Distortionary Fundraising for Energy Efficiency Subsidies: Implications for Efficient and Equitable Program Design

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Abstract

State regulators in the U.S. require subsidies for energy efficient durable goods as an important piece of energy conservation policy, and spending on these programs has grown by 18% per year since the early 2000s. This paper examines the economic efficiency and distributional equity impacts of appliance subsidies on top of pre-existing regulations like the Energy Star label. Employing household level data on program participation and energy usage from a large utility, I estimate a discrete-continuous model of appliance purchase and utilization. I find that increases to the energy price used to fund the subsidy programs account for over 80% of the total reductions in energy use and over 35% of the change in total welfare caused by the policies. These effects are not captured by traditional evaluations that assume non-distortionary fundraising. My results also suggest the current program reduces consumer surplus even accounting for energy consumption externalities and private market failures. However, the program might improve total welfare if the regulator values transfers to producers and could lower the time and hassle costs of program participation. Finally, I find substantial scope for fundraising changes, point of sale rebates, and means-tested eligibility to improve program efficiency and equity.

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1 Introduction

Subsidies for energy efficient durables are an important public policy in many parts of the United States. Nationwide spending on rebates and incentives for efficient washing machines, refrigerators, pool pumps, and other durables has grown by 18% per year since the early 2000s, reaching over $7.4 billion in 2014. These programs are primarily intended to reduce environmental externalities associated with energy consumption and to alleviate potential market failures that might lead to privately suboptimal investment in energy efficient durables. An essential but frequently ignored characteristic of most energy efficiency subsidies is that fundraising occurs by raising the marginal price of electricity.[1] This fundraising distortion directly affects energy usage, which is a common benchmark for program effectiveness.

This paper addresses three questions: (1) How do energy efficiency subsidies and the associated fundraising activities affect consumer surplus, producer surplus, and environmental damages (economic efficiency), (2) who benefits from these policies (distributional equity), and (3) what policy design changes can be made to improve efficiency and equity? In contrast to previous work that assumes that fundraising is non-distortionary, I allow the energy price change associated with these policies to play an important role in answering both program evaluation and program design questions. This energy price distortion is not only of academic interest: Since the electricity price affects all end uses of electricity, its impact on energy conservation could be large relative to the previously-studied subsidy channel that affects a single appliance class.

The key methodological feature of my work that allows me to answer these questions is a model of household appliance purchase and utilization in the spirit of Dubin and McFadden (1984). The policy changes the subsidy amount and the electricity price, which in turn affect both the discrete appliance choice and the continuous utilization decision.[2] While many evaluations rely on experimental or quasi-experimental appliance price variation, there are no evaluations that simultaneously take advantage of variation in the price of energy (Allcott and Kessler 2015, Allcott and Greenstone 2017, Boomhower and Davis 2014, Davis 2008, Davis et al. 2014, Fowlie et al. 2015, Houde and Aldy 2014). An advantage of these experimental evaluations is their ability to control for inframarginal participation (i.e. subsidy recipients who would have still purchased an energy efficient appliance in the absence of the rebate) and selection into program participation (i.e. observable and unobservable differences between participants and non-participants) to recover the effect of the subsidy on appliance adoption and energy usage. However, this work does not

[1]In many states, fundraising through higher electricity prices is required by law as part of the subsidy program. The appendix contains several examples. Programs are also funded by raising natural gas prices, but I study electric appliances in this paper. Although fundraising through marginal electricity prices is common, there are a few notable exceptions to this funding design. Fowlie et al. (2015) and Houde and Aldy (2014) study subsidies that were part of the federally funded stimulus following the 2009 financial crisis.

[2]The discrete appliance purchase choice depends not only on appliance prices, but also on the price of energy. Analogously, the continuous appliance utilization decision depends on both the price of energy and the household's appliance holdings.

measure the effect of the entire policy on energy consumption, since all households are affected by the energy price change leaving the experimenter without a low-energy-price control group.[3] My approach retains the ability of experimental evaluations to control for selection and inframarginal participation, while also allowing for changes to the price of energy caused by the program.

An additional advantage of the model of household decisionmaking is its ability to predict how consumers would behave when faced with a policy that hasn't yet been implemented. Since experimental evaluations identify energy consumption treatment effects that are local to the experimental variation in appliance prices, it's difficult to understand how consumers might respond if faced with a policy that hasn't been observed in the data. However, it's precisely the household response to prices that haven't been observed in the data that are of greatest interest to a lawmaker contemplating program changes. My model of behavior permits ex-ante program design, which provides a feasible method of developing more efficient and more equitable programs.

To estimate my model, I study a washing machine program in a large U.S. utility territory.[4] This was the most popular subsidy in utility I study, although the approach is applicable to other durable goods subsidies as well. For every household, I observe participation status in the washing machine rebate program as well as monthly energy consumption. I take advantage of quasi-experimental variation in energy and appliance prices to recover consistent estimates of the parameters of the household utility function. Using the estimated primitives of the household utility function, I can predict both discrete appliance purchase and continuous energy utilization choices under a range of different subsidy amounts and energy prices.

My results highlight the importance of the energy price change in a comprehensive program evaluation. I find that the energy saved through the electricity price change is five times greater than energy saved through the efficient appliance purchased because of the subsidy.[5] This large effect of the electricity price change is not surprising given the the price of electricity affects all end uses of electricity in all households, even households who did not participate in the program. The subsidy on the other hand only saves energy used for clothes washing and only affects behavior for a small set of marginal households whose appliance purchase decision was changed by the rebate.

The large reduction in energy use has a theoretically ambiguous effect on consumer welfare. Reductions in environmental externalities are beneficial, but savings come at the cost of decreased

[3]An experiment with all of the features relevant to an actual subsidy program would need to randomize both the subsidy *and* the energy price across otherwise similar households. Randomizing the subsidy across similar customers within a utility territory (and changing the energy price based on corresponding subsidy) would be preferable, but this seems un-implementable given utility company concern for equal treatment of similar customers. Another alternative would be to randomize the program across utility territories, but it might be challenging to control for differences in customers across such large regions of space.

[4]My agreement with the data provider prevents me from disclosing the identify of the utility company.

[5]This result is easily sanity-checked via a back of the envelope using off-the-shelf estimates of the relevant elasticities. I describe the relevant inputs and perform this calculation using a range of values of the needed elasticities in the appendix.

private surplus from energy use.[6] My results suggest that the two programs I study reduce total welfare, even accounting for the environmental externality and appliance market failures that potentially lead to privately sub-optimal investment in energy efficient durables. This is primarily due to the large private time and hassle costs of program participation. However, Borenstein and Bushnell (2017) provide evidence that the retail price of electricity in this utility territory is greater than the social marginal cost of electricity use, so program fundraising through higher electricity prices further reduces total welfare.[7] Furthermore, the washing machine program is regressive in terms of the dollar transfers from poor to wealthy neighborhoods. Although Energy Star appliance purchase is slightly lower in poorer neighborhoods, program participation even conditional on Energy Star appliance purchase increases in income. This suggests lower awareness or higher unobserved (e.g. cognitive) costs of program participation in low-income areas, and I show average differences on the order of \$100 in these costs between the lowest-income and highest-income neighborhoods in my sample.

To explore welfare-improving program design changes, I develop a general policy objective function that incorporates notions of both efficiency and equity. Using insights from the optimality conditions of this objective function, I propose three alternatives the current policy that improve efficiency and equity. First, simply changing fundraising for the policies from a distortionary per-kWh charge to a fixed monthly charge reduces the deadweight loss associated with the policies. This fixed-fee fundraising also benefits poor households without significantly increasing the burden on other parts of the income distribution. Second, applying the subsidy at the point of sale reduces the welfare costs associated with the time and hassle of program participation. Finally, means testing the subsidy amount has two beneficial effects: It not only makes the income redistribution created by the program more progressive, but it also prevents producers from raising prices to capture all of the surplus from a point of sale program.

The remainder of this paper proceeds as follows: In Section 2, I begin with a discussion of the implementation of energy efficiency subsidies and affected margins of household behavior. Sections 3 and 4 describe my discrete-continuous model of durable choice and the data I use as inputs in the model respectively. Section 5 solves the utility-maximization problem for optimal household behavior, and Section 6 derives moment conditions based on the results of Section 5. In Section 7, I present the program evaluation results and discuss implications for the welfare effects of the program, and Section 8 explores the key economic costs that affect the current program. Finally, in Section 9, I discuss several alternatives to the existing policy that have better economic efficiency and distributional equity properties.

[6] Allcott and Kessler (2015) and Allcott and Greenstone (2017) examine the private welfare costs of participation in similar programs (e.g. time and hassle disutility) under the assumption that fundraising is non-distortionary.

[7] Borenstein and Bushnell (2017) also note that there is substantial scope in many parts of the country to improve welfare by moving the retail price of electricity closer to the social marginal cost of electricity.

2 Setting

State regulators known as Public Utilities Commissions (PUCs) regulate most electric and gas utilities in the U.S.[8] Many regulators require utility companies to offer "public purpose" programs to correct perceived market failures such as the environmental externalities associated with energy use.[9] In many states, energy efficiency subsidies are one of the largest line-items in the public purpose program budget. These subsidies generally take the form of rebates for customers who purchase Energy Star appliances or make efficiency upgrades to their homes or business.[10,11] In principle, these programs could save energy by encouraging greater adoption of efficient appliances. Furthermore, this rebate assistance might be especially useful for lower-income households who in the absence of these rebates might purchase fewer efficient appliances.

Subsidized appliances and home upgrades vary somewhat across utility service territories, but common examples include washing machines, refrigerators (Houde and Aldy 2014), pool pumps, water heaters, weatherization (Fowlie et al. 2015), compact fluorescent lightbulbs, and home energy audits (Allcott and Greenstone 2017). Each of these programs creates similar economic incentives for appliance adoption and utilization, and hence the intuition developed by studying the washing machine program will also apply to other subsidy policies offered across the U.S.[12]

To claim the washer rebate, a customer first purchases a new Energy Star model.[13] The customer then completes an online or paper application and attaches proof of purchase, and upon receipt of the rebate application the utility issues a check or credits the customer's next bill. Some program participants would have purchased an Energy Star appliance even without the rebate incentive, while other households purchase a qualifying appliance and don't claim the rebate. Each

[8] Many states refer to the regulator as a Public Service Commission (PSC), and in some cases these agencies are also called railroad commissions since railroads were one of the first regulated natural monopolies. PUCs don't have jurisdiction to regulate many of the activities (such as prices) of municipally owned and other public utilities, but many of the largest utilities in the U.S. are investor-owned companies that *are* regulated by state utility commissions. While not subject to PUC jurisdiction, municipal utility companies also run public purpose programs that are similar in purpose and structure so I will not treat them separately. The appendix contains more information on the regulatory landscape relevant to this research.

[9] The most commonly cited market failure is the pollution externality arising from energy use. However, there are many other potential market failures such as landlord tenant incentives, myopia, or salience about durable good energy use. Gillingham and Palmer (2014) provide an excellent review.

[10] The programs list qualifying appliance models, and sometimes there are Energy Star models that do not qualify. However, for expositional ease, I will use the phrase "Energy Star appliance" synonymously with "qualifying appliance" to denote durables that are eligible for a rebate.

[11] Energy price subsidies for low income households are a slightly larger budget item than the energy efficient appliance subsidies in CA, but these two are the dominant public purpose programs. Low-income price subsidies are about 45% of the public purpose budget, and energy efficiency subsidies are about 37%. In California, there are also a few smaller public purpose programs that fund solar investment and demand response that make up the remaining 18% of the public purpose expenditures CPUC (2016a).

[12] In the appendix, I use a back of the envelope calculation to show the applicability of my framework to other programs.

[13] All residential customers are eligible for the rebates as long as they have not claimed a rebate for the same appliance in the last five years. A complete list of qualifying models is available from the utility website. Both brick-and-mortar and online purchases qualify.

year, about 1.8% of households in this utility territory claim the washering machiner rebate.

Since it's expensive to subsidize participating households, regulated utilities pass the cost of these programs on to their customers. Fundraising occurs by applying a per-unit charge to *all* electricity consumed by *all* of the utility customers in the service territory.[14] As a result of energy efficiency subsidies, residential electricity prices increase by 3.3% on average for customers in this utility territory.[15,16] This has several important implications: First, it means that the fundraising activities directly affect energy consumption, one of the policy outcomes of interest. This implies that the relevant marginal cost of public funds is specific to the programs, and furthermore that the cost could even be negative if the externality reductions are greater than the private distortions to consumption utility. Second, the fundraising might also affect appliance purchases in a way not captured through existing studies, since higher energy prices creates a stronger incentive for households to purchase efficient appliances.

In order to capture the entire effect of the program or perform ex-ante evaluations of alternative policies, it's important to model the link between the two margins of household behavior. These links determine which households are marginal to a given subsidy and energy price vector, how much energy marginal households might save conditional on participation, and how the change in energy price affects non-participating customers. A model of household behavior that incorporates these features is convenient because it allows the researcher to understand the effect of existing programs as well as to perform ex-ante evaluations of proposed program changes. In the next section, I develop such a model and show how it can be used for program evaluation and design.

3 Consumer Utility Model

I model the relationship between appliance purchase and utilization as the solution to a household's utility maximization problem. Households trade off consumption of a numeraire good with consumption of energy services such as clean laundry. Energy Star appliances are more expensive to purchase but cheaper to operate, so consumers will choose which appliances to purchase and

[14] This is true for the utility I study, as well as for many utilities across the country. Commercial, agricultural, and industrial customers also pay a public purpose charge in their bills to fund theses programs, but I focus on residential customers because of data availability. The same distortions I study in the residential context will also exist in the other sectors, and they will perhaps even be exacerbated since the non-residential customers are likely to be more elastic to the price of electricity.

