-0.044	-0.00022	-0.0025
	(0.017)	(0.001)	(0.002)	(0.018)	(0.002)	(0.005)	(0.027)	(0.001)	(0.003)
Rebate×2-3 Wks. Pre	-0.022*	0.00051	-0.0046	-0.017	0.0061*	-0.0097	-0.036*	0.0011	-0.0012
	(0.011)	(0.001)	(0.003)	(0.011)	(0.003)	(0.005)	(0.015)	(0.001)	(0.003)
Rebate×4-6 Wks. Pre	-0.026*	0.00031	-0.0046	-0.012	0.0027	-0.0053*	-0.024	0.00066	-0.0032
	(0.012)	(0.001)	(0.003)	(0.012)	(0.001)	(0.002)	(0.016)	(0.001)	(0.003)
Rebate×7-9 Wks. Pre	-0.030***	0.0012	-0.0051*	-0.0093	0.0012	-0.0049	-0.030**	0.00021	-0.0035
	(0.007)	(0.001)	(0.002)	(0.008)	(0.001)	(0.003)	(0.009)	(0.000)	(0.004)
Rebate×10+ Wks. Pre	0.0034	-0.0003	-0.0033*	0.0038	0.0013	-0.0027	-0.0062	0.00045	0.000089
	(0.006)	(0.001)	(0.002)	(0.008)	(0.001)	(0.002)	(0.005)	(0.000)	(0.003)
Post-Rebate Period									
Rebate×1 Wk. Post	0.0074	-0.00056	-0.0017	-0.0078	-0.0023	0.00039	0.018	-0.00033	0.0026
	(0.023)	(0.001)	(0.004)	(0.018)	(0.004)	(0.003)	(0.027)	(0.001)	(0.005)
Rebate×2-3 Wks. Post	-0.0048	0.000029	0.0026	-0.006	0.0067*	-0.0059	-0.0056	-0.0011	0.0024
	(0.015)	(0.001)	(0.003)	(0.015)	(0.003)	(0.003)	(0.018)	(0.001)	(0.005)
Rebate× 4-6 Wks. Post	-0.02	0.00009	-0.0000026	-0.0049	0.0036	-0.00094	-0.026	0.0003	-0.00073
	(0.018)	(0.001)	(0.003)	(0.017)	(0.002)	(0.003)	(0.014)	(0.000)	(0.005)
Rebate×7-9 Wks. Post	-0.022	0.00082	-0.002	-0.0044	0.0049	-0.0059*	-0.033	0.00025	0.0019
	(0.021)	(0.001)	(0.002)	(0.018)	(0.003)	(0.003)	(0.017)	(0.001)	(0.006)
Rebate×10+ Wks. Post	-0.026	-0.00023	-0.0027	-0.016	0.0059*	-0.0059**	-0.036*	0.00093	-0.00073
	(0.017)	(0.001)	(0.002)	(0.018)	(0.003)	(0.002)	(0.015)	(0.001)	(0.005)
# Obs.	12450	12450	12450	12100	12100	12100	12600	12600	12600
R^2	0.996	0.901	0.915	0.996	0.936	0.917	0.995	0.989	0.766
# Clusters	50	50	50	50	50	50	50	50	50

Notes: All specifications have state-year fixed effects and week-of-sample fixed effects. The dummy variable for the pre-announcement period is omitted. Standard errors (in parentheses) clustered at the state level. * ($p < 0.05$), ** ($p < 0.01$), *** ($p < 0.001$).

Table A.4—: The Effect of Rebates on Expected Appliance Energy Use: Micro-Data and Controlling for Demographics

