Abstract

The Energy Star certification is a voluntary labeling program managed by the US Environmental Protection Agency (EPA) that favors the adoption of energy efficient products. I use unique micro-data on the US refrigerator market to show that consumers respond to certification in different ways. Some consumers appear to rely heavily on Energy Star and pay little attention to electricity costs, others are the reverse, and still others appear to be insensitive to both electricity costs and Energy Star. I then develop a structural model of demand to capture the degree of sophistication with which consumers account for the energy efficiency attribute. Using the structural demand model, I simulate the effects of the Energy Star program on the US refrigerator market. My results suggest that the program may have uncertain effects on energy savings and social welfare. Three factors contribute to this finding. On one hand, the Energy Star certification may increase the perceived quality of the certified products and induce consumers to invest too much in energy efficiency. On the other hand, the Energy Star certification partly crowds out efforts to fully account for energy costs and induces consumers to invest too little in energy efficiency. This effect may even dominate. Using an oligopoly model calibrated for the US refrigerator market, I also show that firms’ product lines and pricing decisions play an important role in determining the sign of the welfare effects, and whether Energy Star leads to energy savings.

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1. Introduction

The role of certification programs is to disclose information and help consumers distinguish high-quality products from lemons (Viscusi 1978). Although product certifications address informational market failures, their welfare effects can be ambiguous. Theoretical analyses have shown that the desirability of a certification depends on a confluence of factors such as the market structure, heterogeneity in consumers’ preferences, and consumers’ sophistication in the way they respond to the certification (Dranove and Jin 2010).

The goal of this paper is to quantify the welfare effects of the Energy Star certification accounting for the role of consumer heterogeneity and sophistication. The Energy Star program is a voluntary labeling program for energy intensive durables managed by the US Environmental Protection Agency (EPA). The rationale for the program is that energy efficiency is a dimension of quality that is complex, hard to assess and not fully salient to consumers. Certification is aimed at providing simple and salient information to guide consumer choices toward more energy efficient products.

Using unique micro-data on the US refrigerator market and variation in the labeling of Energy Star products due to the revision of the certification requirements, I show that the Energy Star label influences purchase decisions. I then investigate heterogeneity in the estimates and find that the Energy Star label might act as a substitute for information on electricity costs. In particular, consumers that value Energy Star highly tend to be less sensitive to electricity costs, and vice versa. A non-negligible fraction of consumers also appears to not value Energy Star and to not consider electricity costs.

I interpret these patterns as evidence that consumers account for energy efficiency with different degrees of sophistication. This heterogeneity motivates a structural demand model where I explicitly model consumers’ decision to rely on Energy Star certification or electricity costs when comparing refrigerators. I rationalize the observed heterogeneity with behavioral parameters consistent with utility maximization, which allows me to investigate a rich set of counterfactual scenarios.

My demand model is closely related to the directed cognition model of Gabaix and Laibson (2005) and is inspired from classic models of consumer search and information acquisition (e.g. Stigler 1961; McCall 1965). In particular, I assume that ex ante consumers are uncertain about energy costs and the meaning of the Energy Star certification. Prior to making a purchase, consumers decide, based on the value of information, whether to collect and process information about energy
costs or Energy Star, or to remain uniformed. In this framework, the Energy Star certification serves as a heuristic that partly resolves uncertainty related to the value of energy efficiency.

Using a multinomial logit model, I provide a first set of estimates for the sensitivity to prices, electricity costs, rebates, and Energy Star label. My base specification suggests that households are highly sensitive to refrigerator prices, with an own price elasticity of -6.29. I find that adding the Energy Star label on a refrigerator leads to a 15.5% increase in market share, on average. The impact of Energy Star rebates is positive, smaller than the effect of the label, and tends to not be statistically significant. Finally, I find that consumers appear to be sensitive to electricity costs. Under various assumptions about consumers’ expectations about the lifetime electricity costs of refrigerators, I find that the implicit discount rate that rationalizes consumers’ decisions range from 17.2% to 20.3%.

I allow heterogeneity in the above estimates and I find that there exists latent consumer types consistent with the hypothesis that consumers account for the energy efficiency attribute with different degrees of sophistication. This heterogeneity motivates the fully structural model where consumer sophistication is endogenized. Estimates from the fully structural model suggest that about 23.1% of the consumers do not pay attention to Energy Star or electricity costs, 24.1% of the consumers have a very large willingness pay for Energy Star and 52.8% of the consumers behave as if they were primarily relying on electricity costs. The estimates also suggest that consumers with higher income value energy efficiency more, controlling for consumer sophistication.

Turning to counterfactual scenarios, I find that the Energy Star program may not increase social welfare. If the US refrigerator market was not subject to Energy Star and firms were to offer only refrigerator models that just meet the minimum energy efficiency standards, consumers could be better off, even if we account for the increase in the environmental externality cost. Using an oligopoly model of the US refrigerator market, I show that if we also account for firms’ optimal response to Energy Star, we reach different conclusions. In a world without Energy Star, firms might discriminate more in the energy efficiency dimension, i.e., they would offer highly energy efficient products, and products that bunch at the minimum energy efficiency standard. This has an unexpected effect; if Energy Star were not in effect, consumers would purchase more energy efficient products, on average. Interestingly, under the various scenarios considered for the welfare analysis, firms tend to be better off in a world with Energy Star.

The contribution of this paper is threefold. First, I provide an estimate of the energy savings and welfare effects associated with the Energy Star program for the US refrigerator market. Second,
I contribute to the literature on information disclosure and certification programs. I propose a theory of how information from a certification program influences consumers' decisions and provide an empirical strategy to estimate the model. Third, the paper contributes to the large literature on estimating consumer preferences for energy intensive durables. I propose a novel framework that allows me to distinguish between heterogeneity that arises from consumers using different behavioral rules to account for energy efficiency, and heterogeneity that arises due to differences in economic variables, such as income.

Large energy savings are often attributed to the Energy Star program (Webber, Brown, and Koomey 2000; Sanchez, Brown, Webber, and Homan 2008). Estimating these savings poses a number of challenges. First, it requires isolating the effect of the program, especially the label, on consumer decisions. However, the lack of availability of sales data for the appliance markets has hampered such effort. To my knowledge, this paper provides the first estimate of the effect of the Energy Star label using transaction data. Second, changes in prices and types of products available on the market should also be accounted for. In several markets and especially for the refrigerator market, there is clear evidence that manufacturers optimize with respect to the Energy Star program. Ideally, we would like to compute energy savings considering a counterfactual scenario where both consumers and manufacturers optimize without being subject to the Energy Star program. This paper addresses these challenges. In addition to energy savings, changes in consumer surplus associated with Energy Star can also be computed, while accounting for firms' responses.

There are few theoretical analyses of certification and information disclosure programs that account for consumers' limited ability to interpret and process complex information. Fishman and Hagerty (2003) and Hirshleifer and Teoh (2003) are two exceptions that respectively investigate whether consumers' bounded rationality justifies mandatory disclosure programs and how information should be presented. The modeling paradigm in these studies assumes that a fraction of consumers does not process information and takes this fraction as given. I propose a model where consumers differ in their ability to collect and process (energy) information, and I explicitly model consumers' decision to rely on a particular piece of information. I will demonstrate that endogenizing consumers' response to Energy Star provides insight into how the program influences choices and unveils a number of unintended consequences. In particular, I will show that for some consumers the Energy Star label increases the perceived quality of the certified products. This effect might be due to environmental preferences and consumers' higher willingness to pay for green products. It is also possible that consumers are subject to an Energy Star Halo Effect (Boatwright, Kalra, and Zhang 2008), and infer that the quality of other attributes is higher because a product is more
energy efficient. If this is the case, then Energy Star certification biases consumer choices and thus induces consumers to invest in too much in energy efficiency. Alternatively, it is possible that the Energy Star certification partly crowds out efforts to compute energy costs and leads consumers to invest too little in energy efficiency. The intuition behind this result is that consumers may choose to simply buy an Energy Star product, rather than make the complex energy savings calculation that would have led them to purchase an even more efficient product. As a result, in a scenario where consumers rely primarily on Energy Star to account for energy efficiency, the market shares for the most energy efficient models on the market would be lower than in scenario where consumers compute energy costs. It is then possible that removing the Energy Star certification would lead to more energy efficient choices, on average. I will show that for a range of not too restrictive parameter values this crowding out effect might be dominating for the US refrigerator market.

Since the seminal paper of Hausman (1979), many studies have attempted to estimate how consumers value energy efficiency. A common finding (see Train 1985 for an early review) is that consumers make purchase decisions as if they were steeply discounting future energy costs of durables, a phenomenon known as the Energy Paradox (Jaffe and Stavins 1994). The present paper contributes to this literature by providing a new set of estimates of consumers’ valuation for energy efficiency accounting for the role of consumer heterogeneity and sophistication.

The remainder of this paper is organized as follows. Section 2 outlines the Energy Star program for the US refrigerator market. Section 3 presents a model of consumer demand for energy intensive durables. Section 4 follows with an overview of the data. Section 5 presents my empirical strategy. Section 6 presents the estimation results. The welfare analysis is presented in section 7, and conclusions follow.

2. A Primer on Energy Star and the US Refrigerator Market

The Energy Star program was established by the US EPA in 1992. The goal of the program is to favor the adoption of energy efficient durables by residential and commercial consumers. The EPA sets voluntary energy efficiency standards and certifies products that meet or exceed the standards. Qualifying products can be labeled with an Energy Star logo (Figure 1). The logo does not provide detailed information about energy efficiency. The program complements minimum energy efficiency standards and the mandatory energy label EnergyGuide, which provides detailed technical information on energy consumption and costs (Figure 1). While minimum energy
efficiency standards place a lower bound on efficiency, Energy Star aims to induce more efficient purchases by providing simple and salient information to consumers.

The Energy Star standard for refrigerators is defined relative to the minimum energy efficiency standard. Since April 2008, a full-size refrigerator that is certified Energy Star must consume 20% or less electricity than the minimum energy efficiency standard established for this refrigerator model. The minimum energy efficiency standard for refrigerators varies as a function of size, door style (single door, top-freezer, bottom-freezer and side-by-side), and attributes (ice-maker and defrost technology).

The periodic revisions of the Energy Star standards is a crucial feature of the program. The EPA revises the stringency of the standards using various criteria, such as the proportion of Energy Star products offered on the market, the market share of Energy Star products and the availability of new technologies (McWhinney, Fanara, Clark, Hershberg, Schmeltz, and Roberson 2005). The stringency of the standards is ultimately determined by US EPA upon consultation with different stakeholders, such as manufacturers, part providers, retailers, analysts and environmental groups. For full-size refrigerators, the standard has been revised in 2001, 2004 and 2008. Revisions in standards are usually announced by US EPA about one year in advance.

When a revised standard comes into effect, the EPA requires that manufacturers and retailers remove the Energy Star label on certified products that do not meet the more stringent standard. Refrigerator manufacturers have also responded to the changes in the standard by offering new models that meet the revised standard and by discontinuing models that are decertified. Figure 2 illustrates this and plots the choice set across years for one particular type of full-size refrigerator: bottom-freezer refrigerators with an ice-maker. Each dot represents a refrigerator model available on the market and the minimum standard and the Energy Star standard, which are both function of the refrigerator size, are plotted for each year. Manufacturers offer products that bunch at the standards. As the Energy Star standard changes, manufacturers not only offer new products that meet the revised standard, but also discontinue refrigerator models that meet the outdated standard.¹

An important institutional feature of the US electricity markets is that several electric utilities are subject to regulations that incentivize them to promote energy efficiency measures to consumers. Rebate programs tied to the purchase of Energy Star products have been arguably one of the most popular energy efficiency measures pursued by US electric utilities. Thus, apart from the

¹This pattern holds for other types of full-size refrigerators.
informational component, financial incentives may play a role in favoring the adoption of Energy Star products (Datta and Gulati 2009). I account for this in my empirical strategy and I distinguish between the information effect and the rebate effect associated to the program.

3. An Information Acquisition Model for Energy Intensive Durable

In this section, I present a model of durable purchasing decision in which consumers can update their beliefs about energy costs by collecting and processing information.

The model shows how different levels of sophistication can affect purchasing decision and result in Energy Star having a meaningful effect despite the label being a summary of otherwise available energy information.

3.1. Set-Up

Consider a discrete choice model where consumer $i$ receives utility level $U_{ij}$ from purchasing an energy intensive durable $j$. The value of option $j$ is a function of its quality ($\delta_j$), price ($P_j$), expectation of annual energy cost ($C_j$) and an idiosyncratic taste parameter ($\epsilon_{ij}$):

$$U_{ij} = \delta_j - \eta P_j - \theta C_j + \epsilon_{ij}$$

In equation (1), the parameter $\eta$ is the consumer’s sensitivity to prices and corresponds to the marginal utility of income, while $\theta$ is the sensitivity to energy cost.

$C_j$ is the product of energy price and energy consumption. I assume that with limited information a consumer will have few ways to make an accurate forecast of $C_j$ for each option $j$ in his choice set. Before collecting information, the consumer’s knowledge about $C_j$ is then imperfect, and is modeled with a prior distribution $F$, where $C_j \sim F$, $\forall j$. The consumer can collect energy information and learn the value of $C_j$ for each $j$. In the context of purchasing a refrigerator, the process of information acquisition and learning may consist of taking the time to look at the EnergyGuide label, understand the various pieces of information, look up the electricity prices, and perform mental calculations to compute energy costs.

Consumer’s purchasing decision is modeled as a two-step process. To begin, the consumer observes the quality $\delta_j$ and the price $P_j$ for each refrigerator. Then, the consumer can collect

\footnote{I assume that the consumer’s expectations about prices and utilization are constant, which is a reasonable assumption for my empirical application.}
and process energy information at a cost $K$. By doing so, the consumer observes a realization $c_j$ from $F$ for each $j$. If the consumer does not collect/process information, no learning occurs and the consumer only knows the average energy cost for all refrigerator models, which is given by $E[C_j] = \int_{c} cf(c)dc = \mathcal{C}$, where $f(c)$ is the probability density of $F$. Afterwards, the idiosyncratic taste parameters $\epsilon_{ij}$ are realized. Finally, the consumer decides which refrigerator to purchase.

Consumer $i$ will search for energy information if the following inequality holds:

$$(2) \quad -K + E_{\epsilon|C} \left[ \max_j \{U_{ij}(\delta_j, \eta P_j, C_j, \epsilon_{ij}) \} \right] \geq E_{\epsilon} \left[ \max_j \{E_{C} \{U_{ij}(\delta_j, \eta P_j, C_j, \epsilon_{ij}) \} \} \right]$$

When the consumer does not collect and process energy information, the expected energy costs are the same for all products and do not influence the purchase decision. So the model offers a simple way to capture consumer inattention to energy costs. I next discuss how the impact of the Energy Star certification can be modeled in this framework.

