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Consumer response to energy label policies: Evidence from the Brazilian energy label program[☆]

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ABSTRACT

The PBE program made the adoption of energy labels mandatory in the Brazilian refrigerator market. In this paper, we examine the effects of PBE using data from a nationally representative sample of households and a structural model of appliance choice. We document a modest increase in the valuation of energy costs by Brazilian consumers. However, the program is unable to eliminate the energy efficiency gap, in that consumers undervalue energy costs both pre-and post-PBE. Moreover, our policy simulation documents little product switching and heterogeneity in responses. All in all, while the PBE program aimed to both reduce energy consumption and increase energy efficiency, we can only claim robust evidence of the latter.

1. Introduction

Information programs have been introduced in several countries in the past three decades to help mitigate both informational and behavioral issues arising upon the purchase of energy-intensive products, chief among them the energy efficiency gap (EEG).[1] These programs, which have been termed the "third wave" of pollution control (Tietenberg, 1998), and of which energy labels are a leading particular case, are one way to mitigate the consequences of asymmetric information arising from the unobservability of energy efficiency by consumers. To do so, energy labels mandate the display of information of energy-related data in each appliance.[2] For instance, a number of programs aim to induce energy efficient choices by providing information about energy consumption, energy efficiency, potential energy savings, or examples of energy savings.[3]

Energy labels provide detailed and reliable (third party certified) information in order to lessen asymmetric information and uncertainty in future returns to energy savings, while likely lowering the

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[1] The EEG is the fact that consumers do not fully take into account the lifetime operating costs of an energy-intensive product upon its purchase.

[2] Energy labels oftentimes display both absolute and relative measures of energy efficiency of a product. While the former (displayed in, say, energy consumption over a certain period) allows inferring the operating cost of the product, the latter (typically displayed in terms of grades, say from A to G) provides consumers with intuitive information of how a given product compares to competing products.

[3] Information programs can range from demand-side management programs organized by utilities to federal programs such as US initiatives EnergyStar and EnergyGuide.

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cognitive cost of decision-making upon the purchase of energy-intensive products.[4]

This paper addresses the impact of making adherence to an information program mandatory. In particular, it quantifies the impact of a shift from the voluntary to the mandatory adoption of energy labels on the valuation of energy costs, and to which extent they help closing the energy efficiency gap. One of the purported benefits of information disclosure is that it facilitates matching between consumers and products (Dranove and Jin, 2010). Consumers may switch towards higher quality products (vertical sorting) or to products whose characteristics best meet their idiosyncratic needs (horizontal sorting). What is less clear is the role of making participation on a program – in particular the adoption of energy labels – mandatory. On the one hand, mandatory adoption may increase the salience and the credibility of such a program, leading to increases in consumer welfare and non-trivial product switching. On the other hand, these effects will likely be negligible if consumers had already incorporated the information provided by the program prior to it becoming mandatory.

Our study takes advantage of a nationally representative survey of Brazilian households (the PPH survey) to examine this issue. We focus on the PBE energy label program (*Programa Brasileiro de Etiquetagem*), whose policy objectives are both the reduction of energy consumption and the increase in energy efficiency of household appliances. Although energy labels had already been introduced in the mid-1990s, their adoption was made on a voluntary basis; it was only from 2003 that they became mandatory. Quantifying the effect of energy policies in the Brazilian market is a feature of interest in itself due to it being one of the largest emerging economies, and the guidance such understanding arguably provides to other emerging economies given its relatively high levels of urbanization and income per capita. Moreover, understanding the trends in energy consumption in emerging economies is a pressing issue (Gertler et al., 2016); while total energy consumption is expected to grow 18 percent in OECD countries, the corresponding figure is 90 percent in non-OECD ones for 2010–2040 (EIA, 2013) . Finally, the survey allows uncovering how the effects of the program differ across households, an important issue in economies with substantial heterogeneity and inequality.

Empirical strategy. We specify and estimate a structural economic model of appliance choice according to which a household chooses the appliance that maximizes their conditional indirect utility taking into account a number of product characteristics – in particular lifetime expected operating costs – and interacting household demographics with product characteristics to control for endogeneity. Our choice model is a random coefficients logit model which accounts for consumer heterogeneity at the household level and can arbitrarily approximate any choice model (McFadden and Train, 2000). We allow for heterogeneity at the household level in both prices and operating costs. In fact, to more realistically conform with the institutional setting, where consumers knowingly face different choice environments, we will interact lifetime operating costs with period fixed-effects.

Contribution and related literature. This paper contributes to different strands of the literature. First, it contributes to the literature which examines the energy paradox (or energy efficiency gap). This literature goes back at least to Hausman (1979) and Dubin and McFadden (1984). Examples of papers quantifying the valuation of energy efficiency for appliances include Revelt and Train (1998) and Davis (2008), Davis et al. (2013) whereas Metcalf and Hassett (1999) examines the valuation of home improvement investments. We contribute to this literature by examining a household-level dataset based on a representative sample for an emerging economy. This allows us to control for heterogeneity at the micro level, mitigates potential sample selection issues and avoids the potential problems associated with stated preference methods.

Second, we provide a quantitative evaluation of the impact of an information program on consumer choice. This relates to an important literature within Industrial Organization examining quality disclosure and certification surveyed in Dranove and Jin (2010). Empirical contributions to this literature – whose theoretical branch goes back at least to Grossman (1981) and Milgrom (1981) – include Mathios (2000), who documents that making previously voluntary disclosure information mandatory adversely affected the sales of high-fat dressings; Jin and Leslie (2003), who examine the effect of mandatory disclosure of restaurant hygiene grade cards on their hygiene quality; Bollinger et al. (2011) who look at the effect of the posting of nutritional information on calorie consumption; Frondel et al. (2017), who study the effect of mandatory disclosure rules for energy information on house asking prices, and a number of papers looking at the health and managed care industry (Jin, 2005; Abaluck and Gruber, 2011; Handel and Kolstad, 2015; Ketcham et al., 2011, 2019).

Despite the important role played by information programs among energy policies, there is little empirical evidence on how economic agents respond to them, especially in a revealed preference setting.[5] In fact, both Allcott and Greenstone (2012) and Mason (2013) note the absence of large-scale evaluations of the impact of energy efficiency labeling on consumer choices. Among the few papers using revealed preference data, Alberini et al. (2016) study the impact of fuel economy labeling in the Swiss vehicle market using market-level data; they find a price premium for vehicles with the highest rating whereas Houde and Aldy (2017) quantifies consumer response to different energy labels in the US refrigerator market using retailer transaction data.[6] Our contribution to this strand of the literature is to document the role of heterogeneity and product differentiation in durables markets, whose corollary is the limited amount of product switching by consumers.

Third, we study one emerging economy facing challenges today that are likely to be faced by other emerging economies in the future. This so happens because Brazil has a high level of urbanization and per capita income when compared to other emerging economies, which together are to respond to the bulk of the increase in energy consumption in the coming decades (Wolfram et al., 2012). In fact, for the period 2010–2040, energy consumption is expected to grow by 90 percent for non-OECD countries (as compared to 18 percent for OECD countries) according to estimates in EIA (2013). We contribute to this literature by combining revealed preference data and survey data containing demographics as well as data informing awareness of the energy label. This allows us to examine the differential effects of the program across demographic strata and to distinguish between well- and ill-informed households. In particular, it enables us to document the differential effects of the program across education and income levels – two key features of many emerging economies – even among households equally informed about the program.

2. Institutional background

Historically, electricity consumption tends to grow hand-in-hand with GDP. Thus, it is not surprising the U.S. Energy Information Administration forecasts total energy consumption to grow by 18 percent

[4] An additional channel outside of the scope of this paper is via the supply side; for instance, Newell et al. (1999) find that requiring energy efficiency product labeling increased the responsiveness of energy-efficient innovation in home appliances to energy price changes.

[5] Using stated preference methods, Newell and Siikamäki (2014) and Davis and Metcalf (2016) have examined how (different versions of) energy labels impact consumer choice.

