Hysteresis and the Social Cost of Corrective Policies: Evidence From a Temporary Energy Saving Program

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April 7, 2015

[PRELIMINARY DRAFT. PLEASE, DO NOT CITE.]

Abstract

This paper studies how one may overestimate the social cost of a long-run corrective policy by neglecting the possibility of hysteresis, i.e. that the policy in earlier periods may have lasting impacts in later periods. In a price-theoretic framework, we show that one statistic is key to evaluate such a bias: the long-term impact of a similar but temporary policy that was known to be temporary. We then provide evidence of the importance of hysteresis, and estimate such a statistic, for a policy-relevant behavior: residential electricity use in a developing country context. We study the 10-year impact of a 9-month long policy in Brazil, which aimed at large temporary reductions in residential electricity use. We exploit the fact that customers of some distribution utilities were not subject to the policy through a difference-in-difference strategy. Using utility-level administrative data, we find that the temporary policy led to a long-run and stable reduction in average electricity use of 11%, or about half of the short-run impact. Using individual monthly billing data for one distribution utility, we find that 69% of customers were still consuming less electricity four years after the policy ended. Household-level microdata suggest that the main mechanism of hysteresis is a persistent change in consumption habits. Incorporating our estimates into our framework illustrates that, neglecting the possibility of hysteresis, one could dramatically overestimate the social cost of long-run corrective policies.

Policymakers may want to change behaviors of economic agents that may be privately optimal but are socially suboptimal. Such corrective policies are desirable when the social gain from addressing the externality outweighs the social cost of the policy. In a standard partial-equilibrium setup, the social cost in any period depends on the size of the required behavioral change and the associated change in agents' welfare. The main intuition from price theory is that the later is captured by agents' demand (or supply) curve for the behavior. Inducing large and lasting changes in a behavior that presents a low price elasticity is thus seen as carrying a high social cost. As a result, it may not be considered desirable even when the associated externality is sizable. This influential argument rests on the assumption that the level of a behavior only depends on the concurrent economic environment. It leaves out the possibility that part of the impact of the policy in earlier periods may persist in the long run, even in the absence of the policy in later periods. This paper studies the importance of such hysteresis for the social cost of corrective policies.

Hysteresis is defined as the failure of an effect to reverse itself as its underlying cause is reversed (Dixit, 1989). We use the term hysteresis to refer to the possibility that there may be multiple steady states for a given behavior and that a temporary policy could move economic agents between steady states. This is in contrast with the persistence that is sometimes studied in the literature (e.g., Allcott and Rogers, 2012). Observing a delay before a behavior returns to its prior level once some incentives are removed could result from a difference between short- and long-run elasticities. The implications are known in this case: long-run elasticities should be used to evaluate the social cost of long-run policies. Several theories allow for hysteresis.[1] However, there is much less evidence that it is an empirically relevant phenomenon in many contexts of interest.

We proceed in steps. First, we use a price-theoretic framework to illustrate how one would overestimate the social cost of a long-run corrective policy by neglecting the possibility of hysteresis. We highlight a key statistic to evaluate this bias: the long-term impact of a similar but temporary policy that agents expected to be temporary. Second, we provide evidence of the importance of hysteresis, and estimate such a statistic, in a policy-relevant behavior: residential electricity use in a developing country context. We estimate the 10-year impact of a 9-month long electricity saving program that was imposed on millions of Brazilian households in 2001 and that led to dramatic short-run reductions in residential electricity use. Exploiting administrative data and differences in the implementation of the policy across regions, we find that about half of the short-run impact subsisted in the long run. Household level microdata suggest that the main mechanism of hysteresis was a change in electricity utilization habits. Finally, we incorporate our estimates into our conceptual framework to illustrate implications for the social cost of corrective policies.

[1] For example, asymmetric adjustment costs (e.g. learning costs). Habit formation à la Becker and Murphy (1988) allows for, but does not imply, the existence of multiple steady states. Therefore, it certainly implies a difference between short and long-run elasticities, but may or may not imply hysteresis.

We begin by showing why hysteresis matters for the social cost of corrective policies in a simple theoretical framework. The intuition is straightforward. Consider a policymaker that imposes a permanent change in behavior, e.g. a 20% reduction in residential electricity use. In the absence of hysteresis, one would assume that the policy distorts behavior by 20% in all periods. Yet, in the presence of hysteresis, part of the reduction in later periods is already caused by the policy in earlier periods and should not be double-counted as caused by the concurrent policy in later periods. An estimate of the *long-term* impact of a similar but temporary policy that agents *expected to be temporary* quantifies the degree of hysteresis and thus the residual distortion that the permanent policy would cause in later periods. Studying long-term impacts rules out any persistence resulting from a difference between short- and long-run price elasticities. Studying a policy that was known to be temporary rules out any persistence that would not be due to the temporary policy but due to past responses in anticipation of the policy in future periods. Integrating the demand (or supply) curve over the estimated residual distortion vs. the 20% reduction evaluates how one would overestimate the social cost of the policy in later periods by neglecting the possibility of hysteresis.

We then study the long-term impact on residential electricity use of the temporary electricity saving program that was implemented during the so-called 2001 Brazilian electricity crisis. Our empirical setting is ideal to provide evidence of hysteresis because the policy was known to be temporary and because we can study impacts up to ten years after the policy ended. Several theories also suggest that hysteresis is more likely to be relevant for large changes in behaviors.[2] The Brazilian program led to the largest short-run reductions in household electricity use among temporary electricity saving programs around the world (Meier, 2005).[3]

Our empirical setting is also relevant in itself. First, energy use is expected to continue to be a major source of greenhouse gas emissions in the future. Potential energy savings from residential electricity use have attracted a lot of attention.[4] Yet, existing estimates of price elasticities are typically low. Thus, inducing large and persistent changes in residential electricity use is an example where the social cost may be considered too large despite sizable externalities. Second, most of the growth in energy use is forecast to come from the developing world. In particular, greenhouse gas emissions from residential electricity use are growing rapidly (IPCC, 2014). Yet, the energy saving potential of households in developing countries, who are poorer, own fewer appliances, are more credit-constrained, and consume less energy to begin with, is largely unknown.

[2]Hysteresis in a model with asymmetric adjustment costs (e.g. learning costs) may rely on a policy pushing agents to pay possibly high fixed costs. Hysteresis in a rational habit formation model relies on the existence of multiple steady states and on a policy pushing agents far enough from their prior steady state (Becker and Murphy, 1988).

[3]Other policies led to smaller reductions in average electricity use at a given point in time and/or were shorter lived.

[4]Improving the energy efficiency of residential electricity use 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 electricity saving programs in at least 24 states in the US. Scenarios to mitigate the impacts of climate change typically involve large reductions in electricity use from buildings (IPCC, 2014).

In the beginning of 2001, electricity generation capacity was severely reduced in some regions of Brazil. A temporary shock to the streamflow level in the rivers that serves the hydroelectric power plants in these regions led to historically low water levels in their reservoirs (see Figure 1a). Brazil relies heavily on hydroelectric generation and low transmission capacity constrained transfers of electricity across regions. In order to prevent generalized blackouts, the government implemented a temporary electricity saving program from June 2001 to February 2002 in affected areas, which aimed at reducing residential electricity use by 20%. Residential customers were assigned individual quotas and were subject to a series of incentives to consume below their quota.[5]

We estimate the short- and long-term impacts through a difference-in-difference comparing distribution utilities subject to the policy to those that were exempt. We use data on average residential electricity use per customer from monthly administrative reports for every distribution utility in Brazil between 1991 and 2011. We confirm that the electricity saving program had large short-run impact (-23%). Our main contribution is to show that half of the short-run impact persisted in the long run (-11%).[6] Consumption levels partially rebounded after the policy ended but point estimates are stable from 2005 onwards (see Figure 1b). It is thus unlikely that our estimates are due to a difference between short- and long-run elasticities rather than hysteresis.

We present many empirical tests supporting our results. Our estimates are robust to controlling for a series of confounders such as changes in electricity tariffs, demographics (Levinson, 2014), income levels, or climate. Moreover, utility-specific impacts estimated by synthetic control methods find negative long-term impacts for *every* distribution utility subject to the policy. We also rely on longitudinal monthly billing data from 2000 to 2005 for three million customers of one affected utility. We show that changes in average electricity use are similar in the aggregate data and in a random sample of individual customers observed every month in the billing data. This balanced panel is free of composition effects by construction. Almost all of these customers consumed less electricity during the crisis than a year before (92%) and most of them continued to consume less electricity four years after the crisis (69%). The median customer reduced electricity use by 31% and 16.5% during the crisis and four years after, respectively. These figures are larger for customers with higher baseline consumption and there is a strong correlation at the customer level between short-run (during the crisis) and long-run (four years later) changes in consumption. Av-

[5] Incentives cannot be translated in a given increase in tariffs because they included nonlinear pecuniary incentives (fines or bonuses for consuming above or below the quota, respectively) and non-pecuniary incentives (threats of disconnection for consuming above the quota and moral suasion from conservation appeal campaigns).

[6] There is little work on the long-run impact of the 2001 Brazilian electricity crisis and its electricity saving program on residential electricity use. Bardelin (2004) and Maurer, Pereira and Rosenblatt (2005) provide some descriptive evidence on short-run impacts with aggregate data. Pimenta, Notini and Maciel (2009) use time-series techniques. Mation and Ferraz (2011) use a similar difference-in-difference strategy to investigate impacts on firms' productivity. At last, Reiss and White (2008) present time-series evidence on how households responded to price increases and conservation appeals during the 2000 California's energy crisis.

erage effects thus came from large and persistent responses by most customers. Finally, household surveys of appliance ownership and utilization habits conducted both before the crisis and several years later suggest that the main mechanism of hysteresis was the formation of new habits.

We recognize that one may be concerned about the external validity of our evidence. This is an issue in any empirical setting (Allcott, 2012), which may be seen as more severe in our case given the uniquely large short-term changes in behaviors. However, the uniqueness of our setting does not come from a lack of interest in policies aimed at large changes in behaviors such as residential electricity use. It comes from the fact that such policies are rarely implemented. It is therefore particularly interesting to exploit an opportunity to learn from such a policy when available. This is particularly true if the reason why such policies are considered politically infeasible is because their social cost is assumed to be too large. Furthermore, the fact that we find persistent effects for all affected utilities, which differ in the characteristics of their local demand, and for most of the three million customers within one of these utilities, brings some external validity to our evidence.

This paper contributes to a large literature on the economics of corrective policies, dating back to at least Pigou (1920). The existing literature typically fails to consider the role of hysteresis for policies that aim at changing behaviors in the long run. In so doing, we show that one may largely overestimate the social cost of such corrective policies and we identify estimable "sufficient statistics" to evaluate this bias.[7] Moreover, our analysis of the Brazilian program indicates that taking hysteresis into account can be quantitatively important in a policy-relevant context. A back-of-the-envelope calculation implies that, neglecting the possibility of hysteresis, one could overestimate the social cost of a 10-year long version of a similar policy by 170%.

This paper also contributes to the growing empirical literature that investigates the presence and mechanisms of persistence in various behaviors of interest. Several papers study the persistence of some impacts after a policy was suspended.[8] It is sometimes unclear whether their estimates actually capture hysteresis. Agents may have expected the policy to continue with some probability and the persistence is often observed for a relatively short period of time.[9] Moreover, to the extent that some do capture hysteresis, one could directly use our framework to evaluate the overestimation bias from neglecting hysteresis for the social cost of corrective policies in their context. Existing studies do not consider this implication of their results.

[7]Hysteresis essentially implies that behaviors in different periods are complement and the same argument would apply to any corrective policy that aims at changing two complementary behaviors. We are not aware of existing work applying this idea to intertemporal behaviors.

[8]E.g. Charness and Gneezy (2009), Giné, Karlan and Zinman (2010), Ferraro and Price (2013), Bryan, Chowdhury and Mobarak (2014), Dupas (2014), Fujiwara, Meng and Vogl (2014), Acland and Levy (2015), Miller (2014), Allcott and Rogers (2012) and Ito, Ida and Tanaka (2015).

[9]For instance, Allcott and Rogers (2012) find a persistent change in electricity use after some incentives were suspended and estimate that it would take about five years for the effect to disappear in their context. They have only access to two years of post-intervention data, however. We would have reached a similar conclusion with a similar data limitation. Instead, we can show that average electricity use does not return to counterfactual levels in our context.

Finally, this paper participates to a small but growing empirical literature that studies issues related to energy consumption in developing countries.[10] We show that a temporary shock that forced Brazilian households to rationalize their electricity use impacted consumption levels in the long run. Moreover, this hysteresis seems to arise mostly from the formation of new habits rather than from physical investments.[11] Our results thus open up an exciting research agenda: how could policymakers foster energy-efficient habits at an earlier stage of development to limit the rapidly growing energy demand in the developing world, which will account for most of the growth in greenhouse gas emissions in the future.

