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What Changes Energy Consumption, and for How Long?

New Evidence from the 2001 Brazilian Electricity Crisis

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New Evidence from the 2001 Brazilian Electricity Crisis*

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Abstract

There is little evidence from impact evaluation studies of ambitious residential energy conservation programs, especially in developing countries. In this paper, I investigate the short– and long–term impacts of the most ambitious electricity conservation program to date. This was an innovative program of private incentives and conservation appeals implemented by the Brazilian government in 2001–2002 in response to supply shortages of over 20%. I find that the program reduced average electricity consumption per customer by 25% over a nine–month period in affected areas. Importantly, the program reduced consumption by 12% in the long run. Such persistent effects, which arose mostly from behavioral adjustments, may substantially improve the cost–effectiveness of ambitious conservation programs. Finally, I show that a price elasticity estimated out–of–crisis would have to be increased fivefold to rationalize conservation efforts by the private incentives alone. Appeals to social preferences likely amplify consumers' responsiveness in times of crisis.

Keywords: residential energy conservation, price and non–price policies, long–term effects, developing countries

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1 Introduction

Energy conservation is on the policy agenda around the globe. Residential electricity consumption, in particular, has attracted a lot of attention.[1] Yet, energy conservation is notoriously difficult to incentivize. Typical estimates of the price elasticity of residential electricity demand, for instance, are relatively low and it is unclear how much of an impact non–price policies can have. In fact, there is little evidence from impact evaluation studies of ambitious conservation programs. By triggering lumpy adjustments inherent in the use of energy (e.g., investments or habits), such programs may turn out more cost–effective, and may even induce long–term effects. There is also little evidence from the developing world where households consume much less energy, on average. Most of the growth in energy demand comes from developing countries. Moreover, with vulnerable infrastructures and the difficulty of accurately planning capacity investments, their rapidly rising demand brings the risk of dramatic supply shortages (Wolfram et al., 2012).[2]

In this paper, I investigate the short– and long–term impacts on residential electricity consumption of the largest electricity conservation program to date. This was an innovative program of private incentives and conservation appeals implemented by the Brazilian government in areas facing supply shortages of over 20%. Rolling blackouts were only considered as options of last resort. The Brazilian electricity crisis lasted from June 2001 to February 2002. Its major cause was exceptionally low rainfall, in a country relying heavily on hydro–electric generation. After the 2000–2001 summer, hydro–reservoirs' water levels were at their lowest in 40 years in the two affected electric subsystems (North–East and South–East/Midwest; see Figure 1a). In contrast, generous rain dissipated any risk of shortages for utilities in the third subsystem (South). This differential impact was entirely due to weather and to limited transmission capacity across subsystems.

This paper addresses three questions. First, I investigate how much conservation effort an ambitious program can achieve, and from which customers, in a context of relatively low baseline electricity consumption.[3] I use 15 years of monthly administrative reports for every electric utility in Brazil and employ a difference–in–difference strategy comparing utilities subject or not to

[1]Improving the energy efficiency of residential electricity demand is often viewed as the most cost–effective policy to abate greenhouse gas emissions around the world (McKinsey, 2009). Utilities have to meet specific energy saving targets through customer conservation programs in at least 24 states in the US.

[2]In more advanced countries, imbalances between supply and demand may arise from catastrophic events, such as the recent Japanese earthquakes, or demand shocks, such as hot summer days (Meier, 2005).

[3]The average residential customer consumed less than 200 kWh per month at the time.

the government program. This allows me to estimate its effect on average residential electricity consumption during the crisis. I then exploit monthly billing data for three million residential customers of an affected utility to study the distribution of customers' responses.

Second, I investigate whether the impacts of a temporary energy conservation program can persist in the long run. I rely on the same empirical strategies and estimate impacts up to 10 years after the crisis. Combining different data sources, I provide evidence on the underlying mechanisms.

Finally, I investigate the relative roles of private incentives and conservation appeals in explaining conservation efforts during the crisis. Every customer was assigned a quota, typically set at 80% of baseline consumption. Larger consumers were charged fines for exceeding their quotas; smaller consumers were offered bonuses for consuming below their quotas. The government also carried out a large conservation appeal campaign in cooperation with utilities and media outlets. I begin by exploiting quasi–exogenous variation in individual private incentives. I then use indirect inference techniques ("moment matching"; Gouriéroux and Monfort, 1996) to estimate parameter values of a standard model of consumption necessary to rationalize customer behaviors through the private incentives alone. I deduce the size of potentially large effects of appeals to social preferences from the difference between these estimates and parameter values estimated out–of–crisis.[4]

I obtain three main findings. First, average residential consumption per customer dropped substantially during the crisis. Figure 1b displays seasonally adjusted trends in average residential consumption by electric subsystem. Trends were similar among subsystems prior to the crisis. At the launch of the government program in June 2001, consumption decreased by about 34% in the two affected subsystems (North–East, South–East/Midwest). Consumption stayed low for the duration of the crisis; no blackouts were ever necessary. Consumption also decreased by 9% in the third subsystem (South) because of national policies and possible spillovers from conservation appeals. I therefore attribute a 25% average reduction to the conservation program. This is a very large effect. The result holds across seasons, across utilities, and controlling for changes in base electricity tariffs. Average effects came from large responses by most customers across the distribution of consumption levels. Energy theft, prevalent in many developing countries, is unlikely

[4]Voluntarily conserving electricity in response to conservation appeals amounts to contributing anonymously to a public good. Indeed, there was no real way to observe conservation efforts among neighbors during the crisis, and the chances for a given household to be "pivotal" in averting generalized blackouts were essentially nil. I thus define social preferences broadly to encompass phenomena such as altruism, patriotism, social comparison, or "moral suasion" (Reiss and White, 2008).

to have played any major role.

Second, the conservation program reduced average residential consumption per customer by 12% in the long run (using comparable utilities at baseline). Figure 1b shows that consumption only partially rebounded at the end of the crisis. Consumption levels, higher in the affected South–East/Midwest than in the unaffected South prior to the crisis, were similar after the crisis and were still similar in 2011. This result holds controlling for electricity tariffs and other relevant variables (e.g., household income) matched to the concession area of each utility. Average effects came again from widespread responses across the distribution of consumption levels. Interestingly, most of the persistence is due to behavioral adjustments. Sales of domestic appliances did not increase during the crisis. The adoption of compact fluorescent light bulbs (CFLs), encouraged by national tax incentives, did increase sharply but not differentially in affected areas. In contrast, households reported systematic and persistent changes in the way they used domestic appliances and consumed electricity, in surveys conducted in 2004–2005. Popular conservation strategies during the crisis, such as unplugging freezers and avoiding standby power use, were still more prevalent at the time of the surveys among households that had been subject to the conservation program. Simulations based on an engineering model reveal that households must have resorted to a series of severe conservation strategies. For instance, unplugging 50% of freezers could only achieve a 4% reduction.

Last, conservation behaviors during the crisis cannot be rationalized by standard responses to the private incentives. If price were the only mechanism at work, a 25% reduction would have required a price increase of 125%, given an elasticity of $-.2$ that I estimate out–of–crisis. Many customers faced a much smaller price increase. Customers with no private incentives to reduce consumption below quotas, only fines for exceeding their quotas, reduced consumption by 20% below their quotas (first moment). Moreover, a 20% quasi–exogenous increase in individual quotas increased electricity use by only 3.2% (second moment). I estimate values for the two parameters of the model from Borenstein (2009), price elasticity and standard deviation of consumption, such that the model accurately predicts both empirical moments, given the prevailing private incentives. Importantly, the model only has to explain additional conservation efforts beyond the persistent effects. Yet, parameter values are far outside the range of existing estimates. For instance, the price elasticity must be increased fivefold in order to explain behaviors through private incentives alone. Many customers thus behaved as if voluntarily conserving electricity to avert blackouts.

The findings of this paper contribute to a literature on the long–run impacts of temporary policies. I show that a temporary program can have sizable persistent effects for more than 10 years through behavioral adjustments. Such a result relates to the theoretical literature on habit formation (Becker and Murphy, 1988). *Consumption capital*, however, does not decay in my context. The findings provide strong support to the idea that large fixed costs, rational or not, hinder households' adoption of energy conservation strategies (Allcott and Greenstone, 2012).[5]

The findings of this paper also contribute to the literature on the impact of price and non–price policies on energy demand. I estimate a price elasticity of residential electricity demand of about $-.2$ in a developing country context by exploiting variation in electricity tariffs over time and across utilities after the crisis.[6] Price–based conservation programs in developed countries only induce sizable reduction in residential electricity demand (i) through severalfold price increases, (ii) for heavy users of air conditioning or electric heating, and (iii) with technologies that allow remote control of multiple end use.[7] I estimate a very large effect on most customers in the absence of these features in Brazil. Consumption changes are in fact too large to be due to standard responses to the pecuniary incentives. Non–price policies have been shown to have a positive, yet limited, effect on residential electricity demand. My results imply that appeals to social preferences may be particularly powerful at stimulating contributions to essentially public goods in times of crisis.[8]

[5]Acemoglu et al. (2012) and Aghion et al. (2012) argue that temporary policies promoting greener technologies may have persistent effects on the supply side through directed technical change. Davis and Kilian (2011) show persistent consequences of distortions in the US natural gas market because of lumpy investments in domestic appliances. Charness and Gneezy (2009) find that temporary incentives to attend a gym still had an effect a few weeks post–intervention. Allcott and Rogers (2012) find that an information and social comparison intervention still had a small effect (1.5%) on residential electricity consumption in the US a few months after the intervention was discontinued. Allcott and Greenstone (2012) argue that, given the fixed costs implied by many energy efficient investments, there is no evidence for the energy efficiency gap advanced by engineering studies (McKinsey, 2009).

[6]The existing literature on residential electricity demand uses mostly aggregate national data and time–series techniques (Schmidt and Lima, 2004; Pimenta et al., 2009). Ito (2012a) obtains a similar figure in the US. On the one hand, one may expect larger responses from poorer populations. On the other hand, poorer consumers may have fewer margins of response given low penetration rates of many domestic appliances. In a Latin American context, Bastos et al. (2011) find a price elasticity of -0.15 for natural gas.

[7]Faruqui and Sergici (2010) review 15 experiments across several countries. Ito (2012b) finds that a large rebate program had an impact only on heavy users of air conditioning. Leighty and Meier (2011) find that electricity demand fell by 25% in Alaska during a three–month supply crisis following a 500% price increase, implying a very small elasticity.

[8]The US Opower program, which features personalized feedback and social comparison, reduces electricity use by at most 2% (Ayres et al., 2009; Allcott, 2011; Allcott and Rogers, 2012). Meier (2005) reviews qualitative evidence of non–price policies from several episodes of supply shortages. Reiss and White (2008) argue that public appeals reduced electricity demand during the California crisis. In a different context, Mulligan (1998) argues that appeals to social preferences (patriotism) explain the high civilian labor supply in the US during World War II. Voluntary contributions to public goods are common (Andreoni, 2006). In lab experiments, this phenomenon is amplified when

Finally, I contribute to a literature on the impacts of infrastructure constraints, supply crises, and policies aimed at resolving them. Because energy demand is notoriously difficult to incentivize, most governments ration energy directly in the face of energy shortages (Maurer et al., 2005). The findings of this paper demonstrate that direct rationing policies may not be necessary, thus avoiding harmful allocative inefficiencies.[9]

The paper proceeds as follows. Section 2 provides important background information, an overview of the data, and relevant descriptive statistics. Section 3 presents a standard model of electricity consumption, estimates its parameters out–of–crisis, and discusses the model's predictions given the prevailing private incentives during the crisis. Section 4 estimates the short– and long–run impacts of the government program, and Section 5 provides evidence for the underlying conservation strategies adopted by residential customers. Section 6 investigates the relative roles of private incentives and conservation appeals. Section 7 concludes.

2 Background

This section provides relevant information on electricity distribution in Brazil and on the electricity crisis, including details of the conservation program. I then present the data used throughout the paper. Finally, I use the data to describe the context of my study. In particular, I provide descriptive statistics on residential electricity consumption and its main drivers across utilities in Brazil.

2.1 Electricity distribution in Brazil

The National Interconnected System, the major electricity system in Brazil, is divided into four subsystems with limited transmission capacity at the time of the electricity crisis: North (6.5% of total load), North–East (14.5%), South–East/Midwest (62%), and South (17%). In 2000, 81% of the production capacity relied on hydropower.[10] More than 60 local monopolies (utilities) distribute electricity to end consumers. Housing units are typically metered separately; meters are read and

contributions aim at avoiding the loss of an existing public good, particularly if the loss is large (Iturbe et al., 2011).

[9]Recent work highlights the dire consequences of resource shortages on households' welfare (Baisa et al., 2010; Burlando, 2012). Davis and Kilian (2011) find that allocative inefficiencies from past rationing policies in the US natural gas market amounted to $3.6 billion annually. Fisher–Vanden et al. (2012) study China's power shortages in the early 2000s and the effects of a rolling blackout policy. They find that blackouts were costly and that firms responded by outsourcing more of their production.

[10]This share is now around 72% (http://www.ons.org.br). Appendix Figure B.1 presents a map of Brazil.

bills are sent monthly. Electricity theft (illegal connections) is a serious concern as it amounts to 15% of the total load in parts of the country.

Electricity prices are regulated by a federal agency (Agência Nacional de Energia Elétrica, ANEEL) and are relatively high. The main residential tariff is a flat unit price per kilowatt hour (kWh). An alternative tariff for low–income and small consumers offers percentage discounts on the main tariff depending on the quantity consumed, creating nonlinearities in prices.[11] Price changes typically modify the main tariff and therefore imply a proportional change in every marginal price. In contrast to the typical framework in the US, the regulatory framework in Brazil is a price–cap mechanism. Prices are *revised* every four to five years to guarantee utilities' economic viability but, between these revisions, demand risk falls entirely on utilities. Yearly price *adjustments* only factor in changes in non–manageable costs (e.g., transmission or energy) and are thus not endogenous to local demand. Price changes occur at different times for different utilities.[12]

2.2 The 2001–2002 electricity crisis

There is little existing work on the impacts of the Brazilian electricity crisis on electricity consumption. Bardelin (2004) and Maurer et al. (2005) provide some descriptive evidence with aggregate data. Pimenta et al. (2009) use time–series techniques. In concurrent but independent work, Costa (2012) studies some of the questions addressed in this paper with limited data.[13] Finally, Mation and Ferraz (2011) investigate impacts on firms' productivity.

2.2.1 History of the crisis

The major cause of the crisis was a particularly unfavorable rainfall pattern. Figure 1a displays the evolution of hydro–reservoirs' water levels in the main subsystems. Levels were low in every

[11] In June 2001, the main tariff was R$.208/kWh (US$.08) in Rio de Janeiro. Marginal prices in the alternative tariff were R$.073 (up to 30 kWh), R$.125 (up to 100 kWh), R$.188 (up to 140 kWh), and R$.208 (above 140 kWh). Minimum consumption levels are also charged, and local taxes increase the price eventually paid by customers.

[12] See ANEEL (2005). The price–cap mechanism is aimed at encouraging utilities to address electricity theft.

[13] Costa (2012) studies only the observed aggregate effects of the electricity conservation program. My work innovates in both content and data. In particular, I investigate the distribution of conservation efforts, I address the question of energy theft, and I study the relative role of the price and non–price policies of the conservation program using monthly billing data for three million customers. Moreover, I provide robust estimates of the aggregate effects by (i) constructing a unique dataset of monthly residential electricity tariffs for every utility constructed from copies of legal documents from 1996 to 2011 and (ii) by matching census data (2000 and 2010), population estimates (IBGE), and formal employment records (RAIS) for each municipality to the concession area of every utility. The first versions of our respective work are available at http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2028684 and http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2097195.

subsystem in 2000, but generous rain later dissipated the risk of shortages in the South. In contrast, because of exceptionally low rainfall in the 2000–2001 summer, water levels were at their lowest in 40 years in the North–East and South–East/Midwest in March 2001. This differential impact across regions was entirely due to weather and to the limited transmission capacity across subsystems.[14] By late April, it was clear that severe reductions in consumption were necessary to avoid imminent imbalances between demand and supply.[15] Details were unclear but a government program based on economic incentives was announced, to start on June 1 (*Globo*, April 23, 2001). The Brazilian Association of Distribution Utilities (ABRADEE) supported instead the use of blackouts because "financial penalties were unlikely to succeed, in part due to the lack of demand elasticity" and the expected length of the crisis (Maurer et al., 2005; *Veja*, May 3, 2001).

The electricity conservation program came into force on June 4, 2001. It involved individual quotas, fines, bonuses, and threats of disconnections. A large information and conservation appeal campaign was also launched with the collaboration of utilities and media outlets. Rolling blackouts were part of a Plan B that was never implemented. The objective of the program was to reduce electricity use by 20% in the North–East and South–East/Midwest subsystems. Measures were expected to apply until February 2002 (*Veja*, July 19, 2001). Mation and Ferraz (2011) provide ample evidence that the crisis, the conservation program, and its differential implementation across subsystems were mostly unanticipated.[16]

On February 19, the president announced the end of the crisis for March 1. Bonuses were maintained for an extra month but fines were immediately suspended. The government hoped that conservation efforts would persist because "the population had been educated and conscientized during the threat of blackout and would therefore continue to save electricity" (*Veja*, February 19,

[14]The crisis would have been avoided, however, had capacity been expanded adequately. Realized demand was never above projected demand between 1998 and 2001, but growth in demand outpaced growth in generation capacity prior to 2001. Several infrastructure projects were delayed or canceled, for instance. See Comissão de Análise do Sistema Hidrotérmico de Energia Elétrica (2001), Maurer et al. (2005), and Mation and Ferraz (2011) for more discussion on the cause of the crisis and the exogenous role of rainfall in the differential treatment across subsystems.

[15]This was despite a first set of national policies in early April. Among these measures were the giveaway of efficient light bulbs in low–income neighborhoods, a 15% reduction in electricity consumption in federal public buildings, the import of energy from Argentina, and the construction of new thermoelectric facilities (*Veja*, April 5, 2001).

[16]For instance, President Cardoso's approval rates dropped differentially in areas subject to the government program after its announcement. Measures were expected to end when reservoirs would reach 50% of their capacity (*Veja*, February 16, 2002). The government program was extended to three utilities in the North subsystem from August 2001 to December 2001. These utilities' many customers served by isolated electricity systems were not subject to any measure. Because of the different timing and because my data do not differentiate utilities' residential consumption from "isolated" and "connected" customers, I do not consider the North subsystem in this paper. A 7% reduction in the South was considered achievable through voluntary measures only (*Veja*, June 5, 2001).

2002). According to a specialized periodical, "people were giving signals that they learned how to avoid wasting electricity" (*Energia Elétrica*, March 15, 2001).

2.2.2 Private incentives of the electricity conservation program

The government established measures for every sector of activity during the crisis. I present here the rules for residential customers, which were repeated in the media and on electricity bills.

A. Quotas. Typical residential customers were assigned a quota equal to 80% of a *baseline* corresponding to their average consumption in May, June, and July 2000. Quotas were set at 100% of baseline (resp. 100 kWh) for small consumers with baseline below 100 kWh (resp. with baseline between 100 kWh and 125 kWh). Individual letters explaining their quotas were sent to customers prior to their first affected billing cycle.[17] Finally, because the situation was improving and because consumption is higher in the summer, quotas were revised up in December 2001 and January 2002.

B. Fines and bonuses. Economic incentives took the form of fines for larger consumers. A customer exceeding her quota would be charged a per–unit fine for every kWh consumed above 200 kWh (50% of the marginal price up to 500 kWh and 200% above 500 kWh). Figure 2 illustrates how these incentives modified the cost of electricity. For customers with a quota of 250 kWh, consuming above the quota entailed a 50% increase in the marginal price but also a discrete cost increase of about R$5 (US$2). Bonuses targeted mostly smaller, and poorer, consumers. A customer consuming less than her quota and less than 100 kWh would receive a per–unit bonus for every kWh reduced below her quota (200% of the marginal price). Fines and bonuses were directly passed on to monthly bills. In September 2001, an additional per–unit bonus was offered for individuals with quotas below 225 kWh (100% of the marginal price). Fines were suspended in February but bonuses were still paid for the February–March billing cycle.

C. Threats of disconnections. Customers could, in theory, be subject to power cuts of three to six days for exceeding their quotas. In practice, utilities did not have enough staff to implement this rule. Importantly, power cuts were prohibited by a municipal law in Rio de Janeiro (Lei Municipal 3266/2001). As a result, customers in my billing data were only subject to pecuniary incentives.

[17] Such a letter is reproduced in the Appendix. Figure B.3 displays the mapping between baseline and quota.

2.2.3 Conservation appeals

Meier (2005) refers to the *strong national commitment to conservation* as a main component of the electricity conservation program. Daily reports on TV compared conservation efforts to government targets. Energy conservation advice and stories of "exemplary" behaviors were shared repeatedly in the media to promote awareness and encourage participation. The government made sure to impose a more stringent conservation target for public buildings to set the example. Moreover, media reports and messages on electricity bills included appeals to social preferences and patriotism.

2.2.4 Other factors

Other factors may have played a role in the short and long run. Taxes on efficient light bulbs were reduced, and taxes on electric showers, water heaters, and incandescent light bulbs were temporarily increased (Decreto 3827, May 21, 2001). Efficiency standards for domestic appliances were adopted (Lei 10295, October 17, 2001). No such policies related to household investments are able to explain the extent of conservation efforts during the crisis because electricity use rebounded sharply at the end of the crisis. Moreover, because these policies applied nationally, they are also unable to explain the differential impact that has persisted across subsystems after the crisis.[18]

2.3 Data

A. ANEEL administrative data

Every utility reports total electricity consumption, total revenues, and total number of customers for each sector (e.g., residential) to the regulator (ANEEL) each month. I obtained these data from 1991 through 2011 and constructed a monthly panel of average consumption per customer (consumption/customers) and average price (revenues/consumption) for each sector of every utility. I have a balanced panel of 44 utilities in the North–East, the South–East/Midwest, and the South (47 utilities from 2000 onward due to the division of concession areas over time). I also match census

[18] Customers may have also updated their belief of the risk of future shortages. Appendix Figure B.2 shows that, over the last 20 years, the rainfall pattern in 2000–2001 was a unique outlier. Even in the South, reservoir levels were very low in 2000. The situation of the reservoirs was stable in the South–East/Midwest but more variable in the South after the crisis. The risk of new shortages was thus not smaller in the South. Accordingly, an *insurance fund* established to avoid subsequent crises was financed through a nationwide increase in electricity tariffs (R$.49 per 100 kWh). Moreover, the country had already experienced weather–induced electricity shortages in the South (January–March 1986), the North–East (March 1987–January 1988), and the North (late 1990s). See Maurer et al. (2005). Generation and transmission capacity have also increased nationally, reducing the risk of localized shortages.

data (2000 and 2010), population estimates (IBGE), and formal employment records (RAIS) for each municipality to the concession area of each utility. Finally, I construct a unique dataset comprising monthly electricity tariffs for each sector of every utility from copies of legal documents published by the regulatory agency from 1996 to 2011.

B. LIGHT billing data

I further exploit a unique dataset comprising individual monthly billing data for the universe of customers (high voltage excluded) of LIGHT, the utility serving Rio de Janeiro and 31 surrounding municipalities (South–East). The data span January 2000 to December 2005. They include the dates of each billing cycle, the location of each metered unit, the quantity consumed, and the cost of every bill component. A given customer is uniquely identified over time as long as she stays in the same housing unit. There were about three million residential customers in 2000.

C. PROCEL surveys and other supplementary data

I use micro–data from surveys conducted in 2004–2005 by PROCEL, the National Electrical Energy Conservation Program, to investigate the conservation strategies adopted by residential customers. The surveys capture appliance ownership and consumption habits at the time as well as retrospective information on conservation behaviors before and during the electricity crisis. The sample includes 4975 residential customers from 18 different utilities in the North–East, the South–East/Midwest, and the South. The sampling design is detailed in PROCEL (2007a, 2007b, 2007c, 2007d). Location information only identifies regions.

I complement these data with time–series data on sales of appliances from manufacturers' reports, on imports of compact fluorescent light bulbs (CFLs) from PROCEL, and on sales of electric showers across Brazilian states from a leading manufacturer. I also use an engineering model constructed to estimate load curves from residential customers of LIGHT (personal communication with Professor Reinaldo Souza) to simulate the impact of specific conservation measures.

Finally, I use the Brazilian Household Expenditure Surveys (POF, Pesquisa de Orçamentos Familiares) conducted in 1996–1997, 2002–2003, and 2008–2009. The surveys record households' appliance ownership and the year of purchase. The more recent surveys are representative of the overall population. These data allow me to further investigate patterns in the purchase of domestic appliances around the time of the crisis. I confirm these patterns using yearly household surveys (PNAD, Pesquisa Nacional por Amostra de Domicílios) that record ownership of a few appliances.

Location information only identifies states and the largest metropolitan areas in these datasets.

2.4 Descriptive statistics

Table 1 compares relevant descriptive statistics across utilities in the North–East, the South–East/Midwest, and the South in 2000. I present statistics separately for LIGHT, the utility for which I have detailed billing data. Average residential electricity consumption per customer was higher in the South–East/Midwest, in particular for LIGHT, and lower in the North–East prior to the crisis. The pattern follows differences in median household income. Overall, average residential electricity consumption per customer was lower in Brazil than in more developed countries. A major reason is the lower penetration of domestic appliances. While most households owned a refrigerator in the South–East/Midwest and the South, less than 50% owned a washing machine and less than 10% had air conditioning. Ownership rates were much lower in the poorer North–East.