	Refrigerators			Clothes Washers			Dishwashers		
Rebate Period Only	-0.0017***			-0.0089			-0.00092		
	(0.0005)			(0.005)			(0.001)		
Rebate Period, 2 Mos. Pre, 2 Wks.. Post		-0.00068*			-0.0033			-0.0011	
		(0.0003)			(0.002)			(0.001)	
Dynamic Effect of Rebates									
Rebate Period									
Rebate×Wk. 1			-0.0024			-0.054***			-0.0041
			(0.0013)			(0.0077)			(0.0029)
Rebate×Wks. 2-3			-0.00011			-0.018*			-0.0018
			(0.0021)			(0.0074)			(0.0007)
Rebate×Wks. 4-6			-0.00051			-0.0012			-0.00067
			(0.0006)			(0.0032)			(0.0007)
Rebate×Wks. 7-9			-0.0013			0.0013			-0.0011
			(0.0011)			(0.0034)			(0.0007)
Rebate×Wks. 10+			-0.0017			0.0011			-0.0009
			(0.0011)			(0.0032)			(0.0006)
Pre-Rebate Period									
Rebate×1 Wk. Pre			0.0015			0.0062*			-0.0001
			(0.0009)			(0.0028)			(0.0011)
Rebate×2-3 Wks. Pre			0.0012			0.0047			0.00032
			(0.0011)			(0.0040)			(0.0007)
Rebate×4-6 Wks. Pre			0.00091			0.0042**			-0.00024
			(0.0009)			(0.0015)			(0.0006)
Rebate×7-9 Wks. Pre			0.0019			0.0038			-0.0000039
			(0.0011)			(0.0026)			(0.0005)
Rebate×10+ Wks. Pre			-0.00012			-0.00031			0.00016
			(0.0007)			(0.0013)			(0.0006)
Post-Rebate Period									
Rebate×1 Wk. Post			0.0002			0.0038			-0.0062
			(0.0011)			(0.0040)			(0.0034)
Rebate×2-3 Wks. Post			-0.0015			0.0019			-0.0016
			(0.0010)			(0.0038)			(0.0009)
Rebate×4-6 Wks. Post			0.00012			0.0043*			-0.00057
			(0.0010)			(0.0018)			(0.0007)
Rebate×7-9 Wks. Post			0.00067			0.0043			-0.000093
			(0.0008)			(0.0025)			(0.0007)
Rebate×10+ Wks. Post			0.000084			0.0073*			0.00036
			(0.0007)			(0.0028)			(0.0005)

Notes: All specifications have state-year fixed effects, week-of-sample fixed effects, and controls for demographics. The dummy variable for the pre-announcement period is omitted. Standard errors (in parentheses) clustered at the state level. * ($p < 0.05$), ** ($p < 0.01$), *** ($p < 0.001$).

Table A.5—: Impact of Rebates on Sales, Expected Appliance Energy Use, and ES Market Share with Pre-Annoucement Linear Time Trends

	Rebate Period Only			**Rebate Period, 2 Months Pre, 2 Weeks Post**			**Rebate Period, 3 Months Pre, 3 Months Post**		
Dep. Var.:	log(sales)	log(kWh)	ES	log(sales)	log(kWh)	ES	log(sales)	log(kWh)	ES
Refrigerators									
Est.	0.10***	-0.0037**	0.020***	0.012	-0.00013	0.0021	0.0065	0.00021	-0.0014
s.e.	(0.020)	(0.001)	(0.005)	(0.007)	(0.0003)	(0.002)	(0.006)	(0.0005)	(0.0013)
# Obs	12450	12450	12450	12450	12450	12450	12450	12450	12450
R^2	0.996	0.903	0.917	0.995	0.902	0.916	0.995	0.902	0.916
Clothes Washers									
Est.	0.069***	-0.017***	0.021***	0.0099**	-0.0017	0.00092	0.0044	0.00017	-0.00098
s.e.	(0.015)	(0.004)	(0.005)	(0.003)	(0.001)	(0.001)	(0.005)	(0.001)	(0.0012)
# Obs	12100	12100	12100	12100	12100	12100	12100	12100	12100
R^2	0.996	0.936	0.918	0.996	0.936	0.917	0.996	0.936	0.917
Dishwashers									
Est.	0.098***	-0.00049	0.0073**	0.023**	-0.000092	0.00034	-0.00023	-0.00012	-0.00029
s.e.	(0.018)	(0.000)	(0.003)	(0.008)	(0.0003)	(0.001)	(0.009)	(0.0003)	(0.0017)
# Obs	12600	12600	12600	12600	12600	12600	12600	12600	12600
R^2	0.995	0.989	0.767	0.995	0.989	0.767	0.995	0.989	0.767

Notes: The dummy variable for the pre-announcement period is omitted. Standard errors (in parentheses) clustered at the state level. * ($p < 0.05$), ** ($p < 0.01$), *** ($p < 0.001$). All specifications have week-of-sample, state-year fixed effects and state-specific pre-announcement linear time trends.

