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How Consumers Respond to Product Certification and the Value of Energy Information

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Abstract

I study how consumers respond to competing pieces of information that differ in their degree of complexity and informativeness. In particular, I study the choice of refrigerators in the U.S., where a mandatory disclosure labeling program provides detailed information about energy cost, and a certification labeling program provides a simple binary-star rating related to energy use. I find that the coarse certification may help some consumers to pay attention to energy information, but for others, it may crowd out efforts to process more accurate, but complex, energy information. The effect of the certification on overall energy use is thus ambiguous.

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1. Introduction

In several markets, firms must disclose detailed information about certain dimensions of product quality while being subject to certification programs that provide simpler information signals about these same dimensions of quality. For instance, in the U.S., the Centers for Medicare and Medicaid Services publish a booklet with detailed information about Medicare Advantage contracts together with a five-star rating that ranks these contracts along a single dimension. In the financial sector, publicly-traded firms disclose detailed financial and operating information, but credit rating agencies also assign letter grades, a coarse summary of the default risk, on which investors rely heavily.

In these various settings, consumers and investors are exposed to competing pieces of information that differ in their degree of complexity and informativeness. A rationale to offer a certification that provides a coarse summary of otherwise readily available information is that consumers may differ in their ability to collect and process information. As a result, some consumers might prefer to rely on simple and salient pieces of information, and forgo more accurate, but harder to process, information. This paper investigates whether consumers trade off coarse and complex information.

My focus is on energy labels, which are important policies, in the U.S. and elsewhere, used to induce consumers to purchase more energy efficient durables, and ultimately address externalities associated with energy use. For instance, the Federal Trade Commission requires each appliance model offered in the U.S. to prominently display the EnergyGuide label, which provides detailed information about energy use and operating cost (Figure 1(b)). At the same time, appliance manufacturers can also certify their products using the ENERGY STAR (ES) certification, a binary-star rating that identifies the most energy-efficient models within a product class (Figure 1(a)). The main rationale of the ES program is to offer a simple heuristic to compare products in the energy dimension.

To answer whether consumers trade off energy information, I estimate a choice model using a theory of rational attention allocation (Sims 2003).[1] The model takes the form of an information acquisition model (e.g., Stigler 1961; McCall 1965; Gabaix et al. 2006), where consumers select to

[1]Recently, Sallee (2014) also proposed a model of rational attention allocation to study why consumers might be inattentive to energy information.

rely on different pieces of information or even dismiss all energy information altogether. Using this framework, I show that a coarse certification may not necessarily improve welfare if consumers are heterogeneous in their costs of collecting and processing information. The ES certification may help some consumers find energy-efficient products, but for other consumers, it may crowd out the effort to collect and process more detailed and accurate information.

I estimate the model with microdata on the U.S. refrigerator market. I find that a fraction of consumers value the ES certification well beyond the energy savings associated with certified products. Others rely on a local measure of electricity cost and do not value the certification; this fraction of consumers is more prevalent among the higher-income group. A large fraction of consumers also appears to neither value the certification nor consider energy operating cost, and this fraction is much larger for the lower-income group. Each latent type is identified by specific substitution patterns that can be captured by relative movement in market shares. In particular, the fact that the ES certification corresponds to a binary attribute whereas energy cost is a continuous attribute reveals the fraction of consumers that are prone to rely on either pieces of energy information.

The finding that a certification can act as a substitute for readily available detailed information and that consumers may misperceive the information signal associated with certification is a cautionary lesson about combining disclosure and certification policies. What is perceived to be the strength of the ES program may be its weakness—the simple and salient ES label may divert some consumers from relying on more complex, but accurate, energy information. In my policy simulation, holding firms' strategies constant, consumers would be slightly better off, by a few dollars, in a world without certification.

The results are among the first estimates of the behavioral effects of energy labels using a revealed preference approach combined with market-level data. Recently, Newell and Siikamäki (2014) used an online survey with hypothetical choices and also found that the ES label has a large impact on choices, and that consumers' willingness to pay (WTP) for the label goes beyond the expected energy savings associated with the certification.[2] Davis and Metcalf (2016) used

[2]Sammer and Wüstenhagen (2006) found similar results for the EU energy label. Consumers' stated-WTP for the letter grade "A" was also above the cost savings associated with the letter.

a similar approach to study how consumers respond to the EnergyGuide label and an enhanced label with local electricity costs. They found that most consumers tend to rely primarily on the information presented on the label and do not seek further information. This more recent finding is consistent with my results, which suggest that only a fraction of consumers rely on a local measure of electricity cost. In the car market, Allcott (2013*a*) provided survey evidence that consumers may misunderstand some pieces of information on fuel economy labels and have limited ability to perform calculations to compute energy operating costs.[3] My results complement these findings and have important implications for the design of energy policies that target energy demand. Consumers' inattention to energy efficiency or misperceptions of energy costs are an often-cited justification for minimum standards. Recent empirical evidence has, however, been mostly confined to the car market (e.g., Klier and Linn 2010; Li, Timmins and von Haefen 2009; Busse, Knittel and Zettelmeyer 2013; Allcott and Wozny 2013) and suggests that inattention to car operating costs may in fact be modest. This article shows that the degree of inattention to energy costs in the appliance market is highly heterogeneous, and only a fraction of consumers does not pay attention to this attribute. As shown by Farhi and Gabaix (2015), quantifying heterogeneity in misperceptions is important for the design of optimal policy accounting for behavioral bias. In the energy context, heterogeneous misperceptions provide one argument in favor of a Pigouvian quantity instrument, such as a standard, relative to a price instrument.

Outside the energy context several empirical studies have investigated certification programs similar in nature to ES (Dranove and Jin 2010).[4] My empirical analysis also complements the structural demand models of Abaluck and Gruber (2011); Handel and Kolstad (2015); Ketcham, Kuminoff and Powers (2016*b*); and Ketcham, Kuminoff and Powers (2016*a*), which aim to explicitly study attention allocation and heuristics used in complex choice environments. My contribution is to show that heterogeneity in the response to certification takes a particular form; the heterogeneity patterns suggest different degrees of sophistication in the way consumers can collect and process

[3]Heinzle (2012) showed that the sign of the bias for expected energy operating costs is also ambiguous. In one stated preference study, she found that consumers may tend to overestimate the energy operating costs of televisions.

[4]For instance, Darden and McCarthy (2015) show how consumers respond to the star rating provided for Medicare Advantage contracts. Jorion, Liu and Shi (2005) shows that the letter-grade used by rating agencies impact stock prices and that this effect is much more pronounced after the adoption of the Fair Disclosure regulation in 2003.

information. From the broader industrial organization standpoint, this suggests that a coarse certification that is highly valued—even by a small fraction of consumers—could facilitate product differentiation and exacerbate market power.

The remainder of this article is organized as follows. Section 2 provides a primer on energy labels for the U.S. appliance market. Section 3 develops a framework to model how a coarse certification can impact purchase decisions for energy-intensive durables. Section 4 gives an overview of the data, and discusses sources of identification. Section 5 presents the empirical strategy and discusses identification. Section 6 presents the results. The policy analysis is presented in Section 7, and conclusions follow.

2. **A Primer on Energy Labels for the Appliance Market**

In the US appliance market, two different labeling schemes provide energy information to consumers: the EnergyGuide and the ES certification. The EnergyGuide program was established in 1979 and is managed by the Federal Trade Commission. The program covers most types of appliances and several consumer electronics products. The main feature of the program is the requirement that each product offered in the marketplace prominently displays a large yellow label with detailed technical information about its annual energy use and operating cost. The content of the EnergyGuide label has been revised several times since the inception of the program. In its most recent version (Figure 1(b)), the label displays the annual electricity (or gas) consumption of the product, an estimate of the annual operating cost based on the national average price of energy, and a scale comparing this cost with the costs of similar products.

Because the EnergyGuide label reports only an estimate of the operating cost based on a national average price even though electricity prices vary widely across the United States, the label alone does not perfectly inform consumers. Computing an accurate estimate of the local energy operating cost thus remains a complex and costly task in the appliance purchasing decision. In addition to taking the time to look at the EnergyGuide label and understand the various pieces of information, consumers must also look up the local electricity price and perform mental calculations to compute the operating cost over the lifetime of the product. The label can influence consumers via two channels: it may lower information acquisition costs for crucial pieces of information related to energy operating costs and it may also increase the salience of energy efficiency as a dimension of quality.

The salience of energy efficiency was the main rationale that the Environmental Protection Agency (EPA) invoked to establish the ES certification in 1992. The primary feature of the ES program is a simple label that contains no technical information and is similar to a brand logo (Figure 1(a)). Only products that meet a certain certification have the right to display the label. The ES certification is voluntary and manufacturers ultimately decide whether to certify products that meet the ES requirement. The ES label is displayed on certified appliances as a way to both increase the salience of the energy efficiency attribute and to provide a simple heuristic to trade off products in this dimension of product quality.

The ES certification requirement for appliances is binary.[5] Under this system, the requirement is defined relative to the federal minimum energy efficiency standard. For instance, before April 2008, a full-size refrigerator could be certified if it consumed at least 20% less electricity than the minimum energy efficiency standard established for this refrigerator model.

A crucial feature of the ES program is that the certification requirements are revised periodically. The EPA revises the stringency of a requirement in a specific appliance category using various criteria, such as the proportion of certified products offered on the market, the market shares, and the availability of new technologies (McWhinney et al. 2005). The stringency of a requirement is ultimately determined by the EPA upon consultation with different stakeholders, such as manufacturers, part providers, retailers, analysts, and environmental groups. The EPA usually announces a revision one year in advance.

3. An Information Acquisition Model for Energy-Intensive Durables

This section develops a model of durable good purchase, which explicitly incorporates attention allocation to different pieces of energy information. The goal is to develop a framework that can be used to quantify how energy information affects consumers' behavior and ultimately consumer welfare. The model also provides a simple positive economic theory that explains why consumers

[5] In 2013, the EPA introduced a two-tier system in some product categories. In addition to the ES certification, some products can also earn the "Most Efficient" certification. I focus on the binary system.

may prefer to rely on coarse information in a setting where more detailed and accurate energy information is readily available, or even dismiss all relevant information altogether.

Prior to collecting and processing information, knowledge about the energy cost of each product j in a given region r at time t, denoted C_{jrt}, is considered to be imperfect. Imperfect information stems from the fact that the energy operating cost of each product is not readily available. In order to have to have an accurate estimate of C_{jrt}, consumers must search for information about local electricity prices, present and future, and the expected lifetime of the product, and then perform net-present value calculations.[6] A consumer i can learn the value of C_{jrt} only by incurring a cost $K_i(e_i)$, where e_i represents the effort to collect and process energy information. Define $\mathcal{I}(e_i)$ as the consumer's knowledge about energy costs for a given level of effort. The expected energy cost of product j at the time of purchase is given by $E[C_{jrt}|\mathcal{I}(e_i)]$.

Consumer i values product j, among J alternatives, as a function of its quality (δ_{ij}), its price (P_{jrt}), whether the product is ES certified or not at time t (D_{jt}), and an idiosyncratic taste parameter (ϵ_{ijrt}):

$$U_{ijrt} = \delta_{ij} - \eta P_{jrt} - \theta E[C_{jrt}|\mathcal{I}(e_i)] + \tau D_{jt} + \epsilon_{ijrt}. \tag{1}$$

A consumer's purchasing decision is modeled as a two-step process. In the first step, the consumer is uncertain about energy costs, the meaning of the certification (denoted S), and whether a product is certified or not.[7] A consumer observes the quality and the price for each appliance, and then decides how much effort to expend collecting and processing energy information. I assume that the consumer can choose one out of three effort levels. A consumer may collect and process enough information to form accurate expectations about the energy costs associated with each option, and thus makes a purchase decision perfectly informed (denoted $e = I$). In this case, $E[C_{jrt}|\mathcal{I}(e_i = I)] = C_{jrt}$, where C_{jrt} is an accurate forecast of the local energy cost of product

[6] Note that even if the information provided by the EnergyGuide label was an unbiased estimate of lifetime energy operating costs, which it is not, not all consumers would necessarily understand this information perfectly. The model is thus also observationally equivalent to a model where consumers have tastes for information complexity/simplicity. Consumers that have tastes for simpler information are modeled with uninformative priors and high costs to collect and process information.