Figures 3a and 3b show that the distributions of average electricity consumption, average electricity price, and median household income overlap between utilities in the South–East/Midwest and in the South. In contrast, utilities in the North–East had systematically poorer populations and lower levels of electricity use. This implies that utilities in the South (not subject to the conservation program) may not constitute a suitable control group for utilities in the North–East. A parallel trend assumption may not hold with very different initial values, especially in the long run. To explore such a concern, I compare trends in the same variables between the 2000 and 2010 censuses using the following specification:[19]

$$log(y_{i,t}) = a_i + \beta \ \mathbf{I}\,(t = 2010) + \gamma \ \mathbf{I}\,(t = 2010 \ \& \ Treat_i = 1) + \epsilon_{i,t}$$

where y is a variable of interest, a_i is a fixed effect for utility i, and $Treat$ is an indicator for utilities in the North–East and the South–East/Midwest. $\epsilon_{i,t}$ is an error term for utility i in census year t, clustered by utility. The coefficients γ are reported in Table 2 for models excluding the North–East (column 1) or the South–East/Midwest (column 2). Median household income grew 9% faster in the North–East than in the South, while ownership rates of refrigerators and washing machines grew 23.5% and 38% faster over the 10–year period. This pattern is consistent with the "S–curve"

[19] Appendix Table B.1 displays more descriptive statistics from the 2000 census. Appendix Table B.2 displays the descriptive statistics from the 2010 census. The 2010 census does not record ownership of air conditioners.

relationship between income and appliance ownership (Wolfram et al., 2012). Trends are mostly comparable between the South–East/Midwest and the South. However, median household income and mean electricity consumption grew faster in the South by about 10% and 12%, respectively. I relate the latter trend to the conservation program. I am able to control for changes in median household income and other trends in the empirical analysis because distributions overlap between utilities in the South–East/Midwest and in the South. In contrast, controls would entirely rely on parametric assumptions when comparing trends in electricity consumption in the North–East and in the South. Consequently, I do not focus on the North–East in the study of long–term effects.

3 Responses to private incentives in a standard theoretical model

This section discusses theoretical predictions of a standard model of consumption. I first describe the model. Then I estimate its parameters out–of–crisis. Finally, I incorporate my estimates into the model and simulate customers' responses to the private incentives of the electricity conservation program. This provides a benchmark to compare with actual consumption behaviors during and after the crisis. Because incentives varied by customer category, I focus on customers with quotas around 250 kWh during the crisis, in this section and throughout the paper. These customers were only subject to fines, as illustrated in Figure 2. This simplifies the analysis.

3.1 A standard model of electricity consumption

Fines created nonlinearities in the cost of electricity. Nonlinear schedules are typical for residential electricity pricing. In this context, demand is often modeled as $q_i = h_i p(q_i)^\eta$, with consumption q, price p, and price–elasticity η (Borenstein, 2009; Ito, 2012a).[20] h_i allows for heterogeneity in the propensity to consume electricity (habits/appliances). Price depends on quantity because of the nonlinear schedule. In the case of the electricity conservation program, fines changed marginal prices and discontinuously increased the cost of consuming above the quota (Figure 2).

The above model requires customers to know the quantity they will consume over a billing cycle. In practice, electricity demand is subject to unexpected shocks, and most customers are unable to predict the prevailing marginal price at the time of consumption. Borenstein (2009) thus proposes

[20]Income effects are generally assumed away: electricity constitutes a small share of households' budget. As I focus on relatively large consumers, rather than poorer households, income effects are likely to be small in my context too.

an alternative model in which customers set consumption rules based on some expectation of the relevant price levels, and only update these rules upon receiving feedback from electricity bills. I follow Borenstein (2009) and assume that per–cycle customers' utility is of the form

$$U(\overline{q}_i) = E\left[u(q_i)\right] = V_i(\overline{q}_i) + W_i - \int C(q_i) f\left(q_i|\overline{q}_i\right) \tag{1}$$

with wealth W, $\overline{q}$ the expected quantity given the consumption rules adopted, and V the utility derived from electricity consumption. $C(q)$, the cost of electricity, is uncertain because of demand shocks. I further assume the following functional form (Ito, 2012a):

$$V_i(\overline{q}_i) = \begin{cases} a_i \frac{1}{1+1/\eta} \overline{q}_i^{\,1+1/\eta}, & \eta \neq 1 \\ a_i \ln(\overline{q}_i), & \eta = 1 \end{cases} \tag{2}$$

where a_i captures heterogeneity in the propensity to consume electricity. Finally, I assume that q_i is normally distributed with mean $\overline{q}_i$ and standard deviation $\sigma\overline{q}_i$ (Borenstein, 2009).

I use the model to simulate responses to the private incentives of the conservation program for LIGHT customers with quotas around 250 kWh. I proceed by steps. I exploit the fact that prices were linear at baseline. First–order conditions give $a_i\overline{q_i}^{1/\eta} = p$. For a given price elasticity η, I pin down a_i by setting p (in real terms) and $\overline{q_i}$ at their baseline level ($250/.8 = 312.5$ kWh). Then, given a value of σ, one can obtain the expected quantity $\overline{q_i}$ maximizing utility under any (nonlinear) cost function. I obtain first estimates of σ and η.

3.2 Estimating the price elasticity of residential electricity demand in Brazil

I rely on the utility–level panels of average consumption and electricity tariffs to provide a first credible estimate of the price elasticity of residential electricity demand in Brazil. I exploit tariff variation over time between utilities. Specifically, I regress the logarithm of average residential consumption on the logarithm of the main residential tariff for utility d in region r in year t:

$$Log(kWh_{d,r,t}) = \sum_d a_d + \sum_{r,t} \beta_{r,t} + \eta Log(Price_{d,t}) + \epsilon_{d,r,t} \tag{3}$$

where a_d and $\beta_{r,t}$ are utility and year–by–region fixed effects. $\epsilon_{d,r,t}$ is an error term clustered by utility. I consider yearly variations (averaging prices and quantities) because demand typically responds with a lag. I use all the years post–crisis. η captures a price elasticity "out–of–crisis."

There are two major concerns with equation (3). First, there is rarely a unique price of electricity. In Brazil, the main residential tariff is essentially linear, but an alternative tariff for low–income and small consumers offers nonlinear percentage discounts on this unit price. Changes in residential prices, however, typically apply to the unit price. Therefore, percentage changes in the main tariff capture percentage changes in prices throughout the whole distribution of electricity consumption.

Second, changes in prices may be endogenous to changes in quantities. The price–cap mechanism limits such a concern in Brazil. Every four to five years, prices are revised to guarantee utilities' economic viability. Between *revision* years, demand risk entirely falls on utilities and yearly price *adjustments* are not endogenous to changes in consumption by design.[21] Price revisions may create some endogeneity, biasing estimates of η away from 0. I directly assess the extent of endogeneity in two ways. First, I run the same regression instrumenting the main tariff by its cost–of–energy component calculated by the regulator (exogenous to the firm on a yearly basis). This instrument is available for every utility from 2005 onward. Second, I estimate equation (3) excluding years of price *revisions* and including utility–specific fixed effects for each between–revision period. The only variation left comes from price *adjustments*.

Results are presented in Table 3. I estimate η at $-.21$ (column 1) and $-.18$ (column 2) with the full variation in tariffs from 2003 and 2005, respectively. Estimates using only the variation from price adjustments (column 3) or the IV strategy (column 4) fall within the same range ($-.2$ and $-.19$, respectively). Price endogeneity does not appear to be a major issue in our setting. I thus control directly for the main electricity tariff in regressions estimating the short– and long–term effects of the conservation program.[22]

[21] See ANEEL (2005). This was confirmed through personal communications with ANEEL. It is actually a central part of the incentive structure to increase utilities' performance.

[22] The identifying variation in column (1) is displayed graphically in Appendix Figure B.4. I obtain similar results by instrumenting average prices with the main residential tariffs. A price elasticity of $-.2$ is similar to recent estimates from the US (Ito, 2012a). Reiss and White (2005) obtain an elasticity of $-.39$ in the US. The authors note, however, that their result is at the upper end of existing estimates, and they find much smaller price elasticities for households without electric heating or air conditioning. This is the relevant context for most customers in Brazil.

3.3 Discussing the extent of uncertainty in own electricity consumption

Borenstein (2009) uses a balanced panel of 10,000 California households observed monthly over five years to explore the extent of uncertainty in customers' own electricity consumption. For each customer, he separately estimates

$$ln(kWh_t) = \sum_{j=1}^{12} \alpha_j + \beta \; ln(kWh_{t-1}) + \gamma \; time\_trend + \nu_t \tag{4}$$

where α_j is a calendar month fixed effect and β is the serial correlation in monthly consumption. The root mean squared error (RMSE), the standard deviation of the regression, indicates how well the model predicts consumption. Borenstein (2009) obtains a median RMSE of 0.17 (average 0.2). It implies that a median customer using this model is able to predict consumption with a standard error of 17%. I replicate this approach for a balanced panel of 6610 randomly selected customers from Rio de Janeiro with quotas around 250 kWh who were observed continuously from 2000 to 2005. I obtain a median RMSE of 0.14 (average 0.16). Results are similar for other customer categories. In practice, customers may use more or less information to form their expectations.

3.4 Predictions of the standard model

I use the model and informed values for its parameters to simulate customers' responses to any cost function (see Appendix). I consider changes in the cost of electricity in the first five months of the crisis (before any change in quotas) and in the same months the following year (post–crisis). These changes are due to real increases in the main tariff and to the private incentives of the conservation program. I focus on customers with quotas around 250 kWh whose private incentives are illustrated in Figure 2. Results are qualitatively similar for other customer categories.

Customers are predicted to bunch at their quotas during the crisis in the absence of uncertainty. This is shown graphically in Figure 2. The increase in marginal price shifts consumption below baseline ($A \rightarrow B$) but still above the quota. The discontinuous increase in the cost of electricity at the quota is sufficient for customers to further reduce consumption to the quota ($B \rightarrow C$). Table 4 displays simulation results. The "bunching" result without uncertainty is reproduced in the first row of column (1). With uncertainty, the model predicts higher consumption levels, around 280 kWh (second row). Customers expecting to consume just below (resp. above) the quota end up consuming above it (resp. below it) in some states of the world. The expected marginal price thus increases (resp. decreases) on the left (resp. right) of the quota, and the discontinuity in the cost of electricity at the quota disappears. Customers then choose to consume above the quota. Column (2) considers consumption after the crisis. The model predicts consumption levels 5% below baseline because the real electricity tariff increased by 25% in Rio de Janeiro from 2000 to 2002 (given a price elasticity of $-.2$). Uncertainty has no effect when prices are again linear.

The persistent drop in electricity consumption after the crisis in Figure 1 suggests that customers did make long–term adjustments during the crisis. Median consumption levels for our customer category were 3.3% below the quota after the crisis (241.5 kWh). The propensity to consume electricity, a_i, decreases if incentives trigger discrete adjustments. In column (3), I assume that a_i adjusted immediately to a new level consistent with observed median consumption levels after the crisis. The model must then only explain additional conservation efforts during the crisis.[23] This corresponds to moving A (the baseline) just to the left of the quota on Figure 2. Customers are now predicted to consume at that level in the absence of uncertainty (248.5 kWh). With uncertainty, the model predicts lower consumption levels (231 kWh or 7.5% below the quota) because uncertainty increases expected marginal prices on the left of the quota.

Median consumption levels were in fact 21.8% below the quota for our customer category. The simulation results imply that such large conservation efforts cannot be explained by standard responses to the private incentives of the conservation program. In Section 6, I provide additional evidence that reasonable increases in parameter values are unable to rationalize consumption behaviors during the crisis. Yet the rebound in consumption levels at the end of the crisis (Figure 1) indicates that marginal conservation efforts during the crisis were due to crisis–specific stimuli. Other factors (e.g., conservation appeals) must have played an important role.[24]

[23] The new value of a_i is obtained from the same first–order condition using post–crisis price and quantity. The assumption also takes care of mean reversion issues. Adjustment costs are assumed to be sunk.

[24] Even out–of–crisis, the standard model may not accurately describe behavior. Ito (2012a) shows that customers confuse *marginal* with *average* prices. This alternative model actually predicts larger, not smaller, consumption levels during the crisis because customers' sensitivity to fines is reduced.

4 Short– and long–run impacts of the conservation program

This section analyzes the short– and long–run impacts of the electricity conservation program. I compare trends in average electricity consumption per customer between utilities subject or not to the program. The depth of the electricity crisis, the government measures, and the differential impact across subsystems are unlikely to have been anticipated by customers. Other policies adopted before, during, or after the crisis were implemented nationally. I reinforce the causal interpretation by controlling for trends in other relevant variables, such as price and income. By exploiting detailed billing data on the universe of LIGHT customers, I go beyond average effects and investigate the distribution of conservation efforts among customers. I first present graphical evidence, then turn to the statistical analysis.

4.1 Graphical evidence

A. ANEEL administrative data

Figure 1b displays seasonally adjusted trends in average residential electricity consumption per customer for utilities in the North–East, the South–East/Midwest, and the South. Trends were similar prior to the crisis, although average levels were different. In June 2001, consumption decreased sharply in every subsystem. National policies or spillovers from conservation appeals may explain the 9% drop in the South. After the crisis, consumption remained at its crisis level in the South, suggesting long–term impacts of the national policies. However, reductions were more substantial for utilities subject to the conservation program. Consumption dropped by over 30% during the crisis. It rebounded at the end of the crisis but stayed well below pre–crisis levels, by about 20% in the South–East/Midwest. Since then, it evolved similarly in the South–East/Midwest and in the South. These patterns strongly indicate a persistent impact of the conservation program. Long–term impacts are less evident from comparing the North–East and the South, possibly because of the rapid growth in appliance ownership in the poorer North–East (Table 2).

Trends in Figure 1b may be sensitive to outliers given the limited number of utilities. Figure 3c displays the distribution of changes in average consumption during the crisis and up to nine years after the crisis compared to the same months in the year preceding the crisis. Every utility experienced a drop in consumption during the crisis. Consumption decreased by 4%–11% in the

South and by over 20% for every utility subject to the conservation program. Reductions were typically larger in the South–East/Midwest. Aggregate impacts during the crisis cannot be due to direct effects of low rainfall because several utilities, such as LIGHT, mostly serve urban areas. Aggregate long–term effects also hold broadly. The distribution of long–term changes in the South–East/Midwest is systematically below the same distribution in the South.

Long–term trends in average electricity use may be influenced by other factors. Figures 3d and 3e display the relationships between long–term changes in average electricity consumption, median household income, and the main residential electricity tariff for every utility. Long–term impacts on average consumption comparing the South–East/Midwest and the South hold, conditional on a given change in median income and electricity price.

B. LIGHT billing data

Data on monthly aggregates are subject to two limitations. First, compositional changes in utilities' customer bases may affect average consumption levels. This is more likely to be an issue in the long term. It may matter in the short term if, for instance, many customers connected themselves illegally to the grid instead of paying for metered electricity. Second, aggregate data provide no information on the distribution of customers' responses. I address these concerns using individual billing data from LIGHT customers.

Figures 4a and 4b use a balanced panel of 44,817 randomly selected customers. The sample is not subject to serious composition issues or electricity theft because I only include customers metered and billed continuously from 2000 to 2005. Panel (a) displays average electricity consumption in each billing month since 2001 compared to the same month in 2000. Because of staggered billing, bills sent in month t cover consumption in months t and $t-1$. The government program applied to billing cycles starting after June 4, 2001. In many cases, the June bill thus covered consumption after that date but not yet subject to fines and bonuses (billing cycles starting in May). Yet average consumption reductions had already reached 22.5% in the June bill. Conservation appeals started on June 4. Moreover, tax changes on goods such as efficient light bulbs came into force on June 1. Consumption fell more than 30% below 2000 levels during the crisis. Fines were suspended in the March 2002 bill. Average consumption rebounded immediately even though bonuses were still offered to smaller consumers. Consumption levels remained about 20% lower until 2005. The pattern observed in Figure 1b thus holds for a balanced panel of continuously metered customers.

Panel (b) displays Kernel densities for electricity consumption billed in August (winter) in 2000, 2001, 2002, and 2005. The 2001 density is stochastically dominated by the other ones. Average reductions were sizable at all consumption levels during the crisis. The post–crisis densities are very similar in 2002 and 2005. They fall exactly between the crisis and pre–crisis densities. Average reductions in panel (a) thus came from large responses at every level of consumption.[25]

Figure 4c displays the distribution of conservation efforts for a set of customers facing the same incentives during the crisis. I construct another balanced panel of 10,341 LIGHT customers from Rio de Janeiro with quotas around 250 kWh (248 kWh–253 kWh). During the crisis, these customers were subject to the private incentives (fines) illustrated in Figure 2. I present Kernel densities for consumption levels normalized to the quota in the first five months of the crisis (before any change in quota) and in the same months in 2002 (post–crisis). I find no bunching at the quota.[26] The large majority consumed below their quotas during the crisis. In 2002, 57% of customers were still consuming below the quota. The median customer consumed 21.8% and 3.3% below the quota during and after the crisis, respectively. In the same month in 2005, the median customer was also consuming below the quota (not shown). Similar results hold for other customer categories: customers with quotas around 190 kWh (resp. 340 kWh) consumed 18.8% (resp. 26.1%) and 2.5% (resp. 7.1%) below the quota during and after the crisis, respectively.

Individual billing data reveal that the severe drop in average consumption during the crisis and the lower consumption levels after the crisis are due neither to compositional effects nor to the behavior of specific groups of customers. A large majority of customers, throughout the whole distribution of consumption levels, did reduce electricity consumption dramatically.

4.2 Statistical analysis

I now turn to the statistical analysis of the short– and long–run impacts of the electricity conservation program. I begin by exploiting the panel of utilities' average monthly residential consumption

[25] Appendix Figure B.5 shows mean consumption compared to quotas for each consumption category at baseline during and after the crisis. For each category, consumption was more than 15% below the quota or about 32% below baseline during the crisis. Larger consumers reduced consumption by more than 25% below their quotas or 40% below baseline. After the crisis, average consumption was still below the quota for all but the smallest consumption categories. Considering shifts in the distribution of consumption in Figure 4b avoids mean reversion issues (Borenstein, 2009; Ito, 2012a). Reproducing Appendix Figure B.5 as if the crisis happened in 2004 (placebo) reveals that mean reversion cannot explain the low consumption levels on the graph.

[26] I find no bunching in monthly graphs, for different customer categories, and when using small bandwidths (no smoothing). Similarly, Borenstein (2009) finds no bunching around kinks induced by block–pricing in California.

(ANEEL administrative data) in a generalized difference–in–difference strategy comparing utilities subject or not to the government program over time. I control for changes in electricity tariffs and other relevant variables available at a high frequency. I then evaluate the robustness of my results in two ways. First, I compare time–series estimates from the ANEEL administrative data to time–series estimates based on individual billing data for balanced panels of LIGHT customers. This allows me to address issues of composition and electricity theft. Next, I investigate the robustness of the estimated long–term effects matching information on other relevant controls from the 2000 and the 2010 census data to the concession area of each utility.

4.2.1 Main difference–in–difference results

I start by regressing the logarithm of average residential consumption per customer for utility d from region r in month m of year t on dummies for various time periods p. I include separate period dummies for utilities subject or not to the conservation program during the crisis:

$$Log(kWh_{d,r,m,t}) = \sum_{d} a_d + \sum_{r,m} \beta_{m,r} + \sum_{p} [\gamma_p + \delta_p Treatment_d] + X_{d,r,m,t} + \epsilon_{d,r,m,t} \qquad (5)$$

where α_d is a utility fixed effect, $\beta_{m,r}$ is a calendar month–per–region fixed effect, and γ_p is a time–period fixed effect. I use yearly indicators before and after the crisis. I divide the crisis years into pre–crisis (early 2001, reference time period), crisis (June 2001–February 2002), and post–crisis (rest of 2002) periods. δ_p captures a difference–in–difference estimator for each time period. $\epsilon_{d,r,m,t}$ is an error term clustered by utility. I use unweighted regressions.

No extraordinary tariff adjustment took place in June 2001 or February 2002 besides the conservation program. Tariffs were increased on December 21, 2001, for utilities subject to the program, but the increase was limited to a mere 2.9% for residential customers.[27] Other price changes followed the usual regulatory framework. Nevertheless, prices may have evolved differentially in later years, biasing estimates of long–term effects. Therefore, I use the panel of electricity tariffs from 1996 onward and control for the logarithm of the main residential tariff when estimating equation (5). Additionally, I include yearly data on population size, formal employment, and median formal wages (in logs) that can be matched to the concession area of each utility (until 2010).

[27] Camara de Gestão da Crise de Energia, Resolução 91. A smaller national price increase also served to finance a newly created insurance fund (Camara de Gestão da Crise de Energia, Resolução 115).

Estimates are displayed graphically in Figure 5 with 95% confidence intervals. Results are similar without controls.[28] In panel (a), I reproduce estimates of the time–period fixed effects, γ_p. Average consumption dropped by 9% in the South during the crisis. It then stayed low until 2006 to reach pre–crisis levels again only in 2010.

Panels (b)–(c) of Figure 5 separately display estimates of the difference–in–difference coefficients, δ_p, for the North–East (panel b) and the South–East/Midwest (panel c). Estimates in panel (b) are mostly descriptive because the parallel trend assumption is unlikely to hold in the long term between utilities in the poorer North–East and in the South. Average electricity consumption and household median income do overlap for most utilities in the South–East/Midwest and in the South. I restrict the sample to these utilities in panel (d).

Pre–crisis differences were small (even if sometimes significant) for utilities in the South–East/Midwest, supporting the difference–in–difference strategy. Average electricity consumption dropped sharply when the conservation program came into force. I estimate an impact of 21.5% in the North–East and 25% in the South–East/Midwest during the crisis. Consumption levels rebounded after the crisis but were still lower compared to the South. The differential effect rapidly decreased in the North–East.[29] In contrast, it stayed over 12% in the South–East/Midwest until the last sample year. Improving sample comparability between utilities in the South–East/Midwest and in the South only confirms these results (panel d). Given my estimate of the relevant price elasticity, a 25% (resp. 12%) reduction in residential electricity use during the crisis (resp. today) corresponds to a price increase of 125% (resp. 60%) out–of–crisis.

4.2.2 Robustness checks using individual billing data

I compare here time–series estimates for LIGHT customers based on (i) the ANEEL administrative data and (ii) individual billing data for a balanced panel of customers (see Section 4.1). I regress the logarithm of average consumption in month m of year t on a set of time–period dummies, p:

$$Log(kWh_{m,t}) = \sum_m \beta_m + \sum_p \gamma_p + \epsilon_{m,t} \tag{6}$$

[28] The corresponding tables are in the Appendix. Long–term effects are slightly smaller in absolute value without controls (Appendix Tables B.3 and B.4).

[29] Rapid growth in appliance ownership in the North–East may explain why effects did not persist. Conservation strategies adopted in the North–East may also have been less persistent given the lower baseline consumption.

where β_m and γ_p are calendar–month and time–period fixed effects, respectively. I use yearly dummies before and after the crisis. I divide the crisis years into pre–crisis (early 2001, reference time period), crisis (June 2001–February 2002), and post–crisis (rest of 2002) periods. $\epsilon_{m,t}$ is an error term. I use data from 2000 to 2005, the years covered in the billing data. For statistical inference, I include Newey–West standard errors with three lags below estimates of γ_p in Table 5.

Time–series estimates are very similar with both datasets (columns 1 and 2). I find a drop in average consumption levels greater than 42% during the crisis for LIGHT customers. Consumption levels were still lower in 2005, with reductions of more than 20%. Thus, until 2005, results from Figure 5 are unlikely to be due to compositional effects or noise in the ANEEL administrative data.

Electricity theft is also unlikely to explain my results, even though it is prevalent in Brazil. The quick rebound in electricity consumption in February 2002 suggests that marginal conservation efforts were not due to investments, such as establishing illegal connections to the grid. It is difficult to reject, however, a significant role of theft in infra–marginal efforts or long–term effects with only aggregate data. Utility–level data on distribution losses yield inconclusive results.[30] The individual billing data are therefore particularly useful. Electricity theft may only occur in the balanced panel in column (2) in Table 5 if customers have both legal and illegal connections to the grid, because I drop customers with zero metered consumption in three consecutive months. Theft is more prevalent among smaller and poorer consumers in Brazil. In column (3), I use the same panel but only consider the top decile of consumers in every month. In column (4), I use a balanced panel restricted to customers of Leblon, a wealthy neighborhood of Rio de Janeiro. Time–series estimates are greater in absolute value for larger and wealthier consumers. Figure 4b also shows that consumption was reduced throughout the whole distribution of consumption levels, both in the short and in the long run. Finally, even if some relatively large or wealthy consumers have illegal connections, this share is likely to be small. It may therefore influence mean but not median effects. Figure 4c shows that median effects were comparable to mean effects and that the majority of customers severely reduced consumption. This accumulation of evidence indicates

[30]Total electricity load did decrease during the crisis, but the decrease also came from other sectors of activity (industry, commerce, government). Utilities report yearly information on distribution losses to the regulator. Unfortunately, many utilities did not provide this information prior to 2000. The data are also very noisy when divided into technical (engineering estimates) and non–technical (load residuals, including theft) losses. I use yearly reports of technical and non–technical losses from 1998 to 2009 for 20 utilities in the South–East/Midwest and in the South in Appendix Table B.6. I find large persistent, but not significant, reductions in technical losses. This is mechanical if engineering losses are proportional to load. Estimates for non–technical losses vary widely from year to year.

that electricity theft plays at most a minor role in my estimates of the impacts of the conservation program.

4.2.3 Robustness checks of long–term effects using census data

Composition effects cannot explain the drop in electricity use for LIGHT customers up to 2005. A given customer base, however, may have experienced different trends in relevant variables over the last decade. For instance, median household income grew faster in the South than in the South–East/Midwest on average (Table 2). I investigate here the robustness of the long–term effects for utilities in the South–East/Midwest compared to the South.[31] I focus on 10–year differences and control for data from the 2000 and 2010 censuses. Data that can be matched to the concession area of each utility at a higher frequency are rare. I estimate the following regression:

$$log(kWh_{i,t}) = a_i + \beta\, \mathbf{I}\,(t = 2010) + \gamma\, \mathbf{I}\,(t = 2010\ \&\ Treat_i = 1) + X_{i,t} + \epsilon_{i,t} \tag{7}$$

where $\epsilon_{i,t}$ is an error term for utility i in census year t clustered by utility. Table 6 displays the difference–in–difference coefficient, γ. Average residential electricity consumption decreased by about 12% for utilities in the South–East/Midwest compared to the South. Results are similar without including any time–varying covariates (column 1) and controlling for changes in the main residential tariff (column 2), changes in median household income (column 3), and changes in population size, average household size, urbanization, employment, and the share of housing units with bathrooms (column 4). Results are also very similar when I restrict the sample to utilities with overlapping levels of average electricity consumption and median household income in 2000 (bottom panel).[32]

[31] Because average electricity consumption and median household income do not overlap between utilities in the North–East and in the South, controlling for relevant trends would entirely rely on functional form assumptions.