[6] Houde and Aldy (2017) also finds substantial heterogeneity in consumer responses; while most consumers are unresponsive to any energy-related information, those who respond to such information use coarse summaries of energy efficiency (the EnergyStar label) as a substitute for more detailed and accurate information.

in OECD countries and 90 percent in non-OECD countries for the period 2010–2040 EIA (2013, Table 1). Our study examines the Brazilian market. Brazil is a country whose GDP increased by 40 percent in the 2000s, leading to substantial increases in its consumer market and middle class in the period 2003–2009.[7] Moreover, its degree of urbanization and per capita income are higher than those of other important emerging economies. It thus seems sensible to think that other emerging economies will be able to draw lessons from the findings for the Brazilian market today.

2.1. The Brazilian energy label program (PBE)

The PBE program regulates energy labels *Etiqueta Nacional de Conservacão de Energia, ENCE* in the Brazilian market.[8] While available since the mid-1980s, the label's adoption became mandatory only from 2003. In line with information programs elsewhere, the aim of introducing the label was *"to inform energy consumption and/or energy efficiency (…) according to Brazilian and/or international standards (…)"* INMETRO (2003, par. 1.1).[9] That is, be it in letter or spirit, the regulation appears to give equal weight to energy consumption and energy efficiency.[10] This is important because focusing on only one objective might result in unintended consequences as illustrated in Fig. 1, which represents refrigerators in size-energy consumption space. Products on the market are located within the shaded area (feasible set) in each graph, the energy efficiency of a product is obtained as the slope of the line which connects the origin to its representation in size-energy consumption space, and the solid line represents the energy efficiency frontier, the set of products of minimal energy consumption for a given size.[11]

Panel A in Fig. 1 illustrates the case where the policy variable is energy consumption; in this case, the policy's objective is to make a consumer switch from a product, say A, to another product located at its left, but not necessarily more energy efficient. Panel B illustrates the case where the policy variable is energy efficiency; here, the policy's objective is to make a consumer switch from a product, say B, to another product located at a steeper line segment, but not necessarily lower energy consumption. Finally, Panel C illustrates the case where both energy consumption and energy efficiency are policy variables, where the policy's objective is to make a consumer switch from a product, say C, to another product which dominates it on both energy consumption and energy efficiency.

Starting with refrigerators, energy labels covered increasingly more appliances over time. As is common for labels, they include information on both absolute and relative measures of energy consumption, so as to allow consumers to compare operating costs of different products. The label's appearance is similar to labels used in other markets: in the case of refrigerators – see Fig. 2 – it contains basic information about the product such as the brand, model, type of defrosting, size of the refrigerator (in liters), size of the freezer (if available, in liters) and the freezer temperature. Importantly, the label also displays information regarding energy consumption, namely the tested consumption (in KWh/month) and the energy efficiency class, which ranges from A (most efficient) to G (least efficient).

The adoption of the labels, inspired by the US EnergyGuide ones, was entirely voluntary until 2002, becoming compulsory from January 2003. Despite their voluntary character, energy labels were quickly adopted in the refrigerator market (over 70% of refrigerator sales in our sample were of labeled models in 2002), so that unraveling (Grossman, 1981; Milgrom, 1981) had already taken place before our sample period. We attribute this to two main reasons, namely the highly concentrated market and the low cost of providing energy efficiency information through labels.[12] Thus, if a producer decides to adopt the energy label, it likely does so for all of its products, which command a non-trivial share of the market.

Despite their widespread use, energy labels arguably gained increasing visibility (due to media coverage and advertising campaigns) and credibility at the eyes of consumers after they became mandatory, with the regulator playing the role of an unbiased certifier (Dranove and Jin, 2010), official advertising campaign stressing the importance of energy labels, and product ads being required to display energy label information.

In our empirical analysis, we focus on the market for refrigerators. This pragmatic choice is justified by a number of factors. First, refrigerators are responsible for a substantial share of the electricity consumption within a household. In fact, Cardoso and Nogueira (2005) estimate that refrigerators are responsible for 28–30 percent of the total energy consumption of the typical Brazilian household, making them central to the energy labels.[13]

Second, the relatively high unit price of a refrigerator and its long lifetime makes it more likely that its purchase receives close scrutiny when it comes to weighing its price against their characteristics, especially operating costs. Thus, one would intuitively expect that rejecting the null hypothesis of correctly trading-off price and lifetime operating costs using data on refrigerators would have more power than doing so for, other, less valuable, and less energy-intensive products.[14]

Third, refrigerators were owned by a substantial and stable share of 84–88 percent of households in the Brazilian market in the early 2000s, according to the Brazilian Statistics Office.[15] Thus, selection

[7] These increased from 48.5mn to 57.8mn and 19mn to 30mn, respectively, according to estimates from the Brazilian Statistics Bureau (IBGE). Information on energy consumption per PPP dollar of GDP is presented in 6 in Appendix.

[8] In what follows we refer to as the *PBE program* the policy *mandating* the adoption of energy labels starting from January 2003. Appliances awarded an A in the energy label were eligible to display an additional label (the PROCEL *energy efficiency* label) if additional conditions were met. That is, in contrast with the energy labels under the PBE program, the PROCEL label arguably has a clearer – and single – aim to inform energy efficiency. While the energy labels under the PBE program are closely related to the US EnergyGuide labels and especially the EU energy labels, the energy efficiency labels are closely related to the Energy Star label – see Houde (2018) for background and a comparison of EnergyGuide and Energy Star labels.

[9] In practice, the regulation is based on standards ISO 7371, 8187, 5155, and 8561 for household refrigerator appliances adapted for the tropical climate, see INMETRO (2003).

[10] The legal framework outlined in the law seems to treat energy consumption and energy efficiency as equivalent and/or substitutes, see www.planalto.gov.br/ccivil_03/leis/LEIS_2001/L10295.htm. However, the potential difference in treatment between energy consumption and energy efficiency appears in the display of the energy label; the regulation mandates that the energy efficiency rating should be displayed in font size 32 whereas the energy consumption information should be displayed in font size 22, both in bold. See Fig. 2 for details.

[11] From conversations with industry players, the shape depicted in Fig. 1 is determined by technological constraints; see below for empirical evidence consistent with the graphs.

[12] Electrolux-owned brands Electrolux and Prosdócimo and Whirpool-owned brands Consul and Brastemp jointly commanded over two-thirds of the market, with the remaining being served by a competitive fringe. LG and Samsung entered the market in the late-2000s, after the end of the sample period.

[13] Studies document refrigerators account for 34% of energy consumption, followed by electric showers with almost 20% Lins et al. (2002, Table 3).

[14] As pointed out in Golove and Eto (1996) and Palmer et al. (2012) , credit (or liquidity) constraints may also help explain the EEG given the likely higher upfront cost of energy efficient appliances, especially major items such as refrigerators.

[15] For perspective, Davis and Metcalf (2014) report that 68.2 percent and 79.1 percent of Mexican households own a refrigerator in 2000 and 2005, respectively.

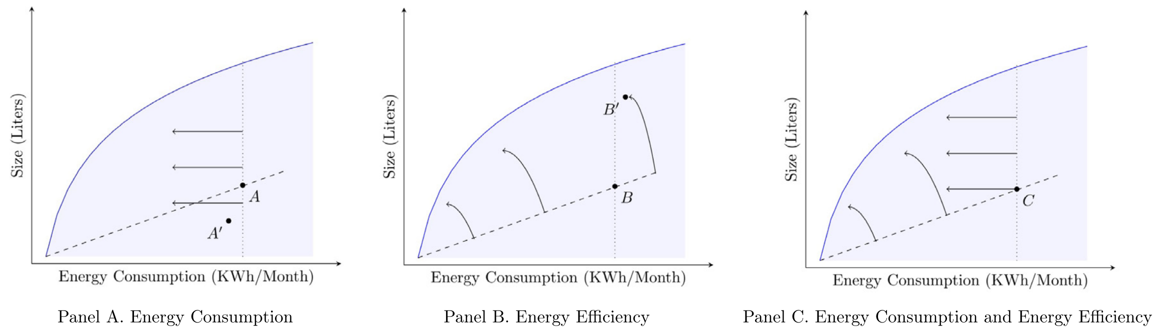


Fig. 1. Policy variables of information programs. Note: This figure summarizes the effects of alternative policy objectives in size-energy consumption space. In each panel, the shaded region denotes the set of available products, the full line denotes the energy efficiency frontier (products with minimal energy consumption for a given size), and the slope of the dashed line denotes the energy factor (size/energy consumption), a measure of energy efficiency. Panel A depicts the case where energy consumption is the policy variable; reactions are towards the left of point A, but can be below it (see point A'), so energy efficiency can worsen. Panel B depicts the case where energy efficiency is the policy variable; reactions are towards a steepening of the dashed line, but might result in increased energy consumption (see point B'). Panel C depicts the case where both energy consumption and energy efficiency are policy variables, and both are expected to improve.
Source: Elaborated by the authors.