Table A.6—: Impact of Rebates on Sales, Expected Appliance Energy Use, and ES Market Share with State Fixed Effects

	Rebate Period Only			**Rebate Period, 2 Months Pre, 2 Weeks Post**			**Rebate Period, 3 Months Pre, 3 Months Post**		
Dep. Var.:	log(sales)	log(kWh)	ES	log(sales)	log(kWh)	ES	log(sales)	log(kWh)	ES
Refrigerators									
Est.	0.058^{***}	-0.0019^{*}	0.0079	0.0076^{*}	-0.00013	0.001	0.0062	-0.000047	-0.00034
s.e.	(0.014)	(0.001)	(0.005)	(0.003)	(0.0002)	(0.001)	(0.005)	(0.0003)	(0.0010)
# Obs	12450	12450	12450	12450	12450	12450	12450	12450	12450
R^2	0.995	0.878	0.897	0.995	0.878	0.897	0.995	0.878	0.897
Clothes Washers									
Est.	0.032^{**}	-0.015^{***}	0.013^{**}	0.0045^{*}	-0.0038^{**}	-0.00013	0.0036	-0.0026	-0.0013
s.e.	(0.012)	(0.004)	(0.004)	(0.002)	(0.001)	(0.001)	(0.003)	(0.002)	(0.0013)
# Obs	12100	12100	12100	12100	12100	12100	12100	12100	12100
R^2	0.996	0.915	0.902	0.996	0.914	0.901	0.996	0.914	0.901
Dishwashers									
Est.	0.051^{***}	-0.00082	0.0042	0.0095^{**}	-0.00033^{*}	-0.0013	0.0028	-0.00035	-0.0015
s.e.	(0.012)	(0.001)	(0.004)	(0.003)	(0.0002)	(0.002)	(0.004)	(0.0002)	(0.0022)
# Obs	12600	12600	12600	12600	12600	12600	12600	12600	12600
R^2	0.994	0.985	0.722	0.994	0.985	0.722	0.994	0.985	0.722

Notes: The dummy variable for the pre-announcement period is omitted. Standard errors (in parentheses) clustered at the state level. * ($p < 0.05$), ** ($p < 0.01$), *** ($p < 0.001$). All specifications have week-of-sample and state fixed effects.

Table A.7—: Impact of Rebates on Sales, Expected Appliance Energy Use, and ES Market Share without Problematic States

	Rebate Period Only			**Rebate Period, 2 Months Pre, 2 Weeks Post**			**Rebate Period, 3 Months Pre, 3 Months Post**		
Dep. Var.:	log(sales)	log(kWh)	ES	log(sales)	log(kWh)	ES	log(sales)	log(kWh)	ES
Refrigerators									
Est.	0.093***	-0.0037**	0.022***	0.014	-0.00043	0.0035	0.0072	0.000036	0.00037
s.e.	(0.021)	(0.001)	(0.005)	(0.009)	(0.0004)	(0.003)	(0.005)	(0.0005)	(0.0012)
# Obs	11205	11205	11205	11205	11205	11205	11205	11205	11205
R^2	0.995	0.898	0.911	0.995	0.898	0.91	0.995	0.898	0.910
Clothes Washers									
Est.	0.060***	-0.018***	0.022***	0.010*	-0.0023	0.0012	0.0044	-0.00036	-0.00027
s.e.	(0.017)	(0.004)	(0.005)	(0.005)	(0.002)	(0.002)	(0.003)	(0.001)	(0.0011)
# Obs	10890	10890	10890	10890	10890	10890	10890	10890	10890
R^2	0.996	0.933	0.913	0.996	0.933	0.913	0.996	0.933	0.912
Dishwashers									
Est.	0.090***	-0.00066	0.0067*	0.028**	-0.00029	0.000017	-0.0015	-0.00041	0.00012
s.e.	(0.018)	(0.0005)	(0.003)	(0.010)	(0.0005)	(0.001)	(0.006)	(0.0003)	(0.0012)
# Obs	11340	11340	11340	11340	11340	11340	11340	11340	11340
R^2	0.995	0.988	0.76	0.995	0.988	0.76	0.995	0.988	0.760

Notes: The dummy variable for the pre-announcement period is omitted. Standard errors (in parentheses) clustered at the state level. * ($p < 0.05$), ** ($p < 0.01$), *** ($p < 0.001$). All specifications have week-of-sample and state fixed effects.

