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Keywords: energy efficiency, energy paradox, energy efficiency gap, information label, electricity demand, energy demand, mixed logit, household appliance.

JEL Codes: D12, D83, L15, L68, Q48

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This draft: June 2019

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1 Introduction

Consumers of energy-intensive products are expected to trade-off price and lifetime operating costs of such products, since electricity bills and fuel costs are a non-trivial share of a typical household's expenditure. In addition to consumers, this trade-off is also important for the environment, public policy and businesses. Moreover, efficient taxation – in particular, the choice between fuel tax and fuel economy/emission standards – depends on how consumers address this trade-off. Finally, firms are expected to introduce products and set prices according to (expected) consumer behavior.

Thus, it does not come as a surprise that the study of this trade-off has become a central topic in energy demand since at least Hausman (1979). The empirical evidence is mixed (see Greene (2010); Helfand and Wolverton (2011) for recent reviews). However, there has been enough evidence in the last three decades that consumers undervalue (or heavily discount) future energy costs that researchers coined the term Energy Paradox (Jaffe, Newell and Stavins, 1999) to denote it.[1] Moreover, the frequent findings of undervaluation motivated a large literature on the "Energy Efficiency Gap" (EEG), the fact that consumers do not make apparently high-return energy efficiency investments.[2]

The leading explanations for the energy paradox are information problems and behavioral failures (Sanstad, Hanemann and Auffhammer, 2006). On the informational front, problems include consumers' lack of information about product availability and/or the (future) operating costs of the marketed products. On the behavioral front, problems include consumers not appropriately taking into account reductions in future energy costs when making purchasing decisions about energy-intensive product today.

In this paper, we address the role of incentives (behavior) in mitigating the EEG. Our study takes advantage of a nationally representative survey of Brazilian households to examine three issues. First, we examine whether consumers correctly value the energy efficiency of appliances in the Brazilian market. Quantifying the EEG (if it exists) in the Brazilian market is a feature of interest in itself due to its 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. Understanding the path of energy consumption increases 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).

Second, we assess the role of economic incentives during the PERCEE energy savings program (*Programa Emergencial de Redução do Consumo de Energia Elétrica*) on the EEG by comparing households facing a binding quota for their electricity use with those who were not constrained by it. PERCEE was a temporary program (9 months) aiming to reduce electricity consumption by 20 percent in response to the *Brazilian energy crisis* (2001). Its importance is such that it has achieved the largest reduction in electricity use among temporary savings programs worldwide (EIA, 2005). By looking at the extensive (or long-run) margin (appliance replacement) of adjustment to this important shifter in energy demand, we complement the literature which looks mostly at the intensive (or short-run) margin of adjustment to policies (Reiss and White, 2005, 2008) and subsidy programs of appliance purchase or replacement (Davis, 2010; Davis and Metcalf, 2014).

Empirical Strategy We aim to test the null hypothesis that consumers correctly value lifetime energy costs of durable products against the two-sided alternative that they either

[1] For instance, Hausman (1979) and Dubin and McFadden (1984) obtain implicit discount rates of 20-25 percent when studying the market for air conditioners and heaters, respectively.

[2] See Gillingham, Newell and Palmer (2009) for a survey and reasons underlying its existence.

under- or overvalue them. Thus, under the null hypothesis, product prices and quantities react to lifetime operating costs as if consumers are indifferent between them. Intuitively, this can be assessed by testing whether the ratio of the coefficients on lifetime energy costs and product prices equals one when estimating a demand system.

To empirically evaluate our research questions, we focus on the purchase of household appliances, in particular refrigerators. We specify and estimate a structural economic model of appliance choice whereby 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 controlling for household demographics. In particular, we rely on 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, we will interact lifetime operating costs with indicators of the different sub-periods (policy regimes) in our sample where consumers knowingly faced different choice environments, e.g. governmental policies.

Refrigerators are convenient since there is little room for discretion in their use (Gately, 1980; Houde and Aldy, 2017), which will allow us to simplify the canonical discrete-continuous model of a household's joint decision on appliance choice and utilization into a simpler, more tractable, discrete choice problem of appliance choice. Refrigerators are, moreover, important enough as a share of energy consumption – roughly 30 percent according to estimates for the Brazilian market (see Section 2) – to merit careful consideration from the part of consumers in the case of a purchase. As a result, rejecting the null hypothesis of correct valuation of expected energy costs in the case of refrigerators is arguably more powerful than for other appliances.

Our analysis relies on a unique dataset constructed from a variety of sources. Our starting point is PPH, a household survey on domestic appliances and usage habits, which is representative of the Brazilian market. PPH provides demographic information, the portfolio of appliances owned by a given household, when such appliances were purchased, estimates of utilization, and conservation measures. The PPH data is combined with three other data sets, the first comprising electricity prices disaggregated at the regional level; the second consisting of product prices from primary data used to construct price indices in the Brazilian market; and the third comprising additional product characteristics of all refrigerators marketed during the sample period.

Main Findings We find that consumers generally undervalue energy costs. However, consumers do react to incentives to conserve energy introduced by the PERCEE program. It is only for such consumers that the null hypothesis of correct valuation of energy costs cannot be rejected in one of our specifications. This is consistent with the view that PERCEE increased the cost of inattention for consumers for which the incentives were binding.

The reaction to the temporary PERCEE program is, however, short-lived, with consumers reverting to their previous (under)valuation of energy costs before long once PERCEE is over. That is, perhaps non-surprisingly, consumers tend to rapidly adjust once constraints on their behavior are lifted.

Heterogeneity is ever present in our demand and valuation estimates, but its statistical significance is confined to price rather than cost-period components. This heterogeneity in responses in the extensive margin complements previous findings in Reiss and White (2005, 2008) for the intensive margin of adjustment using electricity billing data. Our findings can also be reconciled with recent findings in concurrent work by Costa and Gerard (2018) according to which reactions in the intensive margin (reductions in electricity use) are long-lived; (non-trivial) adjustments in the extensive margin (appliance replacement) are bound to have significant and long-lasting effects due to the energy intensity and the durability of household appliances.

We use the estimates from our model carry out a set our counterfactual exercises, in which we start by decomposing the EEG into information and incentives components. We take advantage of the institutional setting to compare consumers whose behavior was constrained during the rationing program and those whose behavior was not: while the former were facing a binding energy quota, the latter were in a more comfortable situation, thus not facing incentives to reduce energy use. As a result, we associate the difference in valuations of energy costs between these two groups with the incentive motive behind the EEG. Then, by assuming that both constrained and unconstrained consumer types were exposed to the same amount of information, the information motive behind the EEG amounts to the difference between the valuation of constrained consumers and the correct valuation of energy costs. That is, we argue that the EEG of constrained consumers occurs only due to information motives whereas that of unconstrained consumers was a composition of incentive and information motives.

Implications The implications of undervaluation are several. First the constraints faced by households during PERCEE led them to more carefully evaluate the energy efficiency of refrigerators, conditional on purchase.

Second, if electricity generation creates emissions – as is the case especially when PERCEE was in place due to investment in thermo plants –, undervaluation leads to large private welfare losses stemming from the additional creation of pollutants. The Brazilian energy crisis was a supply-side phenomenon triggered by a combination of a swift GDP growth and electricity demand in the Brazilian market together with the lack of investment in generation and distribution. When the country was hit by the worst drought in 70 years, hydro generation which was back then responsible for 94 percent of the energy supply was hit the hardest.

Third, the undervaluation or energy costs makes standards preferred to taxes(Parry, Walls and Harrington, 2007), which is bound to have profound effects on the design of tax system of an economy given the importance of the electricity sector in particular and energy-intensive sectors in general.

Fourth, lower demand for energy efficient products results in less economies of scale in the production of those products, and ultimately underinvestment in energy-efficient innovation (Newell, Jaffe and Stavins, 1999).

Contribution and Related Literature This paper contributes to different strands of the literature. First, it contributes to the literature which examines the energy paradox. 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 (2010); Davis, Fuchs and Gertler (2013); Metcalf and Hassett (1999) is an example of the valuation of home improvement investments.[3]

Our contribution here is the construction of a household level dataset which is based on revealed preference and a nationally representative survey. This allows us to control for heterogeneity at the micro level, mitigates potential sample selection issues and avoids the potential problems of stated preference methods. Given the industry we focus on and/or our methodology, the most closely related papers are Revelt and Train (1998); Davis (2008); Grigolon and Verboven (2014).

[3]In a closely related literature, a number of recent studies have quantified the valuation of energy efficiency from vehicle purchases, taking advantage of the availability of high quality data. The findings are mixed, as previously documented by Greene (2010) and Helfand and Wolverton (2011); some papers find that consumers do not undervalue (Busse, Knittel and Zettelmeyer, 2013; Grigolon and Verboven, 2014; Sallee, West and Fan, 2015) whereas others find that they modestly undervalue operating costs, e.g. Allcott, Mullainathan and Taubinsky (2014).

Second, the paper contributes to a better understanding of the EEG. Existing research has often mentioned factors such as imperfect information and cognitive costs as potential sources of the energy paradox (Jaffe and Stavins, 2004; Howarth and Sanstad, 1995). To our knowledge, we are the first to decompose the EEG and quantify the relative importance of its parts.[4] Taking advantage of the institutional setting, we are able to distinguish consumers facing from those not facing incentives to reduce energy consumption under the PERCEE program. Under the assumption that both consumer types were exposed to the same information, and incentives were introduced only through PERCEE, the difference in the valuation of energy efficiency between these two groups can then be attributed to incentives whereas the EEG of households facing a binding energy quota can be attributed to information only. Thus, we can decompose the EEG into information and incentives (behavior) components.

Third, we study how households adjust on the extensive margin to a major, temporary shifter in energy demand in the form of a rationing program, and how they react after the end of such program. In contrast with most of the literature, which tends to focus mostly on adjustments on the intensive margin (for instance, (Reiss and White, 2005, 2008; Costa and Gerard, 2018) , look at billing data), we focus on appliance purchases. Refrigerators are responsible for a sizable share of residential electricity consumption in that they are estimated to account for 30 percent of the energy use in a typical Brazilian household (see Section 2 for details). Given their cost and importance, their purchase is more likely to receive careful scrutiny by the household members, making any rejection of our null hypothesis of correct valuation of energy costs more powerful than in the case of other appliances (or the intensive margin). In the few cases the literature has focused on the extensive margin as we do, the policies of interest were either subsidies (Davis, 2010) or replacement programs (Davis and Metcalf, 2014). In our case, the PERCEE program imposes incentives, but consumers are free to decide about how to comply with such quota – in particular, whether to purchase or replace an appliance, and which product to purchase if that is the case.

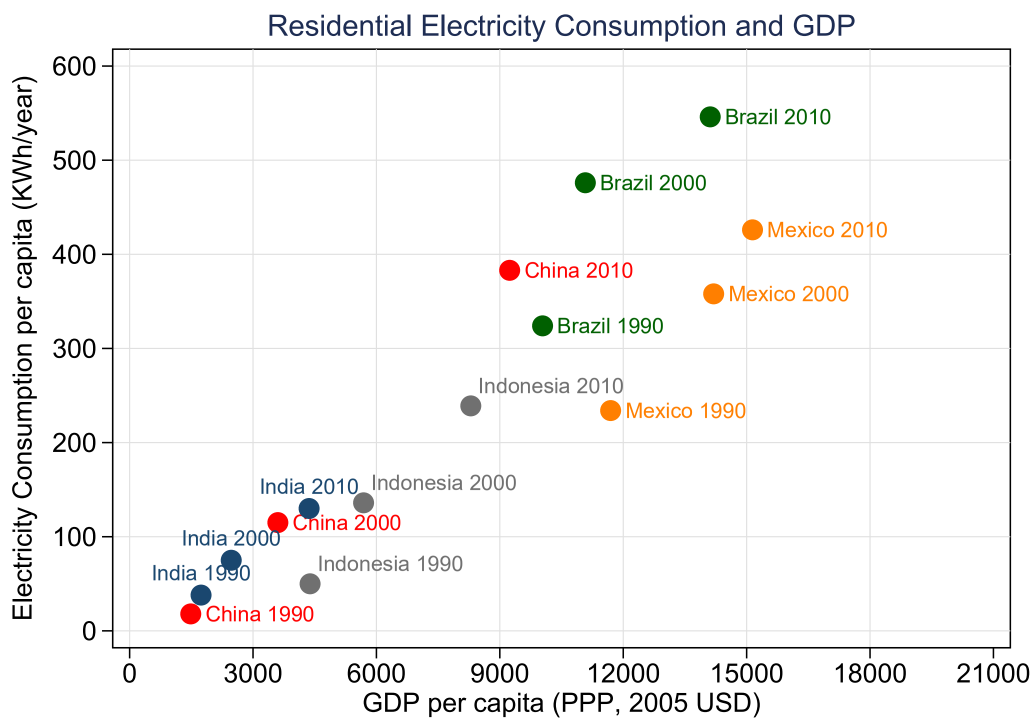
Finally, we study one emerging economy facing challenges today that are likely to be faced by other emerging economies in the future, see Figure 1. This so happens because Brazil has a high level of urbanization and per capita income when compared to other emerging economies, which is were energy consumption is bound to increase the most in the coming decades (Wolfram, Shelef and Gertler, 2012; EIA, 2013).

2 Institutional Background

Electricity consumption tends to grow in tandem with GDP in per capita terms, see Figure 1 for selected emerging economies. Thus, it comes as no surprise that U.S. Energy Information Administration forecasts total energy consumption for the period 2010-2040 to grow by 18 percent in OECD countries and 90 percent in non-OECD countries (EIA, 2013, Table 1). That is, emerging economies are bound to increase their electricity consumption substantially in the coming decades.

[4]Although there are several related papers, to the best of our knowledge no one has sought to decompose the EEG. For instance, Greene (2010) estimates an EEG coming from incomplete information and loss aversion whereas Sallee (2013) relate the valuation of energy efficiency to search costs.