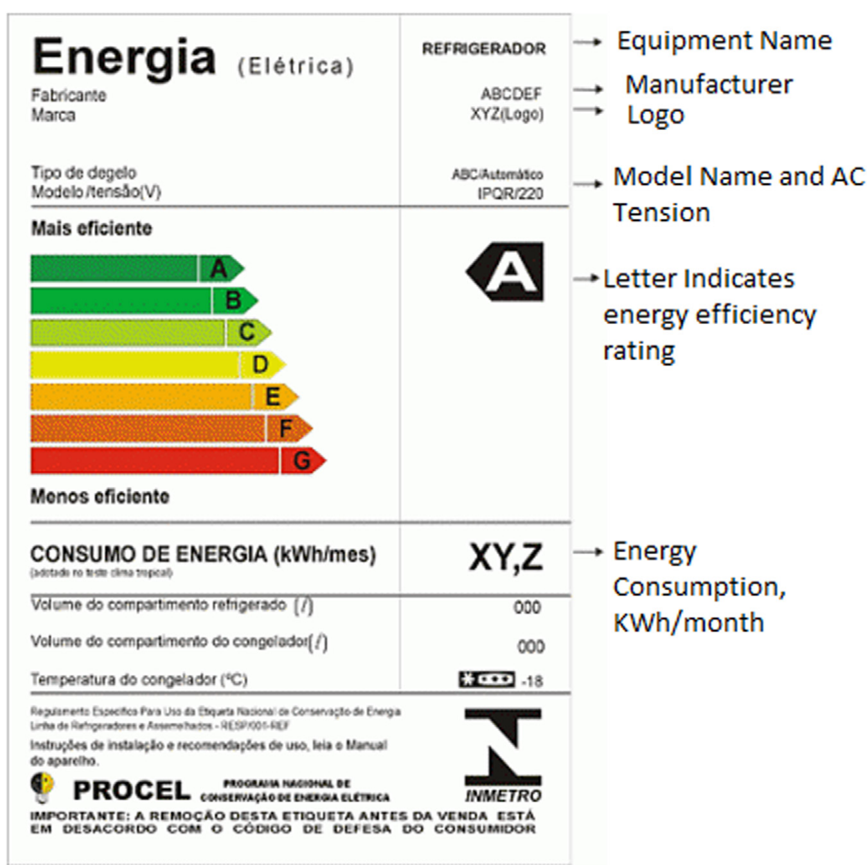


Fig. 2. Sample energy label. Note. This figure displays a sample energy label (*Etiqueta Nacional de Conservacão de Energia, ENCE*). The upper panel identifies the type of appliance (refrigerador, refrigerator), its brand and model, and type of defrosting. The panel underneath displays a measure of relative energy efficiency ("A"), whereas the panel immediately below reports the energy consumption (in KWh/month). The next panel reports the volume of the refrigerator and freezer compartments and the freezer temperature. Finally the bottom panel displays information about the energy label regulations and the certifiers. According to the regulations, all fonts in the label should be Arial; the energy efficiency rating (letter A above) should be displayed in font size 32 and bold whereas the energy consumption (XY,Z above) should be displayed in font size 22 and bold.

issues due to say, income, are likely less severe than in other emerging economies.[16]

Fourth, refrigerators have not witnessed any major technological innovation during our sample period. This is in stark contrast with

[16] In contrast with other markets, see e.g. Davis et al. (2013), Gillingham et al. (2012), split incentives in the adoption of energy efficient products are not prevalent in the Brazilian market, where appliances are typically owned by the resident of a dwelling.

products such as TV sets and personal computers. That is, while the purchase of a TV set might have been triggered by a new technological breakthrough such as LCDs or plasma screens, the purchase of a refrigerator is more likely to have occurred due to replacement reasons.[17]

Finally, refrigerators have a relatively simple product attribute space and offer a limited role for discretionary use, in contrast with other appliances such as TV sets, washing machines and dishwashers (Gately, 1980; Houde, 2018). That is, once a refrigerator is purchased and its basic settings adjusted, it will hardly suffer any adjustment from the part of its owner.[18]

3. Data

We combine a number of datasets, from survey data to primary product price data used in the construction of inflation indices for the Brazilian economy to detailed characteristics of refrigerators.

Survey on household appliances and usage habits (PPH)[19]. PPH is a nationally representative survey which interviewed 4310 households in 16 Brazilian states and the Federal District. Households were selected via two-way cluster sampling; first, clusters were defined according to electricity consumption levels, then according to municipality size. Finally, households were selected within a cluster according to population characteristics.[20] The survey questionnaire is divided into five sections. Section 1 asks basic information such as a household's address, size, composition, educational attainment of individual members and size of dwelling. Section 2 asks detailed information on any and all appliances owned, including model and date of purchase. Section 3 asks information on energy consumption, detailed usage of appliances, including frequency, intensity and time of use. Section 4 asks further household information such as household income, details of dwelling and automobile ownership. Finally, Section 5 asks detailed information about energy conservation, including energy-saving measures, whether the household has knowledge of the energy label and what it represents and whether the household replaced their incandescent light bulbs with fluorescent ones.[21] Given the institutional aspects of the refrigerator market, characterized by product lines launched at the yearly frequency, it was possible to double-check the year in which a refrigerator was declared to be purchased by a household in the PPH with the year a given product was marketed.

Electricity prices. We have obtained retail electricity prices since January 2003 from ANEEL, the Brazilian electricity regulator. We have obtained prices for previous months (January 1998–December 2002) by manually checking official ANEEL rulings of price changes. Electricity prices change little over time (and orders of magnitude less than automobile fuel prices, for instance), and are uniform across households within a consumption bracket and market since utilities are local monopolists. Given the existence of a pricing block structure, we have accounted for the prices actually paid by households given their consumption levels.

Discount rate. The discount rate to be used in the analysis should reflect the opportunity cost of the funds used to purchase the refrigerator, which typically depends on whether the consumer has saved beforehand or is financing the product. In what follows, we use the real interest rate paid out by the Brazilian savings account (*caderneta de poupanca*) which pays out at the monthly frequency a real, after-tax, rate of 6 percent per year.[22] This financial instrument is the main (potentially only) financial instrument widely accessible to the whole population, and thus the main way for low-income consumers to save for the purchase of a durable product. The savings account is also widely used due to its wide recognition as an attractive investment in view of its high remuneration and short maturity (OECD, 2011).[23]

Product prices. We obtain prices for refrigerators from the monthly price survey carried out by the Instituto Brasileiro de Economia (IBRE) at Fundacão Getulio Vargas for the period 1998–2005. The prices are primary data used to calculate leading price indices maintained by Fundacao Getulio Vargas, which are of widespread use within the Brazilian economy. All prices are deflated and expressed in 2005 prices.

Additional product characteristics. We compile information on product characteristics such as brand, model, size (volume, in liters), and number of doors from a combination of sources. First, from the product guides issued by the PBE program. Second, from online sources with the manuals of household appliances in the Brazilian market. Third, from the previous literature on PBE in the area of Engineering, such as Jannuzzi (2002), Cardoso (2008), Melo (2009).