[15] The 3.3% price increase refers to all of the program run by this utility. The washer program I study in this paper cause a fraction of this price increase.

[16] Since the utility recovers its average costs, one doesn't need to worry about fungibility of funds. A \$1 increases in program spending translates (by law) into an additional \$1 of required revenue that gets collected through the electricity rates. The only margin to change is how much of the revenue gets collected from customers on different tiers of the increasing block electricity tariff. According to the EIA, over 95% of the customers in this utility were on an increasing block price for their electricity in 2013 (EIA Form 861). While the increase in the marginal price on each tier is statutorily the same across tiers, it's possible that the actual incidence is different. However, the utility itself doesn't have any incentive to favor on tier over another, so it's unlikely that this is an issue.

how much to use them to maximize their total utility.

The model follows the discrete-continuous choice intuition developed by Dubin and McFadden (1984), but I make several innovations to account for unobserved heterogeneity in program participation costs and preferences for energy consumption. These additions to the Dubin-McFadden framework allow each household to have unobservable idiosyncratic preferences for energy use that affect the incentive to purchase an efficient appliance. They also allow households to differ in their unobservable time and hassle costs of program participation.[17]

3.1 Direct Utility

The model consists of forward looking consumers in a stationary environment and therefore collapses to a series of static decisions. Each consumer i is endowed with a type vector $(\alpha_i, \theta_i, \vec{\epsilon_{ij}}, g_i)$ that includes an "energy service type" α_i, a rebate cost type θ_i, appliance preference type $\vec{\epsilon_i}$, and a neighborhood income group type g_i. The household knows its type, but only g_i is observed by the econometrician. The energy service type affects the level of agent i's demand for loads of clean laundry, refrigeration, space heating and cooling, and other energy services. The vector $\vec{\epsilon_i}$ has one element for each discrete choice j, and these elements are allowed to be correlated across j. I abstract from differences across appliances in brand, size, and features other than the Energy Star attribute, so there are four appliance choices j available to each household: No appliance purchase (j = C), Non-Energy Star appliance purchase (j = B), Energy Star appliance purchase with no rebate (j = A), or Energy Star purchase plus rebate (j = A$^+$). The rebate hassle cost type θ_i affects the private costs of applying for the rebate and choosing option $j = A^+$, and since the discrete choices A^+ and A correspond to exactly the same Energy Star durable, I let $\epsilon_{iA^+} = \epsilon_{iA}$. Finally the neighborhood income group type allows for parameter heterogeneity for household in high income and low income areas. The variable g_i can take one of five values that correspond to quintiles of the zipcode-level distribution of median household income. If household i lives in a zipcode where the median household income is in the bottom 20% of zipcode median household incomes, then $g_i = 1$. Table 1 summarizes the discrete choices and the consumer types.

In period 0, the household makes an appliance purchase choice j (including a no-purchase outside option) given its type. The period 0 appliance purchase affects the cost of consuming energy services for the 10-year expected lifetime of the appliance, so all else equal high α types will be willing to trade off higher fixed appliance purchase prices for lower marginal operating costs. When making the period 0 purchase decision, the agent accounts for uncertainty in its future demand for

[17] Dubin and McFadden (1984) make an empirical simplification that prevents preferences for energy service consumption from affecting appliance ownership. In their setup, appliance ownership affects energy consumption, but the reverse channel is shut down. Other discrete-continuous choice models have been applied to a range of problems including which car to purchase and how much to drive Bento et al. (2009) and which telephone service to subscribe and how many calls to make Wolak (1996), among others. Some of this later work models the full feedbacks between the two choice margins. However, I leverage monthly energy use data to incorporate richer household-specific heterogeneity.

energy services caused by local weather, unexpected changes to vacation plans, or other time-varying idiosyncratic shocks. These shocks are mean independent of idiosyncratic preferences for appliances and energy consumption, so $\mathbb{E}[\nu_{ijt}|\alpha_i, \epsilon_i] = 0$. Since α_i already incorporates household-specific heterogeneity in preferences for energy service consumption, mean independence is analogous to the assumption that household preferences aren't systematically changing over time. Although the agent accounts for uncertainty over idiosyncratic future demand shocks ν_{ijt}, it does not make the period 0 appliance purchase with the assumption that it can re-optimize its decision again in the future if prices, technology, or the *distribution* of these idiosyncratic demand shocks change.[18]

In subsequent months, the household will maximize a felicity function (per-period utility function) by consuming the optimal mix of a numeraire good and energy services given its period 0 appliance purchase. Although the household makes this consumption in each subsequent period, the model is static in the sense that there are no changes to the appliance holding state variable after the initial decision period. This means that in period 0 the agent considers the expected present discounted value of owning each type of appliance before deciding on a purchase.

Consumer i with type $(\alpha_i, \theta_i, \epsilon_{ij}, g_i)$ makes the purchase price and operating cost tradeoff just discussed to solve the following utility maximization problem:

$$\max_{(j,\vec{s})} \quad U(j, \vec{s_{ijt}}) = \underbrace{n_{i0} + \xi_{ij}(\theta_i) + \sigma_{g_i}\epsilon_{ij}}_{\text{Period 0 Purchase Utility}} + \underbrace{\mathbf{E}_\nu \left[\sum_t \delta^t \left(n_{it} + \frac{1}{2\beta^{\mathbf{s}}_{g_i}} (s_{ijt} - \alpha_i - \nu_{ijt})^2 \right) \right]}_{\text{Expected PDV Future Operating Utility}} \tag{3.1}$$

$$\text{subject to} \quad I_{i0} \geq n_{i0} + p^{\mathbf{a}}_{ij}, \tag{3.2}$$

$$I_{it} \geq n_{it} + p^{\mathbf{s}}_{ijt} \cdot s_{ijt},\ t \in \{1, \ldots, 120\}. \tag{3.3}$$

The decision variables are appliance purchase j and energy service consumption in each period s_{ijt}. Walras's Law implies the appliance choice is equivalent to a choice of numeraire consumption in period 0 (n_{i0}), and energy service consumption choices each month t are equivalent to numeraire consumption choices n_{it}.

The term $\xi_{ij}(\theta_i)$ represents individual-by-choice specific constants that capture both observable and unobservable features of each discrete choice. As a normalization, I set the no-purchase $\xi_{iC} = 0$ for all customers. Customers who purchase a new, non Energy Star appliance ($j = B$) receive utility $\xi_{iB} = \tau_{g_i}$ for purchasing a new appliance net of shopping hassle costs. This parameter is allowed to vary across neighborhood income groups g but not within g. Customers who purchase an Energy Star washer still receive the utility of owning a new appliance τ_{g_i}, but they also receive utility

[18] In other words, households assume a stationary distribution of idiosyncratic shocks to preferences for energy services, and a stationary and degenerate distribution of energy prices, appliance prices, appliance technology, and subsidy amounts. I don't observe any subsidy changes in the data I present in the next section, so the assumption is not at odds with my empirical setting.

κ_{g_i} from the additional features of the Energy Star model relative to the conventional model, so $\xi_{iA} = \tau_{g_i} + \kappa_{g_i}$. Finally, those who purchase the Energy Star model and claim the rebate incur disutility θ_i associated with the time and energy it takes to fill out the rebate paperwork, so $\xi_{iA^+}(\theta_i) = \tau_{g_i} + \kappa_{g_i} + \theta_i$. The only parameter that varies at the household level is θ_i, while the other product fixed effects only vary across neighborhood income groups. To normalize the scale of the utility, I set the marginal utility of income to 1 so that utility is expressed in dollars and I allow the parameter σ_{g_i} to increase or decrease the variance of ϵ.

All households discount future utility at a monthly rate of δ, and each month after $t = 0$ the period utility is given by $n_{it} + \frac{1}{2\beta^{\mathbf{s}}_{g_i}}(s_{ijt} - \alpha_i - \nu_{ijt})^2$.[19] The parameter β_{g_i} affects the convexity of the utility function in numeraire / energy service space, so this will dictate the price elasticity of demand for energy services.

Prices and income enter the budget constraints in Equations 3.2 and 3.3. The household income in period t is denoted I_{it}, the price of the jth appliance choice is given by $p^{\mathbf{a}}_{ij}$, and the price of energy services in period t conditional on ownership of appliance j is given by $p^{\mathbf{s}}_{ijt}$. The price of energy services is inversely related to the efficiency of the appliance, and directly proportional to the price of electricity. I will provide the exact definition of $p^{\mathbf{s}}_{ijt}$ in Section 4 when I describe the data. Table 2 summarizes the variables included in the model.

Figure 1 shows indifference curves in the numeraire energy service consumption space with stylized budget constraint for an efficient appliance ($j = A^+$ or $j = A$) and an inefficient appliance ($j = B$ or $j = C$). Note that there is a bliss level of energy service consumption given by $\alpha_i + \nu_{ijt}$. This is intuitive for energy services, since too much laundry wears out clothing and too much refrigeration could freeze food and beverages left in the refrigerator. Since utility is quasilinear, indifference curves are parallel shifts along the vertical numeraire axis, and if the price for energy services was zero, the agent would choose to consume at its bliss point $\alpha_i + \nu_{ijt}$. The price of energy services is proportional to the price of electricity, and for any given electricity price schedule an Energy Star appliance will produce more services for a given dollar expenditure on energy, hence the more efficient appliances flatten the slope of budget constraint. Since the upfront cost is also higher, there is a downward shift in the intercept of the budget constraint associated with the Energy Star appliance.[20]

[19] In my primary empirical specification, I assume $\delta = (1/1.05)^{1/12}$ so that households discount at a 5% annual rate. Results for other discount factors are available upon request, but in general the fixed effects explain the largest part of variation in discrete choice.

[20] In the appendix I provide the theoretical results when the household optimizes with respect to the nonlinear electricity price schedule.

4 Data

I combine data relating to appliance purchase and energy consumption behavior from several different sources. The first dataset contains monthly account-level electricity consumption and rebate program participation data for over 80,000 households in a large utility territory. This dataset, which I'll refer to as my "primary data", was obtained under a non-disclosure agreement that prevents revealing the identity of the utility company. In addition to monthly household-level energy consumption spanning October 2010 - August 2015 for each customer, I observe information on whether or not the household claimed a rebate from their utility, the date of the rebate claim, and type of rebate (e.g. washer subsidy, refrigerator subsidy, etc.). The rebate data only covers the 2013 calendar year, so this period will correspond to the period 0 choice stage described above.[21] I also observe parcel characteristics for all households. These include home square footage, number of bedrooms, the year the home was built, and the zipcode field of the home address. Finally, I merge median household income at the zipcode level with the household characteristics to allow for preference heterogeneity based on neighborhood income.[22] Summary statistics for my primary dataset are provided in Table 3.

4.1 Latent Appliance Purchase Decisions

To understand the share of non-rebate households who made choices $j \in \{A, B, C\}$, I supplement rebate claim information in my primary dataset with information on appliance purchases from the 2009 Residential Energy Consumption Survey (RECS).[23] From the RECS dataset, I non-parametrically compute the probability that each household in my primary dataset purchased a non-Energy Star appliance ($j = B$) or didn't make an appliance purchase ($j = C$).

To implement this procedure, I divide the RECS households into discrete bins based on income,

[21] I show in the appendix that the distribution of appliance purchase across years is roughly stationary, meaning that program participation and market shares in 2013 are likely to be representative of program participation and market shares in an arbitrary year.

[22] The parcel characteristics were merged to the billing data before the data were provided to me, so I observe a unique id for each household but not the actual household name or full address.

[23] RECS is a nationally representative survey administered by the Energy Information Administration roughly every four years, and it contains a rich set of household-level microdata such as structure attributes, occupant characteristics, and appliance holdings that I use to compute purchase probabilities for households in my primary dataset. The survey has over 10,000 US households, 1,000 of whom are in the same state as the utility I study. Although RECS data is survey-based, a trained surveyor collects the data on site with a laptop computer, mitigating concerns that households might not whether or not their appliance is EnergyStar certified. The survey has two key questions that I use to ascertain appliance purchase probabilities and preferences for the EnergyStar label. First, the survey asks "About how old is your [clothes washer / refrigerator]? Your best estimate is fine." The household chooses from this list of discrete choices: (1) Less than 2 years old, (2) 2 to 4 years old, (3) 5 to 9 years old, (4) 10 to 14 years old, (5) 15 to 19 years old, and (6) 20 years or older. The second question asks "Is your [clothes washer/refrigerator] an Energy Star appliance?" Using these two questions and the set of parcel and demographic characteristics that overlap in the RECS and in my primary energy consumption data, I can non-parametrically compute $Pr_{iA} + Pr_{iB}$ and Pr_{iC} for households in my primary dataset.

home size, and home age.[24] Within each RECS bin, I compute the mean purchase probability of appliance $j \in \{B, C\}$ as $\hat{\mathbb{I}}_j = {}^1\!/_R \sum_r \mathbb{I}_{rj}$ where R is the total number of RECS households in this bin, r is an index for RECS households in the bin, $\mathbb{I}_{rC}$ is an indicator variable that equals 1/2 if household r responded that they purchased a non-Energy Star washer (fridge) j in the last two years, and $\mathbb{I}_{rC} = 1/2$ if the household responded they haven't purchased a washer (fridge) in the last two years.[25] The indicator is equal to 1/2 rather than 1 since the RECS information only gives me bi-annual flows. However, since the age distribution is stationary in the RECS dataset, 1/2 of the two year flow is a good estimate of the one year flow.