Figure 1: **Per Capita Residential Electricity Consumption and GDP (PPP)**



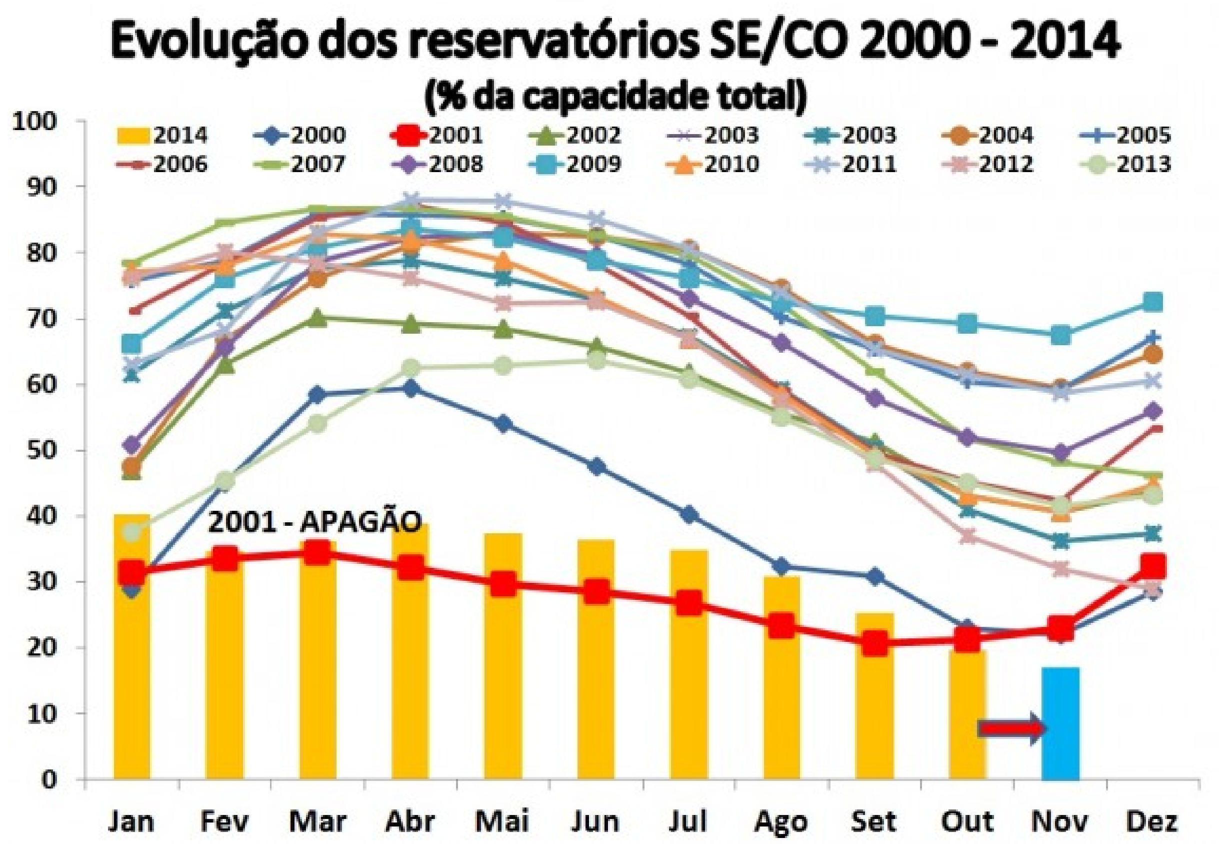
Note. This figure displays per capita residential electricity consumption and GDP (PPP) for selected emerging economies using data from the International Energy Agency (IEA). GDP per capita is expressed at purchasing power parity (PPP) and 2005 USD.

Our study examines the the effects of the PERCEE program on the Brazilian market (see details below), focusing on the purchase of refrigerators. Brazil is a country whose GDP increased by approximately 40 percent in the 2000s and whose degree of urbanization and per capita income are higher than those of other important emerging economies.[5] As a result, it seems natural to think that other emerging economies will be able to draw lessons from the findings for the Brazilian market today.

Some of the problems faced by the Brazilian electricity market happened exactly because the growth experienced by the Brazilian economy following the economic stabilization in the mid-1990s was not met by increases in the electricity supply. In fact, the lack of investments in generation and distribution in the late 1990s and the worst drought in 70 years led to what became known as the Brazilian Energy Crisis ("Crise do Apagão"); hydro-power was responsible for 94 percent of the electricity generated in the country and 81 percent of the production capacity in the country in year 2000 ONS (2011). Reservoir levels were on a downward trend, reaching less than 40 percent of capacity in the fourth quarter of that year, see Figure 2. The deterioration of reservoir capacity led Brazilian policymakers to devise policies which were introduced starting from May 2011, in what became known as the PERCEE program.

[5] The improvements in its terms of trade, the introduction of social programs and an increase in both public and private investment in the early 2000s led the country experience an increase in (formal) employment and income. Moreover, the formalization of labor relations combined with increased credit availability resulted in an ever larger demand for durable products such as household appliances and automobiles, thanks to substantial increases in its consumer market (middle-class), which grew from 48.5mn to 57.8mn (19mn to 30mn) from 2003 to 2009, according to estimates from the Brazilian Statistics Bureau (IBGE).

Figure 2: **Reservoir Levels in Southeast-Midwest Brazil, 2000-2014**



Note. This figure displays the evolution of reservoir levels in the Brazilian Southeast and Midwest regions as a percentage of total capacity for years 2000-2014 at the monthly frequency. Source: Climatempo, based on ONS data, `http://www.climatempo.com.br/noticias/271106/brasil-esta-pior-do-que-na-epoca-do-apagao/`.

2.1 The PERCEE Program

Program Overview The PERCEE program, introduced as a response to the Brazilian Energy Crisis, was responsible for the largest reduction in electricity use among temporary savings programs worldwide (EIA, 2013). PERCEE was designed to reduce total electricity consumption in Brazil by 20 percent; it was enacted in May 2001 and was in place from June 2001.

The PERCEE program consisted of four sets of measures, namely a nonlinear electricity price increase, an electricity rationing scheme consisting of an energy quota, an energy conservation campaign and an investment program in thermoelectric plants.[6] While the investment program aimed at increasing electricity supply in the short- to medium-run was PERCEE's less visible aspect, the other three sets of measures were widely publicized in the media and also reached consumers via letters starting from May 2001 – see Figure 3 for one example – and their monthly electricity bills, which consumers receive by mail.

At the time, Brazilian energy taiffs were nonlinear, implying nonlinear budget constraints for households (Hanemann, 1984; Hausman, 1985). Instead of adopting steep tariff increases across the board, which were deemed as highly unpopular by policymakers, the PERCEE program introduced nonlinear tariff increases for heavy users. As a result, tariffs increased by 50 percent for electricity consumption in the bracket 200-500 KWh/month and by 200 percent for consumption in excess of 500 KWh/month.

The energy quota was imposed on households consuming over 100 KWh/month. For such households, the quota was set to 80 percent of a household's pre-crisis average energy consumption, based on meter readings from the period May-July 2000, thus one year before PERCEE's inception (and thus credibly exogenous). Households consuming less than 100 KW/month faced an arguably non-binding quota of 100 KWh/month.

PERCEE also introduced a bonus-malus system around the energy quota. Households consuming less than the quota in a given month would be rewarded by means of a bonus proportional to the below-quota consumption in the following bill, whereas households not meeting the quota would incur a malus twice as steep as the bonus.[7]

Finally, PERCEE was comprised of an energy conservation campaign with heavy advertising in all media throughout the period (notably TV ads), very much in the spirit of California's campaign in a similar period (Reiss and White, 2008).

With the rainy season beginning in late 2001 and the reversal of the downward trend in reservoir levels (see Figure 2), several PERCEE measures were eased in November and especially December 2001; quotas were revised upwards and benchmark months used to set the quota were also changed to reflect the higher electricity consumption in summer months. Crucially, Brazil's Northern region was allowed out of PERCEE in December 2001,which effectively signalled to consumers that the program was reaching an end. However, PERCEE officially ended in February 2002, when reservoir levels were already in excess of 60 percent of capacity, see the Appendix for details.

Program Information The information regarding PERCEE reached consumers via three channels. First, through letters sent to their homes from May 2001 which contained three

[6] The measures adopted were typically nonlinear which in adition have also changed during the period the program was in place. These reasons combined with the already complex issue of analyzing multi-part tariffs make it difficult to explicitly model PERCEE's constraints.

[7] While it was initially announced that households (consistently) not attaining the quota would be liable to energy cuts, these were ruled out for violating the Brazilian Consumer Code already in May 2001. For instance, daily newspaper Folha de São Paulo reports as early as 28 May 2001 that the then Attorney General expressed concerns due to the fact that energy cuts under PERCEE were not consistent with measures contemplated in the Brazilian Consumer Code, according to which energy cuts were only allowed in the case of overdue electricity bills, see `http://www1.folha.uol.com.br/folha/dinheiro/ult91u22774.shtml`.

pieces of information – see Panel A in Figure 3 for a letter sent to a household in the state of Rio de Janeiro. One such piece of information is the household's energy consumption quota (358 KWh/month in this particular case); another is the fact that if the household does not attain the energy consumption quota it would be liable to energy cuts (later overruled, see above); finally, the fact that a household consuming below the quota would be eligible to a bonus.

Figure 3: **Information about PERCEE Program**

Light

Rio de Janeiro, 30 de maio de 2001

Prezado Cliente,

Atendendo à Resolução nº 4 da Câmara de Gestão da Crise de Energia Elétrica, a Light informa a sua meta de consumo: (1)

358 kWh/mês

De acordo com a mesma Resolução, a partir do dia 04 de junho, os consumidores que ultrapassarem suas metas ficarão sujeitos à suspensão do fornecimento de energia elétrica. (2)

Assim, fique atento ao seu consumo e lembre-se que, se ele for menor do que a sua meta, você poderá ter direito a um bônus. (3)

Com a sua participação e a participação de todo o Rio de Janeiro, vamos enfrentar melhor o desafio do racionamento. Isso tem um nome:

Energia Solidária.

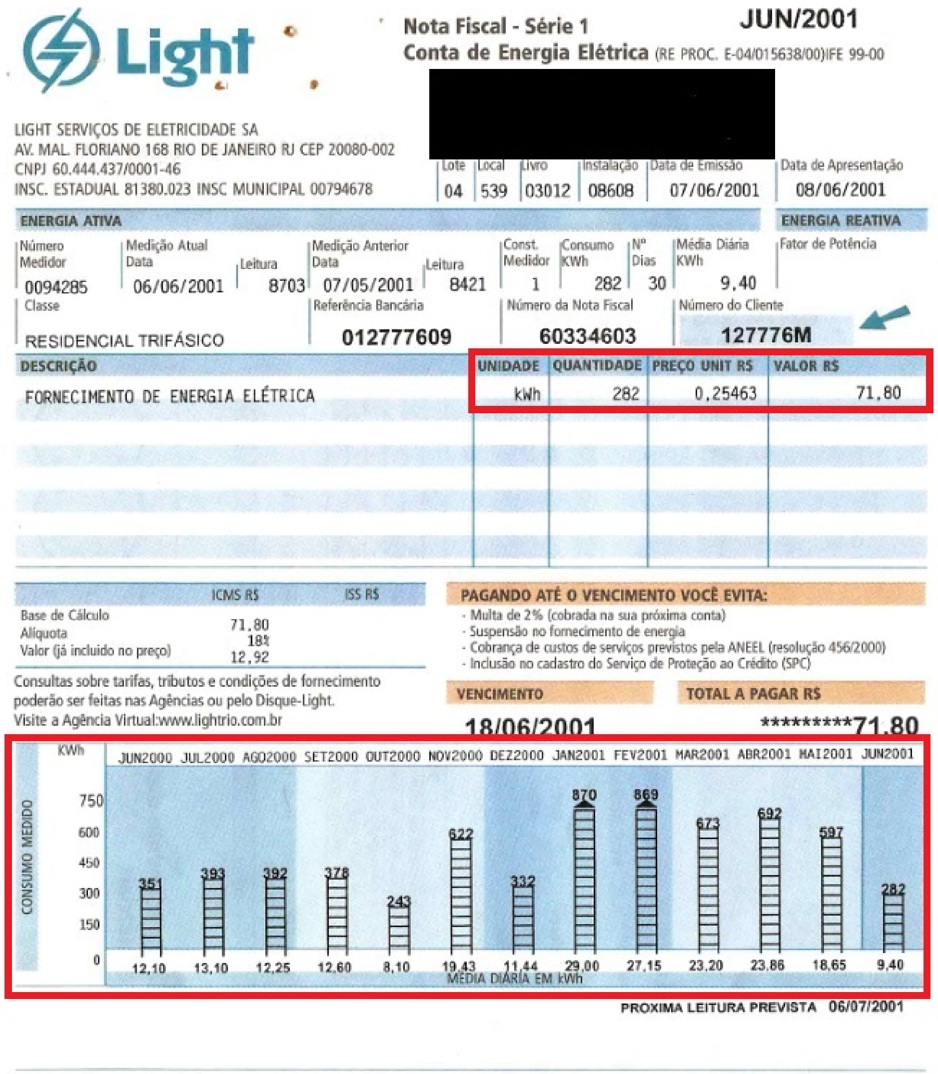
Para maiores informações sobre recionamento:

- 0800-282-0120
- Agências Light
- www.lightrio.com.br

Desde já, agradecemos a sua compreensão.

Light Serviços de Eletricidade S.A.

Panel A. First letter informing consumers about PERCEE



	JUN2000	JUL2000	AGO2000	SET2000	OUT2000	NOV2000	DEZ2000	JAN2001	FEV2001	MAR2001	ABR2001	MAI2001	JUN2001
KWh	351	393	392	378	243	622	332	870	869	673	692	597	282
MÉDIA DIÁRIA EM kWh	12,10	13,10	12,25	12,60	8,10	19,43	11,44	29,00	27,15	23,20	23,86	18,65	9,40

Panel B. Sample electricity bill (monthly frequency)

Note. Panel A displays the first letter sent to a consumer in the Brazilian state of Rio de Janeiro with information about the PERCEE rationing program. (1) Informs household of energy consumption quota (here, 358 KWh/month); (2) Informs household that not meeting the quota is liable to penalties; (3) Informs household that consuming below the quota is eligible to a bonus.

Second, consumers received information via their monthly electricity bills, delivered by mail. For instance, Panel B in Figure 3 displays the first bill received by the same household in the state of Rio de Janeiro which received the letter displayed in Panel A. The information displayed is standard, with details on the meter reading, the electricity consumption (282 KWh in this case), the unit price per KWh, the net price, taxes etc. Perhaps most interestingly, the bottom part of the bill reports the consumption in the current month together with the consumption in the 12 previous months (in particular, for June 2000). The bars displayed show a clear seasonal pattern in that electricity consumption increases in warmer months (here, November 2000-April 2001) due to the use of air conditioning.

Finally, consumers received information through PERCEE's extensive media campaign. The campaign emphasized behavior in both the intensive and extensive margins; on the intensive front, the campaign stressed concrete energy conservation measures such as switching off the lights of empty rooms and taking shorter showers.[8] On the extensive margin, the campaign stressed measures such as the importance of purchasing energy-efficient appliances whereas the only concrete measure strongly emphasized was the replacement of old, inefficient, light bulbs with more efficient ones.

All in all, there are no reasons to believe that PERCEE induced households to replace their refrigerators in order to attain the energy quota, be it because individual energy quotas were based on previous consumption, be it because regulators expected the advertised measures to deliver the desired energy savings, or be it because this would mean replacing a durable product when facing a temporary policy.[9]

2.2 Household Appliances: Refrigerators

Our empirical analysis focuses on the market for refrigerators for several reasons. First, refrigerators have a relatively simple product attribute space and are subject to limited discretionary use (Gately, 1980; Houde and Aldy, 2017). In practice, once a refrigerator is purchased and its basic settings adjusted, these are unlikely to be frequently adjusted.[10]

Second, refrigerators were owned by a substantial – and stable – share of households in the Brazilian market, with more than 84% of all households in Brazil owning one in 2000 according to the Brazilian Statistics office.[11] This mitigates selection concerns due to income, especially in comparison to other emerging economies.[12]

Third, refrigerators command a non-trivial share of electricity consumption within a household. For instance, Cardoso (2008) estimate that refrigerators are responsible for 28-30 percent of the total energy consumption of the typical Brazilian household.