Table A.8—: Impact of Program Characteristics on Expected Energy Savings

Dependent Variable: Percentage Energy Savings in Each State			
	Refrigerators	Clothes Washers	Dishwashers
Rebate Amount ($)	-0.0037	0.024***	0.0010*
	(0.0019)	(0.0041)	(0.00038)
Duration (weeks)	0.0020	-0.0039	0.00025
	(0.0015)	(0.0042)	(0.00028)
Advalorem=1	1.60	-2.74	-0.36*
	(0.84)	(2.03)	(0.13)
Online=1	-0.036	1.16	-0.021
	(0.55)	(1.20)	(0.083)
Reservation System=1	-0.21	-1.18	0.050
	(0.52)	(1.19)	(0.081)
Recycling Requirement=1	-0.30	0.053	0.24*
	(0.57)	(1.36)	(0.091)
Recycling Incentive=1	0.56	-0.082	0.010
	(0.76)	(1.76)	(0.11)
Eligibility Criteria=2	1.34	-1.81	0.41
	(0.95)	(3.73)	(0.22)
Eligibility Criteria=3	1.32	-1.37	0.41
	(1.20)	(3.94)	(0.23)
Eligibility Criteria=4	0.64	-1.69	0.55*
	(1.45)	(3.98)	(0.24)
# Obs.	42	42	36
R^2	0.332	0.611	0.621

Notes: The dependent variable is the average energy savings in each state measured in percentage. A positive sign means that a "feature" increases savings. For instance, increasing the rebate amount for clothes washers from $0 to $100 increases savings by 2.4%. The savings were estimated over the rebate period, two months before the start of the rebate period, and two Wks. Post the end of the rebate period. The dummy "advalorem" takes the value one when ad valorem rebates are offered. The dummy "online" takes the value one if rebates could be claimed online. The dummy "reservation system" is zero if consumers had to buy then apply, and takes the value one if reservations were allowed. The eligibility criteria are coded as follows: (1) ES (omitted), (2) ES baseline with marginal rebate increases for higher efficiency, (3) more efficient than ES, and (4) more efficient than ES baseline with marginal rebate increases for higher efficiency. Standard errors in parentheses. * ($p < 0.05$), ** ($p < 0.01$), *** ($p < 0.001$)

Table A.9—: DOE's C4A Energy Savings Estimates

	kWh/y saved (D&R)	$\overline{kWh}/y^{ES} - \overline{kWh}/y^{Non-ES}$ (NPD, non-sales weighted)	$\overline{kWh}/y^{ES} - \overline{kWh}/y^{Non-ES}$ adjustment: 5-year Accelerated Replacement	% Freeriders No Accelerated Replacement	% Freeriders 5-year Accelerated Replacement
Refrigerator	116	65	97	$< 0\%$	$< 0\%$
Washer	257	201	344	$< 0\%$	25%
Dishwasher	57	34	82	$< 0\%$	30%

Notes: Sources: Department of Energy (DOE), D&R International (2013), and NPD Marketing Group. The difference in average electricity consumption between ES and non-ES models ($\overline{kWh}/y^{ES} - \overline{kWh}/y^{Non-ES}$) is the difference observed in the choice set of the NPD data for the years 2010-2011 (Table 6). The adjustment for the accelerated replacement uses the sales-weighted average electricity consumption purchased in the year 2001 observed in the NPD data. For refrigerators, the 2001 average is obtained directly from the DOE data that provide information on the appliances replaced.

Table A.10—: Cost-Effectiveness Analysis: No Adjustment for Accelerate Replacement

	Δ kWh/y	Rebate ($)	Cost-Effectiveness ($/kWh saved) Proportion of Freeriders/Non-Switchers						
			0%	25%	50%	70%	85%	90%	92%
Refrigerators									
ES vs. Non-ES	-65	128	0.13	0.18	0.26	**0.44**	0.88	1.31	**1.64**
Top 5% vs Bottom 95%	-183	128	0.05	0.06	0.09	**0.16**	0.31	0.47	**0.58**
Top 10% vs Bottom 90%	-165	128	0.05	0.07	0.10	**0.17**	0.34	0.52	**0.65**
Top 20% vs Bottom 80%	-142	128	0.06	0.08	0.12	**0.20**	0.40	0.60	**0.75**
Clothes Washers									
ES vs. Non-ES	-201	107	0.04	0.05	0.07	**0.12**	0.24	**0.35**	0.44
Top 5% vs. Bottom 95%	-115	107	0.06	0.08	0.12	**0.21**	0.41	**0.62**	0.78
Top 10% vs. Bottom 90%	-116	107	0.06	0.08	0.12	**0.20**	0.41	**0.61**	0.77
Top 20% vs. Bottom 80%	-121	107	0.06	0.08	0.12	**0.20**	0.39	**0.59**	0.74
Dishwashers									
ES vs. Non-ES	-34	84	0.16	0.22	0.33	**0.55**	**1.10**	1.65	2.06
Top 5% vs. Bottom 95%	-108	84	0.05	0.07	0.10	**0.17**	**0.35**	0.52	0.65
Top 10% vs. Bottom 90%	-83	84	0.07	0.09	0.13	**0.22**	**0.45**	0.67	0.84
Top 20% vs. Bottom 80%	-57	84	0.10	0.13	0.20	**0.33**	**0.65**	0.98	1.23

Notes: The rebate amount for each appliance category is the non-weighted average of the rebate amount offered by each state. The estimates in bold correspond to the proportions of freeriders and non-switchers estimated (Table 5). For all appliances, we assume a lifetime of 15 years.