For each household i in my primary dataset, I directly observe program participation status $\mathbb{I}_{iA^+}$. For households in my primary dataset that didn't claim the rebate (i.e. $j \in \{A, B, C\}$), I use the sample average of the RECS purchases $\hat{\mathbb{I}}_j$ in the same bin as an unbiased estimate of the expected value of the choice indicator $\mathbb{E}[\mathbb{I}_{ij}]$.[26] In particular, if $\mathbb{I}_{iA^+} = 0$, then I assume that $\mathbb{E}[\mathbb{I}_{iA}] = 1 - \hat{\mathbb{I}_{iB}} - \hat{\mathbb{I}_{iC}}$, $\mathbb{E}[\mathbb{I}_{iB}] = \hat{\mathbb{I}_{iB}}$, and $\mathbb{E}[\mathbb{I}_{iC}] = \hat{\mathbb{I}_{iC}}$. If $\mathbb{I}_{iA^+} = 1$, then the expected value of the other indicators is 0. Since the RECS sample is representative of US household (stratified by state) and since I only use RECS households in the same state as my utility, the RECS sample average should be an unbiased estimator of $\mathbb{E}[\mathbb{I}_{ij}]$ since its a representative sample from the same population. I show summary statistics for the variables used to bin the households in Table 4. Since RECS households are used to compute the expected choices for multiple households in my primary dataset, I cluster by bin to allow for arbitrary within-bin heteroskedasticity and autocorrelation. Table 5 summarizes the mean purchase probabilities for households in each zipcode income quintile.

4.2 Appliances Prices

Although the RECS data has detailed appliance holding information, it doesn't provide any insight about appliance prices. To match household in my primary dataset with the appliance prices that they may have faced when they made their purchase decision, I use the Nielsen Retail Scanner database to construct an appliance price index that varies across locations. Nielsen collects price and quantity data at retailers across the country, and while most of the products recorded are grocery items, they also have information on a few appliances such as refrigerators. Since the dataset does not include sales prices for washing machines, I use the refrigerator price index to capture spatial variation for all durable appliacnes including washers. The goal of the price index is to provide variation across space in appliance prices that are driven by transportation costs from the nearest warehouse, retail space rental costs, as well as the level of local demand that will depend on demographic characteristics. While I would ideally be able to have appliance-specific

[24] I use a k-means clustering algorithm to divide the RECS data into 50 bins.

[25] Notice that households who choose option $j = C$ might have an Energy Star washer that's older than two years. In the next section, I discuss how I incorporate this possibility into the estimation.

[26] I'm matching households to the nearest bin based on the Mahalanobis distance in the income, home size, and home age variables.

price indices, many of these cost shocks are likely to be similar across different appliance categories. It's also important to point out that with my quasilinear utility funciton, only the spatial price *variation* and not the overall price *level* is important in the model.

To construct the price index, I identify the most popular refrigerator in the data so that price variation isn't contaminated by differences in the composition of appliances sold in different areas. Nielsen defines each retailer's geographic market, as well as the first three digits of each retailer's zipcode. My markets are defined as the intersection of the Nielsen markets and the unique three digit zipcode prefix. For each of my markets, I define $p_{m_i}^{index} = \bar{p}_{m_i}/p^{q50}$, where m_i is the market where household i is located, $\bar{p}_{m_i}$ is the average price in market m_i, and p^{q50} is the median price across all markets in the data. The appliance price a household i faces is given by $p_{ij}^{\mathbf{a}} = p_j^{\mathbf{a}} \cdot p_{m_i}^{index}$ where $p_{A+}^{\mathbf{a}} = p_A^{\mathbf{a}}$ is the nationally advertised online price for a typical Energy Star appliance and $p_B^{\mathbf{a}}$ is the online price for a typical conventional appliance.

The appliance price index is a potentially imperfect way of capturing the variation that's relevant for households choices. Even if the index actually reflects price variation across markets, there is a lingering concern that prices are affected by local demand rather than differences across space in the supply curve. Note however, that since I have product fixed effects, any unobserved product-specific features that are correlated with price levels are captured by the parameters τ, κ, and θ. Furthermore, income and other demographics are allowed to affect appliance price levels, but I do need to assume that demographics are independent of price differences. If there are product-by-market factors that are correlated with the product-by-market price differences, then I can use the Neilsen market definitions to construct price instruments. Including product-by-Neilsen-market fixed effects in the model removes demand shocks that might be correlated with price differences, and leaves residual price variation that could be caused by factors such as transportation costs or inventory mistakes that are unrelated to demand.[27] These fixed effects require a substantially larger computational burden to compute.

4.3 Computing Latent Energy Service Consumption

The final object that I need in the model is energy service consumption, s. Energy services are produced as households use their appliances to convert electricity into clean laundry, refrigeration, light, etc. The electricity input measured in kilowatt hours (kWh) is observed in my primary billing data, so the last missing piece is the production function that converts energy into services.

Since energy services are a composite of clean clothes, refrigeration, lighting, heating and cooling services, etc., it's helpful to normalize s so we can interpret its units. Let one kWh of electricity

[27] The intuition follows the spirit of Gentzkow and Shapiro (2010) and Hausman (1979) and relies on regional (Neilsen market) price variation that is driven by regional demographic characteristics. Both empirical evidence and qualitative industry reports suggest that a substantial amount of price variation is determined regionally, with generally small residual variation at the local level (DellaVigna and Gentzkow 2017).

consumed by a households who owns a conventional washer produce one unit of energy services.[28] Let the parameter ω_{ijt} be the fraction of total kWh of electricity used by households i with washer j in month t and let γ_j be efficiency of washer j relative to the conventional washer. It follows that energy service consumption is given by

$$\begin{aligned} s_{ijt} &= (\gamma_j)(\omega_{ijt})kWh_{it} + (1-\omega_{ijt})kWh_{it} \\ &= \Big[1+\omega_{ijt}(\gamma_j-1)\Big]kWh_{it} \end{aligned}$$

where kWh^{it} observed total energy consumption. The appendix contains a more detailed derivation of this expression. The parameter $\gamma_B = 1$ because of my normalization, so notice that this expression indicates that $s_{iBt} = kWh_{iBt}$. To determine the production function γ_j for the other appliances, I use estimates from the U.S. Department of Energy. The DOE estimates that Energy Star washers use 25% less energy per load than conventional washers, so $\gamma_{A^+} = \gamma_A = {}^1\!/\!(1-.25) \cdot \gamma_B = 1.33\gamma_B$. The outside option C includes households that purchased an Energy Star or a conventional washer more than a year ago, so I use the weighted average of the market share of these two purchase options from the RECS data for appliances older than two years to compute γ_C.[29]

The expression above now just requires an estimate of ω_{ijt} to compute s_{ijt}. I estimate ω_{ijt} using monthly plug-level data from Pecan Street and the same procedure I presented for the purchase probability estimation. In addition to using income, home size, and home age to discretize the Pecan Street data, I also use mean monthly temperature. This allows the share of energy consumed by washing machines and refrigerators to decrease during hot months where the air conditioning is running. It follows that the price of energy services is

$$p^{\mathbf{s}}_{ijt} = \frac{p^{kwh}_{it}}{1+\omega_{ijt}(\gamma_j-1)}$$

The price of electricity, p^{kWh}_{it}, varies over time and across 10 different regions in the utility territory, and I collected these prices from the utility's regulatory filings with the PUC.[30]

[28] Clearly I can normalize the scale of energy services. Aggregating the modeled and unmodeled appliances, however, is not without loss of generality.

[29] Although there have been a number of economists who have suggested that engineering estimates such as the ones I use here overstate actual savings (Fowlie et al. (2015),Davis et al. (2014)), these concerns shouldn't apply to my particular setting because I explicitly model the behavioral responses that would create a divergence from the engineering calculations and the experimentally measured savings in previous economic studies. It is easy to plug various appliances into a watt meter and measure how much energy is consumed for a load of laundry, an hour of refrigeration at a given temperature, etc. This is the calculation upon which I base my estimates of γ_j.

[30] The 10 different baseline regions are defined by a customer's zipcode. This utility offers several different pricing plans to its electricity customers, including time of use pricing and critical peak pricing. Despite offering several plans, only 6.8% of customers were enrolled in one of these plans in 2015, up from less than 5% in 2013. This information is available from the EIA's form 861, which collects information on US utilities. The form is available from https://www.eia.gov/electricity/data/eia861/ There is also a special rate for low-income households. Since the households in my dataset are mostly owner-occupied units, the fraction of low-income customers is less than the full

5 Estimable Equations

After transforming the observed data into the variables described in the model (the focus of Section 4), there are two steps left to estimate the model's parameters. First, I solve the expected utility maximization problem to compute the agent's optimal energy service consumption and appliance choices. This requires assumptions about the distributions that produced the (unobserved) realizations of the structural error terms $(\vec{\epsilon_i}, \theta_i, \nu_{ijt})$. The second step is to derive a set of moment conditions that will identify the model's parameters. This section focuses on the agent's optimal choices, and Section 6 describes the derivation of the moment conditions that define the estimated parameters.

Rewriting the household's utility maximization problem

$$\begin{aligned} \max_{(j,\vec{s})} \quad & U(j, \vec{s_t}) \\ \text{subject to} \quad & I_{i0} \geq n_{i0} + p^{\mathbf{a}}_{ij}, \\ & I_{it} \geq n_{it} + p^{\mathbf{s}}_{ij} \cdot s_{ijt},\ t \in \{1, \ldots, 120\}. \end{aligned}$$

I can solve for the optimal amount of energy service consumption conditional on appliance j and a realization of demand shock ν_{ijt}, which results in the expression

$$s_{ijt} = \alpha_i + \beta^{\mathbf{s}}_{g_i} p^{\mathbf{s}}_{ijt} + \nu_{ijt} \tag{5.1}$$

Substituting the optimal energy service consumption back into the utility function and integrating over the distribution of ν produces the expected conditional indirect utility associated with each discrete choice j, which I denote by $\mathbf{E}_\nu V_{ij}$.[31,32] This is an expected utility maximization problem since the time-variant shocks to energy service demand ν_{ijt} are unobserved by the household when it makes its period 0 appliance purchase, so each agent maximizes expected utility by integrating over the distribution of ν.

Although the econometrician has less information than the household and doesn't observe the realizations of $\vec{\epsilon_i}$ or θ_i, I can integrate over the distributions of $\vec{\epsilon_i}$ and θ_i to compute the probability that $\mathbf{E}_\nu(V_{ij}) > \mathbf{E}_\nu(V_{ik}), \forall j \neq k$. This gives the probability household i makes discrete choice j given the observables and the distribution of the structural errors.

Let the error terms $\epsilon_{iA}, \epsilon_{iB}$, and ϵ_{iC} follow a generalized extreme value distribution where I

utility sample.

[31] I suppress the arguments $(\vec{I_{it}}, p^{\vec{\mathbf{s}}}_{ijt}, p^{\mathbf{a}}_{ij})$ for notational convenience.

[32] The interested reader is directed to the appendix for the derivation of the indirect utility functions from the consumer's maximization of her direct utility.

allow for correlation between the purchase options. The CDF is given by

$$F(\epsilon_{iA}, \epsilon_{iB}, \epsilon_{iC}) = exp\Big[- \big(exp(-{\epsilon_{iA}}/{\rho}) + exp(-{\epsilon_{iB}}/{\rho})\big)^{\rho} - exp(-\epsilon_{iC})\Big] \tag{5.2}$$

It follows that the correlation between ϵ_{iA} and ϵ_{iB} is $1-\rho^2$ and that $corr(\epsilon_{iC}, \epsilon_{ij}) = 0$ for $j \neq C$. The vector $\vec{\epsilon}$ is drawn independently across individuals. I assume the random parameters θ_i are distributed proportional to a Rayleigh random variable with negative support and factor of proportionality λ_{g_i}, and θ is independent of $\vec{\epsilon}$. The results are qualitatively robust to other distributions of θ, but the Rayleigh distribution is intuitive because the mode does not occur at 0, meaning most people have a non-zero cost of filling out rebate paperwork. For notational convenience, let $\mu_{ij}(\theta_i) = \mathbf{E}_{\nu}(V_{ij}) - \epsilon_{ij}$ be the piece of the indirect utility that doesn't depend on ϵ_i. It follows that

$$\begin{aligned} Pr_{iA^+} &= Prob(\mathbf{E}_{\nu}(V_{iA^+}) > \mathbf{E}_{\nu}(V_{iA}), \mathbf{E}_{\nu}(V_{iB}), \mathbf{E}_{\nu}(V_{iC})) \\ &= Prob(-\theta_i < \text{Sub.}, \epsilon_{iB} - \epsilon_{iA} < {1}/{\sigma_{g_i}}(\mu_{iA^+}(\theta) - \mu_{iB}), \epsilon_{iC} - \epsilon_{iA} < {1}/{\sigma_{g_i}}(\mu_{iA^+}(\theta) - \mu_{iC})) \\ &= \int_R dF\vec{\epsilon}dF\theta \end{aligned}$$

where R is the region in which the inequalities in the second line hold and $F\vec{\epsilon}$ is the joint distribution of ϵ_A, ϵ_B, and ϵ_C. Notice that the agent has already taken expectations over the distribution of future shocks ν, so the probability of choosing a given option only requires integration over ϵ and θ.[33] Given the distribution for $\vec{\epsilon_i}$ in Equation 5.2 and the distribution of θ, the probability of purchasing the Energy Star appliance and claiming the rebate is given by[34]

$$Pr_{iA^+} = \int_{-\text{Subsidy}}^{0} f_{\theta}(\theta) \cdot \frac{(1 + exp(-{(\mu_{iA^+}(\theta) - \mu_{iB})}/{\sigma_{g_i}\rho}))^{\rho - 1}}{exp(-{\mu_{iA^+}(\theta)}/{\sigma_{g_i}}) + (1 + exp(-{(\mu_{iA^+}(\theta) - \mu_{iB})}/{\sigma_{g_i}\rho}))^{\rho}} d\theta \tag{5.3}$$

An important feature of this setting is that when the subsidy equals 0 (i.e. is not offered), then the probability of choosing option $j = A^+$ is 0. The parameter θ_i, which represents the hassle cost of filling out the rebate application, changes the basic structure of the nested logit model and allows $\lim_{\theta \to 0} Pr_{iA^+} = 0$. Note that this would not be the case in a logit model, and there would be a large discrete change in Pr_{iA^+} when the subsidy option was removed relative to when a subsidy of \$0.01 was offered.