Fourth, refrigerators are expensive products for the average Brazilian household, to the extent that for 60 percent of the households in our sample a refrigerator costs more than their monthly income. It is then reasonable to think that its purchase receives close scrutiny when it comes to weighing its price against their characteristics, especially operating costs. Thus, rejecting the null hypothesis of correctly trading-off price and lifetime operating costs using

[8]Taking shorter showers are arguably an important measure of energy savings since showers tend to be electric in the Brazilian market and Brazilians typically shower daily, at times more than once per day.

[9]In fact, the number of refrigerator purchases in years 2000 and 2001 in our data are very similar, which more consistent with the view that consumers were replacing their refrigerators.

[10]Anecdotal evidence suggests to adjustments in settings being more likely to happen due to temperature changes than electricity prices, something we aim to account for empirically. Reassuringly, it was very unusual for refrigerators on the Brazilian market in the early 2000s to have temperature controls on the front door.

[11]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.

[12]In contrast with other markets, see e.g. Davis, Fuchs and Gertler (2013); Gillingham, Harding and Rapson (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.

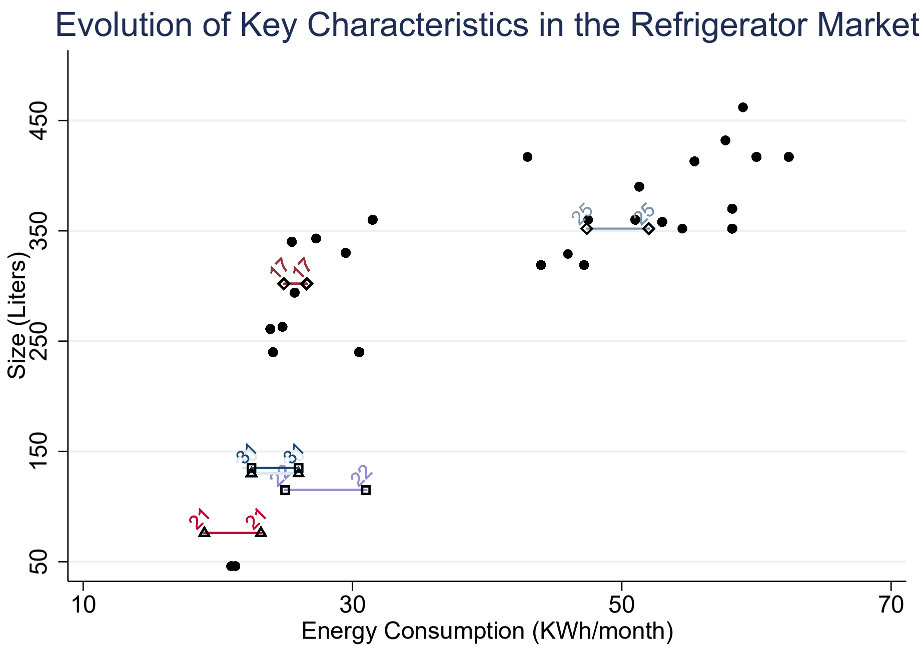
data on refrigerators would arguably have more power than doing so for, other, less valuable, and less energy-intensive products.[13]

Finally, refrigerators have not witnessed major technological innovations during the sample period, as compared to other products such as personal computers and TVs. As a result, the purchase of a refrigerator is more likely to have occurred due to replacement motives.

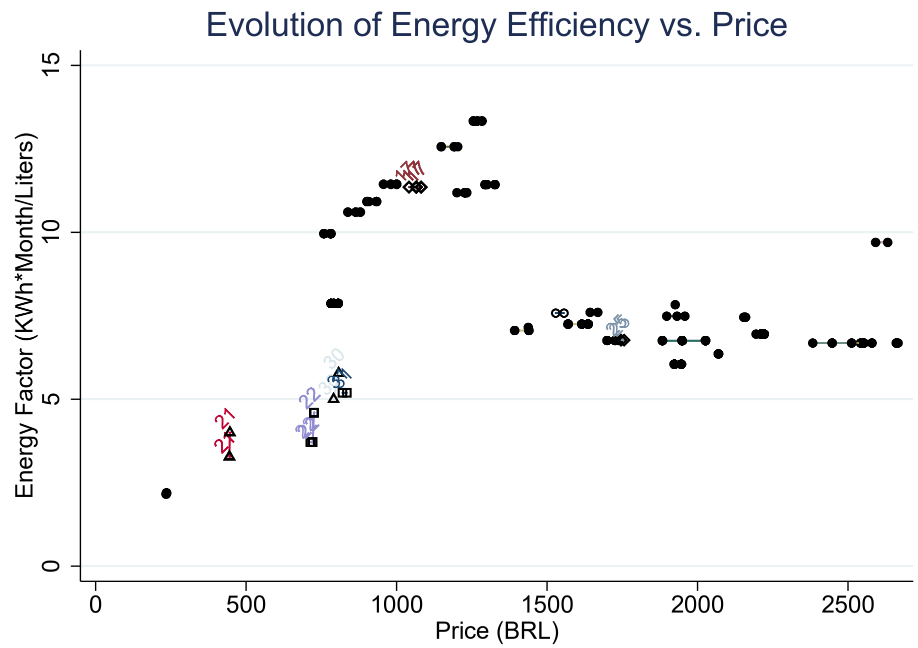
To gauge the impact of the PERCEE program on the refrigerator market, Figures 4 and 5 display a number of graphics on describing its supply and demand sides, respectively. Panel A in Figure 4 displays the relation between two key characteristics when it comes to refrigerators, namely energy consumption and size (volume). The first thing to note is that there seem to be three clusters of products which do not seem to change over time. Moreover, most products are marketed with the same characteristics before, during, and after the PERCEE program – the exceptions are few and far between, which suggests that firms did not react strongly to the PERCEE program in characteristic space. Panel B displays the relation between energy efficiency and price. Perhaps surprisingly, this relation is mostly stable over time. This suggests that there has been surprisingly little technological innovation in terms of energy efficiency and that manufacturers did not price-discriminate during the PERCEE program.

[13]As pointed out in (Golove and Eto, 1996; Palmer, Walls and Gerarden, 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. However, the stabilization experienced by the Brazilian economy, and the surge in credit instruments and credit availability, allowed the population to finance the purchase of durables. Informal, within-household schemes such as pooling resources are not unheard of either when it comes to the purchase of durables. Due to the potential importance of this channel, we make sure to control for household demographics in our empirical analysis.

Figure 4: **Evolution of Product Characteristics – Supply-side**



Panel A. Refrigerator Size vs. Energy Consumption



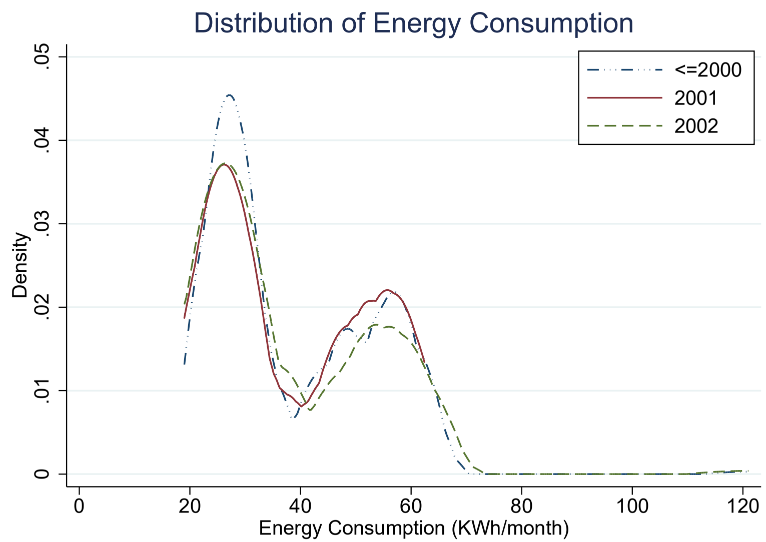
Panel B. Energy Efficiency vs. Prices

Note: This figure summarizes changes in product lines in the Brazilian refrigerator market by focusing on the relations between refrigerator size and energy consumption (Panel A); and energy efficiency vs. refrigerator prices (Panel B). In Panel A, products for which there was no change in characteristics between 1998 and 2002 are displayed with a dot whereas products which experienced technological improvements are displayed with lines connecting hollow symbols (circles, diamonds, and squares) and with numbers reported next to them (all such products experienced a decrease in energy consumption, thus an increase in energy efficiency). In Panel B, which displays figures for years 2000-2002 to avoid clutter, the vertical axis corresponds to the slope of Panel A, and all symbols are potentially connected through lines to reflect changes in prices over time. Note that increases in the energy factor do not seem associated with price increases.

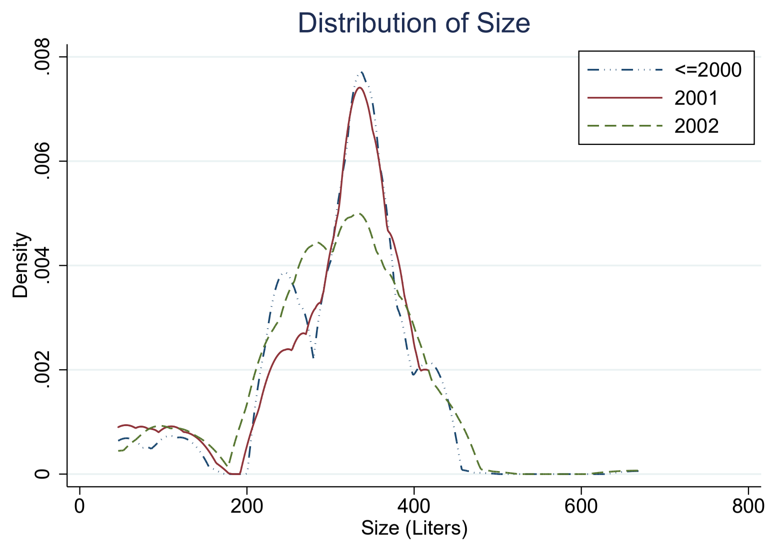
Figure 5 displays how distributions of product characteristics evolved over time from the demand-side, i.e. sales-weighted. For each panel, we calculate the density based on the data of the refrigerators purchased by the households in the sample. Panel A shows how the distribution of energy consumption is bi-modal regardless of the period considered. Panel B shows how the purchase of larger refrigerators (above 400 liters) dropped during 2001 as a response to the PERCEE program. Finally, Panel C shows that the distribution of energy efficiency is bi-modal in all years, with no clear pattern of how it evolves over time.

Taken together, both anecdotal and descriptive evidence for the refrigerator market suggest a number of features for the market. On the supply-side, product lines and pricing were to a large extent stable during the sample period. The action seems to have been concentrated on the demand side, potentially due to the PERCEE program.

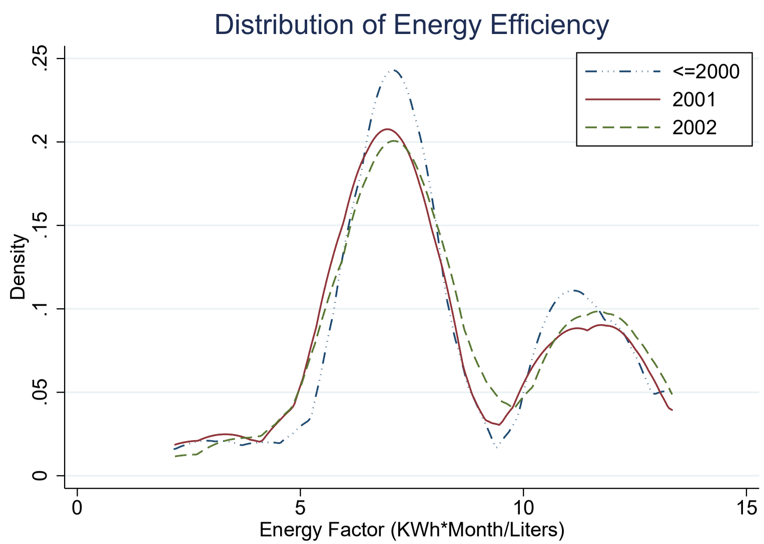
Figure 5: **Distribution of Selected Product Characteristics – Demand-side**



Panel A. Energy Consumption



Panel B. Size



Panel C. Energy Efficiency

Note: This figure displays the evolution of key product characteristics according to refrigerator sales.

3 Data

We combine different datasets to perform our analysis, see the Appendix for details. These range from survey data to primary product price data used in the construction of price indices to detailed product characteristics.

Survey on household appliances and usage habits (PPH). [14] This nationally representative survey interviewed 4310 households in 16 Brazilian states, in addition to 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. Next, households were selected within a cluster according to population characteristics.[15] The survey questionnaire is divided into five sections, namely (1) Identification and basic household characteristics; (2) Ownership of household appliances; (3) Usage of household appliances; (4) Socio-economic characteristics of the household; and (5) Energy conservation measures.

Section 1 asks basic information about a household, such as its address, size, composition, educational attainment of individual members, and dwelling size. Section 2 asks detailed information about appliances owned, including model and purchase date. Section 3 asks information about energy consumption and appliance usage, 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 measures, e.g. whether the household replaced their incandescent light bulbs with fluorescent ones.

In what is crucial for our purposes, the PPH survey asks a number of questions regarding the Brazilian Energy Crisis and the PERCEE program. In particular, it asks households whether energy conservation measures adopted during the energy crisis were enough to attain the energy quota set by the PERCEE rationing program (see the Appendix for details). The answer to this question is used below to identify households for which the energy consumption quota was binding, i.e. a measure of incentives to reduce energy consumption during the crisis.[16]

Approximately one-third of all surveyed households have purchased refrigerators during the sample period. 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 with the year a given product was marketed.[17]

[14] 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.

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

[16] This is obtained from Question 12.3 of the survey. We define the indicator of a binding energy quota as having a value of one if the measures under PERCEE were insufficient to attain the energy quota; or if they were enough, but of very difficult implementation. As a robustness check, we have also performed the empirical analysis using the answers to arguably less objective Question 12.4, which asks households how they evaluate the change in their quality of life as a result of the PERCEE rationing program. Despite the qualitatively similar results, we feel that Question 12.3 more directly represents the effect we aim to capture, namely whether the energy quota was binding for a given household.

[17] This feature will also guide our empirical analysis below; while we have reliable information about the year when a refrigerator was purchased, the information about the month of purchase is less reliable. As a result, our time dimension is measured in years instead of months, despite the risk of defining as constrained households those who did purchase a refrigerator, say, before PERCEE was introduced in 2001. To gauge the potential bias incurred in making such assumption, assume for one moment that everyone who purchased a refrigerator in 2001 and self-declares as constrained is a constrained household who purchased a refrigerator during PERCEE. Then, the valuation of energy efficiency for binding households is underestimated since it includes households

Electricity prices We have obtained retail electricity prices since January 2003 from ANEEL, the 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 block pricing structure, we have accounted for the prices actually paid by households given their consumption levels.