Combining datasets. Since the PPH dataset does not have information at the SKU (stock keeping unit), we match the products in a multi-step procedure. First, we match models by brand, model, size and number of doors, but not its version. In the few cases where more than one match occurred, we followed the literature and matched products via their baseline (entry) version, which is typically its best-selling one. This procedure allowed the identification of most products in the dataset.[24] For the remaining unmatched products, we estimate a hedonic price regression on the matched products whose estimates are projected on the unmatched ones.

4. Empirical strategy

We specify a random coefficients logit model using household-level data. The starting point is a microeconomic model of rational behavior for individual households. Households buy one of the products available on the market, the one yielding the highest utility among the

[17] For perspective, Cardoso (2008) estimate the reduction in the average consumption of refrigerators to be 3 percent per year.

[18] Anecdotal evidence points to consumers adjusting refrigerator temperatures in some regions during summer due to higher temperatures, but typically not as a response to changes in electricity prices. Moreover, it was highly unusual for refrigerators on the Brazilian market in the early 2000s to have easily accessible controls, e.g. on the front door.

[19] in portuguese, *pesquisa de posses de equipamentos e hábitos de uso* (PROCEL, 2007). the survey was conducted by a joint-venture between eletrobrás (latin america's biggest power utility company, and tenth largest in the world) and the brazilian ministry of mining and energy (mme). the pph survey is broadly similar to the us residential energy consumption survey (recs), covering customers of all regions and electricity distributors across the country.

[20] See http://www.uc.pt/org/inescc/P3E/p3e_padroes_comportamentos_ReinaldoSouza for details.

[21] PPH survey also asks a number of questions regarding the Brazilian Energy Crisis and the PERCEE program which allow to distinguish between households for which the energy consumption quota was binding to those from which it was not, an issue important when devising the empirical strategy, see Huse and Koptyug (2017) for details.

[22] For perspective, Allcott et al. (2014) use the average between the long-run average return of the S&P 500 (an equity index, whose Brazilian counterpart small investors do not have access to) and the deflated interest rates from the Survey of Consumer Finances.

[23] The fact that informal channels such as loans from relatives (who often live under the same roof) are also widely used speaks further in favor of the adoption of savings rate.

[24] We were able to identify roughly 70 percent of the refrigerators. Since interviewers performed the visits equipped with leaflets listing all products marketed in a given period, products which we were unable to identify are typically old refrigerators purchased outside of the sample period.

available products.[25] Households have a unit demand and choose among J products. Household i obtains the following utility from product j purchased at period t ($i = 1, \ldots, H; j = 1, \ldots, J; t = 1, \ldots, T$)

$$U_{ijt} = \beta_{ip} p_{jt} + \beta_{ic} E(C_{jt}|I_{it}) + X_{jt}\beta + \varepsilon_{ijt}$$

where p_{jt} and $E(C_{jt}|I_{it}) := \tilde{C}_{jt}$ are, respectively the product price and its expected discounted lifetime operating costs, conditional on the information I_{it} available to household i at period t; X_{jt} are additional characteristics of product j at period t. Finally, ε_{ijt} is an idiosyncratic taste parameter, often assumed to follow a Type 1 Extreme Value distribution.

The willingness-to-pay (WTP) for characteristic j is the ratio of the marginal utility of the characteristic and the marginal utility of its cost. In particular, the WTP for energy costs is given by

$$\upsilon_{ic} := \frac{\partial U_{ijt}/\partial \tilde{C}_{jt}}{\partial U_{ijt}/\partial p_{jt}} = \frac{\beta_{ic}}{\beta_{ip}}$$

The null hypothesis of correct valuation of energy costs against the two-sided alternative is $H_0 : \upsilon_c = 1 \; vs \; H_A : \upsilon \neq 1$.

Within this framework, the role of information programs – energy labels in particular – is to streamline or increase the salience of information related to energy consumption and/or energy efficiency.

Note that the decision to purchase a household appliance is comprised of two components, namely the discrete decision of which product to purchase and the continuous decision of how much to utilize such product. These decisions are typically correlated in that consumers trade-off the price of a product and its lifetime operating costs. In fact, under the null hypothesis of full information and rationality, consumers trade-off the price of an appliance (or a portfolio thereof) and its lifetime operating cost one-for-one. Failing to account for the interdependence between the discrete and continuous decisions will typically result in selection bias. In what follows, we rely on the limited discretionary margin in the use of refrigerators and model the decision to purchase a refrigerator using a discrete choice model, see Section 2 for background.[26,27]

We compute the (expected) present discounted value of operating cost of appliance j at time period t for household i is

$$c_{ijt} = AC_{ijt}\left[1 - \frac{1}{(1+r_{it})^n}\right]\frac{1}{r_{it}}$$

where AC_{ijt} is the annual operating cost of appliance j at period t for household i, r_{it} is the discount rate faced by household i upon purchase of the product, and n is the lifetime of a refrigerator.

Household heterogeneity. In what concerns heterogeneity, we aim to capture a number of important features given the Brazilian institutional setting. First, we want to account for unobserved household heterogeneity in both price and cost, which is pursued using random coefficients.

Second, we want to account for heterogeneity arising from the institutional setting, e.g. the different regimes induced by the sub-periods in our sample. We let households have different sensitivities to the cost component in different sample sub-periods by interacting cost and time period indicators; the resulting cost–period variable is further endowed with a random coefficient to allow for a richer pattern of heterogeneity.

Third, we want to account for the fact that the price sensitivity of a household also depends on its characteristics. This has shown to be important for both durables Berry et al. (1995) and consumer products (Griffith and Nesheim, 2018), and we believe it to be especially important for durables such as refrigerators in an emerging economy. As a result, we allow price sensitivities to depend on income and a random coefficient.

Finally, to allow for the potential correlation between household demographics and product characteristics, we will interact a subset of those variables. Formally, we account for heterogeneity in preferences by defining the vector of household coefficients as

$$\beta_i = \beta^* + \Pi D_i + \Sigma \nu_i$$

where β_i is the $K-$vector of household i coefficients for all product characteristics, β^* is a $K-$vector of coefficients which are common across households, D_i is a $(d \times 1)$ vector of demographics, Π is a $(K \times d)$ matrix of coefficients that measure how the individual coefficients vary with demographics, Σ is a matrix of random coefficients, and ν_i are unobserved household characteristics which are assumed to follow a multivariate Lognormal distribution, $\nu_i \sim \mathcal{L}(0, I_K)$.[28] It then follows that the parameter vector to be estimated is given by $\theta := (\beta^*, \Pi, \Sigma, \gamma)$.

The above estimation strategy assumes away a number of potentially important features in the industry. For instance, it abstracts from the purchase of used refrigerators; in our favor, this seems to be a negligible market in the country. Moreover, appliances such as refrigerators are durable products, so previous ownership of a refrigerator (and its state, neither of which we observe) is likely to affect the current demand for refrigerators. Our estimation approach thus represents a pragmatic modeling approximation to actual choice behavior in the industry, yet consistent with the bulk of the literature.

Identification. Identification of the cost parameters relies on the variation of electricity prices interacted with the energy consumption of the products on the market. Electricity prices vary both cross-sectionally and over time, plus across energy consumption brackets (which is also taken into account in our calculations). Energy consumption of refrigerators varies mostly cross-sectionally, i.e. across products, whereas time series variation is smaller. The main source of identification of the cost parameters thus comes from the fact that we observe the same product being sold on different cross-sectional markets, at different prices and lifetime operating costs (itself a function of electricity prices and discount rates).

Identification of the price parameters relies on the variation of refrigerator prices across markets and over time. The main concern regarding the identification of the price coefficients is that price is likely correlated with unobserved product characteristics of a product, such as its reputation. Although this is a major concern when using aggregate data, this is slightly less so in the case of micro data. This so happens because firms are assumed to set prices at the (national) market level and not to react to demand shocks at the local (or household) level,

[25] Note that we do not consider the existence of an outside good in our analysis. Our focus is on how the policies of interest influence which product to purchase, not the timing of the decision to purchase, and is consistent with the purchase of appliances with replacement motives.

[26] As detailed below, we also control for household demographics likely to affect any residual discretionary use of refrigerators in our empirical specifications and interact them with product characteristics.