Association of Unemployment Rate and SEEARP Program Design

The Department of Energy provided discretion to state agencies in the design and implementation of their respective State Energy Efficient Appliance Rebate Programs (SEEARP). States varied the design of their programs in terms of:

- Indicator variables for the eligibility of refrigerators, dishwashers, and clothes washers in rebate programs.
- Rebate amounts for each of: refrigerators, dishwashers, and clothes washers.
- Percentage-based rebates in lieu of fixed-value rebates.
- Program start date and duration.
- Availability of online rebate claims.
- Availability of advance reservations.
- Means-testing of program eligbility.
- Targeting rebates to elderly and/or disabled individuals.
- Required recycling of existing appliance.

We evaluate the extent to which these program design attributes are correlated with state economic conditions, specifically unemployment rates. We use the Bureau of Labor Statistics' average seasonally-adjusted monthly unemployment rate by state for 2009 and the one-year difference in unemployment rates between 2009 and 2008 ($UR_i^{2009} - UR_i^{2008}$).

To assess the association between energy-efficient appliance rebate program design and state economic conditions, we estimate regression models for each of the fourteen program characterstics described above. In the first set of models, we regress each of the program characteristics (R) on the unemployment rate (UR) with the 50-state cross-section:

$$(1) \qquad R_i = \alpha + \beta_1 UR_i + \epsilon_i$$

In the second set of models, we regress each of the program characteristics (R) on the first difference in the unemployment rate with the 50-state cross-section:

$$(2) \qquad R_i = \alpha + \beta_1 \Delta UR_i + \epsilon_i$$

Estimating these two models with our 14 program design characteristics yields 28 regression models. First, note that the unemployment rate – in level and in first differences – explains very little variation in the state program design charcteristics. In only three of 28 models does the unemployment rate explain at least five percent of the variation in a given design characteristic (and in none of these models is at least 10 percent of the variation explained).

Second, in only five of the models are the unemployment rate coefficient estimates statistically significant at the 10 percent or smaller levels. Let us describe these five in detail. The decision about whether to have a dishwashers rebate program in a state is correlated with the state's 2009 unemployment rate. A one standard deviation increase in the unemployment rate would increase the likelihood of a dishwashers rebate program by 13 percent. While only statistically significant at the 10 percent level, the unemployment rate and first difference in unemployment rates regressions show that the likelihood that a state program would design rebates as a percentage of the sale price increases in both measures. A one standard deviation increase in the unemployment rate and a one standard deviation increase in the first difference in unemployment rates would increase the likelihood of a percentage rebate scheme by 12 percent and 9 percent, respectively. States with higher unemployment rates (levels regression) and large increases in unemployment rates over 2008-2009 (first difference regression) appear to have an earlier state date to their rebate programs. A one standard deviation increase in either the unemployment rate or the first difference in the unemployment rate would move up the start date of the rebate program by twelve days. While statistically significant (at the 5 percent and 10 percent levels, respectively), we don't believe that such a modest change in start dates is economically meaningful in light of the length of the Great Recession as well as other factors influencing the start of the programs (such as the timing of passage of the American Recovery and Reinvestment Act, the timing of the publication of the Department of Energy requests for proposals, etc.).

Finally, note that the unemployment rate – in levels and in first differences – does not explain the magnitude of the rebates offered for the appliances in our study. The coefficient estimates cannot be distinguished from zero and, for that matter, the signs on the estimated coefficients are not consistent, with three negative and three positive. There is no evidence of a systematic relationship between a state's local economy – specifically its local labor market – and the setting of rebate amounts in the state's rebate program.