[32] Given the small number of independent observations, coefficients on these controls are imprecisely estimated. Sample size and degrees of freedom considerations limit the number of controls one can add. However, results are similar with controls for housing unit size, formal employment, and agricultural employment (not shown). Appliance ownership is potentially endogenous if consumers changed their purchasing decisions during and after the crisis. Estimates remain large (9%) including such controls. The difference may also reflect nonlinear income effects.

5 Mechanisms

I have established that severe reductions in electricity use can be induced rapidly, and for as long as a nine–month period, without relying on any blackouts. Moreover, a temporary conservation program led to persistent reductions in electricity consumption. This echoes findings from the literature that energy consumption choices involve investments and/or adjustments. In this section, I shed light on the conservation strategies actually adopted by customers.

5.1 Residential electricity consumption by source

The previous section has estimated reduction in electricity use of 34% in the South–East/Midwest on average (9%+25%) and of 40% for LIGHT customers. Such reductions require drastic changes in the efficiency or the use of domestic appliances. For instance, I decompose average residential electricity consumption by source in Table 7. I use an engineering model constructed to estimate load curves from residential customers of LIGHT.[33] The model includes seven sources of electricity use: lighting from incandescent light bulbs, lighting from other light bulbs, refrigerator, freezer, electric shower, air conditioner, and TV. It uses data on average penetration rate, average power, and average daily usage for each source. In 1999, average consumption from these sources was about 220 kWh. Lighting and refrigeration amounted to about 27% and 31%, respectively. Electric showers, which heat water through an electrical device in the shower head and are common in Brazil, amounted to over 19% of electricity use in 1999. This was twice the electricity use of TVs. Finally, air conditioning reached 30 kWh on average (14%) but most air conditioning is used in the summer only. The model omits a few other sources of electricity consumption. For instance, standby power use could amount to 10 kWh–20 kWh a month at the time.[34]

5.2 Appliance replacement

Households may have reduced electricity use by replacing older appliances with newer, more efficient, models. Replacing domestic appliances is expensive, however, particularly in Brazil, where the cost of credit has always been high. Ex ante, appliances' manufacturers expected net losses

[33] Personal communication with Professor Reinaldo Souza, Pontifícia Universidade Católica do Rio de Janeiro.

[34] Personal communication with PROCEL and Correio Braziliense (May 26, 2001).

from the electricity crisis (Folha de São Paulo, June 5, 2001). Large chain stores in fact considered that sales of appliances suffered from the crisis (Folha de São Paulo, March 6, 2002).

5.2.1 Compact fluorescent light bulbs (CFLs)

Figure 6a displays data from PROCEL, the National Electrical Energy Conservation Program, on yearly imports of CFLs, not produced domestically. Imports of CFLs, encouraged by lower federal taxes at the start of the crisis, more than doubled in 2001. Imports returned to their pre–crisis levels afterward but kept rising over the years. As a result, the penetration rate of CFLs in residential units was much higher after the crisis (PROCEL surveys conducted in 1997 and 2005). Interestingly, the increase was large in every region and even larger in the South, not subject to the conservation program during the crisis. In surveys (see Section 5.3), households confirm that they adopted efficient light bulbs during the crisis and continued using them afterward (Appendix Table B.8). The engineering model in Table 7 was revised in 2002 to include new data on light bulbs' penetration rates. Applying the prevailing distribution after the crisis, holding constant other usages in 1999, reduces electricity use by 12 kWh or 5.5% (bottom panel in Table 7, row a). CFL adoption may thus explain part of the drop in electricity consumption in the South. It cannot explain, however, the differential effects in the South–East/Midwest.

5.2.2 Purchase of new domestic appliances

Figure 6b displays data from manufacturers' reports on yearly sales of various electricity–intensive domestic appliances relative to sale levels in 1994. There was no particular increase in sales in the years of the crisis (2001 and 2002), except for air conditioners. Air conditioners had a small penetration rate, however. Moreover, the difference–in–difference results hold when considering only winter months (Appendix Table B.5). As a result, the purchase of new appliances cannot explain the short– and long–term effects of the conservation program. These results are confirmed by looking for differential trends across regions in appliance ownership and in the purchase of new appliances in survey data (Appendix Table B.7, and Figures B.7 and B.8).

Figure 6b does not include electric showers. In the Appendix, I display monthly sales data from one of the leading manufacturers of electric showers in Brazil, separately for the South and the South–East/Midwest (Appendix Figure B.9). Sale volumes did not increase differentially in the

South–East/Midwest. Less powerful models were sold during the crisis but impacts on the average power of models sold were small (10%). As a result, the purchase of new electric showers and the type of model bought cannot explain the short– and long–term effects of the conservation program.

Energy savings from the appliances bought in 2001–2002 are unlikely to explain the reductions in electricity use during and after the crisis. In surveys (see Section 5.3), few respondents actually reported replacing appliances for more efficient ones during the crisis (Appendix Table B.10).[35]

5.3 Changes in consumption behaviors

Conservation appeals encouraged households to change their consumption behaviors during the electricity crisis. Many specific behaviors were suggested in electricity bills and through the media. Media coverage provides anecdotal evidence that households did adjust consumption habits.[36] The quick rebound in electricity use in February 2002 implies that marginal conservation efforts during the crisis were due to behavioral changes rather than investments. Nevertheless, it is unclear whether changes in consumption habits persisted after the crisis. Table 8 provides evidence on consumption behaviors using micro–data from household surveys conducted by PROCEL in 2004–2005 for customers of 18 utilities in Brazil (PROCEL, 2007a–2007d).

Panel A in Table 8 uses retrospective information on 14 conservation measures and whether households adopted such measures before, during, or after the crisis. Panel B uses retrospective information about the use of eight major domestic appliances and whether households used these appliances less in 2005 than they did before the crisis. This information was only collected for households subject to the conservation program. I focus on the South–East/Midwest because of the more persistent effects.[37] Fifty percent of households report having adopted a new conservation measure during and after the crisis. In all cases, the share of respondents adopting a particular behavior was higher during and after the crisis. Differences are particularly large for behaviors associated with the use of electric showers, refrigerators, and washing machines. In 2005, households report having reduced usage compared to before the crisis for about 40% of their domestic appliances (conditional on owning some appliance). Seventy percent of households reduced usage of at least

[35] Only one in eight households reported such a substitution during the California crisis (Lutzenhiser, 2002).

[36] Lights were kept off (*O Globo*, June 4, 2001), households reduced the use of appliances (*Com Ciência*, July 10, 2001) or went more often to buy groceries after turning off their freezers (*Folha de São Paulo*, March 5, 2002).

[37] Appendix Tables B.9 and B.10 present responses for different conservation measures and appliances. These surveys have been used, for instance, in Ghisi et al. (2007). Tables for the North–East are available upon request.

one appliance. Many households purchased freezers in the years of galloping inflation prior to 1995, allowing them to buy food on payday and store it for the month (Meier, 2005). Some of these were likely superfluous at the time of the crisis. Accordingly, 38% of households reduced their use of freezers.

Panels A and B in Table 8 provide only time–series evidence of changes in behaviors and thus cannot be directly associated with the conservation program. In panel C, I use instead information on consumption behaviors asked of every household in 2005. I compare responses in the South–East/Midwest to responses in the South for three conservation strategies often mentioned in relation to the crisis (Meier, 2005; private communication with PROCEL): unplugging freezers, avoiding standby power use, and adopting CFLs.[38] Column (1) controls for seven electricity consumption categories (dummies). Column (2) adds linear controls in household size, housing tenure, and the number of bathrooms. It also adds dummies for household earnings categories, gender and education of the household head, housing unit size and type, residence condition, neighborhood type, roof material, wall material, floor material, and the type of water access. Unplugging freezers and avoiding standby power use remained more prevalent in the South–East/Midwest in 2005. Households in the South were more likely to report leaving their appliances on standby for almost every appliance.[39] In contrast, CFL penetration rates were actually higher in the South, although the difference is reduced by half when controlling for household characteristics.

In the bottom panel in Table 7, I simulate the impact of different conservation behaviors on average electricity use. In row (b), I assume that customers not only adopted CFLs but also reduced lighting by 50%. This saves 36 kWh or 16% of electricity use. Unplugging 50% of freezers (a stronger response than the difference in Table 8) only saves about 4% (row c). Reducing TV use by 50% would have had a similar impact (row d); reducing the use of electric showers by 50% would have had an impact twice as large (row e). Air conditioning cannot explain the severe drop in electricity use in winter months. Yet it could have had a large effect in the summer. Reducing air conditioning by 50% saves 15 kWh on average (row f); it could thus have saved about 60 kWh in the summer. These simulations show that CFL adoption or the unplugging of freezers cannot explain most of the reduction in electricity use during and after the crisis. Households subject to

[38]Other cross–sectional comparisons could be misleading. For instance, households in the South–East/Midwest may be more likely to set their electric showers in the colder "summer mode" because of higher temperatures.

[39]Table B.11 displays results for each appliance separately.

the conservation program must have resorted to a series of severe conservation strategies.[40]

6 The relative roles of private incentives and conservation appeals

The conservation program induced a 25% reduction in electricity consumption on average during the crisis, on top of the 9% reduction observed for customers not subject to the program. This is a uniquely large response. A 25% reduction would require a 125% price increase, given the price elasticity estimated out–of–crisis, if price were the only mechanism at work. For many customers, however, the cost of electricity did not increase that much. In this section, I show that standard responses to the private incentives of the conservation program cannot explain customers' behaviors during the crisis. I proceed in two steps. First, I use quasi–exogenous variation in quotas provided by the assignment rule for recent movers. This allows me to estimate an elasticity of consumption with respect to the quota. I then use indirect inference techniques and estimate parameter values of the model of Section 3 necessary to rationalize both median consumption levels during the crisis and the quota elasticity. I deduce the size of potentially large effects of appeals to social preferences from comparing the estimated "crisis" price elasticity to the price elasticity estimated out–of–crisis.[41]

I consider customers with relatively large baseline consumption levels from Rio de Janeiro. First, their private incentives were simpler to understand because they were subject only to fines.[42] Second, the rebound of consumption levels in the February–March 2002 billing cycle suggests that marginal conservation efforts were not due to bonuses (fines, but not bonuses, were suspended at the time). Finally, the quasi–exogenous variation in quota applies to larger consumers. I focus again on customers with quotas around 250 kWh. Results are qualitatively similar for other categories.

[40] Lutzenhiser (2002) interviewed 400 households that experienced price spikes and public appeals in 2000–2001 in the San Diego area during the California crisis. The most frequently reported conservation strategy was a reduction in the use of existing appliances.

[41] The design of the conservation program does not allow me to identify the role of specific incentives. The distribution of consumption levels is smooth over the few kinks and discontinuities in incentives using billing data for LIGHT customers. Customers who consumed just below their quotas and were granted bonuses did not behave differently in later months than customers who missed the bonus by just one kilowatt hour (available upon request). Most customers subject to fines reduced consumption well below their quotas and never received fines. Any impact of being "discontinuously" charged a fine is thus obtained from a selected group.

[42] Bonuses were mostly out of reach; power cuts were prohibited in Rio de Janeiro.

6.1 Movers and quasi–exogenous variation in quotas

The quotas of customers who moved into their metered housing unit after the baseline period (May–July 2000) were based on their first three billing months. Because of seasonal variation in electricity use, customers who moved in the summer of 2000–2001 were allocated more generous quotas. Figure 7a displays average electricity consumption prior to the crisis for a balanced panel of LIGHT customers (dash line). Consumption is lower in winter months and higher in summer months. The solid line shows average quotas by moving date for customers who moved into their metered housing units in the same months (sample described below). After May 2000, the solid line follows the seasonality pattern of the dash line.

A. Sample selection

I select customers whose first monthly bill was sent between March 2000 (no earlier bills) and February 2001 (at least three months of pre–crisis consumption) and who were billed continuously for at least three years. I restrict attention to customers from Rio de Janeiro whose average consumption in the three months prior to the crisis falls in the top quartile of the movers' consumption distribution. Seasonality is stronger for larger consumers. The sample has 18,293 customers.

B. Quasi–exogenous variation in quota

The variation in quota in Figure 7a reaches up to 50%. Panel (b) compares the distribution of quotas between customers who moved in around baseline (May–July) and later in 2000 (October–December). The latter distribution stochastically dominates the former; the median quota differs by 28%, from 250 kWh to 320 kWh. The associated change in incentives corresponds to offering a non–binding quota to the representative customer in Figure 2. The standard model predicts that she would then consume her baseline quantity without uncertainty, implying a quota elasticity of 1. With uncertainty, she would consume below baseline because the marginal price increases at the quota, implying a smaller quota elasticity.

C. Empirical strategy

I estimate the impacts of quotas (and the associated incentives) on consumption as follows. I regress the logarithm of average consumption during the crisis, kWh_i^{crisis}, on the logarithm of the quota. I then instrument the quota of customer i by the average quota of movers (excluding i) who received their first bill in the same week w as i.

$$log(kWh_{i,w}^{crisis}) = \alpha + \beta \; log(quota_{i,w}) + X_{i,w} + \nu_{i,w} \tag{8}$$

$$log(quota_{i,w}) = \gamma + \delta \; log(Avquota\_sameweek_w) + X_{i,w} + \rho_{i,w} \tag{9}$$

where ν and ρ are individual error terms clustered by moving week. I consider only average consumption in the first five months of the crisis because quotas were extended at the end of 2001.

The instrument is valid only if customers who moved in at different times are comparable. Figure 7c compares the distribution of average consumption levels in the three months prior to the crisis for the same two groups of movers. The distributions overlap closely. Customers who moved at different times had similar pre–crisis consumption levels in my sample. I test this directly below and control for the logarithm of pre–crisis consumption in $X_{i,w}$. The billing data include no customer characteristics but I further control for neighborhood fixed effects. Finally, I am particularly interested in responses at the median. Indeed, the median quota for customers whose quota was based on the *baseline* period is around 250 kWh. I thus consider quantile regressions.

D. Results

Figure 7d offers a preview of the results. It displays the distribution of average consumption levels during the crisis for the same two groups of movers. Customers who moved in later in the year and had larger quotas consumed more electricity. However, the effect is very small.

Column (1) in Table 9 displays the coefficient, δ, from estimating the first–stage equation (9). The instrument is strong. Because the coefficient is close to 1, I present reduced–form results in the remaining columns. I find no effect of the instrument on average consumption prior to the crisis (column 2). At both the mean and the median, the quota elasticity is around .17 without controls (column 3) and .16 controlling for pre–crisis consumption and neighborhood effects (column 4). A 20% higher quota thus increases consumption by only 3.2%. The effects are 50% smaller but still significant in 2002 (column 5). In later years, they become smaller and noisier (not shown). The absence of persistent effects may derive from the small impact estimated during the crisis. Long–term reductions in electricity consumption may also be due to other stimuli (e.g., conservation appeals) or to infra–marginal conservation efforts during the crisis. Finally, general equilibrium effects may weaken the link between consumption during and after the crisis over time.[43]

6.2 Rationalizing observed behaviors

Median consumption levels of customers subject only to fines for exceeding their quotas were well below quotas during the crisis. Large quasi–exogenous increases in quotas induced only small increases in consumption. This section estimates parameter values of the model of Section 3 necessary to rationalize these behaviors by the prevailing private incentives of the conservation program. I find that the price elasticity must be increased, unrealistically, at least fivefold in order to explain behavior solely by responses to the private incentives.

A. General approach

I use indirect inference techniques ("moment matching"; Gouriéroux and Monfort, 1996). I search for parameter values such that the model's predictions match two empirical "moments": (M1) the low median consumption levels during the crisis and (M2) the small elasticity of consumption with respect to the quota. In particular, I minimize the inner product of the difference between the model's simulated moments and both empirical moments. The two parameters to estimate are the crisis–specific price elasticity and the standard deviation of consumption. I use empirical moments from the sample of movers from Rio de Janeiro. Median consumption levels were 18.7% below the quota in the first five months of the crisis (M1) for movers with quotas around 250 kWh, and whose quotas were based on the baseline period. I estimated a quota elasticity of .16 (M2). Importantly, I obtain a lower bound for the crisis–specific elasticity. Indeed, I assume that customers' propensity to consume electricity adjusted immediately to a level consistent with post–crisis consumption levels. The model thus only has to explain conservation efforts beyond the persistent effects, as in column (3) in Table 4.[44] Finally, I verify that the parameterized model accurately predicts out–of–sample behaviors. For this purpose, I use median consumption levels during the crisis for the balanced panel of LIGHT customers with quotas around 250 kWh.

B. Estimation results

[43] Yet there is a high correlation between consumption changes during and after the crisis (Appendix Figure B.10). Quantile regressions do not include neighborhood effects because estimators would be inconsistent. As a robustness check, I performed a placebo analysis assuming that the crisis occurred in 2004–2005 instead (selecting movers in a similar way). Placebo estimates are never significant and are very close to 0 (results available upon request).

[44] For movers whose quota was based on the baseline period and was around 250 kWh, median consumption levels were around 3.6% in the same five months in 2002. See Appendix for further details.

Intuitively, the parameters are identified. The small quota elasticity implies a significant degree of uncertainty. A high price elasticity is necessary to match the low consumption levels. I am able to match the empirical moments closely, including out–of–sample (Table 10). The model requires a large degree of uncertainty. A standard deviation of .4 is more than twice the realized uncertainty in Section 3. More strikingly, the model requires a price elasticity around .95 during the crisis, after already taking into account the long–term effects. This is much higher than existing estimates from the literature. Moreover, larger estimates are typically obtained for heavy users of electric heating or air conditioning (Reiss and White, 2005). The empirical moments above were obtained for a period of the year characterized by little use of air conditioning or heating in Rio de Janeiro.

C. Discussion

Because estimated parameter values are so far from typical values found in the literature, they indicate that conservation efforts at the margin were not responding to the risk of fines. Customers may have been sensitive instead to appeals to social preferences and may have voluntary contributed to avoid blackouts and severe shortages. Players voluntarily (over–)contribute to avoid losing a public good in laboratory experiments, particularly if the loss is large (Iturbe et al., 2011).

Alternatively, customers may have misunderstood their private incentives and largely overestimated the cost of exceeding their quotas. To test this hypothesis, one would ideally compare the behaviors of customers who received different feedback on the actual cost of non–compliance. I present graphical results for a related exercise based on a selected sample in Appendix Figure B.11. I focus on customers who severely reduced consumption at the start of the crisis, but for some reason, consumed closer to their quotas in August–September. Customers consuming just above the quota (discontinuity) received a fine and potentially learned the actual cost of non–compliance. If customers were over–estimating this cost, they should *increase* consumption upon being fined. In the following months, customers who received a fine responded by further *reducing* consumption.[45]

Loss averse customers would also behave as if they overestimated the cost of non–compliance. Performing a similar moment matching exercise as above, I estimate the "perceived penalty" for exceeding quotas consistent with the two empirical moments (Appendix Table B.12). The model requires a perceived penalty of R$115, or 22 times the actual cost of consuming above the quota. This is an unrealistic degree of loss aversion. Finally, customers may have been uncertain about

[45] I assume away income effects.

future policies. Such uncertainty, however, should have pushed customers to consume *more* rather than *less* electricity because of the use of grandfathering in first quota assignment rules.

7 Conclusion

The conservation program implemented during the Brazilian electricity crisis reduced residential electricity consumption by 25% over a nine–month period. Average effects were due to large responses from most customers across the distribution of consumption levels. A 25% reduction is a very large effect, particularly in a context of low baseline consumption levels and little use of air conditioning or electric heating. Importantly, the temporary program reduced residential electricity consumption by 12% in the long run in the South–East/Midwest. This corresponds to a reduction of $1.2 billion in electricity bills in 2011 or to a spared capacity of 850 MW, the capacity of an average nuclear reactor.

This paper provides evidence that large energy conservation programs may trigger substantial lumpy adjustments that persist in the long run, and may thus turn out more cost–effective than less ambitious programs. A complete evaluation of the welfare consequences of the Brazilian conservation program for residential customers is, however, beyond the scope of this paper. Adjustment costs, rational or not, may have been sizable. Such an evaluation is also complicated by the fact that appeals to social preferences played a major role in stimulating conservation efforts during the crisis. Non–price policies have been suggested in a range of policy areas. Yet there is still little evidence on the utility loss they impose on economic agents. The social cost of non–price policies may be high if they induce a sense of moral coercion rather than moral duty, a feeling of guilt rather than a warm glow, or if they divert individuals' attention away from other utility–relevant decisions. This appears as a particularly important avenue for future research.

The findings of this paper also suggest that individuals may be willing to voluntarily conserve energy whenever a common threat is widely accepted and perceived as imminent.[46] These features have yet to be associated with major environmental concerns such as climate change.

[46] In Japan, peak summer electricity consumption was also recently reduced by 15% through voluntary measures only (http://www.nytimes.com/2011/09/26/opinion/in-japan-the-summer-of-setsuden.html?_r=1).

References

Acemoglu, Daron, Philippe Aghion, Leonardo Bursztyn and David Hemous (2012). *The Environment and Directed Technical Change.* American Economic Review, 102(1), pp. 131-166.

Aghion, Philippe, Antoine Dechezlepreêtre, David Hemous, Ralf Martin and John Van Reenen (2012). *Carbon Taxes, Path Dependency and Directed Technical Change: Evidence from the Auto Industry.* NBER Working Paper 18596.

Allcott, Hunt (2011). *Social Norms and Energy Conservation.* Journal of Public Economics, 95(9–10), pp. 1082–1095.

Allcott, Hunt and Michael Greenstone (2012). *Is There an Energy Efficiency Gap?* NBER Working Paper No. 17766.

Allcott, Hunt and Todd Rogers (2012). *The Short–Run and Long–Run Effects of Behavioral Interventions: Experimental Evidence from Energy Conservation.* NBER Working Paper 18492.

Andreoni, James (2006). *Philanthropy.* Handbook of the Economics of Giving, Altruism, and Reciprocity, volume 2, pp. 1201–1269.

ANEEL (2005). *Tarifas de fornecimento de energia eltrica.* Agncia Nacional de Energia Eltrica, Cadernos Temticos ANEEL 4: 30 p.

Ayres, Ian, Sophie Raseman and Alice Shih (2009). *Evidence from Two Large Field Experiments That Peer Comparison Feedback Can Reduce Residential Energy Usage.* NBER Working Paper 15386.

Baisa, Brian, Lucas Davis, Stephen Salant and William Wilcox (2010). *The Welfare Costs of Unreliable Water Service.* Journal of Development Economics, 92(1), pp. 1–12.

Bardelin, Cesar (2004). *Os efeitos do racionamento de energia elétrica ocorrido no Brasil em 2001 e 2002 com ênfase no consumo de energia elétrica.* Dissertação de Mestrado em Sistemas de Potência, Universidade de São Paulo: Escola Politécnica.

Bastos, Paulo, Lucio Castro, Julian Cristia and Carlos Scartascini (2011). *Does Energy Consumption Respond to Price Shocks? Evidence from a Regression–Discontinuity Design.* IDB Working Paper Series No. 234.

Becker, Gary and Kevin Murphy (1988). *A Theory of Rational Addiction.* Journal of Political Economy 96(4), pp. 675–700.

Borenstein, Severin (2009). *To What Electricity Price Do Consumers Respond? Residential Demand Elasticity Under Increasing-Block Pricing.* Mimeo, Energy Institute, University of California at Berkeley.

Burlando, Alfredo (2012). *The Impact of Transitory Income Shocks on Birth Weights: Evidence from a Blackout in Zanzibar.* Mimeo, Department of Economics, University of Oregon.

Charness, Gary and Uri Gneezy (2009). *Incentives to Exercise.* Econometrica 77(3), pp. 909–931.

Comissão de Análise do Sistema Hidrotérmico de Energia Elétrica (2001). *Desequilíbrio entre oferta e demanda de energia elétrica.*
http://antonioguilherme.web.br.com/artigos/relatoriokelman.pdf.

Costa, Francisco (2012). *Just Do It: Temporary Restrictions and New Consumption Habits.* Mimeo, London School of Economics.
http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2028684.

Davis, Lucas and Lutz Kilian (2011). *The Allocative Cost of Price Ceilings in the US Residential Market for Natural Gas.* Journal of Political Economy, 119(2), pp. 212–241.

Faruqui, Ahmad and Sanem Sergici (2010). *Household Response to Dynamic Pricing of Electricity: A Survey of 15 Experiments.* Journal of Regulatory Economics, 38(2), pp. 193–225.

Fisher–Vanden, Karen, Erin Mansur and Qiong Wang (2012). *Costly Blackouts? Measuring Productivity and Environmental Effects of Electricity Shortages.* NBER Working Paper No. 17741.

Ghisi, Enedirr, Samuel Gosch and Roberto Lamberts (2007). *Electricity End–Uses in the Residential Sector of Brazil.* Energy Policy, 35(8), pp. 4107–4120.

Gouriéroux, Christian and Alain Monfort (1996). *Simulation–Based Econometric Methods.* Oxford University Press.

Ito, Koichiro (2012a). *Do Consumers Respond to Marginal or Average Price? Evidence from Non-linear Electricity Pricing.* Working Paper 210R, Energy Institute @ Haas.

Ito, Koichiro (2012b). *Does Conservation Targeting Work? Evidence from a Statewide Electricity Rebate Program in California.* Mimeo, Stanford University.

Iturbe–Ormaetxe, Iñigo, Giovanni Ponti, Josefa Toms, and Luis Ubeda (2011). *Framing Effects in Public Goods: Prospect Theory and Experimental Evidence.* Games and Economic Behavior 72(2), pp. 439-447.

Leighty, Wayne and Alan Meier (2011). *Accelerated Electricity Conservation in Juneau, Alaska: A Study of Household Activities that Reduced Demand 25%.* Energy Policy 39, pp. 2299–2309.

Lutzenhiser, Loren (2002). *An Exploratory Analysis of Residential Consumption Survey and Billing Data: Southern California Edison, Summer 2001.* Sacramento: California Energy Commission, Report no. 400-02-006F.

Mascarenhas, Henrique Ribeiro (2005). *O setor de eletrodomésticos de linha branca: um diagnóstico e a relação varejo-indústria.* Master's thesis, Fundaçao Getulio Vargas, São Paulo.

Mation, Lucas and Claudio Ferraz (2011). *How Do Firms React to Infrastructure Constraints? Evidence from Brazil's Energy Shortage.* Working paper, Department of Economics, Pontifícia Universidade Católica do Rio de Janeiro.

Maurer, Luiz, Mario Pereira and José Rosenblatt (2005). *Implementing Power Rationing in a Sensible Way: Lessons Learned and International Best Practices.* Energy Sector Management Assistance Program Report, World Bank.