[27] Alternatively, this corresponds to the assumption that utilization conditional on product choice is perfectly inelastic, as in Grigolon and Verboven (2014). This is consistent with empirical findings of a small and statistically insignificant rebound effect, which is typically found in the literature, see e.g. Davis (2008) who finds a price elasticity of clothes washing of −0.06. Thus, our empirical strategy is arguably closer in spirit to Hausman (1979) 's covariance probit model than Dubin and McFadden (1984) 's discrete–continuous model.

[28] This results in valuations of energy efficiency which are also lognormally distributed. The Lognormal distribution has been proposed as a convenient distribution for random coefficients in discrete choice models in Revelt and Train (1998) and has been used widely since then. We specify heterogeneity to come from Lognormal random draws to avoid ill-defined moments of the distribution of the valuation parameter υ. As pointed out in Daly et al. (2012), one alternative parameterization would be to treat the price coefficient as having no heterogeneity and thus divide the numerator mixing distribution by a scalar. However, we feel heterogeneity is crucial to model the price sensitivity of consumers in a realistic way (in fact, it is shown below to be statistically significant).

be it because they are unable to observe them or because doing so would only affect a negligible subset of consumers. However strong, this assumption is consistent with most of the literature using micro data, see Petrin and Train (2009) for an exception. To address the above endogeneity concerns, we take advantage of the panel structure of the data, which allows the use of a number of fixed-effects and moreover directly control for heterogeneity. Formally, we assume prices and the components of operating cost to be uncorrelated with the error term conditional on consumer and product characteristics. First, product fixed-effects soak up (time-invariant) product characteristics unobserved by the econometrician and related to, say, product reputation that may be correlated with the cost and price components. As model characteristics may well change in ways that are correlated with the cost components, we also control for (time-varying) product characteristics.

Second, time and region fixed-effects control for unobservable heterogeneity stemming from the realization of economic shocks in a given period and market.

Third, we control for household demographics which are likely to influence the choice of a refrigerator. These include controls for income, household size, and size of dwelling.

Finally, to account for the fact that household demographics are likely correlated with product characteristics – due for instance to consumers sorting into products according to their characteristics – we interact these two sets of variables. Examples of such interactions are those between price and income, and refrigerator volume and household size.

To quantify the effect of making energy labels mandatory, let $\mathbb{P} = \mathbb{P}(E, \theta)$ define the vector of purchase probabilities of each marketed product under a given environment E (e.g., product characteristics, household demographics) and parameter vector θ. The counterfactual estimates are obtained by imposing the PBE (2003–2005) parameter estimates to data from year 2002. Under the null hypothesis of no effect of mandating adoption of energy labels, actual and counterfactual estimates should be equal.

Limitations. There are two main limitations of our study. First, the static character of the consumer decision problem, consistent with a setting where the refrigerator decision is taken for granted instead of formally modeled. Second, the focus on the discrete decision to purchase a refrigerator in contrast to a discrete–continuous decision problem whereby the consumer jointly decides which appliance to purchase and how much to utilize it. Those limitations are imposed onto us due to the sample characteristics and data availability, being in line with most of the related literature.

5. Results

5.1. Demand estimation

Setup. Our demand specifications are comprised of product characteristics, household demographics, the interaction between some of them, and the specification of household heterogeneity.[29] Among product characteristics, we consider product fixed-effects and refrigerator size (volume, measured in liters), the (expected) lifetime operating cost (cost hereafter), and price. To better reflect the institutional setting, we interact the cost variable with period indicators, which will result in time-varying valuations of energy efficiency pre- and post-PBE.

We assume energy prices follow a random walk, which is consistent with the regulatory framework consisting of a price-cap mechanism whereby prices are revised every 4–5 years.[30] We also follow the literature (see e.g. Cardoso (2008)), in that we assume the (expected) lifetime of a refrigerator is 16 years.[31]

We include household characteristics such as dwelling size, an indicator of freezer ownership, household size, in addition to interactions between price and income, refrigerator size and dwelling size, refrigerator size and household size.

Demand estimates. Table 1 reports demand and valuation estimates of alternative RC logit specifications. All specifications have controls for dwelling size, in addition to time fixed-effects (making valuations be identified mostly from the cross-sectional variation in the data), and interactions of refrigerator size and size of dwelling, and a price–income interaction. Given the lack of energy label-related variables, the way the impact of making the energy labels compulsory is materialized via changes in the coefficients of the cost–period interactions, which in turn affect the valuation of energy costs. Importantly, these time-varying coefficients coexist with period fixed-effects, which control for period-specific shocks in the refrigerator market. Throughout our analysis, we use robust standard errors due to the small number of potential clusters.

The estimates across columns are in line with economic theory and typically statistically significant. Although refrigerator size (volume) loads negatively, the associated total marginal effect obtained after computing the interactions volume-dwelling size and volume-household size results in positive albeit typically not significant effects.

Among heterogeneity (standard deviation) parameters, price is statistically significant throughout at either the 10 or 5 percent significance level. The lack of significance of the pre-PBE cost–period heterogeneity parameters suggest a roughly homogeneous valuation of consumers to the lifetime operating costs of a refrigerator. On the other hand, the cost–period interactions become statistically significant once the PBE energy label becomes mandatory. That is, despite their voluntary adoption by all major producers prior to PBE, the fact that labels became compulsory still resulted in heterogeneous valuations (and reactions) by households.

To account for heterogeneity across geographic markets, Columns (2) and (4) include region fixed-effects. Moreover, as the portfolio of household appliances may well influence the purchase of a new appliance (see e.g., Reiss and White (2005)) – in particular, households owning a freezer might, for instance, decide to purchase a smaller refrigerator – we control for freezer ownership in Columns (3) and (4). Finally, Column (4) has the full set of demographics, interaction terms and fixed-effects, thus encompassing all previous specifications. Thus, Specification (4) is our baseline specification.

Valuation of energy costs: Mean estimates. Average valuations of energy costs are reported in Table 1. The estimates are largely robust across columns and suggest undervaluation of energy costs in the pre-PBE period ($\upsilon_{pre-PBE} = 0.559$) followed by slightly larger valuations ($\upsilon_{PBE} = 0.631$) – see Column (4). That is, undervaluation of energy costs persists once the PBE energy labels became mandatory.[32] With the valuation estimates, we test two hypotheses of interest regarding the *average valuations of energy costs.* First, we test the null of equal valuations pre- and post-PBE against the two-sided alternative. Second, we test the

[29] To make the specification comparable to a wide array of alternatives in the literature, we refrain from using stated/self-declared variables such as label awareness. Nevertheless, these are used in our analysis below. Moreover, the lack of time variation in the energy label ratings prevents to separately identify them from the product fixed-effects.

[30] This is also consistent with evidence documented in Anderson et al. (2011) for consumer expectations' about future fuel prices.

[31] This is similar to EIA (2013) and Houde (2018), who assume a lifetime of 19 and 18 years, respectively.

[32] For perspective, Busse et al. (2013) document correct valuation of fuel costs, whereas Allcott et al. (2014, Table 4) report valuation estimates in the range 0.42-0-77 under the assumption that fuel prices follow a martingale, which is closer to our setting. Using a framework closer to ours, and market-level instead of household-level data, Grigolon et al. (2014) document modest undervaluation of fuel costs whereas Huse and Koptyug (2017) document undervaluation using micro-level data.

Table 1
Demand and average valuation estimates.