The rest of the paper proceeds as follows. Section 1 presents our theoretical framework. Section 2 introduces our empirical setting and Section 3 our empirical strategy. Section 4 presents our main results and the many robustness checks supporting them. Section 5 investigates the mechanisms of hysteresis. Section 6 uses our estimates to illustrate the importance of taking hysteresis into account for the social cost of corrective policies. Section 7 concludes.

1 Conceptual framework

In this section, we provide a theoretical framework to illustrate how one may overestimate the social cost of long-run corrective policies by neglecting the possibility of hysteresis in the behavior of interest.[12] We present here the simplest version of the model. We discuss some extensions, but leave the related derivations to the Appendix.

Hysteresis could emerge in several models, which would predict the same observable outcome. For instance, hysteresis may emerge in a rational habit formation model à la Becker and Murphy (1988) as long as there are multiple steady states and that a policy pushes agents far enough from their prior steady state. Hysteresis may also occur in a model with asymmetric adjustment costs if a policy pushes agents to pay some costs that cannot be reverted back (e.g., learning costs; Bryan,

[10] Wolfram, Shelef and Gertler (2012) argue that existing forecasts underestimate the future growth in residential energy demand in the developing world because of an S-curve relationship between income and ownership of domestic appliances. They also highlight that a rapidly rising energy demand also brings the risk of dramatic supply shortages in developing countries because of vulnerable infrastructure and the difficulty of accurately planning capacity investments. Davis, Fuchs and Gertler (2014) find that an appliance replacement program in Mexico did not generate the expected energy saving because of households' behavioral responses to the new appliances. Zhou et al. (2011) estimate that CO2 emissions from energy consumption would be greatly reduced if there was continued improvements in appliances' standards and labeling in China. Allcott, Collard-Wexler and O'Connell (2014) and Fisher-Vanden, Mansur and Wang (2015) examine firms' short-run responses to recurrent power shortages in India and China, respectively.

[11] This should not be surprising. Households in developing countries are poorer and more credit-constrained, and habit formation is relevant for residential electricity use even in developed countries (e.g., Ito, Ida and Tanaka, 2015).

[12] We could instead consider the role of hysteresis for the welfare effects of temporary policies. In the presence of hysteresis, a temporary policy will deliver a persistent correction of the externality, if the prior level of the behavior was too high from a social perspective. Properly accounted for, this may partly mitigate the social cost borne by economic agents in moving between steady states. This does not imply, however, that a temporary policy would be desirable as the level of electricity use in the new steady state may also remain too high from a social perspective.

Chowdhury and Mobarak, 2014; Dupas, 2014). We do not take a strong stand on the underlying model at play and simply assume that policies that affect past levels of a behavior may affect agents' utility from their level of the behavior in the long run. We illustrate the importance of hysteresis assuming that price theory can be used to evaluate the social cost of corrective policies. However, hysteresis could also emerge from "behavioral" theories, such as models with biased beliefs or myopia about the returns to changing one's behavior (e.g., Acland and Levy, 2015; Gruber and Köszegi, 2001). We return to this point later in the paper.

1.1 Setup

Consider a representative-household two-period model of electricity use.[13] The periods are assumed to be long enough such that the level of electricity use in the two periods would be independent in the absence of hysteresis, i.e. there is no difference between short- and long-run elasticities. We adopt a standard partial-equilibrium setup to focus attention on the role of hysteresis. In particular, we assume away income effects and redistributive concerns, and we model the household as fully rational and forward looking. For simplicity, we also assume that goods are produced competitively at constant marginal costs. These assumptions allow us to illustrate the role of hysteresis for the social cost of corrective policies using simple consumer surplus concepts.

The household chooses electricity consumption x_i at price p_i and ordinary consumption c_i at normalized price 1, given income y_i in periods $i = 1, 2$. The per-period utility is represented by $u_i(c_i, x_i, s_i) = c_i + v_i(x_i, s_i)$, where s_i is the household's propensity to consume electricity. This is a reduced-form variable that is aimed at capturing possible mechanisms of hysteresis. Changes in electricity use may affect the future propensity to consume because the household develops new (steady-state) consumption habits, learns about ways to consume electricity more efficiently, develops a taste for appliances with different characteristics, etc.[14]

We assume that $v_i(x_i, s_i)$ is strictly increasing and concave in x_i and that $\frac{\partial v_i(x_i,s_i)}{\partial s_i} \leq 0$ for all $x_i, s_i \geq 0$. For instance, the household derives less utility from a consumption bundle (c_i, x_i) if her habits or lack of knowledge about energy-efficient behaviors require more electricity to provide the same services. The propensity to consume in the first period is given, but in the second period, it is allowed to depend on the level of electricity use in the first period: $s_2 = s(s_1, x_1)$, with $0 \leq \frac{\partial s(s_1,x_1)}{\partial s_1}, \frac{\partial s(s_1,x_1)}{\partial x_1} \leq 1$. Finally, we assume that $\frac{\partial^2 v_i(x_i,s_i)}{\partial x_i \partial s_i} > 0$ for all $x_i, s_i \geq 0$: the higher the propensity to consume (e.g., to use electrical appliances), the higher the marginal utility of

[13] The model can be easily adapted to apply to other behaviors of interest or extended to a multi-period setup.

[14] We allow for direct (costly) investments in one's propensity to consume electricity in an extension of our model. Note that it is unclear whether investments in physical capital such as energy-efficient appliances would lead directly to hysteresis. A corrective policy may simply push agents to anticipate future investments in new appliances and physical capital decays. Of course, hysteresis may arise if agents' preferences or information sets change when they buy energy-efficient appliances, such that they continue to buy energy-efficient appliances subsequently.

consumption (e.g., the greater the disutility from not having access to their services). This complementarity introduces some path dependency to the utility derived from electricity use and allows for hysteresis in electricity use. Specifically, the household solves:

$$\max_{c_1,c_2,x_1,x_2} u_1 + \beta u_2 = c_1 + v_1(x_1,s_1) + \beta\left[c_2 + v_2(x_2, s(s_1,x_1))\right] \quad \text{s.t. } c_i + p_i x_i \leq y_i$$

The parameter β accounts for discounting or differences in the relative length of the two periods. Substituting in for c_i, we obtain the following first-order conditions:

$$x_1 : \frac{\partial v_1(x_1,s_1)}{\partial x_1} + \beta \frac{\partial v_2(x_2,s(s_1,x_1))}{\partial s}\frac{\partial s(s_1,x_1)}{\partial x_1} = p_1 \quad ; \quad x_2 : \frac{\partial v_2(x_2,s(s_1,x_1))}{\partial x_2} = p_2 \qquad (1)$$

The left- and right-hand sides of each first-order condition capture the benefit and the cost of marginal changes in electricity use, respectively. These must be equal at an optimum. As expected, the household will use less electricity in the first period if the propensity to consume electricity in the second period depends on past choices and the household is aware of this relationship.

1.2 The social cost of a long-run corrective policy

Without government intervention, the first-order conditions and baseline electricity prices in the two periods, p_{10} and p_{20}, will determine baseline electricity use, x_{10} and x_{20}. Now, suppose that the government wants the household to reduce electricity use to $\overline{x_1} < x_{10}$ and $\overline{x_2} < x_{20}$. We are interested in the social cost or deadweight loss of such a corrective policy. In our framework, this is the change in the household's indirect utility: $DWL = V(\overline{x_1},\overline{x_2}) - V(x_{10},x_{20})$. We can recover it by tracing the change in indirect utility along any path from (x_{10},x_{20}) to $(\overline{x_1},\overline{x_2})$. In our setting, it is natural to first consider changing x_1 to $\overline{x_1}$ and then changing x_2 to $\overline{x_2}$, holding constant $\overline{x_1}$. In the presence of hysteresis, we have to take into account the fact that the optimal level of x_2 at price p_{20} will change in the first step as can be seen from the first-order condition for x_2. We have:

$$\begin{aligned}
DWL &= \int_{x_{10}}^{\overline{x_1}} \frac{dV(x_1,x_2)}{dx_1}dx_1 + \int_{x_2(\overline{x_1})}^{\overline{x_2}} \frac{dV(\overline{x_1},x_2)}{dx_2}dx_2 \\
&= \int_{x_{10}}^{\overline{x_1}} \left[\frac{\partial v_1(x_1,s_1)}{\partial x_1} + \beta\frac{\partial v_2(x_2,s(s_1,x_1))}{\partial s}\frac{\partial s(s_1,x_1)}{\partial x_1} - p_{10} + \beta\frac{\partial x_2}{\partial x_1}\underbrace{\left[\frac{\partial v_2(x_2,s(s_1,x_1))}{\partial x_2} - p_{20}\right]}_{=0}\right]dx_1 \\
&\quad + \beta\int_{x_2(\overline{x_1})}^{\overline{x_2}} \left[\frac{\partial v_2(x_2,s(s_1,\overline{x_1}))}{\partial x_2} - p_{20}\right]dx_2 \\
&= \int_{x_{10}}^{\overline{x_1}} \left[p_1(x_1) - p_{10}\right]dx_1 + \beta\int_{x_2(\overline{x_1})}^{\overline{x_2}} \left[p_2(x_2|\overline{x_1}) - p_{20}\right]dx_2 \qquad (2)
\end{aligned}$$

where $x_2(\overline{x_1})$ is defined by $\frac{\partial v_2(x_2, s(s_1, \overline{x_1}))}{\partial x_2} = p_{20}$. Equation (2) shows that three empirical objects are sufficient to evaluate the deadweight loss of the policy (besides the parameter β). The first one is the inverse demand curve in period 1, $p_1(x_1)$, which factors in any effect on utility and behavior in period 2 from changes in x_1. It could be identified using exogenous price increases in period 1. The second one, $p_2(x_2|\overline{x_1})$, is the inverse demand curve in period 2 for a given value of x_1, and thus a given propensity to consume in period 2. It could be identified using exogenous price increases once in period 2, following a temporary policy that changes x_1 to $\overline{x_1}$. The third one is the degree of hysteresis, the change in x_2 caused by the change in x_1. It could be identified from the impact on electricity use in period 2 of a similar temporary policy. Equation (2) is a familiar expression for the social cost of a behavioral change. It corresponds to the sum of the area under the properly defined inverse demand curve and above the baseline price level in each period. In the second period, the integral is only taken over the residual change in quantity because any change in utility from changing x_2 to $x_2(\overline{x_1})$ is already accounted for in the first integral.[15]

Assuming away hysteresis, the expression for the deadweight loss would be:

$$\begin{aligned} DWL_{NoH} &= \int_{x_{10}}^{\overline{x_1}} \left[\frac{\partial v_1(x_1, s_1)}{\partial x_1} - p_{10}\right] dx_1 + \beta \int_{x_{20}}^{\overline{x_2}} \left[\frac{\partial v_2(x_2, s_1)}{\partial x_2} - p_{20}\right] dx_2 \\ &= \int_{x_{10}}^{\overline{x_1}} \left[p_{1,NoH}(x_1) - p_{10}\right] dx_1 + \beta \int_{x_{20}}^{\overline{x_2}} \left[p_{2,NoH}(x_2) - p_{20}\right] dx_2 \qquad (3) \end{aligned}$$

where NoH stands for the assumption of no hysteresis. Equation (3) differs in two respects from equation (2). First, the inverse demand curve in a given period is assumed to be independent of electricity use in the other period. This may not be a source of bias in itself. A researcher assuming away hysteresis would identify the inverse demand curves in equation (3) using the same variation that identifies the inverse demand curves in equation (2). Second, equation (3) neglects the fact that the optimal level of x_2 will change with the level of x_1. This will be a source of bias as it implies taking the integral under the demand curve in the second period over a larger interval.

Figure 2 provides a graphical illustration. Without government intervention, the equilibrium in period 1 and 2 would be at points C and I, respectively. Reducing quantity in period 1 to $\overline{x_1}$ increases the household's marginal utility for x_1, which can be traced along the inverse demand curve $p_1(x_1)$. In the presence of hysteresis, this would reduce x_2 endogenously to $x_2(\overline{x_1})$. The demand curve $p_1(x_1)$ would factor in any change in utility from such endogenous changes in x_2.

[15] The same argument applies to any two behaviors that are complement (hysteresis essentially implies that behaviors at different points in time are complement). Suppose for instance that one smokes only when drinking. A policy that reduces drinking would thus also reduce smoking. The demand curve for drinking captures the associated utility from smoking and so the demand curve for drinking is sufficient to measure any change in utility from the associated change in smoking. Now suppose that a policy also reduces smoking below the initial level. The reduction in smoking that took place because of the reduction in drinking should not be double-counted.