Discount rate We use the Brazilian federal long-term interest rate, TJLP. This rate is set by the Brazilian Monetary Council (CMN) at the quarterly frequency. The TJLP oscillated between 10-14 percent per year during the sample period, thus being higher than discount rates typically used for developed economies and consistent with the faster rate of economic growth experienced by emerging economies.

Product prices We obtain prices for refrigerators from the monthy 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.

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 2001-2005 guides issued by the PROCEL program. Second, from online sources with the manuals of household appliances in the Brazilian market. Third, from the previous literature on PROCEL in the area of Engineering, such as Cardoso (2008); Jannuzzi (2002).

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 detailed in the Appendix. 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. 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

4.1 Demand Estimation

The decision to purchase a household appliance is comprised of the discrete decision of which product to purchase and the continuous decision of how much to utilize the purchased product. These decisions are typically correlated since consumers likely trade-off the price of a product and its lifetime operating costs. 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. Ignoring the interdependence between the discrete and continuous decisions will typically result in selection bias (Heckman 1979). In our empirical analysis, we follow much of the literature (Gately 1980, Houde 2014) and rely on the limited discretionary margin in

which are not constrained. In contrast, the valuation of households with a non-binding quota is unaffected.

the use of refrigerators to model the decision to purchase a refrigerator using a discrete choice model.[18]

Model specification We estimate the demand for refrigerators using a random coefficients logit model. Our starting point is a microeconomic model of rational behavior for individual households. Households buy one of the products available on the market, the one which yields the highest utility among the available products.[19] The econometrician observes individual choices, prices and a set of characteristics for each of the J products available for a number of markets and periods as well as a set of household demographics. Letting i index households and j index products, define the conditional indirect utility of a household as

$$u_{ij} = x'_{ij}\beta_i + y'_i\gamma_i + \varepsilon_{ij}$$

where $x'_{ij} = (p_{ij}, c_{ij}, \tilde{x}'_{ij}), i = 1, ..., H; j = 1, ..., K$ is a vector of product characteristics; y'_i is a vector of household characteristics such as income; ε_{ij} is a mean-zero stochastic term with a type-1 extreme value (T1EV) distribution. Product characteristics include product prices, p_{ij}, and a vector of additional product characteristics $\tilde{x}'_{ij}$ such as refrigerator size. The (expected) present discounted value of operating cost of appliance j at household i is given by

$$c_{ij} = AC_{ij}\left[1 - \frac{1}{(1+r_i)^n}\right]\frac{1}{r_i}$$

where AC_{ij} is the annual operating operating cost of appliance j at household i, r_i is the discount rate by household i upon purchase, and n is the lifetime of a refrigerator.[20]

Household heterogeneity We aim to capture a number of important sources of heterogeneity given the institutional setting. First, we want to account for unobserved household heterogeneity in both price and cost, which is done via random coefficients.

Second, we want to account for heterogeneity arising from (i) the different regimes induced by the sub-periods in our sample and (ii) the potentially differential responses due to incentives in place during the PERCEE program. That is, we want to allow households to have different sensitivities to the cost component in different sample sub-periods, which is done by introducing interactions between cost and time period indicators; the resulting cost-period variable is endowed with a random coefficient to allow for an even richer pattern of heterogeneity. Importantly, to account for the different incentives during PERCEE, the cost-period interaction for year 2001 is further interacted with an indicator of a binding or non-binding energy quota constraint.

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 (BLP 1995) and

[18]Equivalently, this corresponds to the assumption that utilization conditional on product choice is perfectly inelastic, as in Grigolon, Reynaert and Verboven (2015). 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. In an attempt to mitigate any remaining concerns about this assumption, we control for household demographics likely to affect any residual discretionary use of refrigerators and interact them with product characteristics.

[19]We do not consider the existence of an outside good, since our focus is on how the policy of interest influence which product to purchase, not the timing of the decision to purchase. This is consistent with the purchase of a refrigerator with replacement motives.

[20]The annual operating cost can be decomposed as the product $AC_{ij} = t_i\kappa_j h_{ij}$ of the tariff t_i paid by household i (measured in monetary units per energy consumption, BRL/KWh), the energy consumption κ_j of appliance j (measured in KWh) and the intensity of use h_{ij} of appliance j at household i (measured in hours/year).

consumer products (Griffith, Nesheim and O'Connell 2015), and arguably especially important for durables marketed in an emerging economy. Thus, we allow price sensitivities to depend on income and a random coefficient.[21]

Finally, to allow for the potential correlation between household demographics and product characteristics, we interact a subset of those variables. Figure 6 provides a timeline which summarizes the setup and the parameters to be estimated.

[21] Although full generality would call for prices to be interacted with period indicators, this type of specification proved numerically challenging. This is suggestive of problems in jointly identifying time-varying cost and time-varying price parameters with the data at hand.

Figure 6: **Timeline and Model Parameters**

Period:	1999-2000	2001	2002
Event:	*pre-policy*	*policy*	*post-policy*
Policy:		PERCEE	
Demand Parameters:			
Cost (time-varying):	$\beta_{ic,1999-2000}$	$\beta_{ic,2001}^{binding}, \beta_{ic,2001}^{non-binding}$	$\beta_{ic,2002}$
Price (time-invariant):	β_{ip}	β_{ip}	β_{ip}
Valuations:	$\upsilon_{i,1998-2000}$	$\upsilon_{i,2001}$ $\upsilon_{i,2001}^{binding}, \upsilon_{i,2001}^{non-binding}$	$\upsilon_{i,2002}$
Remark:		*consumers face incentives to meet energy quota*	

Note. This table illustrates the connection between the institutional background and the parameters we estimate. We consider four sub-periods, one of which coincides with the PERCEE program (2001). We report heterogeneous individual cost and price coefficients, all of which are comprised of a mean and a standard devation (random coefficient). We further interact cost with sub-period dummies, so that valuation distributions are allowed to vary across sub-periods. Finally, we distinguish between constrained and unconstrained households while the PERCEE program was in place.

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, $\nu_i \sim \mathcal{L}(0, I_K)$.[22] It then follows that the parameter vector to be estimated is given by $\theta := (\beta^*, \Pi, \Sigma, \gamma)$.

Estimation Following the literature (see Train 2009), the estimation is performed using Simulated Maximum Likelihood (SML), with the likelihood function given by

$$lnL(\theta) = \sum_{i=1}^{I} \sum_{j=1}^{J} d_{ij} ln(p_{ij})$$

where d_{ij} is the indicator that household i chose product j. The choice probabilities take the form

$$p_{ij} := Prob(d_i = j) = \int \frac{exp\left(\sum\limits_{k=1}^{K} x_{jk}\beta_{ik} + \sum\limits_{k=1}^{D} y_{ik}\gamma_{ik}\right)}{\sum_{s=1}^{J} exp\left(\sum\limits_{s=1}^{K} x_{sk}\beta_{ik} + \sum\limits_{k=1}^{D} y_{ik}\gamma_{ik}\right)} \phi(\beta_i|\beta^*, \Pi, \Sigma)$$

where $\phi(.|.)$ is the density of a Lognormal random variable.

Our 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 current ownership of a refrigerator (and its state, neither of which we observe) is likely to affect the current demand for refrigerators. Arguably, our estimation approach represents a pragmatic modeling approximation to actual choice behavior in the industry which is 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 mostly cross-sectionally, but also over time and across energy consumption brackets. Energy consumption of refrigerators also both cross-sectionally and over time, due to improvements in product characteristics over time. 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.

Identification of the price parameters relies on the variation of refrigerator prices across markets and over time, combined with product entry and exit. 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 reputation or quality. Although this is a major concern

[22] 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 avoids any ill-defined moments of the distribution of the valuation parameter v as documented in the case of the Normal distribution. An alternative parameterization would be to treat the price coefficient as having no heterogeneity and thus divide the numerator mixing distribution by a scalar (Daly, Hess and Train, 2012). However, we feel heterogeneity is crucial to model the price sensitivity of consumers in a realistic way, see the results below.

when using aggregate data, this is slightly less of a concern in the case of micro data; firms are assumed to set prices at the (national) market level and not to react to demand shocks at the local (or household) level, 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. Importantly, note that PERCEE provides important variation in the incentives and information facing consumers, respectively, to identify the parameters of interest.

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, especially product fixed-effects. We also 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. [23] To the extent that characteristics such as product quality are time-invariant, product fixed-effects provide a natural way to control for them. 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.

Finally, to account for the fact that household demographics are likely correlated with product characteristics, we interact these two sets of variables. For instance, we include interactions between refrigerator volume and household size since larger families households are likely to purchase larger refrigerators.

4.2 Policy Effects

In what follows, we quantify different aspects of the PERCEE program. First, we quantify the effect of PERCEE on the valuations of energy efficiency for households for which the energy quota is binding and for those for which it is not. This is important because PERCEE has a very different impact on the valuation of energy efficiency depending on whether the energy quota constraint was binding for a given household.

Next, we quantify the long-run – or memory – effects of the PERCEE program. That is, we quantify how household behavior changes once the incentives in place by the PERCEE program are lifted, in comparison to pre-PERCEE valuations. If a policy has no long-run effects, then its pre- and post- valuations should be equal. That is, once any constraints on household behavior are removed, the valuations of energy efficiency should revert back to their original (pre-policy) levels. However, it may also be the case that the information provided while a program was in place has resonated on household above and beyond its very duration, so that it managed to (re)shape their preferences.

Let $\mathbb{P} = \mathbb{P}(E, \theta)$ define the vector of purchase probabilities of each marketed product under a given environment E (product characteristics, household demographics) and parameter vector θ. We denote our variables of interest, e.g. energy consumption, by an index i . A counterfactual is obtained as the vector of purchase probabilities resulting from the combination of an environment and a parameter vector belonging to a different period. The program effect is obtained as the difference between actual and counterfactual outcomes. With this framework in place, the effect of PERCEE on households for which the energy quota is binding

[23] Arguably, in the market for refrigerators reputation is more likely to manifest itself at the brand level, in contrast with other products such as automobiles. Nevertheless, we have adopted specifications with product fixed-effects after experimenting with brand fixed-effects.

and non-binding can be measured as, respectively,

$$\begin{aligned}\pi_i^b &:= \mathbb{P}(E_{1999-2000}, \hat{\theta}_{2001}^b) - \mathbb{P}(E_{1999-2000}, \hat{\theta}_{1999-2000}), i = EC, S, EE, CS \\ \pi_i^{nb} &:= \mathbb{P}(E_{1999-2000}, \hat{\theta}_{2001}^{nb}) - \mathbb{P}(E_{1999-2000}, \hat{\theta}_{1999-2000}), i = EC, S, EE, CS\end{aligned}$$

where the estimates of the parameter vector are obtained from the baseline specification and the environment is taken to be the pre-PERCEE period, and EC, S, EE, and CS denote energy consumption, size, energy efficiency, and consumer surplus, respectively. For instance, given the choice set and households on the market in 1999-2000, the average counterfactual energy consumption, say, can be obtained by applying the valuation parameters prevailing for binding households in 2001, obtaining the corresponding purchase probabilities and weighing the energy consumption of each product by its purchase probability. Under the null hypothesis of no effect of the PERCEE program, π_i^b and π_i^{nb} are equal to zero.

Similarly, the long-run effect of the PERCEE program can be written as

$$\mu_i := \mathbb{P}(E_{2002}, \hat{\theta}_{2002}) - \mathbb{P}(E_{2002}, \hat{\theta}_{1999-2000}), i = EC, S, EE, CS$$

where now the prevailing valuation estimates for 2002 are compared to those in the 1999-2000 environment. Testing the null hypothesis that the PERCEE program has no long-run effects amounts to testing the null hypothesis that μ_i equals zero against the two-sided alternative.

Another effect of interest is the effect of the policy on different population sub-groups. For instance, the changes in energy efficiency between households with high and low educational attainment. Letting G be an indicator of membership to a group, the effect of the differential effect across educational attainment of the PERCEE program on consumers for which the energy quota was binding is given by

$$\pi_i^{b,G} := [\pi_i^b | G = 1] - [\pi_i^b | G = 0], i = EC, S, EE, CS$$

One particular case of the above is the case of treatment effects, where G denotes treatment,$G = 1$ ($G = 0$) denotes the sub-group of treated (non-treated) households.

5 Results

5.1 Demand Estimation

Our demand specifications are comprised of product characteristics, household demographics, the interaction between them, and the specification of household heterogeneity. Among product characteristics we consider product fixed-effects and refrigerator 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, see Figure 6 and details below.

We assume energy prices and the interest rate to follow random walks, which is consistent with evidence documented in Anderson, Kellogg and Sallee (2013) and the recent literature, e.g. Allcott, Mullainathan and Taubinsky (2014) and Grigolon and Verboven (2014).[24] This assumption is also consistent with the regulatory framework consisting of a price-cap mechanism whereby prices are revised every 4-5 years. We also follow the literature (see e.g. Cardoso and Nogueira 2007), in that we assume the (expected) lifetime of a refrigerator is 16 years.[25]

[24]This is moreover consistent with findings documented in Alquist, Kilian and Vigfusson (2013) survey, according to which complex models do not outperform simple models with expectations based only on current energy prices.

[25]This is similar to Houde and Aldy (2017), who assume a lifetime of 19 and 18 years, respectively.

Household demographics include income per capita and size of dwelling, household size, an indicator of freezer ownership, and region fixed-effects whereas the interactions between product characteristics and household demographics include price-income, volume-size of dwelling, and volume-household size terms. Unless when explicitly mentioned otherwise, all specifications include time (period) fixed-effects.

Demand estimates Table 1 reports demand and valuation estimates of six RC logit specifications. All specifications displayed have size of dwelling as one of the demographics, in addition to interactions of volume and size of dwelling, and of price and household income.[26]

The starting point is Specification (1), whose mean parameters in line with economic theory and typically statistically significant – the exception being refrigerator volume, which is not significant in any specification. Among heterogeneity (standard deviation) parameters, price is statistically significant throughout either at the 10 or at the 5 percent significance level. The lack of significance of most cost-period heterogeneity parameters suggest a roughly homogeneous valuation of consumers to the lifetime operating costs of a refrigerator across different periods. The only stance where cost loads statistically significant is when interacted with the indicator of the 2003-2005 period, which is when the PROCEL energy label becomes mandatory; this is so for Specifications (4) and (6). Our reading from these findings is that consumers respond in a heterogeneous fashion to the information contained in labels, which then became mandatory. That is, despite their voluntary adoption by all major producers prior to PROCEL, the fact that labels became compulsory still resulted in heterogeneous reactions by households.

Specification (2) and onwards include time (period) fixed-effects, in what can be seen as an additional challenge for the identification of the cost-period parameters. However, these are only marginally affected in terms of point estimates and not at all in terms of significance.

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 decide to purchase a smaller refrigerator, for instance – we control for freezer ownership in Specification (3). This time, the impact on demand estimates is more pronounced, especially when it comes to the price and some of the cost mean parameters, but such changes are not strong enough to affect statistical significance.