### 3.2. Energy Star as a Heuristic

The Energy Star certification partly informs about energy costs and can serve as a heuristic to compare products in a binary manner along the energy dimension. I model its effect as follows. Prior to collecting information, the consumer has some beliefs about energy costs and Energy Star. As before, the consumer’s belief about the energy cost of the $j$-th refrigerator is given by the prior distribution $F$, $\forall j$. Uncertainty related to the Energy Star certification stems from the fact that the Energy Star label carries no information about its meaning. A priori, the consumer is uncertain about the meaning of the Energy Star certification, but can learn it by searching for additional information. Moreover, I also assume that the consumer is also uncertain about whether a product is certified Energy Star or not. With probability $q$, the consumer believes that product $j$ is certified.

If the consumer knows the meaning of the Energy Star certification, he will then know that the energy costs of Energy Star products are below a particular threshold corresponding to the Energy Star standard. Denote this threshold by $S$. If the consumer does not collect energy information, his belief about the meaning of Energy Star, $S$, is given by a prior distribution $G$. If the consumer learns the meaning of the certification, he observes a realization $s$ from $G$. Define the indicator variable $D_j$ that takes the value one if product $j$ is certified Energy Star and zero otherwise. For

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3As it is customary in the literature (e.g. Rust (1986)), I assume that the idiosyncratic taste parameters, $\epsilon_{ij}$, are only realized at the time of making a purchase, but the consumer has a prior on their distribution.
a given realization $s$, the expected energy cost of an Energy Star product $j$ is:

$$E[C_j(s)|D_j = 1] = E[C_j|C_j \leq s] = \frac{1}{F(s)} \int_{\underline{c}}^{s} cf(c)dc \equiv C_0(s),$$

where $\underline{c}$ is the lower bound of the support of $F$. Similarly, the expected energy cost of a non-Energy Star product $j'$ is given by:

$$E[C_{j'}(s)|D_j = 0] = E[C_{j'}|C_{j'} > s] = \frac{1}{1 - F(s)} \int_{s}^{\overline{c}} cf(c)dc \equiv C_1(s),$$

where $\overline{c}$ is the higher bound of the support of $F$.

The timing is now as follows. The consumer first chooses his effort level for collecting and processing information, defined by the variable $e$, which now takes three values. A consumer that selects $e = l$, does not collect energy related information. At $e = m$, the consumer only collects information related to Energy Star, and learns the meaning of the Energy Star and which products are certified. Finally, for $e = h$, the consumer collects and processes enough information to form expectations about the energy costs associated with each option. After choosing $e$, the idiosyncratic taste parameters $\epsilon_{ij}$ are realized and the consumer decides which refrigerator to purchase.

The optimal level of effort is given by the following optimization problem:

$$\max_{e \in \{l,m,h\}} \mathcal{V}(e)$$

$$\mathcal{V}(e) = -K(e) + E_{e,D,S,C} \left[ \max_j \{U_{ij}(\delta_j, P_j, C_j(S), D_j, \epsilon_{ij})\} | I(e) \right],$$

where $K(e)$ is the information acquisition cost that varies with $e$ and $I(e)$ represents consumer’s knowledge about energy costs at the time of purchase.

### 3.3. Comparative Statics

In Appendix A, I show formally that the model makes intuitive predictions on how information acquisition costs and uncertainty influence the information acquisition decision. In particular, a consumer should always choose to be fully informed if there are no extra costs to do so, i.e., the consumer is better off with more information. However, when it is costly to collect and process information, some consumers may prefer to select the maximum level of effort than to not collect information at all, but could prefer a medium level of effort than a maximum one. Energy Star may thus crowd-out efforts to fully account for energy information. The model also predicts that
a consumer is more likely to collect and process information if he is more uncertain ex ante (i.e., when prior beliefs have a large variance).

4. Data and Preliminary Evidence

The primary data were provided by a large appliance retailer. The retailer offers a large selection of refrigerator models, has at least one brick-and-mortar store in each US state and a national online store. The main data consist of all transactions where a full-size refrigerator was bought. The data cover the period 2008-2010. For each transaction, I observe the date, the model of the refrigerator, attributes, the suggested retail price, the promotional price, the manufacturer price, the manufacturer price, taxes paid, and the zipcode of the store where the transaction was made. For a subset of transactions, I also observe consumer demographics, such as household size, income, education, homeownership, housing type and age of the head of the household. I restrict attention to transactions with demographic information and that can be attributable to households that have to pay for their electricity bills. In particular, I only consider transactions made by homeowners living in single family housing units that bought no more than one refrigerator in any given year. This rules out heterogeneity in the sensitivity to energy costs due to the split incentive problem (Blumstein, Krieg, Schipper, and York 1980), i.e., the fact that some consumers of energy intensive durables do not pay for energy costs. For the structural estimation, a random sub-sample of the transactions that fit the above criteria is used. I next discuss the construction of the key variables used in the estimation, and their main sources of variation.

4.1. Energy Star Certification

Following the revision of the Energy Star standard for refrigerators in April 2008, a large number of refrigerator models lost their Energy Star certification. Using data that cover a time period before and after the revision in the standard, it is possible to observe the same refrigerator model being sold at the same store, with and without the Energy Star label. This variation in labeling can then be used to identify how consumers value the Energy Star certification.

EPA maintains an historical list of Energy Star refrigerator models, it was then possible to match each of the refrigerator models in my sample with EPA’s list and determine which refrigerators lost their certification. For the year 2008, I observe 1335 different refrigerator models; 581 of which lost their certification.

The manufacturer price does not vary across time, and corresponds to the manufacturer price the retailer paid when a given refrigerator model entered the market.
their certification. For the same year, there were 4702 refrigerator models available on the whole US market; 1542 of which lost their Energy Star certification.

When Energy Star standards are revised, manufacturers and retailers are required to remove any references to Energy Star for refrigerator models that do not meet the new standards. For each refrigerator model sold in a specific store, I do not observe the exact date that the Energy Star label was removed. However, the retailer policy is to coordinate the change in labeling across all stores and to implement the change close to the date mandated by the EPA. I assume all refrigerators that were decertified in 2008 lost their Energy Star label on the last week of April 2008.

Before April 2008, Energy Star refrigerators had to consume, at least, 15% less electricity than the minimum energy efficiency standard; following the revision, the stringency was set at 20%. To illustrate the effect of the decertification, Figure 3 shows the variation in weekly sales for three types of refrigerators: models that just meet the minimum energy efficiency standards, models that were certified Energy Star and 15% more efficient that the minimum standard (decertified models), and models that meet the revised Energy Star standard (at least 20% more efficient that the minimum standard). Total sales for each refrigerator type are normalized by their average weekly sales in the pre-revision period. We observe that before the revision, all three types of models had similar sales patterns. Around the time that the standards changed (seventeenth week of 2008), we however observe a large decrease in the sales of refrigerators that lost the Energy Star certification. Part of this decrease is attributable to the change in certification, changes in prices and changes in inventories (i.e., out-of-stock effect). My empirical strategy will allow me to quantify to which extent this decrease can be attributable to consumers’ response.

4.2. Prices

The sample contains large and frequent variations in prices. Promotions are usually coordinated among products of a specific brand, but are not model specific, and last on average a week (7.6 days). I then exploit the temporal variation in prices to identify consumers’ sensitivity to the retail price. From the transaction level data, I construct weekly and store specific price time series for each product. Missing prices for a specific product sold in a given store are imputed first using the average weekly prices of the same product sold in other stores located in the same state. Online prices are used to impute the remaining missing prices. I use the average tax rate observed in each store and trimester to compute prices gross of sales tax.
Figure 4 plots the percentage change of average weekly prices relative to the suggested retail price together with the percentage change in weekly sales relative to average weekly sales for each refrigerator model in my sample. Figure 4 suggests that most of the promotions consist of price reductions between 0% and 20%, and that correlation between sales and prices is negative and relatively large ($\rho = -2.54$).

Identification of the price coefficient requires accounting for sources of endogeneity. Because promotions are primary implemented at the national level and for specific brands, marketing effects correlated with promotions can be purged with brand-week fixed effects. Although, it is possible that promotions are correlated to unobservable local market specific factors, I will show that once I control for product fixed effects and brand-week fixed effects, using prices in other stores as an instrument, as in Hausman (1996) and Nevo (2000), the estimate of price coefficient decreases only slightly. Issue of price endogeneity appears to be marginal. For my preferred estimator, I will not instrument for price.

4.3. Electricity Prices

I observe the same refrigerator models being sold at stores located in different electric utility territories. This allows me to control for product fixed effects and to use cross-sectional variation in average electricity prices across regions to identify the sensitivity to electricity prices. The identifying assumption is that consumers with similar characteristics shopping for refrigerators in a similar retail environment, but living in markets subject to different electricity costs are observed.

The electricity cost of each refrigerator model is computed using the yearly electricity consumption reported by the manufacturer and the average electricity price of the county where each household lives. In some specifications, I also use average price at the state level. Average electricity prices are computed using the EIA-861 form of the Energy Information Administration (EIA 2008). Assumptions and methodology to construct the average electricity prices are described in appendix.

If consumers trade off electricity costs with other attributes, market shares of more energy efficient refrigerators should be larger in markets subject to higher electricity prices. Figure 5 shows a correlation pattern that suggests that consumers perform such trade-off; in markets subject to such}

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\(^5\)I do not observe the zipcode of each household, but the zipcode of the store where each purchase was made. I thus assume that households live in the same county that they purchase their refrigerator.
higher electricity prices, consumers tend to purchase refrigerators that consume less electricity on average.

A concern about using cross-sectional variation in electricity prices as a source of identification is that stores located in markets with higher electricity prices may systematically differ from other stores. There are two potential confounding effects that I should account for. First, stores in markets with higher electricity prices have different inventory and may tend to offer more energy efficient refrigerator models. I control for this source of bias by using discrete choice models that explicitly model the choice set in each store. Second, marketing effects related to the concept of energy efficiency might be more pronounced in markets with higher electricity prices. Using OLS regressions, I find that region specific unobservables can be an important source of bias, but can be easily accounted for using a fixed effect strategy.

4.4. Rebates

In the US, several electric utilities, and local and state governments offer rebate programs to encourage the adoption of energy efficient appliances. Rebate programs for refrigerators are very similar in nature. Consumers claim the rebates by filling a form that must be submitted by mail or online. The new refrigerator purchased must meet a given energy efficiency criterion, which for most programs consist of the Energy Star certification. A complete description of these programs is available in the database of State incentives for renewables and efficiency (IREC 2011). In 2008, of the 127 different programs that offered rebates for energy efficient refrigerators, 93 programs required that the new refrigerator be certified Energy Star. For these programs the rebates amount varied from $20 to $200, with a mean value of $51.

As with electricity prices, I match each household to a county based on shopping location, and exploit cross-sectional variation in rebate amount across counties to identify consumers’ sensitivity to rebates. Figure 6 plots the market share for Energy Star products as function of rebate amounts. The variation in the market shares is important, and positively correlated with the average rebate amount available in different markets.

Note that I do not observe whether a given consumer takes advantage of a rebate program available when making a purchase. Borrowing terminology from the program evaluation literature, I will interpret the coefficient that measures the sensitivity to rebates as an intent to treat estimator (Imbens and Angrist 1994), i.e., the average effect of the rebate on sales multiplied by the probability of taking advantage of the rebate program.
4.5. Choice Set

As illustrated by Figure 2, the Energy Star program influences refrigerator manufacturers’ product line decisions. As a result, during the period 2008-2010, but especially in 2008, product entry and exit in the US refrigerator market led to important variation in the choice sets offered to consumers.

To control for the effects of product entry and exit, I construct store-trimester specific choice sets. More precisely, if at least one refrigerator model has been sold during a particular trimester at a given store, I assume that all consumers shopping at this store during this trimester could purchase this model.  

5. Empirical Strategy

The goal is to estimate the model presented in Section 3 for the US refrigerator market. Five key behavioral parameters need to be estimated. These are 1) the sensitivity to retail price, 2) electricity cost, 3) rebate amount, 4) Energy Star label, and 5) the costs of collecting and processing energy information. My empirical strategy is as follows. I first use a simple multinomial logit model to obtain average effects, investigate the sources of identification, and perform robustness tests. I then show heterogeneity patterns in the estimates using a latent class model, and a more flexible variant. I finally estimate the fully structural model, which rationalizes the observed heterogeneity.

5.1. Multinomial Logit Model

Consumer $i$ living in region $r$ at time $t$ derives utility $U_{ijrt}$ from refrigerator model $j$:

$$U_{ijrt} = \tau D_{jt} - \eta P_{jrt} + \psi R_{rt} XD_{jt} - \theta C_{jr} + \gamma_j + \epsilon_{ijrt},$$

where $D_{jt}$ is a dummy variable that takes the value one if product $j$ is certified Energy Star at time $t$ and zero otherwise. The variable $C_{jr}$ is the annual electricity cost of product $j$ sold in region $r$. The variable is constructed by multiplying the annual kWh consumption as reported by the manufacturers and average electricity prices in region $r$. $P_{jrt}$ is the retail price gross of sales.

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6The construction of the choice set for the second trimester of 2008, which just follows the revision of the Energy Star standard, is particularly important for the identification of the effect of the Energy Star label. For this trimester, I use a more restrictive criterion to construct the choice set to account for a possible out-of-stock effect. I assume that a model is available only if at least one sale is observed in the last four weeks of the second trimester of 2008.
tax and $R_{rt}$ is the rebate amount for the purchase of Energy Star refrigerators offered in region $r$. The variables $\gamma_j$ and $\epsilon_{ijrt}$ denote respectively the product fixed effect, and the idiosyncratic taste parameter. As it is customary, the idiosyncratic taste parameters are i.i.d. and Type I extreme value distributed, which yields closed-form expressions for the choice probabilities.

The model is estimated by maximum likelihood, where the likelihood is constructed with the choice probabilities of a large representative sub-sample of consumers (see appendix for more details on the sampling procedure). The choice probabilities do not include an outside option (no purchase or purchase at other store options) because the counterfactual scenarios will simulate consumers' choices conditional on the decision to purchase at a given store.

Adding an outside option, we can obtain a linear expression for the market shares in region $r$ at time $t$ (Berry 1994). To investigate issue endogeneity, notably with respect to market-specific unobservables, I will also estimate the following linear model:

$$\ln(q_{jrt}) = \tau D_{jt} - \eta P_{jrt} \psi R_{rt} XD_{jt} - \theta C_{jr} + \gamma_j + \alpha_r + \alpha_t + \zeta_{jrt}$$  

(7)

where $q_{jrt}$ is the quantity of refrigerator $j$ sold during week $t$ in region $r$, and $\zeta_{jrt}$ is a market specific unobservable. I account for the outside option by adding region ($\alpha_r$) and time fixed effects ($\alpha_t$). To investigate whether there is a possible correlation between $\zeta_{jrt}$ and prices, I rely on two strategies. First, I add brand-week fixed effects. As discussed earlier, this should account for marketing campaigns that are enacted with promotions. Second, I instrument for prices in a given region using prices in other regions and estimate the model via two stage least squares (2SLS).