[7] I assume that the consumer is uncertain about whether a product is certified, even though it prominently displays the ES label, due to possible psychological costs to detect whether or not a product is ES-certified.

j. Alternatively, a consumer may only collect information related to the certification (denoted $e = ES$). He will then learn the true meaning of the certification and which products are certified, but not the exact energy cost of each option. For ES-certified products, the expected energy costs are then $E[C_{jrt}|D_{jt}]$. Finally, a consumer may decide not to update his priors, and thus remain uncertain about energy costs, the meaning of the certification, and whether a product is certified or not (noted $e = U$). In this case, prior beliefs are uninformative—that is, all options in the choice set have the same expected energy cost ex ante: $E[C_{jrt}|\mathcal{I}(e_i = U)] = \bar{C}$. In the second step, the consumer chooses one of the J alternatives. When priors are uninformative, it is as if the consumer dismisses all energy-related attributes altogether.

Prior to making a purchase, the consumer's effort to collect and process information is given by the solution to the following optimization problem:

$$\max_{e=\{U,ES,I\}} -\mathcal{K}_i(e) + E_{\epsilon,D,\mathcal{C}}\left[\max_j\{U_{ijrt}(\delta, P, C, D, \epsilon)\}|\mathcal{I}(e)\right]. \tag{2}$$

When consumers are heterogeneous with respect to the costs of collecting and processing energy information, a fraction of the population will rely on energy costs, another will rely on the ES certification, and others will dismiss all energy-related attributes.

In this framework, the certification influences consumers via two mechanisms. First, it can be used as a heuristic to compare products in a binary manner along the energy dimension, and thus partly informs about energy costs. If consumers rely on ES, instead of an accurate forecast of energy cost, they would value certified products more based on their expected energy savings: $E[C_{jrt}|D_{jt} = 1] - E[C_{j'rt}|D_{j't} = 0]$. According to this mechanism, the certification brings welfare gains because it allows consumers to economize on information costs while it still provides some information about energy use and cost. Consumers at the source of the welfare gains are the ones that would not consider energy-related attributes if the certification were not in effect, but would otherwise rely on the signal provided by the ES certification.

A second mechanism is the effect of the certification itself on preferences and perception of quality. That is, consumers might value certified products beyond their expected energy savings and might value the exact same appliance with and without the certification differently. There are a number of reasons why the certification might have such an effect. ES products are often advertised as being environmentally friendly. Consumers might thus derive warm glow (Andreoni 1990) from purchasing certified products, respond to social norms, or experience social prestige. Under this interpretation, the certification impacts how consumers experience the product and provides a positive utility shock. It is also possible that consumers correlate certified products with better quality and are subject to what marketers refer to as the halo effect (Boatwright, Kalra and Zhang 2008). In this case, the certification provides an illusion of higher quality by indirect association, and biases consumers. Mullainathan, Schwartzstein and Shleifer (2008) refer to this phenomenon as transference. Empirically, these explanations are hard to disentangle, but they are important to recognize as they have different welfare implications.

In certain regions of the U.S., the ES certification also influences purchases via a third mechanism, which is the effect of consumer rebates offered by various entities. Rebate programs have been a popular approach used by local governments as well of electricity utilities to promote ES-certified products. These rebates provide an explicit financial motivation to adopt ES products, in addition to the informational effects.

4. **Data and Environment**

The primary data source consists of all transactions made at a large US appliance retailer during 2008-2011 in which a full-size refrigerator was bought. The retailer offers a large selection of appliance models and has at least one brick-and-mortar store in each state in addition to a national online store. For each transaction, I observe the date, the model of the refrigerator, detailed attributes, the manufacturer's suggested retail price (MSRP), the retailer's price, the wholesale price, the taxes paid, and the zip code of the store where the transaction was made. For a large subset of transactions ($\approx$ 40%), I also observe consumer demographics, such as household size, income, education, homeownership, housing type, political orientation, and age of the head of the household. This demographic information is transaction-specific and is collected by a data aggregator. For the estimation, I use a large random sample of transactions for which demographic information is available.

I focus on refrigerators for two reasons. First, during the sample period, there were two events that led to the decertification of ES refrigerators. Second, refrigerators are one of the few energy-intensive durables for which utilization behavior has little impact on energy consumption. I can thus infer energy operating costs accurately using engineering information and electricity prices, and rule out utilization as a source of unobserved heterogeneity, which has important implications on how to interpret the results.

They are four variables that are crucial for the identification of the empirical model: the ES certification, prices, electricity costs, and rebates. Below I discuss the source of variation in each of these variables. I provide additional details on the data and stylized facts in the appendix.

4.1. ENERGY STAR Certification

When a new certification requirement comes into effect, the EPA requires that manufacturers and retailers remove the ES label from certified products that do not meet the more stringent requirement. For products that display the ES logo on the EnergyGuide label, firms are also required to clearly identify that these products are decertified by masking the logo. Using data that cover the period before and after the revision in the standard, I observe the same refrigerator model being sold at the same store with and without the ES certification. This variation identifies how consumers value the ES certification, controlling for other product attributes.

During the sample period, the ES certification requirement for full-size refrigerators was revised on April 28, 2008.[8] Prior to this revision, ES refrigerators had to consume at least 15% less electricity than the minimum energy efficiency standard; the revision set the stringency at 20%.

For the year 2008, there were 2,524 refrigerator models available in the whole US market, and 1,278 models lost their certification (Table 1). In the retailer's sample, there are 1,483 models for that year, with 674 models that were decertified. The large number of decertified models provides good statistical power for identification, and more importantly covers all product classes, but it brings two challenges. First, manufacturers and retailers adjust to the revision in certification by introducing new models and removing decertified models. This is illustrated by Figure 4 (Appendix

[8]This corresponds to the effective date. The revision was announced exactly one year in advance by the EPA.

A), which shows that firms adjusted their product lines quickly, within one or two years, in response to the revision in the certification requirement. Second, I do not observe the exact date that the ES certification was corrected on each product. Although the retailer's policy is to coordinate the change in certification across all stores, and to implement the change close to the date mandated by the EPA, I cannot ensure that all store managers complied with the policy on an exact date.

To control for the effects of product entries and exits, I construct trimester–zip code–specific choice sets. For each refrigerator model, I identify the first and last trimesters for which a model was sold at least once in a zip code,[9] and I assume that consumers shopping at this location between these two trimesters could purchase this particular refrigerator model.

As a robustness test, I also exploit a second decertification event that did not suffer from the issues associated with the 2008 event. In January 2010, the EPA announced that 21 refrigerator models from two different brands had been subject to an incorrect testing procedure, which resulted in underestimation of their electricity consumption. The revised test confirmed that these models did not meet the certification requirement and should be decertified. The sample contains 14 of these models. Unlike the 2008 revision, this event came as a surprise for manufacturers and retailers. The EPA also mandated that the retailers print new EnergyGuide labels and that they remove all references to ES after the public announcement on January 20, 2010. This event thus induced a sharp discontinuity in certification that rules out the effect of anticipation by firms. Moreover, enforcement—or the threat of enforcement—by the EPA was likely to be more important given the small number of models affected. One caveat is that this small sample of refrigerator models may not be representative of the whole market. Table 1 shows that the prices of these models were higher than average, which suggests that these models targeted higher-income households.

4.2. **Prices**

Throughout the sample period, the retailer had a national pricing policy and implemented large and frequent variations in prices that were model specific. I exploit this high-frequency temporal variation in prices to identify consumers' sensitivity to prices.[10] The identification argument here

[9]Most zip codes contain only one store.

[10]A second source of variation in prices comes from the two decertification events. As shown in Figure 5 (Appendix A), the prices of decertified models dipped below the prices of other models post-decertification.

is similar to that of Einav, Jenkins and Levin (2012): abrupt variations in prices identify price elasticities as long as they are not correlated with slow-moving trends in demand. I argue that this exclusion restriction is likely to hold in the present context. The retailer relies on a high-low pricing strategy where the timing and size of the price changes are set on a model-by-model basis. As a result, the retailer's prices are somewhat correlated within brands and periods of the year, but there is substantial idiosyncratic variation left even when I account for those effects. This is illustrated by Figure 2. Each panel plots the weekly variation in price for the nine most popular models of a specific brand. The plain line corresponds to the median change in price relative to the average price over the lifetime of the product, where the median is taken across zip codes. The gray band identifies the 25^{th} and 75^{th} percentile of changes, also taken across zip codes. The fact that these percentiles tend to be very close to the median for most weeks suggests that local store managers follow the national pricing policy. The dashed line plots the median change in price after controlling for brand-specific week-of-sample fixed effects. These fixed effects capture seasonal as well as contemporaneous brand specific temporal shocks. Even after accounting for those shocks, the large dispersion in prices persists. These patterns are not restricted to the most popular models or to a specific brand. This significant randomness in how the retailer set prices is consistent with the classical model of Varian (1980) where retailers play a mixed strategy that consists of randomizing prices to screen between uninformed and informed consumers.

Although there is rich variation in prices, endogeneity might still be an issue, and as a result the estimated coefficient on price will not be free of any biases. For instance, as discussed by Ackerberg and Rysman (2005), product entries and exits might impact demand elasticities in an unexpected manner. However, I will show that the coefficient on price is robust to various specifications. More importantly, it is unlikely that the remaining sources of biases confound the identification of the heterogeneity patterns in preferences for energy information, which is the main focus of the empirical investigation.

The 2010 decertification had an especially dramatic effect—the prices of decertified models dropped sharply just after the announcement by as much as 15%. Given that these abrupt changes in relative prices were driven by the timing of the government regulation, it is unlikely that they were correlated with demand shocks.

4.3. **Electricity Prices**

The energy operating cost of each refrigerator model that enters the choice model is the annual electricity consumption reported by the manufacturer multiplied by the average electricity price of the region where the purchase was made. I assume that consumers form time-unvarying expectations about electricity prices using the current local average price. The time-unvarying assumption can be justified in two ways. First, electricity prices, unlike gasoline prices, have been very stable over the sample period. For instance, between 2008 and 2010, the national average electricity price remained virtually unchanged (Table 1). Second, time-unvarying expectations are consistent with evidence in the car market suggesting that consumers tend to simply rely on the current gasoline price to forecast future prices (Anderson et al. 2011).

Ito (2014) showed that households' total energy usage responds to variations in average electricity prices within California, which suggests that fairly local average electricity prices are the most appropriate measure. Most online tools provided by the EPA and retailers to estimate energy savings associated with ES, however, rely on a state average. I will report estimation results using two different levels of aggregation: state and county average electricity prices. The structural estimator, however, makes it clear that the behavioral responses to these two different measures of average prices identify different primitives. For instance, when county average prices are used, the model identifies the share of consumers that are sophisticated enough to collect and process information about county-level electricity prices.

The main source of identification of the coefficient on electricity cost comes from the fact that the same refrigerator models are being sold at stores located in different electric utility territories at different points in time. This allows me to control for product fixed effects and demographic information, and use cross-sectional and temporal variation in average electricity prices across regions to identify the sensitivity to electricity prices.

4.4. **Rebates**

An important institutional feature of the US electricity market is that several electric utilities are subject to regulations that incentivize them to promote energy efficiency measures to consumers.

Several electric utilities have opted to offer rebate programs to encourage the adoption of energy-efficient appliances. These rebate programs are all similar in nature. Consumers claim rebates by filling out forms that must be submitted by mail or online. The purchased refrigerators must meet a given energy efficiency criterion, which for most programs consists of the ES certification. Financial incentives are thus one factor influencing the adoption of ES products, which I account for in the demand model. A complete description of U.S. rebate programs is available in the database of state incentives for renewables and efficiency (DSIRE). The number of active rebate programs and the amount of the rebate offered by each program vary over time. In 2008, 87 utilities offered a rebate program for ES refrigerators, and this number increased to 133 in 2010 (Table 1).