Table A.11—: Economic Conditions and SEEARP Design: Cross-Sectional Analysis I

	Refrigerator	Dishwasher	Clothes Washer	Refrigerator Rebate	Dishwasher Rebate	Clothes Washer Rebate	Percent Based Rebate
Unemployment Rate	0.007	0.068**	0.014	-0.93	3.23	2.89	0.060*
	(0.027)	(0.029)	(0.030)	(11.00)	(6.73)	(12.09)	(0.031)
Constant	0.74	0.14	0.72***	146.97	51.46	101.07	-0.39*
	(0.24)	(0.27)	(0.26)	(93.04)	(58.56)	(99.52)	(0.21)
N	50	50	50	50	50	50	50
R^2	0.0011	0.087	0.0265	0.0001	0.0044	0.0014	0.073

Notes: Robust standard errors in parentheses (* p<.10 ** p<.05 *** p<.01).

Table A.12—: Economic Conditions and SEEARP Design: Cross-Sectional Analysis II

	Start Date	Duration	Online Claims	Reservations	Means-tested	Disabled/ Elderly	Recycling Required
Unemployment Rate	-6.11**	0.25	0.000	-0.008	0.007	-0.011	0.014
	(2.97)	(1.95)	(0.037)	(0.038)	(0.016)	(0.009)	(0.032)
Constant	18405.22***	32.59*	0.42	0.45	-0.019	0.13	0.13
	(27.98)	(17.30)	(0.32)	(0.33)	(0.12)	(0.10)	(0.28)

Notes: Robust standard errors in parentheses (* p<.10 ** p<.05 *** p<.01).

Table A.13—: Economic Conditions and SEEARP Design:
First Differences Analysis I

	Refrigerator	Dishwasher	Clothes Washer	Refrigerator Rebate	Dishwasher Rebate	Clothes Washer Rebate	Percent Based Rebate
ΔUnemployment Rate	-0.029	0.10	0.054	-18.34	-5.44	4.87	0.095*
	(0.054)	(0.066)	(0.057)	(29.01)	(16.62)	(26.26)	(0.048)
Constant	0.89***	0.39*	0.67***	196.50**	95.73*	110.18	-0.18*
	(0.17)	(0.23)	(0.20)	(92.96)	(54.69)	(78.70)	(0.104)
N	50	50	50	50	50	50	50
R^2	0.005	0.049	0.020	0.012	0.003	0.001	0.044

Notes: Robust standard errors in parentheses (* p<.10 ** p<.05 *** p<.01).

Table A.14—: Economic Conditions and SEEARP Design:
First Differences Analysis II

	Start Date	Duration	Online Claims	Reservations	Means-tested	Disabled/ Elderly	Recycling Required
ΔUnemployment Rate	-12.25*	-1.97	0.013	-0.048	0.023	-0.050	0.032
	(6.96)	(4.39)	(0.074)	(0.073)	(0.032)	(0.039)	(0.066)
Constant	18392.01***	40.90***	0.38	0.53**	-0.032	0.20	0.14
	(24.97)	(14.74)	(0.24)	(0.24)	(0.093)	(0.14)	(0.21)
N	50	50	50	50	50	50	50
R^2	0.045	0.0054	0.0006	0.0088	0.012	0.059	0.005