5.2. Latent Class Models

I account for heterogeneity by first estimating a mixed logit with three latent classes. At time $t$, a consumer $i$ of type $e$ living in region $r$ receives utility $U^e_{ijrt}$ from refrigerator model $j$:

$$U^e_{ijrt} = \tau^e D_{jt} - \eta^e P_{jrt} + \psi^e R_{rt} XD_{jt} - \theta^e C_{jr} + \gamma_j + \epsilon_{ijrt}$$  

(8)

where all behavioral parameters indexed by $e$ can vary in an unrestricted way across latent classes.

In region $r$ at time $t$, define the probability that consumer $i$ of type $e$ chooses product $j$ by $H^e_{i,j,r,t}$ and the probability that he is of type $e$ by $Q^e_i$. The probability that consumer $i$ chooses

$^7$Consistent with the information acquisition model, I assume that the source of heterogeneity is intrapersonal, i.e., consumers are of a specific type, but can change type with a certain probability at different points in time (Hess and Train 2011). Because I observe each consumer only once, this assumption is purely
product $j$ is given by:

$$H_{ijrt} = \sum_e H^e_{ijrt} \cdot Q^e_i$$

(9)

The probability $Q^e_i$ is parameterized as follow:

$$Q^e_i = \frac{\exp(K^e + \beta^e X_i)}{\sum_e \exp(K^e + \beta^e X_i)}$$

(10)

where $X_i$ is a vector of covariates that describes consumer $i$. The constant $K^e$ and the vector of coefficients $\beta^e$ are parameters that need to be estimated.

To allow for a richer representation of unobserved heterogeneity, I next estimate a model with a large number of latent classes and recover non-parametrically the joint distribution of $\tau$ and $\theta$, using the estimator proposed by Fox, Kim, Ryan, and Bajari (2011) (FKRB). The estimator works as follows. Suppose that $\tau$ is known to have support on the $[\underline{\tau}, \bar{\tau}]$ interval, and similarly $\theta$ has support on $[\underline{\theta}, \bar{\theta}]$. FKRB propose to take a large but finite number of grid points on the intervals, and treat each point has a random coefficient with an unknown frequency that needs to be estimated. Taking all combinations of grid points, say $M$, we can form the choice probabilities for each combination, $m$, and approximate the choice probability for each consumer $i$ by averaging over all the random coefficients:

$$H_{ijrt} \approx \sum_{m=1}^{M} \alpha_m \cdot H^m_{ijrt}(\beta^m)$$

(11)

where $\alpha_m$ is the unknown frequency of the pair of coefficients: $\beta^m = \{\tau^m, \theta^m \}$, and $H^m_{ijrt}(\beta^m)$ is the choice probability evaluated at $\beta^m$. As shown by FKRB, the fact that dependent variable of the model $H_{ijrt}$ is linearly related to the parameters $\alpha$, allows to consistently estimated $\alpha$ using inequality constrained least squares. This estimator is thus appealing because of its computational simplicity. This however comes at a cost. The estimator is prone to suffer from the curse of dimensionality, and requires some subjectivity in the choice of grid points.

For the present application, I will fix $\eta$, $\psi$ and $\gamma_j$ at their MLE estimates (Model 1, Table 2), and center the support of $\tau$ and $\theta$ around the MLE estimates. The support of $\tau$ is approximated with eleven grid points, and the support of $\theta$ is approximated with nine grid points. Moreover, to allow smoothness in the distribution of random parameters, I will model the joint of density $\tau$ and $\theta$ as a mixture of normal densities, instead of point masses. Additional details on the implementation can be found in Appendix C.

cosmetic and made to facilitate the interpretation of the model. Ultimately, I can only identify the share of consumers that belongs to a particular latent class.
5.3. Information Acquisition Model

To estimate the fully structural model, I maintain the assumption that the idiosyncratic taste parameters are extreme value distributed. In addition, I assume that the information acquisition costs have an unobservable idiosyncratic component that is also Type I extreme value distributed. For a level of effort, $e$, the cost for consumer $i$ is given by:

$$K_i(e) = K^e + \beta^e X_i + \nu_{ie},$$

where, as in (10), $X_i$ is a vector of demographics, and the constant $K^e$ and the vector of coefficients $\beta^e$ parameterize the average information acquisition cost. $\nu_{i,e}$ is a mean zero stochastic component of the cost and gives rise to closed form solutions for the probability of choosing effort $e$:

$$Q_i(e) = \frac{\exp(-K^e - \beta^e X_i + E_{e,D,S}[\max_j \{U_{ijrt}\} | I(e)])}{\sum_k \exp(-K^k - \beta^k X_i + E_{e,D,S}[\max_j \{U_{ijrt}\} | I(k)])}$$

At the moment of choosing the effort level, consumer $i$ is uncertain about the electricity costs ($C_j$), the meaning of the Energy Star label ($S$), the certification ($D_j$), and the idiosyncratic taste parameters. Because $\epsilon$ is extreme value distributed, the expectation in (13) simplifies to:

$$E_{e,D,S,C}[\max_j \{U_{ijrt}\} | I(e)] = E_{D,S,C}[\log \left( \sum_j U_{ijrt} \right) | I(e)]$$

To evaluate the expectation in 14, I specify beliefs about electricity costs and Energy Star as follows. I will assume that consumers take the average electricity price in their county as given and have a prior on the annual amount of kWh consumed by refrigerators. The prior consists of a distribution $F$ normally distributed with a mean and variance that matches the empirical distribution of electricity consumption of all the refrigerator models available on the US market, for the trimester the purchase was made. Note that because the choice set changes between trimesters, notably due to the revision in Energy Star standards, I effectively allow the prior on electricity consumption to vary across time.

Beliefs about the meaning of Energy Star, $G$, is modeled with a flat prior. Specifically, the Energy Star threshold (previously noted $S$) is uniformly distributed, with a support centered at the mean of $F$, the prior for electricity consumption.

Ex ante, consumers are also uncertain about whether a product is certified or not. I set the prior for the probability that product $j$ is certified Energy Star, $q$, equal to the share of products that are certified Energy Star in their choice set, i.e., their local store. Therefore, the probability that consumers believe that $N$ products are Energy Star certified among the $J$ products available
is given by a binomial distribution with mean $Jq$. I thus effectively assume that consumers have rational expectations with respect to the number of Energy Star models in their choice set.

Finally, I need to specify learning. I will assume that learning is unbiased and realized before the purchase decision. Upon deploying effort $e = h$, consumer $i$ living in region $r$ learns a realization $c_{r,j}$ from $F$ that corresponds to the true value of the electricity consumption (kWh/year) of refrigerator $j$. Consumers will multiply this number by the average electricity price in region $r$, which is assumed to be known. If $e = m$, consumers learn the true the meaning of Energy Star, i.e., the realization $s$ from $G$ will be such that the expected electricity cost for all Energy Star refrigerator models $(C_{r,1}(s))$ in a region $r$ will correspond to the true average electricity cost of Energy Star models in this region. The same will be true for non-Energy Star models.

I assume that ex ante consumers are completely unaware of the rebate programs available in their regions and learn the existence of the rebate program only if they collect and process energy information, i.e., if $e = m$ or $e = h$. Therefore, under this assumption the existence of a rebate program in a particular region does not influence the level of effort to collect and process information, but does influence the purchase decision.

As in the multinomial logit and latent class models, I introduce a constant $\tau$ that corresponds to the Energy Star perceived added quality if a product $j$ is certified Energy Star ($D_j = 1$). If consumers value Energy Star refrigerators beyond their electricity cost savings, this will be captured by the coefficient $\tau$. The model thus allows me distinguishing whether consumers adopt Energy Star products purely based on financial or non-financial motives. I will assume that $\tau$ is only realized at the time of making a purchase for consumers that search for energy information (i.e., $e = m$ or $e = h$), is unexpected, and differ for $e = m$ and $e = h$.

For the estimation, I approximate the expectation in (14) with respect to the distributions of $D$, $S$ and $C$ with Monte Carlo integration. I then form the simulated likelihood similarly to the latent class model; the probability that consumer $i$ chooses product $j$ is given by:

$H_{ijrt} = \sum_k \tilde{H}_{ijrt}(k) \cdot Q_i(k),$

where $H_{i,j,r,t}(e)$ are the simulated choice probabilities conditional on the information set determined by the level of effort, $e$. 


Under the above assumptions about beliefs and learning, the alternative specific utility for each level of effort is given by:

(16) \[ U_{ijrt}^h = -\eta P_{jrt} + \psi R_{et}XD_{jt} + \tau^h D_{jt} - \theta C_{jr} + \gamma_j + \epsilon_{ijrt} \]
\[ U_{ijrt}^m = -\eta P_{jrt} + \psi R_{et}XD_{jt} + \tau^m D_{jt} - \theta E_{C,r,D_j}(s) + \gamma_j + \epsilon_{ijrt} \]
\[ U_{ijrt}^l = -\eta P_{jrt} - \theta E_{D,S,C}[C_{r,D_j}(S)] + \gamma_j + \epsilon_{ijrt} \]

Note that if \( e = l \), the expectation \( E_{D,S,C}[C_{r,D_j}(S)] \) is the same for all \( j \), and is not influencing the choices. The model therefore assumes that consumers that do not search for energy information make purchase decisions as if they were not paying attention to electricity costs and Energy Star. For consumers that rely on Energy Star information (\( e = m \)), the expectation \( E_{C,r,D_j}(s) \) takes only two possible values, and the difference \( E_{C,r,1}(s) - E_{C,r,0}(s) \) corresponds to the expected electricity cost savings, in region \( r \), associated with Energy Star. The present specification accounts for two mechanisms by which the Energy Star certification influences choices. First, there is the purely financial motive, i.e., the fact that Energy Star products lead to electricity cost savings. Second, there is the effect of the label on consumers, which might both capture consumers’ willingness to pay for green products and/or higher perceived quality for energy efficient products. If consumers do not value Energy Star products beyond their electricity cost savings, we should expect that the parameter \( \tau \) will take a value close to zero.

Unlike for the latent class model, behavioral parameters that are related to the marginal utility of income do not vary across consumer types. Because the proposed theory does not make explicit predictions on how collecting and processing energy information impact the marginal utility of income, it is restricted to be equal for across effort levels. To account for this dimension of heterogeneity, I will estimate the model separately for different income groups.

5.4. Identification

Identification of each consumer type in the information acquisition model comes from two sources. First, the 2008 revision in the Energy Star standards led to a variation in the labeling of certain products and meaning of Energy Star. Consumers that shopped for refrigerators before and after the revision faced a similar label, but with a different meaning. A change in the meaning of the Energy Star induces variations in the relative benefits of collecting and processing Energy Star information, and thus offers a way to identify search costs. This source of identification is
however only valid if consumers’ priors about the location of the Energy Star standard change as the standard is revised. This is not a particularly restrictive assumption. US EPA, manufacturers and retailers usually market the Energy Star program by making general claims about the relative gains of Energy Star products, which might influence priors.

A more subtle, but perhaps robust source of identification comes from heterogeneity in substitution patterns between refrigerator models. In particular, the existence of substitution patterns that violate the independence of irrelevant alternatives (IIA) hypothesis in specific ways is a source of identification of each consumer type. The following example illustrates this point.

Consider a market with only three refrigerator models, all with the same quality, but with different levels of energy consumption. Figure 7 represents the location of each refrigerator model in the quality-energy efficiency characteristics space, before and after the revision in the Energy Star standards, for three types of consumers. Panels (a) and (f) represent the location of the refrigerator models in the quality-energy cost characteristics space for consumers that fully account for energy costs. For this consumer type, all products are located at a different address in the characteristics space; the IIA hypothesis should be systematically violated. Moreover, revision in the Energy Star standard (Panel (f)), represented by the line $s$, should not influence the substitution patterns. Panels (b) and (e) represent the location of the same models in the quality-Energy Star characteristics space for consumers that rely on the Energy Star certification to account for the energy efficiency attribute. These consumers perceived Energy Star refrigerator models as perfect substitutes and revision in the Energy Star standards will impact this perception (Panel (e)). For this consumer type, the IIA hypothesis should hold within the class of products that have the same Energy Star certification (and with similar quality). Finally, for consumers that do not account for the energy efficiency attribute at all, all products are located at the same address in the characteristics space and will be perceived as perfect substitutes. The IIA hypothesis will hold for all products with similar quality, irrespectively of their location in the energy efficiency dimension.

To summarize, the existence of consumers with different degree of sophistication with respect to the way they account for energy efficiency implied different patterns of substitution. Ultimately, each consumer type will then be identified by events that reveal substitution patterns between products. Examples of such events are relative price changes and product entry and exit, which are both frequent and important in my data.
6. Results

6.1. Multinomial Logit Model

Table 1 reports the results of the multinomial logit model estimated on sales aggregated at the state level. All models use the log of the state weekly sales of each refrigerator model as a dependent variable. Because some refrigerator models do not sell in every state every week, only refrigerator models with significant sales, namely the 20% most popular models, are considered and I add one sale to all observations. All transactions of the restricted sample for the year 2008 are used. Models 1-4 are estimated via ordinary least squares and account for different fixed effects. Models 5 and 6 use prices in other markets as an instrument for prices and are estimated via two-stage least squares.

The first two models yield estimates that are different from the others four models by a large margin. Moreover, the estimate of the sensitivity to energy costs has a positive sign, which is unexpected. Once I control for state fixed effects, all estimates are well-behaved; they have a sign consistent with the theory, and are stable across specifications. This suggests that issues of endogeneity can be primarily attributed to state specific unobservables.

Model 4 includes brand-week fixed effects. The estimates of this model are similar to the ones of Model 3. Moreover, the brand-week fixed effects do not explain a high a portion of the variance. This suggests that brand-specific nationwide marketing campaigns have a negligible impact on the estimates.

Using prices in other geographical markets as instruments decreases the estimate of the sensitivity to prices from -0.129 (Model 4) to -0.148 (Model 5); a difference that is statistically significant at the 1% level. Using a Hausman specification test, I reject the null hypothesis that the OLS specification (Model 4) is consistent and efficient. For the estimates of interest, the biases are however marginal from an economic standpoint.