McKinsey (2009). *Pathways to a Low–Carbon Economy: Version 2 of the Global Greenhouse Gas Abatement Cost Curve.* Report from McKinsey & Company.

Meier, Alan (2005). *Saving Electricity in a Hurry: Dealing with Temporary Shortfalls in Electricity Supplies.* OECD/IEA.

Mulligan, Casey (1998). *Pecuniary Incentives to Work in the United States during World War II.* Journal of Political Economy, 106(5), pp. 1033–1077.

Pimenta, Amanda, Hilton Notini and Luiz Felipe Maciel (2009). *Brazilian Electricity Demand Estimation: What Has Changed after the Rationing in 2001? An Application of Time Varying Parameter Error Correction Model.* Mimeo, Getulio Vargas Foundation.

PROCEL (2007a). *Posses e Hábitos de Uso de Aparelhos Elétricos: Classe Residencial, Relatório Centro–Oeste.* ELETROBRÁS - Centrais Elétricas Brasileira.

PROCEL (2007b). *Posses e Hábitos de Uso de Aparelhos Elétricos: Classe Residencial, Relatório Nordeste.* ELETROBRÁS - Centrais Elétricas Brasileira.

PROCEL (2007c). *Posses e Hábitos de Uso de Aparelhos Elétricos: Classe Residencial, Relatório Sudeste.* ELETROBRÁS - Centrais Elétricas Brasileira.

PROCEL (2007d). *Posses e Hábitos de Uso de Aparelhos Elétricos: Classe Residencial, Relatório Sul.* ELETROBRÁS - Centrais Elétricas Brasileira.

PROCEL (2007e). *Simulação de Potenciais de Eficiência Energética para a Classe Residencial.* ELETROBRÁS - Centrais Elétricas Brasileira.

Reiss, Peter and Matthew White (2005). *Household Electricity Demand, Revisited.* Review of Economic Studies, 72(3), pp. 853–883.

Reiss, Peter and Matthew White (2008). *What Changes Energy Consumption? Prices and Public Pressures.* RAND Journal of Economics, 39(3), pp. 636-663.

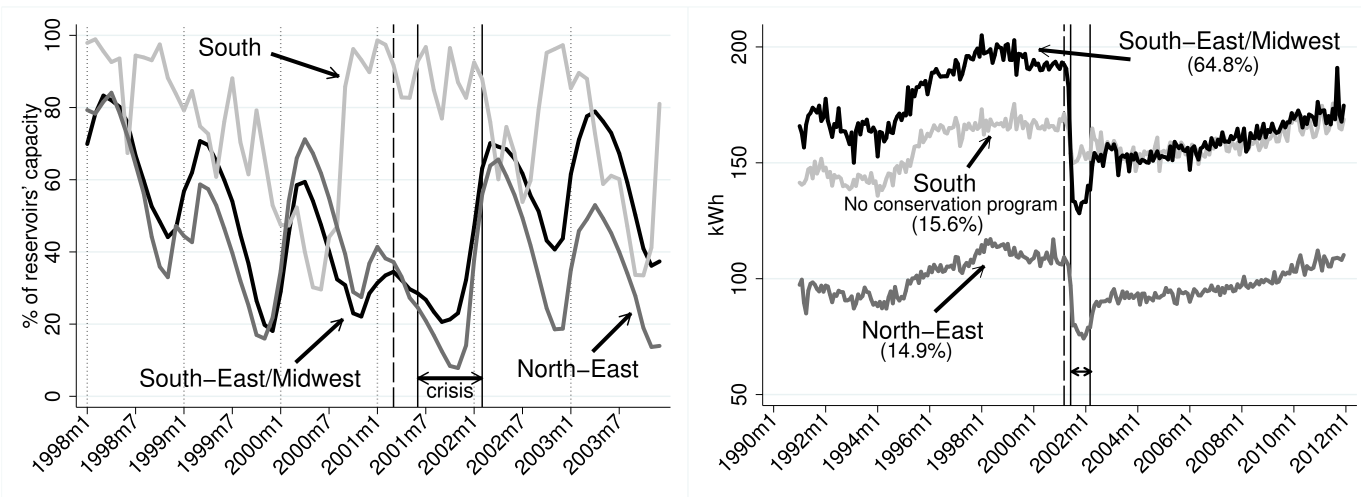
Schmidt, Cristiane and Lima, Marcos (2004). *A Demanda por Energia Eltrica no Brasil.* Revista Brasileira de Economia, 58(1).

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

Figure 1: Cause and consequences of the electricity crisis and its conservation program

(a) Level of the hydro–reservoirs

(b) Average residential electricity consumption



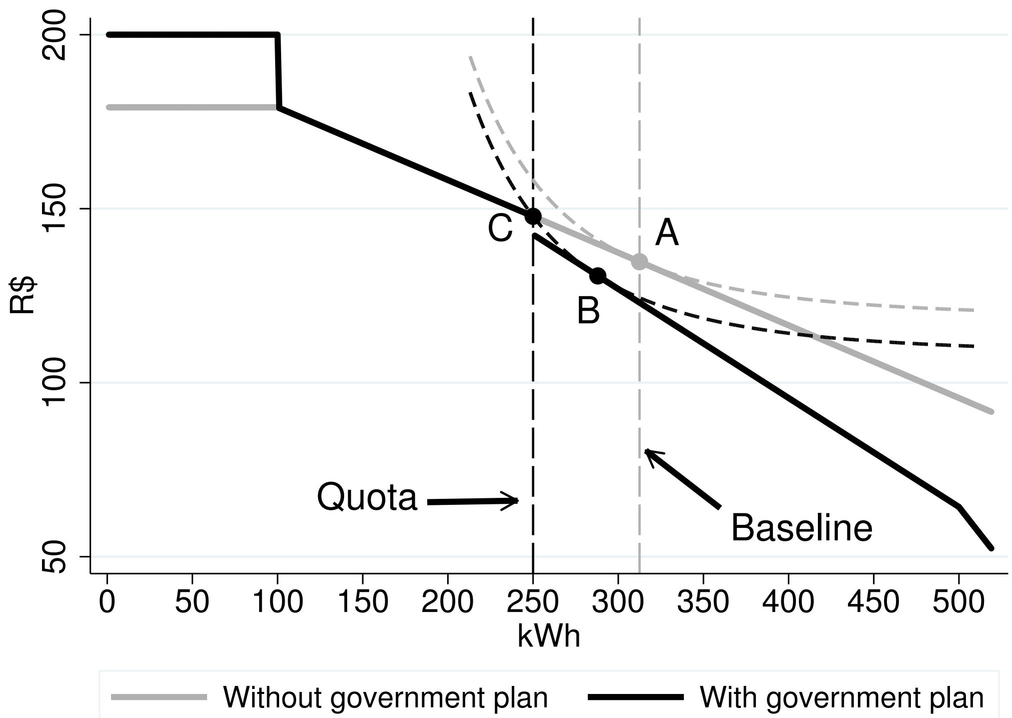
Source: ONS and ANEEL (personal communication)

Panel (a) presents the evolution of hydro–reservoirs' capacity in the three main subsystems in Brazil. In the North–East and the South–East/Midwest, there is a clear seasonal pattern, with high rainfall in the summer (dotted lines indicate January). In the summer of 2000–2001, rainfall was exceptionally unfavorable in these regions, leading to dangerously low reservoir levels. The need to reduce electricity demand was first mentioned by government officials in March 2001 (dashed line). The South experienced low levels in 2000, but generous rainfall replenished reservoirs rapidly, eliminating any risk of shortage there. A conservation program was implemented in the North–East and the South–East/Midwest between June 2001 and February 2002 (crisis period, solid vertical lines).

The overall effects of the conservation program are visible on panel (b), which depicts monthly average residential electricity consumption per customer for utilities in each subsystem (unweighted, seasonally adjusted). Subsystems' shares of total residential consumption are presented in parentheses. Trends were similar prior to June 2001. Consumption then dropped everywhere. The drop was more substantial, however, for utilities subject to the conservation program (treatment). Average residential consumption for these utilities partially rebounded after February 2002. Patterns in the South–East/Midwest suggest a differential effect compared to the South (no conservation program), which has persisted until now.

Figure 2: Private incentives of the conservation program and predictions of the standard model

(for customers with a quota of 250 kWh)



Example for customers assigned a quota of 250 kWh (80% of average consumption in May–July 2000). I assume a budget of R$200 and a tariff p of R$.208/kWh (LIGHT, June 2001). The fines included in the conservation program (a) increase the marginal price above the quota (by 50% up to 500 kWh, then 200%) and (b) increase the cost discretely at the quota (by R$5.2):

$$Fines = \mathbb{1}\{200 < kWh < 500\}\, .5p\,(kWh - 200) + \mathbb{1}\{kWh \geq 500\}\,[2p\,(kWh - 500) + .5p\,(300 - 200)]$$

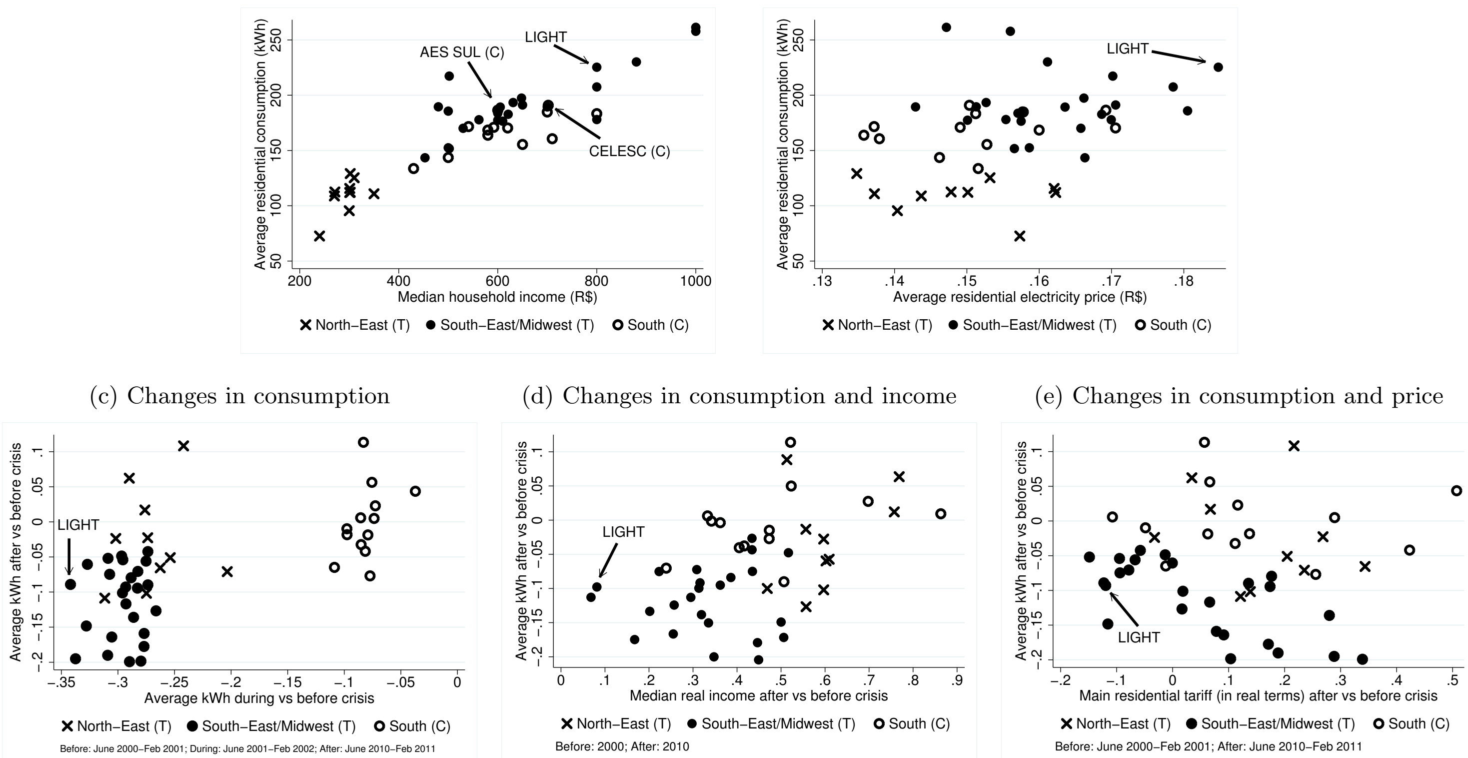
Because of bonuses, the cost of electricity is nil if consuming below 100 kWh. To predict consumption choices under the conservation program, I use a standard model of consumption behavior (see Section 3) and the price elasticity estimated in Section 3.2.

The change in the marginal price shifts consumption from A (baseline) to B. However, because of the discontinuous increase in the cost of electricity at the quota, customers bunch at their quotas (B→C). If customers cannot control their electricity consumption perfectly, they face a continuous budget curve below the black line on the left of C and above it on the right of C (see text for details). In this case, there would be no bunching. In Section 6, I investigate the impact of the quotas on electricity consumption by exploiting the fact that households who moved into their housing units shortly before the crisis were allocated essentially non–binding quotas. This corresponds to assigning quotas at A.

Figure 3: Income, electricity price, and electricity consumption (before, during, and after the crisis)

(a) Consumption and income in 2000 (b) Consumption and price in 2000

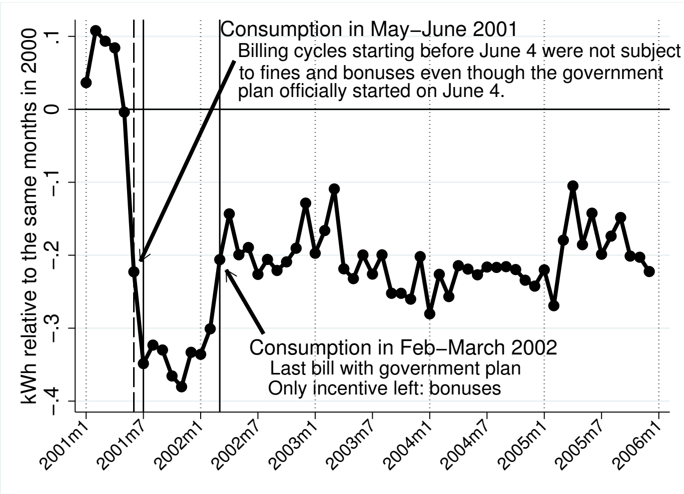
(c) Changes in consumption (d) Changes in consumption and income (e) Changes in consumption and price



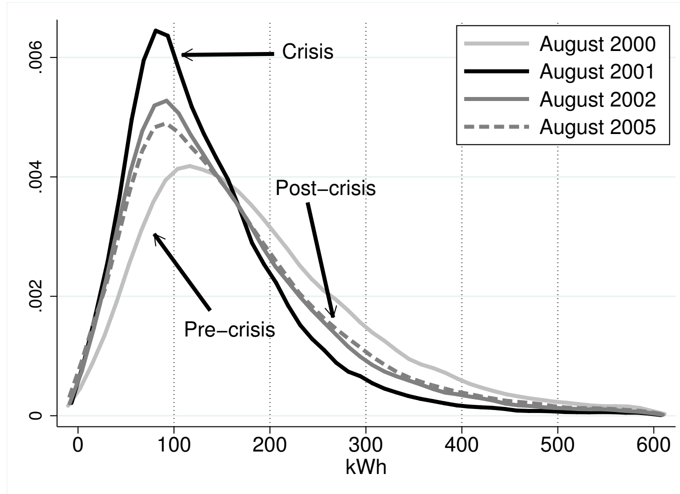
Each observation corresponds to a utility and its concession area. In 2000, the exchange rate was about R$1.9≃US$1. Panels (a) and (b) present pre–crisis descriptive statistics. Panel (a) displays the relationship between median household income and average residential electricity consumption (per customer). Income and consumption overlap between utilities in the South–East/Midwest and the South, but households in the North–East are systematically poorer, using less electricity. Panel (b) displays the relationship between average residential electricity prices and consumption. There is some overlap in prices among utilities in all three subsystems. Panel (c) displays the relationship between relative changes in average residential consumption during the crisis (horizontal axis) and up to nine years after the crisis (vertical axis) compared to the same months in the year preceding the crisis. During the crisis, consumption was reduced for every utility but more severely in the North–East and the South–East/Midwest. Long–term differences in trends between the South–East/Midwest and the South are not due to outliers. Panel (d) displays the relationship between the long–term changes in consumption (vertical axis) and relative long–term changes in household median real income (horizontal axis). Household income in the North–East, lower before the crisis, grew relatively more. For similar income growth, relative consumption is lower in the South–East/Midwest than in the South. Panel (e) displays the relationship between the long–term changes in consumption (vertical axis) and relative long–term changes in the main residential electricity tariffs (horizontal axis). For similar changes in prices, relative consumption is lower in the South–East/Midwest than in the South.

Figure 4: Changes in electricity consumption using individual billing data (LIGHT customers)

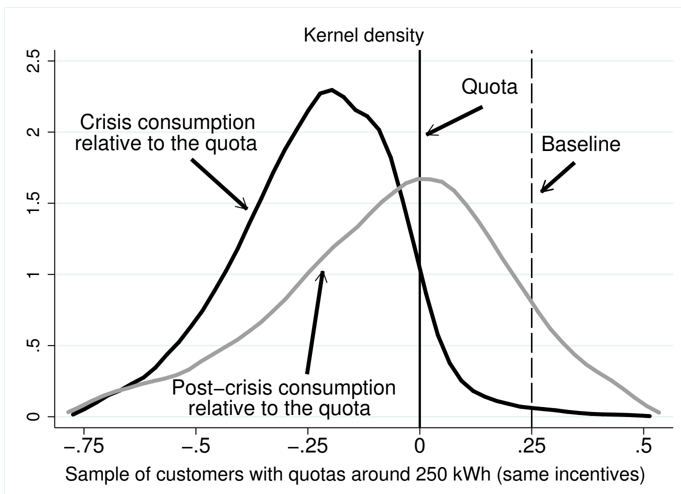
(a) Monthly average consumption relative to 2000



(b) Distribution of consumption levels over time



(c) Distribution of conservation efforts for same quota customers

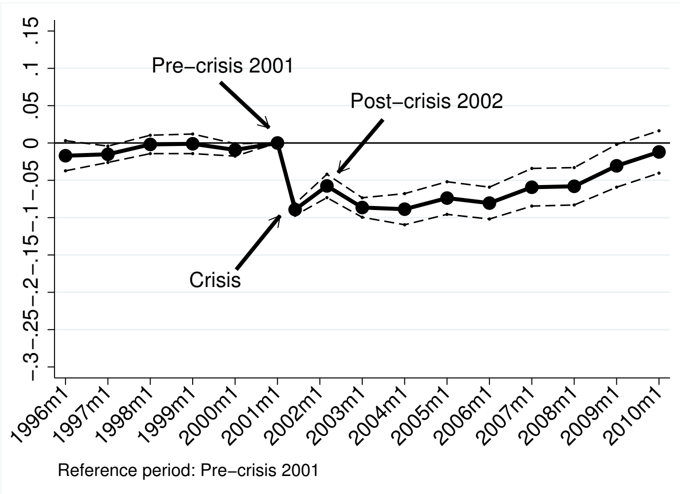


In panels (a) and (b), I use a balanced panel of 44,817 randomly selected LIGHT customers billed each month between 2000 and 2005 to avoid compositional issues. Bills sent in month t cover consumption from (part of) months t and $t-1$. The government program (including conservation appeals) officially started on June 4, 2001, and applied to billing cycles starting after that date. Therefore, because of staggered billing, the bill sent in June covered consumption after June 4, but was not subject to fines and bonuses (billing cycles starting in May or early June). The first bill including fines and bonuses for everybody was sent in July.

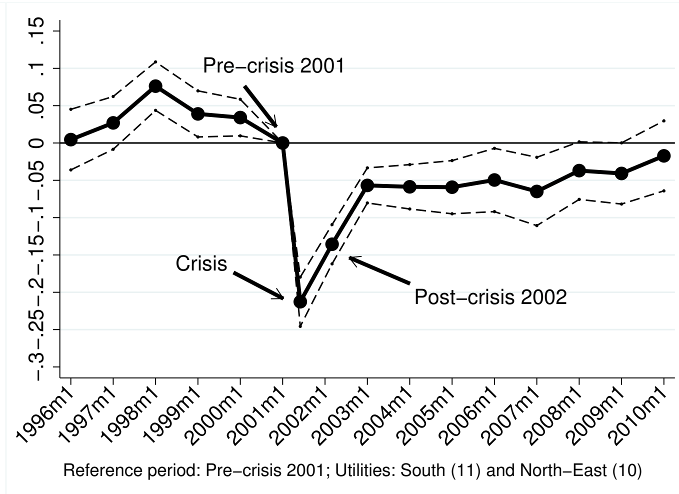
Panel (a) displays average electricity consumption in each billing month since 2001 compared to the same month in 2000. During the crisis, consumption fell more than 30% below 2000 levels. In February 2002, fines for consuming above the quota were suspended. Even though bonuses (to low-consuming customers) were still offered in the March 2002 bill, average consumption rebounded immediately. Consumption levels remained about 20% lower until 2005. Panel (b) displays Kernel densities (Epanechnikov kernels, optimal bandwidths) for electricity consumption billed in August (winter) in 2000, 2001, 2002, and 2005. The short– and long–run "average reductions" came from large reductions in electricity use at every level of consumption. In panel (c), I investigate the distribution of conservation efforts for a set of customers facing exactly the same incentives (described in Figure 2). I construct another balanced panel of 10,341 LIGHT customers from Rio de Janeiro whose quotas fell between 248 kWh and 253 kWh. I present Kernel densities (Epanechnikov kernels, optimal bandwidths) for consumption levels normalized to the quota in the first five months of the crisis (before any change in quota) and in the same months in 2002 (post-crisis). The median customer in this sample consumed 21.8% below her quota during the crisis and 3.3% below her quota in 2002.

Figure 5: Difference–in–difference results

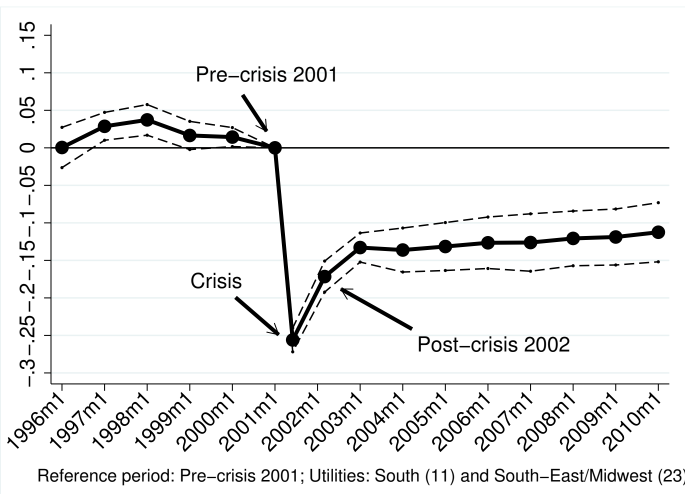
(a) Trend in the South (C)



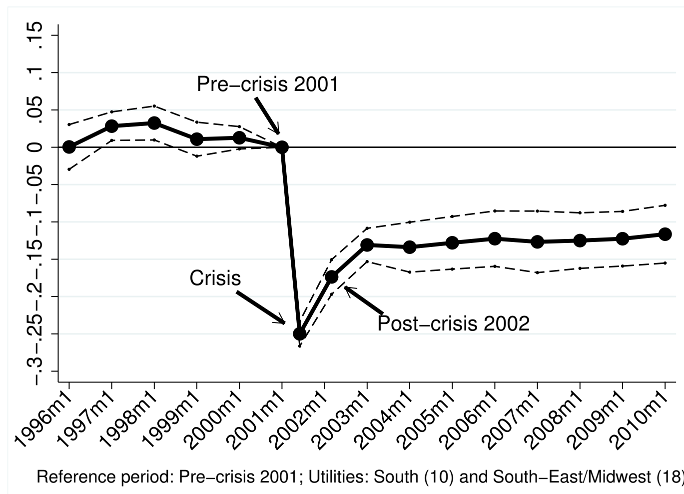
(b) North–East (T) vs South (C)



(c) South–East/Midwest (T) vs South (C)



(d) South–East/Midwest (T) vs South (C), restricted sample



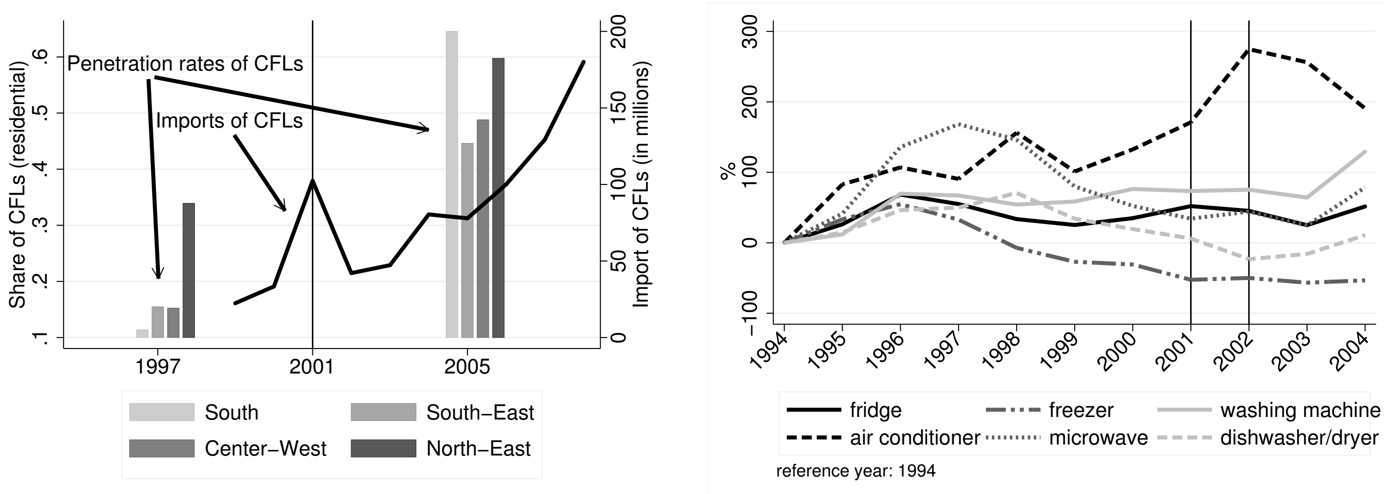
95% confidence interval in dash (s.e. clustered by utility). Data from 1996 to 2010. The graphs display coefficients from regressing the logarithm of monthly average electricity consumption per customer for each utility on time–period dummies (trends in the South, not subject to the conservation program) and those dummies interacted with an indicator for utilities subject to the conservation program during the crisis (difference–in–difference estimators in every time period). The reference period corresponds to the first months of 2001, prior to the crisis. Regressions include utility and calendar month–per–region fixed effects, and control for the logarithm of the main residential electricity tariffs (see Section 4.2.2) and available municipal yearly data matched to the concession area of each utility (log population, log share formally employed, log real median formal wage). Panel (a) reproduces coefficients on the time–period dummies (yearly dummies, three dummies for 2001–2002 to isolate the crisis period). Panel (b) presents the differential trends in the North–East (T) compared to the South (C). Panel (c) does the same, comparing utilities in the South–East/Midwest (T) and in the South (C). Panel (d) restricts the sample in panel (c) to utilities with overlapping average consumption and median income levels in 2000.