	Variables	[1]		[2]		[3]		[4]	
Mean	Cost x DV(pre-PBE)	−7.336	***	−7.353	***	−7.452	***	−7.439	***
		(0.401)		(0.412)		(0.507)		(0.500)	
	Cost x DV(PBE)	−7.422	***	−7.475	***	−7.652	***	−7.654	***
		(0.452)		(0.533)		(0.679)		(0.686)	
	Price	−6.926	***	−6.997	***	−7.118	***	−7.139	***
		(0.476)		(0.529)		(0.596)		(0.631)	
	Price x Income	−15.417	***	−15.458	***	−15.609	***	−15.619	***
		(0.270)		(0.281)		(0.318)		(0.329)	
	Volume	−0.006	*	−0.002		−0.007	**	−0.007	**
		(0.003)		(0.003)		(0.003)		(0.003)	
	Volume x Dwelling size	0.001		0.002	*	0.001		0.001	
		(0.001)		(0.001)		(0.001)		(0.001)	
	Volume x HH size	0.002	**			0.002	**	0.002	**
		(0.001)				(0.001)		(0.001)	
Std. Dev.	Cost x DV(pre-PBE)	−0.011		0.005		−0.009		−0.009	
		(0.016)		(0.017)		(0.020)		(0.020)	
	Cost x DV(PBE)	0.801	**	0.892	*	0.848	*	0.828	*
		(0.332)		(0.508)		(0.441)		(0.477)	
	Price	0.363	**	0.397	**	0.363	*	0.371	*
		(0.173)		(0.173)		(0.200)		(0.201)	
	Average Valuations								
	$\upsilon_{pre-PBE}$	0.503		0.522		0.542		0.559	
	υ_{PBE}	0.633		0.685		0.632		0.631	
	Demographics								
	Dwelling Size	Yes		Yes		Yes		Yes	
	DV(Owns freezer)					Yes		Yes	
	Household size					Yes		Yes	
	Fixed-effects and Additional Controls								
	Product FEs	Yes		Yes		Yes		Yes	
	Region FEs			Yes				Yes	
	Time FEs	Yes		Yes		Yes		Yes	
	cost–period interactions	Yes		Yes		Yes		Yes	
	Log-likelihood	−2299.18		−2281.82		−2241.52		−2203.16	
	N	29602		29602		29374		29374	

Note. This table displays estimates from Random Coefficients Logit (RCL) models with Lognormally distributed parameters on price and cost–period terms. The random draws are independent. Robust standard errors are reported in parentheses. DV(.) denotes dummy variable. All models are estimated using 300 Halton draws.

*Significance levels for 10 percent.

**Significance levels for 5 percent.

***Significance levels for 1 percent.

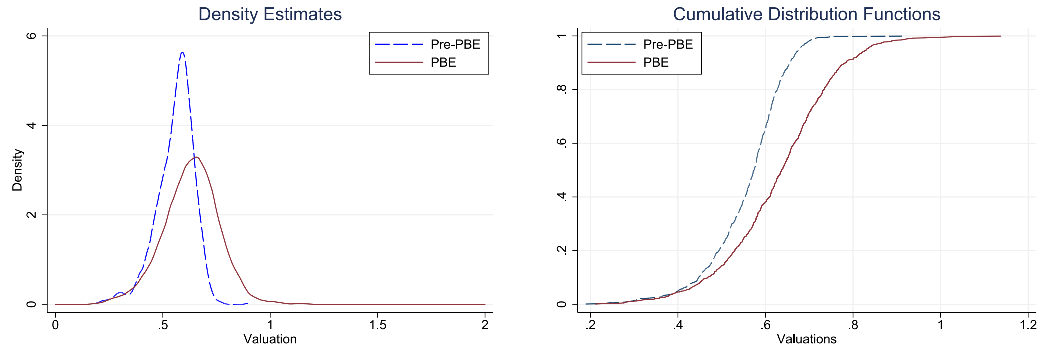
null of correct valuation of energy costs, $H_0 : \upsilon = 1$ against the two-sided alternative for both periods. For the former, we cannot reject the null hypothesis, which suggests that making energy labels mandatory does not affect average valuations of energy costs, despite the moderate increase (approximately 13 percent) in average valuations. For the latter, we reject the null hypothesis in both cases at the 1 percent significance level.

Valuation of energy costs: Distributions. As average valuations do provide only an incomplete picture of the underlying distribution of valuations in a model allowing for heterogeneity, in Fig. 3 we examine the distributions of the valuation of energy costs underlying the baseline estimates, see Panel A for the density estimates and Panel B for the associated cumulative distribution functions. While Panel A suggests that the PBE valuation distribution is more dispersed and tilted towards the right as compared to its pre-PBE counterpart, Panel B suggests that the distribution associated to PBE dominates its pre-program counterpart in the first-order stochastic sense.[33] To investigate this is in more detail, we test the null hypothesis of equality of the distributions of υ_{PBE} and $\upsilon_{pre-PBE}$ using a Kolmogorov–Smirnov test. We obtain a test statistic of 0.351 rejecting the null hypothesis at the one percent significance level. That is, while there has not been an increase in average valuations, there has been an increase in the valuation of energy costs in the *distributional sense*, which is of interest in the case of models with heterogeneity.[34]

Taken together, the results suggest that mandating the adoption of PBE energy labels had a modest impact on the valuation of energy costs, thus reducing "internalities". This finding can be related to the theoretical literature on certification, according to which information disclosure may fail to affect demand (i) if it is irrelevant for the decision-maker; (ii) if it is difficult to understand; or (iii) if it confirms what consumers already know (Dranove and Jin, 2010). Since energy labels were already adopted pre-2003 on a voluntary basis for the major brands operating in the Brazilian market, the rationale for a small change in valuations could most likely be justified by a combination of (ii) and (iii). However, while we reject the equality of the mean valuations of energy costs, the increase in heterogeneity following the PBE program results in distributions for which we reject the null of equality.

[33] Letting $F_V(.)$ denote the cumulative distribution function of a random variable V, X FSD-dominates Y iff $F_X(z) \leq F_Y(z)$ for all z with strict inequality for some z.

[34] We perform KS tests due to both their simplicity and the fact that our setting looks relative standard; for instance, it is reasonable to assume that the valuations being compared are independent. We are aware of the fact that we perform the KS test on estimates rather than data, but rely on results by Ackerberg et al. (2012) according to which (in the context of two-step semi-parametric models) for practical purposes one can obtain estimates of semi-parametric variances using standard formulas derived in the parametric literature, i.e. ignore the semi-parametric nature of the problem.



Panel A. Density Estimates

Panel B. Cumulative Distribution Functions

Fig. 3. Distribution of valuation parameters. Note. This figure displays kernel density estimates of the valuation of energy costs in Panel A and the corresponding cumulative distribution functions in Panel B.

5.2. Overall policy effects

In what follows, we quantify a number of policy effects of mandating energy labels. For each table, the first column (labeled "Actual") reports estimates for year 2002, thus before the PBE program. The counterfactual estimates are obtained by imposing the PBE (2003–2005) parameter estimates to data from year 2002. Under the null hypothesis of no effect of mandating adoption of energy labels, actual and counterfactual estimates should be equal. To provide perspective on the estimates, we will compare our estimates of changes in the energy factor to the increase of energy efficiency on the supply-side for the period 1998–2005, which is 0.17, or 1.9 percent, per year; the average energy factor for year 2002 (pre-PBE) is 9.80.

Effect on product characteristics. The estimates in Table 2 summarize the average effects of making the energy label mandatory. Given the small share of consumers switching products (8.33 percent), overall responses to the PBE program are typically small. The low fraction of consumers switching products is consistent with a market of differentiated products, as is the case of refrigerators; consumers have preferences for brands and refrigerator characteristics, which endows each product with a degree of localized market power, in contrast with what occurs in homogeneous product markets. As a result, energy consumption remains essentially constant, from 31.55 to 31.57 KWh/month. In contrast, there is an increase in refrigerator size of over 5 liters (or 1.79 percent), which results in an increase in 0.25 in the energy factor – this is over 2.5 percent (or 1.5 times) the yearly, long-run, technological improvement in this market.

We also examine the effects on the sub-sample of switchers. The average increase in the energy factor is 3.03 (40.95 percent), with a small increase in energy consumption (0.28 KWh/Month, or 0.68 percent) and a substantial increase in refrigerator size (62.70 liters, or 20.96 percent). That is, consumers switching products as a response to the PBE program will react in a way consistent with Panel B in Fig. 1, with improved energy efficiency and worsened energy consumption.