Table 2 presents the maximum likelihood estimates of the multinomial and nested logit, where the likelihood is constructed with the individual choice probabilities. In these specifications, the outside option is not considered, and refrigerator models with relatively low sales are now included in the choice set. The maximum likelihood estimator produces estimates on prices, rebates and

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8 Due to proprietary reasons, the number of refrigerator models that fits this criteria will not be disclosed.
9 The restricted sample contains only transactions made by homeowners living in single family housing units that bought no more than one refrigerator in any given year.
electricity costs that are larger than the OLS estimates, the estimate of the effect of the Energy Star label is however replicated more closely.

One concern about estimating the model via maximum likelihood with a large number of product fixed effects is that it biases the estimates due to the incidental parameter problem (Lancaster 2000). The incidental parameter problem arises in applications where \( N \to \infty \) and \( T \) is fixed. The fact that I observe the same products sold multiple times in different markets should alleviate the problem. To investigate whether this is an important source of bias, I re-estimated the model on a sub-sample 50\% larger (Model 2, Table 2). The estimates replicate the estimates obtained using a smaller sub-sample, suggesting that the size of the sub-sample initially used (Model 1) is large enough to overcome the incidental parameter problem.

Adding brand-week fixed effects has little impact on the estimates. This slightly reduces the estimates of the effect of the Energy Star label. Like in the OLS regressions, nationwide marketing campaigns are not an important source of bias.

Product entry and exit at the time the Energy Star standard is revised can be a source of bias, especially for the estimate of the effect of the Energy Star label. If regions of the product space where decertified models are located become more congested, this could induce a decrease in market share of decertified models simply because they have more substitutes. I propose three estimators that aim to control for this. I first introduce correlation in the error terms using a nested logit (Model 4). In particular, I use a nest structure (see Figure 8) where Energy Star and non-Energy Star are located in different nests. Under this specification, decertified models are not perfect substitutes with new models that have similar attributes (other than the Energy Star certification). As a result, decrease in market share for decertified models will not be purely induced by the IIA assumption. In Model 5, in addition of using the nested logit, the number of models that enter each nest is also added as a covariate. As shown by Ackerberg and Rysman (2005), such model can be consistent with utility maximization and allows to relax restrictions on how unobserved characteristics (i.e., the logit term) vary as the choice set changes. The estimates of Models 4 and 5 both suggest a lower estimate of the effect of the Energy Star label, about half the size of the estimate from the multinomial logit. Adding the number of models in each nest also reduces (in absolute term) the estimate of the sensitivity to electricity costs. The other coefficients are however similar. The third approach (Model 6) uses a different strategy and estimates the model using consumer-specific choice set, which allows to restrict the size of the choice set, and partly controls for the expansion/contraction in the overall size choice set. In this specification,
information about size purchased is used to recover the consideration set of each consumer.\textsuperscript{10} For each consumer, I assume that only refrigerators no smaller or larger than 3 cu. ft. of the size purchased are included in the consideration set.\textsuperscript{11} The estimates (Model 6, Table 2) suggest that using consumer-specific consideration sets impacts mostly the estimate of the sensitivity to electricity costs, but not the other estimates.

To assess the external validity of the 2008 revision in the Energy Star as a source of identification, I exploit a different natural experiment to identify the label effect. In January 2010, the EPA found that a number of Energy Star refrigerator models had undergone problematic testing procedures. As a result, their electricity consumption was underestimated. The EPA concluded that these refrigerator models were not meeting the Energy Star standard, and issued a public statement that 21 refrigerator models would be decertified. I observe 16 of these refrigerators in my sample. Model 7 estimates the multinomial logit model using data covering this period (10 weeks before the decertification, and 5 weeks after). The estimates suggest that the models that were decertified in 2010 had a 26\% decrease in market share, on average.

Focusing on the base model (Model 1), I find that the price elasticity is -6.29 (Table 3). This is large, but not surprising. Each refrigerator model has several close substitutes, and manufacturers and retailers offer generous promotions. Consumers can easily substitute across models and time (i.e., delay a purchase) to take advantage of the promotions, which both contribute to a high sensitivity to prices.

My estimates suggest that removing the Energy Star label on a refrigerator model leads to a 15.5\% decrease in sales (Table 3). Again, this large effect can be attributable, in part, to the existence of several close substitutes. In particular, at the time that new Energy Star standards come into effect manufacturers offer new refrigerator models that are close substitutes to models that lose their certification, but meet the new standards, thus facilitating substitution.

The impact of Energy Star rebates is positive and small in comparison to the label effect. Although it is not statistically significant, I next interpret its marginal effect. Offering a $50 rebate increases sales by 3.0\% on average (Table 3). As discussed earlier, we should interpret the estimate of the sensitivity to rebates with the caveat that we do not observe whether consumers take advantage of a rebate program. Note that if we were able to observe whether a consumer claimed a rebate, and consumers were perfectly rational in the way they account for rebates, the

\textsuperscript{10}For refrigerators, size is the main attribute that restricts the options of a consumer.

\textsuperscript{11}Using different cut-off values, e.g., 2, 2.5 or 3.5 cu. ft. does not change the results significantly.
coefficient for the sensitivity to rebates should match the coefficient for sensitivity to prices, i.e.,
be equal to the marginal utility of income. In the present case, the coefficient for the sensitivity to
rebates can be interpreted as the marginal utility of income times the probability that a consumer
takes advantage of the rebate. For the estimates obtained, this probability is 13.0%.

Assuming a rebate amount of $50, the combined effect of the Energy Star label and the rebate
is 20%. The Energy Star program has a non-negligible effect on sales. This is consistent with the
fact that refrigerator manufacturers respond strongly to the program.

The estimate of the sensitivity to electricity costs suggests a cost elasticity of -1.35. To compare
with previous estimates (e.g., Train 1985), I compute the implied discount rate that rationalizes
consumers’ decisions. I maintain the assumptions of section 3 and assume that consumers form
time-unvarying expectations about annual electricity costs. Moreover, I assume that consumers do
not account for the effect of depreciation. I assume that consumers compute the lifetime electricity
cost \((L_{C_{r,j}})\) by summing and discounting the expected annual electricity costs \((C_{r,j})\) over the
lifetime of the durable:

\[
L_{C_{r,j}} = \sum_{t=1}^{L} \rho^t C_{r,j} = \frac{1 - \rho^L}{1 - \rho} C_{r,j},
\]

where \(L\) is the lifetime of the durable, \(\rho = 1/(1 + r)\) is the discount factor and \(r\) is the (implied)
discount rate.

Consistent with the fact that \(|\eta|\) corresponds to the marginal utility of income, the coefficient
for the sensitivity to annual energy costs in the demand model \((\theta)\) is a reduced form parameter
that corresponds to:

\[
\theta = \eta \frac{1 - \rho^L}{1 - \rho}
\]

Assuming a lifetime of 12 years, 18 years or infinity, the implied discount rate \((r)\) is respectively
17.2%, 19.4% or 20.3%. This is significantly lower than previous estimates that range from 35%
to more than 60% (Meier and Whittier 1983). To put these numbers in 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).
6.2. Heterogeneity

**Latent Class Model.** Table 4 presents the estimates of the latent class model with three latent classes. The estimation was performed on the same sub-sample of transactions as for the multinomial logit (Model 1). Overall, the estimates suggest the existence of three distinct types of consumers that differ in the way they account for electricity costs, rebates and Energy Star.

For the first latent class (Class 1), the coefficients for the sensitivity to electricity costs and rebates are not statistically significant, but the estimate of the sensitivity to Energy Star is large and significant. For the third latent class (Class 3), we observe the opposite. The estimate of the sensitivity to electricity costs is high, but the label effect is small and marginally significant. The estimates of the second latent class (Class 2) corresponds to an intermediate case. The sensitivity to electricity cost is negative but small, and the effect of Energy Star is 19.2%, which is similar to the effect size found with the homogeneous model.

The shares of consumers that belong to the first, second and third latent classes are respectively 9.9%, 62.5% and 27.7% (Table 4). Those are averages over all consumers, these probabilities vary by demographics.

In sum, the latent class model shows heterogeneity patterns that suggest an inverse correlation between the parameters $\tau$ and $\theta$ (Class 1 vs. Class 3), i.e., consumers that rely primarily on Energy Star tend to be less sensitive to electricity costs, and vice-versa. This is a first evidence suggesting that the Energy Star label may act as a substitute for electricity costs information. The next set of results provides further evidence of such pattern.

**Joint Distribution of $\theta$ and $\tau$.** The estimator proposed by Fox, Kim, Ryan, and Bajari (2011) (FKRB) is now used to recover the joint distribution of the parameters $\theta$ and $\tau$. For the estimation, all other parameters were held fixed at the values obtained from the maximum likelihood estimation. Figure 9 plots the contour map of the joint distribution. The FKRB’s estimator identifies three areas with a positive density. There is a cluster centered at $\tau \approx 1.2$ and $\theta \approx 0$, which means that there is a group of consumers with a high sensitivity to Energy Star, but low sensitivity to electricity costs. The second cluster, which has the largest probability mass, is centered at $\tau \approx 0$ and $\theta \approx -4.2$. This suggests the existence of a group of consumers with a high sensitivity to electricity costs, but that does not value Energy Star (beyond energy savings). Finally, there is a third cluster located at the origin ($\tau \approx 0$ and $\theta \approx 0$), which suggests that some consumers simply do not value energy information. Altogether, the heterogeneity patterns identified are consistent
with the idea that consumers differ in their degree of sophistication with which they account for energy information.

6.3. Information Acquisition Model

The information acquisition model was estimated on the same sub-sample used for the multinomial logit model and the latent class model. Table 5 presents the estimates. First, note that the coefficient for the sensitivity to prices is of the same order of magnitude as for the other models, however, the sensitivity to electricity costs is higher. As a result, the discount rate implied by these two parameters now ranges from 5.8% to 11.8% (Table 5). The above result suggests that some consumers do trade off the purchase cost of a refrigerator with its electricity cost in a way that is consistent with other investment behaviors.

Turning to the effect of the Energy Star label, I find that consumers that search for electricity costs \((e = h)\) respond positively to the label. The estimate of the coefficient \(\tau^h\) is 7.9%, which is lower than for the conditional logit model. For consumers that search for Energy Star information \((e = m)\), the estimate of the label effect is large, 77.8%. This implies that these consumers value Energy Star well beyond their relative energy savings.

6.4. Interaction with Income

An important restriction of the information acquisition model is that the marginal utility of income is constrained to be constant across different levels of effort. This was imposed on the model because the theory provides no mechanisms by which collecting and processing energy information impacts the marginal utility of income. The source of heterogeneity modeled so far is assumed to be entirely intra-personal. However, as shown by the estimates of the latent class model, the estimates of the marginal utility of income varies across latent classes, suggesting that income could also be a source of inter-personal heterogeneity.

To account for the role of income, I estimated the information acquisition model for three different income groups. For comparison purpose, I have also estimated the multinomial logit model for these same income groups.

Table 6 presents the results. Focusing on the price coefficients, we observe an inverse correlation between consumers’ sensitivity to prices and income levels, i.e., the marginal utility of income, \(|\eta|\), decreases with income. Meanwhile, lower income consumers are also less sensitive to electricity
costs. The implied discount rate has thus an inverse relationship with income (Table 6, and Figure 10).

The effect of the Energy Star label varies across income levels. Consumers in the upper income group have the highest willingness to pay for Energy Star products, irrespectively of their beliefs about electricity costs. Interestingly, the effect of the label varies the most with respect to the effort levels. Consumers that rely primarily on Energy Star tends to respond strongly to the certification itself. For households in the lowest income group, the effect of the Energy Star label is negative when \( e = h \). This suggests that these consumers do not see extra benefits in purchasing an Energy Star refrigerator, beyond the energy savings it brings, while consumers with higher income systematically value the certification beyond the energy savings. Overall, I conjecture that these patterns are correlated with environmental preferences. High income consumers might have a higher willingness to pay for green products, and derive non-market benefits from purchasing them.

Looking at the effort probabilities (Table 7), the estimated share of consumers that does not value Energy Star or electricity costs \((e = l)\) is 23.1%. I find that about 52.8% of the consumers behave as if they were discounting electricity costs \((e = h)\) and 24.1% of consumers rely on Energy Star \((e = m)\). These probabilities vary by demographics. Table 7 reports these probabilities for the three income groups. Lower income group tend to have a high probability to have a low effort \((e = l)\), while it is the opposite for the higher income group. For the low income group, the probability that they rely on Energy Star \((e = m)\) is close to zero. The above numbers correspond to averages taken over the whole population of consumers. Figure 11 plots the empirical distribution of effort probability for a sample of 50,000 consumers. For the low and high effort probabilities, the distributions have most of their masse at the extremes; i.e., consumers have either a high probability to account for energy information or a low. This finding has important implication for the design and targeting of energy information.

Overall, the information acquisition model produces estimates that are consistent with the hypothesis that there are different types of consumers with different levels of sophistication with respect to how they account for the energy efficiency attribute. Moreover, I find evidence that consumers with different income levels value energy efficiency differently, controlling for their degree of sophistication. An important extension for future research will be to the present analysis to investigate whether other economic variables are also correlated with the valuation of energy efficiency.
7. Welfare Analysis

This section investigates the welfare effects of the Energy Star program for the US refrigerator market. Estimates of the overall effects of the program are obtained by simulating counterfactual scenarios where the Energy Star program is not in effect. To construct the counterfactual scenarios, in addition of modeling consumers' purchasing behavior, it is also necessary to make assumptions regarding how firms will respond to the removal of the program. Four scenarios are considered.

The first scenario holds constant the responses of the firms. That is, the product lines and prices offered are taken as given, and the demand model is simulated assuming that consumers do not have access to the Energy Star label and rebates. This scenario then provides an estimate of the short-term effects of the program, and it allows isolating the effects of the demand alone. The second scenario assumes that firms respond to the removal of the program, but in a very particular manner. I assume that in a market without Energy Star, firms will offer refrigerator models that bunch exclusively at the minimum energy efficiency standard. This equilibrium outcome is possible if firms believe that consumers would not value energy efficiency if Energy Star were not in effect. This is an extreme assumption that aims to provide an upper bound for the estimates of energy savings. Previous studies of the Energy Star program (Webber, Brown, and Koomey 2000; Sanchez, Brown, Webber, and Homan 2008) implicitly have made this assumption. The third scenario accounts for firms' responses in a more realistic manner. Using a static multi-product oligopoly model calibrated for the US refrigerator market, I solve for the firms' optimal product lines and pricing decisions in a market with and without Energy Star. The fourth scenario also uses the oligopoly model, but with a different estimate of the firms' marginal costs of providing energy efficiency.

I next outline the general approach used to construct the counterfactual scenarios, with a special emphasis on the oligopoly model. I follow with a discussion of the welfare measure.