[33] If the agent observed ν but the econometrician did not, then I would also integrate over the distribution of ν in the expression for the probability of each discrete choice. Also, since utility is quasilinear in income it follows that indirect utility is linear in ν. This means that uncertainty created by the variance of θ doesn't affect the agent's choice. If the agent were risk averse, then a higher variance of ν would create a stronger incentive to purchase an energy efficient appliance.

[34] I provide details of this derivation in the appendix, as well as the expressions for Pr_{ij} for the other discrete choices j.

6 Estimation and Identification

I use a generalized method of moments strategy for estimation since this allows me to impose instrumental variable moment conditions to deal with endogenous energy prices as well as impose the cross equation restrictions implied by the discrete-continuous choice interdependence. I use simulation to compute the integrals in Equation 5.3 and the other market share equations. I derive moment conditions below to estimate the parameters.[35] A complete summary of the moment conditions is available in the appendix.

6.1 Unobserved Heterogeneity α_i and Energy Price Endogeneity

Recall that a household's demand for energy services is given by the expression $s_{ijt} = \alpha_i + \beta^{\mathbf{s}}_{g_i} p^{\mathbf{s}}_{ijt} + \nu_{ijt}$. I have already discussed the intuition that high α households are more likely to purchase efficient appliances, so unobserved heterogeneity embodied by α_i is correlated with $p^{\mathbf{s}}$.[36] A second source of endogeneity arises because the utility company charges an increasing block price for electricity consumption, meaning that the marginal price of electricity is an increasing functions of consumption; this generates another source of correlation between α_i and the price of energy services.[37]

I assume that households respond to the marginal price of electricity and take advantage of within customer-by-tier variation in the price schedule to identify β_g and α_i.[38] Notice that by taking a 12-month difference of the household's consumption consumption, I obtain

$$\Delta s_{ijt} = \beta^{\mathbf{s}} \Delta p^{\mathbf{s}}_{ijt} + \Delta \nu_{ijt} \tag{6.1}$$

where $\Delta s_{ijt} = s_{ijt} - s_{ij,t-12}$. The change in idiosyncratic preferences $\Delta\nu_{ijt}$ might still be correlated with the change in prices Δp_{ijt} if customers move to a different tier. To alleviate this concern, I only use the within-tier price variation from customers who stayed on the same tier between the

[35] Presently, I do not estimate the parameter ρ. Instead, I estimate the model using several different values of ρ in a range that's seems intuitive and report the corresponding estimates for the other parameters.

[36] This can be checked mathematically by noting that $\partial Pr_{AB}/\partial\alpha > 0$

[37] This is a very common form of pricing in electricity. Although the utility offers other pricing plans such as time of use pricing, the block pricing was by far the most popular with over 95% of residential customers in the utility territory in 2013.

[38] Since there are no income effects in my model, household optimization with respect to the full nonlinear price schedule and optimization with respect to the marginal price is equivalent on the interior of each price tier. However, optimization with respect to the full nonlinear price schedule implies bunching, which I do not observe. Customers could also optimize with respect to the average price they face in the previous month. Ito (2014) provides evidence of this phenomenon when customers face a complicated multi-part price schedule. This assumption does not change the theory developed up to this point, but if there is autocorrelation in consumption it substantially complicates the econometrics since price idiosyncratic demand in the current month is correlated with price in the previous month.

two periods.[39] I then use the moment conditions

$$\mathbf{E}[(\Delta s_{ijt} - \beta^{\mathbf{s}} \Delta p^{\mathbf{s}}_{ijt} - \beta^{w} \Delta w_{it}) \cdot (\mathbb{I}^{tier}_{it} \cdot \Delta p^{\mathbf{s}}_{ijt})] = 0 \quad \forall j \tag{6.2}$$

$$\mathbf{E}[(\Delta s_{ijt} - \beta^{\mathbf{s}} \Delta p^{\mathbf{s}}_{ijt} - \beta^{w} \Delta w_{it}) \cdot (\mathbb{I}^{tier}_{it} \cdot \Delta w_{it})] = 0 \quad \forall j \tag{6.3}$$

in my estimation, where t is January of 2014, $t-12$ is January 2013, w_{it} is the mean temperature (**w**eather) for household i in month t, and $\mathbb{I}^{tier}_{it} = 1$ if the customer is on the same tier in t and $t-12$ and 0 otherwise. The control for mean temperature and using ν^* instead of ν as the residual is an important correction since there are in-sample differences between t and $t-12$ that explain some of the differences in usage.[40] Energy service consumption in period $t-12$ is $s_{ij,t-12} = kWh_{i,t-12}[1 + \omega_{iC,t-12}(\gamma_C - 1)]$ since ω_C and γ_C incorporate the fact that some non-purchasers have Energy Star appliances. Conditional on β_{g_i}, $\alpha_i = \bar{s_{ijt}} - \beta_{g_i} \bar{p^{\mathbf{s}}_{ijt}}$, which is simply the parameter I would get from a linear regression with customer-by-tier fixed effects and a coefficient for monthly mean temperature.

Identifying Variation for α_i and β_g Variation in the energy price instrument occurs because the price schedule shifts by different amounts at different levels of energy consumption. Intuitively, the parameter β_g is identified by comparing the average within-tier change in consumption for each customer in zipcode income quintile g to the average within-tier change in price. These price changes are unrelated to energy service demand since they result from the exogenous changes to the utility's cost of electricity procurement. In particular, the utility is allowed by the regulator to pass costs of generation on to its customers, so when the price of natural gas changes, the price of electricity will eventually adjust up or down to reflect the higher or lower cost of generation. Once β_g is pinned down, α_i is identified for each individual by correcting their average level of consumption for the average marginal price they face.

6.2 Product Fixed Effects and Variance of the Logit Error

To identify the product fixed effects, I match observed market shares in the data to mean purchase probabilities across households. Since I observe whether or not a household claimed the subsidy ($\mathbb{I}_{iA^+}$), I first impose the moment conditions

$$\mathbf{E}\left[(\mathbb{I}_{iA^+} - Pr_{iA^+})Z\right] = 0 \tag{6.4}$$

[39] This is a more restrictive form of the variation that is used in a simulated instrument identification strategy. For the customers who don't change tiers, the simulated instrument is simply the price movement on the customer's tier.

[40] The interpretation of ν^* is the piece of ν that's not explained by a linear trend in temperature. I get a larger elasticity if I omit this since Jan 2014 was colder than Jan 2013.

where $\mathbb{I}_{iA^+}$ is an indicator vector that equals 1 if customer i claimed the rebate and 0 otherwise and $Z = (1, \mu_{iA^+}(\theta))'$ is a vector of instruments. The first element of Z simply requires that on average the market share of program participants implied by the model be equal to the observed number of program participants in the data. The second element of Z is is the part of the indirect utility that does not contain ϵ. This second instrument pins down the variance of ϵ as I will describe below.

To allow me to estimate the other fixed effect parameters, I impose the moment conditions

$$\mathbf{E}\left[(\hat{\mathbb{I}}_{ij} - Pr_{ij})Z\right] = 0, \quad j \in \{B, C\} \tag{6.5}$$

Note that $\hat{\mathbb{I}}_{ij}$ is a random variable with a mean that should equal the actual market share of choice j since the RECS data is a representative sample of customers in this state. The variance of $\hat{\mathbb{I}}_{ij}$ is given by $\hat{\mathbb{I}}_{ij}(1-\hat{\mathbb{I}}_{ij})/R_i$ where R_i is the number of RECS households in this bin used to compute $\hat{\mathbb{I}}_{ij}$. To correct for heteroskedasticity and correlation induced by using the same RECS households to compute the expected value of $\mathbb{I}_{ij}$ for multiple households in my primary dataset, I cluster by the RECS bin.

Identifying Variation for Product Fixed Effects and Logit Error Variance The fixed effects τ_g and κ_g and the parameter λ_g that governs the distribution of θ_i are identified by equating market shares in the data to average purchase probabilities in the model. For example, many households in the data purchase energy efficient washing machines but few participate in the program, so a large (negative) mean of the distribution of θ rationalizes low program participation given the popularity of Energy Star appliances. Similar arguments follow for the other fixed effect parameters.

To understand how σ_{g_i} is identified, consider two extreme cases. If the appliance price and consumption utility is totally uncorrelated with purchase probabilities, then the only thing that can explain differences in discrete choices across customers is differences in ϵ. In this case, σ_{g_i} would be large. If on the other hand appliance prices and preferences for energy service consumption are strong predictors of discrete choices, then the deterministic portion of my model will explain most of the variation in appliance choice and the residual variation explained by the logit error will be small. In other words, the variance of ϵ is identified by the amount of variation in purchase probabilities explained by the deterministic portion of my model relative to the unexplained variation that gets rationalized by ϵ. Part of this variation is depicted graphically in Figure 3, which shows how the washer program participation rate changes with the price of the Energy Star washing machine. Each circle is a market, and the x-axis shows the share of households in the market who participated in the washing machine program during the 2013 period 0 and the y-axis shows the Energy Star washer price constructed using the price index described in the previous section.

7 Results

Parameter estimates for the washing machine program are presented in Figures 4 and 5 and in Table 6. Here I'll highlight the own price elasticity of energy service demand and the distribution of the parameter θ since these have important implications for the welfare impact of the programs. The own price elasticity of energy service demand in Figure 4 decreases in magnitude in income. Households in the wealthiest areas are least price sensitive, with an elasticity of -0.13, while households at the low end of the income distribution are the most price sensitive, with an elasticity of -0.66. Since changes in consumer surplus are proportional to the elasticity of demand, this suggests that low-income households are likely to be more adversely affected by the electricity price change associated with the program. Figure 5 shows the distribution of θ_g for each income quintile. I plot the same simulated draws from a Rayleigh distribution that I used in estimation. Notice that with the exception of the bottom two quintiles of the neighborhood income distribution, the distribution of θ increases in income in a first order stochastic dominance sense. This suggests that low income households have a larger cognitive burden of filling out the rebate application than households in wealthier areas. This estimate follows from the descriptive feature of the data in Table 5 that a higher share of Energy Star appliance purchasers claim the rebate in high-income areas relative to low-income areas. Table 6 describes the other parameters for the washing machine program.

7.1 Energy Savings and Environmental Benefits

To evaluate the energy savings caused by the program, I use the model to generate counterfactual appliance holdings and energy consumption if households were not offered the subsidy and consequently faced a lower electricity price.[41,42] Consider the expression

$$E[kwh|(p^{\mathbf{a}}, p^{\mathbf{s}})] = \sum_{i=1}^{N} \sum_{j} \left(Pr_{ij}(p^{\mathbf{a}}, p^{\mathbf{s}}) \cdot kWh_{ij}(p^{\mathbf{a}}, p^{\mathbf{s}}) \right) \tag{7.1}$$

that predicts consumption for an arbitrary appliance price / energy service price vector $(p^{\mathbf{a}}, p^{\mathbf{s}})$. Equation 7.1 accounts for the change in adoption, the change in usage conditional on adoption, and

[41] The thought experiment here represents the amount of energy that would be saved by raising prices for 1 year to fund a yearlong program, then lowering prices at the end of the year (but where customers expected the higher prices to persist for the 10-year horizon of their durable purchase decision). Savings in this thought experiment accrue from one year of higher prices and 10 years of Energy Star appliance ownership for the marginal households who changed their behavior in response to the program.

[42] Also notice that in some parts of the U.S., cap-and-trade markets for carbon dioxide and other air pollutants exist. If these caps bind and regulators measure / count savings from energy efficiency programs as part of the cap, then reductions in energy consumption due to higher retail electricity prices and greater adoption of energy efficient durables will be offset by increases in emissions from other covered sectors. In this case the benefit isn't emissions reductions, it relaxing the emissions cap constraint and allowing additional economic activity.

the selection of adopters.[43] Let $p^{\mathbf{a},act}$ denote the net-of-subsidy appliance prices under the actual program, let $p^{\mathbf{a},0}$ be the appliance prices without the subsidy, and let $p^{\mathbf{s},0}$ describe the energy price that would prevail if the program didn't exist or if the program was funded through a fixed charge to monthly bills. Taking the difference of 7.1 evaluated at the price vectors $(p^{\mathbf{a},0}, p^{\mathbf{s},0})$ and $(p^{\mathbf{a},act}, p^{\mathbf{s},act})$ then gives expected monthly energy savings from the actual program. To compute total savings, I multiply monthly savings by $\sum_{t=1}^{12} \delta^t$ and then correct for the marginal households who purchased an appliance in 2013 but who will save energy for the entire lifetime of the appliance.[44] Energy savings for a counterfactual subsidy program funded through a non-distortionary fixed fee on customer bills are computed in the same manner using $(p^{\mathbf{a},act}, p^{\mathbf{s},0})$ instead of $(p^{\mathbf{a},act}, p^{\mathbf{s},act})$ to evaluate 7.1.