In addition to utility rebate programs, state governments also offered financial incentives for ES appliances during the sample period. In 2010, as part of the stimulus effort, the federal government allocated funds to all US states and territories to establish temporary rebate programs to encourage the adoption of energy-efficient products. Each state had sovereignty over the design of its rebate program, which led to important variations in the rebate amount across regions and time. During the 2010-2011 period, 44 states offered rebates for ES-certified refrigerators. The average rebate amount was \$128, and the state rebates varied from \$50 to \$600. Some programs lasted for only one day (e.g., Illinois and Texas); the longest-running program was in Alaska and lasted 639 days (Houde and Aldy 2017).

In the estimation, the rebate amount offered to each consumer is the average rebate amount in each county, which includes the utility and state rebates, when both are available. Utility rebates vary annually and by county, whereas state rebates vary weekly.

5. **Empirical Strategy**

To obtain an econometric specification of the information acquisition model, I assume that the information acquisition costs have an unobservable idiosyncratic component, ν_{ie}, that is Type I extreme value distributed.[11] For a level of effort, e, the cost for consumer i is given by

$$\mathcal{K}_i(e) = K^e + \beta^e X_i + \nu_{ie}, \tag{3}$$

where X_i is a vector of demographics, and the constant K^e and the vector β^e are coefficients that I estimate.

The choice model takes the following general form:

$$Q_{irt}(j) = \sum_{e=\{U,ES,I\}} H_{irt}(e) P^e_{irt}(j), \tag{4}$$

where $Q_{irt}(j)$ are the choice probabilities for product j, in zip code r, and week t. The choice probabilities vary with observable demographic information; the subscript i thus refers to a particular combination of demographic variables. $H_{irt}(e)$ are the information acquisition (effort) choice probabilities, and $P^e_{irt}(j)$ are the product choice probabilities conditional on e. The alternative-specific utilities, U_{ijrt}, that enter $P^e_{irt}(j)$ for each level of effort are

$$\begin{aligned}
e = I: &\quad U^I_{ijrt} = -\eta P_{jrt} + \psi R_{rt} \times D_{jt} - \theta C_{jrt} + \delta_{ij} + \epsilon_{ijrt} \\
e = ES: &\quad U^{ES}_{ijrt} = -\eta P_{jrt} + \psi R_{rt} \times D_{jt} + \tau^{ES} D_{jt} - \theta ESAVINGS_{rt} \times D_{jt} + \delta_{ij} + \epsilon_{ijrt} \\
e = U: &\quad U^U_{ijrt} = -\eta P_{jrt} + \delta_{ij} + \epsilon_{ijrt}.
\end{aligned}$$

When $e = I$, consumers form a perfect forecast of the operating cost for each product in the choice set by multiplying the annual electricity consumption of refrigerator j and the average county electricity price in region r. When $e = ES$, the term $ESAVINGS_{rt}$ is the difference between the average operating cost of ES and non-ES refrigerators, in region r at time t. The effect of the certification is included for $e = ES$, which means that consumers can value certified models beyond purely energy savings for the various reasons described above (e.g., warm glow or halo effect). The effect of rebates is included for both $e = I$ and $e = ES$. If consumers are uninformed ($e = U$), they trade off refrigerators only with respect to prices and non-energy related attributes.

[11]The idiosyncratic component of the costs ν_{ie} can also be interpreted as the idiosyncratic *tastes* for energy information. This captures the fact that some consumers may understand well the meaning of the energy labels, but may decide not to rely on them because they do not find this attribute important enough relative to other attributes.

The term δ_{ij} is a product fixed effect that is consumer-specific. It consists of a dummy for each product that captures all time-invariant attributes and a vector of product attributes interacted with demographic information.[12] Finally, I assume that that the idiosyncratic taste parameters, ϵ, are Type I extreme value distributed and follow the same distribution across types.

Evaluating the expectation in (2) poses two challenges: it requires specifying consumers' beliefs about electricity costs and ES, and computing a large multidimensional integral. The latter is particularly challenging for large choice sets, as in the present application (Table 1). The former brings an identification issue given that I do not observe consumers' beliefs at the moment they make a purchase decision. This implies that the information acquisition costs that enter the effort choice probabilities are not identified. I circumvent these two difficulties by using a flexible representation of the expectation at different levels of effort. In particular, I approximate the expectation with variables that capture the characteristics of the choice set faced by each consumer, which are related to the decision of whether to process energy information.

As discussed by Sallee (2014), in a rational search model consumers might be inattentive to energy efficiency if the variance in the value of other attributes is large relative to the variance in electricity costs. The intuition is that the ex ante value of information increases with the variance in beliefs. Therefore, if consumers have limited resources to spend on processing information, they should allocate attention such that learning about attributes has the highest expected returns. With this intuition in mind, I specify the effort choice probabilities as follows:

$$H_{irt}(e) = \frac{e^{V_{irt}(e)}}{\sum_k e^{V_{irt}(k)}}, \tag{5}$$

[12]For the estimation, education, household size, political orientation, and age of the head of the households are interacted with attributes that are strongly correlated with energy efficiency, specifically size and door design (top-freezer versus other designs).

where

$$V_{irt}(e = I) = -K^I - \beta^I X_i + \gamma_1^I MeanElec_{rt} + \gamma_2^I VarElec_{rt} + \gamma_3^I NbModels_{rt} + \gamma_4^I VarPrice_{rt}, \tag{6}$$

$$V_{irt}(e = ES) = -K^{ES} - \beta^{ES} X_i + \gamma_1^{ES} MeanES_{rt} + \gamma_2^{ES} VarES_{rt} + \gamma_3^{ES} NbModels_{rt} + \gamma_4^{ES} VarPrice_{rt},$$

$$V_{irt}(e = U) = 0.$$

The variables $MeanElec_{rt}$ and $VarElec_{rt}$ are the mean and variance of electricity costs for all products offered in region r at time t, $MeanES_{rt}$ is the proportion of ES models offered, $NbModels_{rt}$ is the number of models in the choice set in a given region, and $VarPrice_{rt}$ is the variance in prices. The estimation is performed via maximum likelihood. Additional details about the estimation procedure are discussed in Appendix B.

5.1. **Identification**

The information acquisition model is a special case of a mixed logit with three discrete latent classes. It can also be interpreted as a sorting model, where the effort choice probabilities capture why consumers self-select to pay attention to a particular piece of energy information. The information acquisition costs are not identified because consumer beliefs are not specified. My goal is to identify the share of consumers in each latent class, and the behavioral parameters that enter the choice probabilities for the purchase decision (η, θ, τ^{ES}, and ψ).

The latent classes capture unobserved heterogeneity in the valuation of energy efficiency. As it is customary in discrete choice models, events that induce specific substitution patterns identify heterogeneity. In the present application, the coarseness of the certification requirement and the continuous nature of the information related to electricity costs each yields different substitution patterns allowing me to identify each latent class. To illustrate, consider a market with only three refrigerator models, all with the same quality, but with different levels of energy consumption. Figure 3 represents the location of each refrigerator model in the quality-energy efficiency characteristics space, before and after the revision in the ES standards, for three types of consumers.

Panels (a) and (d) represent the location of the refrigerator models in the quality-energy cost characteristics space for consumers that are fully informed about energy costs. For this consumer type, products are located at a different address in the characteristics space. How market shares will vary for a relative change in prices will then be a function of the distance between products due to the difference in electricity costs. Note that for this consumer type, a revision in the ES standard, illustrated on Panel (d) by the line s, should not influence the substitution patterns. Panels (b) and (e) represent the location of the same models in the quality-ES characteristics space. This corresponds to a graphical representation of consumers that rely on the ES certification to account for the energy efficiency attribute. These consumers perceive ES refrigerators as perfect substitutes. The revision in the ES standard impacts this perception (Panel (e)). For this consumer type, the Independence of the Irrelevant Alternative (IIA) hypothesis should hold within the class of products that are certified (and with similar quality). Finally, for consumers that do not account for the energy efficiency attribute at all, Panels (c) and (f), all products are located at the same address in the characteristics space and are perceived as perfect substitutes. The IIA hypothesis should hold for all products with similar quality, irrespective of their location in the energy efficiency dimension.

In the present model, the consumer-specific quality dummies, δ_{ij}, fix the location of each product in the characteristics space. Large and frequent variation in prices, the two decertification events, product entry and exit, and variation in electricity prices and rebates all provide the source of variation to induce substitution patterns that are specific to each latent class as described above. The relative movement in market shares in response to each of those variables, controlling for quality in the non-energy dimension, identify the latent classes. For instance, suppose that for a combination of demographic i, the relative market shares for products j and k for that demographic group, denoted σ_{ij} and σ_{ik} respectively, are not impacted by variation in electricity costs, but respond to change in certification for say product k; this would identify the share of consumers responding to the ES certification, but not electricity costs. The discrete choice model approach allows me to compare a large number of products for different demographic groups at once, but it is still the relative movement in market shares for each pair of products, for a given demographic group i, that identifies the model.

In sum, the discrete and binary nature of the ES certification allows me to distinguish the share of consumers that trade off energy efficiency using the certification from consumers that use a more continuous measure, such as an estimate of electricity costs. For consumers that dismiss all energy information, only prices and quality will matter in their decision, and thus impact market shares.

6. Results

Before presenting the results from the information acquisition model, I present the results from a simple conditional logit. The conditional logit serves as a benchmark to characterize the preferences of an average consumer for various income groups and to investigate the sources of variation in the data.

I perform the estimation of both the information acquisition model and the conditional logit on three large samples of transactions randomly drawn from each income tertile.[13] I sample from the set of transactions that contain complete demographic information. Moreover, I consider only transactions made by homeowners living in single family housing units that bought no more than one refrigerator during the period 2008-2011. The rationale to consider this restricted set of transactions is to select households that are the most likely to pay for their electricity bills. The estimation samples thus rule out heterogeneity in sensitivity to energy costs due to the split incentive problem (Blumstein et al. 1980), that is, the fact that some consumers of energy-intensive durables do not pay for energy costs (e.g., contractors or some renters).

6.1. Conditional Logit

The alternative-specific utility for the conditional logit is:

$$U_{ijrt} = \tau D_{jt} - \eta P_{jrt} + \psi R_{rt} \times D_{jt} - \theta C_{jrt} + \delta_j + \epsilon_{ijrt} \tag{7}$$

where the variable C_{jrt} is the annual electricity cost of operating product j based on expectations in week t in zip code r. Unless otherwise specified, I compute C_{jrt} using the county average electricity

[13]Income information is coded with a categorical variable that takes nine values. The lowest tertile corresponds to annual household income of less than \$50,000. The second tertile corresponds to household income equal to or greater than \$50,000, but less than \$100,000. The third tertile corresponds to income equal to or greater than \$100,000.

price for the year that week t belongs to. P_{jrt} is the weekly retail price, which includes all the local sales taxes, and R_{rt} is the average rebate amount offered in zip code r in week t, which includes utility and state rebate programs. D_{jt} is a dummy variable that takes the value one if product j is certified at time t and zero otherwise. The variables δ_j and ϵ_{ijrt} denote, respectively, the product fixed effects, and the idiosyncratic taste parameters, which are assumed to be i.i.d. and type I extreme value distributed. The choice probabilities do not include an outside option (no purchase or purchase at other stores) because the policy analysis focuses on how energy information influences which product to purchase at a given store, not the timing or location of the decision.

Table 2 presents the estimates obtained with various specifications of the conditional logit for the three income groups. For all models, robust standard errors clustered at the zip code level are reported. Model 1 is the simplest and only controls for product fixed effects.

The coefficient on price (η) is negative and large in absolute value. The own-price elasticity evaluated at the mean price ($1,300) is -5.41, -4.75, and -4.16 for the lowest, medium, and highest income tertiles, respectively.

