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Assessing the effects of a large temporary energy savings program: Evidence from a developing country[☆]

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A B S T R A C T

We examine the effects of a large temporary energy-savings program on the valuation of energy efficiency by Brazilian households, as well as its counterfactual energy savings. Using a representative sample of Brazilian households, we specify and estimate a structural model of appliance choice and document that (i) the program only increases the valuations of households facing incentives in the form of an energy consumption quota introduced by the program; (ii) the effect of incentives dominates other components of the energy efficiency gap; (iii) the effect of the program on valuations is temporary, with these essentially reverting to prior levels after the end of the program; (iv) heterogeneity in valuations is prevalent; (v) focusing only on the purchase of new refrigerators, the counterfactual energy savings are non-trivial, being equivalent to the yearly electricity consumption of a city with 1.15 mn inhabitants. The findings suggest that short-lived reactions to temporary programs on the extensive margin are non-trivial and have log-run implications via the purchase of durables.

1. Introduction

Consumers of energy-intensive products are expected to trade-off the purchase price against the lifetime operating costs of such products, since the latter often comprise a non-trivial share of household expenditures. In addition to consumers, this trade-off is also important for the environment, public policy and businesses: the choice of policy instrument(s) depends on how consumers address this trade-off and firms are expected to introduce products and set prices according to (expected) consumer behavior.

The study of this trade-off has become a central topic in energy demand since at least Hausman (1979). Since then, there has been enough evidence pointing to the undervaluation (or heavily discounting) of future energy costs by consumers, to the point that researchers coined the term Energy Paradox (Jaffe et al., 1999) to denote it.[1] 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

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[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, well above market discount rates.

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investments. The literature has shed light on several explanations for the EEG, from market failures to behavioral anomalies to model or measurement errors (Sanstad et al., 2006; Gerarden et al., 2017).

This paper assesses effects of PERCEE,[2] the program responsible for the largest reduction in electricity use among temporary savings programs worldwide (EIA, 2005). Specifically, we quantify the effect of the PERCEE policy measures – in particular, incentives – on the valuation of energy costs and on the EEG. PERCEE consisted of a package of measures enacted in order to induce households to reduce their electricity consumption by 20 percent at short notice. This was required due to a foreseen shortfall in electricity supply resulting from the alarmingly low levels of water reservoirs supplying the Brazilian hydro plants in early 2001.

Our study relies on 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 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. 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 PERCEE on the EEG by comparing households facing a binding quota for their electricity use with those who were not constrained by it. 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, 2016).

Third, we assess whether temporary programs can have a long-term effect in what concerns energy savings, the valuation of energy costs, and the reduction of the EEG.

Empirical strategy. We test the null hypothesis that consumers correctly value lifetime energy costs of durable products against the two-sided alternative that they either 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 and 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 of interest for several reasons. First, refrigerators are typically purchased for replacement motives, i.e., their purchase is less likely to follow fashion, season, trends or the introduction of a new product line. Second, there is little room for discretion in their use (Gately, 1980a), which will allow us to replace the canonical discrete–continuous model of a household's joint decision of appliance choice and utilization with a simpler, more tractable, discrete choice problem of appliance choice. Refrigerators are, moreover, important enough as a share of energy consumption 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 (Survey of Ownership and Habits - in Portuguese *Pesquisa de Posse e Hábitos*), 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 households generally undervalue energy costs. However, households do react to incentives to conserve energy introduced by the PERCEE program, so much so that their valuation distribution dominate those of other households in the first-order stochastic (FOSD) sense, be it in the same period – as compared to households whose energy use was unconstrained – be it as compared to households purchasing appliances in other sub-periods of the sample.

The reaction to the temporary PERCEE program is, however, short-lived, with households largely reverting to pre-PERCEE (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, even in the extensive margin.

Heterogeneity is ever present in our estimates and can be witnessed when assessing valuation distributions and components of the EEG. 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

[2] In Portuguese: *Programa Emergencial de Redução do Consumo de Energia Elétrica*, or Emergency Program for Reducing Electricity Consumption

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.

When quantifying those effects using a counterfactual exercise, we quantify the reduction in energy use to be equivalent to the energy use of a city of 1.15 mn inhabitants. As we interpret the reaction to the policy on the extensive margin as a lower bound to the effect of the program, we take this as evidence of a sizeable effect of the PERCEE program.

Implications. The implications of our results are as follows. First, even temporary constraints on energy consumption can affect consumer behavior on the extensive margin. That is, we document the transitory changes in preferences induced by PERCEE to have long-run implications through the purchase of durable products.

Second, PERCEE generated both private and social benefits. While the former materialize via the lower operating costs of refrigerators, the latter materialize via a reduced demand for electricity which in turn results in a lower requirement of (high-emission) thermo-electric plants, the way in which supply adjusted in the short- and medium-term in the Brazilian market.

Third, while the temporary, short-term, character of the policy had effected mostly the demand side of the market, the results suggest that a long-run policy would likely also have an effect on its supply-side, generating increased economies of scale in the production of energy-efficient products, and ultimately increased investment in energy-efficient innovation (Newell et al., 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 – for a survey, see Gerarden et al. (2017). 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; Davis, 2010; Davis et al., 2014; 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) and Davis (2008).

Second, the paper contributes to the understanding of the EEG. Taking advantage of the institutional setting, we are able to distinguish consumers facing from those not facing incentives to reduce energy consumption. This allows us to quantify the importance of incentives in inducing energy savings.

Third, we study how households adjust on the extensive margin to a major, temporary energy demand shifter 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) and Costa and Gerard (2018) look at billing data), we focus on appliance purchases. 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, 2016). In our case, the PERCEE program introduces a package of measures, notably an energy quota, 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.

Fourth, by conducting a counterfactual exercise, we quantify the effects of the program on the extensive margin, which we take as a lower bound to the overall effect of the PERCEE program.

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

2. Institutional background

Electricity consumption tends to grow in tandem with GDP in per capita terms, see Fig. 1 for selected emerging economies. Thus, it comes as no surprise that the 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.

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.[4] 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.

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 its 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

[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 et al., 2013; Sallee et al., 2016) whereas others find that they modestly undervalue operating costs, e.g., Allcott et al. (2014). Finally, Huse and Koptyug (2021) show that the undervaluation of energy efficiency is mitigated when information becomes more salient to consumers.

[4] 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).

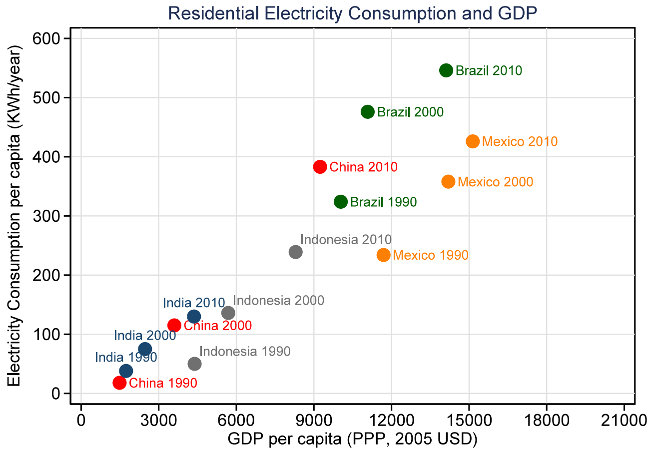
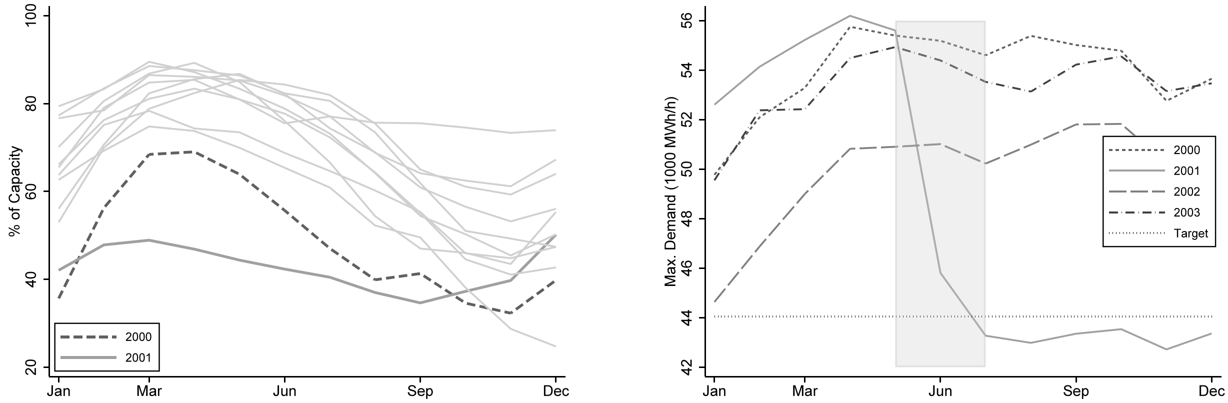