To determine the environmental benefit of the actual and counterfactual programs, I multiply the kWh electricity savings by estimates of the social cost of 1 kWh. I use a social cost of $0.10, which is on the high end of estimates from Holland et al. (2016) and Borenstein and Bushnell (2017). This ensures I will obtain a conservative estimate of the ratio of costs to benefits.[45] The social cost accounts for the environmental damages like greenhouse gas emissions and local air pollution as well as the cost of generating the electricity. An important thing to point out is that the lowest price of electricity in this utility territory is above the $0.10 social marginal cost of consumption. The reason is that this utility (and many others) recover fixed costs of maintaining the transmission infrastructure and other activities through higher marginal prices. Consequently adding funding for this program to marginal prices pushes the price further from the social optimum. This suggests that a Pigouvian tax on electricity is efficiency decreasing in this utility territory, and I'll show in the next section that this is indeed the case. However, it's worthwhile pointing out that Borenstein and Bushnell (2017) find substantial scope to improve economic efficiency by raising the price of electricity in many utility territories.

Expected environmental benefits for a program funded through a fixed monthly fee in households' utility bill and the actual program funded through the distortionary electricity price change are listed in Panel A of Table 7. Notice in the last column of the table that only 17.7% of environmental benefits are achieved by the fixed fee program. In other words, a program evaluation that ignored the effect of the energy price change would only capture 17.7% of the total effect on energy use if the actual funding occurred through marginal electricity prices.

7.2 Economic Efficiency Impacts of the Subsidy Program

While energy savings and environmental benefits are an important program benchmark, total welfare is perhaps a more economically-founded policy objective. Welfare includes not only the environment benefits caused by the program, but also changes in consumer and producer surplus. In

[43] Recall that the price of energy services is determined by the choice of the price of electricity and the price of Energy Star appliances depends on the level of the subsidy.

[44] This correction is given by adding $\sum_i \sum_{t=13}^{120} \delta^t Pr_i(Marginal) \cdot (\Delta kWh_i | Marginal)$ to energy savings

[45] Program benefits could easily be scaled up or down by a different social cost of electricity consumption.

this section I add the change in consumer and producer surplus to the environmental benefits of the program to compute the program's impact on total welfare.

Change in Consumer Surplus To compute changes in consumer surplus, I evaluate the indirect utility function at the price vectors $(p^{\mathbf{a},0}, p^{\mathbf{s},0})$, $(p^{\mathbf{a},act}, p^{\mathbf{s},0})$, and $(p^{\mathbf{a},act}, p^{\mathbf{s},act})$ described above. Since the econometrician doesn't observe the realizations of ϵ, I simulate from the distribute of ϵ to compute the expected value of the upper envelope of the conditional indirect utility function across choices j.[46,47]

Panel B of Table 7 shows the net change in total surplus for the actual (per-kWh fundraising) and the counterfactual fixed-monthly-fee program that doesn't distort energy consumption decisions. I compute the change in consumer surplus by adding money metric indirect utility across households.[48] Notice in the first row of Panel B1 that consumer surplus falls in both the actual (per-kWh) program and the fixed-monthly-fee alternative. In Section 8, I'll decompose the loss of consumer surplus into the pieces caused by the energy price distortion, the private time and hassle costs of participation, and the expenditure on more efficient appliances.[49]

Producer Surplus and Imperfect Competition in the Appliance Market Panel B in Table 7 reports the change in producer surplus from the per-kWh and the fixed-fee programs. There are two relevant producers in this setting, utility companies and appliance producers. Utilities are regulated so roughly they earn zero economic profits.[50] Consequently appliance producers and retailers are the only agents on the supply side who might earn economic rents.

In the second row of Panel B1 in Table 7, I show the change in producer surplus generated by the actual variable-charge program and the alternative fixed-fee program. In both cases, I assume that half of the difference between the conventional appliance and the Energy Star appliance is producer surplus and the other half represents higher production costs of the Energy Star good.

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[46] Since utility is quasilinear, the indirect utility function is the negative of the expenditure function (plus a constant). I derive the expenditure function in the appendix.

[47] Small and Rosen (1981) and Williams (1977) show that the expenditure function of many discrete choice models can be integrated to compute compensating variation, and convenient closed-form expression is available for logit models. The change in consumer surplus in a conditional logit model is given by the expression $\Delta\mathbf{E}(CS_i) = ln\big(\sum_{j=1}^{J_1} e^{V_{ij}^1}\big) - ln\big(\sum_{j=1}^{J_0} e^{V_{ij}^0}\big)$, where J_1 is the choice set with new prices, product attributes, etc, and J_0 is the original choice set as in Train (2009). Although this framework can be easily extended to my discrete-continuous model and to multiple price changes, the analogous expression in my model does not have a closed form. Consequently, I simulate from the distribution of my structural error terms to compute expected compensating variation and expected changes in indirect utility for each household in my sample.

[48] In the appendix, I'll consider consumer surplus if the regulator values \$1 differently for a low-income and a high-income household.

[49] Subsidized households don't necessarily value the appliance at the full purchase price, so if the price is reflective of production costs then subsidizing purchase creates an inefficient allocation of resources absent an appliance market failure justifying the subsidy.

[50] Operating costs are passed directly on to customers through higher prices, and regulators try to ensure that companies earn a fair rate of return on capital investment such as electricity transmission lines.

This is roughly a 20% markup above marginal cost. In the appendix, I solve the producers' profit maximization problem and demonstrate that this 20% markup is consistent with given the estimated demand side of the market and monopolistic competition on the supply side.

Notice that even accounting for producer surplus and environmental benefits, program costs outweigh program benefits. It follows that the washer subsidy program is not justified in this utility territory solely through the environmental externality at a social cost of electricity consumption of \$0.10.[51] However, some studies have suggested that consumers might not make privately optimal investment in energy efficient durables, potentially justifying the subsidy policy on the grounds of private market failures Gillingham et al. (2009).

Private Appliance Market Failures To incorporate private market failures, I employ the intuition developed in Allcott et al. (2014). These authors show that many types of appliance market failures can be incorporated into a discrete-continuous model like mine by allowing the household to discount the present discounted value of consumption utility at the time of purchase by a factor Γ. At the time of purchase, the household has indirect utility

$$V_j = I_0 - p_j^A + \xi_j(\theta) + \sigma\epsilon_j + \Gamma \cdot \mathbb{E}_\nu \left[\sum_t \delta^t \big(I_t - p_j^S (\frac{1}{2}\beta^S p_j^S + \alpha + \nu_{jt}) \big) \right] \tag{7.2}$$

where $\Gamma < 1$, but after purchase the household's experience utility is given by setting $\Gamma = 1$ in expression 7.2.[52] Panel B2 of Table 7 shows the change in consumer surplus and net welfare change if there is a small market failure and households only value consumption utility at $\Gamma = .75$ when they make their purchase decision. Two features of these results are worth highlighting: First, the distortionary fundraising exacerbates the appliance market failure because households discount the disutility that will be incurred in the future because of the higher energy prices when they make their appliance purchase.[53] Second, the fixed fee program is more attractive when there is an appliance failure than when there is no market failure since it helps to encourage more adoption of Energy Star durables and correct for the private market failure. Panel B3 shows a large market failure where $\Gamma = .25$ and households significantly discount consumption utility at the time of purchase. The welfare costs of the distortionary program are further amplified, and the costs of the non-distortionary program decrease.

[51] Again, this statement is specific to the particular utility territory I study; in locations where the social cost of electricity consumption is above the price, then the programs would push the price in the correct direction.

[52] Qualitatively the same phenomenon can be shown by setting $\Gamma = 1$ in the decision utility and $\Gamma > 1$ in the experience utility. This is the approach I take since in my estimation $\Gamma = 1$. In ongoing work I am estimating Γ using the variation in how households trade off purchase price with operating costs.

[53] If the retail electricity price were below social marginal costs, then there would be two competing effects: fundraising energy efficiencies through increases to the marginal price of electricity would move the electricity price in the right direction, but it would also imply that the private mis-optimization was more severe. Consequently it's ambiguous if distortionary fundraising could improve welfare when households make appliance purchase "mistakes."

8 Decomposing Economic Costs

In each of the scenarios considered in Panel B of Table 7, I show that the existing program decreases total welfare at a social cost of \$0.10 per kWh. There are three main channels through which the program generates economic costs: (1) First, the electricity price change distorts household energy consumption decisions and creates deadweight loss, (2) second the time, hassle, and cognitive burden of applying for the rebate represents an economic cost, and finally (3) the cost of producing more energy efficient durables is a burden on society that's justifiable from an efficiency perspective only if households value these appliances at their cost of production. In this section I describe the relative importance of each of these forces, and I relax the assumptions from Table 7 that the parameter θ represents real economic time and hassle costs.

8.1 Costs of Distortionary Fundraising

The last column of Table 7 shows the ratio of benefits and costs from the non-distortionary program to the actual program. It's worth emphasizing that this ratio also represents the amount of total benefits and costs that would be captured by an evaluation of a distortionary program that mistakenly assumed that fundraising didn't affect the energy price. The discrepancy between the two types of program is large: Only 17.7% of the effect on energy consumption and as little as 3.3% of the change in welfare are captured. The size of the fundraising distortion on consumer surplus can be seen by comparing consumer costs of the distortionary program (-\$75,646) and the consumer costs of the fixed fee program (-\$63,987). The difference between these numbers suggests that the energy price distortion creates close to \$12,000 of lost consumer surplus, or roughly \$0.15 per household per year (for the price change caused by this washing machine program).

Across each scenario of Panel B in Table 7, the program funded from a fixed-fee on monthly bills performs better than the distortionary program. However, eliminating the distortionary fundraising does not reduce the costs of the program to zero. This is primarily because the hassle costs of participating in the program and the cost to society of producing more efficient appliances are also large, especially in Panel B1 where there is no privately sub-optimal investment in energy efficiency. In fact comparing the net welfare effect of the distortionary program to the non-distortionary program, there is only about a \$6,710 difference in the welfare costs even though the total distortion is close to \$70,000 and the total program budget is \$74,292. This implies that the program fundraising only implies a \$0.09 marginal cost of public funds (the time and hassle costs of program participation further increase the marginal cost of public funds). In this context, however, it's important to note that this fundraising cost could be driven to zero by levying a fixed charge on monthly electricity bills.[54]

[54] It's unlikely that a small charge of about \$1 per year would lead households to disconnect entirely from the grid or change behavior because of unmodeled income effects.

8.2 Welfare if $\theta^* \neq \theta$ is Welfare Relevant

Although time and hassle costs of program participation are large, the social burden embodied by the parameter θ could be the result of a mistake rather than the manifestation of a true cost. If large values of θ are the result of unawareness of the program or households who forget to mail in the rebate paperwork, then the actual welfare effect of the program can be evaluated by allowing the estimated parameter θ to enter the decision utility and a different parameter θ^* to enter the experience utility. Table 8 shows the economic efficiency of the actual policy of $\theta^* = 0$. Environmental benefits and producer surplus from Table 7 are the same, but losses of consumer surplus due to hassle costs are eliminated entirely. Notice that the hassle costs of the rebate paperwork (if they're a real welfare cost) represent a much larger burden to households than the distortion to the energy price change without an appliance market failure.

Panel B of Table 8 show that the program would be welfare enhancing if $\theta^* = 0$, or in other words if the rebate process was automatic and prices didn't change in response. However, net benefits to consumers are still negative since consumers pay for the program fundraising and for appliances. Appliance producers and retailers, however, benefit significantly from additional sales of Energy Star appliances.

8.3 Inframarginal Participation and the Economic Costs of Wealth Transfers

Although the programs would increase welfare if there were no time or hassle costs of program participation, the policies would still generate an overall loss of consumer surplus and wealth transfers to participating households and appliance producers. However, many of the participating household would have purchased an Energy Star appliance even without the subsidy incentive, so their behavior was not changed by the program. I use the word "inframarginal" to describe these households.

Inframarginal participation in the programs is inefficient if the regulator doesn't value wealth transfers because these households receive a pure income transfer that has a cost to society of θ_i. Since inframarginal households make the same appliance and energy consumption choices that they would have made in the absence of the subsidy policy, they do not save any energy relative to a counterfactual in which they were not offered a subsidy.

With estimates of the model parameters, I can compute expected number of program participants who were inframarginal to the subsidy incentive and the higher energy prices. Mathematically, a household is inframarginal to the subsidy if $V_{iA^+} > V_{iA}$ but $V_{iA} > V_{iB}, V_{iC}$. Since I never observe ϵ, I can't determine inframarginal individuals, but I can compute the probability that a household is inframarginal as $Pr(V_{iA^+} > V_{iA} > V_{iB}, V_{iC})$ where V_{ij} is the conditional indirect utility associated with discrete choice j. This expression is given by

$$Pr(V_{iA^+} > V_{iA} > V_{iB}, V_{iC}) = \int_{-\text{Subsidy}}^{0} f_\theta(\theta) \cdot \frac{(1 + exp(-(\mu_{iA}-\mu_{iB})/\sigma_{g_i}\rho))^{\rho-1}}{exp(-\mu_{iA}/\sigma_{g_i}) + (1 + exp(-(\mu_{iA}-\mu_{iB})/\sigma_{g_i}\rho))^{\rho}} d\theta \tag{8.1}$$

$$= Pr(V_{iA} > V_{iB}, V_{iC}) \int_{-\text{Subsidy}}^{0} f_\theta(\theta) d\theta \tag{8.2}$$

It follows from this expression that inframarginal participation increases in the utility of $j = A$ and decreases in the utility of $j = B$. If the program affected the energy price as well, then an inframarginal household is one who prefers A^+ to all other choices at price vector $(p^{\mathbf{a},act}, p^{\mathbf{s},act})$ but who prefers A to B and C at price vector $(p^{\mathbf{a},0}, p^{\mathbf{s},0})$. Expected inframarginal participation with respect to both the subsidy and the price change is easily evaluated by simulating from the distributions of ϵ and θ.