The coefficient on the ES dummy (τ) is positive and statistically significant for all three income groups. The ratio of τ and the marginal utility of income, τ/η, corresponds to the marginal willingness to pay (WTP) for the ES certification itself. The WTP is modest and increasing with income. It is $30.0 for the low-income tertile, $44.6 for the medium-income tertile, and $56.9 for the high-income tertile.

For all three income groups, the coefficient on electricity cost (θ) is negative and significant, but implies that consumers steeply discount operating energy costs. Comparing θ with the coefficient on price informs us about the extent to which consumers trade electricity costs with the purchase price. In Appendix C, I show that, under various assumptions about the lifetime of a refrigerator, consumers' expectations of future electricity prices, and depreciation, the implicit discount rate that rationalizes consumers' decisions is as high as 34% for the lowest-income group, but drops to 17% for the medium-income group, and 10% for the highest-income group.

Finally, the coefficient on ES rebates (ψ) is positive and small, but is statistically significant only for the two lowest-income tertiles. If we were able to observe whether a consumer claimed a rebate R, and there were no hassle costs associated with claiming a rebate, the coefficient on rebates would exactly match the coefficient on price—that is, it would be equal to the marginal utility of income. In the present application, the ratio of ψ/η is 21%, 11%, and 5% from the lowest to the highest income group, respectively. Lower-income households thus respond more to rebates.

The above results are robust to various alternative specifications. Model 2 is similar to Model 1, but distinguishes between the two decertification events. I include a dummy for the ES certification that takes a value of zero if a product lost its certification in 2008, and a second ES dummy that takes a value of zero if a product lost its certification in 2010. The estimates suggest positive certification effects, but the 2010 estimates are larger relative to 2008. For 2008, the WTP for the certification itself is still positively correlated with income levels, but this pattern does not hold for 2010. Comparing the estimates from the two events should be done, however, with the caveat that only a small number of products from specific brands were decertified in 2010. They are, therefore, not representative of the whole market, and some income groups might value those products more. Moreover, EPA's enforcement—or the threat of enforcement—of the decertification likely differed in the two cases. Nonetheless, the fact that the estimates from the 2010 event are large and significant is reassuring given that these estimates are unlikely to be biased by firms' product line decisions in anticipation of the decertification.

Model 3 includes demographic information interacted with product attributes with the goal of capturing regional or temporal differences in consumer demographics correlated with operating costs and rebate programs. Given that I use cross-sectional variation to identify the coefficients on electricity cost and rebates, a concern is that the behavioral responses to electricity costs or rebates are confounded by region-specific preferences for attributes correlated with energy use. This could occur if, for instance, high-income consumers that prefer large refrigerators live disproportionately in regions with low electricity prices. Consumer sorting due to short-term substitution might also be an issue, especially for the identification of the coefficient on rebates, which were generous, but short-lived in some regions. In Model 3, I thus include a vector of product attributes strongly correlated with refrigerator energy use, namely, size, ice-maker option, and door design interacted with the rich set of demographics available: household size, income, education, political orientation, and age of the head of the household. The estimates of Model 3 closely replicate the ones of Model

1, suggesting that the cross-sectional and temporal variations in electricity costs and rebates are not confounded by preference heterogeneity.

I present additional robustness tests in the appendix (Tables 5-7). In the previous section, I have argued that product-specific weekly variation in prices can be exploited to identify the coefficient on price and I have shown that, even after controlling for brand-week fixed effects, substantial idiosyncratic variation remains in the price time series of each product. Model 4 confirms this. Including brand-week fixed effects has little impact on the coefficient on prices or other coefficients. The fact that the coefficient on the ES certification remains unchanged under this specification also suggests that the behavioral response captured by the 2010 decertification event is not influenced by a negative perception of the brands impacted by the event. Model 5 shows that using state electricity prices instead of county averages does not impact the implicit discount rate, and this is true for the three income groups. In Model 6, I flexibly control for product age by including a dummy variable for each quarter of the year that a product has been on the market. The goal is to address the concern that the price variation might be correlated with the age (shelf life) of a product or that the age of decertified products might be systematically correlated if manufacturers and retailers perfectly anticipated the 2008 decertification and made product lines based on this. For all three income groups, product age has little impact on the coefficient on price, whereas the coefficient on the ES certification changes by only a few percentage points. The last robustness test consists of investigating the effect of the consideration set. In the previous specifications, I have assumed that consumers were choosing among all full-size refrigerators offered by the retailer in a given zip code. Refrigerator size, however, is likely to restrict some consumers, as a kitchen is commonly designed to accommodate a refrigerator of a certain size. In Model 7, I thus create consumer-specific consideration sets based on the size of the refrigerators consumers bought. In particular, I assume that consumers were considering only products within +/- 5 cubic feet of the overall refrigerator capacity that they ended up purchasing. This criterion cut the choice set by half, on average. Doing so has little impact on most estimates, with the exception of the coefficient on electricity cost. In this model, the coefficient is smaller (in absolute terms), which suggests higher implicit discount rates.

Overall, the main results from the simplest specification (Model 1) are robust to various alternative specifications. For all three income groups, both the ES certification and electricity cost impact purchase decisions, although the coefficients on electricity cost imply large implicit discount rates. The exact values of the implicit discount rates are sensitive to the definition of the consideration set, but heterogeneity across income groups follows intuitive and robust patterns. Consumers in the lowest income tertile value the ES certification less, respond more to ES rebates, and have a higher implicit discount rate relative to higher-income consumers.

6.2. **Information Acquisition Model**

Table 3 presents the estimation results of the information acquisition model for each income group. Comparing the estimates of the coefficient on electricity cost (θ) of the information acquisition model with the conditional logit (Table 2) shows the importance of accounting for heterogeneity in consumer sophistication. Whereas the conditional logit model suggests a large undervaluation of energy efficiency, this phenomenon has a more nuanced interpretation in the information acquisition model. For consumers that rely on electricity costs ($e = I$), the implicit discount rate is lower and on par with other investment decisions. It is 7.5%, 7.9%, and 2.8% for the first, second, and third income tertiles, respectively. The fact that the implicit discount rate for higher-income households is smaller relative to the other two income groups is particularly interesting as it suggests lower short-term borrowing costs for this income group.

The latent probabilities that classify consumers into different information types suggest that the share of perfectly informed consumers is increasing with income. For the first income tertile, it is 34%, on average.[14] This share increases to 50% for the second income tertile, and 56% for the third tertile. The share of uninformed consumers follows the opposite pattern. It is 45%, 41%, and 27% for the first, second, and third income tertiles, respectively. Finally, the share of consumers that relies primarily on ES is relatively constant across the three groups (21%, 10%, and 17%). For this last consumer type, the willingness to pay for the ES certification is very high. It is $163 for the first income tertile, $422 for the second tertile, and $430 for the third tertile. These revealed preferences

[14] The latent probabilities that determine consumer sorting into different types is a function of demographics and characteristics of the choice set. The probability that a consumer is of a given type thus varies across consumers and regions. The average reported in Table 3 is taken over the whole population.

WTP estimates are consistent with the stated preferences estimates of Ward et al. (2011), which range from \$250 to \$349 for refrigerators. In my structural model, the certification effect captures the willingness to pay for certified products that goes beyond the average monetary value of the energy savings associated with ES products. These high values of the WTP for the certification itself thus imply that the certification enacts strong preferences or biases that lead to the adoption of ES products. Whether ES is a useful heuristic from a welfare standpoint is unclear. The large WTP for the certification itself is puzzling and could suggest that consumers might have a biased perception of the overall quality of certified products.

Relative to the conditional logit (Table 2), the coefficients on rebate increase, are positive, and become significant for the lower-income groups. Again, this shows the importance of accounting for heterogeneity. Consumers in the two lower-income groups respond more to rebates, which is consistent with the idea that, relative to richer households, they may be more willing to incur the hassle costs of claiming a rebate.

The coefficients that enter the latent probabilities show interesting patterns. Households with a graduate degree are more likely to be classified as fully informed. Older households of smaller size are more likely to be fully informed or rely on the ES certification. Democrats are more likely to be uninformed. As predicted by a rational model of search (Sallee 2014), a large variance in prices increases inattention to energy efficiency. Consistent with the theory, in regions with high electricity costs, consumers are also more likely to fully process energy information as the opportunity cost of dismissing this piece of information is higher. As expected, a larger proportion of ES models also increases the probability that consumers use ES as a decision heuristic.

The present framework provides a number of interesting insights regarding the existence of a so-called Energy Efficiency Gap (Jaffe and Stavins 1994), the apparent fact that consumers tend to underinvest in energy saving technologies. First, it is attributable to the existence of a share of uninformed consumers that dismiss the energy efficiency attribute altogether and this share is larger for lower-income households. Second, in this particular context, credit constraints do not seem to be a main barrier to adoption—for the share of consumers that value future electricity costs, the discount rate is low, although low income households have a higher discount rate. Finally, the effect of the ES certification is controversial. The large WTP for the certification itself may imply that some consumers invest too much in energy saving technologies.

7. The Value of Energy Information

In this section, I develop a framework based on the information acquisition model that can be used to quantify the welfare effects of various information-based policies. As an illustration, I focus on showing how removing the ES certification impacts consumer welfare.

According to the information acquisition model, for consumers that do not fully process energy information, there is a discrepancy between the electricity costs they believe they would pay and the electricity costs they effectively pay. My welfare measure is an extension of Leggett's formula[15] that accounts for consumers sorting into different groups based on their costs of collecting and processing energy information.

To start with, I make the following two assumptions. First, if $e = I$, decision utility equals experienced utility. Second, the costs of collecting and processing information, $\mathcal{K}_i(e)$, do not impact experienced utility. The first assumption implies that perfectly informed consumers have unbiased beliefs. The second assumption implies that the costs of collecting and processing information are perceptual in nature and do not impact welfare.[16]

Under these assumptions, the experienced utility is given by

$$U^I_{ijrt} = \delta_{ij} - \eta P_{jrt} + \psi R_{rt} \times D_{jt} - \theta C_{jr} + \epsilon_{ijrt}. \tag{8}$$

Whether the effect of the ES certification should be included in Equation 8 can be debated. The high estimates for the willingness to pay for the certification could reflect a behavioral bias, e.g.,

[15] I would like to thank Nick Kuminoff for pointing out to me the existence of Leggett (2002)'s work and a very helpful discussion about it. Recently, Allcott (2013*b*); Ketcham, Kuminoff and Powers (2016*b*,*a*) also specifically addressed issues of welfare measurement with consumers' biases using a framework similar to Leggett (2002).

[16] Under this interpretation of the information acquisition costs, the choice model is consistent with the model of tax salience of Chetty, Looney and Kroft (2009) and the internality concept of Allcott, Mullainathan and Taubinsky (2014).

the halo effect, or the manifestation of preferences. I use a lower bound on the change in consumer surplus by considering a measure that simply excludes the certification effect.[17]

In Appendix E, I show that for a policy change $\mathcal{P} \rightarrow \tilde{\mathcal{P}}$, the compensating variation (CV) for a specific income group differs from the standard expression for the multinomial logit (Small and Rosen 1981) in two ways. First, there are two correction terms taking the form $\sum_j^J P_i^{ES,U}(U_{ij}^I - U_{ij}^{ES,U})$, which have an intuitive interpretation. For the case where $e = ES$ (respectively, $e = U$), the correction term represents the expected difference between experienced and decision utility for relying on the ES certification (respectively for being uninformed) instead of a measure of local electricity cost. Second, the welfare measure is a weighted sum of the differences in welfare for the three consumer types, where the weights are the latent probabilities, H^e. This weighted sum arises because I do not observe consumers sorting into different types due to unobserved heterogeneity in information acquisition costs.

I can also decompose the welfare measure to evaluate the value of information for each consumer type. For instance, the value of energy information (VOI) for $e = ES$ is given by

$$VOI_i = \frac{1}{\eta}\left\{ln\sum_j^J exp(U_{ij}^I) - ln\sum_j^J exp(U_{ij}^{ES}) - \sum_j^J P_i^{ES}(U_{ij}^I - U_{ij}^{ES})\right\}, \tag{9}$$

which simply corresponds to the opportunity cost of relying on the certification. A similar expression can be used to estimate the value of energy information for uninformed consumers ($e = U$).