The loss in utility from reducing quantity to $\overline{x_1}$ is then the triangle BCD (assuming locally linear demand curves). One would arrive to the same conclusion when assuming away hysteresis, if using the same information to recover the inverse demand curve in period 1, $p_{1,NoH}(x_1)$ (*NoH* stands for no hysteresis). Further reducing x_2 to $\overline{x_2}$ (for a given $\overline{x_1}$) then increases the household's marginal utility for x_2 which can be traced along the inverse demand curve $p_2(x_2|\overline{x_1})$. The associated loss in utility is the triangle GHJ. Neglecting the possibility of hysteresis, one would arrive to a different conclusion even if using the same information to recover the inverse demand curve $p_{2,NoH}(x_2)$. Tracing the change in marginal utility along the whole interval from x_{20} to $\overline{x_2}$, one would obtain a loss in utility corresponding to the larger triangle GIL. The bias is the area HILJ.

An estimate of the degree of hysteresis, $x_{20} - x_2(\overline{x_1})$, is key to evaluate this bias. Consider for instance a policy that aims at a given long-run change in electricity use $D = \frac{\overline{x_1} - x_{10}}{x_{10}} = \frac{\overline{x_2} - x_{20}}{x_{20}}$. With a linear approximation for the demand curves, and assuming that the same variation is used to identify the demand curves in equations (2) and (3), the bias becomes:

$$|DWL_{NoH}| - |DWL| = \frac{1}{2}\beta \frac{p_{20}x_{20}}{|\eta_2|}\left[[D]^2 - \left[D - \frac{x_2(\overline{x_1}) - x_{20}}{x_{20}}\right]^2 \frac{1}{x_2(\overline{x_1})/x_{20}}\right] \tag{4}$$

$$\frac{|DWL_{NoH}| - |DWL|}{|DWL|} = \frac{\beta p_{20}x_{20}\left[[D]^2 - \left[D - \frac{x_2(\overline{x_1}) - x_{20}}{x_{20}}\right]^2 \frac{1}{x_2(\overline{x_1})/x_{20}}\right]}{\frac{|\eta_2|}{|\eta_1|} p_{10}x_{10}[D]^2 + \beta p_{20}x_{20}\left[D - \frac{x_2(\overline{x_1}) - x_{20}}{x_{20}}\right]^2 \frac{1}{x_2(\overline{x_1})/x_{20}}} \tag{5}$$

Evaluating the bias (in level or percentage) requires estimates of the price elasticities in periods 1 and 2, η_1 and η_2, and an estimate of the impact in period 2 of a similar policy implemented only in period 1, $x_{20} - x_2(\overline{x_1})$. In this paper, we focus on estimating the later statistic. This is because it is the key source of bias and because there is limited evidence on its possible magnitude.[16] We then provide a quantitative illustration of the importance of hysteresis for the social cost of corrective policies by evaluating equations (4) and (5) for given values of the other parameters.[17]

1.3 Extensions

We discuss here how our results carry on to various extensions (see Appendix for further details).

First, we consider an extension of the model where the household can make direct (costly) investments I_i in its propensity to consume electricity. We show that using the same three empirical

[16] In contrast, an extensive literature focuses on estimating price elasticities for residential electricity use. Long-run price elasticities are always difficult to estimate. In the Appendix, we estimate a medium-run price elasticity for the years following the Brazilian temporary policy that we study. However, we are unable to do so for the years leading to (or for the months of) the temporary policy.

[17] A linear approximation is likely worse for large changes in behavior, but our purpose is only to illustrate the possible magnitude of the bias.

objects as in equation (2), one measures an upper bound for the deadweight loss and thus a lower bound for the bias (in absolute values). The inverse demand curve $p_1(x_1)$ will capture the utility loss of changing x_1 to $\overline{x_1}$, taking into account such endogenous investments. Similarly, the inverse demand curve $p_2(x_2|\overline{x_1})$ will capture the utility loss of changing x_2 for the propensity to consume resulting from the corrective policy in period 1. However, if the household had known ex-ante about the policy in period 2, it might have chosen a different value of the investment in period 1, thus reducing its overall utility loss. A similar argument would apply if we were extending the model to allow for other endogenous behaviors such as saving and borrowing.

Second, we can allow for heterogeneity in households' preferences and in the degree of hysteresis. In this case, the social cost of a policy that aims at aggregate changes in behavior can still be evaluated using aggregate inverse demand curves and the aggregate degree of hysteresis in equation (2), as long as the corrective policy is implemented efficiently (e.g. using tradable quotas or Pigouvian taxes).[18] In so doing, one would measure again an upper bound for the deadweight loss and thus a lower bound for the bias (in absolute values). We recognize that the temporary policy that we study may not have allocated the aggregate change in behavior efficiently across agents. However, we are not directly interested in the social cost of a long-run version of the exact same policy. We then abstract from allocative inefficiencies when using our estimates to illustrate the importance of taking hysteresis into account for the social cost of corrective policies.

Finally, households could be *naive* about the effect of their current choices on their future propensity to consume. In this case, a corrective policy would also address an "internality" problem by reducing consumption levels, which were suboptimally high from a private perspective. This would be another reason why neglecting the possibility of hysteresis overestimates the social cost of the policy. Agents could also have biased beliefs about the effect of their current choices on their future propensity to consume. As long as agents underestimate such an effect, this would also be a reason why neglecting the possibility of hysteresis overestimates the social cost of the policy. The opposite would be true if agents overestimate the effect. We provide some suggestive evidence that, if anything, agents underestimate this effect in our empirical application.

1.4 Connecting the theory to the data

A few comments must be made before moving to the empirical exercise.

First, the empirical analog of the key statistic $x_{20} - x_2(\overline{x_1})$ is the *long-term* impact of a temporary corrective policy. This is important because short- and long-run elasticities are likely to differ for many behaviors of interest. As a result, some persistence of an impact in the aftermath of a cor-

[18] An implication is that we can allow for the behavior of interest to change in discrete amounts at the individual level as long as the aggregate demand curves are smooth. This would be the case in a model with fixed adjustment costs (e.g. learning costs), as long as thresholds triggering adjustments are smoothly distributed in the population.

rective policy may result from the slow convergence towards a prior steady state rather than from hysteresis. It is clear that the deadweight loss of a policy that aims at changing behaviors in the long run should be based on long-run elasticities even in absence of hysteresis. How long is "long enough" for the persistence to capture hysteresis will depend on the behavior under consideration and on whether the estimated persistence is stable (vs. decays) over time.

Second, it is important to estimate the long-term impact of a policy that agents expected to be temporary. Otherwise, part of the persistence of a temporary policy may result from past (sunk) responses in anticipation of a possible continuation of the policy. This would not be a problem in the simple model presented above because the only way to anticipate a possible continuation of the policy is to change electricity use in period 1. However, it would be a problem in a model with, e.g., direct investments in the propensity to consume. In this case, past investments in anticipation of a possible continuation of the policy will affect future electricity use directly, and not only through its effect on electricity use during the temporary policy. As a result one would overestimate the effect on future behaviors of inducing changes in behaviors during the temporary policy.

Finally, several theories suggest that hysteresis is more likely for larger changes in behaviors (e.g. habit formation, fixed adjustment costs). Agents may be also able to deal with very brief constraints without making significant adjustments to their behavior or forming new habits. Therefore, the ideal experiment to provide evidence of hysteresis and discuss implications for the social cost of corrective policies would randomize a policy that aims at relatively large changes in behavior, for a temporary period that is not too short and that agents know to be temporary, and whose persistent impact can be estimated over a relatively long period of time afterward.

2 Background and data

In the remainder of this paper, we assess the degree of hysteresis in a behavior of interest by exploiting a natural experiment that shares many features of the ideal experiment described above. We study the 10-year impact of a 9-month long policy in Brazil that was known to be temporary, and that led to the largest short-run reductions in household electricity use among temporary electricity saving programs around the world (Meier, 2005). Identification requires additional assumptions with a natural experiment, but it would be challenging for a controlled experiment to share all these features. One limitation of the policy that we study is that it did not rely on a unique efficient and easily-replicable instrument to achieve its short-run reductions in electricity use. It included individually-assigned quotas and a set of (nonlinear) pecuniary and non-pecuniary incentives for households to consume below their quotas, which changed over time and may have affected households differently. We have little to say about the design of the specific policy in our empirical setting and its optimality. Our interest is that the policy allows us to provide clear evidence of hysteresis in a policy-relevant context. We then use our estimates to illustrate the possible implications of neglecting hysteresis for the social cost of corrective policies.[19]

2.1 The temporary electricity saving program of the 2001 crisis

The temporary electricity saving program that we study was implemented in response to an exceptional shortage in electricity supply in specific areas of Brazil in 2001. Starting with a brief overview of the electricity distribution system, we provide here the necessary information about the 2001 crisis and its electricity saving program. More information is available in the Appendix.

2.1.1 Electricity distribution in Brazil

The major national electricity system in Brazil is divided into four subsystems: North (6.5% of total load in 2000), Northeast (14.5%), Southeast/Midwest (62%), and South (17%). Almost all households had access to the electricity grid in the South and the Southeast/Midwest in 2000. In contrast, the electricity grid was not fully developed in the two other subsystems at the time, but it developed rapidly in following years thanks to strong support from the federal government (e.g. program "Luz Para Todos"). The Brazilian electricity system relies almost exclusively on hydrological resources. In 2000, hydropower was responsible for 81% of the production capacity and 94% of the electricity generated in the country (ONS, 2011). More than 60 local monopolies (distribution utilities) distribute electricity to end-consumers and housing units are typically metered and billed separately every month. Finally, electricity theft – i.e. illegal connections to the grid – is a serious concern in Brazil. It amounts to 15% of the total load for some distribution utilities.

Electricity prices are regulated by a federal agency (Agência Nacional de Energia Elétrica, ANEEL). 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. Price changes typically modify the main tariff and therefore imply a proportional change in every marginal price. The regulatory framework is a price-cap mechanism. Every four or five years, prices are *revised* to guarantee the economic viability of distribution utilities. However, demand risk falls entirely on them between revision years. Yearly price *adjustments* only factor in changes in non-manageable costs, such as energy costs (ANEEL, 2005).[20]

[19] In our back-of-the-envelope calculations, we must also assume that the social cost comes only from distorting quantities. This may or may not be the case with pecuniary, and especially non-pecuniary incentives. Such considerations are beyond the scope of our paper. Note that any policy that aims at changing aggregate behavior in such a large scale would likely stimulate a set of non-pecuniary incentives (e.g., peer pressure) at least endogenously.

[20] The price-cap mechanism encourages distribution utilities to address electricity theft. Price revisions and adjustments occur at different times for different utilities. In June 2001, the main tariff was US$.229/kWh in Rio de Janeiro. Marginal prices in the alternative tariff were US$.08 (up to 30 kWh), US$.137 (up to 100 kWh), US$.207 (up to 140 kWh), and US$.229 (above 140 kWh). Monetary values are in US$ of 2012 throughout the paper (R$1.82=US$1).

2.1.2 History of the 2001 electricity crisis

The 2001 electricity crisis was entirely due to supply factors. In particular, it was due to exceptionally low streamflow in the rivers that served hydropower plants in specific areas of the country, combined with infrastructure constraints on generation and transmission capacity. Figure 1a displays the evolution of hydro-reservoirs' water levels in the Southeast/Midwest and in the South. We focus on the two largest subsystems in our analysis because of their similar development stage at the time (see next section). Water levels follow a seasonal pattern in the Southeast/Midwest with heavy rain upstream of the reservoirs replenishing them during the austral summer. Levels were low in the two subsystems by 2000. In the Southeast/Midwest, they reached their lowest point in 40 years (for the season) in March 2001 because of exceptionally low summer rainfall. The Northeast and the North were facing a similar situation (not shown). In contrast, generous rain dissipated any risk of shortages in the South in 2001. Importantly, there was limited transmission capacity across subsystems such that the South could not supply much electricity to the other subsystems. Moreover, while growth in demand had never outpaced growth in projected demand in the years prior to 2001 (see Appendix), it outpaced growth in generation capacity. This was a nationwide issue and experts later concluded that the South would have faced a similar crisis if its hydropower plants had experienced a similar situation as in the Southeast/Midwest (Kelman, 2001).

By late April, it became clear that electricity use had to decrease to avoid generalized blackouts. The government announced that an incentive-based electricity saving program would start in June, although details remained unclear (*Globo*, April 23, 2001).[21] Distribution utilities supported instead the use of rolling blackouts because "financial penalties were unlikely to succeed, in part due to the lack of demand elasticity" and the expected length of the crisis (*Veja*, May 3, 2001; Maurer, Pereira and Rosenblatt, 2005). Rolling blackouts remained part of a plan B that never became necessary. The government program started on June 4, 2001, and from the very start, it was expected to last until February 2002 (end of next rainy season; *Veja*, July 19, 2001). The objective was to reduce electricity use by 20% in the Southeast/Midwest. The program also applied in the Northeast, and to a lesser extent in the North, but not in the South. Mation and Ferraz (2011) provide ample evidence that the crisis, the electricity saving program, and its differential implementation across subsystems, were mostly unanticipated.[22]As expected, the crisis officially ended in February 2002, but according to a specialized periodical, "people were giving signals that they

Minimum consumption levels are also charged, and local taxes increase what customers eventually pay.