Panel (a) reveals a significant drop in electricity consumption for utilities not subject to the conservation program (9%). This corresponds to the impact of national policies (e.g., price subsidies for efficient light bulbs) and possible spillovers from conservation appeals. Even this effect appears to be long–lasting. The other panels show the overall impact of the conservation program (private incentives and conservation appeals) in the two treated subsystems. Average electricity consumption further dropped by 20% in the North–East and 25% in the South–East/Midwest during the crisis. The crisis had long–term impacts in the South–East/Midwest (12% until 2010). The apparently smaller long–term effects in the North–East are confounded by the fact that utilities in the South do not constitute a suitable control group for utilities in the North–East: customers in the North–East were systematically poorer with lower penetration rates of electricity–intensive appliances prior to the crisis (see Figure 3 and Table 1). Regression coefficients are reproduced with and without controls in Tables B.3 and B.4 in the Appendix. Results are similar but the long–term effects are somewhat larger with price controls.

Figure 6: Trends in appliance sales in Brazil around the crisis

(a) Penetration rates and imports of CFLs

(b) Relative sales of appliances

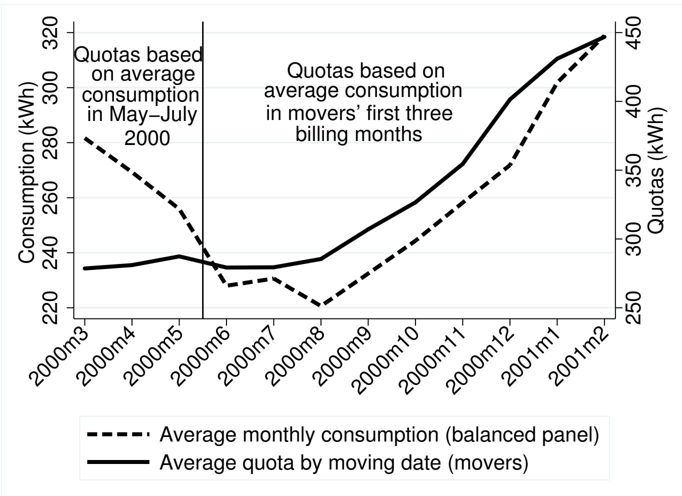


Data for panel (a) come from PROCEL, the National Electrical Energy Conservation Program. Nearly 100% of compact fluorescent light bulbs (CFLs) are imported in Brazil. During the crisis, imports of CFLs more than doubled. Afterward, imports returned to their pre–crisis levels but kept rising over the years. As a result, the penetration rate of CFLs in residential units was much higher after the crisis (surveys conducted in 1997 and 2005). In surveys, households confirm that they adopted efficient light bulbs during the crisis and continued using them afterward (Table B.8). Interestingly, the increase was large in every region and even larger in the South, not subject to the conservation program during the crisis. CFL adoption, which was encouraged by lower federal taxes at the time of the crisis, may thus explain part of the drop in electricity consumption in every region during the crisis (including the South). It cannot explain, however, the differential effects comparing the South–East/Midwest and the South. The higher penetration rate in the North–East in 1997 may be due to CFL distribution programs conducted in the 1990s in a few northeastern cities (personal communication with PROCEL).

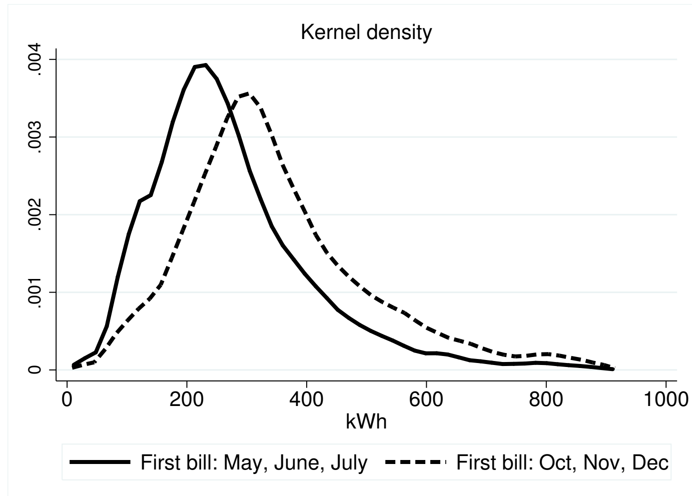
Data for panel (b) come from Mascarenhas (2005, based on manufacturers' reports). The graph displays yearly sales of various electricity–intensive domestic appliances relative to sale levels in 1994. There was no particular increase in sales in the years of the crisis (2001 and 2002), except for air conditioners. Air conditioners had a small penetration rate (Table 1), however, and the difference–in–difference results hold when considering only winter months (Table B.5). As a result, the purchase of new appliances cannot explain the short– and long–term effects of the conservation program. These results are confirmed by looking for differential trends across regions in appliance ownership and in the purchase of new appliances using survey data (Table B.7, and Figures B.7 and B.8). The data used in panel (b) do not include electric showers, an important source of residential electricity consumption in Brazil. In the Appendix (Figure B.9), I show sale patterns from one of the leading manufacturers of electric showers in Brazil, separately for the South and the South–East/Midwest. Sales of electric showers did not increase during the crisis in Brazil and did not increase differentially in the South–East/Midwest. Less powerful models (consuming less electricity) were sold in the South–East/Midwest during the crisis, but the impact of these sales on the average power of the models sold was small (10% reduction in power). As a result, the purchase of new electric showers and the type of model bought conditional on a purchase cannot explain the short– and long–term effects of the conservation program.

Figure 7: Quasi-exogenous variation in movers' quotas and impact on consumption levels during the crisis

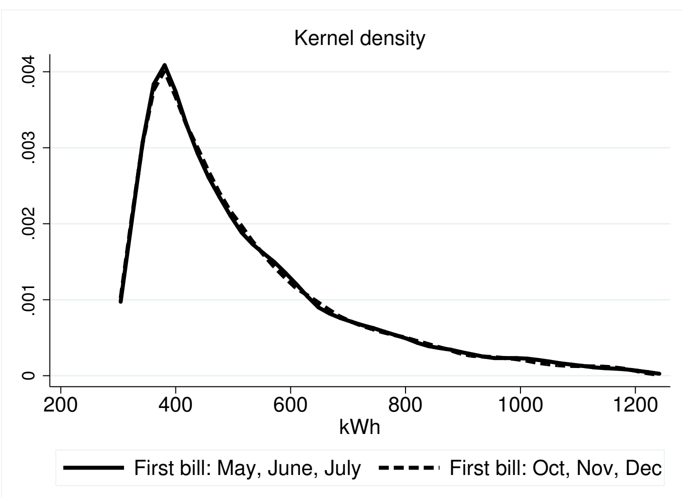
(a) Seasonality in electricity consumption and variation in movers' quotas by moving date



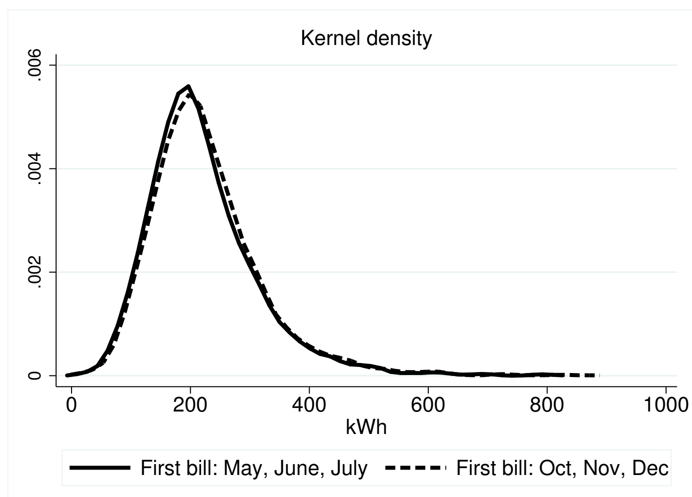
(b) Comparison of quota distributions for different moving dates



(c) Pre–crisis consumption (selection)



(d) Crisis consumption (impact)



Quota assignment rules for customers who moved into their metered housing units after the *baseline* period (May–July 2000) offer quasi–exogenous variation in quotas. Panel (a, dash) shows the clear seasonality in average monthly electricity consumption prior to the crisis for LIGHT customers (less electricity use in winter, June–September). Panel (a, solid) shows average quota levels by moving month for a sample of movers from Rio de Janeiro (selected as large consumers prior to the crisis; see text). Their quotas were based on their first three monthly bills if they moved in after May 2000. The seasonality in consumption translates into larger quotas for customers who moved in after the winter. Panel (b) shows that the quota distribution for customers who moved in later in the year in 2000 stochastically dominates the quota distribution for customers who moved in around the *baseline* period; the median quota differs by more than 25% (320 kWh vs 250 kWh). Panel (c) shows that the same two groups had similar consumption levels in the three months prior to the crisis. Panel (d) shows that the group with larger quotas appears to consume only a little more electricity in the first five months of the crisis. A large increase in quota thus had only a very small effect on electricity consumption. Kernel densities use Epanechnikov kernels and optimal bandwidths.

Table 1: Descriptive statistics in 2000

	(1) South	(2) South–East/Midwest	(3) LIGHT	(4) North–East
Mean electricity consumption (kWh)	168	192.3	225.3	109.5
Mean electricity price (R$/kWh)	.1515	.162	.1848	.1489
Median income (R$)	615.8	648.9	800	294.7
Has bathroom	.907	.9536	.9744	.6886
Has electricity	.9781	.9841	.9986	.9034
Has refrigerator	.9266	.9242	.972	.6563
Has washing machine	.4495	.3712	.5536	.0923
Has air conditioner	.0707	.0625	.3111	.0452
Utilities	13	24	1	10

Units of observation: utilities as of 2000. LIGHT is the utility serving the municipality of Rio de Janeiro and surrounding municipalities. Statistics are obtained by matching data at the household level from the 2000 census to the concession area of each utility. Data on average residential consumption and average price are obtained from the ANEEL administrative data. Additional descriptive statistics are presented in Table B.1 in the Appendix. The exchange rate in 2000 was about R$1.9≃US$1.

Prior to the crisis, average residential electricity consumption per customer was higher in the South–East/Midwest, in particular in Rio de Janeiro, and lower in the North–East. The pattern follows differences in median household income. Utilities in the North–East had systematically poorer populations and lower levels of electricity use. Overall, average residential electricity consumption was low in Brazil compared to more developed countries. One reason is a relatively high price of electricity. Another reason is a lower penetration of domestic appliances. While most households owned a fridge in the South–East/Midwest and the South, less than 50% owned a washing machine and less than 10% had air conditioning. Ownership rates were much lower in the poorer North–East.

The descriptive statistics suggest that utilities in the South may not constitute a suitable control group for utilities in the North–East: with very different initial values of appliance ownership, a parallel trend assumption may not hold, especially in the long run.

Table 2: 10–year difference (2000–2010) in trends compared to the South

	(1) South–East/Midwest		(2) North–East	
Log mean electricity consumption	-.1195***	(.0262)	-.0279	(.0388)
Log mean electricity price	-.083	(.068)	-.1125	(.0904)
Log main electricity tariff	-.0716	(.0699)	.0103	(.0756)
Has bathroom	-.0389*	(.0206)	.1756***	(.0473)
Has electricity	-.0055	(.0072)	.0682**	(.0274)
Has refrigerator	-.0038	(.0185)	.2354***	(.0353)
Has washing machine	-.0065	(.0944)	.3813***	(.104)
Log median household income	-.1003**	(.0502)	.0878*	(.05)
Observations	74		46	
Clusters	37		23	

Units of observation: utilities as of 2000. Significance levels: *10%, **5%, ***1% (s.e. clustered by utility). Utility–level data are matched to household–level data from the 2000 and 2010 censuses in the concession area of each utility. Ownership of air conditioners was not captured in the 2010 census. Data on average residential consumption and average price in 2000 and 2010 are obtained from the ANEEL administrative data. I created a dataset on the actual electricity tariffs for every utility from 1996 to 2011 by analyzing every legal price–setting resolution published by the national regulation agency (ANEEL). The descriptive statistics for 2010 are presented in Table B.2 in the Appendix.

The table displays estimates of a difference–in–difference estimator for several outcomes (listed in the left–hand side column) comparing utilities (and the population of their concession area) in the North–East (column 1) and in the South–East/Midwest (column 2) to utilities in the South. Regressions include utility and year fixed effects.

Median household income grew 9% faster in the North–East than in the South. More strikingly, ownership rates of refrigerators and washing machines grew 23.5% and 38% faster over the 10–year period. An income elasticity above 1 for appliance ownership of poorer households is consistent with the "S–curve" relationship between income and appliance ownership (Wolfram et al., 2012). Trends are mostly comparable between the South–East/Midwest and the South. However, median household income and mean electricity consumption grew faster in the South by about 10% and 12%, respectively. I associate the latter trend to the electricity crisis in the paper. But an income elasticity of 1 for electricity consumption, suggested by the pattern in Figure 3a, could "explain" this change in electricity consumption by the change in income. I am able to control for changes in median household income and other trends in the analysis as there is overlapping support (e.g., in median household income levels and growth rates) between utilities in the South–East/Midwest and in the South. This is not the case when I compare utilities in the North–East (systematically poorer) and in the South. Comparing trends in this case is thus mostly descriptive: controlling for changes in median income would entirely rely on parametric assumptions.

Table 3: Price elasticity out–of–crisis and validation of price controls

	(1)	(2)	(3)	(4)
Dependent variable: Log(yearly mean of average residential consumption)				
Log(yearly mean of main residential tariff)	-.2144***	-.1829***	-.1982***	-.1889*
	(.02911)	(.02611)	(.04715)	(.09728)
First stage dependent variable: Log(yearly mean of main residential price)				
Log(yearly mean of the cost of energy in the main residential tariff)				.1768***
				(.05446)
	OLS	OLS	OLS	IV-2SLS
Years	2003–2011	2005–2011	2005–2011	2005–2011
Exclude variation from revision years	No	No	Yes	No
Observations	432	336	278	336
Clusters	48	48	48	48

Units of observation: utilities from the North–East, South–East/Midwest, and South as of 2002 (s.e. clustered by utility). Significance levels: *10%, **5%, ***1%. Monthly observations are averaged out by year. Data from 2003 to 2011 (see text). The table displays the coefficient (price elasticity) from regressing the logarithm of the yearly mean of average residential electricity consumption on the logarithm of the yearly mean of the main residential eletricity tariff. Every regression includes year–by–region and utility fixed effects. Most customers face the main electricity tariff. Smaller and poorer consumers are offered price discounts depending on the quantity consumed. However, because discounts are typically expressed as % of the main tariff, a proportional change in the main tariff captures proportional changes in prices at every consumption levels.

Column (1) includes every year post–crisis in the data. Column (2) restricts the sample to 2005–2011 because I can test for endogeneity in prices in two ways over these years. I test for endogeneity in price revisions in column (3) by excluding revision years and including utility–specific fixed effects for each between–revision period (see text). In column (4), I instrument price changes using changes in the cost of energy specific to each utility (this is only recorded in price–setting resolutions after 2004).

Using the available price variation post–crisis, I obtain a price elasticity of $-.214$, similar to Ito (2012a). The price elasticity is around $-.183$ using data from 2005 to 2011. The last two columns confirm that there is little endogeneity in price setting in Brazil. In column (3), I obtain a similar price elasticity if I only use variation from price *adjustments* (not endogeneous) and exclude price *revisions* (potentially endogenous). In column (4), I obtain a similar price elasticity if I instrument the variation in prices by the variation in the cost of energy (exogenous to the firm on a yearly basis). Endogeneity would bias estimates away from 0. Because I find no evidence of endogeneity, I control for the main electricity tariff in regressions estimating the short– and long–term effects of the conservation program.

Table 4: Predicted consumption levels based on standard responses to changes in the cost of electricity

Illustration for customers with *baseline* = 312.5 kWh, *quota* = 250 kWh

Price elasticity	st.dev. of consumption	(1) During the crisis no adjustments	(2) After the crisis no adjustments	(3) During the crisis direct adjustments
-.2	0	250	297.7	248.5
	.15	279.2	297.7	230.9

Observed median consumption levels for customers with quotas around 250 kWh:
during the crisis 195.5 kWh, after the crisis 241.75 kWh

Columns (1)–(3) use (simulations of) the standard model of electricity consumption presented in Section 3 to predict consumption levels for LIGHT customers with a quota of 250 kWh (their incentives are illustrated in Figure 2). I consider consumption levels from June to October 2001 (first five months of the crisis) and 2002 (after the crisis). Changes in the cost of electricity are due to real increases in the main tariff and to the private incentives of the conservation program. I use a price elasticity of $-.2$, as estimated in Table 3. Informed values for the standard deviation of consumption are discussed in Section 3.3.

Columns (1) and (2) assume that customers' propensity to consume electricity did not change during the crisis (no long–term adjustments). Column (3) assumes that customers' propensity to consume electricity did adjust at the start of the crisis to a new level consistent with observed consumption after the crisis (see text).

With no uncertainty, customers are predicted to bunch at their quotas (250 kWh) during the crisis (column 1, row 1), as shown in Figure 2. With consumption uncertainty, the model predicts higher consumption levels (column 1, row 2). With uncertainty, customers expecting to consume just below (resp. above) the quota will end up consuming above (resp. below) it in some states of the world. The expected marginal price thus increases (resp. decreases) on the left (resp. right) of the quota. The discontinuity in electricity cost at the quota disappears. Customers then prefer to consume above the quota (see Figure 2). As the main residential tariff of LIGHT increased by 25% from 2000 to 2002, the model predicts consumption levels below baseline after the crisis but well above the quota (column 2). Consumption uncertainty has no effect when prices are linear, which is the case out–of–crisis for these customers. Assuming that long–term adjustments happened immediately after the start of the crisis (column 3), customers are predicted to consume just below the quota with no uncertainty. With consumption uncertainty, the model now predicts lower consumption levels (7.5% below the quota), as uncertainty increases expected marginal prices on the left of the quota.

In reality, median consumption reductions for this group of customers reached 21.8% below the quota (195.5 kWh) during the crisis and 3.3% after the crisis. This suggests that standard responses to the private incentives of the conservation program are unable to explain the large conservation efforts observed during the crisis. In Section 6, I estimate how large the parameters of the standard model must be to rationalize observed consumption behaviors.

Table 5: Comparison of time–series estimates for LIGHT with different datasets and samples

	(1) Aggregate data	(2) Balanced panel (all)	(3) Balanced panel (top decile)	(4) Balanced panel (Leblon only)
Dependent variable: logarithm of monthly average residential electricity consumption				
2000	-.0106	-.0183	-.0364	-.0556
	(.0259)	(.0321)	(.0395)	(.0405)
Crisis 2001	-.43***	-.4201***	-.4814***	-.5253***
	(.0443)	(.0372)	(.0443)	(.049)
Post–crisis 2002	-.2189***	-.2307***	-.24***	-.2373***
	(.0346)	(.0354)	(.043)	(.0427)
2003	-.2408***	-.2632***	-.262***	-.2483***
	(.0323)	(.0352)	(.0418)	(.0394)
2004	-.2582***	-.2801***	-.2856***	-.2732***
	(.0275)	(.0346)	(.0421)	(.0419)
2005	-.2097***	-.2289***	-.2335***	-.2184***
	(.0303)	(.038)	(.0449)	(.0438)

Data from 2000 to 2005. Newey–West standard errors with three lags. Significance levels: *10%, **5%, ***1%. The table displays the coefficients from regressing average residential electricity consumption on time–period dummies for LIGHT customers. Regressions include calendar month fixed effects. The reference period corresponds to the first months of 2001, prior to the crisis. Column (1) uses the ANEEL administrative data. Column (2) uses a balanced panel of 44,817 randomly selected customers observed continuously over 72 months. Column (3) uses only the top decile of this panel in each month. Column (4) uses a balanced panel of 12,054 customers from Leblon, a relatively wealthy neighborhood of Rio de Janeiro.

Time–series estimates are similar when using the aggregate data, a balanced panel of customers, or larger and wealthier consumers. Therefore, measurement issues, composition effects, or energy theft (customers connecting themselves illegally to the grid) are unlikely to play a major role in estimated effects in Figure 5 or Table B.3 (at least until 2005).

Table 6: 10–year difference–in–difference (2000–2010) controlling for census data

	(1)	(2)	(3)	(4)
Dependent variable: logarithm of yearly average residential electricity consumption				
North–East excluded				
Treat × 2010	-.1195***	-.1318***	-.1197***	-.1172***
	(.0262)	(.0272)	(.0308)	(.0327)
Log main residential tariff		-.171**	-.1915**	-.1503
		(.0784)	(.0875)	(.1238)
Log median household income			.135	.3378***
			(.1107)	(.1287)
Observations	74	74	74	74
Clusters	37	37	37	37
Other controls	No	No	No	Yes
Dependent variable: logarithm of yearly average residential electricity consumption				
North–East excluded and overlapping sample				
Treat × 2010	-.1223***	-.1274***	-.1136***	-.1217***
	(.0305)	(.0301)	(.0326)	(.0442)
Log main residential tariff		-.1914*	-.1897*	-.131
		(.1055)	(.1083)	(.1409)
Log median household income			.2367	.4917***
			(.168)	(.178)
Observations	60	60	60	60
Clusters	30	30	30	30
Other controls	No	No	No	Yes

Units of observation: utilities as of 2000. Significance levels: *10%, **5%, ***1% (s.e. clustered by utility). Data from the ANEEL administrative data, from my dataset of electricity tariffs, and from the 2000 and 2010 censuses matched to the concession areas of each utility. The table displays estimates of the difference–in–difference estimator over a 10–year horizon for the logarithm of average residential electricity consumption comparing utilities in the South–East/Midwest (subject to the conservation program) and utilities in the South. The bottom panel further restricts the sample to utilities with overlapping levels of consumption and income. I exclude utilities in the North–East because of the absence of overlap in average electricity consumption and median household income in 2000 with utilities in the South. Regressions include utility and census–year fixed effects (2000 and 2010).

Column (1) does not include additional controls. Column (2) controls for the logarithm of the main residential tariff (see Section 3.2). Column (3) controls for the logarithm of median household income. Column (4) adds controls for the population size, the average household size, the share urban, the share employed, and the share of housing units with bathrooms. Results are consistent across specifications and indicate that the temporary conservation program reduced electricity consumption by 12% in the long run. Results are robust to adding more controls or to control for the logarithm of average electricity prices instrumented or not by the logarithm of the main residential tariff.

Table 7: Electricity use by source for LIGHT customers and potential impact of conservation strategies

(in 1999)	(1) Average number	(2) Average consumption	(3) Relative consumption
Lights (incandescent)	6.16	55.77 kWh	25.10%
Lights (other)	1.37	3.9 kWh	1.76%
Refrigerator	0.98	50.80 kWh	22.87%
Freezer	0.23	17.88 kWh	8.05%
Electric shower	0.62	42.97 kWh	19.34%
Air conditioning	0.35	30.45 kWh	13.71%
TV	1.51	20.39 kWh	9.18%
Baseline consumption in 1999		222.16 kWh	100%
Simulated impact of different conservation strategies			
a. CFL adoption		-12.14 kWh	-5.47%
b. CFL adoption and reduce lighting by 50%		-35.91 kWh	-16.16%
c. Unplug 50% of freezers		-8.94 kWh	-4.03%
d. Reduce TV use by 50%		-10.19 kWh	-4.59%
e. Reduce the use of electric shower by 50%		-21.48 kWh	-9.67%
f. Reduce air conditioning by 50%		-15.23 kWh	-6.85%

Electricity use and simulated impacts based on the *engineering* model constructed to estimate load curves from residential customers of LIGHT (personal communication with Professor Reinaldo Souza, PUC–Rio). The model includes seven sources of electricity consumption: lighting from incandescent light bulbs, lighting from other types of light bulbs, refrigerator, freezer, electric shower, air conditioner, and TV. Usage per day is assumed to be 40min for electric showers, 2h–5h for light bulbs (depending on their type/power), 2h for air conditioners (average over the year; 8h/day in the summer), and 5h for TVs. The model was revised in 1999 (before the crisis) and 2002 (after the crisis) using new data on appliance ownership and light bulbs' penetration rates. Lighting, refrigeration, and electric showers were the main sources of electricity use prior to the crisis.

In the bottom panel, I use the model to simulate the impact of different conservation strategies that echo reported behaviors during the crisis (Table 8). In row (a), I modify the distribution of light bulbs in 1999 to match the distribution in 2002 (CFL penetration rates increased significantly from 1999 to 2002). Based on the model, CFL adoption could have decreased electricity use by 12.14 kWh or about 5.5%. Given high adoption rates in the South after the crisis (Figure 6 and Table 8), the 9% drop in electricity consumption there could have been mostly driven by CFL adoption. In row (b), I assume that customers not only adopted CFLs but also reduced lighting by 50%. This saves 36 kWh or 16% of electricity use. Unplugging 50% of freezers (stronger response than the difference reported in Table 8) saves only 4% (row c). A similar impact would have been obtained by reducing TV use by 50% (row d), while reducing the use of electric showers by 50% would have had an impact twice as large (row e). The reduction in electricity use was large even in winter months. As a result, air conditioning cannot explain the observed electricity conservation during the crisis. Yet it could have had a large effect in the summer: reducing air conditioning by 50% on average saves 15 kWh (row f); it could thus have saved 60 kWh in the summer.