Fig. 1. Per Capita residential electricity consumption and GDP (PPP). Note. This figure displays per capita residential electricity consumption and GDP (PPP) for selected emerging economies using data from the International Energy Agency (IEA). GDP per capita is expressed at purchasing power parity (PPP) and 2005 USD.



Panel A. Reservoir levels in Southeast-Midwest Brazil, 1999-2010

Panel B. Maximum electricity demand

Fig. 2. Overview of the Brazilian market. Note. This figure documents the aggregate supply and demand sides of the Brazilian electricity market, which is strongly dependent of hydro. Panel A 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. Years 2000 and 2001 are highlighted (source is ONS, the National System Operator). Panel B documents the effect of PERCEE at the aggregate demand for electricity. The shaded area denotes the period used to establish the energy quota (May–July 2000). Target denotes the 80 percent energy quota based on aggregate consumption from the reference period.

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 Panel A in Fig. 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. PERCEE had a fast and strong impact on energy consumption, see Panel B in Fig. 2, but with the end of PERCEE in ealy 2002, energy demand increasingly picks up, to the point that energy demand in year 2003 closely tracks pre-PERCEE levels (year 2000).

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, 2005). 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 a package of measures enacted in order to reduce energy consumption. PERCEE's most visible and controversial measure was by far the "energy quota" imposed on ("high-consumption") 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 therefore plausibly exogenous). Households consuming less than 100 KW/month faced a non-binding quota of 100 KWh/month.

When communicating the energy quota, the government also announced the introduction of two measures. First, a "bonus–malus system" around the energy quota whereby households not meeting the quota would incur a malus twice as steep as the bonus. However, the government was ambiguous from the start about the system, e.g., by informing households that they *could* be rewarded by means of a bonus proportional to the below-quota consumption in the following bill. Second, the government also threatened households consistently not attaining the quota that they would be liable to energy cuts. In practice, however, none of these measures was implemented.[5]. The information reached consumers via letters starting from May 2001 and their monthly electricity bills, which consumers receive by mail, see Fig. 3.

Together with the introduction of the energy quota, the government also introduced a nonlinear electricity price increase on top of the existing block pricing scheme. That is, instead of adopting steep tariff increases across the board, which were deemed as highly unpopular by policy-makers, the PERCEE program introduced nonlinear tariff increases whereby 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.

In parallel, the PERCEE program also introduced an energy conservation campaign and an investment program with the aim to expand the capacity of the electricity sector. While the former consisted of 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), the latter consistent on the construction of thermoelectric plants ("peak plants") in order to satisfy the excess demand then existing in the Brazilian market.

With the rainy season beginning in late 2001 and the reversal of the downward trend in reservoir levels (see Fig. 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 signaled 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.

The complexities involved in the analysis of linked rules will lead us to follow the practice in the profession and analyze the measures comprising the package as one (EPA, 2014, chap.5).

Program information. The information regarding PERCEE reached consumers via three channels. First, through letters sent to their homes from May 2001 which contained three pieces of information – see Panel A in Fig. 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 (quickly overruled, see above); finally, the letter also loosely signaled that a household consuming below the quota could be eligible to a bonus.

Second, consumers received information via their monthly electricity bills, delivered by mail. For instance, Panel B in Fig. 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 in middle- and high-income households. Thus, one would expect households subject to an energy quota to face an increasingly tightening one towards the end of the year.

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.[6] On the extensive margin, the campaign stressed measures such as the importance of purchasing energy-efficient appliances with the only concrete measure strongly emphasized being 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.[7]

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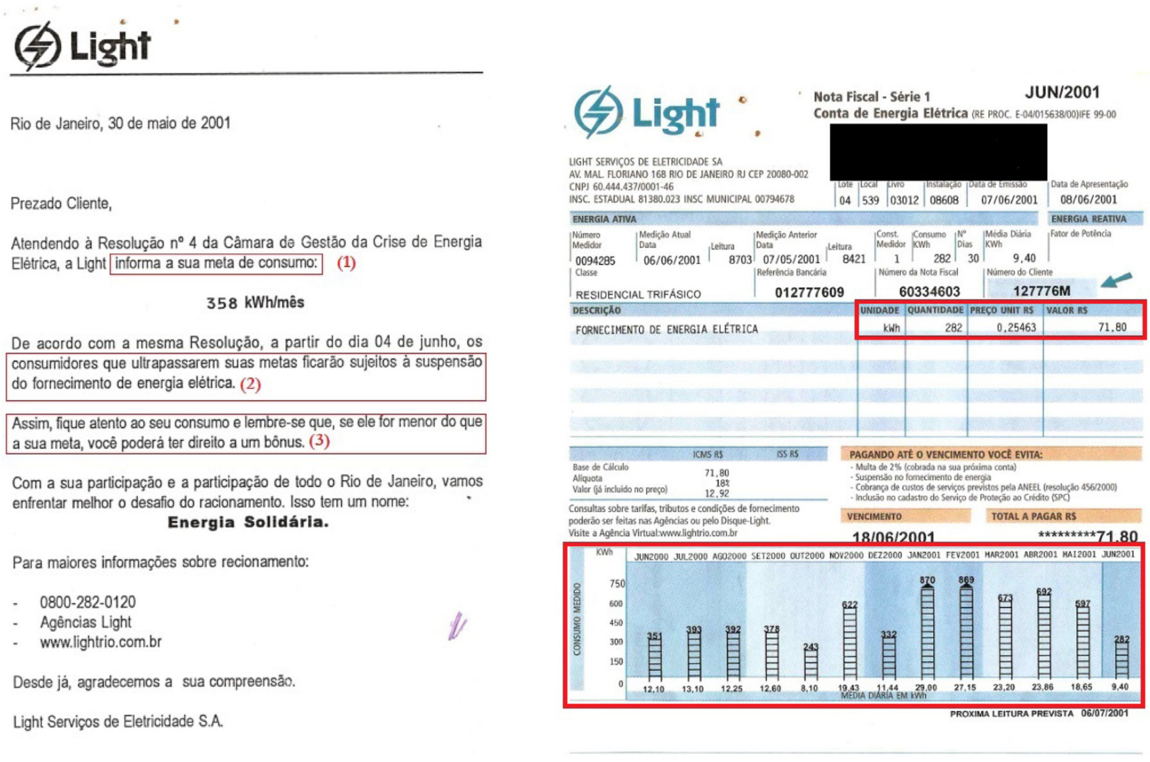
[5] While it was initially announced that households (consistently) not attaining the quota would be liable to energy cuts, these were ruled out for violating the Brazilian Consumer Code already in May 2001. For instance, daily newspaper Folha de São Paulo reports as early as 28 May 2001 that the then 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.