Table 9 shows the expected number of program participants whose purchase was marginal to the subsidy and the higher energy prices.[55] Out of a total of 1,486 expected participants, notice that only 420 (28%) were marginal to the subsidy incentive. This means that over two thirds of participants didn't change their behavior and simply received a wealth transfer by claiming the rebate.[56]

Column 2 of Table 9 shows that inframarginal households have larger expected lifetime energy "savings" than marginal households. I use "savings" to describe the change in energy consumption experienced by these households after purchasing an Energy Star appliance, not savings caused by the program. This is intuitive, as households with strong private incentives to invest in an Energy Star appliance will be less likely to be on the margin; they make the energy efficient appliance purchase even without the rebate incentive. Thus the large share of inframarginal participation means that the program is more effective at transferring wealth than at addressing appliance or environmental market failures. In the next section, I'll explore the implications of the policy if the regulator has preferences to transfer wealth between households in different neighborhoods.

[55] Note that my expected number of participants is higher than the actual number of participants observed in the data. This is because I impose over-identifying restrictions so my model doesn't exactly replicate market shares observed in the data. In expectation, very few households purchased an efficient appliance because of the electricity price change.

[56] The high share of inframarginal households follows from the descriptive features of the survey purchase data described in Table 5. In the RECS data, 68% of washing machine purchasers choose an Energy Star model. This only leaves scope for the program to change the purchase decision of the 32% of washing machine shoppers who are possibly considering the purchase of an inefficient appliance. Boomhower and Davis (2014) estimate close to 50% in a utility rebate program in Mexico, and Houde and Aldy (2014) suggest upwards of 90% for a similar refrigerator program in the US.

9 Distributional Burden and Program Design

The previous section demonstrated that it is unlikely the programs in this utility territory increase aggregate consumer surplus given a variety of assumptions about private market failures and the welfare cost of applying for the rebate. However, it's possible a regulator might have preferences to redistribute wealth across income groups or to increase profits for appliance manufacturers and retailers.[57]

9.1 Distributional Program Burden

Figure 6 shows the distribution of costs and benefits across households in different neighborhood income groups. Each point shows the average change in dollars of consumer surplus for households in a particular zipcode income quintile. With the distortionary energy price change, the households in the first three quintiles experience \$0.99 - \$1.09 of disutility from the program, but households in the top two quintiles only experience about \$0.67 - \$0.72. The higher burden for households in low-income areas arises primarily because of two forces: First, these households are more energy-price elastic implying larger deadweight loss for a given energy price change. Second, participation in the subsidy program is lower, so even conditional on a given amount of bill change less benefits accrue to lower income areas.

These results indicate that the program transfers a substantial amount of wealth relative to the size of the environmental benefit. Furthermore these transfers move wealth from poor neighborhoods to wealthy neighborhoods. In the next section, I suggest several potential policy improvements that are incremental program changes that lead to potentially large program improvements.

9.2 Efficient and Equitable Policy Design

Using the notation from the previous sections, let V_{ij} denote household i's expected indirect utility for appliance j. With quasilinear utility and my logit scale normalization, V_{ij} is expressed in dollars. Additionally, assume that each kWh of electricity consumption create an externality $\phi = \$0.10$ to society. A policy maker might seek to maximize the expected total welfare function given by

$$\sum_i w_{g_i} V_i + w_{ps} PS - \phi \sum_i E[kWh_i] \tag{9.1}$$

where $V_i = max_j(V_{ij})$ is the unconditional expected indirect utility for consumer i, PS is producer surplus, and $E[kWh_i] = \sum_j Pr_{ij} kWh_{ij}$.[58] This setup that embodies the efficiency-equity tradeoff of the program is fairly general, as the welfare weights w_{g_i} and w_{ps} allow the planner to value marginal

[57]These types of preferences are reflected by increasing marginal rates for federal and state income taxes, numerous cash transfer programs that are targeted at the poor, and large R&D subsidies for energy efficiency research.

[58]This framework is equally applicable to many possible alternative specifications for the policy objective function.

changes in income differentially across income groups and appliance producers. To evaluate welfare in the previous sections, I used the weights $w_{g_i} = 1$, implying a Kaldor-Hicks notion of efficiency, but other weights are also justifiable. In this section I focus on three intuitive and relatively easily implementable potential changes to the existing program that improve efficiency and equity for any welfare weights that are weakly decreasing in income. A richer optimal policy design problem is considered in the appendix.

Lump Sum Program Funding The results in Table 7 suggest that fundraising through fixed monthly "connection" charges would improve Kaldor-Hicks efficiency. This result is robust to a variety of different market failures that I have explored in Table 8. A major concern for funding public purpose programs through fixed charges on electricity bills is the perception that this would be regressive. However, Figure 6 highlights that this change would also increase the progressivity of the program's net benefits. In particular, the net costs on low income households would decrease by about \$0.15 - \$0.26 for the bottom four zipcode income groups and only increase by \$0.04 for the highest income group. This is also an easily implementable billing change since many utility companies already charge a fixed monthly connection fee to customers who are plugged into the electricity grid.

Because the lump sum program still creates a social cost, I can compute the size of the appliance market failure needed to justify such a policy by dividing the net welfare costs associated with the program in Table 7 and 8 by the number of marginal households in Table 9. To justify the lump sum program in Panel B1 of Table 7, it would take a private market failure on the order of \$46.28 per marginal participant. In other words, if the average marginal participant undervalued the lifetime operating cost of their appliance by \$46.28, then the program's costs would be equal to its benefits from externality reductions and more privately optimal appliance purchase. Average annual spending electricity consumption for a washing machine is less than \$15.00, so this is equivalent to ignoring roughly a third of the entire cost of electricity consumption over the appliance lifetime.[59]

Rebates at Point of Sale The "fixed-fee" policy improves efficiency and equity, but there is substantial scope for further efficiency improvements. For example, if the regulator could reduce the time and hassle costs of program participation, social welfare would potentially increase. The regulator's problem is the mirror image of the monopolists' problem: Decreasing program participation costs reduces the burden on inframarginal households, but it encourages more households to participate. If the marginal reduction of the burden on the inframarginal participants outweighs the marginal costs incurred by the marginal participants, then reducing the distribution of θ improves welfare.

One way that this might be accomplished would be allowing households to claim the rebate

[59] See `https://www.efficiencyvermont.com/tips-tools/tools/electric-usage-tool`

at the point of sale.[60] In this case, welfare costs for all inframarginal households would decrease to zero and marginal households would also incur no economic costs of program participation. If manufacturers and retailers didn't respond by changing prices, then the effect of this program would be given by the results previously discussed in Table 8. However, a reasonable concern with this approach is that appliance prices *would* increase so that manufacturers would capture most of the subsidy transfers. This might be avoided if there were eligibility criteria based on income. Retailers would offer the same price to everybody, but only households who met the eligibility criteria would be able to claim the rebate at the point of sale.

A Means-tested Point of Sale Program As an example, consider a point of sale program that lowers the hassle costs of participation $\theta = 0$ and provides a \$50.00 to households in the bottom 20% of the zipcode income distribution.[61] Table 10 shows the effect of this policy on the components of total welfare already discussed. In this alternative policy, all households pay an annual \$1.72 connection fee to consume electricity, and the marginal price is set at $p^{\mathbf{s},0}$. Notice that households in the lowest zipcode income quintile receive \$3.60 in consumer surplus, and that this comes by transferring \$1.72 from households in the rest of the income distribution. Although total consumer surplus is still negative, transfers from low-income neighborhoods to high-income neighborhoods have been eliminated.

However, this loss of consumer surplus is offset by a substantial increase in producer surplus of \$1,368,200. If households in this regulator's jurisdiction own the manufacturers and retailers that enjoy this windfall, then this producer surplus ultimately represents gains to households. If the value of producer surplus was 0, then the means tested point of sale policy wouldn't be justified unless there was a substantial private mis-optimization in the purchase of efficient appliances.

This policy is suggestive of scope to substantially improve the efficiency and equity embodied by the subsidy program. By specifying a policy objective that could include economic efficiency and wealth redistribution such as 9.1, policy makers can then determine how to maximize their objective by lowering economic costs of fundraising and participation and by targeting households who have the highest social marginal utility of income. A more general solution to the optimal policy design problem is considered in the appendix, but even with simple changes to the existing policy, I have showed scope for substantial improvements.

10 Conclusion

Because of the increasing role of energy efficiency subsidies in state energy policy, tools for program evaluation and design are more and more relevant. I develop and estimate a model of household

[60] While it wouldn't be costless to implement an automated point of sale system, the fixed costs of getting the computer infrastructure in place for this would be much more important than the marginal cost of actually using it.

[61] This would only require information on the household's zipcode.

preferences for appliance purchase and utilization that can be used to assess the effect of existing policies or alternative policy proposals on total welfare. The framework allows participating households to be different than non-participating households in their preferences for energy consumption, it accounts for the households who participate in the program who would have made the same durable good purchase in the absence of the subsidy policy, and it models how all households – even non-recipient households – decrease their energy consumption in response to the higher energy prices used to fund the programs. I evaluate the energy savings and the change in total welfare associated with the existing program, and I show that the existing policy is only justified under large private market failures or if the regulator values producer surplus generated by increased Energy Star appliance sales. My results suggest that fundraising distortions need to be an integral part of subsidy program evaluation and design. I show that energy price changes used to raise subsidy funds accounts for over 80% of energy savings and over 35% of the welfare loss caused by the policy. Through the lens of the model, I can also compute expected household behavior under various alternatives to the current policy, and I find that fundraising through fixed charges in customer bills simultaneously cuts the economic cost of the program and increases the progressivity of the income redistribution. Finally, I explore how a means-tested policy applied at the point of sale might improve a potential social welfare function that incorporates both notions of equity and efficiency. These insights are explored further in an optimal policy design problem included in the appendix.

Tables

Table 1: Summary of Household Types

Components of Household i's Type	Description
	Known to Household and Econometrician
g_i	Neighborhood Income Group *Household i's zipcode income quintile,* $g_i \in \{1, ..., 5\}$
	Known only to Household
α_i	Preferences for Energy Service Consumption *Household specific intercept in utilization equation*
θ_i	Rebate Hassle Cost *Time and hassle costs of submitting rebate application*
ϵ_{ij}	Idiosyncratic Appliance Preferences *Household-specific tastes for discrete choice* j

Notes: The zipcode income quintile g_i is computed using the zipcode where household i resides and the distribution of zipcode-level median household income from the census. If household i lives in a zipcode whose median household income is in the bottom 20% of the distribution of zipcode-level median household incomes, then $g_i = 1$. For households who live in wealthy zipcodes in the top 20% of the distribution of zipcode median household incomes, then $g_i = 5$.

Table 2: Summary of Variable Definitions

Variable	Description
A. Choice Variables	
Discrete Choice	
$\mathbb{I}_{iA^+}$	Indicator for i chose an Energy Star appliance plus rebate
$\mathbb{I}_{iA}$	Indicator for i chose an Energy Star appliance, no rebate
$\mathbb{I}_{iB}$	Indicator for i chose a Non-Energy Star appliance
$\mathbb{I}_{iC}$	Indicator for i didn't purchase new appliance
Continuous Choice	
s_{it}	Energy Service Consumption in Month t
B. Prices and Income	
I_i	Monthly income
	Median income household i's zipcode
$p^{\mathbf{a}}_{ij}$	Appliance Price
	$p^{\boldsymbol{a}}_{iA^+} = p^{\boldsymbol{a}}_{iA} - Subsidy$
$p^{\mathbf{s}}_{ijt}$	Energy Service Price
	Inversely related to appliance j's efficiency
C. Parameters	
Estimated Parameters	
α_i	Preferences for Energy Service Consumption
	Household specific intercept in utilization equation
β_{g_i}	Utility Concavity
	Determines price elasticity of energy service demand
τ_{g_i}	Utility of owning a new appliance, net of shopping hassle costs
	Does not include appliance purchase price
κ_{g_i}	Utility of owning an Energy Star appliance
	Extra features, warm glow, etc.
λ_{g_i}	Dictates Distribution of θ_i
	$\theta = \lambda_{g_i} \cdot Rayleigh(1)$, $\lambda < 0$
σ_{g_i}	Variance of ϵ_{ij}
	Logit scale normalized to set marginal utility of income $= 1$
Other Parameters	
δ	Monthly Discount Factor
ρ	Affects Correlation of Appliance Purchase Options
	$Corr(\epsilon_{iC}, \epsilon_{iB}) = 1 - \rho^2$

Notes: As described in the text, my framework changes the basic structure of standard logit models because discrete choices A and A^+ correspond to purchase of exactly the same durable. Consequently the idiosyncratic preferences $\epsilon_{iA} = \epsilon_{iA^+}$ for all households. Since the realization of θ_i is unobserved by the econometrician, I estimate the distribution of θ and can therefore determine the distribution of $\xi_{iA}(\theta_i) = \tau_{g_i} + \kappa_{g_i} + \theta_i$. The product fixed effect $\xi_{iA} = \tau_{g_i} + \kappa_{g_i}$, and $\xi_B = \tau_{g_i}$. I normalize $\xi_{iD} = 0$ for all households.

Table 3: Utility Data Summary Statistics

Dependent Variables	N	Mean	SD
2013 Program Participation			
$\mathbb{I}_i(A^+)$ Washer	84,020	0.018	0.13
$\mathbb{I}_i(A^+)$ Fridge	84,020	0.004	0.06
Monthly HH Energy Use (kWh)			
Full Sample: Oct '10 - Aug '15	2,520,360	745.86	453.53
Estimation Sample: Jan '13, Jan '14	168,040	744.93	438.65

Notes: This table contains summary statistics for my primary dataset. I use the same set of customers for the washing machine and refrigerator programs, although there is very little overlap between the two subsidy policies and households generally only participate in a single program. The participation rate shown in for the washing machine program. Monthly income is the census block group median household income, and washer price is the mean of the Energy Star washer price computed using the appliance price index discussed in the text.