To better appreciate the role of heterogeneity in the above estimates, consider Fig. 4, which displays the actual and counterfactual distributions of the product characteristics examined in Table 2 – all reported densities are based on sales-weighted figures, including both switchers and non-switchers. There is substantial clustering in characteristics space, which implies that the existing product lines will to a great extent condition any demand responses. Panel A shows the effect on energy consumption whereas Panel B shows an increase in the market share of refrigerators with approximately 300 liters against losses of those with 250 and 320 liters. Panel C shows how consumers switch from refrigerators with a low energy factor (about 8) to refrigerators with a high energy factor (approximately 12).

In the context of Fig. 1, we document that overall consumer responses to a policy targeting improvements in both energy consumption and energy efficiency have average effects consistent with a policy attaining only an improvement in energy efficiency. Specifically, the estimates in Table 2 are consistent with the change from point B to point B' in Panel B of Fig. 1. That is, an unintended (slight) increase in energy consumption takes place as a result of the improved matching between consumers and products following the PBE program – or as a version of the rebound effect whereby consumers realize they react to the purchase of a refrigerator with higher energy efficiency with an increase in its size – and oftentimes also energy consumption.

We now provide perspective on our findings. We discuss why the PBE program has an effect, the mechanism by which effects materialized, the economic significance of such effects, its supply-side consequences, and whether governmental intervention is required.

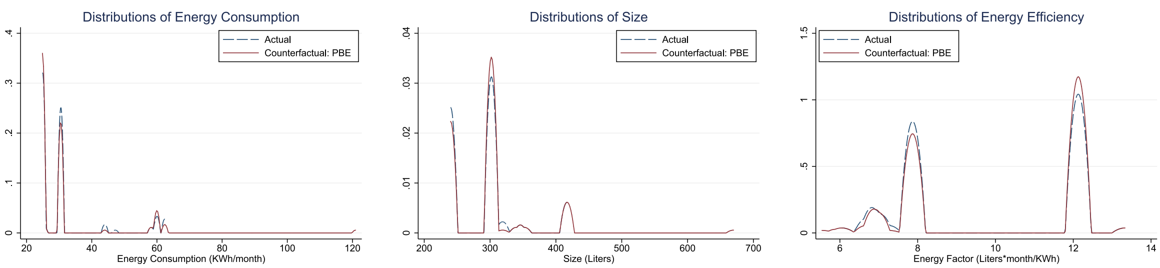
Why is there an effect? Making them mandatory through the PBE program had two potential effects. On the one hand, one could argue that even though energy labels had already been introduced for nearly a decade, making learning a less likely explanation, the fact that the PBE made their display compulsory in advertising campaigns (and to some extent brought energy labels back to the limelight, so to say) made them more salient to consumers looking for a new refrigerator. On the other hand, while the additional media coverage raised the attention of the population, and thus the salience of the policy instrument, the then mandatory character of the label led more credence to the initiative as a whole – this is essentially the argument of increased credibility provided by an unbiased certifier (Dranove and Jin, 2010). As a result, even though consumers are aware of energy consumption and energy efficiency information, the program makes them more likely to take them into account in the decision-making process of purchasing a new refrigerator.

What is the mechanism driving the results? One robust finding in our results is the fact that energy efficiency increased, despite increases in refrigerator size (volume). On the other hand, the effect on energy consumption is less clear, although we document a number of cases where it did increase. Such findings can be rationalized by referring to Panel B in Fig. 1 (see the change from point B to point B') and Panel A in Fig. 3. Arguably, households have limited leeway to choose among refrigerators of different sizes given demographics, e.g. household size, and preferences, e.g. preference for home-cooked food, and income, e.g. liquidity constraints. However, conditional on refrigerator size, households can sort into refrigerators of different energy consumption (and other characteristics, such as brand) and energy efficiency. The effect of the labels, possibly helped by media campaigns and the compulsory display of energy labels in ads, is to raise the salience of energy consumption and energy efficiency. Thus, energy labels make (a subset of) households more likely to switch from refrigerators which are dominated in size-energy consumption space to better-performing products. That is quality disclosure leading to better information transmission to

Table 2
Overall Policy Effects.

	Overall				Switchers			
		Counterfactual		Effect		Counterfactual		Effect
	Actual	*Level*	%	λ	Actual	*Level*	%	λ
Energy Consumption (KWh/Month)	31.55	31.57	0.06	0.02	41.25	41.53	0.68	0.28
Size (Liters)	291.33	296.55	1.79	5.22	299.10	361.80	20.96	62.70
Energy Efficiency (Liters*Month/KWh)	9.80	10.05	2.55	0.25	7.40	10.43	40.95	3.03
Consumers Switching Products (%)	8.33				–			

Note. Effects of the PBE program on energy consumption, size, energy efficiency, and product switching. Estimates based on baseline specification.



Panel A. Energy Consumption Panel B. Size Panel C. Energy Efficiency

Fig. 4. Distribution of policy effects. Note: This figure highlights the heterogeneity in the counterfactual changes in product characteristics. The bandwidths for Panels A–C are 0.5, 5, and 0.15, respectively, and the kernel is always Epanechnikov.

consumers and a better sorting between consumers and products, even at the risk of having unintended consequences, such as the choice of refrigerators with increased energy consumption.

Is the effect economically significant? We quantify the economic effects in Table 3, which summarizes changes in energy consumption, lifetime monetary savings, and the social benefit of carbon savings – both overall and only among switchers. Some effects are a direct consequence of those in Table 2 (Overall Policy Effects). At the household level, overall energy consumption increases by 0.28 KWh/Year, or roughly 1 percent of the monthly energy consumption of the average refrigerator in the sample. The lifetime monetary savings are a low USD 0.71 whereas the social benefit of carbon savings are USD −0.12 per household. Extrapolating the above findings for the Brazilian economy results in an increase of 0.8mn KWh/Year in energy consumption, lifetime monetary savings amount to USD 2.0mn whereas the social benefit of carbon savings is USD -0.3mn. The negative social benefits are essentially due to the increase in energy consumption of refrigerators following the inception of the PBE program. Fig. 5 documents that both private and social benefits were highly heterogeneous, a prevalent feature in our results, be it regarding energy costs as in Panel A, energy savings as documented in Panel B, or social benefits, documented in Panel C.

Conditioning on households who do switch products results in more sizable yet still moderate effects. Table 3 documents that energy consumption increases by 3.36 KWh/Year – or slightly over 10 percent of the monthly energy consumption of the average refrigerator in the sample. Monetary savings are USD 8.45, and the social benefit of carbon savings is USD −1.46, or approximately 0.5 percent of the price of a new refrigerator in year 2002. When extrapolating such effects for the population as a whole, one obtains an increased energy consumption of 9.4mn KWh/Year (comparable to the yearly energy consumption of a city with 170 thousand inhabitants in a country with a population of approximately 200 million), lifetime monetary savings of USD 23.7mn, and social benefits of USD -4.1mn. That is, at the root of the unintended consequences of the PBE program lie the marginal increase in energy consumption documented above.

Is government intervention warranted? What are the policy implications?. While the introduction of the energy labels – and the underlying standard according to which products are compared – already presumes a degree of governmental intervention, additional governmental intervention can be justified on a number of grounds. First, because the downside is very low, since implementation costs are low and had already been incurred by essentially all firms. Second, because governmental involvement, be it through news or advertising, is likely to increase awareness/attentiveness to the program. Third, because the program may generate long-run effects also on the supply-side, with increased energy-efficiency in product lines.

One central unintended consequence of the policy is that despite the increase in energy efficiency, the PBE program also resulted in increased energy consumption, which amounts to the non-attainment of one of the policy objectives of the very program. This is perhaps not surprising given the Tinbergen (1952) rule of economic policy, which states that there needs to be (at least) as many policy instruments as targets one wishes to achieve.[35] Moreover, the heterogeneity of the effects of the program across demographic strata – especially in what concerns educational attainment – suggests that while many households are aware of the energy labels, they do not seem to fully comprehend the information conveyed in them. Taken together, these findings suggest that there may even additional Government intervention may be warranted when it comes to improve the label's design and disseminate information about it.