Specification (4) adds household size and its interaction with refrigerator volume whereas Specification (5) adds region fixed-effects to Specification (3). In either case, demand estimates are only marginal affected.

Finally, Specification (6) – which is our baseline specification hereafter – has the full set of demographics, interaction terms and fixed-effects. Again, demand estimates are only marginally affected, with statistical significance unaffected. Importantly, only price and the 2003-2005 cost variable heterogeneity parameters are statistically significant.

Valuation of energy efficiency – Mean estimates When it comes to the valuation of energy efficiency, Table 1 reports average valuations which are largely robust and no more dispersed than comparable ones in the literature, especially considering the complexity of the models estimated.[27] For instance, the valuation parameters for the period 1999-2000 are in the range 0.831-0.940 whereas those for year 2002 are in the range 0.789-0.956. Moreover, the

[26] Throughout our analysis, we use robust standard errors; the number of potential clusters is small given the yearly frequency of the data and the few cross-sectional markets, rendering any asymptotics based on clustered standard errors unreliable.

[27] For perspective, Allcott, Mullainathan and Taubinsky (2014, Table 4) report valuation estimates in the range 0.42-0-77 under the assumption that fuel prices follow a martingale, the one more comparable to our setting.

Table 1: **Demand and Average Valuation Estimates**

Variables	[1]	[2]	[3]	[4]	[5]	[6]
Mean						
Volume	0.0036	0.0036	0.0030	0.0001	0.0032	0.0003
	(0.0049)	(0.0049)	(0.0049)	(0.0061)	(0.0050)	(0.0061)
Cost x DV(1998-2000)	-7.0233 ***	-7.0373 ***	-7.2450 ***	-7.2300 ***	-7.2514 ***	-7.2594 ***
	(0.4389)	(0.5884)	(0.7373)	(0.7053)	(0.7273)	(0.7152)
Cost x DV(2001) x Bind.	-6.6015 ***	-6.6448 ***	-6.6349 ***	-6.6353 ***	-6.6630 ***	-6.6712 ***
	(0.4710)	(0.6352)	(0.6273)	(0.6350)	(0.6786)	(0.6884)
Cost x DV(2001) x Non-bind.	-7.2064 ***	-7.2266 ***	-7.3173 ***	-7.3761 ***	-7.2378 ***	-7.3109 ***
	(0.4340)	(0.7987)	(0.8871)	(0.9337)	(0.8375)	(0.8952)
Cost x DV(2002)	-6.9778 ***	-6.9942 ***	-7.0496 ***	-7.0310 ***	-7.0206 ***	-7.0130 ***
	(0.3691)	(0.4668)	(0.5075)	(0.4838)	(0.4915)	(0.4746)
Cost x DV(2003-2005)	-6.9764 ***	-7.0094 ***	-7.1588 ***	-7.1606 ***	-7.1435 ***	-7.1589 ***
	(0.4277)	(0.5992)	(0.7532)	(0.6201)	(0.7136)	(0.6200)
Price	-7.0461 ***	-7.0381 ***	-7.2273 ***	-7.2070 ***	-7.2628 ***	-7.2300 ***
	(0.5037)	(0.5734)	(0.6229)	(0.5967)	(0.6526)	(0.6275)
Std. Dev.						
Cost x DV(1998-2000)	0.3880	0.4808	0.6904	0.5734	0.6476	0.5527
	(0.4303)	(0.5726)	(0.8230)	(0.6419)	(0.7588)	(0.6193)
Cost x DV(2001) x Bind.	0.0056	0.0046	0.0039	0.0058	0.0046	0.0091
	(0.0120)	(0.0090)	(0.0060)	(0.0082)	(0.0085)	(0.0131)
Cost x DV(2001) x Non-bind.	0.0679	0.0316	0.0238	0.0206	0.0212	-0.0160
	(0.1619)	(0.0380)	(0.0315)	(0.0306)	(0.0266)	(0.0267)
Cost x DV(2002)	0.0043	0.0055	0.0046	0.0053	0.0045	0.0051
	(0.0138)	(0.0154)	(0.0208)	(0.0185)	(0.0206)	(0.0191)
Cost x DV(2003-2005)	0.7234	0.7122	0.7797	0.7745 *	0.7533	0.7569 *
	(0.5251)	(0.8258)	(1.0088)	(0.4245)	(0.9301)	(0.4491)
Price	0.3694 **	0.3869 **	0.3780 **	0.3420 *	0.3805 **	0.3527 *
	(0.1517)	(0.1622)	(0.1863)	(0.2014)	(0.1890)	(0.2064)
Average Valuations						
$\upsilon_{1998-00}$	0.831	0.847	0.940	0.873	0.935	0.853
$\upsilon_{2001}^{Binding}$	1.176	1.118	1.364	1.343	1.366	1.318
$\upsilon_{2001}^{Non-binding}$	0.643	0.625	0.689	0.640	0.769	0.695
υ_{2002}	0.807	0.789	0.901	0.904	0.956	0.936
$\upsilon_{2003-2005}$	1.046	0.998	1.091	1.067	1.119	1.073
Demographics						
Dwelling size	Yes	Yes	Yes	Yes	Yes	Yes
DV(Owns freezer)			Yes	Yes	Yes	Yes
Household size				Yes		Yes
Region FEs					Yes	Yes
Interactions						
Price-Income	Yes	Yes	Yes	Yes	Yes	Yes
Volume-Dwelling size	Yes	Yes	Yes	Yes	Yes	Yes
Volume-Household size				Yes		Yes
Time FEs		Yes	Yes	Yes	Yes	Yes
Product FEs	Yes	Yes	Yes	Yes	Yes	Yes
Log-likelihood	-2323.66	-2299.18	-2277.57	-2239.00	-2238.48	-2200.44
N	29602	29602	29602	29374	29602	29374

Note. Models estimated are Random Coefficients Logit (RCL) with Lognormally distributed parameters on price and all cost-period terms. The random draws are (independent) Lognormal. Robust standard errors are reported in parentheses. Significance levels are denoted by * (10 percent), ** (5 percent) and *** (1 percent). DV(.) and SD(.) denote dummy variable and standard deviation, respectively. All models are estimated using 300 Halton draws.

estimates exhibit an intuitive pattern which is moreover consistent across all specifications in the table. First, PERCEE increases the valuation of consumers for which the energy quota is binding (1.318 vs. 0.853 as compared to pre-PERCEE valuations, see Specification 6).

Second, the valuation of consumers for which the energy quota is binding is higher than those for which it is not (1.318 vs. 0.695 as per Specification 6).

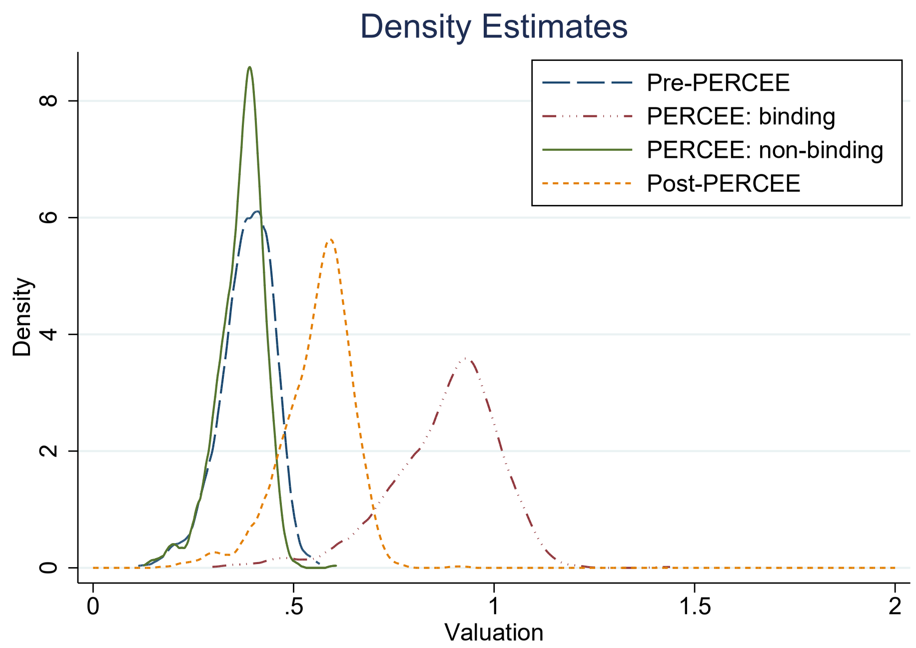
Third, the point estimates of the valuations suggests an over-valuation of energy efficiency by these constrained households which we attribute to the incentives put in place during PERCEE.

Fourth, once PERCEE is over, valuations decrease – but do not return to – pre-PERCEE levels (0.936 post-PERCEE vs. 0.853 pre-PERCEE, as per Specification 6), which suggests a lasting effect of the program above and beyond the incentives in place, i.e. there seems to be a memory effect likely due to the information made salient during the program.

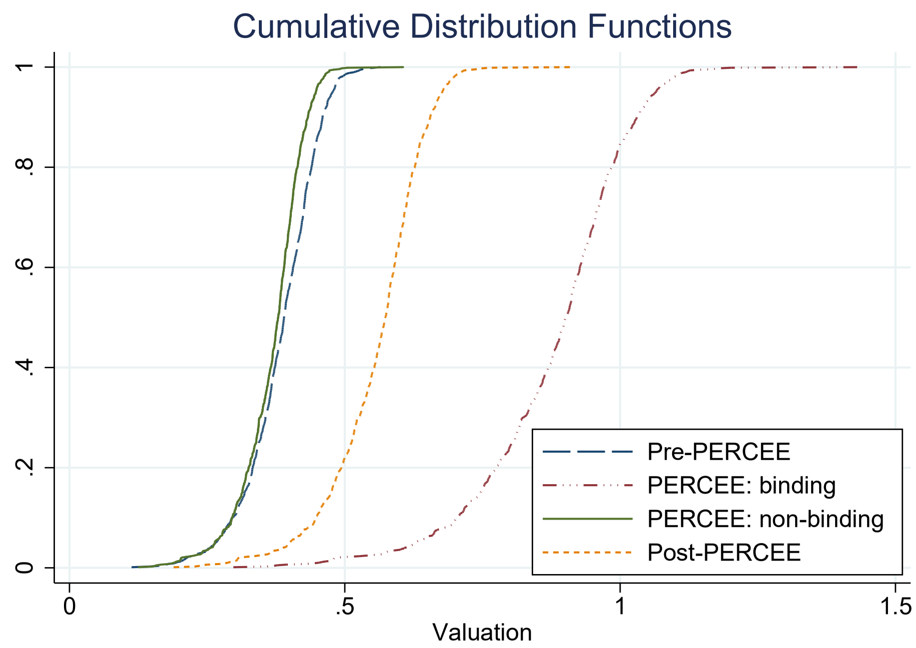
Finally, the introduction of PROCEL induces a further increase in the valuation of energy efficiency (from 0.936 to 1.073 as per Specification 6), suggesting a mild effect of the program.

Once we obtain valuation estimates, we are able to test the null hypothesis of correct *average valuation of energy efficiency*, $H_0 : \upsilon = 1$ against the two-sided alternative. The only case where we are able to reject the null is that of $\upsilon_{2001}^{non-binding}$; that is, except in the case of consumers for which the energy quota is non-binding, one cannot reject the null that the average valuation of energy costs upon the purchase of a refrigerator is equal to one.

Figure 7: **Distribution of Valuation Parameters**



Panel A. Density Estimates



Panel B. Cumulative Distribution Functions

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.

Valuation of energy efficiency – Distributions Average valuations do, however, provide only an incomplete picture of the underlying distribution of valuations. This is especially so given the role played by heterogeneity in the valuation of energy efficiency. To allow a better understanding of the overall pattern of valuations, Figure 6 displays the distributions of the valuation of energy efficiency for the different periods of our sample (based on the baseline, Specification 6). While the ordering of the distributions is consistent with those of their corresponding average valuations, changes in heterogeneity become more apparent when comparing the valuation distributions; for instance, the valuation distribution for 2003-2005 is substantially more dispersed than its 2002 counterpart.

In order to compare valuation distributions we proceed in two steps. First, we graphically compare the empirical distribution functions of valuations pairwise. The findings summarized in Figure 7 suggest that first-order stochastic dominance (FSD) is prevalent in the data.[28]

Second, we aim to formally examine the occurrence of FSD by a pairwise comparison of valuation distributions. We outright reject the null of equality of distributions at the one percent significance level using a standard Kolmogorov-Smirnov test. Specifically, $\upsilon_{2001}^{binding}$ FSD-dominates both (i) $\upsilon_{1998-2000}$ and (ii) $\upsilon_{2001}^{non-binding}$, suggesting an effect of binding energy quotas on the valuation of energy costs when purchasing a new appliance under PERCEE; (iii) $\upsilon_{1998-2000}$ FSD-dominates $\upsilon_{2001}^{non-binding}$, suggesting that non-binding energy quotas result in lower valuation of energy costs; (iv) υ_{2002} FSD-dominates $\upsilon_{1998-2000}$, suggesting a memory effect of the PERCEE program; and (v) $\upsilon_{2003-2005}$ FSD-dominates υ_{2002}, which suggests an overall increase in the valuation of energy efficiency once energy labels become compulsory.[29]

What Drives Incentives? To examine which – if any – demographic variables make the energy quota bind, we estimate probit models where the dependent variable is the binding indicator and household characteristics above and beyond those used in the estimation of demand for refrigerators as covariates. Our final aim is to identify the ultimate drivers of the incentive mechanism under PERCEE.

The findings are reported in Table 2. The main take-away from this exercise is that the household demographics – income, in particular– we observe do not make the energy quota bind under PERCEE. In particular, income is never statistically significant at standard significance levels. The fact that observable heterogeneity at the household level is unable to explain what makes the energy quota bind suggest the key role played by unobserved heterogeneity in the data and reinforces the need to allow for household heterogeneity in the ecnometric model.

Discussion The above results suggest that both PERCEE and PROCEL affected consumer choice. The mechanism by which we believe households were affected during PERCEE are as follows. First, prior to PERCEE households received letters which explicitly mentioned their energy quotas and the incentives in place. Second, the (monthly) electricity bills provided households with information about electricity consumption in previous months. Third, there was a strong energy conservation campaign all over the media. These factors combined made households for which the quota was (close to) binding value energy efficiency highly while PERCEE was in place. This is in stark contrast with households for which the quota was not (close to) binding: these households felt comfortable and less concerned with energy efficiency upon the purchase of their new refrigerator under the period PERCEE was in place.

[28] 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.

[29] We perform KS tests due to their simplicity and to the fact that our setting looks relative standard; for instance, it is reasonable to assume that the valuations being compared are independent. An important literature covers more general settings and alternatives when testing stochastic dominance, see e.g. McFadden (1989), Davidson and Duclos (2000), Barrett and Donald (2003), Linton, Maasoumi and Whang (2005).