Table 4: Comparison of Observables in RECS and Primary Billing Data

	RECS Mean	Primary Data Mean
Income	67,094.63	66,900.64
Home Size	1,522.81	1,649.78
Home Age	39.80	32.44
Tenure at Address	13.69	14.99
N	1,088	84,020

Notes: This table compares means of observable characteristics in my primary dataset and in the RECS data to illustrate that the households are comparable. Income is measured in dollars, home size is measured in square feet, and home age and tenure at the current address are measured in years. I rely on overlapping observable characteristics in both samples to compute an unbiased estimate of the expected (latent) purchase behavior of households in my primary dataset. Income in my primary dataset is median income in household i's zipcode, not household income. Consequently all of my heterogeneity by income is based on neighborhood income, not household income.

Table 5: Washer Purchase Shares by Neighborhood Income Quintile

Neighborhood Income Quintile	Energy Star + Rebate ($j = A^{+}$)	Energy Star, No Rebate ($j = A$)	Non-Energy Star ($j = B$)	No Purchase ($j = C$)
$g_i = 1$	0.8	6.8	0.5	91.9
$g_i = 2$	1.2	6.6	0.5	91.7
$g_i = 3$	1.6	6.3	0.5	91.6
$g_i = 4$	2.1	5.5	0.5	91.9
$g_i = 5$	2.2	4.4	0.3	93.1

Notes: Expected market shares are computed using the data from RECS households with similar characteristics as described in the text. The probability of no purchase and non-Energy Star purchase are directly observable in the RECS data. The share of program participants is directly observable in the primary data.

Table 6: Washer Parameter Estimates

Neighborhood Income Quintile	$\bar{\alpha_i}$	β^S	p^S **Elasticity**	τ	κ	$\bar{\theta_i}$	σ_ϵ
$g_i = 1$	991.690	-1235.023	-0.661	273.397	322.818	-155.952	51.072
	(471.602)	(108.558)	(0.058)	(0.625)	(0.319)	(-2.177)	(0.172)
$g_i = 2$	975.936	-1006.677	-0.633	295.800	280.846	-165.797	67.535
	(489.986)	(90.318)	(0.057)	(0.513)	(0.300)	(-0.582)	(0.211)
$g_i = 3$	1070.034	-1157.515	-0.567	93.641	380.414	-149.728	101.219
	(523.641)	(98.989)	(0.049)	(10.282)	(3.677)	(-27.917)	(5.715)
$g_i = 4$	949.709	-1037.328	-0.564	139.245	352.297	-116.843	99.585
	(513.596)	(109.769)	(0.060)	(1.877)	(1.506)	(-1.208)	(0.312)
$g_i = 5$	692.155	-216.341	-0.132	62.125	382.654	-55.939	96.386
	(380.967)	(127.112)	(0.078)	(11.760)	(9.332)	(-26.881)	(3.917)

Notes: Standard errors reported in parentheses are clustered by RECS bin and are robust to arbitrary within-bin heteroskedasticity and autocorrelation. The first column $\bar{\alpha_i}$ reports the mean and standard deviation of the household-specific energy service consumption intercept in each zipcode income quintile. The standard error for the price elasticity of demand for energy services in the "Elasticity" column is computed using the delta method. The last column labeled θ shows the mean of the distribution of the parameter θ, which is distributed proportional to a Rayleigh(1) random variable.

Table 7: Economic Efficiency under Central Case Assumptions

	Program Financing Method		
	Variable (per-kWh) Charge	Fixed Monthly Charge	Diff
A. Environmental Benefit			
Energy Savings (kWh)			
$\times$ Social Cost per kWh	\$6,009	\$1,061	-\$4,948
	(232)	(65)	(257)
B. Net Benefit			
1. *No Appliance Market Failure*			
Change in Consumer Surplus	-\$75,646	-\$63,987	\$11,659
Change in Producer Surplus	\$50,268	\$50,207	-\$61
Environmental Benefit	\$6,009	\$1,061	-\$4,948
Net Welfare Change	-\$19,369	-\$12,719	\$6,650
	(6,216)	(6,204)	(388)
2. *Small Appliance Market Failure*			
Change in Consumer Surplus	-\$103,865	-\$63,570	\$40,295
Change in Producer Surplus	\$50,268	\$50,207	\$61
Environmental Benefit	\$6,009	\$1,061	-\$4,948
Net Welfare Change	-\$47,587	-\$12,302	\$35,286
	(6,208)	(6,187)	(608)
3. *Large Appliance Market Failure*			
Change in Consumer Surplus	-\$329,610	-\$60,230	\$269,380
Change in Producer Surplus	\$50,268	\$50,207	\$61
Environmental Benefit	\$6,009	\$1,061	-\$4,948
Net Welfare Change	-\$273,333	-\$8,962	\$264,371
	(6,442)	(6,065)	(2,376)

Notes: Standard errors for individual components of net welfare are available upon request. Panel A shows the environmental benefits from a subsidy funded through fixed monthly charges versus distortionary changes to the marginal price of electricity. I have used a social cost per kWh of \$0.10, which is at the high end of estimates from Borenstein and Bushnell (2017). Note that an evaluation that mistakenly assumes non-distortionary fundraising when in fact subsidy monies are raised through marginal electricity prices only captures 17.7% of the effect on energy consumption. Panels B1 - B3 show the change in consumer surplus and producer surplus and net economic benefits under various sizes of the appliance market failure and with the maintained assumption that θ represents a true welfare cost. To compute producer surplus, I let 50% of the markup between the Energy Star an conventional appliance prices to accrue to producers. The change in consumer surplus is therefore the number of marginal participants multiplied by half the average price difference faced by these marginal households. In Panel B2 (small appliance market failure) households discount operating utility by a factor of .75 at the time of purchase relative to the time of consumption. In Panel B3, households discount operating utility by a factor of .25 in their decision utility relative to their experience utility.

Table 8: Economic Efficiency if $\theta^* = 0$ (Rebate Hassle not a Welfare Cost)

	Program Financing Method		
	Variable (per-kWh) Charge	Fixed Monthly Charge	Diff
A. Environmental Benefit			
Energy Savings (kWh)			
× Social Cost per kWh	\$6,009	\$1,061	-\$4,948
	(232)	(65)	(257)
B. Net Benefit			
1. *No Appliance Market Failure*			
Change in Consumer Surplus	-\$26,215	-\$14,562	\$11,654
Change in Producer Surplus	\$50,268	\$50,207	-\$61
Environmental Benefit	\$6,009	\$1,061	-\$4,948
Net Welfare Change	\$30,062	\$36,707	\$6,645
	(6,942)	(6,917)	(387)
2. *Small Appliance Market Failure*			
Change in Consumer Surplus	-\$54,434	-\$14,144	\$40,290
Change in Producer Surplus	\$50,268	\$50,207	-\$61
Environmental Benefit	\$6,009	\$1,061	-\$4,948
Net Welfare Change	\$1,844	\$37,124	\$35,280
	(6,915)	(6,882)	(607)
2. *Large Appliance Market Failure*			
Change in Consumer Surplus	-\$280,179	-\$10,804	\$269,375
Change in Producer Surplus	\$50,268	\$50,207	-\$61
Environmental Benefit	\$6,009	\$1.061	-\$4,948
Net Welfare Change	-\$220,392	\$40,464	\$264,366
	(6,970)	(6,614)	(2,375)

Notes: This table relaxes the assumptions made in Table 7 that θ represents a welfare cost. In all Panels, I let $\theta^* = 0$ enter the experience utility and θ drawn from the estimated distribution of θ enter the decision utility. Analogous to Table 7, a small appliance market failure means households discount consumption utility by a factor of .75 in their decision utility relative to their experience utility.

Table 9: Inframarginal Participation and Energy Savings

	Expected Number of Rebate Recipients	Expected Savings Given Energy Star Purchase (kWh / Appliance Lifetime)
Marginal	419.8	32.38
	(4.41)	(1.14)
Inframarginal	1,066.0	37.43
	(4.16)	(0.62)
Total	1,485.8	
	(2.03)	
Average		34.83
		(0.23)

Notes: The first column shows the expected number of marginal program participants and inframarginal program participants. Inframarginal participation was computed based on simulation so I could account for purchasers who bought an energy efficient appliance because of both the subsidy and the electricity price change channels. In expectation, less than one household changed their because of the energy price change, but almost one third purchased an Energy Star durable because of the subsidy incentive. Consequently Expression 8.1 in the text provides a good approximation of the number of inframarginal participants. The Second column shows energy savings conditional on purchasing an Energy Star appliance. Only marginal households purchase the efficient appliance because of the program, so savings from infarmarginal households are realized with and without the policy. Expected savings conditional on begin a marginal participant are computed from the expression $\sum_i Pr_i(Marginal) \cdot (kWh_{iA} - kWh_{iB} \cdot Pr_{iB}|ES^C - kWh_{iC} \cdot Pr_{iC}|ES^C)/\sum_i Pr_i(Marginal)$ where $Pr_{ij}|ES^C$ is the probability of making discrete choice j given household i has not made an Energy Star appliance purchase.

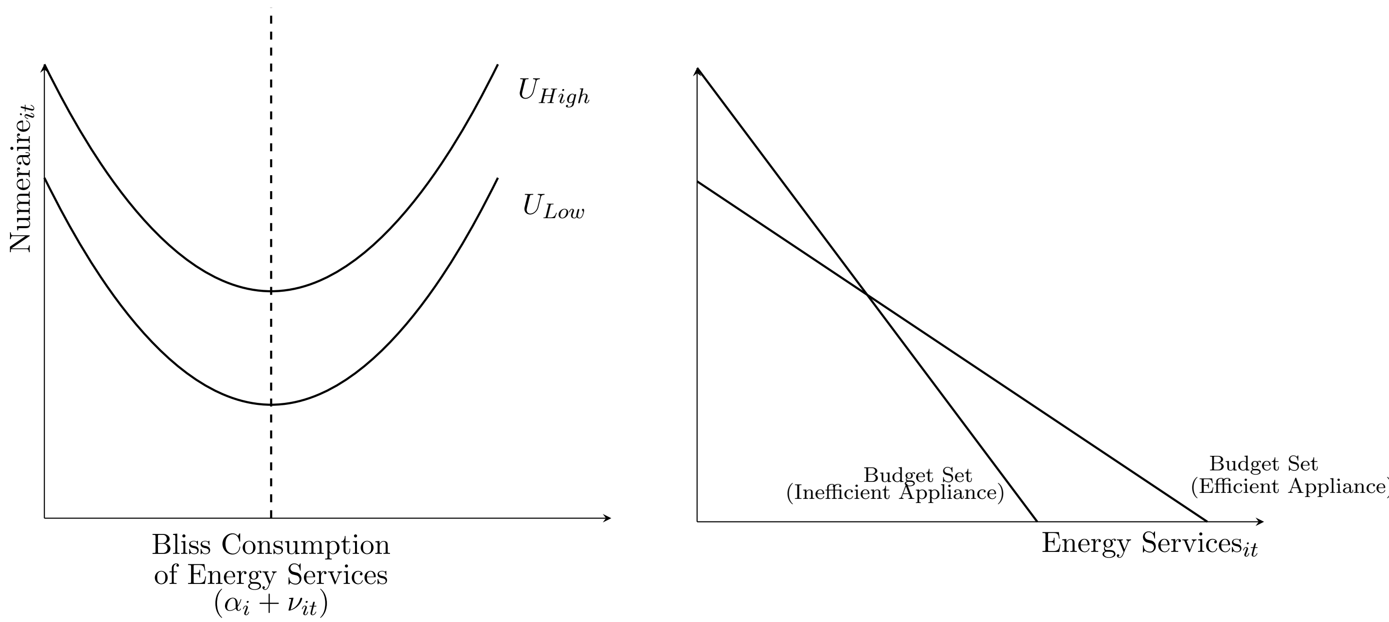
Table 10: Equity Efficiency Improvements

Zipcode Income Quintile	Fixed Fee (per HH)	Subsidy	ΔCS (per HH)
1	\$1.72	\$50.00	\$3.60
2	\$1.72	\$0.00	-\$1.72
3	\$1.72	\$0.00	-\$1.72
4	\$1.72	\$0.00	-\$1.72
5	\$1.72	\$0.00	-\$1.72
× Number of Households per Quintile			16,804
Change in Consumer Surplus			-\$54,996
Change in Producer Surplus			\$1,368,200
Environmental Benefit			\$1,155
Net Welfare Change			\$1,314,359

Notes: This table shows the net welfare change that would be associated with a single program year of a means-tested point of sale policy ($\theta = 0$) if the regulator valued \$1 of income the same for all households. Notice that if producer surplus was given a weight of 0, then this policy would not improve social welfare. Several alternatives to this possible policy change are considered in the appendix.