Notes: Robust standard errors in parentheses (* p<.10 ** p<.05 *** p<.01).

```
Belt and Suspenders and More: Data and Code
Prepared by Sebastien Houde
12/08/15


The paper uses three different datasets.
1. Transaction-level from a large retailer. The raw data are not publicly
available. For replication purpose,
   a dataset aggregated at the week-state level is made available. Sales are
scaled by an unknown constant.
   Except for Tables 3 and 5, all other results in the main sections of the
paper can be replicated with the
   anonymous aggregated data.

2. SEEARP data. These data were obtained from the DOE via FOIA and C4A
program' websites. These data are publicly
   available. Rebate and program information were scrapped from each state's
website.

3. NPD data: These data can be purchased from the NPD Group. Otherwise, these
data are not publicly available.
   These data are used for Table 6 only in the main sections of the paper.


==============================================================================
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Data Cleaning
==============================================================================
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          Process_Aggregation Retailer Data
                    I. Prepare transaction level data.
                    Transaction level data -- not available
                    code\prepare_reg_rebate_kwh_dishwashers.do
                    code\prepare_reg_rebate_kwh_refrigerators.do
                    code\prepare_reg_rebate_kwh_washers.do


                    II. Aggregate transaction-level data to the week-state
level.
                    Week-state averages are scaled by an unknown constant so
                    level are not informative.
                    code\CreateAggregate_dishwashers.do
                    code\CreateAggregate_refrigerators.do
                    code\CreateAggregate_washers.do
                              Scaled data available:

data\sales_kwh_estar_week_dishwashers_2008_2012_scaled

data\sales_kwh_estar_week_washers_2008_2012_scaled

data\sales_kwh_estar_week_refrigerators_2008_2012_scaled

                    III. Prepare scaled data for regressions.
                    code\MakeAggregate_RegReady_dishwashers.do
                    code\MakeAggregate_RegReady_refrigerators.do
                    code\MakeAggregate_RegReady_washers.do
                              Weekly rebate data:
                              data\cash4appliance_dishwashers_weekly_vf
                              data\cash4appliance_washers_weekly_vf
```

```
                   data\cash4appliance_refrigerators_weekly_vf

                   Announcement date:
                   data\Cash4Appliances_announcement


     Process_SEEARP
          code\Construct US SEEARP Dataset 130217.do
          code\process_SEEARP_02232013.do
          code\SEEARP_Select_Appliance.do
                   Compile data available:
                   data\SEEARP US
                   data\SEEARP_US_cleaned

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Figures and Tables for Paper
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     Figure2
          code\plot_national_nb_programs_dishwashers.do
          code\plot_national_nb_programs_refrigerators.do
          code\plot_national_nb_programs_washers.do
                   Scaled week-state data available:

data\sales_kwh_estar_week_dishwashers_2008_2012_scaled

data\sales_kwh_estar_week_washers_2008_2012_scaled

data\sales_kwh_estar_week_refrigerators_2008_2012_scaled

     Figure3
          code\plot_spline_aggregate_dishwashers.do
          code\plot_spline_aggregate_refrigerators.do
          code\plot_spline_aggregate_washers.do
                   Scaled week-state data available:

data\sales_kwh_estar_week_dishwashers_2008_2012_scaled_regready

data\sales_kwh_estar_week_washers_2008_2012_scaled_regready

data\sales_kwh_estar_week_refrigerators_2008_2012_scaled_regready

     Figure4
          I. Run state level regressions
          code\RegRebate_aggregate_vstate_dishwashers_StateYear.do
          code\RegRebate_aggregate_vstate_refrigerators_StateYear.do
          code\RegRebate_aggregate_vstate_washers_StateYear.do
                   Scaled week-state data available:

data\sales_kwh_estar_week_dishwashers_2008_2012_scaled_regready

data\sales_kwh_estar_week_washers_2008_2012_scaled_regready

data\sales_kwh_estar_week_refrigerators_2008_2012_scaled_regready

          II. Plot estimates from Step I.
          code\plot_aggregate_vstate_dishwashers_StateYear.do
          code\plot_aggregate_vstate_refrigerators_StateYear.do
```

```
                code\plot_aggregate_vstate_washers_StateYear.do
                        Estimates from Step I.
                        data\estimate_logkwh_ref_bystate_StateYear
data\estimate_logkwh_dishwashers_bystate_StateYear
                        data\estimate_logkwh_washers_bystate_StateYear


        Figure5
                code\plot_spline_aggregate_MSRP_size_type_dishwashers.do
                code\plot_spline_aggregate_MSRP_size_type_refrigerators.do
                code\plot_spline_aggregate_MSRP_size_type_washers.do
                        Scaled week-state data available:
data\sales_kwh_estar_week_dishwashers_2008_2012_scaled_regready
data\sales_kwh_estar_week_washers_2008_2012_scaled_regready
data\sales_kwh_estar_week_refrigerators_2008_2012_scaled_regready

        Table1
                code\cash4appliances_dishwashers_v2.do
                code\cash4appliances_refrigerators_v2.do
                code\cash4appliances_washers_v2.do
                        C4A data manually processed from the State Rebate
Programs:
                        data\cash4appliance_dishwashers.csv