[21] This was despite a first set of national policies in early April. Among these measures were the giveaway of efficient lightbulbs 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).

[22] For instance, President Cardoso's approval rates dropped differentially in areas subject to the electricity saving program after its announcement. Mation and Ferraz (2011) provide evidence that even industrial customers did not anticipate the (differential) implementation of the program.

learned how to avoid wasting electricity" (*Energia Elétrica*, March 15, 2002).

2.1.3 Incentives of the electricity saving program

The electricity saving program included individually-assigned quotas and a set of incentives for residential customers to consume below their quota. Rules were frequently repeated in the media and on electricity bills, but they were relatively complicated, nonlinear, and changed more than once.[23] Therefore, it is unclear what customers were exactly responding to. However, we are not interested in the specificities of these measures. Our interest is that households reduced electricity use dramatically in response to the policy, which was known to be temporary.

Every customer was assigned a *quota* at the start of the crisis. The typical quota was equal to 80% of a *baseline* corresponding to their average consumption from May to July 2000. Quotas for small consumers were set at 100% of baseline or 100 kWh, whichever was smaller.[24]

The incentive scheme included sticks and carrots. Customers exceeding their quota were charged a *fine* per kWh consumed above 200 kWh, and not per kWh above the quota. Fines thus targeted larger consumers. The unit fine was equal to 50% of the usual tariff up to 500 kWh and then to 200% of the tariff. Customers who exceeded their quotas more than once were also under the *threat of power cuts* of three to six days. Customers consuming less than their quota were eligible for a *bonus* per kWh reduced below their quota. The only guaranteed bonus was for customers consuming less than 100 kWh. The remaining funds from collecting fines would then be divided among other complying customers. The unit bonus was equal to at most 200% of the tariff. We illustrate how these incentives modified the cost of electricity in the Appendix.[25]

In practice, the implementation of these incentives was not smooth. First, households' response to the program was so large that fines did not raise enough money to pay any non-guaranteed bonus. The government then introduced another guaranteed bonus in September 2001 for customers with quotas below 225 kWh, with a unit bonus of 100% of the tariff. Second, distribution utilities did not have enough staff to implement power cuts. So, power cuts were limited to a very few customers and distribution utilities were asked to prioritize those who consumed repeatedly far above their quota. Power cuts were even prohibited in Rio de Janeiro (Lei Municipal 3266/2001), the city for

[23] Firms and the public sector also faced incentives in this period. Mation and Ferraz (2011) look at impacts on firms. We do not consider firms because the nature of their response to temporary corrective incentives may be very different and because changes in the industrial composition of the economy complicates the study of long-term effects. The fact that firms were subject to some incentives is only an issue for our purpose to the extent that it affected households' electricity use indirectly. However, we control for employment or income effects in our empirical analysis.

[24] Quotas were revised upward in December 2001 and January 2002 because the situation was improving. Consumption levels are also typically higher in the austral summer. Customers were informed of their quotas by mail prior to their first affected billing cycle. We reproduce such a letter in the Appendix. We also display the exact mapping between quotas and baseline consumption levels.

[25] Fines and bonuses were added in electricity bills, which could not be negative, limiting the payment of bonuses.

which we have customer-level billing data.

Finally, a massive *conservation appeal* campaign (social incentives) was carried out in collaboration with distribution utilities and media outlets. Daily reports on TV compared achievements to government targets. Energy conservation advice and stories of exemplary behaviors were shared repeatedly in the media to promote awareness and encourage participation. Media reports and messages on electricity bills included appeals to social preferences and patriotism. The government made sure to impose a more stringent conservation target for public buildings to set the example.

Households were also offered a lot of information in the media on how to reduce electricity use. This information reached the whole country, as the main media outlets are national in Brazil. It may thus explain some spillover effects to unaffected areas, but it is thus unlikely to explain any large differential trend between areas subject or not to the electricity saving program. Even if it were, our framework would apply as long as households internalized that information because they were subject to the policy. In fact, we would argue that any policy that aims at changing behavior in such a large scale would spur a market for information.

Other factors could have affected electricity use but not differentially in the Southeast/Midwest and in the South. Tariff changes followed the usual regulatory framework during and after the crisis.[26] Some policies were implemented nationally and are thus part of our counterfactual. Taxes on efficient lightbulbs were reduced, and taxes on electric showers, water heaters, and incandescent lightbulbs were temporarily increased (Decreto 3827, May 21, 2001). Efficiency standards for domestic appliances were adopted (Lei 10295, October 17, 2001), but only implemented in later years. Finally, the rainfall pattern during the 2000-2001 summer was a clear outlier, so there was no rational reason for customers in different subsystems to differentially update their beliefs about the risk of future shortages.[27] Even if they did, it is unclear that they would have consumed less electricity in response, especially after the policy used grandfathering to assign individual quotas.

2.2 Data

Our analysis mostly relies on three sets of data.

A. Utility level administrative data (ANEEL).

[26]This is with the exception of a 2.9% extraordinary increase for distribution utilities subject to the electricity saving program (*Camara de Gestão da Crise de Energia, Resolução 91*, December 21, 2001). Such a small price change is unlikely to drive any of our results. Moreover, we control for tariffs in our empirical analysis.

[27]Accordingly, when the government established an *insurance fund* to prevent subsequent crises, it chose to finance it through a nationwide undifferentiated increase in electricity tariffs (R$.49 per 100 kWh; Camara de Gestão da Crise de Energia, Resolução 115). Reservoir levels were very low in 2000 even in the South. They were also more variable in the South after the crisis. Moreover, the country had already experienced smaller weather-induced electricity shortages in all subsystems in the past (Maurer, Pereira and Rosenblatt, 2005). These previous shortages led to blackouts and not to the implementation of any incentive-based demand management plan.

Our main results are based on longitudinal data at the level of distribution utilities. The regulator (ANEEL) provided us with monthly administrative data from mandatory reports of distribution utilities on total electricity consumption, total revenues, and total number of customers by category (e.g., residential) from 1991 to 2011. Our main outcome, average residential electricity consumption per customer, is equal to total residential consumption divided by the number of residential customers. We also gathered copies of every tariff regulation published by the regulator from 1996 to 2011. As a result, we have a balanced panel of average residential electricity consumption and residential electricity tariff at the monthly level for all distribution utilities. In 2000, we have 26 utilities in the Southeast/Midwest and 17 in the South (numbers vary slightly with sample years due to some concession areas being split). We match our panel of distribution utilities to decennial census data (2000 and 2010) and to yearly data on population (1996-2011), GDP (1999-2011), formal employment, and average temperature (1996-2010), which are available at the municipality level and can be matched using information on the concession area of each distribution utility.[28]

B. Household level billing data (LIGHT).

We use longitudinal data at the customer level for one distribution utility subject to the electricity saving program to evaluate the robustness of our results and to go beyond average effects. We obtained individual billing data from January 2000 to December 2005 for the universe of low voltage customers of LIGHT, the distribution utility serving Rio de Janeiro and 31 surrounding municipalities (Southeast). The data include about three million residential customers in 2000. They detail every bill component and include metering and billing dates, meter location, and the quantity consumed in each month. Customers are uniquely identified over time until they move.

C. Household level survey data (PPH).

We exploit the microdata from the two most recent rounds of the Survey of Appliances and Utilization Habits (PPH, Pesquisa de Posse de Equipamentos e Hábitos de Uso) to shed light on the mechanisms behind our results. The surveys are conducted by the National Electrical Energy Saving Program (PROCEL). A representative sample of residential customers from several utilities was surveyed before the crisis (first round, July 1998 to June 1999) and several years after the crisis (second round, July 2004 to June 2005). The in-house interviews included questions on household characteristics, appliance ownership, and consumption habits. Interviewers were asked to check some of the information directly, e.g. the number of lamps in the living room. We have a repeated cross-section of 8,804 households and 5,448 households from the same ten distribution utilities in 1999 and 2005, respectively. We have 2 utilities in the South (total of 3,122 households) and 8 utilities in the Southeast/Midwest (total of 11,130 households).

[28] Census, GDP and demographic data are from the Brazilian Institute of Geography and Statistics (IBGE). Formal employment is from the Ministry of Labor official records' (RAIS). The average temperature data is from Matsuura and Willmott (2012).

D. Other data.

Finally, we confirm some of our results using time-series data on sales of appliances from manufacturers and the Brazilian Household Expenditure Surveys (POF, Pesquisa de Orçamentos Familiares, with rounds in 1996-1997, 2002-2003, and 2008-2009). Those data are not available at the municipality level and cannot be matched to the concession areas of distribution utilities.

3 Empirical strategy and descriptive statistics

Our main empirical strategy exploits our panel of distribution utilities through a difference-in-difference comparing utilities in the Southeast/Midwest and in the South over time. In this section, we first provide descriptive statistics supporting our approach. We then present our main empirical specification and a series of tests to evaluate the robustness of our results.

3.1 Descriptive statistics

Table 1 provides some descriptive statistics supporting our key identification assumption of a common-trend in average residential electricity consumption for distribution utilities in the Southeast/Midwest and in the South. It also shows that such an assumption is unlikely to hold, especially in the long term, when considering distribution utilities in the other two subsystems subject to the electricity saving program. Columns (1)-(5) compare initial values across distribution utilities in the four subsystems (and for LIGHT separately), namely the mean and range of relevant variables in 2000. Columns (6)-(8) present the differential trend in these variables between 2000 and 2010 comparing utilities in each of the three other subsystems to utilities in the South.[29] Some of the variables discussed below are presented in a similar table in the Appendix.

Before comparing subsystems, note that average residential electricity use was lower in Brazil (below 200 kWh/month in 2000) than in more developed countries (903 kWh/month in the US in 2012; www.eia.gov/tools/faqs). Households were of course poorer and less likely to own major domestic appliances, but electricity was also relatively expensive. The main residential electricity tariff in 2000 (US$.165/kWh) was higher than the US average price in 2012 (US$0.118/kWh).

There are two main reasons to not consider distribution utilities from the Northeast and from the North in our analysis. First, nearly all households in the South had electricity prior to the crisis.

[29] Speficically, we use yearly data from the most recent census years ($t \in 2000, 2010$) and the following specification:

$$log\left(y_{d,t}\right) = \alpha_d + \gamma\, \mathbb{1}\{t = 2010\} + \delta\, \mathbb{1}\{t = 2010\, \&\, d \in \text{TreatRegion}_d\} + \nu_{d,t}$$

where a_d is a fixed effect for distribution utility d, and $TreatRegion$ indicates a distribution utility from a subsystem subject to the electricity saving program. $\nu_{d,t}$ is an error term clustered by utility. Columns (6)-(8) report estimates of $\widehat{\delta}$ for samples including utilities from one of the other three subsystems and the South.

This was not the case in the Northeast and in the North. Moreover, the share of households with electricity increased substantially in these subsystems in the following decade, by 8 to 11 percentage points compared to the South. A common-trend assumption is unlikely to hold when customer bases evolve very differently. Second, households in the Northeast and in the North were poorer and were less likely to own major domestic appliances prior to the crisis – e.g. we observe no common support for the median household income and the share of households owning refrigerators between utilities in the Northeast and in the South. Strong poverty alleviation, as experienced in Brazil in the years following the crisis, can have very different effects on residential electricity use when initial ownership rates are so different (Wolfram, Shelef and Gertler, 2012). Accordingly, the share of households owning a refrigerator, a major domestic appliance in terms of electricity use, increased 15%-26% more compared to the South. This is unlikely to be a consequence of the crisis and thus clearly violates a common-trend assumption.[30]

Distribution utilities in the South constitute a more credible counterfactual for distribution utilities in the Southeast/Midwest. First, nearly all households had electricity prior to the crisis in both subsystems. Second, customer bases evolved at a similar rate in the following decade. Moreover, this does not hide any differential trend in population size, access to electricity, urbanization, household size, dwelling size, or dwelling characteristics. Third, initial ownership rates of major domestic appliances (refrigerator, washing machine, TV, air conditioner), and subsequent growth in ownership rates are comparable. Fourth, initial electricity tariffs were also comparable and did not evolve differentially. If anything, tariffs decreased relatively in the Southeast/Midwest.