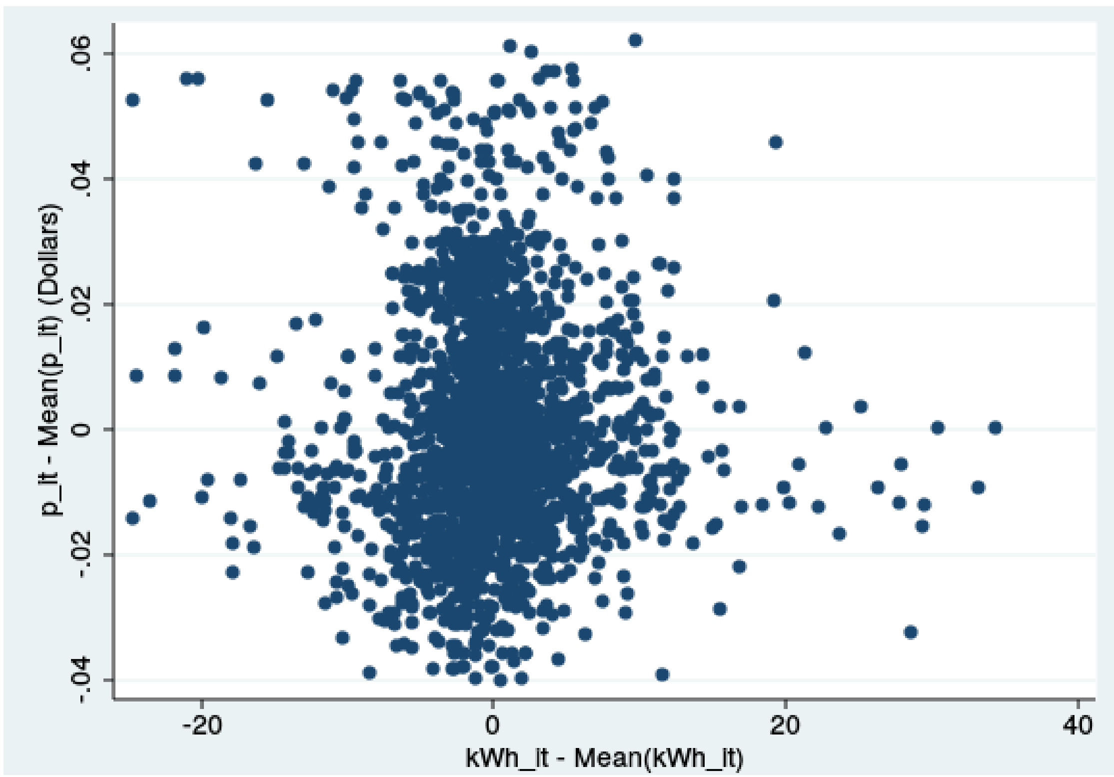
Figures

Figure 1: Direct Utility and Stylized Budget Constraint



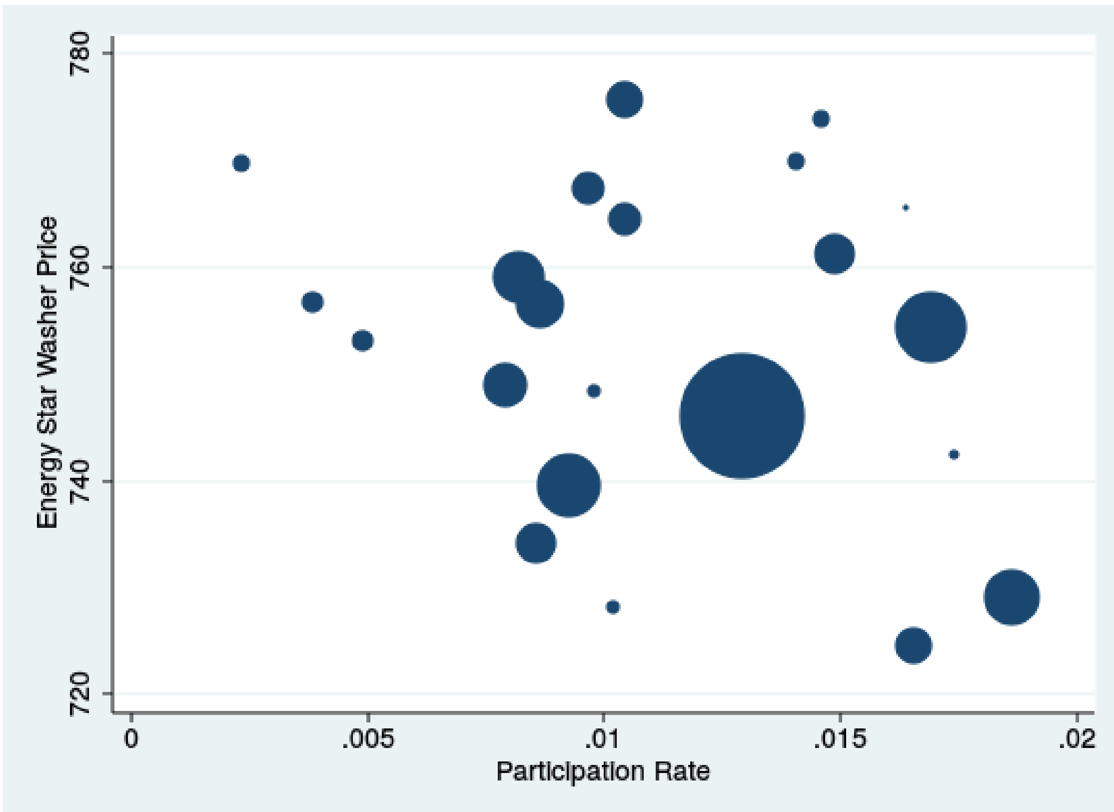
Notes: Figure 1 shows an example of an indifference curve in numeraire / energy service space. Notice that the indifference curves in the left panel are not monotonic, suggesting that energy service consumption past a bliss-level decreases consumption. As described in the text, this is intuitive for energy services. A refrigerator that's too cold might freeze food and beverages, for example. In the right panel, the budget constraints indicate that more efficient appliances cost more to purchase (so the intercept in numeraire space is lower) but are cheaper to operate (so the slope isn't as steep).

Figure 2: Within-Household Variation in Energy Price and Energy Service Consumption



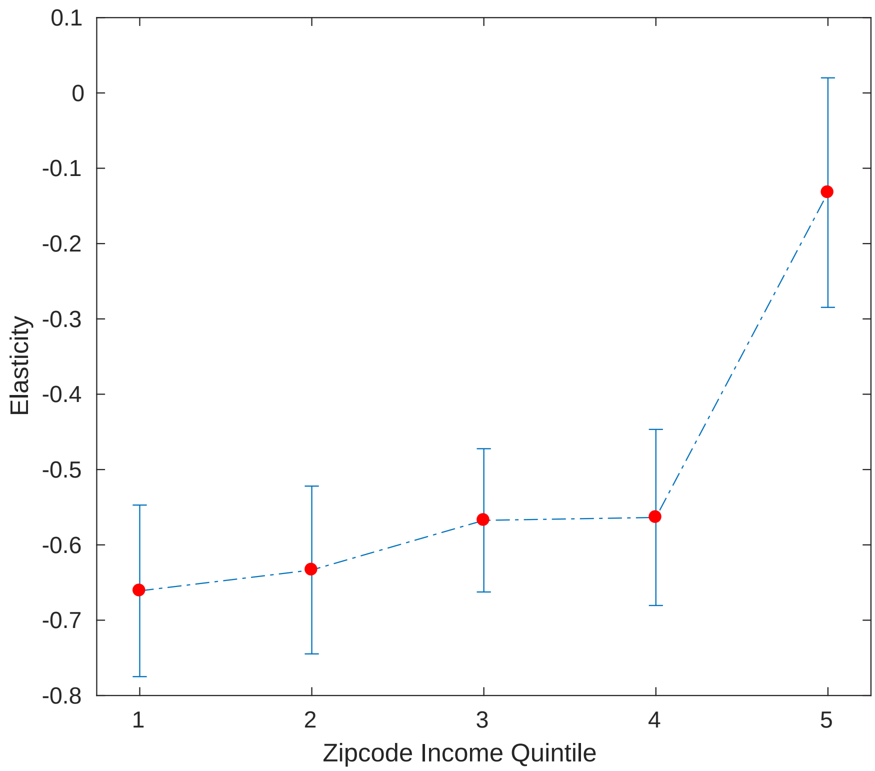
Notes: This panel shows the "within" variation used to estimate the price elasticity of demand for energy service consumption. An observation is a household month. The y-axis shows within household energy price variation and the x-axis shows within household energy consumption variation. This "within" variation is used to identify the parameters β_{g_i}. The plot shows that energy consumption is relatively inelastic for the average household.

Figure 3: Cross-market Appliance Price Variation



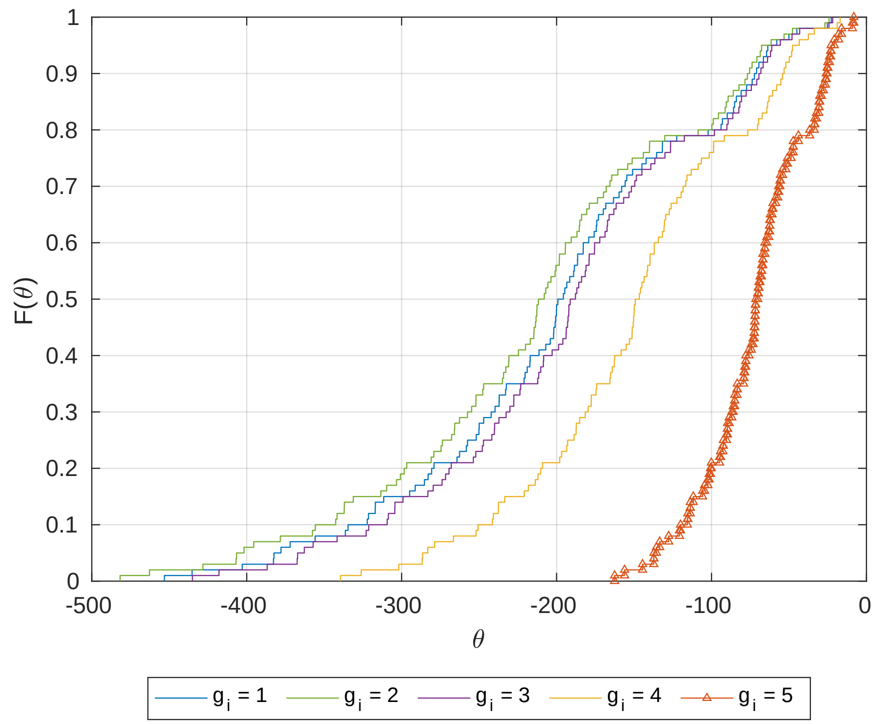
Notes: An observation is a market (unique first three zipcode digits for each Neilsen market). The x-axis shows the mean program participation rate in each market, and the y-axis plots the Energy Star washer price in the market. Marker size is proportional to the number of households in the market. Variation in prices and other components of $\mu_{ij}(\theta)$ is used to identify the variance of the logit error term. The stronger the relationship between the explained component $\mu_{ij}(\theta)$ of utility and market shares, the smaller the variance of ϵ. Intuitively, the more variation in purchases is explained by $\mu_{ij}(\theta)$, the less is explained by variation in ϵ and consequently the smaller the implied variance of ϵ.

Figure 4: Price Elasticity of Demand for Energy Services



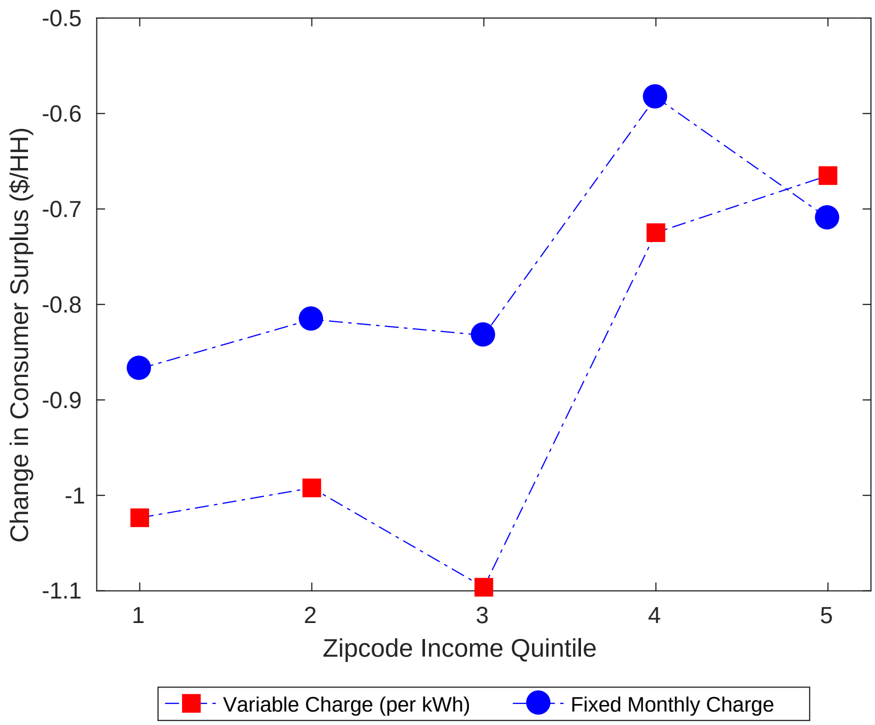
Notes: Each marker represents the average price elasticity of demand for energy service consumption in zipcode income quintile g_i. Robust standard errors are computed using the delta method. Price elasticity $= \beta_{g_i} \cdot p^{\mathbf{s}}/s$.

Figure 5: Simulated Distribution of θ



Notes: The plot shows the simulated empirical distribution of $\theta_{g_i} = \lambda_{g_i} \cdot Rayleigh(1)$. The same 100 draws from a Rayleigh(1) distribution were used for each income quintile. Notice that the distribution increases in income in a first-order-stochastic-dominance sense.

Figure 6: Distributional Burden of Program



Notes: The figure shows the expected change in consumer surplus (measured in dollars) for the distortionary program and the non-distortionary program. Notice that moving fundraising to a fixed-fee rather than an increase to the marginal price reduces loss of consumer surplus in all but the wealthiest 20% of zipcodes.

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