                        data\cash4appliance_washers.csv
                        data\cash4appliance_refrigerators_11212012

        Table2
                code\SumStats_SEEARP.do
                        data\SEEARP_US_cleaned

        Table3
                code\sum_stats_choiceset_2010_2011.do
                        Transaction level data -- not available

        Table4
                code\RegRebate_aggregate_dishwashers.do
                code\RegRebate_aggregate_refrigerators.do
                code\RegRebate_aggregate_washers.do
                        Scaled week-state data available:
data\sales_kwh_estar_week_dishwashers_2008_2012_scaled_regready
data\sales_kwh_estar_week_washers_2008_2012_scaled_regready
data\sales_kwh_estar_week_refrigerators_2008_2012_scaled_regready

        Table5
code\Freeriders_aggregate_SEEARP_dishwashers_vATEbyState.do
code\Freeriders_aggregate_SEEARP_refrigerators_vATEbyState.do
                code\Freeriders_aggregate_SEEARP_washers_vATEbyState.do
                code\RegRebate_aggregate_vstate_dishwashers_StateYear.do
                code\RegRebate_aggregate_vstate_refrigerators_StateYear.do
                code\RegRebate_aggregate_vstate_washers_StateYear.do
                        Non-scaled week-state data -- not available
```

```
          Table6
                   code\sum_stats_choiceset_NPD.do
                   code\sum_stats_choiceset_NPD_SalesWeighted.do
                            NPD data -- contact NPD Group

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Figures and Tables for Online Appendix
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          FigureA1
                   code\SumStats_SEEARP.do
                            data\SEEARP_US_cleaned

          FigureA2
                   code\cash4appliances_dishwashers_v2.do
                   code\cash4appliances_refrigerators_v2.do
                   code\cash4appliances_washers_v2.do

code\plot_timing_refrigerators_washers_dishwashers_SEEARP_v2.do
                            C4A data manually processed from the State Rebate
Programs:
                            data\cash4appliance_dishwashers.csv
                            data\cash4appliance_washers.csv
                            data\cash4appliance_refrigerators_11212012


          FigureA3
                   code\plot_spline_aggregate_dishwashers.do
                   code\plot_spline_aggregate_refrigerators.do
                   code\plot_spline_aggregate_washers.do

          FigureA4

          TableA1
                   code\SumStats_SEEARP_dishwashers.do
                   code\SumStats_SEEARP_refrigerators.do
                   code\SumStats_SEEARP_washers.do

          TableA2

          TableA3
                   code\RegRebate_aggregate_dishwashers.do
                   code\RegRebate_aggregate_refrigerators.do
                   code\RegRebate_aggregate_washers.do
                            Scaled week-state data available:

data\sales_kwh_estar_week_dishwashers_2008_2012_scaled_regready

data\sales_kwh_estar_week_washers_2008_2012_scaled_regready

data\sales_kwh_estar_week_refrigerators_2008_2012_scaled_regready

          TableA4
                   code\prepare_reg_rebate_kwh_dishwashers.do
                   code\prepare_reg_rebate_kwh_refrigerators.do
                   code\prepare_reg_rebate_kwh_washers.do
```

```
                code\RegRebate_kwh_dishwashers_micro.do
                code\RegRebate_kwh_refrigerators_micro.do
                code\RegRebate_kwh_washers_micro.do
                        Transaction level data -- not available

        TableA5
                code\RegRebate_aggregate_dishwashers.do
                code\RegRebate_aggregate_refrigerators.do
                code\RegRebate_aggregate_washers.do
                        Scaled week-state data available:

data\sales_kwh_estar_week_dishwashers_2008_2012_scaled_regready

data\sales_kwh_estar_week_washers_2008_2012_scaled_regready

data\sales_kwh_estar_week_refrigerators_2008_2012_scaled_regready


        TableA6
                code\RegRebate_aggregate_dishwashers.do
                code\RegRebate_aggregate_refrigerators.do
                code\RegRebate_aggregate_washers.do
                        Scaled week-state data available:

data\sales_kwh_estar_week_dishwashers_2008_2012_scaled_regready

data\sales_kwh_estar_week_washers_2008_2012_scaled_regready

data\sales_kwh_estar_week_refrigerators_2008_2012_scaled_regready


        TableA7
                code\RegRebate_aggregate_dishwashers.do
                code\RegRebate_aggregate_refrigerators.do
                code\RegRebate_aggregate_washers.do
                        Scaled week-state data available:

data\sales_kwh_estar_week_dishwashers_2008_2012_scaled_regready

data\sales_kwh_estar_week_washers_2008_2012_scaled_regready

data\sales_kwh_estar_week_refrigerators_2008_2012_scaled_regready

        TableA8
                code\program_characteristics_3appliances.do
                code\reg_aggregate_kwh_state_program_characteristics.do
                        C4A data manually processed from the State Rebate
Programs:
                        data\cash4appliance_dishwashers.csv
                        data\cash4appliance_washers.csv
                        data\cash4appliance_refrigerators_11212012
                        data\Program_Characteristics

        TableA9
                code\sum_stats_choiceset_NPD.do
                        NPD data -- contact NPD Group


        TableA10
                code\sum_stats_choiceset_NPD.do
```

```
                    NPD data -- contact NPD Group

TableA11-TableA14
          code\Economic Data FINAL.do
                    data\SEEARP Characteristics
                    data\State Unemp Rate 2003-2013
                    data\SEEARP Data\SEEARP US
```