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

[7] In fact, the number of refrigerators purchased in years 2000 and 2001 in our data is quite similar, which lends credence to the replacement as the dominant motive of the purchase of a new refrigerator.



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.

Light

Nota Fiscal - Série 1 JUN/2001

Conta de Energia Elétrica (RE PROC. E-04/015638/00)IFE 99-00

[redacted]

LIGHT SERVIÇOS DE ELETRICIDADE SA
AV. MAL. FLORIANO 168 RIO DE JANEIRO RJ CEP 20080-002
CNPJ 60.444.437/0001-46
INSC. ESTADUAL 81380.023 INSC MUNICIPAL 00794678

Lote	Local	Livro	Instalação	Data de Emissão	Data de Apresentação
04	539	03012	08608	07/06/2001	08/06/2001

ENERGIA ATIVA — ENERGIA REATIVA

Número Medidor	Medição Atual Data	Leitura	Medição Anterior Data	Leitura	Const. Medidor	Consumo KWh	Nº Dias	Média Diária KWh	Fator de Potência
0094285	06/06/2001	8703	07/05/2001	8421	1	282	30	9,40	

Classe	Referência Bancária	Número da Nota Fiscal	Número do Cliente
RESIDENCIAL TRIFÁSICO	012777609	60334603	127776M

DESCRIÇÃO	UNIDADE	QUANTIDADE	PREÇO UNIT R$	VALOR R$
FORNECIMENTO DE ENERGIA ELÉTRICA	kWh	282	0,25463	71,80

	ICMS R$	ISS R$
Base de Cálculo	71,80	
Alíquota	18%	
Valor (já incluído no preço)	12,92	

Consultas sobre tarifas, tributos e condições de fornecimento poderão ser feitas nas Agências ou pelo Disque-Light.
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PAGANDO ATÉ O VENCIMENTO VOCÊ EVITA:
- Multa de 2% (cobrada na sua próxima conta)
- Suspensão no fornecimento de energia
- Cobrança de custos de serviços previstos pela ANEEL (resolução 456/2000)
- Inclusão no cadastro do Serviço de Proteção ao Crédito (SPC)

VENCIMENTO	TOTAL A PAGAR R$
18/06/2001	*********71,80

PROXIMA LEITURA PREVISTA 06/07/2001

Panel A. First letter informing consumers about PERCEE

Panel B. Sample electricity bill (monthly frequency)

Fig. 3. Information about PERCEE program. 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 *could* be rewarded by means of a bonus.

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, 1980a). In practice, once a refrigerator is purchased and its basic settings adjusted, these are unlikely to be frequently adjusted, if at all.[8]

Second, refrigerators were owned by a substantial – and stable – share of households in the Brazilian market, with 85.1% and 87.8% of all households in Brazil owning a refrigerator in years 2001 and 2005, respectively.[9] This mitigates selection concerns due to income, especially in comparison to other emerging economies.[10]

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 data on refrigerators would arguably have more power than doing so for, other, less valuable, and less energy-intensive products.[11]

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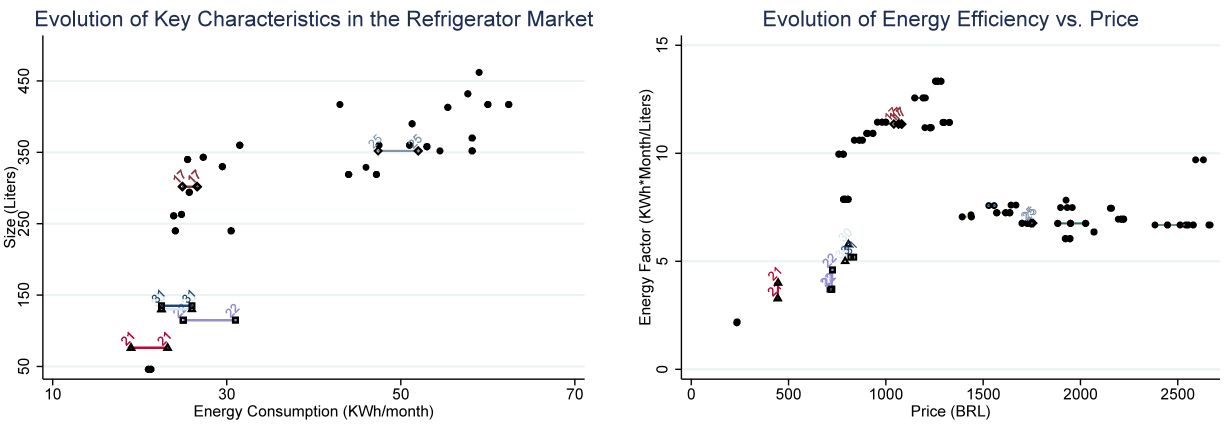
8 Anecdotal evidence suggests adjustments in settings to be more likely to happen due to temperature changes than electricity prices, something we aim to account for empirically. Moreover, it was very unusual for refrigerators on the Brazilian market in the early 2000s to have temperature controls on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

9 According to the PNAD survey of the Brazilian Statistics Bureau. For perspective, Davis and Metcalf (2016) report that 68.2 percent and 79.1 percent of Mexican households own a refrigerator in 2000 and 2005, respectively.

10 In contrast with other markets see, e.g., Davis et al. (2014) amd Gillingham et al. (2012), split incentives in the adoption of energy efficient products are not prevalent in the Brazilian market, where appliances are typically owned by the resident of a dwelling.

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



Panel A. Refrigerator Size vs. Energy Consumption

Panel B. Energy Efficiency vs. Prices

Fig. 4. Evolution of product characteristics – Supply-side. 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) for every product in the sample. 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). The slope of the segment connecting the origin to a given point is its energy factor, measured in liters per KWh/month, a measure of energy efficiency. In Panel B, which displays figures for years 2000–2002 to avoid clutter, the vertical axis corresponds to the energy factor of a given product, 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. Products facing the largest changes are denoted by their product codes.

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.

In what follows, we focus on key aspects on the supply- and demand-sides of the refrigerator market, respectively. Fig. 4 summarizes the supply-side of the refrigerator market. Panel A displays the relation between energy consumption and size (volume) for the products marketed during the sample period, each of which is denoted by a symbol.

The first thing to note is that there seem to be three clusters of products which do not seem to change over time, which suggests that product innovation is limited. That is, most products are marketed with the same characteristics before, during, and after the PERCEE program, with exceptions being few and far between. In other words, this suggests that firms did not react strongly to the PERCEE program in characteristic space, likely due to the temporary character of the PERCEE program.

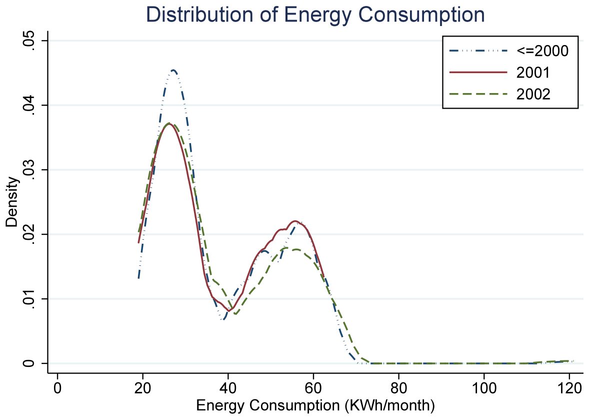
Panel B displays the relation between energy efficiency (as measured by a refrigerator's energy factor, i.e., energy consumption over volume) and price for the same set of products as in Panel A. Although prices could have been adjusted over time, this relation is mostly stable over time. All in all, the evidence in Fig. 4 suggests that there has been little technological innovation in terms of energy efficiency and that manufacturers did not react to the program by, for instance, increasing prices of products with higher energy efficiency.

Fig. 5 focuses on the demand-side, displaying how distributions of product characteristics evolved over time, i.e., the histograms of product characteristics are 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, with the action seemingly being concentrated on the demand side.