Table 2: **Determinants of a Binding Energy Quota**

Variable	[1]	[2]	[3]	[4]	[5]
Income	0.0000455	0.000031	0.0000283	0.0000387	-0.0000335
	(0.000038)	(0.0000417)	(0.0000421)	(0.0000437)	(0.0003942)
Income^2					-1.83e-08
					(2.13e-07)
Income^3					1.12e-11
					(3.92e-11)
Income^4					-9.26e-16
					(2.23e-15)
Dwelling Size		Yes	Yes	Yes	Yes
Year Dummies			Yes	Yes	Yes
Household size		Yes	Yes	Yes	Yes
Region Dummies	Yes			Yes	Yes
Log-Likelihood	-313.89	-311.17	-311.00	-296.52	-295.90
N	773	773	773	696	696

Note. Robust standard errors are reported in parentheses. Significance is given at the 1% level ($***$), 5% level ($**$) and 10% level ($*$). DV(.) denotes dummy variable.

As for the PROCEL program, the modest impact on valuations is likely related to the fact that energy labels were already available for voluntary adoption, so that most of the energy efficiency gains were likely already reaped. This is consistent with 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, the rationale for a small change in valuations could most likely be justified by a combination of (ii) and (iii). The increase in the heterogeneity of valuations during 2003-2005 as reflected by the heavier tails of the valuation distributions for the period (see Figure 5) reflects the fact that consumers process and thus react differently to the release of new information.

The above findings provide evidence of substantial changes in the distribution of valuations in the extensive margin of adjustment, i.e. upon the purchase of new household appliances, above and beyond those adjustment made in the intensive margin, e.g. energy savings due to a more economical use of appliances owned.

5.2 Decomposing the Energy Efficiency Gap

5.2.1 Defining EEG Components

Even if devising a model of incentives and information transmission is outside the scope of this paper, it can be insightful to decompose the EEG into information and incentive components taking advantage of the fact that the PERCEE program affected different households in different ways.

Define the pre-PERCEE energy efficiency gap (EEG) as

$$\Gamma_0 := 1 - \varphi(\upsilon_{1998-2000})$$

where $\varphi(.)$ is a functional of the distribution of valuations. One way is to fix $\varphi(.)$ so that it yields, for instance, the expected value of the distribution of valuations. However, one limitation of this approach is that heterogeneity allowed for in the estimation of the demand system and incoporated into the valuation distribution is disregarded in the analysis.

A second alternative relies on the availability of panel data. If that is the case, then the effect of a policy can vary by household due to the different ways they react to a given policy. Unfortunately, our sample consists of repeated cross-sections, which leads us to explore a third alternative.

Under an assumption of ignorability of treatment (given observed covariates) in the flavor of Rosenbaum and Rubin (1983), one can focus on the quantiles of the distribution of valuations and then recover the whole underlying distribution of valuations. This approach has the benefit of allowing for heterogeneity in a general, nonparametric, way. It relies heavily on the fact that the set of demographics, their interactions with product characteristics, and the fixed-effects we use in our baseline specification are rich enough to control for unobservables at the household level. Focusing on quantiles q of the valuation distribution, one can write the pre-PERCEE energy efficiency gap (EEG) as

$$\Gamma_{q,0} := 1 - \upsilon_{q,1998-2000}$$

As illustrated in Figure **??**, PERCEE affects the behavior of households in different ways, despite the fact that they receive the same kind of information. For those households for which the energy quota is not binding, any changes in behavior whenever PERCEE is introduced occur due to changes in information, e.g. the information provided by the program, which makes clear that a given household is consuming less electricity than its quota and which might

Figure 8: **Relation between Valuations and Components of the Energy Gap**

Valuations:	$\upsilon_{2001}^{non-binding}$	$\upsilon_{1998-2000}$	$\upsilon_{2001}^{binding}$
Gap components:	$\Gamma^{info,nb}$		$\Gamma^{info,b} + \Gamma^{inc}$

Note: This figure illustrates the relation between valuations and the components of the energy gap before and while PERCEE was in place.

make them value energy efficiency differently than before, or make them less attentive to its waste. One can then write the energy efficiency gap of households for which the energy quota under PERCEE is not binding as

$$\Gamma_{q,0} + \Gamma_q^{info,nb} = 1 - \upsilon_{q,2001}^{non-binding}$$

where $\Gamma_q^{info,nb}$ is gap component due to information on the $q-th$ quantile of the valuation distribution of households for which the energy quota was not binding.

In contrast, for households for which the energy quota is binding, any changes in behavior can be attributed to changes in both information and incentives. While information might be related to the increased salience of a household's electricity consumption, incentives are directly related to not meeting the energy quota and the resulting penalties. We thus write the EEG for quantile q of the valuation distribution of binding households as

$$\Gamma_{q,0} - \Gamma_q^{info,b} - \Gamma_q^{inc,b} = 1 - \upsilon_{q,2001}^{binding}$$

where we assume that both information and incentive components faced by households for which the energy quota is binding weakly increase the valuation of energy costs ($\Gamma_q^{info,b}, \Gamma_q^{inc,b} \geq 0$).[30]

By combining the three equations above and plugging in the valuation estimates from our baseline specification, one can solve for $\Gamma_q^{info,nb}$ and $\Gamma_q^{inc,b}$ as follows

$$\begin{aligned} \Gamma_q^{info,nb} &= \upsilon_{q,1998-2000} - \upsilon_{q,2001}^{non-binding} \\ \Gamma_q^{inc,b} &= \upsilon_{q,2001}^{binding} - \upsilon_{q,1998-2000} - \Gamma_q^{info,b} \end{aligned}$$

While the first equation is just the symmetric of π_q^{nb}, the second one relates incentives and information components for households for which the energy quota is binding. Although one cannot separately identify these two components, it is possible to bound them. Under the assumption that $\Gamma_q^{info,b} \geq 0$, one can bound the incentive component as per $0 \leq \Gamma_q^{inc,b} \leq \upsilon_{q,2001}^{binding} - \upsilon_{q,1998-2000}$. As a result, one obtains the following set of estimates.

Set Identification I. *If, as a result of the PERCEE program, (i) the valuations of households for which the energy quota is binding change due to incentive and information components,* $\Gamma_q^{inc,b}$ *and* $\Gamma_q^{info,b}$*, both of which are non-negative; (ii) the valuations of households for which the energy quota is non-binding change due to an information component* $\Gamma_q^{info,nb}$*, wich is non-negative, then*

$$\begin{aligned} \Gamma_q^{info,nb} &= \upsilon_{q,1998-2000} - \upsilon_{q,2001}^{non-binding} \\ \Gamma_q^{info,b} &\geq 0 \\ 0 \leq \Gamma_q^{inc,b} &\leq \upsilon_{q,2001}^{binding} - \upsilon_{q,1998-2000} \end{aligned}$$

The above bounds can be refined if one is prepared to make the stronger assumption that the information effect on binding households is at least as large as the information effect on non-binding ones ($\Gamma_q^{info,b} \geq \Gamma_q^{info,nb}$). This could be justified by the fact that the information provided by the PERCEE letters sent by post (see Section 2) resonated more with households for which the energy quota was binding than with those for which it was not. The second set of estimates is given by the following.

[30] Moreover, note that we allow for potentially different effects of information on binding and non-binding households.

Set Identification II. *If, in addition to (i) and (ii) above, one assumes that the information effect on households for which the energy quota is binding is at least as large as the symmetric of the information effect on non-binding ones, then*

$$\begin{aligned}\Gamma_q^{info,nb} &= \upsilon_{q,1998-2000} - \upsilon_{q,2001}^{non-binding}\\ \Gamma_q^{info,b} &\geq \upsilon_{q,1998-2000} - \upsilon_{q,2001}^{non-binding}\\ 0 \leq \Gamma_q^{inc,b} &\leq \upsilon_{q,2001}^{binding} - \upsilon_{q,1998-2000}\end{aligned}$$

In the particular case that the information effect for binding and non-binding households is symmetric, one obtains the following as the estimates for the components of the EEG.[31]

Point Identification. *If, in addition to (i) and (ii) above,* one assumes that the information effect for binding and non-binding households is symmetric, then

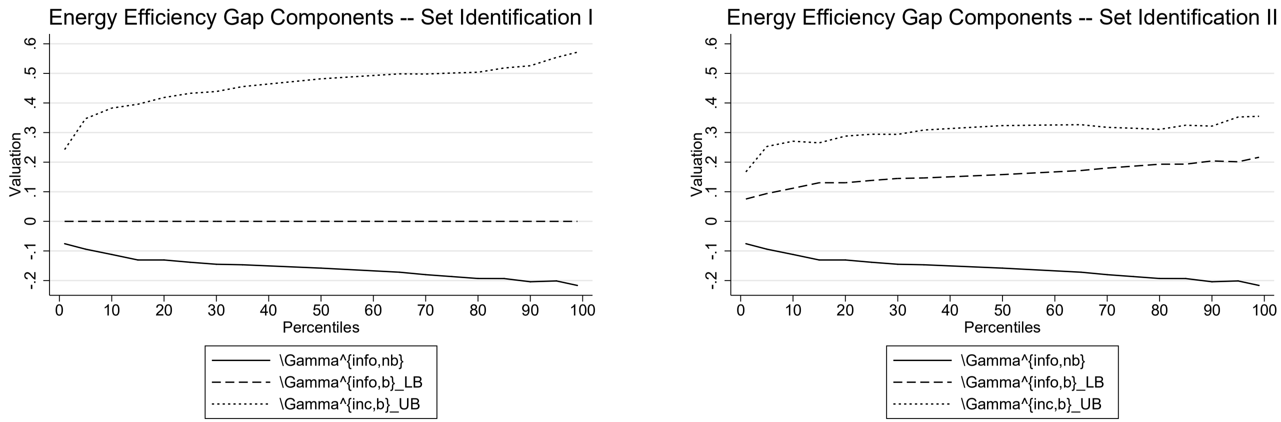
$$\begin{aligned}\Gamma_q^{info,nb} &= \upsilon_{q,1998-2000} - \upsilon_{q,2001}^{non-binding}\\ \Gamma_q^{info,b} &= \upsilon_{q,1998-2000} - \upsilon_{q,2001}^{non-binding}\\ \Gamma_q^{inc,b} &= \upsilon_{q,2001}^{binding} + \upsilon_{q,2001}^{non-binding} - 2\upsilon_{q,1998-2000}\end{aligned}$$

5.2.2 Quantifying EEG Components

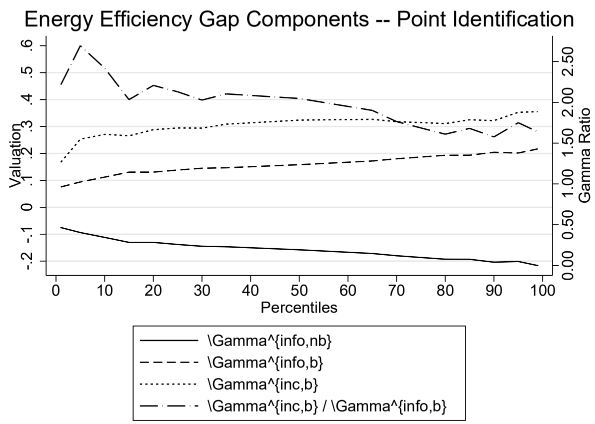
The estimates of the EEG components are displayed in Figure 9. Panel A displays the two sets of set identified estimates (Set Identification I and II, respectively). That is, it displays the (point-identified) information component of the EEG for non-binding households (the same in both graphs), in addition to two versions of the lower bound for the information component for binding households, and two versions of the upper bound for the incentivescomponent for binding households. The left-hand side graph in Panel A ("Set Identification I") displays arguably wide bounds for those households facing a binding energy quota, especially in what concerns the lower bound for the information component. However, the graph suggests that the incentives component dominates its information counterpart.

[31] Using average valuations, the corresponding estimates are (i) $\Gamma^{info,nb} = -0.158$, $\Gamma^{info,b} \geq 0$ and $\Gamma^{inc} \leq 0.465$ in the first case; (ii) $\Gamma^{info,nb} = -0.158$, $\Gamma^{info,b} \geq 0.158$ and $\Gamma^{inc} \leq 0.307$ in the second case; and (iii) $\Gamma^{info,nb} = -0.158$, $\Gamma^{info,b} = 0.158$ and $\Gamma^{inc} = 0.307$ in the third case.

Figure 9: **Decomposition of the Energy Efficiency Gap**



Panel A. Bounds for EEG Components under alternative assumptions



Panel B. Point estimates for the EEG components and ratio of components

Note: This figure displays incentive and information components of the Energy Efficiency Gap. Panel A displays the (point-identified) information component of the EEG for non-binding households, two versions of the lower bound for the information component for binding households, and two versions of the upper bound for the incentive component for binding households. Panel B displays the point-identified versions of the components and the ratio of the incentive-information components for those households for which the energy quota is binding.

The right-hand side graph in Panel A ("Set Identification II") displays tighter bounds for households facing a binding energy quota. Importantly, bounds in one extreme of the distribution appear to be very different from those on the other extreme, documenting the role played by heterogeneity in the valuation of energy efficiency. Nonetheless, the main message remains in that the incentives component dominates its information counterpart.

Finally, Panel B displays the point-identified versions of the components and the incentive-information ratio for those households for which the energy quota is binding. Clearly, the incentives component is at least 50 percent larger than the information component for households facing a binding energy quota. In what follows, we will use estimates for the "Point Identification" case displayed in Panel B. While this does not mean to suggest that the role of information is negligible, it does suggest that incentives play a major role in shaping household behavior, even in the extensive margin.

Conclusion

In this paper, we studied the energy paradox using revealed preference data from a nationally representative household survey in Brazil. Specifically, we examine the purchase of household appliances thus focusing on the external margin of adjustment to different policies. The data allow us to control for household heterogeneity at the very micro level. Moreover, Brazil is a large emerging economy with high urbanization and per capita GDP, thus providing guidance for other emerging economies in the future.

Two policies have shaped consumer choices during the sample period: PERCEE, a temporary rationing program consisting of a set of incentives; and PROCEL, which mandated the adoption of previously voluntarily adopted energy labels. PERCEE is of particular interest due to being responsible for the largest reduction in electricity use among temporary savings programs worldwide EIA (2005).

We estimate a structural mode of appliance choice accounting for heterogeneity at the household (consumer) level. Consistent with the institutional setting, in particular the incentives for reduction of energy use during PERCEE, we allow for heterogeneity in cost both within and across time periods, in addition to heterogeneity in prices.

The PERCEE program leads to higher valuations of energy efficiency, but only among consumers facing incentives to reduce consumption, namely those for which an energy quota was binding. This is the only stance in the paper where we cannot reject the null hypothesis of correct valuation of energy costs, which we otherwise reject in favor of the alternative hypothesis of undervaluation. In particular, valuations after the end of PERCEE revert back to pre-PERCEE levels, suggesting that individuals tend to react to incentives quickly and strongly.

The institutional setting and the survey design enable us to quantify the magnitude of the incentives component of the EEG. This is obtained by comparing valuations of energy efficiency of consumers for which the energy quota during the rationing program was binding with those of consumers not facing incentives for reduction of energy use. With an additional assumption, we are able to identify the information component.

In our counterfactuals, we first close the energy gap on the information and incentives fronts. Next, we examine the effects of making labels compulsory. According to our estimates, the incentives component is roughly twice as large as the information component of the EEG.