7.1. Constructing Counterfactual Scenarios

For each scenario, I compare two market equilibria; a state of the world where Energy Star is not in effect, and a state of the world where Energy Star is in effect. For Scenarios 1 and 2, I simulate the market equilibria using the estimated demand model (information acquisition model interacted with income), and predefined choice sets. For Scenarios 3 and 4, the choice sets are endogenously determined by the oligopoly model.
For all scenarios, the size of the choice set is set equal to the average number of refrigerator models offered by a store in my sample, which is 253. To locate products in the quality space (all non-energy attributes), I use the estimated product fixed effect, obtained from the demand estimation, as the measure of observed quality. To ensure having a representative choice set, I sample 253 products from the 1065 products used in the demand estimation such that the distribution of the products in terms of style, size, and energy efficiency fits the observed distribution for the whole US market in the year 2010.\(^{12}\)

In Scenario 1, the choice set without Energy Star is created by considering that all Energy Star refrigerators had their certification removed, but prices and all other attributes remained constant.

In Scenario 2, in the world without Energy Star, in addition of removing the Energy Star certification, the energy efficiency level of each refrigerator is set equal to the minimum standard. For models already at the minimum, no adjustment is made. I also lower the prices of the models that become less energy efficient proportionally to the change in energy efficiency (e.g., models that become 20% less energy efficient, become 20% cheaper).

In Scenario 3, I take the size of the choice set, the number of products offered by each firm, and the location of the products in the quality space as given, and I use a multi-product oligopoly model to determine how firms set the energy efficiency levels and prices of the products they offer. For internal consistency, I use the oligopoly model to simulate the choice sets corresponding to a market with and without Energy Star.

In Scenario 4, the oligopoly model is simulated with a larger estimate of the firms’ marginal costs of providing energy efficiency.

### 7.2. A Static Multi-Product Oligopoly Model

The multi-product oligopoly model represents a medium-run equilibrium where the firms’ choices of energy efficiency levels and prices are endogenized, but the decisions to enter and exit the market, and to determine the size and characteristics (other than energy efficiency) of product lines are taken as given. My approach closely follows Bento, Goulder, Jacobsen, and von Haefen (2009), Klier and Linn (2012), and Whitefoot, Fowlie, and Skerlos (2011), who investigate how car manufacturers respond to mandatory fuel economy standards.

\(^{12}\)For instance, if 5% of the full-size refrigerators available on the US market in 2010 were top-freezer refrigerators with a size between 12 CU.ft. and 21 CU.ft., and certified Energy Star, I sample 13 products in my sample (5% X 260) that fit this description.
An important feature of the refrigerator market is that manufacturers offer similar products under different brand names.\textsuperscript{13} To circumvent the difficulties associated with the manufacturers’ decision to offer products under multiple brand names, I will focus on modeling the behavior of brand managers. I will assume that each brand manager represents a firm that aims to maximize the profit of his own brand. The brands that I consider are General Electric, Kenmore, Frigidaire, Whirlpool, and a generic brand representing all other brands.

A second important feature of the refrigerator market is that, within a relatively short time, manufacturers can change the energy efficiency level of a refrigerator, with little impact on the overall design.\textsuperscript{14} I take this as evidence that the costs of providing energy efficiency are separable from the costs of providing other attributes.

Under these assumptions, the model is as follows. Consider that they are $K = 5$ brands, and brand manager $k$ offers $J_k$ refrigerator models. Each brand manager maximizes his profit by choosing the energy efficient levels, the vector $f_k = \{f_{k1}, ..., f_{kJ_k}\}$, and the prices, the vector $p_k = \{p_{k1}, ..., p_{kJ_k}\}$, of his $J_k$ refrigerator models, taking the strategies of his competitors as given. Firms face a population of consumers, where the demand for each product $j$ is a function of all prices and energy efficiency levels, and depends on consumers’ valuation of energy efficiency ($\theta$) and of the Energy Star certification ($\tau$).

The problem of the brand manager $k$ consists in solving:

\begin{equation}
\max_{f_k = \{f_{k1}, ..., f_{kJ_k}\}, p_k = \{p_{k1}, ..., p_{kJ_k}\}} \sum_{j=1}^{J_k} (p_{kj} - c_{kj}(f_{kj})) \cdot Q_{kj}(f, p|\theta, \tau)
\end{equation}

where $f = \{f_1, ..., f_K\}$, $p = \{p_1, ..., p_K\}$, $c_{kj}(f_{kj})$ is the brand-model specific cost of model $j$ offered by brand $k$, and $Q_{kj}(f, p|\theta, \tau)$ is the demand.

\textsuperscript{13}This is in part due to numerous mergers and acquisitions, but also because there exist important brands that are not owned by manufacturers (e.g., Kenmore).

\textsuperscript{14}This has been demonstrated by the various revisions in the Energy Star standard, which has shown that manufacturers managed to offer new products that were more energy efficient, but were otherwise similar to previous generations. Interestingly, when the EPA announced in April 2007 that the Energy Star standard would be revised in April 2008, all but one manufacturer notified the EPA that they would not be able to offer new refrigerator models on time to meet the revised standard. Ultimately, most manufacturers were, however, able to offer new models meeting the 2008 Energy Star standard within a year of the date that the EPA made the announcement.
The first order conditions for firm $k$ are given by:

$$\begin{align*}
Q_{kl}(f,p|\theta,\tau) + \sum_{j=1}^{J_k} (p_{kj} - c_{kj}(f_{kj})) \cdot \frac{\partial Q_{kj}(f,p|\theta,\tau)}{\partial p_{kl}} &= 0, \text{ for all } l \in J_k \\
-Q_{kl}(f,p|\theta,\tau) \frac{\partial c_{kl}(f_{kl})}{\partial f_{kl}} + \sum_{j=1}^{J_k} (p_{kj} - c_{kj}(f_{kj})) \cdot \frac{\partial Q_{kj}(f,p|\theta,\tau)}{\partial f_{kl}} &= 0, \text{ for all } l \in J_k
\end{align*}$$

Using the first order conditions of the $K$ brands, the Nash equilibrium corresponds to the strategies $f^*$ and $p^*$ that solve the system of $2 \times J_1 \times J_2 \times \ldots \times J_K$ equations.

### 7.2.1. Estimation: Marginal Cost of Providing Energy Efficiency

To calibrate the model to the US refrigerator market, the cost function $c_{kj}(f_{kj})$ needs to be estimated. Consider that $c_{kj}(f_{kj})$ takes the following exponential form:

$$c_{kj}(f_{kj}) = S(\beta X_{kj}) \cdot \exp(\phi f_{kj})$$

where $X_{kj}$ is a vector of attributes, other than energy efficiency, $^{15}$ $S(\cdot)$ is an unknown function that shifts the cost, and $f_{kj}$ is the energy efficiency level, which will is defined as the inverse of the annual electricity consumption.

For each refrigerator model $j$ in my sample, I observe directly the manufacturer price, which corresponds to the cost $c_{kj}(f_{kj})$ for brand manager $k$. Using that information, and approximating the cost function with a log-linear specification, I estimate the marginal cost of providing energy efficiency using a simple hedonic model that regresses the log of manufacturer prices on observed attributes:

$$\ln(M\text{price}_{j,r,t}) = \alpha + \beta X_j + \phi f_j + \epsilon_{j,r,t},$$

I first estimate (23) by OLS. I also use a more flexible specification, and estimate a generalized additive model, where the attribute size enters (23) with an unknown function that is estimated non-parametrically.

$^{15}$The following attributes are considered: dummies for refrigerator type (top-freezer, side-by-side or bottom-freezer), size interacted with dummies for refrigerator type, size interacted with dummies for overall quality (low: price <$1,000, medium: price >$1,000 & price <$2,800, high: price >$2,800), dummy for ice-maker, dummy for defrost technology (automatic vs. manual), dummy for water dispenser, dummy for an advance cooling technology, dummy for an air filtration technology, dummy for indoor lighting using LED, dummies for brand, and dummies for year the refrigerator entered the market.
Table 9 presents the estimates for the various specifications. Focusing on the first two models, the estimate of $\phi$ is positive, which implies that the costs are increasing and convex in energy efficiency. Using the generalized additive model to control for size does not change the results substantially. The estimates are marginally statistically significant, but the model explains a high proportion of the variance ($R^2 = 87.4\%$). I also investigate heterogeneity in marginal costs (Model 3) by interacting the energy efficiency attribute with refrigerator type (top-freezer, side-by-side, and bottom-freezer). Results however suggest that the costs are decreasing with respect to energy efficiency for side-by-side, and bottom-freezer refrigerators. This suggests a problem with unobserved attributes, which I suspect should be more important for side-by-side and bottom-freezer refrigerators. These refrigerator types tend to be high quality models, have more features, and are more heterogeneous in their design than the simpler top-freezer refrigerators.

For the simulations in Scenario 3, I will use the estimate of the cost function obtained with Model 1 (Table 9). Scenario 4 tests the sensitivity of the results with respect to the marginal cost of providing energy efficiency, and double the estimate of $\phi$ for the simulations. Note that the marginal cost of providing energy efficiency is assumed to be the same for all firms and products. Total product costs are however heterogeneous because they change as a function of product attributes, $X_j$.

7.3. Welfare Measure

The welfare measure accounts for the change in consumer surplus, producer surplus, and externality costs. Note that the EPA deploys substantial efforts to manage and market the Energy Star program. In the present analysis, I will not consider the public funds required to run marketing campaigns, pay salaries of public employees and other operating expenses related to the program, with the caveat that this could be an important cost associated with the program.

**Consumer Welfare.** In the present framework, it is important to note that for consumers that do not fully process energy information or rely on Energy Star, there is a discrepancy between the electricity costs consumers believe they would pay and the electricity costs they effectively pay. That is, the utility they experience differs from the utility they thought they would experience. Similar to Allcott and Wozny (2011), I propose a measure of consumer surplus based on the notion of experience utility. Consistent with the framework of Bernheim and Rangel (2009) for behavioral welfare economics, the proposed welfare measure relies entirely on observed choices.

I first make the following assumption.
**Assumption 1.** If $e = h$, decision utility equals experience utility.

Assumption (1) simply says that under perfect information consumers experience what they believed they will experience. Under this assumption and using the estimates obtained from the information acquisition model, the observed component of experience utility, net of the (observed) costs of collecting and processing information is thus:

$$
OXU_{i,j,r,t} = \hat{\gamma}_j + \hat{\tau}^h D_{j,t} - \hat{\eta} P_{j,r,t} + \hat{\psi} R_{r,t} X D_{j,t} - \hat{\theta} C_{j,r} - K^k - \beta_k X_i,
$$

Note that whether the Energy Star label effect, $\tau^h$ is truly experienced can be debated. If a consumer believes that a product is of higher quality because of the Energy Star label and this belief is never updated, the consumer may experience the perceived quality. It can also be argued that the costs of collecting and processing information should not be treated as part of the consumer surplus, because their identification relies on our assumption about consumers’ priors. In the present analysis, I will thus perform sensitivity analysis and provide estimates of the welfare effects with and without the effects of $\tau^h$ and $K_i(e)$.

To deal with the unobserved idiosyncratic taste parameters $\epsilon_{i,j,r,t}$ and unobserved component of the costs, $\nu_{i,e}$, I will compute the expected consumer surplus (Train 2009). Note that the probability that consumer $i$ chooses and thus experiences product $j$ is given by the choice probabilities in equation (15). Following the estimation, these choice probabilities can be simulated and are our best representation of how each consumer selects his favorite refrigerator. I then derive the expected consumer surplus ($ESC$) by computing the expected experience utility, where the expectation is taken with respect to the observed choice probabilities. For consumer $i$ that lives in region $r$ and makes a purchase at time $t$, the expected consumer surplus ($ESC_{i,r,t}$) is given by:

$$
ESC_{i,r,t} = \frac{1}{\eta} E_{\epsilon,\nu} \left[ \sum_j \sum_k \hat{H}_{i,j,r,t}(k) \cdot \hat{Q}_i(k) \cdot \left( OXU_{i,j,r,t} + \epsilon_{i,j,r,t} - \nu_{i,e} \right) \right]
$$

where I have used the facts that $E_{\epsilon}[\epsilon_{i,j,r,t}] = 0$, $E_{\nu}[K_i(e)] = K^e + \beta^e X_i + \nu_{i,e}$, and that the unobservable components of utility do not enter the choice probabilities. I also multiply by the inverse of the marginal utility of income to convert utils in dollars (Train 2009).

Finally, note that the measure of the consumer surplus should be interpreted as the expected consumer surplus over the lifetime of the refrigerator. To obtain an annual measure, I compute the
immediate-annuity assuming a lifetime of 18 years, and the discount rate implied by the estimates of marginal utility of income (η) and sensitivity to electricity costs (θ).

**Externality Costs.** To quantify the externality costs associated with the electricity generated to operate refrigerators, I focus on the emissions of carbon dioxide (CO₂), sulphur dioxide (SO₂), and nitrous oxide (NOₓ), and use emissions factors recommended by the EPA. I compute the dollar damages associated with carbon dioxide using the recent estimates of the social cost of carbon recommended to assess federal regulations (Greenstone, Kopits, and Wolverton 2011). For sulphur dioxide and nitrous oxide, I rely on two sources, I consider the estimates used by the Department of Energy in the cost-benefit analysis of the 2014 minimum energy efficiency standards for refrigerators (DOE 2011), and the average estimates provided by Muller and Mendhelson (2012). Table 8 presents the emission factors and the damage costs used.

I compute the externality cost associated with each scenario by taking the product of the corresponding average electricity consumption purchased, the market size, the emission factors, and the damage costs of electricity generation. The average electricity consumption purchased is the average of the electricity consumption of the refrigerators sold, weighted by market shares. For the market size, I use the annual shipments of refrigerators in the US for the year 2010, which is 9,01 million units (DOE 2011).

**Producer Surplus.** For each refrigerator model in the choice set, I compute the brand manager’s markup using the estimated cost functions. I compute the average profits by multiplying markups with the simulated market shares. Note that I do not consider the change in manufacturers’ profits in the producer surplus.

**Rebates.** I assume that when Energy Star is in effect, consumers can claim a $50 rebate for purchasing an Energy Star refrigerator. The rebate program is offered by a government agency. When Energy Star is not in effect, I assume that this agency will distribute the amount reserved for the rebate program to all consumers via a lump-sum payment. The amount of the lump-sum payment is set equal to the rebate amount ($50) times the probability that a consumer takes advantage of the rebate amount, previously referred as π (see Table 3), implied by the estimates of the marginal utility of income (η) and sensitivity to rebates (ψ).

**7.4. Results**

For all scenarios, I simulate the demand model 50 times. For each simulation, I sample the demand parameters from their estimated asymptotic distributions, compute various metrics for a world
without and with Energy Star, and take the difference. I report the average and the standard deviation of these differences.