Distribution utilities in the South and in the Southeast/Midwest differ in some respects. For instance, average electricity use and median income levels were on average higher in the Southeast/Midwest in 2000. Median income levels grew also relatively less in the Southeast/Midwest in the following decade, even though labor market outcomes such as employment, formal employment, or farm employment did not evolve differentially (we attribute the differential trend in average electricity use to the impact of the electricity saving program below). Importantly, the range of initial values overlapped for all these variables and many others, as did the range of changes in these values in subsequent years (see Appendix). Therefore, we can control for many relevant variables without relying on purely parametric assumptions (this would not be true using data from the Northeast). One factor that differs systematically between the Southeast/Midwest and the South is climate. Average temperatures are higher in the Southeast/Midwest. This is unlikely to drive any of our results. We show in the Appendix that there is no relationship between changes in average residential electricity use in the Southeast/Midwest and in the South, and either levels or changes in

[30] Additionally, there is a data limitation preventing us to study outcomes in the North subsystem. Many customers there are served by isolated electricity systems. Our utility-level panel data do not differentiate residential consumption from “isolated” and “connected” customers, and the former were not subject to the electricity saving program. The policy also started later (August) and ended earlier (December) in the North.

average temperatures. In sum, the data appear to support our common-trend assumption, as shown in Figure 1b for earlier periods, at least conditionally on controlling for some relevant factors.

3.2 Empirical strategy

We estimate the short- and long-term impacts of the temporary electricity saving program through a generalized difference-in-difference. We regress the logarithm (or the level) of average residential electricity consumption per customer for utility d from region r in calendar month m of year t using the following specification:

$$\begin{aligned} log\left(Av\_kWh_{d,r,m,t}\right) = & \alpha_d + \beta_{r,m} + \gamma_p \mathbb{1}\left\{t \in TimePeriod_p\right\} \\ & + \delta_p \, \mathbb{1}\left\{d \in \text{SE/MW}\& \, t \in TimePeriod_p\right\} + log\left(X_{d,r,m,t}\right) + \nu_{d,r,m,t} \end{aligned} \tag{6}$$

where the coefficients α_d and $\beta_{r,m}$ are fixed effects for each distribution utility and for each calendar month per region (seasonality), respectively. We divide our monthly observations into various time periods, indexed by p. We consider yearly time periods before and after the crisis. We divide 2001 and 2002 into three time periods: pre-crisis (early 2001), crisis (June 2001–February 2002), and post-crisis (rest of 2002). The coefficients γ_p are time-period fixed effects. The coefficients δ_p then capture difference-in-difference estimators for the impact of the temporary electricity saving program in each time period. Finally, we cluster error terms ($\nu_{d,r,m,t}$) at the level of the distribution utility, and distribution utilities are weighted equally in our regressions.[31]

Estimates of δ_p during the crisis and for subsequent time periods can be interpreted as the average treatment effect of the policy on the treated under a common-trend assumption. Of course, it is not possible to test whether this assumption holds in practice. However, we show in Figure 1b that average electricity use had been following roughly the same trend since 1991 in the South and the Southeast/Midwest. Estimates of δ_p for time periods preceding the crisis will directly test for the presence of a common-trend prior to the crisis. Moreover, as explained in Section 2, the timing of the crisis and the differential treatment between subsystem was entirely due to supply factors likely exogenous to potential changes in households' electricity use. A common-trend assumption is thus reasonable in our context, especially in the short run. As we are particularly interested in long-run effects, we then reinforce the common-trend assumption by controlling for variables that may be correlated with other factors affecting electricity use. In particular, we use the

[31] Our independence assumption seems reasonable in our context. The two subsystems cover very large and heterogeneous areas, providing electricity to more than 100 million individuals. Moreover, electricity sector policy, including policies related to electricity efficiency, is centralized at the federal level. We show similar results weighting distribution utilities by their customer base in the Appendix. Results are noisier as they are driven by the few very large distribution utilities in our sample.

variables available at the distribution utility level in each year ($X_{d,r,m,t}$): main residential electricity tariff (1996-2011), population size (1996-2011), GDP (1999-2011), formal employment levels, and average temperature (1996-2010). Our preferred specification includes all these controls and the sample is therefore restricted to a balanced panel of utilities between 1999 and 2010.

3.3 Robustness checks

We undertake four types of empirical tests to evaluate the robustness of our results. First, we obtain similar results when estimating variants of equation (6) with different sample years and the controls available in those years. Second, we show that our estimated average impact is not driven by outliers. To do so, we estimate the impact of the electricity saving program for each distribution utility separately using synthetic control methods (Abadie, Diamond and Hainmueller, 2010). The synthetic control estimator is the difference between an outcome in a *treated* utility during and after the crisis, and the same outcome in a "synthetic" weighted average of *control* utility. The outcome of interest, $Y_{d,t}$, is the demeaned seasonally adjusted logarithm of average monthly residential consumption. The vector of weights W is chosen to minimize: $\| Y_{d0} - Y_{c0}W \| = \sqrt{(Y_{d0} - Y_{c0}W)' V (Y_{d0} - Y_{c0}W)}$, where Y_{d0} and Y_{c0} are vectors containing the values of the outcome in pre-crisis periods in the treated utility and in control utilities, respectively. An optimal choice of V minimizes the mean squared error of the synthetic control estimator.

Third, we investigate whether our estimated long-term impact is robust to controlling for variables that are not available at the yearly level but that are available in the 2000 and 2010 censuses ($X_{d,t}$), such as median household income. We show graphically the relationship between changes in these variables and changes in average electricity consumption between 2000 and 2010. We also estimate the following regression using only data from census years:

$$log(Av\_kWh_{d,t}) = \alpha_d + \gamma\, \mathbb{1}(t = 2010) + \delta\, \mathbb{1}(t = 2010\,\&\, d \in \text{SE/MW}) + log\left(X_{d,t}\right) + \nu_{d,t} \quad (7)$$

where $\nu_{d,t}$ is an error term for utility d in census year t clustered by distribution utility.

Fourth, we use the longitudinal data for LIGHT customers to address a series of confounding explanations that cannot be tackled with utility-level data. We compare changes in average electricity use in LIGHT aggregate monthly data and in a random sample of individual customers observed in every month from 2000 to 2005. This balanced panel does not suffer from composition effects by construction. We then document the persistence of changes in consumption levels during the crisis *at the individual level*.[32] Finally, we investigate other dimensions of the distribution of

[32] We cannot estimate the causal effect of some policy variation among LIGHT customers. First, all customers were subject to some aspects of the policy and rules were complicated and uncertain. Second, we don't know how non-pecuniary incentives were perceived among customers and they may have played a role. Third, there is no discontinuity

changes in consumption levels, which are interesting in themselves and also as a way to address a concern that "electricity theft" responses may explain some of our results.

4 Results

We first present results using utility-level data. We then turn to the customer-level data. Most of our regression results are presented graphically, but corresponding tables with coefficient estimates and standard errors are in the Appendix.

4.1 Utility-level data

Difference-in-difference coefficients $\widehat{\delta_p}$ from estimating our preferred specification of equation (6) are displayed in Figure 3 with their 95% confidence intervals. The sample is restricted to the balanced panel of utilities between 1999 and 2010 such that we can include all the controls available at the yearly level. Panel (a) and (b) consider specifications in logs and levels, respectively. The first few months of 2001 are used as reference period. Point estimates are close to 0 prior to the crisis, supporting our common-trend assumption. Average residential electricity consumption then dropped differentially in the Southeast/Midwest when the electricity saving program came into force. We estimate an impact of -.26 log point (23%) during the crisis, or 41.5 kWh/month. This is the first quasi-experimental estimate of the short-run impact for residential customers, but it is already well known that electricity consumption was successfully reduced at the time. Our main contribution is to show that about half of the short-run impact persisted in the long run. Consumption levels partially rebounded after the crisis but point estimates are stable from 2005 onwards at about -.115 log points (11%), or 19 kWh/month. It is thus unlikely that our estimates are due to a difference between short- and long-run elasticities rather than hysteresis.

Our results are similar if we consider all the possible combinations of sample years determined by the availability of our yearly controls: 1991-2011 (no controls), 1996-2011 (tariffs and population), 1996-2010 (tariff, population, formal employment, average temperature), 1999-2011 (tariff, population, GDP). Point estimates for the log specification are displayed in Figure 4a. We omit confidence intervals for the sake of clarity. The estimated short- and long-run impacts are almost identical in all specifications. Moreover, Figure 4a shows that average electricity consumption followed similar trends in the Southeast/Midwest and in the South since at least 1991. Point estimates are slightly positive between 1997 and 2000, a pattern that is apparent in the raw data in Figure 1b, but they get closer to 0 as we add more controls. Results are also similar if: (i) we consider

or bunching in electricity use at the quota or at other levels where customers faced discontinuities or kinks in their budget. This is consistent with the existing literature (Borenstein, 2009). In an earlier working paper, we showed that even large quasi-exogenous variation in quotas led to only very small variation in consumption (Gerard, 2013).

winter and summer months separately, (ii) if we weight distribution utilities by their customer base at baseline, and (iii) if we restrict the sample to distribution utilities with overlapping support in average electricity use (outcome) and in household median income (not available at the yearly level) at baseline to reinforce our common-trend assumption (see Appendix).

Figure 4b displays synthetic control estimates of the impact of the electricity saving program for each distribution utility. Monthly estimates are averaged into the same time periods as in Figure 3. Darker lines correspond to distribution utilities in the Southeast/Midwest. Lighter lines correspond to placebo estimates in which we compare a given distribution utility in the South to a weighted average of the others. The synthetic controls are able to match the trends pre-crisis closely, including between 1997 and 2000. The estimated short-run impact is large for all the distribution utilities subject to the policy, between -.19 and -.40 log points. Importantly, the long-run impact is also negative for all those utilities. Our estimated average impact is thus not driven by outliers (this can be seen in the raw data in the Appendix). The median and the average of the utility-specific impacts are in fact comparable – e.g. -.13 and -.14 log points in 2011, respectively. In contrast, the median and the average of our placebo estimates are very close to 0 in all years.[33]

Table 2 displays estimates of the long-term impact of the electricity saving program from using equation (7) and controlling for variables available in the 2000 and 2010 censuses. Columns (4)-(6) restrict the sample to distribution utilities with overlapping support at baseline in average electricity use and household median income. The estimated impact is similar when we don't include any control (columns 1 and 4), when we control for the main electricity tariff and median household income (columns 2 and 5), and when we add controls for population size, the share of households living in urban areas, average household size, average dwelling size, the share of dwellings with a bathroom, the employment rate, and the average temperature (columns 3 and 6). The robustness of our results does not come from an absence of variation in these variables. We show graphically in the Appendix that long-term changes in consumption levels are systematically lower for utilities in the Southeast/Midwest than in the South for given baseline levels or long-term changes in all the variables in Table 1 and in its continuation table in the Appendix.

4.2 Customer-level data

Figure 5 presents robustness checks using the longitudinal microdata for LIGHT customers. Panel (a) shows that the time-series in average electricity use for LIGHT is similar when we use (i) the aggregate data at the utility level, (ii) microdata from a random sample of customers in each month, and (iii) microdata from a random sample of customers observed in every month from 2000 to 2005 (balanced panel). This provides additional evidence that composition effects, absent from

[33] We replicated this exercise using the main electricity tariff as outcome. In that case, the range of estimated impacts overlap completely and is centered around 0 for utilities in the Southeast/Midwest and in the South (see Appendix).

the balanced panel by construction, are unlikely to drive our results, at least until 2005 (the LIGHT-specific impact remains large after 2005 in Figure 4b).[34] It also implies that our estimates are not due to electricity theft at the extensive margin. Customers who are obtaining all their electricity through illegal connections to the grid at some point are excluded from the random sample.[35]

Panel (b) shows that average changes in electricity use came from sizable reductions at every level of consumption. It displays Kernel densities for average monthly electricity use before, during, and after the crisis. The density during the crisis is stochastically dominated. Densities one year and four years after the crisis are similar and fall between the crisis and pre-crisis densities. Almost all customers (92%) reduced electricity use compared to before the crisis; the median customer reduced electricity use by 31%. Four years after the crisis, 69% were still consuming less than before the crisis; the median customer was consuming 16.5% less electricity.[36]

Panel (c) shows that average changes in electricity use came from large reductions from most customers *at a given baseline consumption level*. It displays the distribution of changes in average monthly electricity use during and after the crisis compared to before the crisis, for customers with the same baseline consumption (around 300 kWh). Kernel densities are based on electricity use during the first five months of the crisis (and in the same months in other years), when these customers faced the same quota and incentives. As mentioned before, we find no evidence of bunching at the quota. During the crisis, 98% reduced electricity use and the median customer reduced usage by 34%. Four years after the crisis, 78% were still using less electricity than before the crisis; the median customer was using 22% less electricity (mean 19%). We show similar patterns for other baseline consumption levels in the Appendix.

Together, panels (b) and (c) also provide evidence against electricity theft responses at the intensive margin. Establishing illegal connections to the grid to obtain part of one's own electricity use is more likely to take place among poorer and smaller consumers. However, reductions in electricity use were not concentrated among small consumers. We show in the Appendix that they were also large among customers from relatively wealthy neighborhoods. Finally, if electricity theft takes place among relatively large consumers, it is likely to be concentrated within a small

[34] There is no evidence of economically meaningful migration across regions between 2000 and 2010. de Oliveira and de Oliveira (2011) document that the Southeast experienced a net out-migration during the period. However, magnitudes are very small: no larger than 0.2% of the Southeast population and 0.5% of the South population.