This paper thus provides a way to decompose the EEG and provides evidence that consumers react to introduction of incentives as well as their removal, thus fully reacting to temporary shocks, even in the extensive margin. Of course, a complete picture of the market would only be possible by incorporating a realistic model of the supply-side, including incentives to innovate and introduce products. This interesting aspect is left for futuree research.

References

Allcott, Hunt, Sendhil Mullainathan, and Dmitry Taubinsky. 2014. "Energy policy with externalities and internalities." *Journal of Public Economics*, 112: 72–88.

Alquist, Ron, Lutz Kilian, and Robert J Vigfusson. 2013. "Forecasting the Price of Oil." In *Handbook of Economic Forecasting*. Vol. 2 of *Handbook of Economic Forecasting*, , ed. Graham Elliott and Allan Timmermann, 427–507. Elsevier.

Anderson, Soren T., Ryan Kellogg, and James M. Sallee. 2013. "What do consumers believe about future gasoline prices?" *Journal of Environmental Economics and Management*, 66(3): 383–403.

Busse, Meghan R., Christopher R. Knittel, and Florian Zettelmeyer. 2013. "Are consumers myopic? Evidence from new and used car purchases." *American Economic Review*, 103(1): 220–256.

Cardoso, Rafael Balbino. 2008. "Avaliação da economia de energia atribuída ao programa Selo PROCEL em freezers e refrigeradores." PhD diss. Federal University of Itajuba.

Costa, Francisco, and François Gerard. 2018. "Hysteresis and the Welfare Effect of Corrective Policies: Theory and Evidence from an Energy-Saving Program."

Daly, Andrew, Stephane Hess, and Kenneth Train. 2012. "Assuring finite moments for willingness to pay in random coefficient models." *Transportation*, 39: 19–31.

Davis, Lucas W. 2008. "Durable goods and residential demand for energy and water: Evidence from a field trial." *RAND Journal of Economics*, 39(2): 530–546.

Davis, Lucas W. 2010. "Evaluation the Slow Adoption of Energy Efficient Investments: Are Renters Less Likely to Have Energy Efficient Appliances." In *The Design and Implementation of US Climate Policy.* , ed. Don Fullerton and Catherine Wolfram, 301–316.

Davis, Lucas W., Alan Fuchs, and Paul Gertler. 2013. "Cash for Coolers: Evaluating a Large-Scale Appliance Replacement Program in Mexico."

Davis, Lucas W., and Gilbert E. Metcalf. 2014. "Does Better Information Lead to Better Choices? Evidence from Energy-Efficiency Labels." *Ssrn*, , (560).

Dranove, David, and Ginger Zhe Jin. 2010. "Quality Disclosure and Certification: Theory and Practice." *Journal of Economic Literature*, 48(4): 935–963.

Dubin, Jeffrey A, and Daniel McFadden. 1984. "An Econometric Analysis of Residential Electric Appliance Holdings and Consumption." *Econometrica*, 52(2): 345–362.

EIA. 2005. *Saving Electricity in a Hurry.* Paris:OECD Publishing.

EIA. 2013. "International Energy Outlook." Department of Energy, Washington.

Gately, Dermot. 1980. "Individual Discount Rates and the Purchase and Utilization of Energy-Using Durables." *The Bell Journal of Economics*, 11(1): 373–374.

Gertler, Paul J, Orie Shelef, Catherine D Wolfram, and Alan Fuchs. 2016. "The Demand for Energy-Using Assets among the World's Rising Middle Classes." *American Economic Review*, 106(6): 1366–1401.

Gillingham, Kenneth, Matthew Harding, and David Rapson. 2012. "Split Incentives in Residential Energy Consumption." *The Energy Journal*, 33(2): 1–41.

Gillingham, Kenneth, Richard G. Newell, and Karen Palmer. 2009. "Efficiency and economics."

Golove, W. H., and J. H. Eto. 1996. "Market Barriers to Energy Efficiency: A Critical Reappraisal of the Rationale for Public Policies to Promote Energy Efficiency."

Greene, David L. 2010. "How consumers value fuel economy: A literature review." U.S. Environmental Protection Agency, Washington, DC.

Grigolon, Laura, and Frank Verboven. 2014. "Nested Logit or Random Coefficients Logit? A Comparison of Alternative Discrete Choice Models of Product Differentiation." *Review of Economics and Statistics*, 96(5): 916–935.

Hanemann, W. Michael. 1984. "Discrete/Continuous Models of Consumer Demand." *Econometrica*, 52(3): 541–561.

Hausman, Jerry A. 1979. "Individual Discount Rates and the Purchase and Utilization of Energy-Using Durables." *The Bell Journal of Economics*, 10(1): 33–54.

Hausman, Jerry A. 1985. "The Econometrics of Nonlinear Budget Sets." *Econometrica*, 53(6): 1255–1282.

Helfand, Gloria, and Ann Wolverton. 2011. "Evaluating the Consumer Response to Fuel Economy: A Review of the Literature." *International Review of Environmental and Resource Economics*, 5(2): 103–146.

Houde, Sébastien, and Joseph E. Aldy. 2017. "The Efficiency Consequences of Heterogeneous Behavioral Responses to Energy Fiscal Policies."

Howarth, Richard B., and Alan H. Sanstad. 1995. "Discount Rates and Energy Efficiency." *Contemporary Economic Policy*, 13(3): 101–109.

Jaffe, Adam B., and Robert N. Stavins. 2004. "The Economics of Energy Efficiency." In *Encyclopedia of Energy.* , ed. C. Cleveland, 79–90. Amsterdam:Elsevier B.V.

Jaffe, Adam B., Richard G. Newell, and Robert N. Stavins. 1999. "Energy-Efficient Technologies and Climate Change Policies: Issues and Evidence." *Ssrn.*

Jannuzzi, Gilberto De Martino. 2002. "AUMENTANDO A EFICIÊNCIA NOS USOS FINAIS DE ENERGIA NO BRASIL." Campinas.

McFadden, Daniel, and Kenneth Train. 2000. "Mixed MNL models for discrete response." *Journal of Applied Econometrics*, 15(5): 447–470.

Metcalf, Gilbert E, and Kevin A Hassett. 1999. "Measuring the Energy Savings from Home Improvement Investments: Evidence from Monthly Billing Data." *Review of Economics and Statistics*, 81(3): 516–528.

Newell, Richard G., Adam B. Jaffe, and Robert N. Stavins. 1999. "the Induced Innovation Hypothesis and Energy-Saving Technological Change." *Quarterly Journal of Economics*, 114(3): 941–975.

ONS. 2011. “The Decennial Energy Plan (Plano Decenal de Energia, in Portuguese).” ONS, Brasília.

Palmer, Karen, Margaret Walls, and Todd Gerarden. 2012. “Borrowing to save energy: An assessment of energy-efficiency financing programs.” *Resources for the Future.*

Parry, Ian W. H., Margaret Walls, and Winston Harrington. 2007. “Automobile Externalities and Policies.” *Journal of Economic Literature*, 45(2): 373–399.

Petrin, Amil, and Kenneth E. Train. 2009. “A Control Function Approach to Endogeneity in Consumer Choice Models.” *Journal of Marketing Research*, XLVI: 1–45.

PROCEL. 2007. “Pesquisa de Posse de Equipamentos e Hábitos de Uso, Classe Residencial.”

Reiss, Peter C., and Matthew W. White. 2005. “Household electricity demand, revisited.” *Review of Economic Studies*, 72(3): 853–883.

Reiss, Peter C., and Matthew W. White. 2008. “What changes energy consumption habits? Prices versus public pressures.” *RAND Journal of Economics*, 39(3): 636–663.

Revelt, David, and Kenneth E. Train. 1998. “Mixed Logit with repeated choices: Households’ choices of appliance efficiency level.” *The Review of Economics and Statistics*, 80(4): 647–657.

Sallee, James M. 2013. “Rational Inattention and Energy Efficiency.” *NBER Working Paper Series*, 19545: 39.

Sallee, James M., Sarah E. West, and Wei Fan. 2015. “Do Consumers Recognize the Value of Fuel Economy? Evidence from Used Car Prices and Gasoline Price Fluctuations.”

Sanstad, Alan H, W Hanemann, Michael, and Maximillian Auffhammer. 2006. “End-use Energy Efficiency in a Post-Carbon California Economy: Policy Issues and Research Frontiers.” In *Managing Greenhouse Gas Emissions in California.* 6–32.

Wolfram, Catherine D., Orie Shelef, and Paul J. Gertler. 2012. “How Will Energy Demand Develop in the Developing World?” *Journal of Economic Perspectives*, 26(Winter): 119–138.

TECHNICAL APPENDIX

A Data

A.1 Summary Statistics

The following table displays summary statistics of the main variables used in the paper, which we divide into product, household characteristics, and additional characteristics.

Table A1: **Summary Statistics**

Variable	**Mean**	**SD**	**Min**	**Max**
Basic Product Characteristics				
Refrigerator Price (R$)	1388.00	683.79	226.38	7365.43
Refrigerator Volume (liters)	303.68	89.94	46.00	670.00
DV(Frost-free)	0.38	0.49	0.00	1.00
Refrigerator Energy Consumption (KWh/month)	36.81	14.68	17.90	121.00
Expected Lifetime Operating Cost (R$)	677.24	401.72	134.75	3640.05
Basic Household Characteristics				
Household Income Per Capita (R$)	494.56	508.12	19.18	4573.95
DV(Southern Region)	0.20	0.40	0.00	1.00
DV(Southeastern Region)	0.37	0.48	0.00	1.00
DV(Midwestern Region)	0.12	0.33	0.00	1.00
DV(Northeastern Region)	0.26	0.44	0.00	1.00
DV(Northern Region)	0.05	0.22	0.00	1.00
Education – DV(Household Head Finished High School)	0.37	0.48	0.00	1.00
DV(Household Owns Freezer)	0.21	0.41	0.00	1.00
Household Size (Integer)	4.34	1.47	1.00	11.00
Size of Dwelling (Categorical)	2.54	1.18	1.00	6.00
DV(Binding Energy Quota)	0.07	0.25	0.00	1.00
Additional Variables				
Electricity Rate (BRL/KWh)	0.20	0.06	0.10	0.33
Discount Rate (Year)	0.12	0.02	0.10	0.14

Note. This table reports summary statistics of the main variables used in the paper. DV(.) denotes a dummy variable. All monetary values are deflated to 2005 Brazilian reais (R$).

A.2 Matching Products, Prices and Additional Characteristics

A.2.1 Matching PPH Products to Non-price Characteristics

To quantify the the valuation of energy efficiency one needs to estimate a discrete choice model where each consumer is endowed with a choice set, which itself is comprised of the product chosen by a given consumer plus all products available on the market but not chosen by the consumer.

Consumers compare products based on their characteristics, such as price, volume and energy consumption. In what follows, we describe the matching procedure whereby we matched information from three sources namely the actual purchase according to the PPH, the refrigerator retail prices provided by IBRE - Fundacao Getulio Vargas and refrigerator characteristics from various sources, from PROCEL yearbooks to manufacturer catalogues to previous studies.

Had all data sources used a common identifier such as the refrigerator SKUs (stock keeping units), the task would have been straightforward. Since this was not the case, we briefly describe how we manually constructed a "simplified SKU" to match products from the different datasets. In case it was not possible to obtain the price of a product, we resorted to a hedonic price model as described below.

Table A2: **Description of Selected Refrigerator Models in the PPH Survey**

Code	**Trading Name**	**Model/SKU**	**Consumption (CM)**	**Classe (CM)**	**Consumption (PROCEL)**
100	brastemp (marca)	BRASTEMP			
101	brastemp quality 260 litros	BRASTEMP SIMPLES260	32	D	
102	brastemp clean 340 litros	BRASTEMP SIMPLES340	25.5	A	
103	brastemp all refrigerator 360 litros	BRF36	26.5	B	26.5
104	brastemp duplex clean 320 litros	BRM32	44	A	
105	brastemp duplex clean 410 litros	BRM41	53	A	
106	brastemp duplex clean frost free 390 litros	BRM39	58.2	A	
107	brastemp duplex clean frost free (zyrium)	BRG43	57.6		62.4
108	brastemp bottom freezer frost free 420 litros	BRI42	57.7	A	58.2
109	brastemp duplex frost free 340 eletronico	BRM34	51.5	C	47.2
110	brastemp duplex frost free 440 eletronico	BRM44	56	A	50.5
111	brastemp duplex frost free 440 unique	BRV44	56	A	43
112	brastemp duplex frost free 440 eletronico ice magic	BRN44			57.7
113	brastemp duplex frost free 440 eletronico zyrium	BRG44			59.9
114	brastemp inside freezer 350	BRO35			
115	brastemp bottom freezer 330	BRH33			44.1
116	brastemp duplex 360	BRASTEMP DUPLEX360	46	A	
117	brastemp duplex 460	BRD46	55	A	52.4
118	brastemp side by side 700	BRS70	86.4		81.5

Note. This table displays selected information about refrigerators produced by BRASTEMP, the leading manufacturer in the Brazilian market.

The starting point is the set of models reported in the PPH survey, see Table A2 for the case of one particular brand ("BRASTEMP"). Each product is reported using a code ("Code") and the name under which it is marketed ("Trading Name"). In most cases it is possible to back out the SKU from this information. The next step is to match this information with product characteristics other than price, in particular energy consumption. For the sake of robustness, we report two energy consumption measures, one ("Consumption (CM)") from a PhD thesis in Engineering evaluating the energy efficiency of household appliances (Melo (2009), the other being the official PROCEL energy consumption figures ("Consumption (PROCEL)").[32] In the few cases where we could not find energy consumption figures in the above sources (three Electrolux models, two of which high-end products), we resorted to other sources such as Jannuzzi (2002) and Cardoso (2008).

Whenever a full match at the SKU level was not feasible, we adopted a strategy widely used in the literature in that we assume that consumers purchase the version of a brand-model combination with the lowest energy consumption.[33]

Upon the end of the matching procedure, we were able to identify 54 products with at least one measure of energy consumption leaving only 10 unmatched. Importantly, the matched models were by far the best-selling products in the Brazilian market.

A.2.2 Matching PPH Products to Prices

As above, we started with information about refrigerators to construct a "simplified SKU" variable starting with brand-model-volume-number of doors. Crucially, we retrieved information about the month-year a price was observed. Out of the 54 products for which we were able to obtain characteristics, 31 did have exact price matches whereas 23 did not. For these ones, we imputed prices using a hedonic model.

A.3 Hedonic Regression Results

We specify a hedonic model for prices using product information as per the matching procedure detailed above. The specifications we considered were of the form

$$y_{jt} = x'_{jt}\beta + u_{jt}$$

where y_{jt} is either the price or the logarithm of price of product j at period t; the set of covariates comprises product characteristics such as volume and energy consumption in addition to brand fixed-effects, indicators for medium and high volume; frost-free defrosting; 2-door refrigerator; non-standard doors; water dispenser; energy efficiency class A or B (the most efficient ones). Moreover, we also considered state and region fixed-effects.

[32] Melo (2009) uses the same methodology as PROCEL to quantify the energy consumption of refrigerators.