**Removing Energy Star, No Firms’ Responses.** I first consider the impact of removing the Energy Star certification and rebates holding constant the firms’ responses. Results for Scenario 1 in Table 10 show that removing the Energy Star certification and rebates leads to the adoption of more energy efficient products, on average. The average annual electricity consumption of a refrigerator purchased decreases by 5 kWh/year when Energy Star is not in effect. Although, this difference is small, it calls to attention an important unintended consequence of the program—Energy Star may crowd out efforts to account for electricity costs.

The crowding out effect occurs when the Energy Star label acts as a substitute for more complex, but accurate energy information, such as the mandatory label EnergyGuide. By relying on the Energy Star certification, consumers will not perceive the added benefits of refrigerator models that exceed the Energy Star standard, or of smaller size models that are not certified. In my framework, removing the Energy Star certification will induce more consumers to fully account for energy costs, relative to the case where Energy Star is in effect, which in turn could increase the market shares of highly energy efficient refrigerator models. When this effect dominates, choices become more energy efficient without the Energy Star program.

Turning to the change in consumer surplus, the results suggest that removing the certification alone will decrease consumer surplus if we account for the costs of collecting and processing information. The loss is however unrealistically large. As alluded before, these costs are not precisely identified, and depend on how beliefs are specified. I thus recommend to focus on welfare measures that exclude them. Without these costs, consumers are slightly better-off when they do not have access to the certification. This effect arises because a larger faction of consumers make a purchase decision under full information. These consumers are better off, *ex ante*, relative to the case where they rely on the partial information provided by Energy Star.

Excluding the effect of the label from the welfare measure reinforces the above conclusion. This is to be expected. If the label effect is excluded, this means that the label *biases* the purchasing decision toward Energy Star products, and the discrepancy between decision and experience utility becomes more important. *Ex ante*, choices are thus more likely to be suboptimal.
Note that by removing the certification, consumers tend to purchase products that are cheaper. However, firms’ profits increase. The market shares of models with higher markups thus increase.\textsuperscript{16}

Overall, removing the certification, holding constant the firms’ responses and excluding the search cost, increases social welfare.

**Removing Energy Star, Firms Bunching at the Minimum Standard.** Assuming that firms will offer products that bunch exclusively at the minimum standard (Scenario 2), the Energy Star program leads to important energy savings. Without Energy Star, the electricity consumption of a refrigerator purchased increases by 55 kWh/year. While this implies that consumers will pay more to operate their refrigerator, they will however pay lower up-front costs. For the range of estimates of the marginal utility of income and sensitivity to electricity costs that I obtain, the latter effect will dominate. I find that consumers will be better off in a market with less efficient, but cheaper refrigerators.

For firms, it is however the opposite. Offering products that bunch exclusively at the minimum standard leads to lower profit. In fact, the loss in profits dominates the increase in consumer surplus. Under Scenario 2, removing the Energy Star program also reduces social welfare.

**Removing Energy Star, Firms’ Optimal Responses.** Before turning to the welfare results, I show that the oligopoly model predicts that the market outcome of Scenario 2 is in fact unlikely. In particular, I find that if the refrigerator market was not subject to Energy Star, firms would offer products that differ widely in terms of efficiency (and price)—in a world without Energy Star, firms discriminate in the energy efficiency dimension more.

This is illustrated by Figure 12, which shows the choice sets predicted by the oligopoly model, and the choice sets constructed for Scenarios 1 and 2. The choice sets are plotted in the size-electricity consumption dimensions. Clearly, we observe that for Scenarios 3 and 4, in a world without Energy Star, firms find optimal to offer highly energy efficient products. The oligopoly model predicts that the average kWh of a refrigerator offered increases in a world without Energy Star (Table 11). However, without Energy Star, product differentiation in the energy efficiency dimension increases. As shown in Table 11, the difference between the 25\textsuperscript{th} and 75\textsuperscript{th} percentile is 140 kWh/year without Energy Star, and approximately 95 kWh/year with Energy Star (Scenario

\textsuperscript{16}It should be noted that this conclusion depends on the way products were selected and located in the quality space. For instance, I found examples where decreasing the degree of congestion in the quality space, which consists of selecting models with product fixed effects that are far apart, led to a decrease in firms’ profits for this scenario.
3). In Scenario 4, products are even more differentiated, and again differentiation with respect to energy efficiency is more important when Energy Star is not in effect.

Focusing on Scenario 3, we find that in a world without Energy Star, refrigerators purchased are more energy efficient, on average. This is a manifestation of the crowding out effect, which has now been amplified by the fact that firms discriminate more when Energy Star is not in effect. Although, this leads to a reduction in the externality costs, neither consumers nor firms benefit. Consumer and producer surplus both decrease, and overall removing Energy Star leads to a decrease in social welfare. This conclusion is however not robust to the estimate of the marginal cost of providing energy efficiency. Results from Scenario 4 suggest that if Energy Star were not in effect, consumers would be better off. Firms will still have lower profits, but the loss is now smaller ($61 millions vs. $209 millions). As a result, Scenario 4 predicts that the sign of the welfare change is ambiguous. Using the high estimates of the externality costs, removing Energy Star might lead to a gain in social welfare.

8. Conclusion

In the US, the Energy Star program is one of the main policy tools used to address negative externalities associated with the utilization of energy intensive durables. The program is generally considered widely successful (EPA 2010) and has consistently performed well with respect to marketing metrics such as awareness and understanding of the program (EPA 2011). Perhaps the most convincing proof that Energy Star plays an important role in influencing consumers is the fact that market shares for Energy Star products have been steadily high. This paper provides evidence that the Energy Star program influences, quite substantially, purchase decisions. My average estimate suggests that the effect of the Energy Star label alone could increase sales of a particular refrigerator model in a range of 7 to 15%.

My analysis goes one step further and quantifies the welfare effects of the program. Performing various counterfactual scenarios, I find that Energy Star might not lead to more energy efficient choices, on average. I show that the program can partly crowd out efforts to fully account for energy costs, which ultimately reduces the market shares of highly energy efficient refrigerator models. I find that this effect is amplified if we account for the fact that without Energy Star, firms might discriminate more in the energy efficiency dimension. Overall, Energy Star might not contribute to mitigate negative externalities associated with energy intensive durables.
Whether consumers benefit from Energy Star is also unclear. I find that consumers would be better-off if manufacturers were to only offer products that just meet the minimum energy efficiency standard, even after accounting for the externality costs. Put simply, consumers would be better off paying lower prices for refrigerators.

Finally, I find that firms tend to benefit from Energy Star (Scenarios 3 and 4). This has a number of implications. If the US EPA were to remove Energy Star, we could expect that firms will respond by offering their own certification program. A world without Energy Star might thus not correspond to a world without certification for energy efficiency.

The welfare analysis should be interpreted with a number of caveats. First, refrigerator manufacturers presumably optimize dynamically when making product lines and pricing decisions. Revisions in the specifications of the Energy Star program will lead to a different market dynamic. Ideally, the welfare impacts should be measured along a dynamic path, not at a steady-state static equilibrium. Moreover, it should be noted that the demand estimation was carried out on a restricted sample of transactions for a particular retailer. These consumers may not be entirely representative of the whole US refrigerator market. For instance, I find that there is a significant share of consumers that seem to account to electricity costs in their purchasing decision. This share is likely to be lower in a sample that includes renters, and firms such as home builders.

My demand model allows me to elicit a rich set of preferences for energy efficiency accounting for both consumer heterogeneity and sophistication. Perhaps one of the most interesting results from the estimation is the fact that consumers with different income levels respond differently to the Energy Star certification and discount electricity costs at different rates. This result has important implications for the design of energy policies and their distributional effects. As proposed by Allcott, Mullainathan, and Taubinsky (2011), this suggests that there is a greater role for using screening and targeting mechanisms in the design of energy policies.

References


Muller, N. Z., and R. Mendelsohn (2012): “Efficient Pollution Regulation: Getting the Prices Right: Corrigendum (Mortality Rate Update),” American Economic Review, 102(1).


9. Figures

![Energy Star and EnergyGuide labels](image)

**Figure 1.** Energy Star and EnergyGuide labels
Figure 3. Normalized Sales for Different Energy Efficiency Levels, Before and After the 2008 Revision in Energy Star Standard.
Figure 4. Correlation Between Sales and Prices

Figure 5. Correlation Between Energy Efficiency and Electricity Price
Figure 6. Correlation Between Market Share Energy Star and Rebates
Figure 7. (a) Consumers with expectations about energy costs for each model. $s$ represents the Energy Star standard. (b) Consumers that rely on Energy Star. $D = 1$ models certified Energy Star, zero otherwise. (c) Consumers that Dismiss Energy Costs. (d)-(f) Change in consumer preferences after revision of the Energy Star standard $s \to s'$. 
Figure 8. Nested Logit Structure
Figure 9. Joint Estimated Density of Sensitivity to Energy Star and Electricity Costs. The colored areas identified the regions with a positive density. The red areas are the regions with the highest density.
Figure 10. Implicit Discount Rate vs. Sensitivity to Energy Star Under Perfect Information ($e = h$)
(a) Probability that consumer $i$ does not pay attention to energy information.

(b) Probability that consumer $i$ pays attention to Energy Star only.

(c) Probability that consumer $i$ pays attention to all energy information.

**Figure 11.** Empirical Distribution of Effort Choice Probabilities.
(a) Scenario 1: No Firms’ Responses.

(b) Scenario 2: Bunching at the Minimum Standard.

(c) Scenario 3: Oligopoly Model.

(d) Scenario 4: Oligopoly Model, Sensitivity Test.

Figure 12. Choice Sets for Welfare Analysis.
### Table 1. Multinomial Logit with Outside Option: OLS and 2SLS Estimates

<table>
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<tr>
<th></th>
<th>(1) OLS</th>
<th>(2) OLS</th>
<th>(3) OLS</th>
<th>(4) OLS</th>
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**Note:** Only sales for the year 2008 of the 20\% most popular refrigerators are considered. The dependent variable is the log of the weekly quantity sold of product \(j\) in State \(r\). One sale has been added to each market (regionXtime). Prices, rebates, and electricity costs are measured in hundreds of dollars. Energy Star is a dummy variable that takes the value one if the refrigerator is certified Energy Star at time \(t\), and zero otherwise. Elasticities are evaluated at means. Models 1-4 are estimated via ordinary least squares (OLS). Models 5 and 6 use prices in other states as instruments for prices: average weekly prices in California are used to instrument weekly prices in other states, and average weekly prices in New-York are used to instrument weekly prices in California. Models 5 and 6 estimated via two stage least squares (2SLS). Standard errors are clustered at the product level.
Table 2. Multinomial and Nested Logit: MLE Estimates

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</tr>
<tr>
<td>Energy Star ($\hat{\tau}$)</td>
<td>0.155</td>
<td>0.161</td>
<td>0.124</td>
<td>0.080</td>
<td>0.073</td>
<td>0.122</td>
<td>0.266</td>
</tr>
<tr>
<td></td>
<td>(0.029)</td>
<td>(0.029)</td>
<td>(0.024)</td>
<td>(0.019)</td>
<td>(0.020)</td>
<td>(0.031)</td>
<td>(0.079)</td>
</tr>
<tr>
<td>Rebate ($\hat{\psi}$)</td>
<td>0.060</td>
<td>0.094</td>
<td>0.050</td>
<td>0.100</td>
<td>0.040</td>
<td>0.057</td>
<td>0.100</td>
</tr>
<tr>
<td></td>
<td>(0.036)</td>
<td>(0.036)</td>
<td>(0.045)</td>
<td>(0.060)</td>
<td>(0.056)</td>
<td>(0.040)</td>
<td>(0.028)</td>
</tr>
<tr>
<td>Electricity Costs ($\hat{\theta}$)</td>
<td>-2.26</td>
<td>-2.16</td>
<td>-2.33</td>
<td>-2.38</td>
<td>-1.87</td>
<td>-1.33</td>
<td>-2.77</td>
</tr>
<tr>
<td></td>
<td>(0.146)</td>
<td>(0.145)</td>
<td>(0.132)</td>
<td>(0.159)</td>
<td>(0.164)</td>
<td>(0.209)</td>
<td>(0.300)</td>
</tr>
<tr>
<td>Nb of Models</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.054</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.004)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Product FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>BrandXWeek FE</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Nested Logit</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Sub-Sample Size</td>
<td>$N_1$</td>
<td>1.5$N$</td>
<td>$N$</td>
<td>$N$</td>
<td>$N$</td>
<td>$N$</td>
<td>$N_2010$</td>
</tr>
</tbody>
</table>

Note: All models are estimated via maximum likelihood on a sub-sample of transactions. Model 1 is the base specification. The coefficient on price is negative and significant, and corresponds to a price elasticity of -6.29 (Table 3). The coefficient on the Energy Star dummy is positive and significant, and corresponds to a 15.5% increase in market share. The coefficient on rebates is positive and not statistically significant. The coefficient on electricity costs is negative and significant, and corresponds to an implied discount rate ranging from 17.2% to 20.3% (Table 3). Models 2-6 are robustness tests. Model 2 estimates the model on a larger sub-sample of transactions to investigate the incidental parameter problem. Estimates are robust to the size of the sample size. Model 3 adds brand-week fixed effects to account for nation-wide marketing campaigns enacted with promotions. Models 4 and 5 add correlation in the error terms using a nested logit (see Figure 8). Model 5 also adds the number of models in each nest as a covariate. A positive estimate means that models in a given nests are more likely to be chosen the larger the nest is. For Model 6, household specific consideration sets are inferred using information about size purchased. For household i, all refrigerator models that are no smaller or larger than 3 cu. ft. of the refrigerator purchased are assumed to be in the consideration set. Consideration sets are a subset of the refrigerators available at the store visited by household i. Model 7 estimates the base model on a different sub-sample corresponding to year 2009-2010. The change in certification of 16 refrigerator models in January 2010 is used to identify the label effect. For all Models, prices, rebates, and electricity costs are measured in hundreds of dollars. Asymptotic standard errors in parentheses.
### Table 3. Interpretation Multinomial Logit Model

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
<th>Elasticity</th>
<th>Odd Ratio</th>
<th>Related Structural Parameter</th>
<th>Implied Estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price ($\hat{\eta}$)</td>
<td>-0.459 (0.005)</td>
<td>-6.29 (0.069)</td>
<td>Marginal utility of income</td>
<td>same</td>
<td></td>
</tr>
<tr>
<td>Energy Star ($\hat{\tau}$)</td>
<td>0.155 (0.029)</td>
<td>1.17 (0.034)</td>
<td>Label Effect</td>
<td>same</td>
<td></td>
</tr>
<tr>
<td>Rebate ($\hat{\psi}$)</td>
<td>0.059 (0.035)</td>
<td>1.03 (0.036)</td>
<td>Probability of taking rebate ($\hat{\psi} = \hat{\eta} \cdot \hat{\pi}$)</td>
<td>0.130</td>
<td></td>
</tr>
<tr>
<td>Electricity Costs ($\hat{\theta}$)</td>
<td>-2.26 (0.146)</td>
<td>-1.35 (0.087)</td>
<td>Implicit discount rate, $\hat{\theta} = \hat{\eta} \cdot \frac{1 - \rho}{1 - \rho}$</td>
<td>$r_{L=12} = 0.172$</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>$r_{L=18} = 0.194$</td>
<td></td>
</tr>
</tbody>
</table>