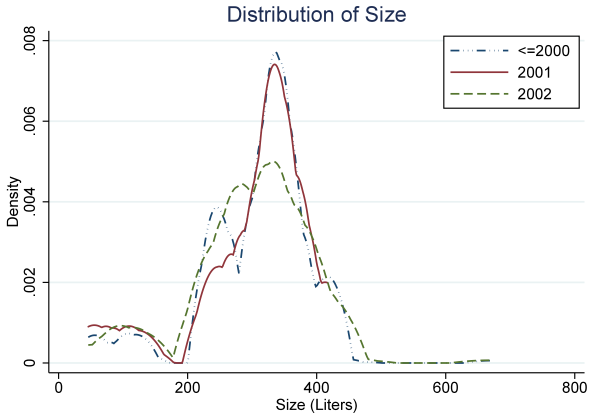
3. Data

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.

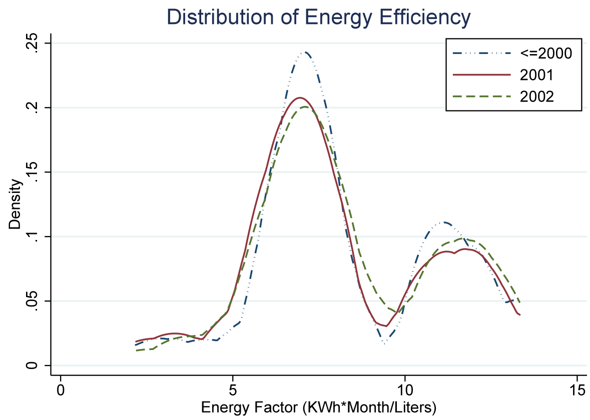
pooling resources are not unheard of either when it comes to the purchase of durables. Due to the potential importance of this channel, we make sure to control for household demographics in our empirical analysis.



Panel A. Energy Consumption



Panel B. Size



Panel C. Energy Efficiency

Fig. 5. Distribution of selected product characteristics – Demand-side. **Note.** This figure displays the evolution of key product characteristics according to refrigerator sales.

Survey on household appliances and usage habits (PPH)[12] This nationally representative survey interviewed 4310 households in 16 Brazilian states, in addition to the Federal District. Households were selected by 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.

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. From (1), one obtains basic household information, such as its address, size, composition, educational attainment of individual members, and dwelling size. From (2), one obtains detailed information about appliances owned by a given household, including model and purchase date. From (3), one obtains information about energy consumption and appliance usage, including frequency, intensity and time of use. From (4), one obtains further household information such as household income, details of dwelling and automobile ownership. Finally, from (5) one obtains 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 Appendix for details). The answer to this question

[12] 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.

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.[13]

Of relevance to our analysis, 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.[14]

Electricity prices. We have obtained retail electricity prices from ANEEL, the electricity regulator (see Huse et al. (2020) for details). 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. The discount rate to be used in the analysis should reflect the opportunity cost of the funds used to purchase the refrigerator, which typically depends on whether the consumer has saved beforehand or is financing the product. In what follows, we use the real interest rate paid out by the Brazilian savings account (*caderneta de poupanca*) which pays out at the monthly frequency a real, after-tax, rate of 6 percent per year. This financial instrument is the main (potentially only) financial instrument widely accessible to the whole population, and thus the main way for low-income consumers to save for the purchase of a durable product. The savings account is also widely used due to its wide recognition as an attractive investment in view of its high remuneration and short maturity.

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

Additional product characteristics. We compile information on product characteristics such as brand, model, size (volume, in liters), and number of doors from a combination of sources. First, from the 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 data sets. As the PPH dataset does not have information at the SKU (stock keeping unit) level, we match the products in a more aggregate level by means of 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 data set. 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

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, 1980b; Houde, 2018) and rely on the limited discretionary margin in the use of refrigerators to model the decision to purchase a refrigerator using a discrete choice model.[15] This framework 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

[13] 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.

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

[15] Equivalently, this corresponds to the assumption that utilization conditional on product choice is perfectly inelastic, as in Grigolon et al. (2014) . This is consistent with empirical findings of a small and statistically insignificant rebound effect, which is typically found in the literature see, e.g., Davis (2008) who finds a price elasticity of clothes washing of −0.06. Thus, our empirical strategy is closer in spirit to Heckman (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.

current ownership of a refrigerator (and its state, neither of which we observe) is likely to affect the current demand for refrigerators. Our estimation approach can thus be seen as a pragmatic modeling approximation to actual choice behavior in the industry and consistent with the bulk of the literature.

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.[16] 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.

Household i obtains the following utility from product j purchased at period t ($i = 1, \ldots, H; j = 1, \ldots, J; t = 1, \ldots, T$)

$$U_{ijt} = \beta_{ip} p_{jt} + \beta_{ic} \tilde{C}_{ijt} + X_{jt} W_{it} \gamma + \tau_t + \varepsilon_{ijt}$$

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

A particular case of the above specification is the logit model, for which $\beta_{ip} = \beta_p$ and $\beta_{ic} = \beta_c$. That is, the price and cost coefficients are not allowed to vary across decision-makers. In this particular case one can then write the willingness-to-pay (WTP) for characteristic k as the ratio of the marginal utility of the characteristic and the marginal utility of its cost. In particular, the WTP for energy costs is given by

$$v_c := \frac{\partial U_{ijt}/\partial \tilde{C}_{jt}}{\partial U_{ijt}/\partial p_{jt}} = \frac{\beta_c}{\beta_p}$$

and the null hypothesis of correct valuation of energy costs against the two-sided alternative is $H_0 : v_c = 1$ vs $H_A : v_c = 1$.

The (expected) present discounted value of operating cost of appliance j at household i is given by

$$\tilde{C}_{ijt} = AC_{ijt} \left[1 - \frac{1}{(1+r_t)^n} \right] \frac{1}{r_t}$$

where AC_{ijt} is the annual operating cost, r_t is the real discount rate at time t upon purchase, and n is the lifetime of a refrigerator.[17]

Following the institutional setting (see Section 3), we assume a constant real discount rate of 6 percent per year. We also assume that energy prices follow a random walk, which is consistent with evidence documented in Anderson et al. (2013) and the recent literature, e.g., Grigolon et al. (2014), Huse and Koptyug (2021).[18] 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 (2008)), in that we assume the (expected) lifetime of a refrigerator is 16 years.[19]

Household heterogeneity. Guided by the institutional setting, we aim to capture a number of important sources of heterogeneity. First, we want to account for heterogeneity arising from (i) the different institutional environments within the sample period; and (ii) the potentially differential responses due to incentives in place during the PERCEE program. Thus, we define sub-periods 1998–2000 ("pre-policy"), 2001 (PERCEE), 2002 ("post-policy I"), and 2003–2005 ("post-policy II", with a different institutional setting, see Huse et al. (2020)), see Fig. 6. Concretely, 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 whether a given household has faced a binding or non-binding energy quota constraint.

Second, we want to account for the fact that the price sensitivity of a household depends on both its observed characteristics and a set of random coefficients which capture unobserved household heterogeneity. This was shown to be important for both durables (Berry et al., 1995) and consumer products (Griffith and Nesheim, 2018), and should also be important for durables marketed in an emerging economy. Thus, in our empirical specification we allow price sensitivities to depend on both income and a random coefficient.[20] Random draws for all coefficients are independently drawn from a Lognormal distribution.[21]

[16] We do not consider the existence of an outside good, since our focus is on how the policy of interest influences which product to purchase, not the timing of the decision to purchase. This is consistent with the purchase of a refrigerator with replacement motives, as in, e.g., Houde (2018)

[17] 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).

[18] This is also consistent with findings documented in Alquist et al. (2013) survey, according to which complex models do not outperform simple models with expectations based only on current energy prices.