[33] For instance, Berry, Levinsohn and Pakes (1995) use baseline versions of a given vehicle model in their study of the automobile industry.

Table A3: **Hedonic Price Regressions**

Dep. Var	(1) LN(Price)		(2) LN(Price)		(3) Price	
DV(Brastemp)	0.2712	***	0.2606	***	194.8117	***
	(0.0134)		(0.0133)		(18.8226)	
DV(Consul)	0.2085	***	0.1962	***	42.7916	***
	(0.0126)		(0.0126)		(16.1439)	
DV(Electrolux)	0.1702	***	0.1547	***	54.0559	***
	(0.0127)		(0.0127)		(17.2989)	
LN(Volume)	1.1762	***	1.1713	***		
	(0.0030)		(0.0031)			
DV(Frost-free)	0.2273	***	0.2287	***	466.9951	***
	(0.0070)		(0.0070)		(10.5427)	
DV(Two-doors)	0.1357	***	0.1336	***	308.9829	***
	(0.0054)		(0.0054)		(14.2901)	
DV(ClassAB)	0.0092	*	0.0097	**		
	(0.0049)		(0.0048)			
DV(Inox-doors)	0.0286	**	0.0376	***	170.6142	***
	(0.0115)		(0.0115)		(18.3889)	
DV(Dispenser)	0.0889	***	0.0895	***	291.4239	***
	(0.0112)		(0.0111)		(18.1715)	
DV(Frigobar)	0.8260	***	0.8596	***	387.6555	***
	(0.0124)		(0.0128)		(21.4840)	
DV(High-volume)	0.5791	***	0.5750	***	2592.5934	***
	(0.0989)		(0.0978)		(157.8602)	
Volume					4.1759	***
					(0.0725)	
Energy Consumption					-4.1424	***
					(0.5116)	
Year Fixed-Effects	Yes		Yes		Yes	
Region Fixed-Effects	Yes		No		Yes	
State Fixed-Effects	No		Yes		No	
AIC	-5,813.27		-5,994.08		115043.16	
BIC	-5.66e+03		-5.79e+03		1.15e+05	
Log-Likelihood	2,928.63		3,026.04		-57499.58	
Observations	8,196		8,196		8,196	

The results are very much in line with intuition in that consumers are willing to pay for features such as colume, lower energy consumption, two doors, frost-free defrosting, and water dispenser. Our preferred Specification, which we use to impute missing prices, is Specification (1), where prices are in logarithmic form.

A.4 Details on PPH Survey Data

The following table displays descriptive statistics for the answers to Questions 12.3 and 12.4 of the PPH survey which are used to measure if the energy quota is binding for a given household. Panel A displays the answers to Question 12.3 ("The measures used to attain the energy quota during the rationing period were..."). Panels B and C display answers to the follow-up questions triggered in case the answer to Question 12.3 was either "enough" or "more than enough". Finally, Panel D displays the answers to Question 12.4. Importantly, note that we compare the answers for years 2001 to those of the full sample, and the shares are remarkably similar, despite the fact that the survey was conducted in 2004 and 2005.

Table A4: **Descriptive Statistics of Selected PPH Survey Questions**

Answer	Full sample N	Full sample Share	Year 2001 N	Year 2001 Share	
Panel A. "The measures used to attain the energy quota during the rationing period were" (Q 12.3)					
Not enough	90	.07	13	.05	$\rightarrow$ b1
Enough	759	.58	138	.57	
More than enough	113	.09	22	.09	
Doesn't know/remember	351	.27	70	.29	
Total	1313	1	243	1	
Panel B. "If answered 'enough' to Q12.3, how difficult was it to attain the energy quota?" (follow-up 1)					
Very	65	.05	9	.04	$\rightarrow$ b2
Little	330	.25	67	.28	$\rightarrow$ b2$'$
Not at all	279	.21	52	.21	
Doesn't know/remember/NA	639	.49	115	.47	
Total	1313	1	243	1	
Panel C. "If answered 'more than enough' to Q12.3, how difficult was it to attain the energy quota?" (follow-up 2)					
Very	3	<.01	1	<.01	$\rightarrow$ b3
Little	51	.04	6	.03	$\rightarrow$ b3$'$
Not at all	57	.04	15	.06	
Doesn't know/remember/NA	1202	.92	221	.91	
Total	1313	1	243	1	
Panel D. "How do you evaluate the change in your quality of life caused by the rationing program?" (Q 12.4)					
Very uncomfortable	99	.08	17	.07	$\rightarrow$ b4
Uncomfortable	203	.15	44	.18	$\rightarrow$ b5
Learned to deal with it	398	.30	72	.30	
No change	494	.38	90	.37	
Doesn't know/remember	69	.05	20	.08	
Total	1313	1	243	1	

Panel E. Construction of measures defining binding energy quota (for refrigerator purchases in year 2001)

	b1	Baseline B=b1+b2+b3	Robustness R=b4+b5
#Households w/ binding quota	13	23	61

Note. This table reports answers to selected questions of the PPH survey. The questions are used to define if a household had a binding energy quota during the PERCEE rationing program.

Our baseline definition of whether the energy quota is binding for a given household is $B := b1 + b2 + b3$. That is the energy quota is taken to be binding if (i) the measures undertaken to attain it were not enough (b1, Panel A); (ii) the measures undertaken to attain it were enough, but it was very difficult to attain the energy quota (b2, Panel B); (iii) the measures undertaken to attain it were more than enough, but it was very difficult to attain the energy quota (b3, Panel C).

Our main alternative measure is $R := b4 + b5$. That is, an indicator taking on value one whether households deemed their quality of life to have changed to "very uncomfortable" or "uncomfortable" (b4 and b5, Panel D) during the PERCEE program. Again, the shares of each answer are remarkably close for the 2001 sub-sample and the full sample.

Panel E briefly compares measures B and R. While the former takes on value one in 23 cases, the latter does so for 61 cases. To formally compare the answers to Questions 12.3 and 12.4, we perform a Chi-Square test of independence. The null hypothesis of independence of the answers is comfortably rejected at the 1 percent significance level. Perhaps unsurprisingly, when replacing measure B with measure R in our empirical specifications, the valuations become slightly lower, but significance levels are unaffected. However, our preference for measure B stems from its less subjective character.

We have also experimented with alternatives to B by exploring different answers to the follow-up questions displayed in Panels B and C. Stricter definitions of a binding quota, i.e. using only $b1$ from Panel A resulted in convergence problems of the estimation algorithm due to the resulting small number of households. Conversely, coarser definitions of the binding indicator, e.g. using $b2'$ and/or $b3'$, were considered unsatisfactory by definition.

B Additional Details on PERCEE

B.1 Institutional Details

Following the failure of the Brazilian federal government to address the Brazilian energy crisis by increasing the generation capacity of thermal power plants and the political cost of steeply increasing electricity prices across the board, the PERCEE program (Programa Emergencial de Redução do Consumo de Energia Elétrica) was enacted in May 2001.[34]

PERCEE was officially in place between June 2001 and February 2002, but some of its measures were eased in late 2001 following the start ofthe rainy season and the increase of reservoir levels in Brazil.

The energy consumption quota imposed on households was 80 percent of a household's pre-crisis average energy consumption for households consuming over 100 KWh/month; households with energy consumption below this threshold were to face a quota of 100 KWh/month.[35] Households consuming less than the quota in a given month would be rewarded by means of a bonus whereas households not attaining the quota would be liable to energy cuts of up to 6 days.[36][37]

[34]Formally, PERCEE was enacted through Resolucao No. 4/2001 of the Câmara de Gestão da Crise de Energia Elétrica, the commission in charge of tackling the energy crisis, see http://www.planalto.gov.br/ccivil_03/Resolu%C3%A7%C3%A3o/RES04-01.htm.

[35]Arguably, by being based on readings for winter months the quota was designed to be tighter than if it had been based on readings from warmer months when air conditioners are more often used. In fact, towards the end of the program, as reservoir levels started to recover (see November-December 2001 in Figure 2), the reference months were changed to summer months.

[36]The bonus was proportional to the below-quota consumption for households consuming in excess of 100 KWh/month and twice as much otherwise.

[37]Energy cuts are arguably difficult and costly to implement, so it comes as no surprise that they were typically not enforced. However, both Resolution No. 4/2001, which creates PERCEE, and its follow-ups established

Initially, the PERCEE program also increased tariffs nonlinear, focusing on heavy users; tariffs increased by 50 percent for electricity consumption in the bracket 200-500 KWh/month and by 200 percent for consumption in excess of 500 KWh/month. However, these increases were followed by an overall tariff increase of 16 percent in August 2001.

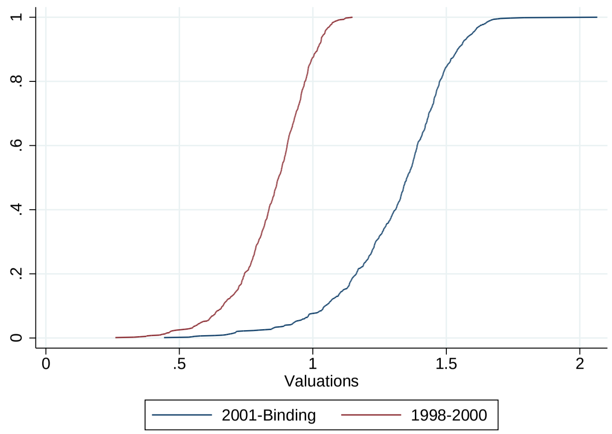
C Robustness and Details on Results

C.1 Details on Valuation Distributions

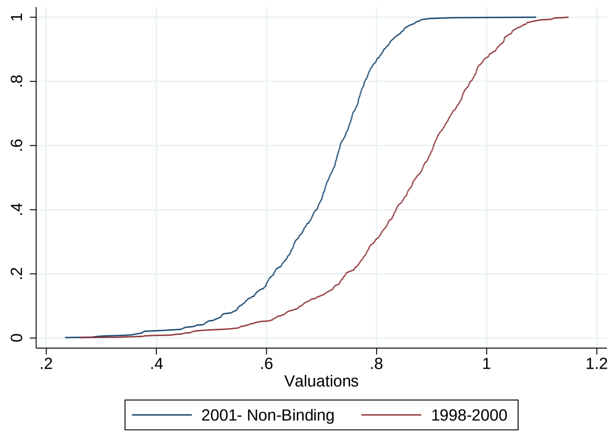
Figure C1 displays cumulative distribution functions of energy efficiency valuations. Panel A displays $\upsilon_{1998-2000}$ and υ^{b}_{2001}; Panel B displays $\upsilon_{1998-2000}$ and υ^{nb}_{2001}; Panel C displays $\upsilon_{1998-2000}$ and υ_{2002}; and Panel D displays υ_{2002} and $\upsilon_{2003-2005}$.

that a household would receive a written notice on its first non-attainment, incur an energy cut of up to 3 days upon its second non-attainment, and energy cuts of 4-6 days thereafter.

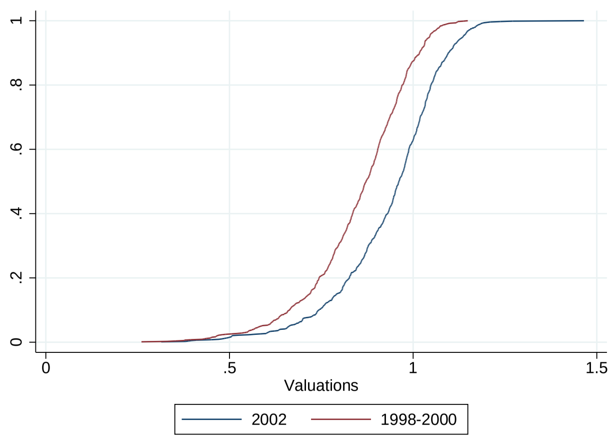
Figure C1: **Cumulative Distribution Functions of Valuations**



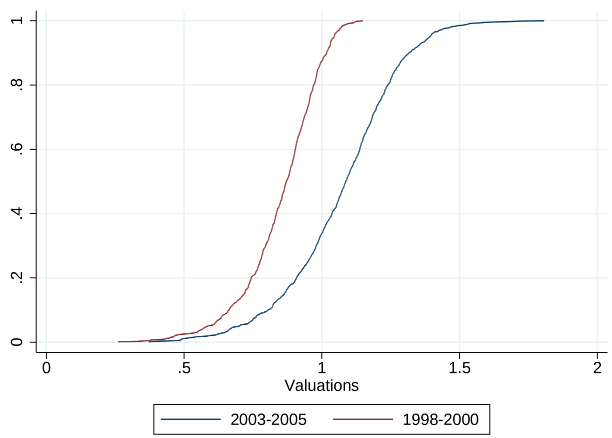
Panel A. $\upsilon_{1998-2000}, \upsilon_{2001}^{b}$



Panel B. $\upsilon_{1998-2000}, \upsilon_{2001}^{nb}$



Panel C. $\upsilon_{1998-2000}, \upsilon_{2002}$



Panel D. $\upsilon_{2002}, \upsilon_{2003-2005}$

C.2 Robustness Checks

We conducted robustness checks in different dimensions, from the specification of heterogeneity to alternative variable definitions to alternative controls. We allowed more general forms of unobserved heterogeneity by allowing for unconstrained correlation patterns for the random coefficients (our baseline specification has uncorrelated random coefficients). Consistent with our reported findings, we obtained mostly insignificant parameters which suggests that either household responses are indeed quite homogeneous when it comes to cost and/or there is not enough variation in the data to identify additional heterogeneity parameters.[38]

We have also experimented with alternative demographic variables such as alternative income measures; alternative product characteristics; and alternative indicators of a binding energy quota, all with largely similar results.

When it comes to interaction terms, due to numerical issues arising in the estimation of specifications with many fixed-effects, we focused on continuous variables with substantial variation for both demographics and product characteristics.[39]

Finally, we experimented with alternative definitions of fixed-effects. When using brand instead of product fixed-effects, we would typically obtain smaller valuation parameters, thus being more likely to reject the null hypothesis of correct valuation of energy efficiency. When experimenting with more general definitions of time fixed-effects (baseline is period instead of year fixed-effects) we would face convergence issues for the RC logit specifications. Finally, we also faced convergence issues when experimenting with more general definitions of region fixed-effects (baseline is aggregating all regions under PERCEE the entire period and discerning between the Southern region, which was exempt from PERCEE, and the Northern region, which was only partially subject to PERCEE).

[38]While it is not entirely obvious how one should interpret the correlation between parameters active in different sub-periods, we estimated specifications more general than our baseline, with the results consistently suggesting that it is difficult to properly identify most parameters; typically, conditional on convergence we would obtain mostly insignificant estimates. We have further explored specifications where correlations across periods are set to zero, but correlations between cost-period interactions and prices are unconstrained, but again obtained mostly insignificant estimates. These findings made us settle for our (more parsimonious) baseline.

[39]Despite this strategy, we still encountered numerical convergence problems in some cases. Moreover, at times having more than one interaction term typically also resulted in non-convergence of the estimation algorithm for the estimated RC logits, despite the ability to estimate their conditional logit counterparts.