Note: Estimates from Model 1 (Table 2) are reported with elasticities and odd ratios evaluated at the means. Prices, rebates, and electricity costs are measured in hundreds of dollars. The last two columns provide the interpretation of the estimates in terms of related structural parameters. The sensitivity to rebate can be interpreted as the marginal utility of income multiplied by the probability of taking advantage of the rebate program. The implicit discount rate is computed assuming that consumers’ expectations about annual electricity costs are constant and computed for different expectations of the lifetime of a refrigerator. Asymptotic standard errors used for the estimates and the delta method is used to compute standard errors for the elasticities and odd ratios.
### Table 4. Latent Class Model

<table>
<thead>
<tr>
<th></th>
<th>Latent Class 1</th>
<th>Latent Class 2</th>
<th>Latent Class 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price ($\hat{\eta}$)</td>
<td>-0.560</td>
<td>-0.430</td>
<td>-0.510</td>
</tr>
<tr>
<td>(0.021)</td>
<td>(0.002)</td>
<td>(0.005)</td>
<td></td>
</tr>
<tr>
<td>Energy Star ($\hat{\tau}$)</td>
<td>0.689</td>
<td>0.192</td>
<td>0.078</td>
</tr>
<tr>
<td>(0.126)</td>
<td>(0.020)</td>
<td>(0.042)</td>
<td></td>
</tr>
<tr>
<td>Rebate ($\hat{\psi}$)</td>
<td>-0.050</td>
<td>0.000</td>
<td>0.230</td>
</tr>
<tr>
<td>(0.274)</td>
<td>(0.061)</td>
<td>(0.111)</td>
<td></td>
</tr>
<tr>
<td>Electricity Costs ($\hat{\theta}$)</td>
<td>0.590</td>
<td>-1.510</td>
<td>-4.660</td>
</tr>
<tr>
<td>(0.480)</td>
<td>(0.090)</td>
<td>(0.2670)</td>
<td></td>
</tr>
<tr>
<td>Latent Probability (mean)</td>
<td>0.099</td>
<td>0.625</td>
<td>0.277</td>
</tr>
</tbody>
</table>

Demographic: Yes  
Product FE: Yes

*Note:* Results from the random coefficient logit with three latent classes estimated with a two-step maximum likelihood method. The first step estimates a multinomial logit model with product fixed effects. The second step treats the product fixed effects as parameters and estimates the behavioral parameters for the three latent classes, and the latent class probabilities. Asymptotic standard errors are computed using the Murphy and Topel (1985)'s approach. The likelihood is constructed with individual choice probabilities for a sub-sample of transactions (same sub-sample used to estimate Model 1, 2). Demographic information (income, education, family size, and age of the head of the household) enters the choice probabilities. The latent probabilities reported correspond to the average probability, where the average is taken over all the consumers in the sub-sample. Prices, rebates, and electricity costs are measured in hundreds of dollars.
Table 5. Interpretation Information Acquisition Model

<table>
<thead>
<tr>
<th></th>
<th>Estimate</th>
<th>Elasticity</th>
<th>Odd Ratio</th>
<th>Related Structural Parameter</th>
<th>Implied Estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price ($\hat{\eta}$)</td>
<td>-0.460</td>
<td>-6.30</td>
<td></td>
<td>Marginal utility</td>
<td>same</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.010)</td>
<td></td>
<td>of income</td>
<td></td>
</tr>
<tr>
<td>Energy Star ($\hat{\tau}^h$)</td>
<td>0.079</td>
<td>0.079</td>
<td>1.08</td>
<td>Label Effect</td>
<td>same</td>
</tr>
<tr>
<td></td>
<td>(0.020)</td>
<td>(0.020)</td>
<td>(0.021)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Energy Star ($\hat{\tau}^m$)</td>
<td>0.778</td>
<td>0.778</td>
<td>2.18</td>
<td>Label Effect</td>
<td>same</td>
</tr>
<tr>
<td></td>
<td>(0.154)</td>
<td>(0.154)</td>
<td>(0.336)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rebate ($\hat{\psi}$)</td>
<td>0.096</td>
<td>0.049</td>
<td>1.05</td>
<td>Probability of taking rebate ($\hat{\tau}$), $\hat{\psi} = \hat{\eta} \cdot $</td>
<td>0.012</td>
</tr>
<tr>
<td></td>
<td>(0.045)</td>
<td>(0.023)</td>
<td>(0.047)</td>
<td>implicit discount</td>
<td>rL=12 =0.059</td>
</tr>
<tr>
<td>Electricity Costs ($\hat{\theta}$)</td>
<td>-3.87</td>
<td>-2.32</td>
<td></td>
<td>Rate, $\hat{\theta} = \hat{\eta} \cdot \frac{1 - \hat{\rho}}{1 - \hat{\rho}}$</td>
<td>rL=18 =0.096</td>
</tr>
<tr>
<td></td>
<td>(0.099)</td>
<td>(0.059)</td>
<td></td>
<td>$\hat{\rho} = \frac{1}{1+\hat{\rho}}$</td>
<td>rL=∞ =0.118</td>
</tr>
</tbody>
</table>

Note: Results from the information acquisition model estimated by simulated maximum likelihood. Product fixed effects are treated as parameters and asymptotic standard errors are adjusted using the Murphy and Topel (1985)'s approach. Monte Carlo integration is used to compute expectations about electricity costs, the Energy Star threshold (meaning of Energy Star) and the probability that a refrigerator is certified. Integration over beliefs approximated with 50 draws from the joint distribution of beliefs. The prior for the electricity costs is a normal distribution corresponding to the true distribution of electricity costs for refrigerators in the region where each consumer lives. The prior for the Energy Star threshold is a uniform distribution. The prior for the probability of certification is a binomial distribution where the probability that a refrigerator is certified is set equal to the share of Energy Star products in the choice set faced by each consumer. The likelihood is constructed with individual choice probabilities for a sub-sample of transactions. The sub-sample is the same than the one used for estimating Model 1, Table 2. Prices, rebates, and electricity costs are measured in hundreds of dollars. Elasticities and odd ratios are evaluated at the means. Delta method is used to compute standard errors for the elasticities and odd ratios.
<table>
<thead>
<tr>
<th></th>
<th>All</th>
<th>Income</th>
<th>Income</th>
<th>Income</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>&lt;$50,000</td>
<td>≥$50,000 &amp; &lt;$100,000</td>
<td>≥$100,000</td>
</tr>
<tr>
<td><strong>Multinomial Logit</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Price ($\hat{\eta}$)</td>
<td>-0.459</td>
<td>-0.589</td>
<td>-0.483</td>
<td>-0.404</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.008)</td>
<td>(0.007)</td>
<td>(0.006)</td>
</tr>
<tr>
<td>Energy Star ($\hat{\tau}$)</td>
<td>0.155</td>
<td>0.056</td>
<td>0.114</td>
<td>0.187</td>
</tr>
<tr>
<td></td>
<td>(0.029)</td>
<td>(0.032)</td>
<td>(0.038)</td>
<td>(0.038)</td>
</tr>
<tr>
<td>Rebate ($\hat{\psi}$)</td>
<td>0.060</td>
<td>0.053</td>
<td>0.085</td>
<td>-0.013</td>
</tr>
<tr>
<td></td>
<td>(0.036)</td>
<td>(0.048)</td>
<td>(0.043)</td>
<td>(0.048)</td>
</tr>
<tr>
<td>Electricity Costs ($\hat{\theta}$)</td>
<td>-2.267</td>
<td>-0.513</td>
<td>-1.343</td>
<td>-2.045</td>
</tr>
<tr>
<td></td>
<td>(0.146)</td>
<td>(0.160)</td>
<td>(0.197)</td>
<td>(0.191)</td>
</tr>
<tr>
<td><strong>Information Acquisition Model</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Price ($\hat{\eta}$)</td>
<td>-0.460</td>
<td>-0.574</td>
<td>-0.480</td>
<td>-0.400</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Energy Star ($\hat{\tau}^h$)</td>
<td>0.079</td>
<td>-0.036</td>
<td>0.085</td>
<td>0.125</td>
</tr>
<tr>
<td></td>
<td>(0.020)</td>
<td>(0.020)</td>
<td>(0.031)</td>
<td>(0.027)</td>
</tr>
<tr>
<td>Energy Star ($\hat{\tau}^m$)</td>
<td>0.778</td>
<td>0.261</td>
<td>0.286</td>
<td>0.497</td>
</tr>
<tr>
<td></td>
<td>(0.154)</td>
<td>(0.096)</td>
<td>(0.074)</td>
<td>(0.037)</td>
</tr>
<tr>
<td>Rebate ($\hat{\psi}$)</td>
<td>0.096</td>
<td>0.023</td>
<td>0.110</td>
<td>0.010</td>
</tr>
<tr>
<td></td>
<td>(0.045)</td>
<td>(0.173)</td>
<td>(0.057)</td>
<td>(0.051)</td>
</tr>
<tr>
<td>Electricity Costs ($\hat{\theta}$)</td>
<td>-3.870</td>
<td>-3.441</td>
<td>-3.090</td>
<td>-3.410</td>
</tr>
<tr>
<td></td>
<td>(0.100)</td>
<td>(0.211)</td>
<td>(0.175)</td>
<td>(0.183)</td>
</tr>
</tbody>
</table>

**Note:** The top panel corresponds to the estimates of the base model (Model 1, Table 2) estimated for different income groups. The estimates in the first column are from the base model with all income groups, and are presented for comparison purpose. The bottom panel presents the estimates from the information acquisition model. The estimation is carried under the same assumptions than for the model presented in Table 5, but for each income group separately.
Table 7. Effort Choice Probabilities: Information Acquisition Model

<table>
<thead>
<tr>
<th></th>
<th>All Income</th>
<th></th>
<th>Income</th>
<th></th>
<th>Income</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>&lt;$50,000</td>
<td>≥$50,000 &amp; &lt;$100,000</td>
<td>≥$100,000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Q(h)</td>
<td>.528</td>
<td>.384</td>
<td>.431</td>
<td>.564</td>
<td></td>
</tr>
<tr>
<td>Q(m)</td>
<td>.241</td>
<td>.092</td>
<td>.268</td>
<td>.362</td>
<td></td>
</tr>
<tr>
<td>Q(l)</td>
<td>.231</td>
<td>.614</td>
<td>.301</td>
<td>.073</td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>.325</td>
<td>.383</td>
<td>.339</td>
<td>.330</td>
<td></td>
</tr>
<tr>
<td>sd</td>
<td>.186</td>
<td>.017</td>
<td>.204</td>
<td>.336</td>
<td></td>
</tr>
<tr>
<td>25th</td>
<td>.219</td>
<td>.012</td>
<td>.093</td>
<td>.249</td>
<td></td>
</tr>
<tr>
<td>50th</td>
<td>.538</td>
<td>.227</td>
<td>.384</td>
<td>.639</td>
<td></td>
</tr>
<tr>
<td>75th</td>
<td>.843</td>
<td>.797</td>
<td>.762</td>
<td>.873</td>
<td></td>
</tr>
</tbody>
</table>

Note: Summary statistics for the estimated effort choice probabilities in the information acquisition model (Table 6). Choice probabilities vary as a function of demographic information: income, education, age of the head of the household and family size. The choice probability for each effort level are computed for all consumers in the sub-sample. The mean, standard deviation, and percentiles are computed for the distribution of choice probabilities in the sub-sample of consumers.
### Table 8. Emission Factors and Externality Costs

<table>
<thead>
<tr>
<th>Non-baseload Output Emission Rates (U.S. Average)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Pollutant</td>
<td>Estimate</td>
</tr>
<tr>
<td>$CO_2$ $a$</td>
<td>1,583 lb/MWh</td>
</tr>
<tr>
<td>$CH_4$ $a$</td>
<td>35.8 lb/GWh</td>
</tr>
<tr>
<td>$N_2O$ $a$</td>
<td>19.9 lb/GWh</td>
</tr>
<tr>
<td>$SO_2$</td>
<td>6.13 lb/MWh</td>
</tr>
<tr>
<td>$NO_x$</td>
<td>2.21 lb/MWh</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Damage Cost (2008 $)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Pollutant</td>
<td>Low Estimate</td>
</tr>
<tr>
<td>$CO_2$</td>
<td>$21.8/t$</td>
</tr>
<tr>
<td>$SO_2$</td>
<td>$2,060/t$</td>
</tr>
<tr>
<td>$NO_x$</td>
<td>$380/t$</td>
</tr>
</tbody>
</table>

Note: (a) Externality costs associated to $CH_4$ and $N_2O$ are assumed to be the same than for $CO_2$. $CH_4$ and $N_2O$ are converted in CO2 equivalent using estimates of global warming potential (GWP). The GWP used for $CH_4$ is 25, and the GWP used for $N_2O$ is 298. Source: IPCC Fourth Assessment Report: Climate Change 2007. (b) Estimate used in the illustrative analysis of the 2012 regulatory impact analysis for the proposed standards for electric utility generating units. (c) Higher value of the estimate used in the Federal Rule for new minimum energy-efficiency standards for refrigerators (1904-AB79).
Table 9. Estimates: Marginal Cost of Providing Energy Efficiency

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Hedonic</td>
<td>Hedonic w. GAM</td>
<td>Hedonic w. Interaction</td>
</tr>
<tr>
<td>Dependent Variable:</td>
<td>log(Manufacturer Price)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \phi )</td>
<td>46.7</td>
<td>40.1</td>
<td>343.1</td>
</tr>
<tr>
<td>( \phi \times D_{\text{Side-by-Side}} )</td>
<td>26.6</td>
<td>26.8</td>
<td>38.9</td>
</tr>
<tr>
<td>( \phi \times D_{\text{Bottom-Freezer}} )</td>
<td>-</td>
<td>-</td>
<td>-499.4</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>-</td>
<td>-475.7</td>
</tr>
<tr>
<td>Nb of Models</td>
<td>3424</td>
<td>3424</td>
<td>3424</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.872</td>
<td>0.874</td>
<td>0.876</td>
</tr>
</tbody>
</table>