This simulation exercise reveals that CFL adoption or the unplugging of freezers cannot explain most of the reduction in electricity use observed during and after the crisis. To reduce electricity consumption by more than 30% during the crisis and more than 20% after the crisis (Figure **??**), LIGHT customers (and affected households in general) must have resorted to a series of severe conservation strategies.

Table 8: Household conservation behaviors during and after the crisis (South–East/Midwest)

	Mean	(1)		(2)		N
		Compared to the South				
Panel A: Specific conservation measures adopted before, during, and after the crisis (2005)						
1+ measure adopted during crisis	.9405	not asked in the South				2825
1+ new measure adopted during vs before crisis	.5129	not asked in the South				2825
1+ measure adopted after crisis	.8619	not asked in the South				2825
1+ new measure adopted after vs before crisis	.4867	not asked in the South				2825
Panel B: Appliances' usage intensity in 2005						
Share of appliances used less than before crisis	.388	not asked in the South				2792
At least 1 appliance used less than before crisis	.6973	not asked in the South				2792
Freezer used less than before crisis	.3774	not asked in the South				530
Panel C: Electricity–consuming behaviors in 2005						
Freezer used permanently (if owned)	.6723	-.2825***	(.0233)	-.2853***	(.0425)	986
Share of appliances on standby when not in use	.3339	-.2161***	(.0125)	-.2418***	(.0173)	3674
Share of light bulbs that are not CFLs	.6484	.3407***	(.0155)	.1745***	(.0203)	3701
Household controls		No		Yes		

Data from household surveys conducted in 2005 (PROCEL, 2007a–2007d). Panel A uses retrospective information about 14 conservation measures and whether household adopted such measures before, during, or after the crisis (see Table B.9 for each conservation measure separately). Panel B uses retrospective information about the use of eight appliances (refrigerator, air conditioner, freezer, electric shower, washing machine, standby appliances, microwave, lighting) and whether households used these appliances in 2005 less than they did before the crisis (see Table B.10 for each appliance separately). Information used in panels A and B was collected only for households subject to the conservation program. 50% of households subject to the conservation program report having adopted a new conservation measure during and after the crisis. In 2005, households report having reduced usage compared to before the crisis for about 40% of their domestic appliances (conditional on owning some appliance). 70% of households reduced usage of at least one appliance. 38% of households reduced their usage of freezers conditional on ownership.

Panel C uses information on consumption behaviors in 2005 asked of every household, and compares responses in the South–East/Midwest to responses in the South for three conservation strategies often mentioned in relation to the crisis (private communication with PROCEL): unplugging freezers, avoiding standby power use, and adopting CFLs. Column (1) controls for seven electricity consumption categories (dummies). Column (2) adds linear controls in household size, housing tenure, and the number of bathrooms; it also adds dummies for household earnings categories, gender and education of the household head, housing unit size and type, residence condition, neighborhood type, roof material, wall material, floor material, and the type of water access. Significance levels: *10%, **5%, ***1% (robust s.e. in parentheses; geographic information only identifies regions). The first two strategies were still more prevalent in the South–East/Midwest in 2005 (see Table B.11 for each standby appliance separately) but CFL penetration rates were actually higher in the South.

Table 9: The impact of exogenous variations in quota (sample of movers)

	(1) Log quota	(2) Log precrisis consumption (3 months)	(3) Log crisis consumption (first 5 months)	(4) Log crisis consumption (first 5 months)	(5) Log postcrisis consumption (same 5 months)
			OLS		
Log mean quota of same–week movers	1.084***	-.0045	.1653***	.1568***	.0699***
	(.0127)	(.0133)	(.0226)	(.0174)	(.0224)
			Quantile regressions (median)		
Log mean quota of same–week movers	.9523***	0	.1759***	.1618***	.09***
	(.0154)	(.0155)	(.0247)	(.0248)	(.0288)
Observations	18293	18293	18293	18293	18293
Controls	No	No	No	Yes	Yes

The quota assignment rule for customers who moved into their metered housing units after the *baseline* period generated variation in quotas entirely due to different moving dates (see Figure 7). Regression results here investigate the impact of this variation (s.e. clustered by moving week). The sample includes LIGHT customers whose first monthly bill was sent between March 2000 (to be sure that customers received no bills in earlier periods) and February 2001 (in order to have at least three months of pre–crisis consumption for every selected customer). I include customers who are observed continuously over a period of at least three years. Finally, I restrict my sample to customers from Rio de Janeiro whose average consumption in the three months prior to the crisis falls in the top quartile of the movers' consumption distribution. Seasonality is stronger for larger consumers.

The table displays the coefficients from regressing several outcomes (listed above each column) on the logarithm of the average quota of customers who moved into their housing units in the same week. I consider both ordinary least squares and quantile (median) regressions because the median quota for customers in this sample who moved into their housing units around the baseline period (May–July 2001) is close to 250 kWh, the quota level used to illustrate incentives and impacts throughout the paper. For quantile regressions, standard errors are obtained by bootstrapping (100 replications).

Column (1) shows that the average quota of same–week movers strongly predicts variations in quotas and could therefore serve as an instrument for movers' individual quotas. Because coefficients are close to 1, I present reduced–form results directly in the remaining columns. Column (2) shows that the same variation had no effect on average consumption levels prior to the crisis. This reinforces the exogeneity of quota variation due to different moving dates. Columns (3) and (4) investigate the impact of this variation on electricity consumption during the crisis. "Crisis consumption" is limited to the first five months of the crisis because quotas were increased in December 2001. Specifications in column (4) include controls for neighborhood (dummies) and pre–crisis consumption (logs). Because quantile regression estimators with fixed effects are inconsistent, I only control for pre–crisis consumption in the bottom panel. Coefficient estimates imply that increasing quotas by 20% (or assigning non–binding quotas) only increased consumption by less than 3.5% during the crisis. Including controls has little effect on my estimates. The effect was much smaller on consumption levels in the same months in 2002 (column 5). In later years, the effect becomes even smaller (and noisier, not shown).

Table 10: Parameter values rationalizing observed consumption behaviors during the crisis

(1)	(2)	(3)	(4)	(5)
			Fit of the model	
Fixed	Estimated parameters		Estimation sample (movers)		Out–of–sample
Price elasticity (out–of–crisis)	Price elasticity (crisis)	st. dev. of consumption	kWh crisis (quota≃250 kWh)	kWh elasticity w.r.t. quota	kWh crisis (quota≃250 kWh)
				Empirical moments	
			203.25 kWh	0.16	195.5 kWh
				Predicted moments	
-0.2	-0.946	0.399	203.24 kWh	0.16	193.76 kWh
	(.0002)	(.0001)			

I extend the model from Section 3 by allowing for a different price elasticity during the crisis. I then estimate parameter values such that the model's predictions match empirical moments in the data. I fix the price elasticity out–of–crisis (estimated in Table 3) but consider the standard deviation of consumption σ as a parameter to estimate. I assume, as in column (3) of Table 4, that customers' propensity to consume electricity did adjust at the start of the crisis to a new level consistent with observed consumption after the crisis. Therefore the model does not need to explain the long–term effects. Details of the estimation are provided in the Appendix. Asymptotic standard errors are provided in parentheses.

The two empirical moments used in the estimation are obtained from the sample of movers from Rio de Janeiro: (i) the median consumption level in the first five months of the crisis for movers whose quotas were based on the baseline period and were around 250 kWh (203.25 kWh); (ii) the elasticity of consumption with respect to quota estimated in Table 9 (.16). To assess the results' robustness, predictions of the parameterized models are also compared to an out–of–sample moment: the median electricity consumption level in the first five months of the crisis for other customers with quotas around 250 kWh (from the balanced panel, 195.5 kWh).

Estimated parameters are such that the model's predictions closely match both the empirical moments used in the estimation and the out–of–sample moment. To rationalize observed behaviors, the model requires more than twice the realized uncertainty from Section 3 and a price elasticity about fivefold larger during the crisis. This is severalfold higher than estimates in the literature, especially in a context where electric heating and air conditioning (winter months in Rio de Janeiro) are limited and where customers do not have advanced monitoring technologies. This is even more striking given that the model only needs to explain the reduction in electricity use beyond the long–term changes. Results thus indicate that the private incentives of the conservation program are unable to explain observed electricity conservation behaviors during the crisis.

A Appendix: Timeline of the crisis

March 2001	Demand management measures inevitable. Still uncertain how to proceed.
April 2001	Conservation program will begin June 1st. General idea of the incentive. Random blackouts may be necessary too.
May 2001	Conservation program revealed: individual quotas, bonuses for consumption below quota, and fines and threats of disconnection for consumption above quota. Not sure if conservation program will continue in 2002.
Early June 2001	Letters with quotas have been sent to customers. Cuts only if repeatedly above quota (second chance) and small consumers not subject to power cuts.
July 2001	Conservation program expected to last until February 2002 but may be suspended or modified earlier.
September 2001	New bonus rule. Power cuts restricted to large over–users and not legal in the city of Rio de Janeiro. Very few power cuts in practice.
November 2001	Situation in the reservoirs is improving. Conservation program should end between December and April.
December 2001	New quota rule. Quotas based on consumption levels in the previous summer or on the initial quota multiplied by an adjustment factor, whichever is higher.
January 2002	Quotas increased again in February and no more fines in February–March (only bonuses). Conservation program will stop at the end of February.
End of February 2002	Conservation program officially over.

B Appendix: Simulations

Simulations of models of decisions presented in Section 6 are performed in Matlab. Codes are available upon request. Results from Table 4 are obtained using the Nelder–Mead algorithm to maximize the utility function under (non–linear) electricity costs. In the case of uncertainty, expected costs are based on 100,000 draws of consumption level q from a normal distribution with mean $\overline{q}$ and standard deviation σq. In the case of responses to average prices instead of marginal prices, I use a fixed–point approach: given a value of $\overline{q}$, I calculate the (expected) average price p and the target consumption $\widetilde{q}$ consistent with such a price: $\widetilde{q} = ap^{\epsilon}$. I then use the Nelder–Mead algorithm to minimize the squared difference between $\overline{q}$ and $\widetilde{q}$.

Results presented in Table 10 are obtained using empirical moments for the sample of movers (see text). The first moment ($M1$) is a median consumption level of 203.25 kWh for customers with quotas of 250 kWh (and whose quotas are based on the baseline period). The second moment ($M2$) is a consumption level of 212.36 kWh if their quotas are increased to 320 kWh (as obtained from an elasticity of consumption w.r.t. quota estimated at 0.16). The simulations take into account the fact that post–crisis median consumption levels are around 259 kWh for the same group of customers (to calibrate a_i, see text). I minimize the inner product of the difference between empirical and simulated moments using the Nelder–Mead algorithm: $\left(\widehat{M1} - M1 \quad \widehat{M2} - M2\right)\left(\widehat{M1} - M1 \quad \widehat{M2} - M2\right)'$. To provide initial values for the algorithm, I first perform a broader grid search. Asymptotic standard errors are obtained by simulating numerical derivatives of the objective function with respect to the parameters (100 simulations) and taking the average of the outer product of these derivatives.

Electricity tariffs were R$.187/kWh, R$.208/kWh, and R$.238/kWh in 2000, 2001, and 2002, respectively.

Table B.1: More descriptive statistics in 2000

	(1) South	(2) South–East/Midwest	(3) LIGHT	(4) North–East
Household				
Urban	.7958	.8618	.9913	.7312
Household size	3.458	3.508	3.29	4.113
Number of rooms	6.164	5.82	5.473	5.619
Has computer	.1006	.1089	.1793	.0453
Individuals (18–55 years old)				
Employed	.6929	.6611	.6135	.5773
Formally employed	.31	.2972	.3038	.1672
Agricultural job	.1259	.1016	.0049	.142

Units of observation: utilities as of 2000 (13 in the South, 24 in the South–East/Midwest, and 10 in the North–East). Statistics are obtained by matching data at the household level from the 2000 census to the concession area of each utility.

Table B.2: Descriptive statistics in 2010

	(1) South	(2) South–East/Midwest	(3) LIGHT	(4) North–East
Household				
Mean electricity consumption (kWh)	167	169.8	203.3	106
Mean electricity price (R$/kWh)	.1683	.1658	.1593	.1486
Urban	.827	.8857	.9908	.759
Household size	3.056	3.102	2.985	3.516
Number of rooms	6.213	5.874	5.423	5.735
Has bathroom	.9803	.9912	.9941	.8802
Has electricity	.9964	.9968	.9994	.9828
Has TV	.9707	.9681	.986	.9341
Has refrigerator	.981	.9744	.9853	.8759
Has washing machine	.6497	.5477	.705	.198
Has computer	.4439	.4344	.5304	.2216
Has air conditioner	N/A	N/A	N/A	N/A
Median income (R$)	896	850.4	865.2	473.2
Individuals (18–55 years old)				
Employed	.7498	.7233	.6746	.575
Formally employed	.4777	.4547	.444	.2624
Agricultural job	.102	.0844	.0046	.1209

Units of observation: utilities as of 2000 (13 in the South, 24 in the South–East/Midwest, and 10 in the North–East). Statistics are obtained by matching data at the household level from the 2010 census to the concession area of each utility (ownership of air conditioners is not recorded in the 2010 census). Data on average residential consumption and average price are obtained from the ANEEL administrative data. Price and income levels are in R$ of 2000. The exchange rate in 2000 was about R$1.9≃US$1.

Table B.3: First difference–in–difference results (no controls)

	(1) Control region		(2) Differential trends in areas subject to the government program		(3)		(4)	
1996	-.0176*	(.0104)	-.0081	(.0199)	.0067	(.0126)	.0133	(.0133)
1997	-.0156***	(.0057)	.0181	(.0163)	.0354***	(.0081)	.0401***	(.0079)
1998	-.0024	(.0063)	.0671***	(.0144)	.0443***	(.0089)	.0443***	(.0099)
1999	-.0016	(.0068)	.0284**	(.0136)	.0254***	(.0078)	.024***	(.0086)
2000	-.0098**	(.0043)	.0287***	(.0102)	.0193***	(.0052)	.0193***	(.0059)
Crisis	-.0902***	(.0039)	-.2124***	(.0167)	-.2552***	(.0082)	-.2486***	(.0087)
Rest of 2002	-.0578***	(.0081)	-.1389***	(.0114)	-.1707***	(.0099)	-.1721***	(.0113)
2003	-.087***	(.0067)	-.0596***	(.0115)	-.1347***	(.0088)	-.1336***	(.0104)
2004	-.0892***	(.0108)	-.0644***	(.0153)	-.1373***	(.0135)	-.136***	(.0157)
2005	-.0743***	(.0114)	-.065***	(.0179)	-.131***	(.0145)	-.1325***	(.0168)
2006	-.081***	(.0112)	-.0521**	(.0207)	-.1224***	(.0157)	-.1231***	(.018)
2007	-.0598***	(.0132)	-.0587***	(.0222)	-.1168***	(.0182)	-.1221***	(.021)
2008	-.0585***	(.0131)	-.0348	(.0222)	-.1096***	(.0184)	-.1137***	(.0212)
2009	-.0311**	(.015)	-.0349	(.0249)	-.1107***	(.0192)	-.1141***	(.0219)
2010	-.0125	(.0148)	-.0053	(.0233)	-.1057***	(.0187)	-.1081***	(.0212)
2011	.0071	(.0122)	-.0049	(.0246)	-.1148***	(.018)	-.1148***	(.0205)
Regions	South		S/NE		S/SE/MW		S/SE/MW	
Restricted sample	No		No		No		Yes	
Observations	2112		4032		6528		5376	
Clusters	11		21		34		28	

Units of observation: utilities as of 1995. Significance levels: *10%, **5%, ***1% (s.e. clustered by utility). Data from 1996 to 2011. The table displays the coefficients from regressing the logarithm of monthly average electricity consumption per customer for each utility on time–period dummies (trends in the South, not subject to the conservation program) and those dummies interacted with an indicator for utilities subject to the conservation program during the crisis (difference–in–difference estimators in every time period). The reference period corresponds to the first months of 2001, prior to the crisis. Regressions include utility and calendar month–per–region fixed effects.

Column (1) reproduces coefficients on the time–period dummies (yearly dummies, three dummies for 2001–2002 to isolate the crisis period). Column (2) presents the differential trends in the North–East (T) compared to the South (C). Column (3) does the same comparing utilities in the South–East/Midwest (T) and in the South (C). Column (4) restricts the sample in column (3) to utilities with overlapping average consumption and median income levels in 2000. Results are similar to the ones discussed in Figure 5 (with controls).

Table B.4: Difference–in–difference results with controls

	(1)		(2)		(3)	
	Differential trends in areas subject to the government program					
1996	.0045	(.0203)	.0005	(.0134)	.0004	(.015)
1997	.0269	(.0177)	.0287***	(.0093)	.0283***	(.0096)
1998	.0762***	(.0162)	.0372***	(.0102)	.0324***	(.0113)
1999	.039**	(.0154)	.0165*	(.0094)	.0108	(.0114)
2000	.0341***	(.0122)	.0143**	(.0063)	.0127*	(.0075)
Crisis	-.2127***	(.0165)	-.256***	(.0079)	-.2499***	(.0082)
Rest of 2002	-.1356***	(.0131)	-.1716***	(.0103)	-.1737***	(.0116)
2003	-.0568***	(.0117)	-.1329***	(.0097)	-.1309***	(.0112)
2004	-.0587***	(.0149)	-.1362***	(.0147)	-.1339***	(.0167)
2005	-.0592***	(.0178)	-.1315***	(.016)	-.128***	(.0176)
2006	-.0496**	(.0212)	-.1266***	(.0171)	-.1225***	(.0185)
2007	-.0649***	(.0229)	-.1262***	(.0191)	-.1267***	(.0206)
2008	-.037*	(.0193)	-.1207***	(.0182)	-.125***	(.0186)
2009	-.0408**	(.0205)	-.1188***	(.0187)	-.1226***	(.0183)
2010	-.0172	(.0234)	-.1125***	(.0197)	-.1165***	(.0193)
Log main residential tariff	-.1127**	(.0482)	-.0738**	(.0334)	-.1252***	(.0368)
Log population	.1712	(.1179)	.0451	(.0819)	-.0043	(.0977)
Log share formally employed	.0824	(.0632)	.0881**	(.0379)	.0582	(.0488)
Log median formal real wage	.0411	(.0895)	-.0867	(.0719)	-.048	(.0808)
Regions	S/NE		S/SE/MW		S/SE/MW	
Restricted sample	No		No		Yes	
Observations	3780		6120		5040	
Clusters	21		34		28	

Units of observation: utilities as of 1995. Significance levels: *10%, **5%, ***1% (s.e. clustered by utility). Data from 1996 to 2011. The table displays the coefficients from regressing the logarithm of monthly average electricity consumption per customer for each utility on time–period dummies (trends in the South, not subject to the conservation program) and those dummies interacted with an indicator for utilities subject to the conservation program during the crisis (difference–in–difference estimators in every time period). The reference period corresponds to the first months of 2001, prior to the crisis. Regressions include utility and calendar month–per–region fixed effects. Regressions also control for the logarithm of the main residential electricity tariffs (see Section 3.2) and available municipal yearly data matched to the concession area of each utility (log population, log share formally employed, log real median formal wage). Population estimates come from IBGE (Instituto Brasileiro de Geografia e Estatística). Data on formal employment and formal wages come from the Brazilian labor ministry (RAIS data; Relação Anual de Informações).

Column (1) presents the differential trends in the North–East (T) compared to the South (C). Column (2) does the same comparing utilities in the South–East/Midwest (T) and in the South (C). Column (3) restricts the sample in column (3) to utilities with overlapping average consumption and median income levels in 2000. Results are presented graphically and discussed in Figure 5. Results are similar when controlling only for the logarithm of the main electricity tariff. Results are also similar if I control for the logarithm of average electricity prices instrumented or not by the logarithm of the main electricity tariff. Because formality levels increased over time, formal wages may not accurately capture changes in household income (selection). I directly control for household income in Table 6.

Table B.5: Difference–in–difference results (winter months and no controls)

	(1) Control region		(2) Differential trends in areas subject to the government plan		(3)		(4)	
1996	-.0098	(.0097)	-.0418**	(.0178)	-.01	(.0116)	-.0024	(.0119)
1997	-.0014	(.0059)	-.0226**	(.0109)	.0209***	(.0078)	.0266***	(.0087)
1998	.0059	(.0049)	.0386***	(.0136)	.0281***	(.0081)	.0269***	(.0093)
1999	.0071	(.0079)	-.0077	(.0132)	.0059	(.0081)	.0034	(.0087)
Crisis	-.0901***	(.0047)	-.214***	(.013)	-.2665***	(.0073)	-.2624***	(.0078)
2002	-.0512***	(.0105)	-.1585***	(.0172)	-.1838***	(.0117)	-.1872***	(.0128)
2003	-.0834***	(.0086)	-.0901***	(.0167)	-.1547***	(.0099)	-.1546***	(.0115)
2004	-.0697***	(.0182)	-.1168***	(.0235)	-.1664***	(.0194)	-.1683***	(.0214)
2005	-.0662***	(.0136)	-.111***	(.0256)	-.1451***	(.0162)	-.1487***	(.0183)
2006	-.0823***	(.0139)	-.0791***	(.0305)	-.1319***	(.0178)	-.133***	(.0201)
2007	-.0563***	(.014)	-.0901***	(.0273)	-.1326***	(.0191)	-.1376***	(.022)
2008	-.0524***	(.0148)	-.0687**	(.0301)	-.1221***	(.0192)	-.1296***	(.0218)
2009	-.0287*	(.0171)	-.0656*	(.0337)	-.126***	(.0209)	-.1301***	(.0239)
2010	-.0084	(.0159)	-.0478	(.0289)	-.126***	(.02)	-.1298***	(.0229)
2011	.0191	(.0128)	-.0419	(.0321)	-.1342***	(.0196)	-.1358***	(.0232)
Regions	South		S/NE		S/SE/MW		S/SE/MW	
Restricted sample	No		No		No		Yes	
Observations	1045		1995		3230		2660	
Clusters	11		21		34		28	

Units of observation: utilities as of 1995. Significance levels: *10%, **5%, ***1% (s.e. clustered by utility). Data from 1996 to 2011, restricted to winter months (May–October). The table displays the coefficients from regressing the logarithm of monthly average electricity consumption per customer for each utility on time–period dummies (trends in the South, not subject to the conservation program) and those dummies interacted with an indicator for utilities subject to the conservation program during the crisis (difference–in–difference estimators in every time period). The reference period corresponds to 2000, as the first months of 2001 prior to the crisis were not in the winter. Regressions include utility and calendar month–per–region fixed effects.

Column (1) reproduces coefficients on the time–period dummies (yearly dummies, three dummies for 2001–2002 to isolate the crisis period). Column (2) presents the differential trends in the North–East (T) compared to the South (C). Column (3) does the same comparing utilities in the South–East/Midwest (T) and in the South (C). Column (4) restricts the sample in column (3) to utilities with overlapping average consumption and median income levels in 2000. Results restricted to winter months are similar to results in Table B.3, excluding air conditioning as a major explanatory mechanism.

Table B.6: Difference–in–difference results for reported distribution losses

	(1) Average residential consumption (logs)		(2) Total losses (logs)		(3) Technical losses (logs)		(4) Non–technical losses (logs)	
1998	.0402***	(.0141)	-.019	(.1373)	.0477	(.1363)	-.167	(.295)
1999	.0124	(.0085)	-.033	(.1375)	.0558	(.184)	-.2543*	(.1431)
2001	-.1491***	(.0078)	-.1731	(.1908)	-.186	(.1694)	-.1428	(.4036)
2002	-.1938***	(.0154)	-.0919	(.1513)	-.144	(.1367)	.0049	(.374)
2003	-.1514***	(.0148)	-.1218	(.1262)	-.1988*	(.1087)	-.0155	(.3792)
2004	-.1635***	(.0219)	-.0812	(.218)	-.1468	(.1858)	-.0242	(.4861)
2005	-.159***	(.0304)	-.1709	(.1528)	-.1854	(.1571)	-.1542	(.3565)
2006	-.1527***	(.0324)	-.1757	(.1099)	-.1527	(.1273)	-.2429	(.3385)
2007	-.1431***	(.0346)	-.2194**	(.1079)	-.2017*	(.1168)	-.3407	(.2663)
2008	-.136***	(.0353)	-.2385*	(.1409)	-.2186	(.1502)	-.3183	(.2943)
2009	-.1291***	(.0366)	-.1346	(.1321)	-.123	(.1458)	-.0093	(.4651)
Clusters	20		20		20		20	
Observations	240		240		240		240	

Units of observation: utilities from the South–East/Midwest and the South reporting technical and non–technical losses prior to 2000 (7 utilities in the South, 13 in the South–East/Midwest). Significance levels: *10%, **5%, ***1% (s.e. clustered by utility). Yearly data from 1998 to 2009. Distribution losses are the share of the load not attributed to particular customers. Distribution losses are divided into technical (engineering estimates) and non–technical (residual, including theft) losses. It is unclear how companies separately identify the two categories and the resulting information is noisy. The table displays the coefficients from regressing several outcomes (listed above each column) on year dummies interacted with an indicator for utilities subject to the conservation program during the crisis (difference–in–difference estimators in every time period). Regressions include year dummies (trends in the South, not subject to the conservation program) and utility fixed effects. The reference period corresponds to 2000.

Column (1) replicates results from Table B.3 at the yearly level for this sample of utilities (consumption was slightly higher in 1998 in Table B.3). The long–term effects on average residential electricity consumption are very similar. Columns (2)–(4) use the data about losses. Results are very noisy. I find large persistent reductions in total and technical losses (columns 2 and 3). This may be mechanical if engineering losses are proportional to load. Estimates for non–technical losses are inconclusive (column 4). They are noisy and vary widely from year to year: they were lower for “treated” utilities in 1999 and 2001; estimates were then similar to 2000 in 2002 to 2004, but lower again after 2005.