[35] There is no good data on electricity theft. Distribution utilities are supposed to report yearly information on distribution losses to the regulator, but many did not provide this information prior to 2000. In the Appendix, we use yearly reports for 24 utilities in the Southeast/Midwest and in the South from 1998 to 2008. The data are very noisy and, if anything, point estimates suggest that non-technical losses (a measure of theft) decreased compared to 2000. In the Appendix, we also use microdata from the Brazilian Household Budget Survey (POF 1996/97, 2002/03 and 2008/09) and find no differential trend in the share of households who do not pay for electricity.

[36] We show similar patterns for summer and winter months separately in the Appendix. We show that customers with higher baseline consumption levels made larger reductions in electricity use proportionally. Considering shifts in the distribution of electricity use in Figure 5b avoids mean reversion issues (Borenstein, 2009; Ito, 2014).

group. This is inconsistent with the evidence in panel (c) that most customers at a relatively large baseline consumption level severely reduced their electricity use during the crisis.

So far, we have implicitly interpreted our results as evidence of hysteresis at the individual level. Panel (d) shows that there is indeed a strong correlation between electricity use during the crisis and four years after the crisis for customers with the same baseline consumption levels (same sample as in panel c). We show similar patterns for other baseline consumption levels in the Appendix. We provide evidence on the mechanisms of hysteresis in the next section.

5 Mechanisms of hysteresis

There are three main mechanisms that could explain a long-run reduction in household electricity use. Households may have permanently changed the quantity of appliances that they own, the type of appliances that they own, or their utilization of these appliances. We shed some light on each of these mechanisms below. To do so, we rely primarily on household-level microdata from the two most recent rounds of the Appliances and Utilization Habits surveys (PPH, 1998-1999 and 2004-2005). We use data from ten distribution utilities in the Southeast/Midwest (8) and in the South (2) that were surveyed in both rounds.[37] Conveniently, our estimated long-term impact on household electricity use is stable starting around the time of the second PPH survey round (see Figure 3). We also use other data sources that are described in more details in the Appendix.

5.1 Asking households directly

A natural starting point to investigate the mechanisms of persistence is to ask households directly. The second round of PPH surveys included a special section for customers of distribution utilities subject to the electricity saving program during the 2001 crisis. For each major domestic appliance, it asked households whether: (1) they were using the appliance as much as before the crisis; (2) they were using it less than before the crisis; (3) they had disconnected or disposed of the appliance during or after the crisis; (4) they had substituted a more energy-efficient model during or after the crisis. Households could only choose one answer and we display the share that chose each answer in Table 3. For each appliance, we also show the average quantity per household and the estimated average monthly electricity use for customers of these utilities prior to the crisis.

A large share of households who owned a given appliance prior to the crisis reported using it

[37] PROCEL did not share with us the identity of those distribution utilities due to confidentiality concerns. Therefore, we cannot match the PPH data to the ANEEL administrative data.

less after the crisis. This is true for electric showers (39%),[38] lights (41%), and freezers (21%),[39] which account for a significant portion of electricity use in Brazil, but also for other appliances. The one exception is for refrigerators, another main source of electricity use. This is in fact reassuring as we don't expect much flexibility in refrigerators' utilization. In contrast, less than 3% of households reported replacing their appliance with a more energy-efficient model, except for lights (9%). Finally, a large share of households reported disconnecting or disposing of their appliance only for the case of freezers (17%) and air conditioners (5%).

The main stated mechanism of persistence is a change in utilization habits. However, households may have changed their utilization habits *and* their appliance stock. Households in the South may also have made some similar changes. We thus further investigate the three mechanisms.

5.2 Appliances' quantity

The PPH surveys recorded data on the quantity of a list of appliances for households in the Southeast/Midwest and in the South in both survey rounds. We investigate any differential trend in appliances' quantity using a difference-in-difference strategy as in the previous sections:

$$Y_{h,d,t} = \alpha_d + \gamma\, \mathbb{1}\,(t = 2005) + \delta\; \mathbb{1}(t = 2005\,\&\, d \in \text{SE/MW}) + log\left(X_{h,d,t}\right) + \nu_{h,d,t} \tag{8}$$

where $Y_{h,d,t}$ is an outcome for household h from distribution utility d in survey round t. We control for utility fixed effects α_d and a survey round fixed effect γ. The coefficient δ is a difference-in-difference estimator under a common-trend assumption. We cannot provide evidence of a common trend prior to the crisis with two repeated cross-sections. We thus control for household characteristics, $X_{h,d,t}$, which may be correlated with different trends in appliance ownership.[40] We also construct an appliance quantity index to avoid multiple-inference problems, normalizing the quantity of each appliance using the average and standard deviation of appliance ownership in the South in 1999 (Kling, Liebman and Katz, 2007). We display difference-in-difference estimates in Table 4A for the five main domestic appliances in terms of electricity use. Results for other appliances are in the Appendix. Standard errors are obtained using the wild cluster bootstrap-t given our small number of clusters (Cameron, Gelbach and Miller, 2008). The resulting confidence intervals are large, typically including 0, so our results based on PPH remain suggestive.

[38] An electric shower consists in an electric heating device placed in a shower head. This is a popular technology in Latin American countries, and other developing countries, where most of households use gas tanks. It has a low fixed cost but a high variable cost (it consumes a lot of electricity).

[39] It is common in many countries for households to have smaller refrigerators than in the US with a small freezer unit, but to have a separate larger (horizontal or vertical) freezer unit.

[40] The vector of household characteristics include income, squared income, number of household members, dwelling size, and dummies identifying wealthier neighborhoods and neighborhoods close to slums ("favelas").

Point estimates are negative for our index and for all appliances, except for lights. They are close to 0 for refrigerators and washing machines, which is consistent with our earlier findings based on census data (see Section 3.1). They are large in magnitude for freezers and air conditioners, which is consistent with the information reported in Table 3. Finally, the coefficient is large in magnitude (and significant) for TVs. In Table 1, we had found no difference in TV ownership. This may be due to the fact that the census measures the share of households with TV while PPH measures the number of TVs per household.[41]

5.3 Appliances' characteristics

The PPH surveys recorded some appliance characteristics correlated with electricity use. We use the specification in equation (8) to investigate any differential trend in these characteristics and in two indices, one for the age of appliances and one for the type (size/power). The sign of all variables is normalized; a positive sign implies a higher propensity to use electricity. Results are displayed in Table 4B for the same five appliances and in the Appendix for other appliances.

Point estimates are positive for our "age" index (older) and for the age of each of our main domestic appliances. Replacing appliances with newer models, likely consuming less electricity, may have been difficult for Brazilian households who are relatively poorer and face a much higher cost of credit than in more advanced countries.[42] In fact, the supply side of the market for domestic appliances expected ex-ante, and reported ex-post, losses from the electricity crisis (*Folha de São Paulo*, June 5, 2001 and March 6, 2002). In the Appendix, we show that there is no discontinuous increase in estimates of national monthly sales of major domestic appliances during the crisis. In contrast, there is a discontinuous decrease in sales for many appliances.[43]

At the margin, we would still expect households to prefer models consuming less electricity when buying an appliance during the crisis. Point estimates are negative for our "type" index and for the size of our main domestic appliances, although standard errors are again large. In the Appendix, we show some related evidence for electric showers: the average power of electric showers sold by a leading Brazilian manufacturer decreased differentially in the Southeast/Midwest during

[41] The difference between the two samples may also be due to a difference in sampling (the census is representative of the Brazilian population; PPH is representative of customers of the ten unidentified utilities who are officially connected to the electricity grid) or to a difference in timing (post-crisis data is from 2005 in PPH and from 2010 in the census), e.g. a temporary effect if, as we discuss in the next section, sales of appliances decreased during the crisis. In the Appendix, we obtain similar estimates using microdata from the Household Budget Survey (POF) from 1996/97, 2002/03 and 2008/09. By 2008/09, we find a roughly zero point estimates for the quantity of refrigerators and TV, and a negative (and larger in magnitude) point estimate for the quantity of freezers owned by households.

[42] In 2001, Brazil was the country with the highest real interest rate in the World Development Indicators of the World Bank. It was 44.65 percent, compared to an average of 8.34 percent for OECD countries.

[43] We obtain those data from Whirlpool, a leading manufacturer, which produces those estimates for its market strategy. It did not share with us the estimation methodology used. At the time of the crisis, the Southeast/Midwest accounted for more than 55% of the national market of refrigerators, for example, and the South for another 20%.

the crisis (by about 10%), but it increased again after the crisis.[44]

Finally, we showed in Table 3 that household reported adopting more energy-efficient lightbulbs during and after the crisis in the Southeast/Midwest. It is well known that compact fluorescent lightbulbs (CFLs) spread rapidly in Brazil during and after the crisis. This national pattern is present in the PPH data; our estimate suggests an average increase of 52 percentage points in the share of CFLs in the South and Southeast/Midwest. However, our difference-in-difference estimate suggests that adoption rates were even higher in the South than in the Southeast/Midwest.[45]

5.4 Utilization habits

The PPH surveys recorded utilization habits correlated with electricity use for many appliances. As above, we use the specification in equation (8) to investigate any differential trend in each of these habits and in a "utilization habit" index. The sign of all variables is again normalized such that a positive sign implies a higher propensity to use electricity. Results are displayed in Table 4C for the same five appliances and in the Appendix for other appliances.

Point estimates are large and negative for our index and for utilization habits related to our main domestic appliances, except again for lights. For instance, households were much less likely to have their separate freezer unit permanently switched on in the Southeast/Midwest after the crisis, which is consistent with information in Table 3. Households were also less likely to regulate the thermostat of their electric shower to the warmest setting. The result is statistically significant even using our large standard errors. A back-of-the-envelope calculation suggests that this behavior alone could have generated enough savings to explain our long-term impact (22 kWh/month).[46]

In sum, the main stated mechanism of hysteresis is a change in habits (living with fewer appliances is also a new habit). We found suggestive evidence that households indeed changed their habits in the Southeast/Midwest. However, we cannot reject that some changes in appliances' characteristics may have also played a role. Note that our conceptual framework applies independently

[44]We obtained data on the monthly sale of all the models of electric showers from Fame, a leading manufacturer, disaggregated by state. The data include the power (wattage) of each model, which is the only relevant measure of electric showers' propensity to use electricity. We could not find similar data for other domestic appliances. The PPH data is too noisy to look at the characteristics of appliances of different ages.

[45]If we consider that this 52 percentage points national increase in adoption consisted of the substitution of an average 60W incandencent lightbulb (with average consumption 10.2 kWh/month) by a 15W CFL (with average consumption 2.25 kWh/month), we would have around 4 kWh/month saved per incandescent lightbulb on average. In 1999, households in the South used on average 5 incandescent lightbulbs, such that CFL substitution would account for a reduction of around 20 kWh/month in the South. This is larger than the time series drop in average electricity use in the South as we can see on Figure 1.

[46]The thermostat of an electric shower head can be switched off or set at "Low Power" (*Modo Verão*) or "High Power" (*Modo Inverno*). An electric shower consumes on average 30% less electricity in Low Power than in High Power. Our kWh figure is obtained by multiplying the estimated impact (-.863), the efficiency gain of regulating the shower to Low Power (30%) and the average electricity consumption of electric showers in High Power (87.1 kWh).

of the specific mechanisms as long as the hysteresis was due to the temporary policy.[47]

6 Implications for the social cost of corrective policies

We established that households reduced electricity use in the long run in response to a temporary electricity saving program. In this section, we use our evidence to illustrate the extent to which neglecting such hysteresis would overestimate the social cost of corrective policies.

First, a temporary policy delivers a persistent correction of the externality in the presence of hysteresis if the prior level of the behavior was too high from a social perspective. The associated gains could balance out part of the social cost of the policy. We estimated that the temporary policy reduced electricity use by 11% in the Southeast/Midwest until at least 2011, which corresponds to 67.8 billion kWh. PROCEL, the electrical energy saving program of the federal government, claims to have obtained reductions in electricity use of 39.6 billion kWh from 2001 to 2011 at a cost of US$366 millions. At that average level of cost-efficiency, PROCEL would thus have had to spend US$627 millions to achieve a similar reduction in electricity use. It is unclear how PROCEL actually measures its impact and our calculation is thus likely to be a lower bound.