I present a counterfactual scenario where the goal is to quantify the value of energy information provided by the ES certification, from the standpoint of consumers alone, on an equilibrium path. In order to do so, I simulate the choice probabilities with and without the ES certification holding constant the strategies of the firms—namely, the product line and pricing decisions. I also set all ES rebates to zero, which rules out the effect of monetary incentives and allows me to isolate the information effects associated with the certification. This simulation exercise thus illustrates how different heuristics to account for energy information benefit or hurt consumers in a given choice environment. For instance, when facing a particular choice set, are consumers better off relying

[17]Given that the coefficient τ^{ES} is large, excluding this term from the experienced component of utility will underestimate how much utility consumers derive from the certification, hence the lower bound.

on detailed energy information, relying on the coarse ES certification, or completely dismissing energy information? I also consider a second scenario where I set the certification effect (τ^{ES}) to zero to show the sensitivity of the results with respect to this parameter. For both scenarios, I simulate the choice probabilities during the 2009-2011 period holding constant the products offered and the prices. I exclude the year 2008 in order to focus on a time period where the ES certification requirement did not undergo a large revision. During the 2009-2011 period, all certified products had to be at least 20% more energy efficient than the federal minimum standard.

Table 4 reports various metrics for the three income groups and the two scenarios. The first row of Table 4 shows the CV associated with the ES certification.[18] Across all three income groups and both scenarios, the CV estimates are small, but negative. This means that consumers are slightly worse off in a market with certification. This is a surprising result, but it can be explained by two effects.

First, the estimates of the value of information for the ES type and the uninformed type (second and third rows of Table 4) help explain the result. Focusing on the first scenario, the value of information for the ES type is larger than the value of information for the uninformed type. This means that consumers would be better off dismissing energy information altogether than using a decision heuristic that relies on the ES certification. This result is driven by the large certification effect, τ^{ES}, which effectively acts as a bias. If I set $\tau^{ES} = 0$, the estimates of the value of information for the ES type are then smaller, albeit by at most 17 cents, across all three income groups, relative to the uninformed type. There are two important conclusions here. First, if the large certification effect is treated as a phenomenon that impacts decision utility, but does not enter experienced utility, it is at the source of a welfare loss. Second, even once I exclude this term from decision utility, the certification has a very low information value in equilibrium. That is, once product

[18] To compute the CV measure, the market without the ES certification corresponds to the baseline policy scenario $\mathcal{P}$, and the market with the ES certification corresponds to the policy change scenario $\tilde{\mathcal{P}}$. The CV is thus the reduction in income that a consumer would be willing to accept in a market with certification to be as well off as in a market without certification. Therefore, a positive estimate for the CV implies that the certification is welfare improving, because consumers would be willing to pay a share of their income to be subject to the certification. A negative value for the CV implies the opposite.

line and pricing decisions are realized, consumers would be as well off ignoring energy information altogether as differentiating products based on their ES certification.[19]

The second reason why the CV estimates on Table 4 are negative is the crowding-out effect induced by the certification. Focusing on Scenario 2, the value of information for the ES type is slightly smaller than for the uninformed type. If the fraction of consumers that are perfectly informed were to stay constant with and without certification, the CV would then be unambiguously positive. However, in a market without certification, the fraction of perfectly informed consumers should always be larger than in a market with certification, which I refer to as the crowding-out effect (see proof in Appendix D). That is, a coarse certification has the unintended consequence of reducing the fraction of perfectly informed consumers in the market. In the present case, removing the certification leads to an increase in the share of perfectly informed consumers. This effect is large enough that it compensates for the small loss in the value of information caused by the removal of the certification.

Overall, the welfare metrics suggest very small effects. Note that those small effects arise even though the magnitude of consumers' misperceptions are large. As shown by the correction terms, consumers dismiss a large component of the lifetime cost of a refrigerator if they rely on ES, or even more if they dismiss energy information. In equilibrium, however, those misperceptions have little impact on consumer welfare. Again, the nature of the choice set offered in equilibrium plays a crucial role here. Given that manufacturers clearly respond to the certification, there is very little benefit for consumers to make a tangible effort to account for energy information.

8. Conclusions

I show that consumers respond to the ES certification, a coarse summary of readily available information about appliance energy use. There is, however, substantial heterogeneity in the way consumers respond to different pieces of energy information. The heterogeneity patterns suggest that the coarse certification acts as a substitute for more detailed and accurate information, and

[19]In Houde (2013), I show that the fact that a fraction of consumers value the certification highly explains why firms offer a large share of certified products in equilibrium and products bunch closely at the ES requirement (Figure 4, Appendix A).

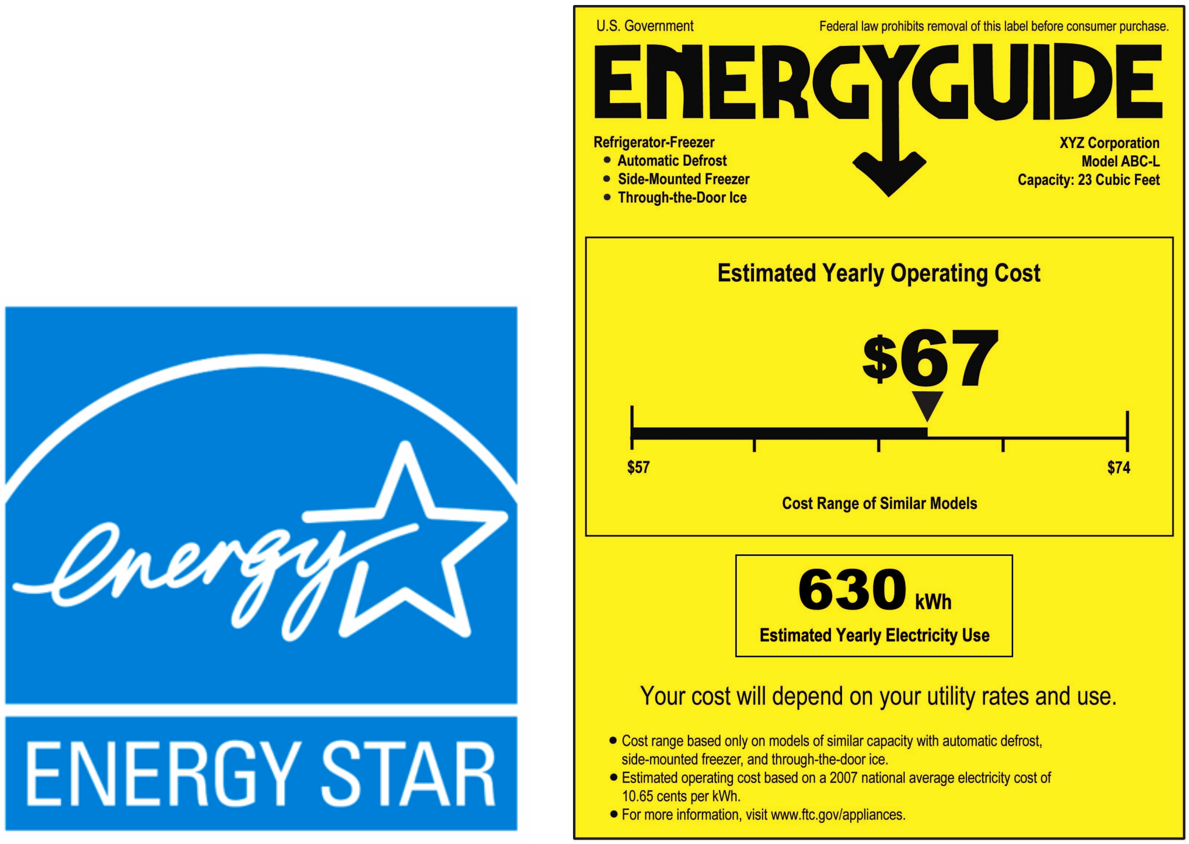
vice versa. In particular, consumers that rely on the ES certification have a large WTP for the ES certification that goes beyond the value of expected energy savings associated with certified products. This suggests that the coarse ES certification is more akin to a brand that some consumers value highly without knowing the precise meaning of the ES certification requirement. Finally, the heterogeneity patterns also suggest that there is a large share of consumers that do not consider energy information in their appliance purchasing decisions, and this share of consumers is larger among lower-income households.

The structural model shows that for observed prices the certification makes consumers slightly worse off. The welfare loss first arises because I consider that the high WTP for the ES certification corresponds to various biases, i.e., the certification impacts the decision utility, but does not affect the experienced utility. The ES certification also crowds out perfectly informed consumers—a second source of the welfare loss. Together, these results suggest that we should pay careful attention to the design of certification programs in the energy, medical, financial, and food sectors. A certification that provides a coarse information signal might be more salient, but misunderstood by consumers. Additional concerns arise when certification and disclosure programs interact. In such cases, providing simple and salient information might divert attention away from more complex, but accurate information.

A natural way to improve the ES certification would be to provide a finer information signal, perhaps with a letter-grade ranking as it is currently done in Europe.[20] Another alternative to a coarse certification is to design policies that impact the choice set offered by manufacturers (or retailers) without distorting the informational signal provided to consumers. How the effects of a manufacturers' tax credit targeted toward energy efficiency compare to a certification deserves further consideration.

[20]This type of ranking might, however, still confuse consumers. For instance, Alberini, Filippini and Bareit (2014) studied a letter-grade system ranking vehicles from A to G, and found a price premium for A-rated vehicles only, which suggests that consumers were not able to process the entire ranking scale.

9. Figures



(a) ES label (b) EnergyGuide label

FIGURE 1. Energy Labels for the U.S. Appliance Market

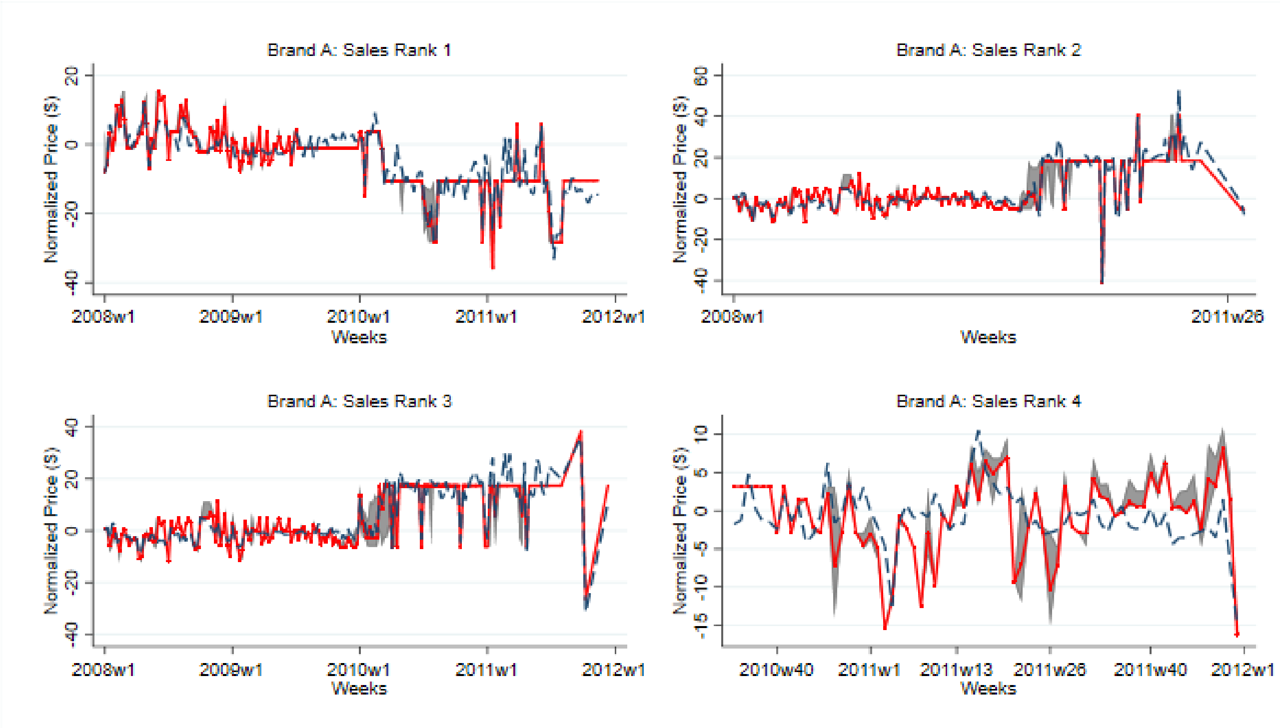


Figure 2. Price Variation for the Four Most Popular Models of Brand A

Notes: The plain (red) line shows the median weekly price change for a particular model. The weekly price change was computed for all zip codes where the model was offered. The median is taken across zip codes. The gray band identifies the 25^{th} and 75^{th} percentiles of the weekly price changes. The dashed (blue) line is the median weekly price change after removing the effect of brand dummies interacted with week-of-sample fixed effects. The figure shows substantial model-specific price variation.