Table B.7: Difference–in–difference for appliance ownership (South–East/Midwest vs South)

	(1) Refrigerator		(2) Refrigerator		(3) Freezer		(4) Freezer	
1996	.0017	(.0071)	-.0003	(.0068)	.0158*	(.0091)	.0146*	(.0088)
1997	.0043	(.0112)	.0003	(.0104)	.0133**	(.0064)	.0064	(.0064)
1998	.0057	(.0159)	.0053	(.0148)	.0149	(.0115)	.0127	(.0117)
1999	.0074	(.0168)	.0083	(.0147)	.0126	(.0102)	.0112	(.0105)
2001	.0085	(.0229)	.0059	(.0205)	.0006	(.0142)	-.0012	(.0139)
2002	.0022	(.0271)	.0019	(.024)	-.0067	(.0157)	-.007	(.0159)
2003	.0063	(.0273)	.0064	(.0236)	-.012	(.0199)	-.0107	(.0193)
2004	.0073	(.0289)	.0074	(.0249)	-.0093	(.0227)	-.0064	(.0221)
2005	.0021	(.0296)	.0008	(.0259)	-.0083	(.0216)	-.0086	(.0213)
2006	-.0002	(.0327)	.0003	(.0287)	-.0106	(.0243)	-.0104	(.0236)
2007	.0019	(.0341)	.0027	(.03)	.0031	(.0253)	.0038	(.0253)
2008	.0067	(.0365)	.0064	(.0325)	-.0001	(.0236)	.0005	(.024)
2009	.0041	(.0375)	.0053	(.0329)	-.0062	(.0267)	-.0022	(.0264)
Household controls	No		Yes		No		Yes	
Observations	882774		861689		882741		861656	
Clusters	26		26		26		26	

Significance levels: *10%, **5%, ***1% (s.e. clustered by state–area). Areas can be of three types: metropolitan, other urban, rural. Data from yearly household surveys representative of the country population (PNAD surveys, conducted in September each year) from 1995 until 2009. The survey was not conducted in 2000 because a census was conducted instead. Unfortunately, the census does not record freezer ownership. Refrigerator ownership rates in 1999 were 91.6% in both the South–East/Midwest and the South. Freezer ownership rates in 1999 were 20.9% and 35% in the South–East/Midwest and the South, respectively.

The table displays the coefficient from regressing an indicator for whether a household owns a refrigerator or a freezer on year dummies interacted with an indicator for states subject to the conservation program during the crisis (difference–in–difference estimators in every time period). The reference year is 1995. Regression includes fixed effects for states subject to the conservation program during the crisis, area type, and year. Columns (2) and (4) include additional controls for household income (cubic), household size, the type of housing unit, the occupancy status, the number of rooms, and whether the unit includes a bathroom. Observations are weighted by the survey weights.

Results indicate no differential trend in refrigerator ownership and at most a very small effect (1%, not significant) in freezer ownership after the crisis.

Table B.8: Substitution toward more efficient light bulbs (South–East/Midwest)

	Category	(1) All	(2) Some	(3) No	Obs.
Did you substitute CFLs for incandescent light bulbs?	$<$ 200 kWh	.29	.1	.61	1901
	$\geq$ 200 kWh	.44	.16	.39	791
Did you keep using the CFLs afterwards?	$<$ 200 kWh	.66	.09	.25	708
	$\geq$ 200 kWh	.72	.08	.2	455

Data from household surveys conducted in 2005 (PROCEL, 2007a–2007d). I use retrospective information about CFLs adoption during and after the crisis. I separate households into two electricity consumption categories. These questions were only asked of households in areas subject to the conservation program during the electricity crisis.

Many households substituted CFLs for incandenscent light bulbs during the crisis and persisted in doing so.

Table B.9: Adoption of specific conservation measures (South–East/Midwest)

Consumption category	(1) < 200 kWh/month Before crisis	(2) < 200 kWh/month During crisis	(3) < 200 kWh/month After crisis	(4) ≥ 200 kWh/month Before crisis	(5) ≥ 200 kWh/month During crisis	(6) ≥ 200 kWh/month After crisis
Turn off lights when away for more than half an hour	.79	.91	.84	.8	.94	.86
Open refrigerator/freezer fewer times	.51	.75	.63	.51	.75	.61
Do not keep warm food in refrigerator/freezer	.58	.79	.71	.62	.83	.72
Reduce shower time when using electric shower	.45	.69	.68	.45	.71	.66
Use summer vs winter setup for electric shower	.46	.63	.62	.52	.66	.63
Use washing machine and dishwasher at full capacity	.29	.44	.44	.41	.6	.58
Accumulate clothes to iron	.39	.57	.56	.47	.67	.64
Switch off air conditioner when away for more than half an hour	.02	.03	.02	.06	.08	.07
Turn off electronic devices not in use for more than half an hour	.51	.64	.59	.54	.66	.61

Data from household surveys conducted in 2005 (PROCEL, 2007a–2007d). I use retrospective information on the adoption of specific conservation measures before, during, or after the crisis (in 2005). I separate households into two electricity consumption categories. These questions were only asked of households in areas subject to the conservation program during the electricity crisis. I report unconditional adoption shares. Nine out of the 14 conservation measures are reported in the table. The other conservation measures are (a) Do not dry clothes behind refrigerator/freezer, (b) Periodically verify if the rubber seal of the refrigerator is in good condition, (c) Do air conditioner maintenance, (d) Consider natural ventilation and lighting when buying, renting, remodeling, or building a housing unit, (e) Explain to household members and/or employees how to best use energy to avoid waste.

In all cases, the share of households adopting a particular behavior was higher during and after the crisis.

Table B.10: Appliance usage after the crisis (South–East/Midwest)

Appliance	Consumption category	(1) Use as before crisis	(2) Use less than before crisis	(3) Disconnected or disposed of	(4) Substituted with more efficient	N
Refrigerator	$<$ 200 kWh	.87	.11	0	.02	1901
	$\geq$ 200 kWh	.9	.08	0	.02	809
Air	$<$ 200 kWh	.25	.67	.08	0	79
conditioning	$\geq 200kWh$	.31	.65	.02	.02	133
Freezer	$<$ 200 kWh	.51	.27	.21	0	193
	$\geq$ 200 kWh	.68	.19	.12	.01	337
Electric	$<$ 200 kWh	.54	.44	.01	0	1767
shower	$\geq 200kWh$	.62	.37	.01	0	747
Washing	$<$ 200 kWh	.37	.62	.01	0	1259
machine	$\geq 200kWh$	.49	.5	.01	.01	723
Standby	$<$ 200 kWh	.55	.38	.07	0	1367
appliances	$\geq 200kWh$	.7	.26	.04	0	676
Microwave	$<$ 200 kWh	.47	.5	.03	0	425
	$\geq$ 200 kWh	.6	.39	.02	0	458
Lighting	$<$ 200 kWh	.47	.46	0	.07	1928
	$\geq$ 200 kWh	.46	.42	0	.11	807

Data from household surveys conducted in 2005 (PROCEL, 2007a–2007d). I use information on whether, in 2005, households (1) used a given appliance as much as before the crisis, (2) used the appliance less than before the crisis, (3) stopped using the appliance, or (4) substituted a more efficient appliance. I separate households into two electricity consumption categories. These questions were only asked of households in areas subject to the conservation program during the electricity crisis. I report share of responses, conditional on ownership of the appliance.

In most cases, respondents report using their appliances less than before the crisis (except for refrigerators, which is reassuring given that we don't expect much flexibility in refrigerator usage). Few report replacing appliances with more efficient products (households could only provide one response for each appliance).

Table B.11: Standby power use (South–East/Midwest)

	Mean	(1) Compared to the South		(2)		N
Is your appliance on standby when not in use?						
TV	.5307	-.1771***	(.0174)	-.2058***	(.0245)	3592
Air conditioner	.1429	-.2834***	(.0478)	-.3387***	(.0557)	373
Sound system	.3939	-.2075***	(.0207)	-.3238***	(.0287)	2531
Radio	.1449	-.0728**	(.0363)	-.0873*	(.0451)	1164
Video	.362	-.1816***	(.0334)	-.1833***	(.0478)	1162
DVD	.4688	-.2894***	(.0307)	-.3815***	(.0465)	979
Computer	.2339	-.1707***	(.0355)	-.1489***	(.0487)	835
Printer	.2179	-.0109	(.0413)	-.0021	(.059)	493
Microwave	.2106	-.3386***	(.0295)	-.2837***	(.0398)	1236
Electric oven	.0221	-.0063	(.026)	-.0373	(.0463)	302
Ceiling fan	.0582	.0435***	(.012)	.0656**	(.0303)	916
TV subscription box	.6667	-.0123	(.0382)	.0454	(.073)	763
Household controls		No		Yes		

Data from household surveys conducted in 2005 (PROCEL, 2007a–2007d). Significance levels: *10%, **5%, ***1% (robust s.e. in parentheses; geographic information only identifies regions). The table displays the coefficient from regressing an indicator for whether households in 2005 reported leaving each appliance on standby when not using it on an indicator for households living in areas subject to the conservation program during the crisis (South–East/Midwest compared to South). Column (1) controls for seven electricity consumption categories (dummies). Column (2) adds linear controls in household size, housing tenure, and the number of bathrooms; it also adds dummies for household earnings categories, gender and education of the household head, housing unit size and type, residence condition, neighborhood type, roof material, wall material, floor material, and the type of water access.

In most cases, households are more likely to avoid wasting standby electricity in the South–East/Midwest. The opposite appears true only for an appliance whose use is associated with hot weather (ceiling fan): temperatures are higher in the South–East/Midwest.

Table B.12: Alternative approach to rationalize observed consumption behaviors during the crisis

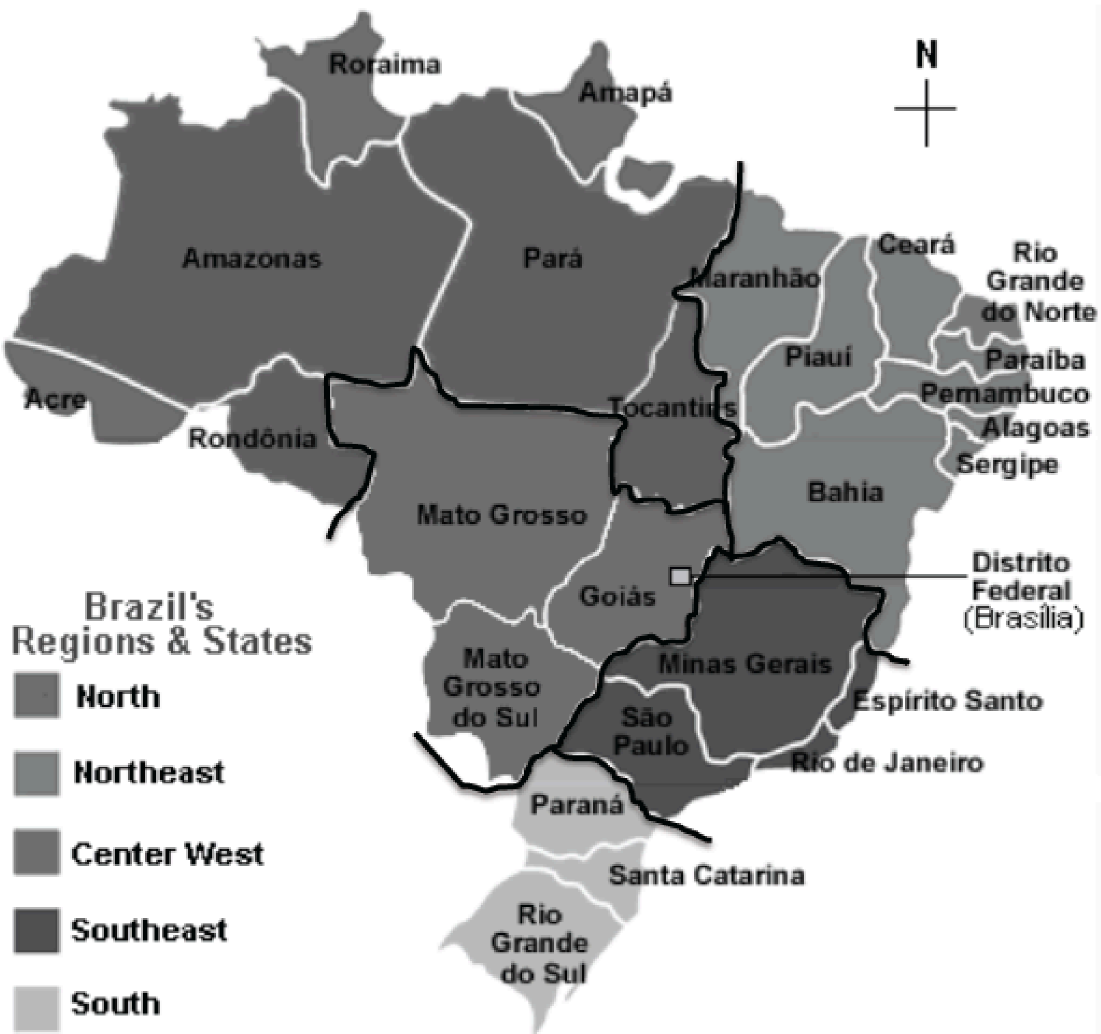
	(1)	(2)	(3)	(4)	(5)
				Fit of the model	
Fixed	Estimated parameters		Estimation sample (movers)		Out–of–sample
Price elasticity	Perceived penalty	st. dev. of consumption	kWh crisis (quota≃250 kWh)	kWh elasticity w.r.t. quota	kWh crisis (quota≃250 kWh)
				Empirical moments	
			203.25 kWh	0.16	195.5 kWh
				Predicted moments	
-0.2	R$115.52	0.5	202.92 kWh	0.168	189.28 kWh
	(.7034)	(0)			

I extend the model from Section 3 by allowing customers to overestimate the penalty for consuming above the quota. I then estimate parameter values such that the model's predictions match empirical moments in the data. I fix the price elasticity (estimated in Table 3) but consider the standard deviation of consumption σ as a parameter to estimate. I assume, as in column (3) of Table 4, that customers' propensity to consume electricity did adjust at the start of the crisis to a new level consistent with observed consumption after the crisis. Therefore the model does not need to explain the long–term effects. Details of the estimation are provided in the Appendix. Asymptotic standard errors are provided in parentheses.

The two empirical moments used in the estimation are obtained from the sample of movers from Rio de Janeiro: (i) the median consumption level in the first five months of the crisis for movers whose quotas were based on the baseline period and were around 250 kWh (203.25 kWh); (ii) the elasticity of consumption with respect to quota, estimated in Table 9 (.16). To assess the results' robustness, predictions of the parameterized models are also compared to an out–of–sample moment: the median electricity consumption level in the first five months of the crisis for other customers with quotas around 250 kWh (from the balanced panel, 195.5 kWh).

Estimated parameters are such that the model's predictions closely match the empirical moments used in the estimation. The match out of sample is not as good as in Table 10. To rationalize observed behaviors, the model requires three times the realized uncertainty from Section 3 and a perceived penalty more than 20 times larger than the actual penalty (R$5.2). This is a striking overestimation, especially given that the model only needs to explain the reduction in electricity use beyond the long–term changes. Results thus indicate that the private incentives of the conservation program are hardly able to explain observed electricity conservation behaviors during the crisis.

Figure B.1: Regions of Brazil



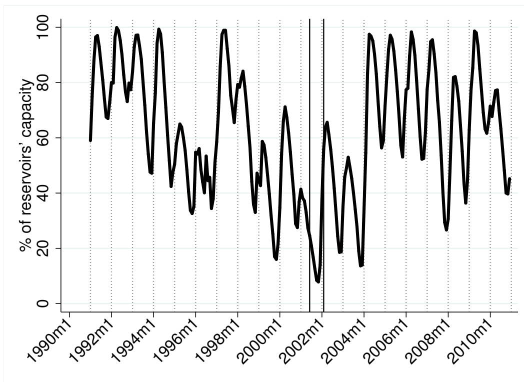
The National Interconnected System includes the following subsystems:

- the South region (South subsystem, not subject to the conservation program);
- the South–East and Midwest regions, with the exception of a few isolated customers in Mato Grosso and Mato Grosso do Sul (South–East/Midwest subsystem, subject to the conservation program from June 2001 until February 2002);
- the North–East region, with the exception of part of Maranhão (North–East subsystem, subject to the conservation program from June 2001 until February 2002);
- the Northeastern states of Para and Tocantins, and part of the state of Maranhão, with the exception of isolated systems (North subsystem, subject to a conservation program from August 2001 until December 2001).

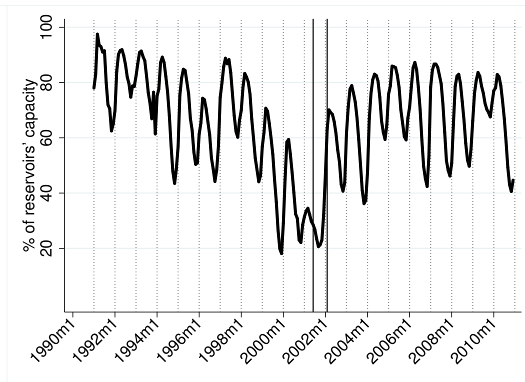
Customers in other states (mostly in the Amazonia) are served by isolated systems.

Figure B.2: Level of the reservoirs in the three main subsystems over 20 years

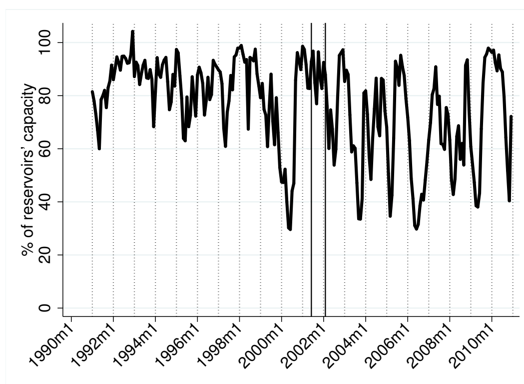
(a) North–East



(b) South–East/Midwest



(c) South

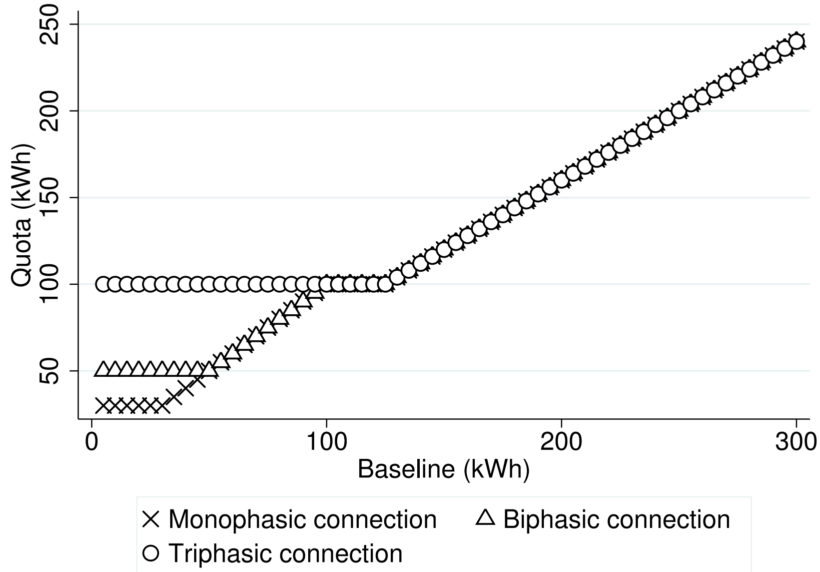


Source: ONS (personal communication)

Dotted vertical lines identify January in each year. Solid vertical lines identify the start and end of the conservation program. The graphs display the evolution of hydro–reservoirs' capacity in percentage of the maximum capacity in the three main subsystems in Brazil. In panels (a) and (b), there is a clear seasonal pattern, with rainfall replenishing reservoirs in the summer. In the summer of 2000–2001, rainfall was exceptionally unfavorable in the North–East and South–East/Midwest, leading to dangerously low levels in 2001. Over a period of 20 years, the rainfall pattern in 2000–2001 was a unique outlier. Even in the South, reservoir levels were very low in 2000. The situation of the reservoirs was stable in the South–East/Midwest but more variable in the South after the crisis. The risk of new shortages was thus not smaller in the South.

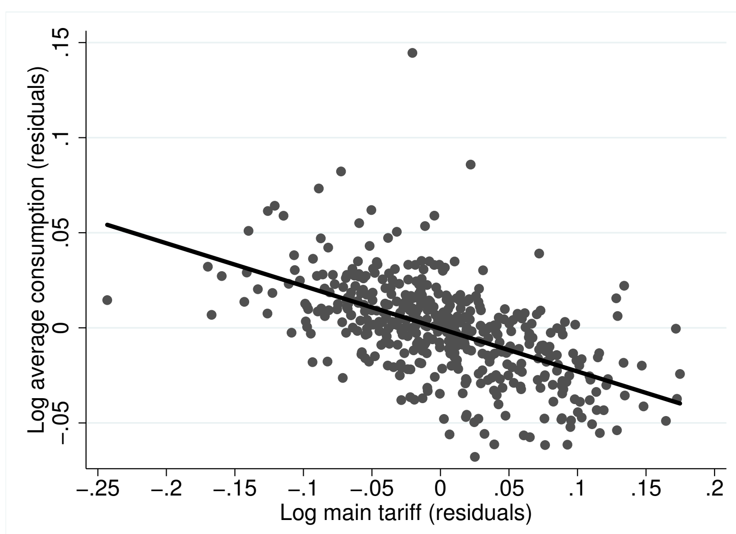
Figure B.3: Main assignment rule for quotas of residential customers during the electricity crisis

(customers of the LIGHT distribution utility)



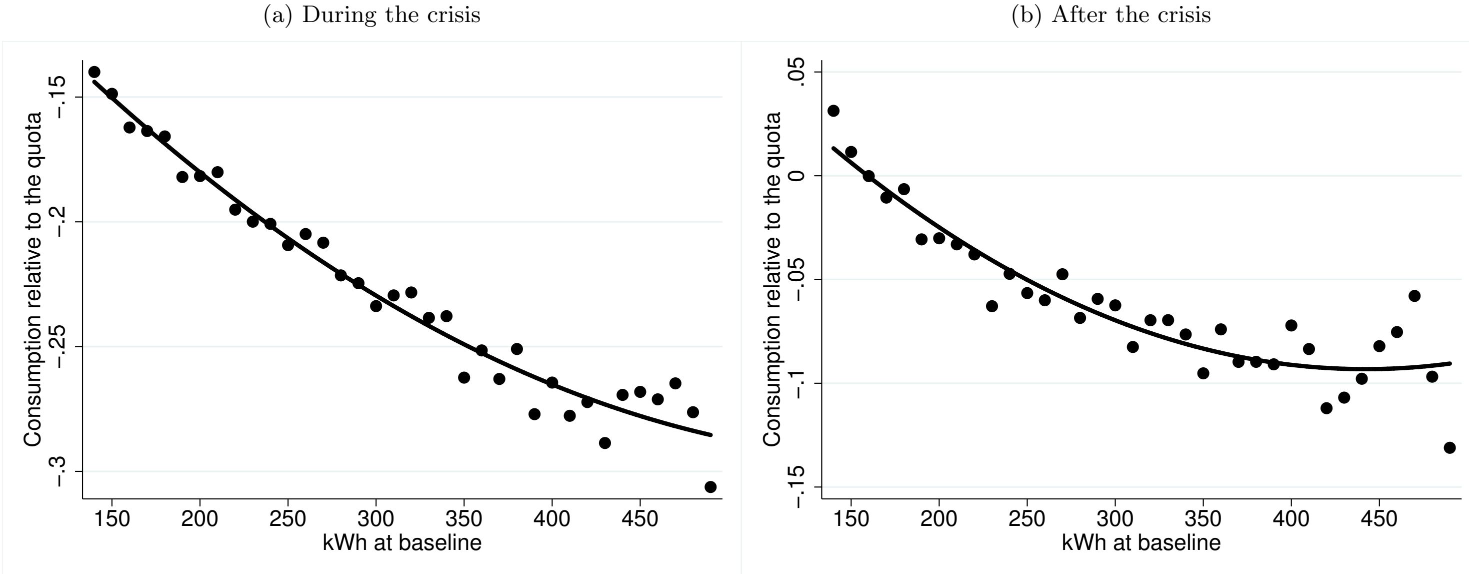
The baseline was defined as the average billed monthly consumption from May to July 2000. Quotas were set at 80% of the baseline for most customers with three exceptions: (i) customers with a baseline below 100 kWh had their quotas set at 100% of baseline; (ii) customers with a baseline above 100 kWh but quotas below 100 kWh with the 80% rule had their quotas set at 100 kWh; (iii) because quotas were based on billed consumption and bills always charge minimum consumption levels in Rio de Janeiro (30 kWh, 50 kWh, and 100 kWh for monophasic, biphasic, and triphasic connections, respectively), quotas were at least equal to these minimum levels.

Figure B.4: Variation behind price elasticity estimates



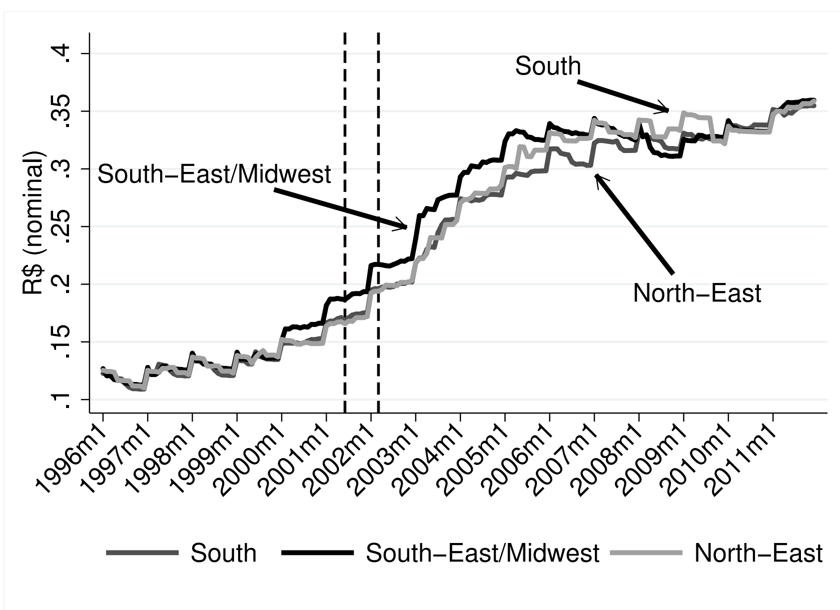
Units of observation: utilities from the North–East, South–East/Midwest, and South as of 2002. Monthly observations are averaged out by year. Data are from 2003 to 2011 (see text). The graph displays the correlation between the logarithm of average yearly residential electricity consumption and the logarithm of the average yearly main residential electricity tariff. It presents graphically the variation behind the price elasticity estimates in column (1) in Table 3. Price and consumption residuals are obtained from first regressing each variable on year–by–region and utility fixed effects.