[19] While the lifetime of a product may well be correlated with its quality or energy efficiency, the lack of detailed data about it led us to pragmatically follow the literature and assume a uniform lifetime of 16 years across products. For perspective, Houde and Aldy (2017) assume a lifetime of 15 whereas the US DOE assumes a lifetime of 18 years in its regulatory impact analysis of minimum efficiency standards.

[20] 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.

[21] 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

Period:	1999-2000	2001	2002	2003-2005
Event:	*pre-policy*	*policy*	*post-policy I*	*post-policy II*
Policy:		PERCEE		
Demand Parameters:				
Cost (time-varying):	$\beta_{ic,1999-2000}$	$\beta^{binding}_{ic,2001}, \beta^{non-binding}_{ic,2001}$	$\beta_{ic,2002}$	$\beta_{ic,2003-2005}$
Price (time-invariant):	β_{ip}	β_{ip}	β_{ip}	β_{ip}
Valuations:	$\upsilon_{i,1998-2000}$	$\upsilon_{i,2001}$ $\swarrow\searrow$ $\upsilon^{binding}_{i,2001}, \upsilon^{non-binding}_{i,2001}$	$\upsilon_{i,2002}$	$\upsilon_{i,2003-2005}$
Remark:		*consumers face incentives to meet energy quota*		

Fig. 6. Timeline and model parameters. 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 deviation (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.

Identification. The identifying variation of the parameters comes from 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 varies 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.

The identifying variation of the price parameters relies on the variation of refrigerator prices across markets and over time, combined with product entry and exit in a given market. 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 when using aggregate data, this is slightly less of a concern in the case of micro data as 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 (see Goldberg (1995) for such an argument when estimating the demand for automobiles). However strong, this assumption is consistent with most of the literature using micro data, see Petrin and Train (2009) for an exception. As an additional step to address endogeneity concerns we employ a number of fixed-effects, thanks to the panel structure of the data. First, we use product fixed-effects, which 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. That is, to the extent that characteristics such as reputation or product quality are time-invariant, product fixed-effects provide a natural way to control for them. This strategy is similar to the use of brand fixed-effects in the cereal market (Nevo, 2001) and the use of product fixed-effects in the refrigerator market (Houde, 2018).[22] 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.

We also control for household demographics which are likely to influence the choice of a refrigerator, such as household size, dwelling size, an indicator of freezer ownership, .

Finally, we account for the fact that household demographics are likely correlated with product characteristics. This is important because, for instance, larger households are likely to purchase larger refrigerators. Concretely, we interact refrigerator volume with both dwelling size and household size, in the spirit of Goldberg (1995) and Houde (2018), in addition to the previously described price–income interaction.

parameter υ 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 et al., 2012). However, we feel heterogeneity is crucial to model the price sensitivity of consumers in a realistic way, see the results below.

[22] Since it is unclear whether reputation is more likely to manifest itself at the brand- or at the product-level, in the market for refrigerators, we have adopted specifications with product fixed-effects after experimenting with brand fixed-effects.

Estimation. Following the literature (see Train and Winston (2007)), estimation is performed using the method of Simulated Maximum Likelihood (SML).

5. Results

5.1. Demand estimates

To quantify the valuation of energy costs, and ultimately energy efficiency, we rely on the estimation of a demand model for the new refrigerator market.

Our demand specifications are comprised of product characteristics, household characteristics, interactions between product and household characteristics, a set of fixed-effects, and the specification of household heterogeneity.

Table 1 reports demand and valuation estimates of alternative demand 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. Moreover, all specifications contain product fixed-effects, cost–period interactions (rather than period fixed-effects) and, cost–period heterogeneity parameters, which in practice often help achieving convergence.[23]

The starting point is Specification (1), whose mean parameters are in line with economic theory and typically statistically significant. Moreover, price-related coefficients are all significant, be it price itself, its interaction with income (both significant at the 1 percent level) or its heterogeneity parameter (at the 10 percent level). The lack of significance of most cost–period heterogeneity parameters suggest a homogeneous valuation of consumers to the lifetime operating costs of a refrigerator within a given time period.

Specification (2) adds region fixed-effects to (1) whereas Specification (3) adds household size and its interaction with refrigerator volume to Specification (1). Specification (4) combines (2) and (4). Finally, as the portfolio of household appliances may well influence the purchase of a new appliance (Reiss and White (2005)) – e.g., households owning a freezer might decide to purchase a smaller refrigerator, for instance – we control for freezer ownership in our preferred Specification (5). Specification (5-Logit) constrains the random coefficients of all variables in (5) to be zero and is reported as a robustness check.[24]

While the specifications are largely robust in terms of parameter estimates, there are some slight differences when it comes to statistical significance. First, the heterogeneity parameter associated to the interaction of cost and the 2003–2005 period becomes significant at the 10 percent significance level starting from Specification (3). We interpret this result as consistent with the fact that consumers reacted in a heterogeneous way to the mandatory adoption of PROCEL energy label (Huse et al., 2020).

Second, the price heterogeneity parameter magnitude decreases and its significance goes from 5 percent in Specifications (1)-(2) to 10 percent in Specifications (3)-(4) to becoming insignificant in (5). We interpret this finding as consistent with the additional controls accounting for heterogeneity in the data. Note, however, that even if the random coefficient associated to price is not significant, the coefficients associated to price and to the price–income interaction are still both significant. We also note that the parameter estimates of Specifications (5) and (5-Logit) are largely similar.

Valuation of energy efficiency. While our main focus is on the distribution of valuations, we briefly discuss average valuations of energy efficiency, also reported in Table 1. First, average valuations are largely robust across specifications. Second, they are largely consistent with comparable ones in the literature.[25] Third, average valuations exhibit an intuitive pattern consistent with the institutional setting. Focusing on Specification (5), valuation estimates of consumers for which the energy quota was binding increase as compared to their 1998–2000 counterpart (to 0.854 from 0.498) whereas the valuations of consumers for which the energy quota was not binding even decrease (to 0.389). With the end of PERCEE, 2002 valuations increase somewhat (to 0.557) when compared to their 1998–2000 counterparts and increase slightly once again in 2003–2005 (to 0.629), likely as a reaction to making energy labels mandatory.[26]

Given the importance of heterogeneity and the price–income interaction in valuations, we now focus on the distribution of valuations. Fig. 7 displays density estimates and cumulative distribution functions of the valuation of energy efficiency for the different periods of our sample (all based on Specification 5). Consistent with the average valuations, the densities in Panel A suggest that the valuation of consumers for which the energy quota is binding during the PERCEE program (PERCEE: Binding) are the highest obtained, followed by those following the mandate of energy label adoption (Post-PERCEE 2003-5), those immediately after PERCEE but before the adoption of energy labels (Post-PERCEE 2002), those pre-PERCEE (pre-PERCEE) and, finally, those of unconstrained consumers during PERCEE (PERCEE: non-binding).

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[23] As the number of potential clusters is small given the yearly frequency of the data and the few cross-sectional markets, we use robust standard errors.

[24] We conducted a number of additional robustness checks but were often constrained by numerical issues. For instance, we have estimated a logit model distinguishing between binding and non-binding households for all periods and could not reject the null of equality of the coefficients for all periods except for 2001. We have also estimated a random coefficients logit model distinguishing between binding and non-binding households for periods 1998–2000, 2001, 2002 but not 2003–2005, with random coefficients for price and the corresponding cost–period interactions. Again, we could not reject the null of equality of the coefficients other than 2001.

[25] For perspective, Allcott et al. (2014, Table 4) report valuation estimates in the range 0.42-0-77 under the assumption that fuel prices follow a martingale, the one more comparable to our setting. Huse and Koptyug (2021) report undervaluation of fuel costs, with estimates hovering around 0.60.