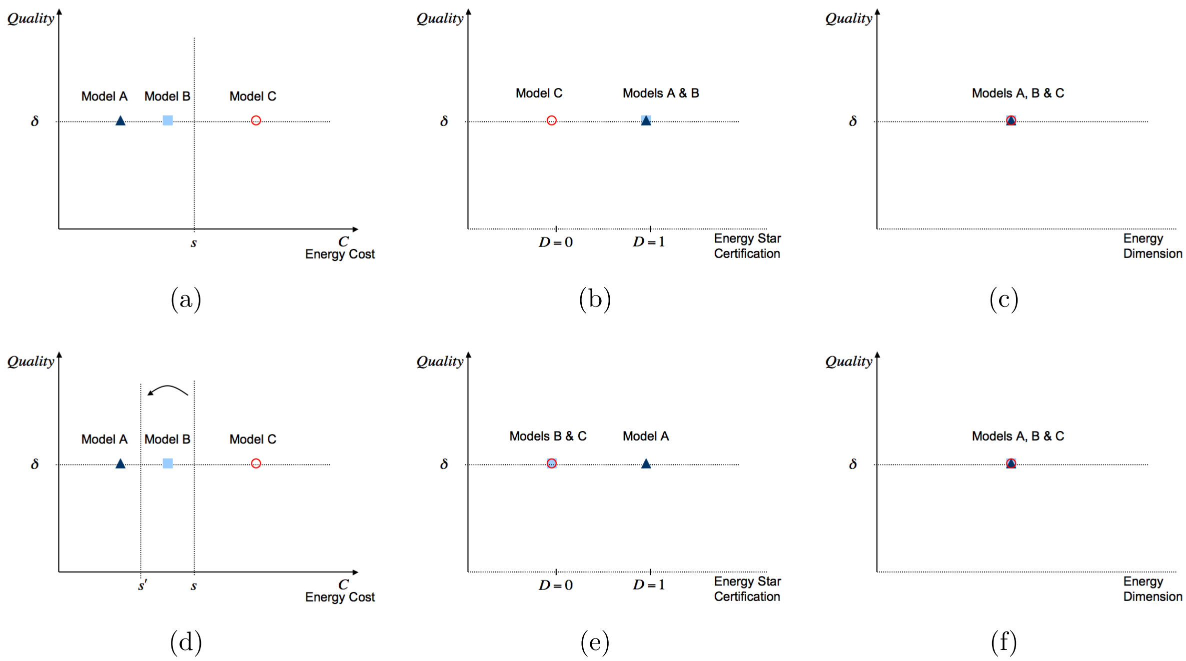


FIGURE 3. (a) Consumers with expectations about energy costs for each model. s represents the ES standard. (b) Consumers that rely on ES. $D = 1$ models certified ES, zero otherwise. (c) Consumers that dismiss energy costs. (d)-(f) Change in consumer preferences after revision of the ES standard $s \to s'$.

10. Tables

Table 1. Summary Statistics

	2008	2010
Choice Set		
# of Refrigerator Models, US Market	2,524	1,496
# of Decertified Refrigerator Models, US Market	1,278	21
# of Refrigerator Models, Retailer's Sample	1,483	1,174
# of Decertified Refrigerator Models, Retailer's Sample	674	14
Average Size of Choice Set (Store-Trimester)	99	92
SD Size of Choice Set (Store-Trimester)	44	37
Price and Duration		
Avg Retail Price	$1,325	$1,411
SD Retail Price Offered	$639	$693
Avg Weekly Price Change	11%	15%
Avg Duration Between Price Change (weeks)	1.4	3.1
Avg Retail Price ENERGY STAR	$1,426	$1,368
Avg Retail Price Non-ENERGY STAR	$1,240	$1,472
Avg Retail Price Decertified Model	$1,416	$2,468
Rebate		
# of Utility Rebate Programs for ENERGY STAR Refrigerators	87	133
# of State Rebate Programs for ENERGY STAR Refrigerators	0	44
Avg Rebate Offered	$48	$104
SD Rebate Offered	$54	$144
Electricity Costs: US Refrigerators		
Avg Elec. Price (County) ($/kWh)	0.113	0.113
Min Elec. Price ($/kWh)	0.03	0.03
Max Elec. Price ($/kWh)	0.420	0.368
Avg Elec. Consumption (kWh/y)	520	506
Avg Elec. Consumption ENERGY STAR (kWh/y)	500	501
Avg Elec. Consumption Decertified ENERGY STAR (kWh/y)	520	547
Avg Elec. Consumption Non-ENERGY STAR (kWh/y)	568	525

Notes: The sample consists of all transactions for which a refrigerator was bought at the retailer. The number of full-size refrigerator models for the whole United States was obtained from the US EPA. According to FTC data, 2,693 full-size refrigerator models were offered on the US market in 2008.

TABLE 2. Conditional Logit by Income Group

	Income <\$50,000			**Income** ≥\$50,000 & <\$100,000			**Income** ≥\$100,000		
	I	**II**	**III**	**I**	**II**	**III**	**I**	**II**	**III**
Retail Price	-0.416***	-0.417***	-0.416	-0.365***	-0.365***	-0.365***	-0.32***	-0.32***	-0.319***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
ENERGY STAR	0.125*		0.123*	0.163***		0.161***	0.181 ***		0.177***
	(0.05)		(0.05)	(0.05)		(0.05)	(0.04)		(0.04)
ENERGY STAR, 2008		0.070			0.138**			0.117 *	
		(0.05)			(0.05)			(0.05)	
ENERGY STAR, 2010		0.312*			0.103			0.222 *	
		(0.14)			(0.11)			(0.10)	
Rebate	0.086***	0.085***	0.084***	0.041**	0.041**	0.042 **	0.016	0.015	0.016
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Elec. Cost	-1.235***	-1.236***	-1.295***	-2.044***	-2.044***	-2.011***	-2.586***	-2.587***	-2.585***
	(0.23)	(0.23)	(0.22)	(0.25)	(0.25)	(0.25)	(0.26)	(0.26)	(0.26)
Product FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls: Demo × Attributes	No	No	Yes	No	No	Yes	No	No	Yes
# Obs	46,097	46,097	46,097	45,487	45,487	45,487	45,249	45,249	45,249
Interpretation									
Own-Price Elasticity	-5.41	-5.42	-5.41	-4.75	-4.75	-4.75	-4.16	-4.16	-4.15
Implicit Discount Rate	0.34	0.34	0.32	0.17	0.17	0.17	0.10	0.10	0.10
WTP ES Label	29.94	-	29.68	44.59	-	43.98	56.56	-	55.55
WTP ES Label, 2008	-	16.72	-	-	37.80	-	-	36.71	-
WTP ES Label, 2010	-	74.93	-	-	28.23	-	-	69.26	-
Prob. Taking Rebate	0.21	0.20	0.20	0.11	0.11	0.12	0.05	0.05	0.05

Notes: Standard errors clustered at the zip code level in parentheses: * ($p < 0.05$), ** ($p < 0.01$), *** ($p < 0.001$). Prices, rebates, and electricity costs measured in hundreds of dollars. Average price of \$1,300 used to compute own-price elasticity. Refrigerator lifetime of 18 years used to compute implicit discount rate.

TABLE 3. Information Acquisition Model

	Income <$50,000		**Income** ≥$50,000 & <$100,000		**Income** ≥$100,000	
Behavioral Parameters Purchase Decision:						
Retail Price (η)	-0.413***	(0.0002)	-0.362***	(0.0001)	-0.317***	(0.0002)
ENERGY STAR τ^{ES}	0.674***	(0.001)	1.528***	(0.002)	1.365***	(0.080)
Rebate (ψ)	0.145***	(0.001)	0.090***	(0.0005)	0.033***	(0.0003)
Elec. Costs (θ)	-4.003***	(0.009)	-3.408***	(0.048)	-4.429***	(0.004)
K^I	1.357***	(0.0004)	0.974***	(0.004)	2.125***	(0.001)
K^{ES}	-6.441***	(0.023)	-5.011***	(0.025)	-3.056***	(0.070)
Educ: College (β_I)	-0.122***	(0.003)	0.691***	(0.014)	0.303***	(0.012)
Educ: Graduate (β_I)	1.717***	(0.031)	2.045***	(0.026)	1.197***	(0.032)
FamSize (β_I)	-0.204***	(0.0001)	-0.318***	(0.003)	-0.049***	(0.007)
Age (β_I)	0.092***	(0.0002)	0.084***	(0.002)	0.011***	(0.001)
Political: Democrats (β_I)	-1.284***	(0.022)	-1.899***	(0.034)	-0.221***	(0.025)
Political: Others (β_I)	-1.920***	(0.008)	-1.338***	(0.013)	-0.200	(0.018)
Educ: College (β_{ES})	-0.271***	(0.002)	0.012	(0.007)	0.105***	(0.007)
Educ : Graduate(β_{ES})	-0.453***	(0.014)	0.843***	(0.018)	0.676***	(0.028)
FamSize (β_{ES})	-0.193***	(0.002)	-0.091***	(0.001)	-0.232***	(0.014)
Age (β_{ES})	0.063***	(0.0002)	0.045***	(0.001)	0.024***	(0.001)
Political: Democrats (β_{ES})	-0.255***	(0.006)	-0.421***	(0.015)	-0.045	(0.024)
Political: Others (β_{ES})	-0.578***	(0.0003)	-0.469***	(0.009)	0.018	(0.025)
mean-ElecCost	0.107***	(0.003)	0.075**	(0.001)	0.105***	(0.008)
var-ElecCost	0.006***	(0.00002)	-0.101***	(0.001)	0.026***	(0.001)
# Models (γ^I)	0.007***	(0.0001)	0.012***	(0.0001)	0.004 ***	(0.0004)
Variance Price (γ^I)	-1.003***	(0.004)	-0.729***	(0.012)	-0.390***	(0.004)
Proportion-Estar	2.837***	(0.002)	0.975***	(0.001)	2.324***	(0.114)
# Models (γ^{ES})	-0.006***	(0.0002)	-0.001***	(0.0000)	-0.003***	(0.001)
Variance Price (γ^{ES})	0.316***	(0.004)	0.211***	(0.004)	0.109***	(0.006)
Interpretation						
Own-Price Elasticity	-5.36		-4.70		-4.12	
Implicit Discount Rate	0.08		0.08		0.03	
WTP ES Label ($)	163.43		422.22		430.33	
Prob. Taking Rebate	0.35		0.25		0.10	
$Q(e = I)$	0.34		0.50		0.56	
$Q(e = ES)$	0.21		0.10		0.17	
$Q(e = U)$	0.45		0.41		0.27	
# Obs.	46,097		45,487		45,249	
LLE	188,088		194,394		195,969	

Notes: Asymptotic robust standard errors in parentheses: * ($p < 0.05$), ** ($p < 0.01$), *** ($p < 0.001$). Prices, rebates, and electricity costs measured in hundreds of dollars. Average price of $1,300 used to compute own-price elasticity. Refrigerator lifetime of 18 years used to compute implicit discount rate.