Figure B.5: Consumption compared to quota (average by baseline consumption levels)



Average electricity consumption in June–October 2001 (panel (a), crisis) and 2002 (panel (b), post–crisis) compared to quotas, as a function of *baseline* consumption levels (average of May, June, and July 2000). Sample based on a balanced panel of LIGHT customers (see text). I restrict attention to customers whose quotas were set at 80% of baseline. At every baseline level, consumption was more than 15% below quota or 32% below baseline during the crisis. Larger consumers at baseline reduced consumption by more than 25% below their quotas or 40% below baseline. After the crisis, average consumption was still below quota for all but the smallest consumption categories. A similar analysis with a placebo sample (as if the crisis had happened in 2004) reveals that mean reversion cannot explain most of the decreasing slope.

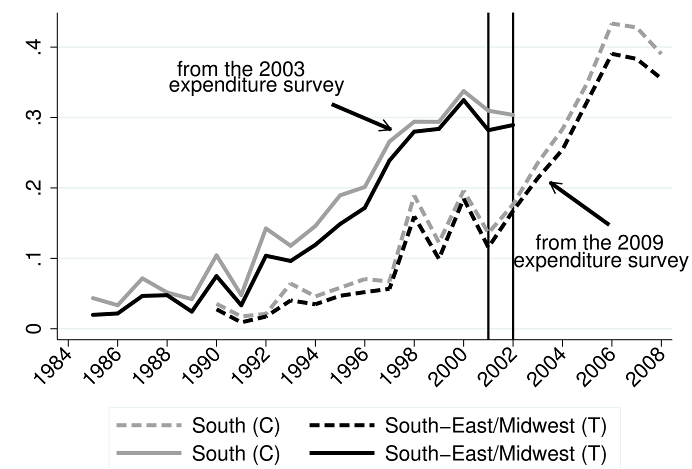
Figure B.6: Monthly average of the main residential electricity tariff by subsystem



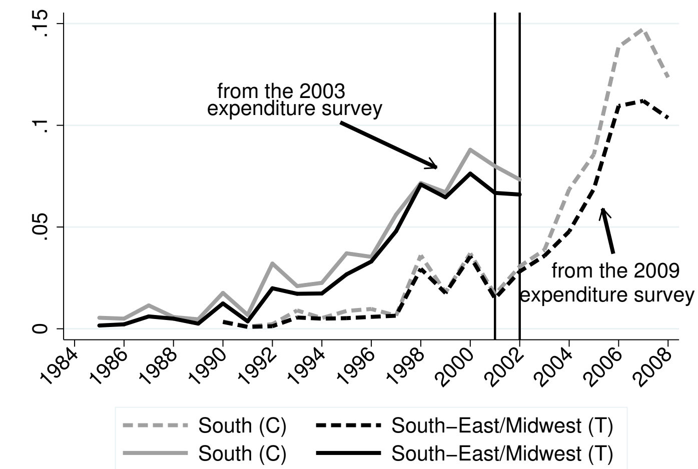
Vertical lines identify the start and end of the crisis (June 2001–February 2002). The graphs present monthly averages of the main residential electricity tariff from my dataset of electricity prices, recording any price–setting resolution published by the regulation agency. Residential electricity tariffs did not increase much faster in the South–East/Midwest than in the South during or after the crisis. They actually decreased after 2007.

Figure B.7: Distribution of appliances' years of acquisition from household surveys (aggregated)

(a) Share of households that bought at least one major domestic appliance in a given year (conditional on ownership)



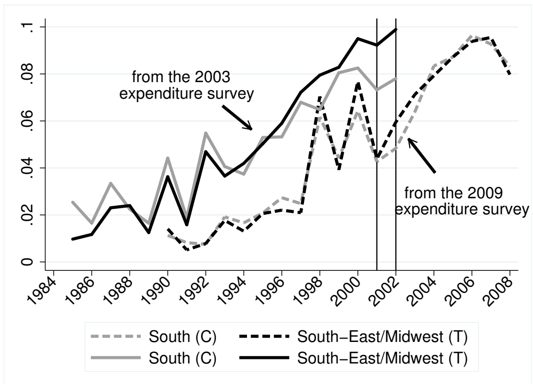
(b) Share of households that bought more than one domestic appliance in a given year (conditional on ownership)



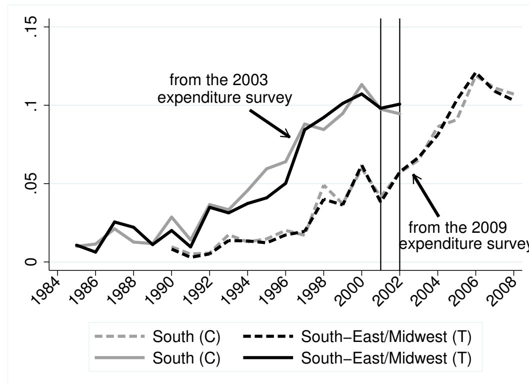
Data are from the 2003 and 2009 Brazilian expenditure surveys (POF). Respondents who report owning a given appliance at the time of interview also report the year of acquisition. In panel (a), I use this information to estimate the share of households who bought at least one of the major domestic appliances owned at the time of the interview in each year. The appliances considered are refrigerator, washing machine, air conditioner, dishwasher, dryer, freezer, fan, color TV, and microwave. Respondents are more likely to report having bought their current appliances in 2000 than in 2001. Households in the South–East/Midwest were actually less likely to have bought appliances in 2001–2002 than households in the South. However, this difference is small and in no way an outlier. In panel (b), I use this information to estimate the share of households that bought more than one of the major domestic appliances owned at the time of the interview in each year. Respondents are more likely to report having bought more than one appliance in 2000 than in 2001. Households in the South–East/Midwest were actually less likely to have bought appliances in 2001–2002 than households in the South. However, this difference is small and in no way an outlier. The higher share of households having bought more than one appliance after 2004 in the South is likely due to a differential increase in household income (Table 2). See Figure B.8 for a similar analysis disaggregated by appliance type.

Figure B.8: Distribution of appliances' years of acquisition from household surveys (disaggregated)

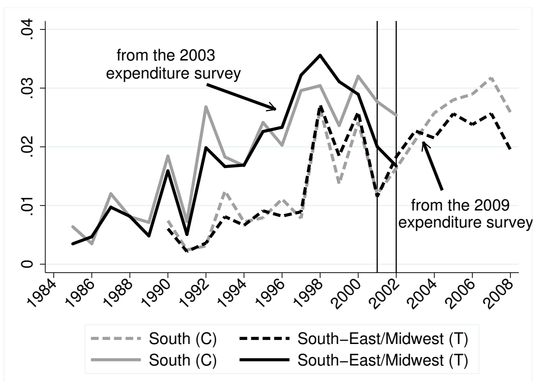
(a) Refrigerator



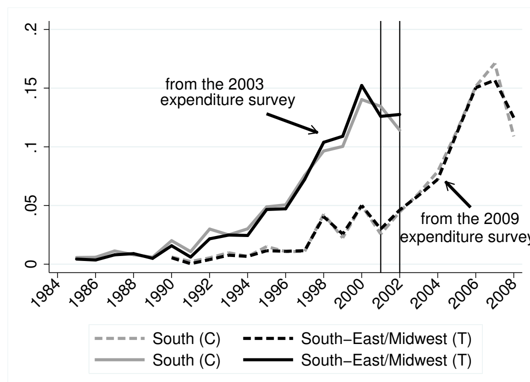
(b) Washing machine



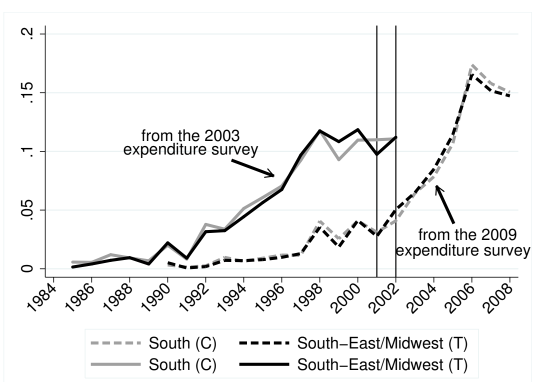
(c) Air conditioner, dishwasher, dryer, freezer



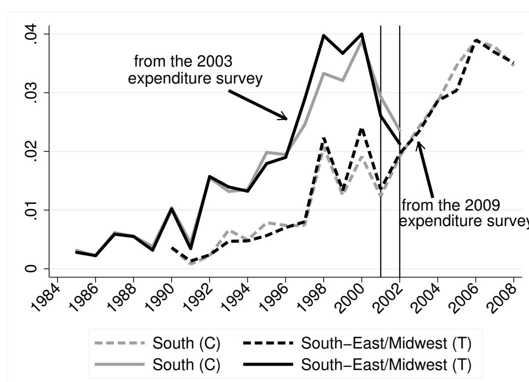
(d) Fan



(e) TV



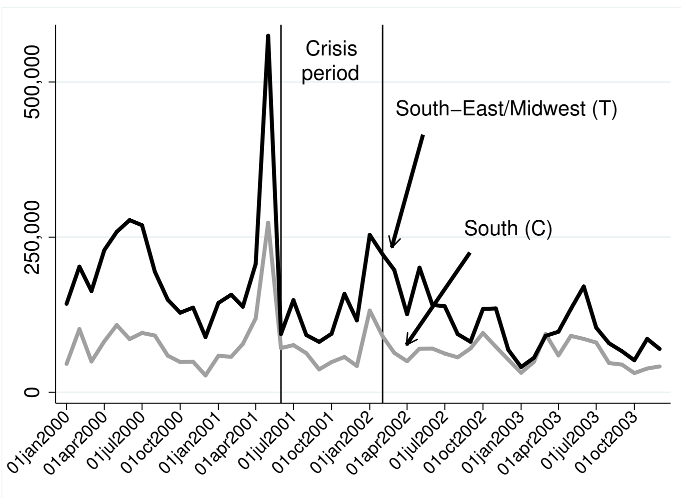
(f) Microwave, mixer



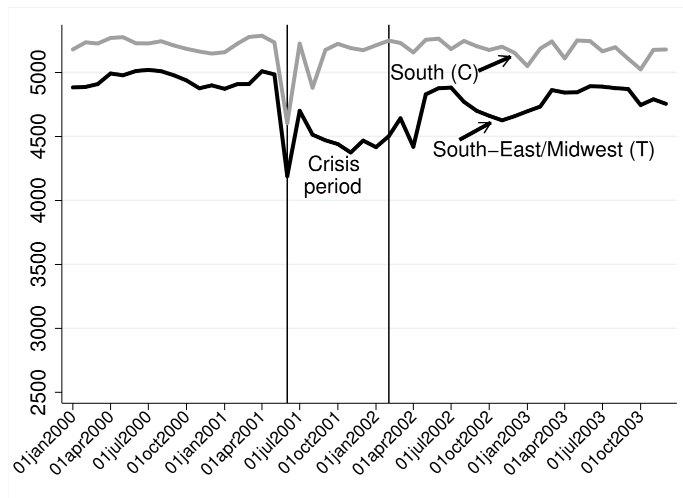
Data are from the 2003 and 2009 Brazilian expenditure surveys (POF). Respondents who report owning a given appliance at the time of interview also report the year of acquisition. I use this information to estimate the share of households who bought a given type of appliance in each year, conditional on ownership at the time of the interview. Appliances with low ownership rates have been pooled (see text). Ownership in 2002–2003 in the South–East/Midwest: refrigerator, 93%; washing machine, 44.3%; air conditioner, 7.8%; dishwasher, 4.6%; dryer, 4.1%; freezer, 16.3%; fan, 61%; color TV, 90%; microwave, 24.6%; mixer, 40.5%. In every case, respondents are more likely to report having bought their current appliances in 2000 than in 2001. For none of the appliances considered is there any strong evidence of an (differential) increase in purchases around the electricity crisis.

Figure B.9: Quantity and type of electric showers sold around the crisis

(a) Total sales (units)



(b) Mean power of the models sold (kWh)

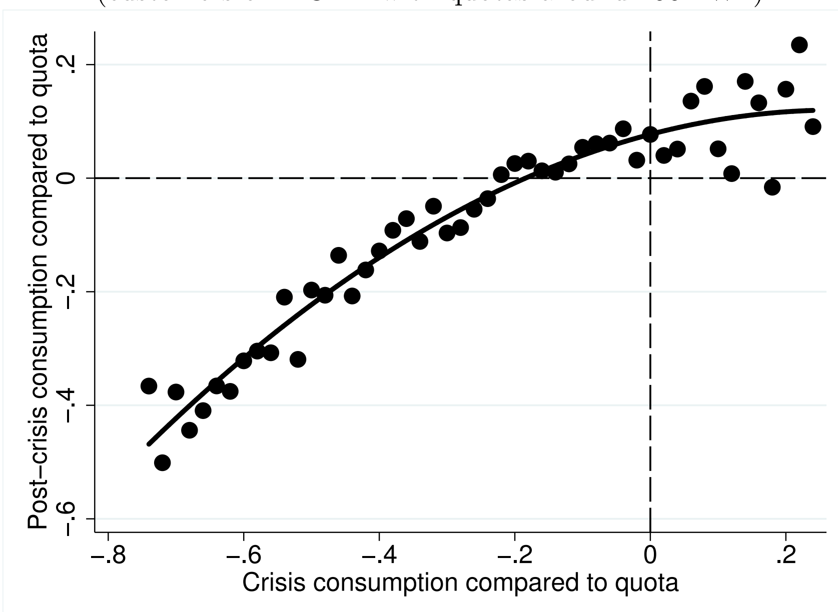


Data are from Fame, one of the leading manufacturers of electric showers in Brazil. Electric showers are responsible for about 20% of residential electricity consumption in the South–East/Midwest and in the South, where their penetration rates are very high (PROCEL, 2007e). Panel (a) displays the monthly volume of sales in the South–East/Midwest and in the South. Panel (b) displays the mean power (in kWh) of the models sold each month. Mean power is higher in the South because of the colder weather.

In early May 2001, the government announced that it would increase federal taxes on the sale of electric showers on May 21, particularly on the most electricity–intensive models. The increase was soon reversed, on June 27, 2001 (personal communication with Fame). Sales immediately spiked right before the tax change, in both the South–East/Midwest and the South. But the type of electric showers sold at the time was no less electricity–intensive than in earlier months. In June 2001, when the tax increase was in place, sales decreased and the average power of the electric showers sold dropped by more than 10% in both the South–East/Midwest and the South. During the crisis, sale levels were not particularly high or differentially higher in the South–East/Midwest. The average power of the model sold stayed lower in the South–East/Midwest by about 10%, revealing a moderate substitution away from more electricity–intensive models. Overall, because of the sales pattern, the "total power" (volume times power) sold in 2001 was similar to other years. As a result, customers' behavior in purchasing electric showers during the crisis cannot explain the short– and long–term effects on electricity consumption.

Figure B.10: Correlation between consumption levels during the crisis and four years later (compared to the quota)

(customers of LIGHT with quotas around 250 kWh)



Based on a balanced panel of randomly selected LIGHT customers continuously observed from 2000 to 2005. The sample is restricted to customers with a quota around 250 kWh (sample as in Figure 4c). Consumption levels are based on the first five months of the crisis (June–October) and the same months in 2005. Consumption levels are normalized to the quota.

The graph shows a clear correlation between conservation efforts during the crisis and relative consumption levels up to four years after the crisis.

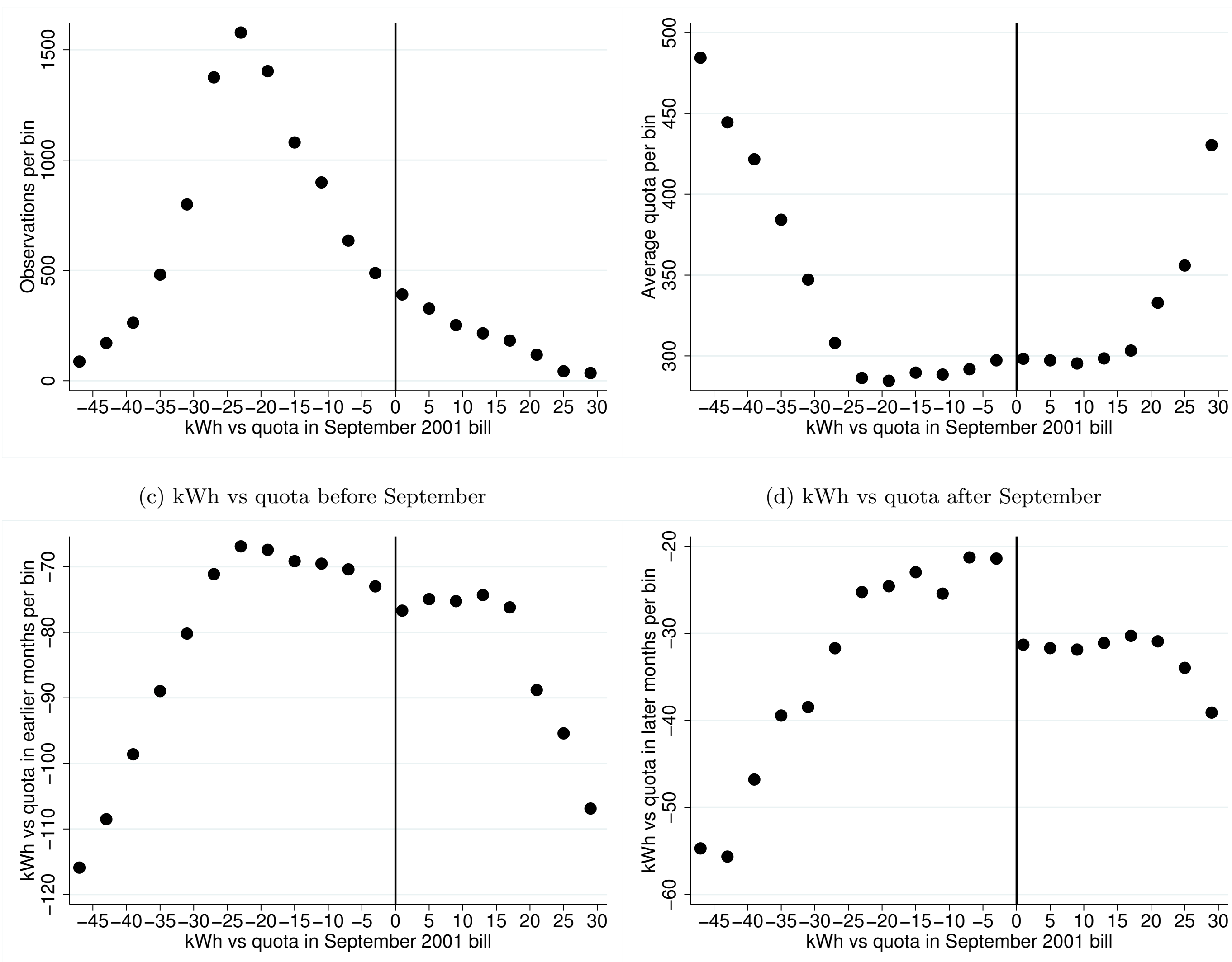
Figure B.11: Discontinuous effect of consuming above the quota in September 2001

(a) Observations per bin

(b) Average quota per bin

(c) kWh vs quota before September

(d) kWh vs quota after September



Figures based on a sample of LIGHT customers from Rio de Janeiro (i) with quotas above 225 kWh (only subject to fines), (ii) who are observed consuming at least 15% below their quotas in the first two months of the crisis, and (iii) who are consuming between 10% below and 10% above their quotas in the September bill (third month of the crisis). The idea is to select customers who reduced consumption severely at the start of the crisis (maybe because they overestimated the cost of non–complying with the quota) but for some reason consumed closer to their quotas in September. Customers consuming just above the quota (right of the vertical line) were then fined and potentially learned the actual cost of non–compliance. I aggregate customers by bins of 4 kWh of electricity consumption in September 2001 compared to the quota (forcing variable).

The distribution of consumption levels around the quota in September (panel a) as well as the distribution of quota levels for customers consuming around their quotas in September (panel b) appear smooth. Customers who consumed just below or just above the quota in September were similarly consuming below their quotas in the first two months of the crisis (panel c). However, in the two months after September (before quotas were extended), customers who received a fine in September apparently responded by further reducing consumption (panel d). This result suggests that these customers were not overestimating the cost of non–compliance before they actually received a fine. It is not straightforward to generalize the result because the sample above is selected: these customers likely consumed closer to their quotas in September for non–exogenous reasons. Indeed their conservation efforts were smaller after September than before.

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:

137 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.

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.

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.

Data de Emissão	Data de Apresentação
05/02/2002	06/02/2002

ENERGIA ATIVA

Número Medidor	Medição Atual Data	Leitura	Medição Anterior Data	Leitura	Const. Medidor	Consumo kWh	Nº Dias	Média Diária kWh
	02/02/2002	0548	03/01/2002	0188	1	360	30	12,00

ENERGIA REATIVA

Fator de Potência

Classe	Referência Bancária	Número da Nota Fiscal	Número do Cliente
RESIDENCIAL TRIFÁSICO			

DESCRIÇÃO	UNIDADE	QUANTIDADE	PREÇO UNIT R$	VALOR R$
FORNECIMENTO DE ENERGIA ELÉTRICA	kWh	360	0,34402	123,84
SOBRETAXA - CONSUMO 201 A 500KWH	kWh		0,17201	27,52
BÔNUS - CONSUMO ABAIXO DA META MÊS ANTERIOR				0,00

	ICMS R$	ISS R$
Base de Cálculo	151,36	
Alíquota	25%	
Valor (já incluído no preço)	37,84	

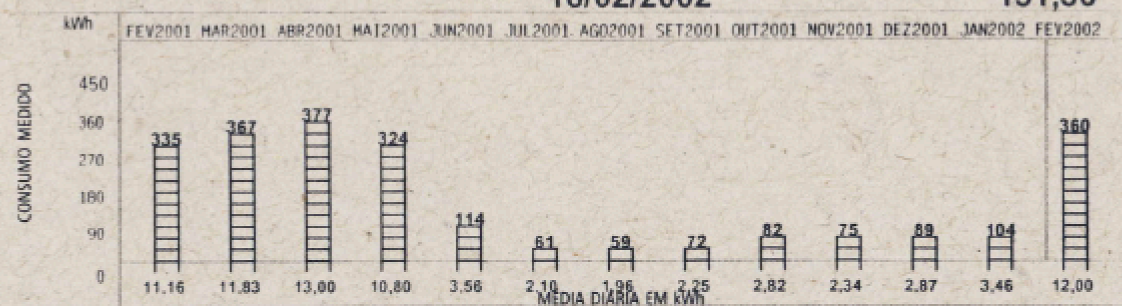
PAGANDO ATÉ O VENCIMENTO VOCÊ EVITA:

- Corte no fornecimento de energia
- Multa de 2% (cobrança na sua próxima conta)
- Cobrança de custos de serviços previstos pela ANEEL (Resolução 456/2000)

Consultas sobre tarifas, tributos e condições de fornecimento poderão ser feitas nas Agências ou pelo Disque-Light. Visite a Agência Virtual: www.light.com.br

VENCIMENTO 18/02/2002

TOTAL A PAGAR R$ ********151,36



Data da Próxima Leitura

04/03/2002

VEJA COMO REDUZIR O CONSUMO DE ENERGIA

APARELHO	DICAS PARA ECONOMIZAR
Geladeira	Evite abrir a porta muitas vezes e guardar alimentos e líquidos quentes.
Chuveiro elétrico	Reduza o tempo de uso do banho para 6 minutos, não esquecendo de desligar o chuveiro ao ensaboar-se.
Ferro elétrico	Acumule a roupa e estabelecer dias para passá-las, evitando deixar o ferro ligado mais de 1h por dia.
Ventilador de teto	Só ligue quando estiver no ambiente.
Aparelho de ar-condicionado	Reduza a potência e diminua em, pelo menos, 1 hora por dia de uso.
Aparelho de som	Evite ligar quando já tiver acionando outro aparelho.
Lâmpadas incandescentes	Substitua por lâmpadas fluorescentes. São 80% mais econômicas e duram 10 vezes mais.
Televisão	Desligue quando ninguém estiver assistindo.
Aspirador de pó	Use, no máximo, dois dias na semana. O aspirador consome o mesmo que 1 aparelho de ar-condicionado.
Torradeira elétrica	Retire da tomada após o uso.
Microondas	Use suportes que permitam esquentar mais de um prato.
Microcomputador	Desligue o computador quando não estiver em uso.
Lavadora de roupas	Acumule a roupa e estabeleça dois dias na semana para lavá-la.
Freezer	Faça uma lista diária de tudo o que precisa e retire os congelados de uma única vez.

Light

A Light com você para enfrentar o desafio do racionamento

SAIBA COMO REDUZIR O CONSUMO DE ENERGIA ELÉTRICA

CHUVEIRO ELÉTRICO (uso diário) - usar menos 5 minutos por dia

1 LÂMPADA - trocar por 1 fluorescente

TELEVISÃO (uso diário) - usar menos 1 hora por dia

LIQUIDIFICADOR (uso diário) - usar menos 5 minutos por dia

LAVADORA DE ROUPAS (2 x por semana) - usar menos 1 hora por dia

MICROONDAS (uso diário) - usar menos 5 minutos por dia

VENTILADOR (uso diário) - usar menos 1 hora por dia

AR CONDICIONADO (7.500 BTU's) - usar menos 1 hora por dia

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3 TELEVISÕES (uso diário) - usar menos 1 hora por dia cada uma

2 APARELHOS DE SOM (uso diário) - usar 1 hora por dia cada um

COMPUTADOR (5 dias por semana) - usar menos 1 hora por dia

LAVADORA DE ROUPAS (2 x por semana) - usar menos 1 hora por dia

LAVA LOUÇAS (uso diário) - usar menos 1 hora por dia

AR CONDICIONADO (7.500 BTU's) - usar menos 1 hora por dia

MICROONDAS (uso diário) - usar menos 10 minutos por dia

CAFETEIRA (uso diário) - usar menos 10 minutos por dia

SECADOR DE CABELO (uso diário) - usar menos 10 minutos por dia

ASPIRADOR DE PÓ (2 x na semana) - usar menos 1hora por dia

LÂMPADAS (uso diário) - usar menos 3 horas por dia

2 LÂMPADAS COMUNS - trocar por duas fluorescentes

VENTILADOR - usar menos 2 horas por dia

A Light está trabalhando muito para que o desconforto de racionamento de energia seja o menor possível. Esse é o papel e a responsabilidade de uma empresa de serviço público: estar sempre a seu lado.

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