[26] We acknowledge the existence of a potential bias in valuation estimates resulting from the mis-classification of households who have purchased a refrigerator in the pre-PERCEE period in 2001 as households for which the energy quota was binding. While valuation estimates of binding households are most likely overstated (since "pre-PERCEE households" where assumed to react to the energy quota imposed by the program), the signs of the biases in the valuations of non-binding households and pre-PERCEE households seem less clear.

Table 1
Demand and average valuation estimates.

Variables	[1]	[2]	[3]	[4]	[5]	[5-Logit]
<u>Mean</u>						
Price X Income	−15.6144***	−15.5993***	−15.5837***	−15.5738***	−15.7452***	−15.9348***
	(0.3081)	(0.3001)	(0.3115)	(0.3059)	(0.3274)	(0.2475)
Cost x DV (1998–2000)	−7.4169***	−7.4275***	−7.4344***	−7.4526***	−7.5699***	−7.5905***
	(0.4456)	(0.4432)	(0.4402)	(0.4469)	(0.5198)	(0.4888)
Cost x DV (2001) X Bind.	−6.8820***	−6.9578***	−6.8928***	−6.9768***	−6.9567***	−7.0213***
	(0.4630)	(0.5278)	(0.4696)	(0.5359)	(0.5171)	(0.6437)
Cost x DV (2001) X Non-Bind.	−7.6055***	−7.5748***	−7.6558***	−7.6514***	−7.7455***	−7.8285***
	(0.5030)	(0.4904)	(0.5304)	(0.5251)	(0.5882)	(0.6478)
Cost x DV (2002)	−7.2836***	−7.2922***	−7.2949***	−7.3143***	−7.3841***	−7.4655***
	(0.3750)	(0.3813)	(0.3772)	(0.3858)	(0.4184)	(0.4671)
Cost x DV (2003–2005)	−7.3238***	−7.3797***	−7.3655***	−7.4261***	−7.5900***	−7.5014***
	(0.4164)	(0.4718)	(0.4163)	(0.4493)	(0.5217)	(0.4199)
Price	−6.8800***	−6.8780***	−6.8545***	−6.8603***	−6.9989***	−7.1438***
	(0.3959)	(0.3962)	(0.3929)	(0.3990)	(0.4230)	(0.3366)
<u>Std. Dev.</u>						
Cost x DV (1998–2000)	0.3506	−0.4329	0.3444	0.3522	0.3855	
	(0.5370)	(0.3850)	(0.4017)	(0.4025)	(0.5024)	
Cost x DV (2001) X Bind.	−0.0038	−0.0038	−0.0025	−0.0050	−0.0034	
	(0.0091)	(0.0136)	(0.0083)	(0.0126)	(0.0081)	
Cost x DV (2001) X Non-Bind.	0.1337	0.0585	−0.0718	−0.0434	−0.0438	
	(0.5215)	(0.0940)	(0.1298)	(0.0595)	(0.0625)	
Cost x DV (2002)	0.0018	0.0016	−0.0067	−0.0071	−0.0047	
	(0.0108)	(0.0123)	(0.0116)	(0.0132)	(0.0168)	
Cost x DV (2003–2005)	0.6572	0.7585	0.7034*	0.7813*	0.8142*	
	(0.5159)	(0.5733)	(0.3482)	(0.3754)	(0.4045)	
Price	0.2818**	0.2928**	0.2489*	0.2590*	0.2014	
	(0.1012)	(0.1086)	(0.1148)	(0.1197)	(0.1756)	
Average Valuations						
$\upsilon_{1998--2000}$	0.500	0.508	0.481	0.474	0.498	0.539
$\upsilon_{2001}^{Binding}$	0.803	0.739	0.779	0.717	0.854	0.951
$\upsilon_{2001}^{Non-Binding}$	0.393	0.400	0.364	0.366	0.389	0.424
υ_{2002}	0.537	0.529	0.521	0.512	0.557	0.610
$\upsilon_{2003--2005}$	0.639	0.644	0.620	0.618	0.629	0.589
Product FE	Yes	Yes	Yes	Yes	Yes	Yes
Volume	Yes	Yes	Yes	Yes	Yes	Yes
Volume–Dwelling size	Yes	Yes	Yes	Yes	Yes	Yes
Volume–Household size	No	No	Yes	Yes	Yes	Yes
Region Dummies	No	Yes	No	Yes	Yes	Yes
HH Size	No	No	Yes	Yes	Yes	Yes
HH owns Freezer	No	No	No	No	Yes	Yes
Dwelling Size	Yes	Yes	Yes	Yes	Yes	Yes
ll	−2326.328	−2283.091	−2284.541	−2242.326	−2224.681	−2225.402
N	29602	29602	29374	29374	29374	29374

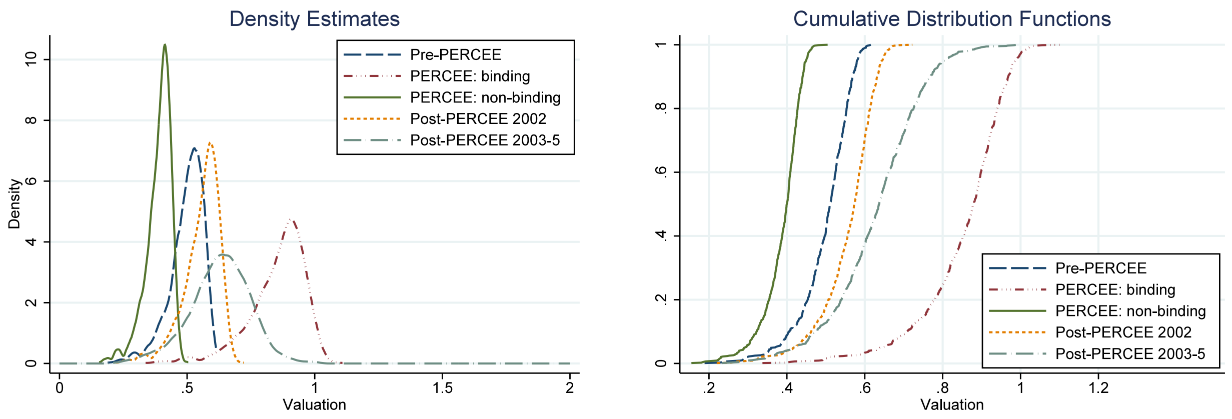
Note. Models estimated are Random Coefficients Logit (RCL) with Lognormally distributed parameters on price and all cost–period terms. The random draws are (independent) Lognormal. Robust standard errors are reported in parentheses. Significance levels are denoted by * (10 percent), ** (5 percent) and *** (1 percent). DV(.) and SD(.) denote dummy variable and standard deviation, respectively. All models are estimated using 300 Halton draws. Model [5-Logit] coefficients were log transformed as to match magnitudes with all previous models, and standard errors were computed using the Delta Method.

In order to formally compare valuation distributions we proceed in two steps. First, we graphically compare the empirical distribution functions of valuations pairwise. The findings summarized in Fig. 7 suggest the occurrence of first-order stochastic dominance (FSD) in the data.[27] 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.[28]

Specifically, the distribution associated to $\upsilon_{2001}^{binding}$ 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

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

[28] 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.



Panel A. Density Estimates

Panel B. Cumulative Distribution Functions

Fig. 7. Distribution of valuation parameters. Note. This figure displays kernel density estimates of the valuation of energy costs in Panel A and the corresponding cumulative distribution functions in Panel B.

$\upsilon_{1998-2000}$, 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.

Discussion. The empirical findings suggest that the PERCEE program 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 were concerned about energy consumption and/or energy efficiency upon the purchase of their new refrigerator under the period PERCEE was in place.