Conclusions and policy implications

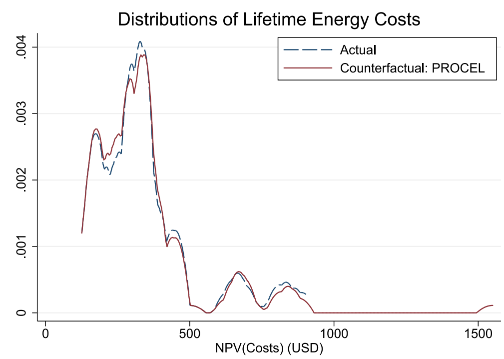
This paper examines the effect of the PBE program, which mandated the adoption of (previously voluntarily adopted) energy labels. Using revealed preference data from a nationally representative household survey in Brazil, we examine the purchase of household appliances, specifically refrigerators. Brazil is a large emerging economy with high urbanization and per capita GDP, thus providing guidance for other emerging economies in the future.

[35] In (macro)economic policy, the issue of multiple policy objectives has been examined since the 1950s, with the Tinbergen rule of economic policy stating that there needs to be (at least) as many policy instruments as targets one wishes to achieve. In contrast, the Theil approach accepts that policymakers have more objectives than instruments, and argues that they have to decide how to deploy such instruments in order to achieve the preferred trade-off between the objectives.

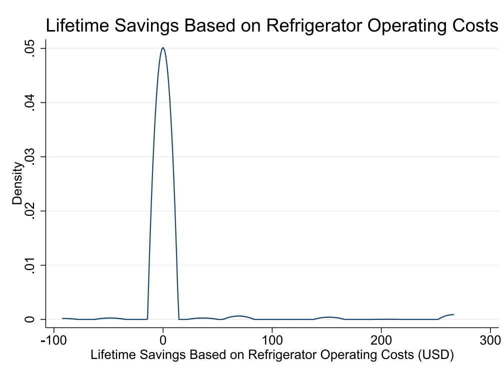
Table 3
Quantification of Private and Social Benefits.

	Variable	Overall	Switchers
Per Household	ΔEnergy Consumption (KWh/Year)	0.28	3.36
	Lifetime Monetary Savings (USD)	0.71	8.45
	Social Benefit of Carbon Savings (USD)	−0.12	−1.46
Aggregate	ΔEnergy Consumption (KWh/Year)	0.8 mn	9.4 mn
	Lifetime Monetary Savings (USD)	2.0 mn	23.7 mn
	Social Benefit of Carbon Savings (USD)	−0.3 mn	−4.1 mn

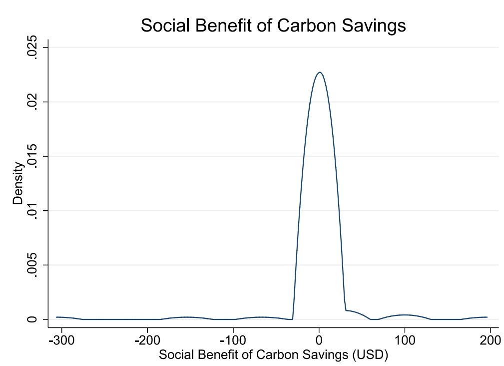
Note. This table reports quantifications of energy savings, monetary savings and the social benefit of carbon savings associated to the two counterfactuals, both for the sample as a whole (overall) and product switchers. The assumptions used are a lifetime of 16 years for refrigerators, a social cost of carbon of USD 85/tCO2 SCC (equivalent to USD 312/tC) following Stern (2006), electricity generation with emissions of 655gCO2/KWh following Miranda (2002, Table 18), a 10 percent discount rate, a BRL/USD: 2.25 exchange rate. To arrive at our aggregate estimates, we estimated the market size to be 2.8mn households as follows. First, we use the number of households reported in the Brazilian Census of year 2000, 44,795,101 households. Then we assume 1/16 of the households replaces a refrigerator in a given year, which yields the 2,799,694 households which we round up to 2.8 million households. This assumes a constant replacement rate during the 16 years refrigerators are expected to last (thus no income or price effects whatsoever) and relies on the accuracy of the sample average as an estimate of the population mean given the sampling design of the PPH survey.



Panel A. Distribution of Lifetime Energy Costs



Panel B. Distribution of Lifetime Energy Cost Savings



Panel C. Distribution of Social Benefits

Fig. 5. Distributions of private and social benefits. Note. This figure documents the heterogeneity in consumer responses in private and social benefits. Panel A displays the distribution of lifetime energy costs for the actual and counterfactual scenarios. Panel B displays the distribution of lifetime savings of the counterfactual with respect with the actual scenario; Panel C displays the distribution of lifetime social benefit of carbon savings of the counterfactual with respect with the actual scenario.

We estimate a structural model of appliance choice accounting for different sources of heterogeneity, especially in prices and energy costs. We find that mandating the adoption of energy labels modestly improves the mean valuation of energy costs, thus reducing “internalities” (Allcott et al., 2014). However, while we cannot reject the null of equality of mean valuations pre- and post-program, we do reject the null of the equality of distributions of valuations of energy costs, a finding we attribute to the increase in the heterogeneity of valuations in energy costs under the PBE program.

We attribute the moderate increase in valuations to a combination of two factors. First, energy labels had already been introduced on a voluntary basis prior to 2003. Second, the refrigerator market had already witnessed an important degree of unraveling (Grossman, 1981; Milgrom, 1981). As a result, making energy labels mandatory conveyed redundant information to an important subset of consumers (Dranove and Jin, 2010). This differential processing of information across consumers following the implementation of the mandatory labeling (Dranove and Jin, 2010) leads to the increase in heterogeneity documented post-PBE. More generally, the heterogeneity in responses to new information in the extensive margin (appliance purchase) complements previous findings in Reiss and White (2005, 2008) for the intensive margin of adjustment using electricity billing data. Despite the increase in valuations, we cannot reject that consumers undervalue energy costs both prior and after the inception of the PBE program, a finding consistent with the existence of an energy efficiency gap. To quantify policy effects, we simulate a counterfactual policy by imposing the parameter estimates from when the PBE program was in place to

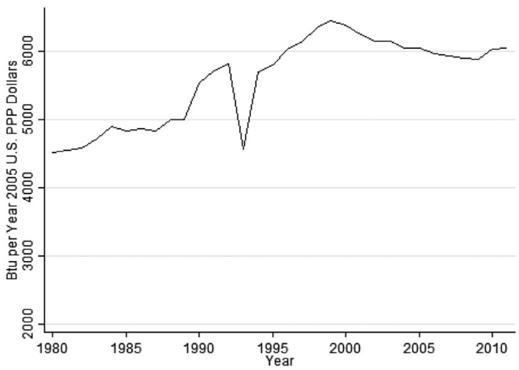


Fig. 6. Brazil: Energy intensity 1980-2011.

the pre-PBE period. Throughout this analysis, in addition to the twin objectives of the program (lower energy consumption and increased energy efficiency) we also assess responses in terms of refrigerator size (measured in liters). The main finding from this exercise is that less than 10 percent of households switch products. Thus, there are stark differences between overall program effects and those among product switchers. For instance, the increase in mean energy efficiency among switchers is over 10 times the increase in energy efficiency for the sample as a whole. Moreover, switchers achieve this marked increase in energy efficiency despite purchasing refrigerators which are larger and marginally more energy-consuming, which can be seen as an unintended consequence of the program. This finding is perhaps not surprising in light of the Tinbergen rule of economic policy, which states that there needs to be (at least) as many policy instruments as targets one wishes to achieve. All in all, while the PBE program aimed to both reduce energy consumption and increase energy efficiency, we can only claim robust evidence of the latter; in the process of better sorting between consumers and products, in our simulations some of those consumers end up switching to products with (marginally) increased energy consumption.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Cristian Huse: Conceptualization, Methodology, Software, Formal analysis. **Claudio Lucinda:** Conceptualization, Methodology, Software, Formal analysis. **Andre Ribeiro Cardoso:** Conceptualization, Methodology, Software, Formal analysis, Writing - original draft.

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Appendix

See Fig. 6.

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