Second, we evaluate equations (4) and (5) to illustrate the quantitative implication of the degree of hysteresis that we estimated for the social cost of a long-run corrective policy. Consider a policy that aimed at reducing electricity use by 23% (average effect during the crisis) over a period of 10 years. Period 1 corresponds to the nine months of the temporary policy and period 2 to the following 111 months. We estimated a necessary residual reduction in electricity use in the second period of 23%-11%=12%. In the Appendix, we estimate a medium-run price elasticity of average residential electricity use of $-.291$ using yearly variation in electricity tariffs across distribution utilities after the crisis. Applying this estimate, the change in marginal utility caused by the policy in period 2 is equivalent to a 79% increase in electricity tariffs assuming away hysteresis, but only a 41.2% increase given our estimated degree of hysteresis. The bias in level is then:

$$|DWL_{NoH}| - |DWL| = \frac{1}{2}\sum_{t=10}^{120} \beta^t \frac{p_t X_t/.89}{.2911}\left[(-.23)^2 - (-.12)^2 \frac{1}{.89/1}\right] = US\$4.14 \text{ billions}$$

where we use a (high) monthly discount rate of 1% ($\beta = .99$), and where $p_t X_t$ is the total monthly bill for residential electricity use in the Southeast/Midwest after the crisis. It is scaled by $\frac{1}{.89}$ to obtain counterfactual amounts ($p_{20}x_{20}$). A bias of US$4.14 billions corresponds to 6.44% of the

[47] The second round of PPH surveys (but not the first round) also asked households about the information that they disposed on energy efficiency. In the Appendix, we show that households in the Southeast/Midwest were more likely to have information on energy efficiency labels and energy savings behaviors after the crisis, but less likely to know what that information implies for how much electricity they can actually save. Note that any energy efficiency policy in Brazil, including information provision, would be implemented nationally by PROCEL.

total (discounted) monthly bill for residential electricity use in the Southeast/Midwest after the crisis. Even if the long-run elasticity were three times larger than the medium-run elasticity, the bias would still amount to US$1.38 billions. Another way to provide some perspective is to express the bias in percentage of the deadweight loss. Using equation (5), we have:

$$\frac{|DWL_{NoH}| - |DWL|}{|DWL|} = \frac{\sum_{t=10}^{t=120} \beta^t \frac{p_t X_t}{.89} \left[(-.23)^2 - (-.12)^2 \frac{1}{.89/1}\right]}{\frac{\eta_2}{\eta_1} \sum_{t=1}^{t=9} \beta^t \frac{p_t X_t}{.89} (-.23)^2 + \sum_{t=10}^{t=120} \beta^t \frac{p_t X_t}{.89^2} (-.12)^2} = 1.7$$

where we assume an equal elasticity in both periods ($\eta_2 = \eta_1$).[48] Assuming away hysteresis, one could then overestimate the social cost of the policy by 170%. This is just an illustrative calibration, but it shows how neglecting the possibility of hysteresis could severely overestimate the social cost of long-run corrective policies. Moreover, it would be even higher if we had assumed a longer time horizon, a lower discount rate, or if we took into account that part of the behavioral response in later periods of the crisis was already caused by the temporary policy in earlier periods.

So far, we have assumed that households perceived the true costs and benefits of changing their behavior. These costs must have been relatively high given that our estimates imply that an average household could save 11% of its electricity bill permanently by reducing electricity use by 23% for a nine-month period. Interestingly, this contrasts with households' reported experience during the crisis. When asked about changes to their life quality during the crisis in PPH surveys, only 24% of households in the Southeast/Midwest reported a decrease in life quality, 48% reported no change in life quality, and 28% reported to have "learned to live comfortably while saving money" (see Table 5). Moreover, 43% of households who managed to reduce electricity below their quota reported that it was "not difficult at all", and 48% reported that it was "not very difficult". The contrast between large long-run private gains and limited short-run private costs suggests that, if anything, households were underestimating the returns from changing their behavior before the crisis. This echoes several theories and findings in the literature (Jaffe and Stavins, 1994). For instance, Bryan, Chowdhury and Mobarak (2014) find that it is difficult to explain the low level of seasonal urban migration in their context given the high persistent return from a one-time incentivized migration. Agents with hyperbolic time discounting would underinvest in their habit formation, even if they were aware of their habit formation process (Gruber and Köszegi, 2001). Of course, agents may not be aware of such a process (Acland and Levy, 2015). Finally, households may have had the correct private costs of changing their behavior. However, these costs may drop dramatically when everybody is subject to a corrective policy because of, e.g., social learning (Dupas, 2014).[49]

[48] We cannot estimate a price elasticity during or before the crisis. It is unclear whether we should expect the price elasticity to have increased or decreased. Moreover, the bias remains large under extreme assumptions: assuming that the elasticity was three times smaller (resp. higher) in the first period, we obtain a bias of 213% (resp. 304%).

[49] The contrast between large long-run private gains and limited short-run private costs of changing behavior is

7 Conclusion

This paper argued that one might overestimate the social cost of long-run corrective policies by neglecting the possibility of hysteresis in the behavior of interest. We provided evidence of the importance of hysteresis in a policy-relevant behavior. We then used our estimates in a simple conceptual framework to illustrate the possibly large magnitude of the bias from not taking hysteresis into account when measuring the social cost of corrective policies.

A limitation of our empirical analysis is that we cannot relate the estimated impact to one specific easily-replicable policy instrument. Moreover, policymakers may not be interested in implementing permanently a policy similar to the temporary policy that we studied. Yet, there is a lot of interest in reducing energy use and the main argument against implementing sizable corrective policies in that context is that the associated social cost would be too large. Our paper implies that such an argument may be overstated. The big question that this study then leaves open is *how* to trigger the emergence of energy-efficient habits in a credit-constrained, low-income, and low-consumption setting. Shaping consumption patterns at an earlier stage of development may help attenuating the pressure of energy demand growth in developing countries.

The application in this paper considers the context of energy demand. However, our argument applies to any context where hysteresis may be relevant. For instance, Bryan, Chowdhury and Mobarak (2014) show that a one-time incentive for Bangladeshi households to migrate during the lean season led to 22% higher migration rates in the short-run and to 7% higher migration rates two and a half years later. In a different setting, Fujiwara, Meng and Vogl (2014) find that a weather-induced 1 percentage point rise in turnout in an election increased voter turnout in the following election by 0.9 percentage points. Assuming that these impacts persist in the long run, one would thus overestimate the social cost of long-run corrective policies by neglecting the degree of hysteresis in those contexts. For instance, using the estimates in Fujiwara, Meng and Vogl (2014) and similar back-of-the-envelope assumptions as in Section 6, the social cost of a policy that aims at a 1 percentage point permanent increase in voter turnout could be overestimated by 1450%.[50]

also consistent with a rational inattention model. Attention costs for energy-saving opportunities may have been high before the crisis (Sallee, 2014). Such costs would be factored in the demand curve for electricity use (and could explain a low price elasticity) and our framework would thus apply.

[50] We assume a constant cost of voting, a constant baseline turnout level (at their mean of 58%), a yearly discount rate of 5%, an infinite time horizon, and a constant elasticity with respect to voting costs.

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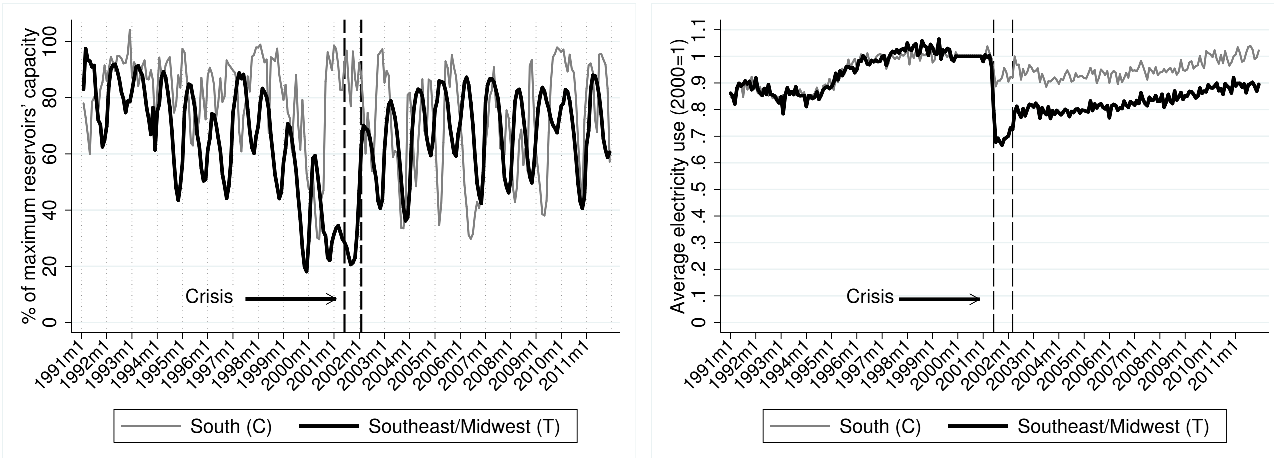
Figure 1: Cause and consequence of the temporary electricity saving program

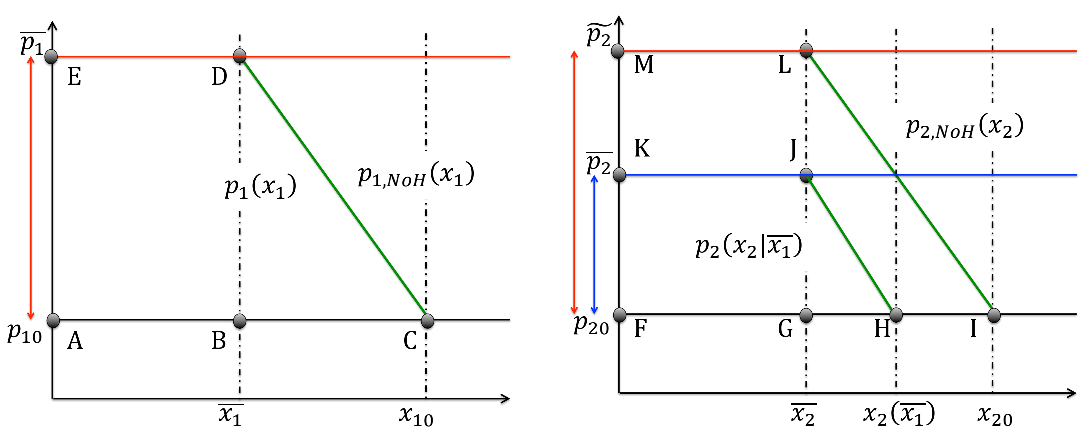
(a) Stocked energy of the hydroelectric reservoirs (b) Average residential electricity use



Panel (a) displays the evolution of hydro–reservoirs' capacity in the Southeast/Midwest and in the South (dotted lines indicate January; official data from ONS, the National System Operator). In the summer of 2000–2001, exceptionally low rainfall upstream of the reservoirs lead to dangerously low levels in the reservoirs in the South–East/Midwest. In contrast, generous rain dissipated any risk of shortages in the South. The electricity saving program was implemented in the Southeast/Midwest from June 2001 to February 2002 (dashed lines). Panel (b) displays the overall impact of the electricity saving program on monthly average residential electricity consumption per customer for distribution utilities in the two subsystems (utility–level administrative data). We present unweighted averages in each month, normalized with respect to the same month in 2000 (seasonality). Trends were similar prior to June 2001. Average residential consumption then dropped, especially for distribution utilities in the Southeast/Midwest, subject to the electricity saving program. Average residential consumption rebounded after February 2002, once the program was suspended, but only partially. Comparing patterns in the Southeast/Midwest and in the South suggests that some of the impact of the temporary electricity saving program persisted until at least the end of our sample (2011).