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

5.2. Lifetime private and social benefits

We quantify the effects of the PERCEE program by performing two policy simulations, one focusing on households facing a binding energy quota and another focusing on households for which the energy quota was not binding during the PERCEE program. In either case, we retrieve parameter estimates for the respective group (for year 2001, i.e., during the PERCEE program), impose those parameter estimates on data from 1998–2000, and compute the counterfactual choices stemming from the changes in preference parameters.

This calculation relies on existing data and a number of assumptions, from information on energy consumption (available for each product), electricity prices (assumed to remain constant over time), and assumptions on the stability of product lines, the lifetime/replacement of the refrigerators (16 years), and the discount rate. (See Fig. 4 for supporting evidence regarding the supply-side.)

The results are summarized in Table 2, whose top panel reports per-household figures. Focusing on households for which the energy quota was binding, the reduction in energy consumption stemming from the refrigerator purchases was 22.6 KWh/Year, or roughly 5.1 percent of the yearly energy consumption of the average refrigerator in the sample (see the Appendix for summary statistics).

The lifetime monetary savings of USD 24.34 amount to approximately 8 percent of the expected lifetime operating cost of the average refrigerator in the sample. Finally, the social benefit of carbon savings is USD 12.70. In contrast, households not facing a binding energy quota reacted in a way that energy consumption stemming from refrigerators increased by 4.9 KWh/Year (1.1 percent of the yearly energy consumption of the average refrigerator in the sample), with lifetime monetary losses of USD 5.32 (approximately 1.75 percent of the expected lifetime operating cost of the average refrigerator in the sample) and a social cost of USD 2.74. The estimates are consistent with the intuition that PERCEE should affect the group facing a binding energy quota more than the group for which the energy quota did not play a role. In fact, the reaction of the former is 4.6 larger than the latter in absolute terms when it comes to changes in energy consumption, 3.5 larger when it comes to lifetime monetary savings, and 4.6 in terms of social benefits.

Table 2
Quantification of private and social benefits.

Variable		Binding	Non-Binding
Per Household	Δ Energy Consumption (KWh/Year)	−22.6	4.9
	Lifetime Monetary Savings (USD)	18.84	−5.32
	Social Benefits of Carbon Savings (USD)	12.70	−2.74
Aggregate	Δ Energy Consumption (mn KWh/Year)	−63.2	13.6
	Lifetime Monetary Savings (mn USD)	68.14	−14.89
	Social Benefits of Carbon Savings (mn USD)	35.57	−7.66

Note. This table reports quantifications of energy savings, monetary savings and the social benefit of carbon savings associated to the two counterfactuals. The assumptions used are a lifetime of 16 years for refrigerators, a social cost of carbon of USD 85/tCO2 SCC (equivalent to USD 312/tC), electricity generation with emissions of 655gCO2/KWh, a 6 percent discount rate, and a 2.25 BRL/USD exchange rate. To arrive at our aggregate estimates, we estimated the market size to be 2.8 mn households as follows. First, we use the number of households reported in the Brazilian Census of year 2000, 44,795,101 households. Then we assume 1/16 of the households replaces a refrigerator in a given year, which yields the 2,799,694 households which we round up to 2.8 mn households. This assumes a constant replacement rate during the 16 years refrigerators are expected to last (thus no income or price effects whatsoever) and relies on the accuracy of the sample average as an estimate of the population mean given the sampling design of the PPH survey.

The bottom panel in Table 2 extrapolates the above figures for the Brazilian population. Focusing on households facing a binding energy quota, the energy savings of 63.2 mn KWh/Year are comparable to the yearly energy consumption of a Brazilian city of approximately 1.15 mn inhabitants, with lifetime monetary savings and a social benefit of USD 68.14 mn and USD 35.57 mn, respectively.[29] For those households not subject to a binding energy quota, the aggregate results amount to an increased energy consumption of 13.6 mn KWh/Year are comparable to the yearly energy consumption of Brazilian city of approximately 250,000 inhabitants, with lifetime monetary losses and a social cost of USD 14.89 mn and USD 7.66 mn, respectively.

The above analysis is arguably better suited for the short-run in that it misses supply-side reactions (see evidence of staleness of responses in Fig. 4). This is potentially important in the long-run because if consumers reveal a higher valuation of energy efficiency, manufacturers are likely to respond by increasing the availability (and likely prices) of energy-efficient products. However realistic, incorporating such features would require a complex model of firm behavior with endogenous product characteristics and is left for future research.

In order to provide perspective on our findings, we briefly discuss why the PERCEE program has an effect, the mechanism by which effects materialized, the economic significance of such effects, its supply-side consequences, and whether governmental intervention is warranted.

Why is there an effect? Through a package of measures, the PERCEE program created incentives for households to conserve energy. In particular, our results suggest that such incentives work even on the extensive margin – the purchase of a new refrigerator – for households for which the energy quota was binding.

What is the mechanism driving the results? Households have relatively little leeway to choose among refrigerators of different sizes given demographics and preferences, e.g. household size and preference for home-cooked food. However, conditional of refrigerator size, households can sort into refrigerators of different energy consumption and energy efficiency. The package of measures introduced by the PERCEE program – in particular the energy quota – generated incentives for households to re-consider their choices in the extensive margin.

Is the effect economically significant? By comparing the magnitudes of changes in energy consumption of households for which the energy quota was binding vs. non-binding, the former reacted by a factor of approximately 4.6, suggesting a non-trivial effect of the PERCEE program. Moreover, the energy savings corresponding to the consumption of a medium-sized city by Brazilian standards (1.15 mn inhabitants) corresponds to the effect only on the purchase of new refrigerators. A number of simpler and/or cheaper measures were suggested and advocated during the PERCEE program, from switching off lights and appliances not in use to replacing light bulbs. Thus, what we quantify here is a lower bound to the effects of the program, conditional on the purchase of a new refrigerator. That is, despite the temporary character of the PERCEE program, the package of measures had an effect (even) on the extensive margin.

Is governmental intervention warranted? Given the urgency and the severity of the crisis, it becomes difficult to argue against governmental intervention in this particular case. Granted, (i) the temporary character of the policy did not incentivize supply-side responses, for instance, with regards to technological innovation in terms of energy efficiency; and (ii) the government faced a trade-off in what regards a more widespread adoption of energy quotas and tariff increases vis-à-vis facing a political backlash from targeting poorer households.

[29] For perspective, the city of Goiânia, capital of the state of Goiás, was the 11th largest state capital by population, with 1.09 mn inhabitants in year 2000, according to the Brazilian Statistics Bureau, IBGE. The population of Brazil in the same year was estimated to be 173.8 mn inhabitants.

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

Fig. 8. Relation between valuations and components of the energy gap. Note. This figure illustrates the relation between valuations and the components of the energy gap before and while PERCEE was in place.

6. Decomposing the energy efficiency gap

6.1. Defining EEG components

Even if devising a model to explain the EEG is outside the scope of this paper, it can be insightful to decompose the EEG into incentive vis-à-vis other components taking advantage of the fact that the PERCEE program affected different households in different ways.

Mean valuations Define the energy efficiency gap (EEG) as

$$\Gamma := 1 - \varphi(\upsilon)$$

where $\varphi(.)$ is a functional of the distribution of valuations. One alternative is to let $\varphi(.)$ be the expected value of the distribution of valuations. Thus, the initial mean EEG (Γ_0) is given by the difference between the correct valuation of energy costs ($\upsilon = 1$) and the mean valuation for the period 1998–2000:

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

The change in the mean valuations of consumers with a binding energy quota can be decomposed into incentive ($\Gamma^{inc,binding}$) and other components ($\Gamma^{oth,binding}$)

$$1 - \upsilon_{2001}^{binding} = \Gamma_0 + \Gamma^{inc,binding} + \Gamma^{oth,binding}$$

whereas the change in mean valuations for consumers with a non-binding energy quota can be written as the result changes in variables other than incentives ($\Gamma^{oth,non-binding}$)

$$1 - \upsilon_{2001}^{non-binding} = \Gamma_0 + \Gamma^{oth,non-binding}$$

With this setup in place, which we summarize in Fig. 8, one can quantify the components of the EEG. First, one readily obtains $\Gamma_0 = 0.502$ and $\Gamma^{oth,non-binding} = 0.109$. While the former informs the "baseline" EEG, the latter implies an increase in the EEG for households not facing a binding energy quota. Alternatively, despite an extensive information campaign being part of PERCEE, including media campaigns and letters sent to households (see Section 2), non-binding households did not act in a way consistent with pro-social behavior.