Table 4. The Value of Energy Information

	Income <$50,000		**Income** ≥$50,000 & <$100,000		**Income** ≥$100,000	
	Scenario 1	Scenario 2 $\tau_{ES} = 0$	Scenario 1	Scenario 2 $\tau_{ES} = 0$	Scenario 1	Scenario 2 $\tau_{ES} = 0$
CV (\$)	-4.7	-1.7	-5.1	-0.6	-11.8	-2.9
$VOI_{e=ES}$ (\$)	28.2	15.9	57.1	13.0	70.2	23.1
$VOI_{e=U}$ (\$)	15.9	15.9	13.2	13.2	23.3	23.3
Mispercetions, $e = ES$ (\$)	-123.5	0.5	-388.1	-5.6	-396.7	-12.8
Mispercetions, $e = U$ (\$)	-592.0	-592.0	-605.7	-605.7	-925.5	-925.5

Notes: To compute the CV measure, the baseline policy scenario, $\mathcal{P}$, is the market without certification, and the policy change scenario, $\tilde{\mathcal{P}}$, is the market with certification. A negative estimate for the CV implies that the certification reduces consumer welfare. For all income groups, the various estimates of CV are small and negative.

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Appendixes

Appendix A. Data Preparation and Additional Stylized Facts

A.1. Product Line Decisions

The following figure shows the location of each refrigerator model offered on the market during the period 2006-2011 in the size and energy use dimensions of the product space. Each figure corresponds to a different refrigerator design. I distinguish top-freezer, bottom-freezer, and side-by-side refrigerators. The first takeaway is that products tend to bunch at the minimum and ES standards. Moreover, the revision of the ES standard led to the introduction of new models. Models that met the previous less stringent ES standards also exited the market in the year or so following a revision.

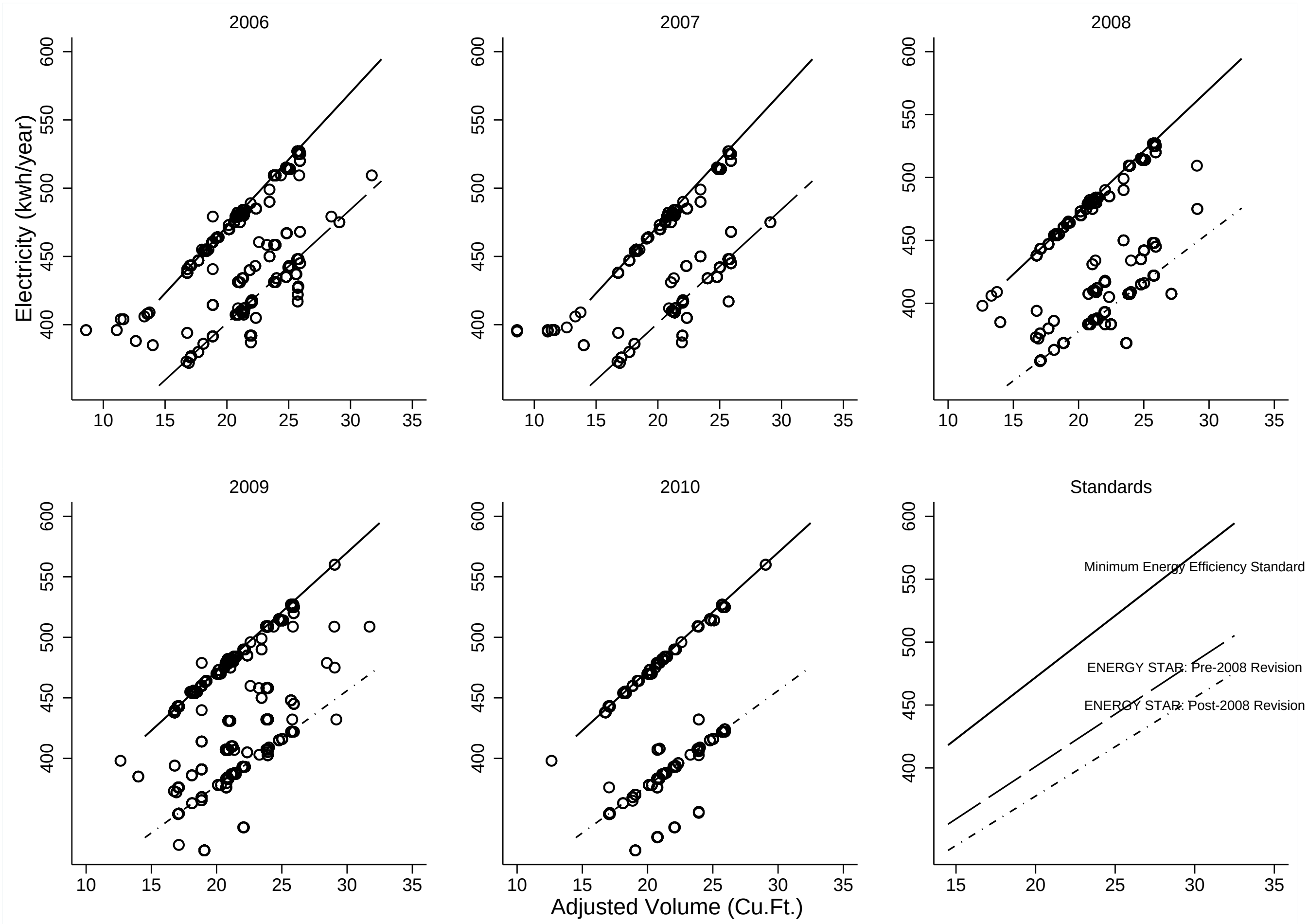
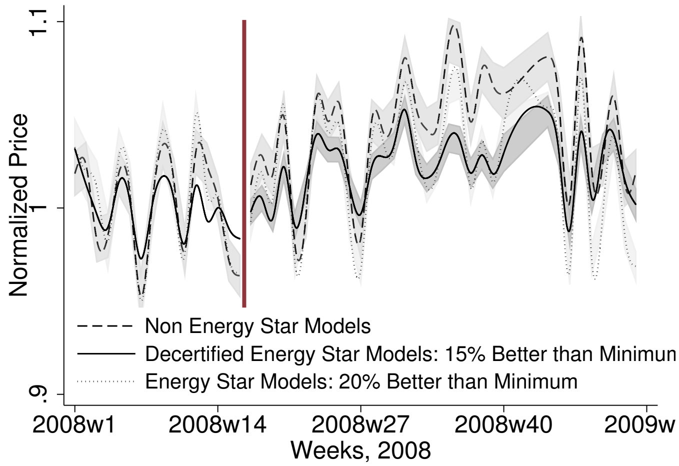


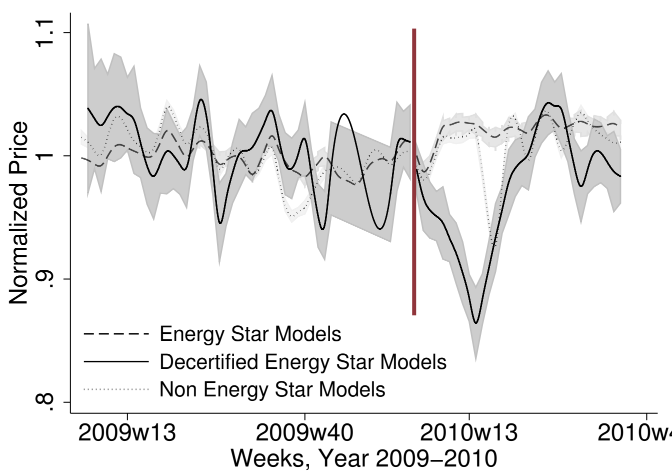
Figure 4. Choice Set Full-Size Top-Freezer Refrigerators: 2006-2010

Notes: Each dot represents a particular refrigerator model that was present on the market in a specific year. Similar patterns exist for other types of full-size refrigerators (e.g., bottom-freezer and side-by-side).

A.2. **Retailer's Prices**



(a) 2008 Decertification



(b) 2010 Decertification

Figure 5. Prices Around Decertification Events

Notes: Each panel displays average normalized weekly prices, with 95% confidence intervals, of refrigerators that belong to different efficiency classes. The top panel shows that the price of decertified models slightly decreased after the decertification, but the change is small. The bottom panel shows a large, but temporary price decrease following the decertification event.

A.3. **Average Electricity Prices**

I observe the zip code of the store where the transaction occurred, not the zip code of the household. Average annual electricity prices for each region are computed using form EIA-861 from the Energy Information Administration (EIA 2008).

The use of average electricity prices is partly motivated by recent empirical evidence (Borenstein 2012; Ito 2014) that suggests that electricity consumers may in fact respond to variation in average prices more so than marginal prices. In the present case, the use of average electricity prices is also dictated by the fact that household location is not perfectly known. Therefore, it is impossible to match households with their exact electricity tariff and infer marginal price.

Average electricity prices at the county level are computed as follows. Using form EIA-861 of the Energy Information Administration, I compute the average residential electric price for each electric utility operating in the United States for the year 2008. I then match electric utility territories with each county where I sampled at least one store. For counties with only one electric utility, I use the average electricity price for this particular utility. For counties with several electric utilities, I take the arithmetic mean of each utility's average price to construct the county-level price.

Appendix B. Estimation Details

To perform the estimation of the demand model, a random subsample of the transactions is used for three different income groups. The subsample is constructed as follows.

First, the subsample is drawn from the set of transactions that fit the following criteria (the restricted sample):

- transactions made by consumers that are homeowners;
- transactions made by consumers living in single family housing units; and
- transactions made by consumers that made no more than one refrigerator purchase during the period 2008-2011.

Second, the following stratified sampling method is used to create the sub-sample. For a given targeted sample size, I sample transactions for three different income groups:

- households with income less than \$50,000;
- households with income between \$50,000 and \$100,000; and
- households with income more than \$100,000.

B.1. **Information Acquisition Model**

The information acquisition is estimated via maximum likelihood. The model is initialized at the parameter values found with the conditional logit (Model 3, Table 2). The optimization is performed with the interior/direct algorithm implemented with the Knitro solver. Analytical gradients are computed and provided to the solver.

The latent class model can converge to saddle points and local optima. A large number (>100) of starting values are thus considered to initialize the optimization. The initial points are random perturbations of the parameter values of the conditional logit. Once the optimization converges, a spectral analysis is performed to rule out saddle points—the eigenvalues of the hessian must be all of the same sign. Among the vectors of estimates that are not saddle points, the one that provides the lowest objective function is selected as the optimum.

Appendix C. **Estimation: Additional Interpretation and Results**

Assuming that consumers form time-unvarying expectations about the yearly operating electricity cost and do not account for the effect of depreciation, the coefficient on electricity cost is a reduced form parameter that relates to the discount factor as follows:[21]

$$\theta = \eta \frac{\rho(1-\rho^L)}{1-\rho}, \tag{10}$$

[21]Under these assumptions, the lifetime energy costs (LC_j) of the durable are given by

$$LC_j = \sum_{t=1}^{L} \rho^t C_j = \frac{\rho(1-\rho^L)}{1-\rho} C_j.$$

where L is the lifetime of the durable, and $\rho = 1/(1+r)$ is the discount factor. The estimates of η and θ can then be used to infer a value of an implicit discount rate r. Assuming a lifetime of 18 years, the implicit discount rate that rationalizes consumers' decisions for the base specification (Model 1, Table 2) is 80% for the lowest-income group, 39% for the medium-income group, and 22% for the highest-income group. To put these numbers into perspective, in its latest cost-benefit analysis of minimum energy efficiency standards for refrigerators, the Department of Energy used a product lifetime of 19 years and discount rates of 3% and 7% (DOE 2011).