Note: Model 1 shows that the manufacturer prices are increasing with energy efficiency level. Energy efficiency is the inverse of the annual electricity consumption of a refrigerator (1/kwh). Model 2 uses a generalized additive model to control for the effect of size. Model 3 interacts dummies for refrigerator type with energy efficiency. The dummy for top-freezer is omitted. To obtain the slope of the cost function as a function of energy efficiency for side-by-side and bottom-freezer refrigerators, the first estimate needs to be added to, respectively, the second and third estimates. All models control for the following attributes: dummies for refrigerator type (top-freezer, side-by-side or bottom-freezer), size interacted with dummies for refrigerator type, size interacted with dummies for overall quality (low: price < $1,000, medium: price > $1,000 & price < $2,800, high: price > $2,800), dummy for ice-maker, dummy for defrost technology (automatic vs. manual), dummy for water dispenser, dummy for an advance cooling technology, dummy for an air filtration technology, dummy for indoor lighting using LED, dummies for brand, and dummies for year the refrigerator entered the market.
### Table 10. The Effects of Removing the Energy Star Standard

<table>
<thead>
<tr>
<th>Scenario 1</th>
<th>Scenario 2</th>
<th>Scenario 3</th>
<th>Scenario 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Firms’ Responses</td>
<td>w Firms’ Responses</td>
<td>w Firms’ Responses</td>
<td>w Firms’ Responses</td>
</tr>
<tr>
<td>Bunching at the Minimum Standard</td>
<td>Marginal Costs x2</td>
<td>Oligopoly Model</td>
<td>Oligopoly Model</td>
</tr>
<tr>
<td>( \Delta_{\text{without ES} - \text{with ES}} )</td>
<td>( \Delta_{\text{without ES} - \text{with ES}} )</td>
<td>( \Delta_{\text{without ES} - \text{with ES}} )</td>
<td>( \Delta_{\text{without ES} - \text{with ES}} )</td>
</tr>
<tr>
<td>Mean</td>
<td>Std</td>
<td>Mean</td>
<td>Std</td>
</tr>
<tr>
<td>Avg kWh Purchased (kWh/year)</td>
<td>-5.23</td>
<td>0.27</td>
<td>54.57</td>
</tr>
<tr>
<td>Externality Cost Low Damage (M$/year)</td>
<td>-1.14</td>
<td>0.06</td>
<td>11.86</td>
</tr>
<tr>
<td>Externality Cost High Damage (M$/year)</td>
<td>-3.74</td>
<td>0.19</td>
<td>39.05</td>
</tr>
<tr>
<td>Avg Price Paid ($)</td>
<td>-8.29</td>
<td>0.48</td>
<td>-82.49</td>
</tr>
<tr>
<td>Consumer Surplus (M$/year)</td>
<td>-4327.47</td>
<td>216.90</td>
<td>-4300.58</td>
</tr>
<tr>
<td>Consumer Surplus w/o Search Cost (M$/year)</td>
<td>-1.14</td>
<td>0.06</td>
<td>11.86</td>
</tr>
<tr>
<td>Total Consumer Surplus w/o Search Cost &amp; w/o Label Effect (( \tau )) (M$/year)</td>
<td>4.56</td>
<td>0.61</td>
<td>31.94</td>
</tr>
<tr>
<td>Profits (M$/year)</td>
<td>54.23</td>
<td>4.02</td>
<td>-776.59</td>
</tr>
<tr>
<td>Welfare Low Damage (M$/year)</td>
<td>-4272.10</td>
<td>216.37</td>
<td>-5089.03</td>
</tr>
<tr>
<td>Welfare High Damage (M$/year)</td>
<td>-4269.50</td>
<td>216.31</td>
<td>-5116.21</td>
</tr>
<tr>
<td>Welfare Low Damage, w/o Search Cost (M$/year)</td>
<td>56.28</td>
<td>4.26</td>
<td>-756.51</td>
</tr>
<tr>
<td>Welfare High Damage, w/o Search Cost (M$/year)</td>
<td>58.88</td>
<td>4.33</td>
<td>-783.70</td>
</tr>
<tr>
<td>Welfare Low Damage, w/o Search Cost &amp; w/o Label Effect (( \tau )) (M$/year)</td>
<td>59.93</td>
<td>4.24</td>
<td>-752.88</td>
</tr>
<tr>
<td>Welfare High Damage, w/o Search Cost &amp; w/o Label Effect (( \tau )) (M$/year)</td>
<td>62.53</td>
<td>4.31</td>
<td>-780.07</td>
</tr>
</tbody>
</table>

**Note:** For each scenario, 50 simulations of the demand model were performed. Each simulation takes a random draw of parameter values from the estimated distributions. For each simulation, the differences between the metrics obtained for the state of the world without Energy Star and the state of the world with Energy Star are computed. For each scenario, the first and second columns report respectively the mean and the standard deviation of the difference in various metrics for the 50 simulations. The externality costs are computed for two estimates of the dollar value of the damage associated to electricity generation. The market size for refrigerators is assumed to be 9.01 millions. The consumer surplus is converted to an annual measure by assuming that consumers will own (and believe they will own) their refrigerators for 18 years. The total welfare is the sum of the total consumer surplus, externality costs, and produced surplus. The last four rows report different estimates of the welfare effects. The welfare estimates without search costs exclude the cost of collecting and processing information from the consumer surplus. The last two rows present welfare estimates where both the search costs and the label effect, captured by the parameter \( \tau \), are excluded. All dollar figures are in 2008 dollars.
### Table 11. Summary Statistics Oligopoly Outcomes: Product Lines and Pricing Decisions

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Mean Estimate: $\phi=40.1$</th>
<th>High Marginal Cost: $\phi = 2 \times 40.1$</th>
</tr>
</thead>
<tbody>
<tr>
<td>kWh offered (kWh/y)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average</td>
<td>539.83</td>
<td>492.63</td>
</tr>
<tr>
<td>25\textsuperscript{th} percentile</td>
<td>473.36</td>
<td>427.52</td>
</tr>
<tr>
<td>50\textsuperscript{th} percentile</td>
<td>579.30</td>
<td>539.79</td>
</tr>
<tr>
<td>75\textsuperscript{th} percentile</td>
<td>679.71</td>
<td>587.46</td>
</tr>
<tr>
<td>Price offered ($)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average</td>
<td>1203.12</td>
<td>1447.88</td>
</tr>
<tr>
<td>25\textsuperscript{th} percentile</td>
<td>744.90</td>
<td>920.88</td>
</tr>
<tr>
<td>50\textsuperscript{th} percentile</td>
<td>1076.42</td>
<td>1299.05</td>
</tr>
<tr>
<td>75\textsuperscript{th} percentile</td>
<td>1532.12</td>
<td>1921.39</td>
</tr>
</tbody>
</table>
Appendix A. Comparative Statics Results

Information Acquisition Costs. Naturally, we should expect that 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 $K(l) = K(h)$, it is optimal for the consumer to select $e = h$.

(ii) Suppose that Energy Star information is available. If $K(l) = K(m) = K(h)$, it is optimal for the consumer to select $e = h$. Moreover, if $K(l) = K(m)$, $e = m$ is strictly better than $e = l$ 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 $\{Y_1, Y_2, \ldots, Y_k\}$. The distribution of $\max_{1 \leq j \leq k} \{Y_j\}$ (first order) stochastically dominates the distribution of $Y_l$ for any $l \in \{1, \ldots, k\}$. This implies that $E[\max_{1 \leq j \leq k} Y_j] \geq E[Y_l]$ for $l = 1, \ldots, k$, and thus,

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

To show (i), it suffices to show that

\[
E_{e,C} \left[ \max_{j} \{U_{i,j}(\delta_j, \eta P_j, C_j, \epsilon_{i,j})\} \right] \geq E_{e} \left[ \max_{j} \{E_{C}[U_{i,j}(\delta_j, \eta P_j, C_j, \epsilon_{i,j})]\} \right],
\]

which implies that 2 holds for $K = 0$. We will show a stronger inequality; in particular, that for any $\epsilon_{ij}$,

\[
E_{C} \left[ \max_{j} \{U_{i,j}(\delta_j, \eta P_j, C_j, \epsilon_{i,j})\} \right] \geq \max_{j} \{E_{C}[U_{i,j}(\delta_j, \eta P_j, C_j, \epsilon_{i,j})]\}.
\]

We observe that this follows from (26) if we set $Y_j \equiv U_{i,j}(\delta_j, \eta P_j, C_j, \epsilon_{i,j})$.

This concludes the proof for (i).

**Crowding-Out Effect.** A simple, but important implication to 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 than to not collect information at all, but could prefer a medium level of effort than a maximum one. Formally,

**Corollary 1.** If $K(m) < K(h)$, then for some consumers $V(l) > V(h) < V(m)$

**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.
Uncertainty about Energy Costs. The present model stipulates that uncertainty in beliefs is the main driver that induces consumers to search for energy information. Therefore, the model should predict that the larger the uncertainty in beliefs, the more likely consumers are to search.

I now show this result. I focus on the case that consumers' beliefs become more uncertain, but remain unbiased. This scenario is notably consistent with Allcott (2010)'s findings that shows that consumers' beliefs about future gas prices are on average unbiased, but largely uncertain.

Consider the following definition. Beliefs about \( X \) represented by a distribution \( \hat{F} \) are more uncertain than beliefs \( F \) if \( F \) second order stochastically dominates \( \hat{F} \):

\[
\int_{b}^{b} F(x)dx \geq \int_{b}^{b} \hat{F}(x)dx
\]

for all \( b \).

**Proposition 2.** If \( \hat{X}_j \sim \hat{F}, \forall j \) and \( X_j \sim F, \forall j \), with \( \int_{b}^{b} F(x)dx \geq \int_{b}^{b} \hat{F}(x)dx \) for all \( b \), then

\[
E_{\epsilon,X,S} \left[ \max_j \{U_{ij}(\delta_j, \eta P_j, X_j(S), \epsilon, \epsilon_j)\} | I(\epsilon) \right] \geq E_{\epsilon,\hat{X},S} \left[ \max_j \{U_{ij}(\delta_j, \eta P_j, \hat{X}_j(S), d, \epsilon, \epsilon_j)\} | I(\epsilon) \right]
\]

**Proof.** First note that by the definition of second order stochastically dominance, if \( X_j \) second-order stochastically dominates \( \hat{X}_j \), and if \( X_j \) and \( \hat{X}_j \) have the same mean, then \( E[h(X_j)] \geq E[h(\hat{X}_j)] \) for all concave function \( h \). Given that the maximum is a concave function, we then have \( E[h(X_j,Y)] \geq E[h(\hat{X}_j,Y)] \) for any variable \( Y \).

Proposition 2 simply says that the larger the variance in energy costs, the higher is the value of information. This also implies that Energy Star will lead to more sub-optimal choices, in expectation, in choice sets where products are largely disperse in the energy efficiency characteristics space.
Appendix B. Data Cleaning and Manipulation

Creating a Random Sample. To perform the estimation of the demand model, a random sub-sample of the transactions is used. The sub-sample is constructed as follow.

First, the sub-sample 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 that one refrigerator purchase in any given year.

Second, I employ the following stratified sampling method to create the sub-sample. For a given targeted sample size, I sample transactions in each state so that the state market shares in the sub-sample are equal to the state market shares in the restricted sample. Sampling is done at the store level. That is, I first randomly select a store in each state and then keep a number of transactions from this store, also randomly selected, to match state market shares. If needed, I sample additional stores until I match state market shares.

The main motivation to sample at the store level is to restrict the number of choice sets that need to be imputed. Moreover, if one is concerned about endogeneity problems that could be eliminated with store fixed effects, the present approach allows me to limit the number of fixed effects to estimate.

Average Electricity Prices. The use of average electricity prices is partly motivated by recent empirical evidence (Borenstein (2010), Ito (2010)) that suggests that electricity consumers may in fact respond to variation in average prices, more than marginal prices. In the present case, the use of average electricity prices is also dictated by the fact that household’s 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 follow. Using form EIA-861 of the Energy Information Administration, I compute the average residential electric price for each electric utility operating in the US for the years 2008. I then match electric utility territories with each of the 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 average price to construct the county level price. Ideally, we would like to weight prices by the number of consumers served by each utility. However, this information is not available at the county level.

Appendix C. FKRB’s Estimator

The FKRB’s estimator models the CDF of the random parameters as a mixture of point masses. Alternatively, FKRB propose to estimate a smooth density by modeling the distribution of the parameters as a mixture of normal densities. This requires to specify $M$ normal basis functions with a predetermined mean and variance, and use simulation to construct the estimator.

In particular, the $m^{th}$ basis function is defined as the product of the marginals of the $K$ random parameters:

$$N(\beta|\mu^m, \sigma^m) = \prod_{k=1}^{K} N(\beta|\mu_k^m, \sigma_k^m)$$
The simulated choice probability is thus given by:

\[
H_{ijrt} \approx \sum_{m} \alpha_{m} \left( \frac{1}{S} \sum_{s=1}^{S} H_{ijrt|\beta_{m,s}} \right)
\]

where \(\beta_{m,s}\) is the \(s^{th}\) draw from the \(r^{th}\) normal basis. The estimate of \(\alpha\) is thus given by:

\[
\hat{\alpha} = \underset{\alpha}{\operatorname{argmin}} \frac{1}{N} \sum_{i=1}^{I} \sum_{j=1}^{J} \left( y_{ijrt} - \sum_{m} \alpha_{m} \left( \frac{1}{S} \sum_{s=1}^{S} H_{ijrt|\beta_{m,s}} \right) \right)
\]

s.t.

\[
\sum_{m} \alpha_{m} = 1, \quad \alpha_{m} \geq 0
\]

For my application, I take \(\eta, \psi\) and \(\gamma_{j}\) as data, and fix them at their MLE estimates (Model 1, Table 2). I model the joint density of the parameters \(\theta\) and \(\tau\) as a mixture of \(M = 108\) normal basis functions. To construct the basis functions, I use 9 marginals for the parameter \(\theta\), and 11 marginals for the parameter \(\tau\). The means of the marginal are defined relative to their MLE estimates (\(\hat{\tau} = 0.155, \hat{\theta} = -2.26\)). In particular, the means of the marginals for the parameter \(\theta\) are: \(\{2.25\hat{\theta}, 2\hat{\theta}, 1.75\hat{\theta}, 1.25\hat{\theta}, \hat{\theta}, 0.75\hat{\theta}, 0.5\hat{\theta}, 0.25\hat{\theta}, 0.05\hat{\theta}\}\). The means of the marginals for the parameter \(\tau\) are: \(\{8\hat{\tau}, 6\hat{\tau}, 4\hat{\tau}, 2.5\hat{\tau}, 1.75\hat{\tau}, 1.25\hat{\tau}, \hat{\tau}, 0.75\hat{\tau}, 0.5\hat{\tau}, 0.25\hat{\tau}, 0\}\). For each marginal, I set the standard deviation as being equal to 0.1% of the mean. The estimation is carried with the matlab package lsqlin.