The quantification of the second component requires solving $\Gamma^{inc,binding} = \upsilon_{1998-2000} - \upsilon_{2001}^{binding} - \Gamma^{oth,binding}$, whose value depends on assumptions on the component $\Gamma^{oth,binding}$. Assuming that consumers facing a binding energy quota only experienced a change in incentives results in $\Gamma^{inc,binding} = -0.356$, i.e., the incentives induced by the energy quota resulted in a substantial decrease of the EEG. On the other hand, assuming the other variables affected both binding and non-binding consumers the same way results in $\Gamma^{inc,binding} = -0.247$, i.e., a less dramatic – yet still sizeable – decrease in the EEG.[30]

Valuation quantiles One limitation of the above approach is that heterogeneity allowed – and accounted – for in the estimation of the demand system and incorporated into the valuation distribution is disregarded in the analysis. Given how important heterogeneity seems to be, we would ideally incorporate it in the quantification of the EEG components.

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 quantile q of the valuation distribution, one can write the pre-PERCEE energy efficiency gap (EEG) as

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

[30] An alternative relies on the availability of panel data. If that were 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 below.

As illustrated in Fig. 8, PERCEE affects the behavior of households in different ways. For those households for which the energy quota is not binding, one can then connect the change in valuations as a result of factors other than incentives for a given quantile q as

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

where $\Gamma_q^{oth,non-binding}$ is the gap component due to factors other than incentives 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 incentives ($\Gamma_q^{inc,binding}$), together with all other explanations for the EEG ($\Gamma_q^{oth,binding}$), so we write

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

Combining the equations above yields

$$\Gamma_{q,0} = 1 - \upsilon_{q,1998-2000}$$
$$\Gamma_q^{oth,non-binding} = \upsilon_{q,1998-2000} - \upsilon_{q,2001}^{non-binding}$$
$$\Gamma_q^{inc,binding} = \upsilon_{q,1998-2000} - \upsilon_{q,2001}^{binding} - \Gamma_q^{oth,binding}$$

As above, while one can identify $\Gamma_{q,0}$ and $\Gamma_q^{oth,non-binding}$ based on the quantiles of the valuation estimates, the same does not hold for $\Gamma_q^{inc,binding}$, which depends on valuation estimates and on $\Gamma_q^{oth,binding}$. One can, however, quantify the incentive component by making suitable assumptions:

Assumption A1 *Households for which the energy quota binds face only an incentive component.*

Assumption A2 *All households react the same way for factors related to energy consumption and energy efficiency.*

While Assumption A1 implies $\Gamma_q^{inc,binding} = 0$, homogeneity Assumption A2 implies $\Gamma_q^{oth,binding} = \Gamma_q^{oth,non-binding} = 0$. Thus, one obtains the following results under A1 and A2, respectively:

Incentive component ic1 Under A1, the EEG of households for which the energy quota is binding is given by

$$\Gamma_q^{inc,binding} = \upsilon_{q,1998-2000} - \upsilon_{q,2001}^{binding}.$$

Incentive component ic2 Under A2, the EEG of households for which the energy quota is binding is given by

$$\Gamma_q^{inc,binding} = \upsilon_{q,2001}^{non-binding} - \upsilon_{q,2001}^{binding}.$$

6.2. *Quantifying EEG Components*

The estimates of the EEG components under the two alternative assumptions are displayed in Fig. 9, displaying $\Gamma_{q,0}$, $\Gamma_q^{oth,non-binding}$, $\Gamma_q^{inc,binding}$ under A1 and $\Gamma_q^{inc,binding}$ under A2.

The first feature of Fig. 9 is how the baseline EEG component $\Gamma_{q,0}$ varies across quantiles. The component decreases monotonically as quantiles increase, from 0.715 for quantile 1 to 0.397 for quantile 99 of the associated valuation distribution, thus suggesting substantial heterogeneity in the sample (for perspective, the average valuation for 1998–2000 is 0.498).

Heterogeneity is also a feature of the component of the EEG associated to households for which the energy quota is non-binding, which also appears in both panels and is represented by $\Gamma_q^{oth,nonbinding}$. This component ranges from 0.062 for quantile 1 to 0.138 for quantile 99 of the associated valuation distribution. Regardless of the exact value, the positive estimates suggest a lack of pro-social behavior of such households.

Finally, the incentive component of the EEG is represented by $\Gamma_q^{inc,binding}(A1)$ and $\Gamma_q^{inc,binding}(A2)$. Under A1, the incentive component implies a reduction of the EEG in the range 0.204–0.419, also increasing monotonically with the quantiles of the associated valuation distribution. Under A2, the reduction is in a more pronounced range, 0.267–0.557.

All in all, the results in Fig. 9 show both the substantial heterogeneity in valuation estimates – and the resulting components of the EEG – as well as the importance of incentives brought up by energy savings programs, such as a binding energy quota.

7. Conclusion

This paper investigates the effects of PERCEE, the program responsible for the largest reduction in electricity use among temporary savings programs worldwide (EIA (2005)).

Using revealed preference data from a nationally representative household survey in Brazil, we focus on how households adjust to PERCEE on the external margin of adjustment, i.e., upon the purchase of a new refrigerator. Specifically, we quantify how households value energy costs as well as the components of the energy efficiency gap.

We estimate a structural model 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.

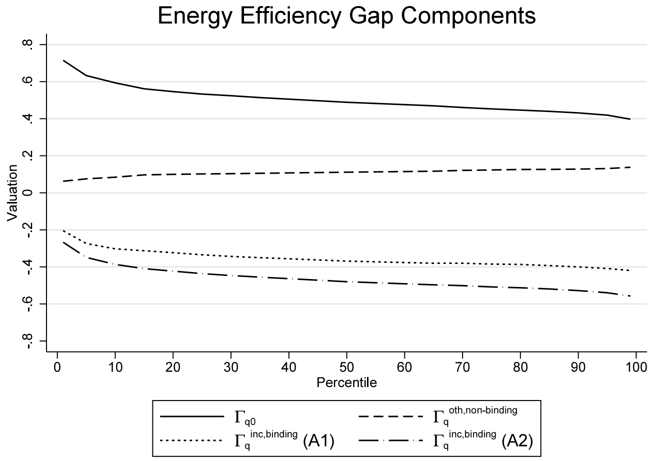


Fig. 9. Decomposition of the energy efficiency gap. Note. This figure displays components of the Energy Efficiency Gap under Assumptions A1 and A2.

The PERCEE program leads to higher valuations of energy costs, but only for consumers facing incentives to reduce consumption by means of a binding energy consumption quota; households not facing such incentive actually decrease their valuation of energy costs.

The counterfactual savings in energy consumption from the purchase of new refrigerators are non-trivial, being equivalent to the yearly electricity consumption of a mid-sized Brazilian state capital (1.15 mn inhabitants) and with corresponding monetary savings and carbon savings associated with such a reduction. We take this effect on the extensive margin as a lower bound to the overall effects of the PERCEE program.

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.

According to our estimates, the incentive component induces a substantial – yet heterogeneous – decrease of the energy gap which dominates its other components.

This paper thus 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.

While a complete picture of the market would only be possible by incorporating a fully-fledged model of the supply-side, including incentives to innovate and introduce products, this interesting aspect is left for future research.

Declaration of competing interest

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

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jeem.2021.102529.

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