Table 5. Alternative Specifications Conditional Logit: Income <$50,000

	I	**IV**	**V**	**VI**	**VII**
Retail Price	-0.416***	-0.409***	-0.416***	-0.416***	-0.413***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
ENERGY STAR	0.12*	0.13*	0.12*	0.12**	0.16**
	(0.01)	(0.01)	(0.05)	(0.01)	(0.01)
Rebate	0.084***	0.085***	0.086***	0.086***	0.074**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Elec. Cost	-1.295***	-1.232***	-1.156***	-1.235**	-0.75***
	(0.22)	(0.23)	(0.26)	(0.23)	(0.23)
Product FEs	Yes	Yes	Yes	Yes	Yes
Controls: Demo × Attributes	No	No	No	No	No
Brand-Week FEs	No	Yes	No	No	No
Avg. Elec. Price	Cty	Cty	State	Cty	Cty
Controls: Product Age	No	No	No	Yes	No
Restricted Choice Set	No	No	No	No	Yes
# Obs	46,097	46,097	46,097	46,097	46,097
Interpretation					
Own-Price Elasticity	-5.41	-5.30	-5.41	-5.41	-5.37
Implicit Discount Rate	0.32	0.33	0.36	0.34	0.55
WTP ES Label	29.68	31.01	29.96	29.94	37.99
Response to Rebate	0.20	0.21	0.21	0.21	0.18

Notes: Standard errors clustered at the zip code level in parentheses: * ($p < 0.05$), ** ($p < 0.01$), *** ($p < 0.001$). Prices, rebates, and electricity costs measured in hundreds of dollars. Average price of $1,300 used to compute own-price elasticity. Refrigerator lifetime of 18 years used to compute implicit discount rate.

TABLE 6. Alternative Specifications Conditional Logit: Income ≥$50,000 & <$100,000

	I	IV	V	VI	VII
Retail Price	-0.365***	-0.361***	-0.365***	-0.365***	-0.361***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
ENERGY STAR	0.16***	0.16***	0.16***	0.16***	0.20***
	(0.02)	(0.02)	(0.05)	(0.02)	(0.01)
Rebate	0.042**	0.041**	0.042**	0.041**	0.049**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Elec. Cost	-2.011***	-2.044***	-1.992***	-2.044***	-0.92***
	(0.25)	(0.25)	(0.26)	(0.25)	(0.24)
Product FEs	Yes	Yes	Yes	Yes	Yes
Controls: Demo × Attributes	No	No	No	No	No
Brand-Week FEs	No	Yes	No	No	No
Avg. Elec. Price	Cty	Cty	State	Cty	Cty
Controls: Product Age	No	No	No	Yes	No
Restricted Choice Set	No	No	No	No	Yes
# Obs	45,487	45,487	45,487	45,487	45,487
Interpretation					
Own-Price Elasticity	-4.75	-4.69	-4.75	-4.75	-4.69
Implicit Discount Rate	0.17	0.17	0.17	0.17	0.39
WTP ES Label	43.98	43.51	44.48	44.59	54.66
Response to Rebate	0.12	0.11	0.12	0.11	0.14

Notes: Standard errors clustered at the zip code level in parentheses: * ($p < 0.05$), ** ($p < 0.01$), *** ($p < 0.001$). Prices, rebates, and electricity costs measured in hundreds of dollars. Average price of $1,300 used to compute own-price elasticity. Refrigerator lifetime of 18 years used to compute implicit discount rate.

TABLE 7. Alternative Specifications Conditional Logit: Income ≥$100,000

	I	IV	V	VI	VII
Retail Price	-0.319***	-0.313***	-0.32***	-0.32***	-0.323***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
ENERGY STAR	0.18***	0.19***	0.18***	0.18***	0.20***
	(0.03)	(0.02)	(0.04)	(0.03)	(0.02)
Rebate	0.016	0.016	0.017	0.016	0.017
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
Elec. Cost	-2.585***	-2.491***	-2.591***	-2.586***	-1.811***
	(0.26)	(0.26)	(0.28)	(0.26)	(0.27)
Product FEs	Yes	Yes	Yes	Yes	Yes
Controls: Demo × Attributes	No	No	No	No	No
Brand-Week FEs	No	Yes	No	No	No
Avg. Elec. Price	Cty	Cty	State	Cty	Cty
Controls: Product Age	No	No	No	Yes	No
Restricted Choice Set	No	No	No	No	Yes
# Obs	45,249	45,249	45,249	45,249	45,249
Interpretation					
Own-Price Elasticity	-4.15	-4.07	-4.16	-4.16	-4.20
Implicit Discount Rate	0.10	0.10	0.10	0.10	0.17
WTP ES Label	55.55	59.86	56.54	56.56	61.70
Response to Rebate	0.05	0.05	0.05	0.05	0.05

Notes: Standard errors clustered at the zip code level in parentheses: * ($p < 0.05$), ** ($p < 0.01$), *** ($p < 0.001$). Prices, rebates, and electricity costs measured in hundreds of dollars. Average price of $1,300 used to compute own-price elasticity. Refrigerator lifetime of 18 years used to compute implicit discount rate.

Appendix D. Comparative Statics Results

Information Acquisition Costs. Consumers will collect and process more energy information the lower the costs to do so. In particular, a consumer should always choose to be fully informed if there are no extra costs. The present model is consistent with this intuition, whether ENERGY STAR information is available or not.

Proposition 1. (i) *Suppose that ENERGY STAR information is not available. If* $\mathcal{K}(e = U) = \mathcal{K}(e = I)$*, it is optimal for the consumer to select* $e = h$*.*

(ii) *Suppose that ENERGY STAR information is available. If* $\mathcal{K}(e = U) = \mathcal{K}(e = ES) = \mathcal{K}(e = I)$*, it is optimal for the consumer to select* $e = I$*. Moreover, if* $\mathcal{K}(e = U) = \mathcal{K}(e = ES)$*,* $e = ES$ *is strictly better than* $e = U$ *for the consumer.*

Proof. This is true by the fact that the expectation of the maximum of random variables is always greater than the maximum of their expectations. In particular, consider some set of random variables $\{Y_1, Y_2, ..., Y_k\}$. The distribution of $\max_{1\leq j\leq k}\{Y_j\}$ (first order) stochastically dominates the distribution of Y_l for any $l \in \{1, ..., k\}$. This implies that $E[\max_{1\leq j\leq k} Y_j] \geq E[Y_l]$ for $l = 1, ..., k$, and thus,

$$E[\max_{1\leq j\leq k} Y_j] \geq \max_{1\leq j\leq k} E[Y_j]. \tag{11}$$

To show (i), it suffices to show that

$$E_{\epsilon,\mathcal{C}}\left[\max_j\{U_{ij}(\delta_j, \eta P_j, C_j, \epsilon_{ij})\}\right] \geq E_\epsilon\left[\max_j\{E_\mathcal{C}\left[U_{ij}(\delta_j, \eta P_j, C_j, \epsilon_{ij})\right]\}\right],$$

which implies that (i) holds for $K = 0$. I show a stronger inequality; in particular, that for any ϵ_{ij},

$$E_\mathcal{C}\left[\max_j\{U_{ij}(\delta_j, \eta P_j, C_j, \epsilon_{ij})\}\right] \geq \left[\max_j\{E_\mathcal{C}\left[U_{ij}(\delta_j, \eta P_j, C_j, \epsilon_{ij})\right]\}\right].$$

This follows from (11) if I set

$$Y_j \equiv U_{ij}(\delta_j, \eta P_j, C_j, \epsilon_{ij}).$$

This concludes the proof for (i).

The proof for (ii) is similar.

Crowding-Out Effect. A simple, but important implication of the above result is that if the costs of processing and collecting ENERGY STAR information are lower than the costs of searching for energy costs, some consumers may prefer to select the maximum level of effort rather than not collecting information at all, but could prefer a medium level of effort over a maximum one. Formally,

Corollary 1. *If $\mathcal{K}(e = ES) < \mathcal{K}(e = I)$, then for some consumers*

$$\mathcal{V}(e = U) < \mathcal{V}(e = I) < \mathcal{V}(e = ES)$$

Proof. The proof follows directly from Proposition 1.

This formally shows that the ENERGY STAR certification induces some consumers to be less informed and crowds out efforts to fully account for energy costs.

Appendix E. Welfare Measure

The derivation of the welfare measure closely follows the approach of Leggett (2002). The key difference is that in the present application the computation of indirect expected utility requires integrating over the distributions of the idiosyncratic taste parameters, ϵ, and idiosyncratic information acquisition costs, ν. Given that these two distributions are assumed to be independent, the indirect expected utility is then simply a weighted sum of the indirect expected utility specific to each consumer type, where the weights are the latent effort choice probabilities $H_i(e)$, i.e.,

$$E[U_i] = \sum_{e=\{U,ES,I\}} H_i(e)E[U_i(e)] \tag{12}$$

Note that the subscripts r and t are omitted to simplify the exposition. Remember that in the present framework, consumer types are identified by e, and three types are distinguished: consumers that are uninformed about energy use and cost ($e = U$), informed about ES but not local energy operating costs ($e = ES$), or perfectly informed about local energy operating costs ($e = I$).

Leggett (2002) derives an expression for $E[U_i(e)]$ where consumers' perceived quality differs from the quality actually experienced. He focuses on the case where the idiosyncratic taste parameters, ϵ, are Type 1 extreme value distributed. His equations 8 and 9 (p. 348-349) show the derivations that can readily be applied in the present context.

Under the assumption that for $e = I$ decision utility coincides with experienced utility, we have

$$E[U_i(e = I)] = ln \sum_j exp(U_{ij}^I) + A, \tag{13}$$

which is the standard log-sum formula for the Type 1 extreme value distribution where A is a constant of integration.

The case where $e = ES$, U_i^{ES} corresponds to the perceived utility in Leggett (2002)'s framework, and U_i^I corresponds to experienced utility. He shows that the indirect expected (experienced) utility if consumers make decisions relying on U_i^{ES} is given by

$$E[U_i(e = ES)] = ln \sum_j exp(U_{ij}^{ES}) + \sum_j P_{ij}^{ES}(U_{ij}^I - U_{ij}^{ES}) + A. \tag{14}$$

For $e = U$, we have a similar expression:

$$E[U_i(e = U)] = ln \sum_j exp(U_{ij}^U) + \sum_j P_{ij}^U(U_{ij}^I - U_{ij}^U) + A. \tag{15}$$

Using the above expressions measured for a policy change $\mathcal{P} \to \tilde{\mathcal{P}}$, we can obtain a measure of compensating variation similar to Leggett (2002) (Equation 10, p. 349). The main difference is that the latent effort choice probabilities now enter the expression.

(16)

$$\begin{aligned} CV_i = \frac{1}{\eta}\Bigg\{ & \tilde{H}_i^I \cdot ln \sum_j^J exp(\tilde{U}_{ij}^I) - H_i^I \cdot ln \sum_j^J exp(U_{ij}^I) \\ & + \tilde{H}_i^{ES} \cdot \left[ln \sum_j^J exp(\tilde{U}_{ij}^{ES}) + \sum_j^J \tilde{P}_i^{ES}(\tilde{U}_{ij}^I - \tilde{U}_ij^{ES}) \right] - H_i^{ES} \cdot \left[ln \sum_j^J exp(U_{ij}^{ES}) + \sum_j^J P_i^{ES}(U_{ij}^I - U_{ij}^{ES}) \right] \\ & + \tilde{H}_i^U \cdot \left[ln \sum_j^J exp(\tilde{U}_{ij}^U) + \sum_j^J \tilde{P}_i^U(\tilde{U}_{ij}^I - \tilde{U}_{ij}^U) \right] - H_i^U \cdot \left[ln \sum_j^J exp(U_{ij}^U) + \sum_j^J P_i^U(U_{ij}^I - U_{ij}^U) \right] \Bigg\}. \end{aligned}$$

Note that the constant of integration A cancels out from the expression only under the assumption that the distribution of the idiosyncratic taste parameters, ϵ, is the same before and after the policy change and across consumer types.