Figure 2: The social cost (deadweight loss) of corrective policies with hysteresis

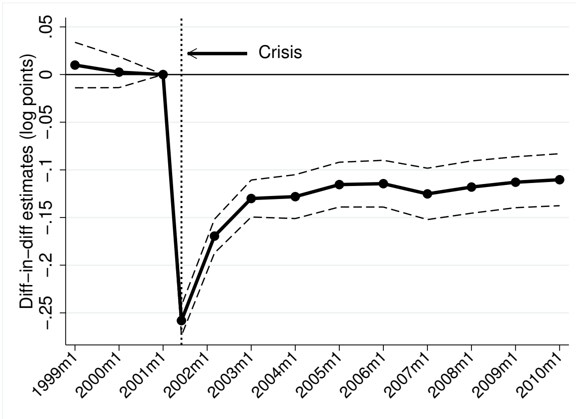
(a) Period 1 (b) Period 2



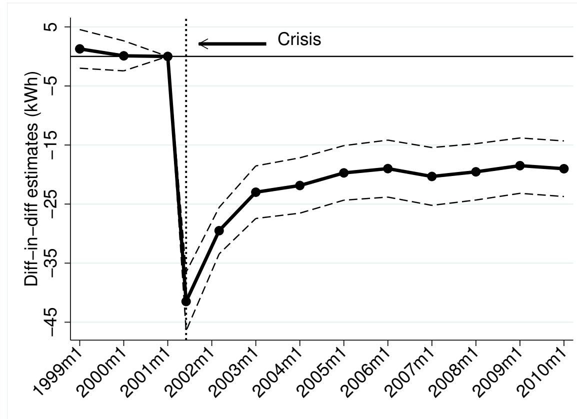
This figure illustrates how one would overestimate the social cost or deadweight loss of corrective policies in the presence of hysteresis. Without government intervention, x_{10} and x_{20} are the equilibrium quantities in period 1 and 2 given baseline prices p_{10} and p_{20}, respectively. Consider a corrective policy reducing quantities to $\overline{x_1}$ and $\overline{x_2}$. Reducing quantity in period 1 to $\overline{x_1}$ increases the household's marginal utility for x_1 which can be traced along the inverse demand curve $p_1(x_1)$. In the presence of hysteresis, this would reduce the quantity in period 2 to $x_2(\overline{x_1})$, absent any government intervention. The demand curve $p_1(x_1)$ would factor in any change in utility from such endogenous changes in x_2. The loss in utility from reducing quantity in period 1 to $\overline{x_1}$ is then the triangle BCD (assuming locally linear demand curves). One would arrive to the same conclusion when assuming away hysteresis, if using the same information to recover the inverse demand curve in period 1, $p_{1,NoH}(x_1)$ (NoH stands for no hysteresis). Further reducing quantity to $\overline{x_2}$ in period 2 then similarly increases the household's marginal utility for x_2 which can be traced along the inverse demand curve $p_2(x_2|\overline{x_1})$. The associated loss in utility is the triangle GHJ. Neglecting the possibility of hysteresis, one would arrive to a different conclusion even if using the same information to recover the inverse demand curve $p_{2,NoH}(x_2)$. Tracing the change in marginal utility along the whole interval from x_{20} to $\overline{x_2}$, one would obtain a loss in utility corresponding to the larger triangle GIL. The bias is the area HILJ. An estimate of the degree of hysteresis, $x_{20} - x_2(\overline{x_1})$, is key to evaluate this bias (along with the demand curves). It could be identified from the long-run impact of a corrective policy implemented only in period 1 (temporary policy).

Figure 3: Main difference–in–difference results on average residential electricity use

(a) in logs



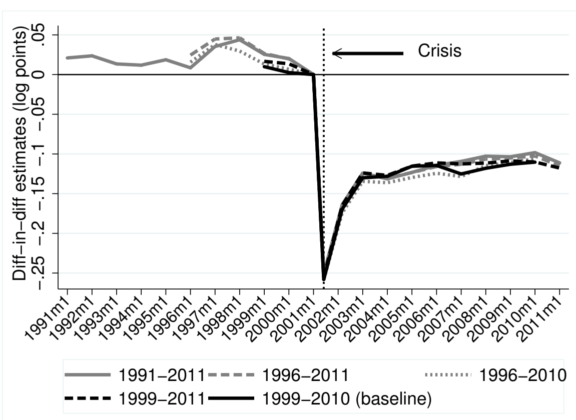
(b) in levels



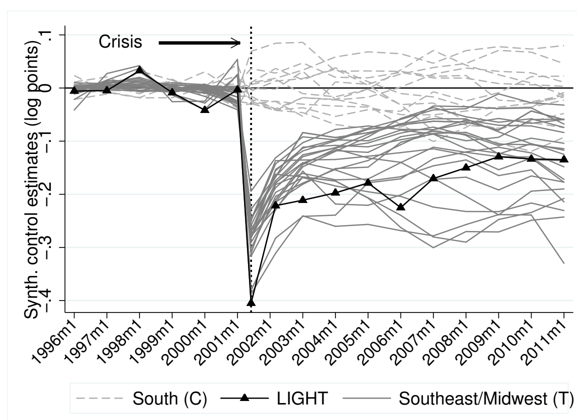
95% confidence interval in dash (s.e. clustered by utility). Utility-level administrative data for distribution utilities in the Southeast/Midwest and in the South from 1999 to 2010. The figures display coefficients from regressing the logarithm (panel a) or the level (panel b) of monthly average electricity consumption per customer for each utility on time–period dummies (yearly dummies, three dummies for 2001–2002 to isolate the crisis period) interacted with an indicator for utilities subject to the electricity saving program during the crisis (difference–in–difference estimators in each time period). The reference period corresponds to the first months of 2001. Regressions include uninteracted time–period dummies, utility and calendar month–per–region fixed effects, and controls for the logarithm or level of the main residential electricity tariff and of available yearly data matched to the concession area of each utility (population size, GDP, formal employment levels, average temperature). Point estimates are close to 0 prior to the crisis, supporting our common-trend assumption. Average residential electricity use then dropped differentially in the Southeast/Midwest when the electricity saving program came into force. We estimate an impact of -.26 log point (23%) during the crisis, or 41.5 kWh/month. Consumption levels partially rebounded after the crisis but point estimates are stable from 2005 onwards at about -.115 log points (11%), or 19 kWh/month.

Figure 4: Robustness checks using utility–level data

(a) Difference–in–difference results for different sample years and their available controls (in logs)



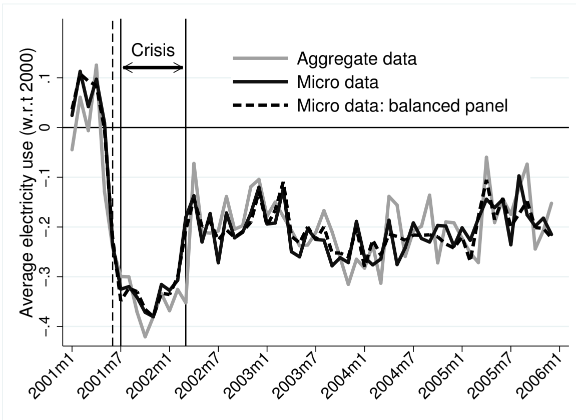
(b) Synthetic control estimates of utility–specific impact (in logs)



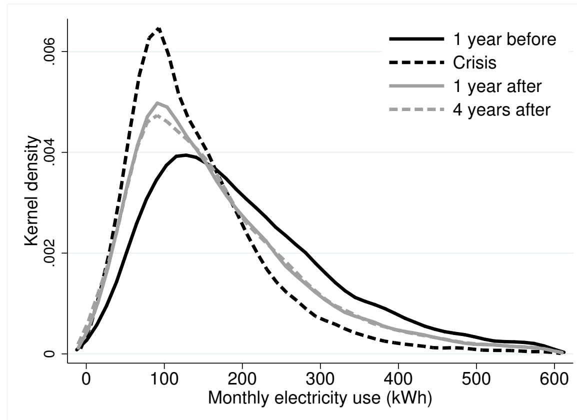
Panel (a) shows that our difference–in–difference estimates in Figure 3a are almost identical if we consider all the possible combinations of sample years determined by the availability of our yearly controls: 1991-2011 (no controls), 1996-2011 (tariffs and population), 1996-2010 (tariff, population, formal employment, average temperature), 1999-2011 (tariff, population, GDP). We omit confidence intervals for the sake of clarity (available in tables in the Appendix). It also shows that trends were similar in the Southeast/Midwest and in the South since at least 1991. Point estimates are slightly positive between 1997 and 2000, a pattern that is apparent in the raw data in Figure 1b, but they get closer to 0 as we add more controls. Panel (b) displays synthetic control estimates of the impact of the electricity saving program for each distribution utility. Monthly estimates are averaged into the same time periods as in Figure 3a. Darker lines correspond to distribution utilities in the Southeast/Midwest. Lighter lines correspond to placebo estimates in which we compare a given distribution utility in the South to a weighted average of the others. The synthetic controls are able to match the trends pre-crisis closely, including between 1997 and 2000. The estimated short-run impact is large for all the distribution utilities subject to the electricity saving program, between -.19 and -.40 log points. Importantly, the long-run impact is also negative for all those utilities. Our estimated average impact is thus not driven by outliers. The median and the average of the utility-specific impact is in fact comparable — e.g. $-.13$ and $-.14$ log points in 2011, respectively. In contrast, the median and the average of our placebo estimates are very close to 0 in all years.

Figure 5: Lessons and robustness checks using longitudinal microdata for LIGHT customers

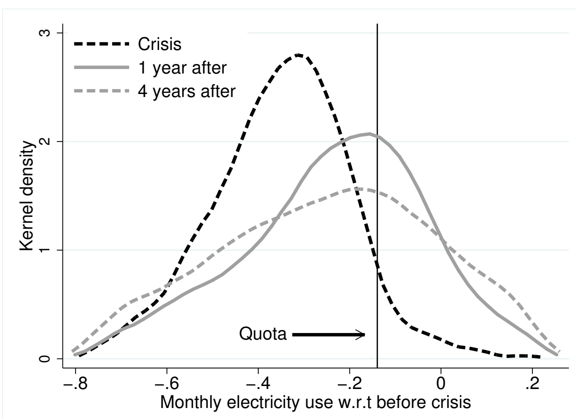
(a) Comparing time–series in average electricity using the utility-level data and the microdata



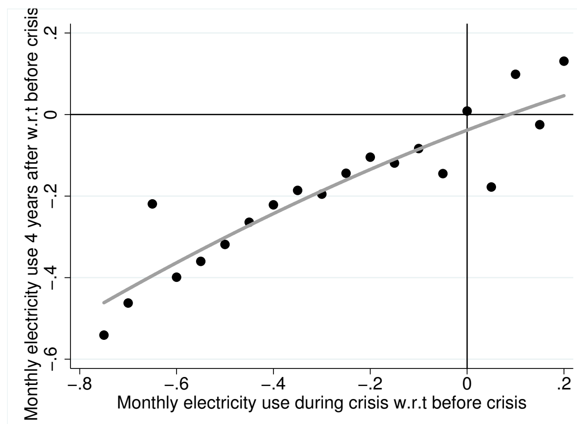
(b) Distribution of monthly electricity use over time for a balanced panel of customers



(c) Distribution of changes in monthly electricity use for a balanced panel of customers with the same baseline level/quota



(d) Correlation between changes in electricity use during and after the crisis for a balanced panel of customers with same baseline level/quota



Individual monthly billing data for the universe of residential customers of LIGHT (Southeast) from January 2000 to December 2005. Panel (a) displays average electricity use for LIGHT customers in each month compared to the same month in 2000. It shows that the time–series is almost identical when (i) we use the aggregate data at the utility level, (ii) microdata from a 2% random sample of customers in each month, and (iii) microdata from a random sample of customers observed in every month from 2000 to 2005 (balanced panel; 44,817 customers). This provides additional evidence that composition effects, absent from the balanced panel by construction, are unlikely to drive our results, at least until 2005 (estimated coefficients are very stable after 2005 in Figure 3). Panel (b) shows that average changes in electricity use came from sizable reductions at every level of consumption. It uses the same balanced panel to investigate changes in the distribution of electricity use over time. It displays Kernel densities for monthly electricity use before, during, and after the crisis. Kernel densities are based on data from June to December, such that we can compare consumption levels up to four years after the crisis. The density during the crisis is stochastically dominated by the other ones. Densities one year and four years after the crisis are very similar and they fall exactly between the crisis and pre-crisis densities. Panel (c) shows that average changes in electricity use came from large reductions from most customers at a given baseline consumption level. It displays the distribution of changes in electricity use during and after the crisis compared to the same months before the crisis, for a subset of the sample in panel (b) in which customers had about the same baseline for quota assignment, and thus faced the same pecuniary incentives during the crisis (10% above and below 300 kWh/month; 4,344 customers). Kernel densities are based on electricity use during the first five months of the crisis (and in the same months in other years), before any change in quotas. The quota is not at $-.2$ (vertical line) because it was based on the baseline months in 2000 (May to July) and not on these five months. We find no evidence of bunching at the quota. During the crisis, 98% reduced electricity use and the median customer reduced usage by 34%. Four years after the crisis, 78% were still using less electricity than before the crisis; the median customer was using 22% less electricity (mean 19%). We show similar patterns for other baseline consumption levels in the Appendix. Panel (d) displays the correlation between individual changes in electricity use during and after the crisis compared to the same months before the crisis, for the same sample as in panel (c). Customers are averaged by bins of 5% changes in electricity use during the crisis. The strong correlation suggests that the long-term impact is due to the persistence of individual changes in electricity use. Kernel densities use Epanechnikov kernels and optimal bandwidths.

Table 1: Descriptive statistics for distribution utilities in the four subsystems

	Descriptive statistics in 2000 Mean [min-max]					Differential trends 2010 vs. 2000 Coefficient, in logs (s.e.)		
	South (1)	LIGHT (2)	Southeast/Midwest (3)	Northeast (4)	North (5)	SE/MW vs. S (6)	NE vs. S (7)	N vs. S (8)
Average residential electricity	166	226	190	107	180	-.113***	-.001	.006
consumption (kWh/month)	[133–191]		[122–261]	[72.7–129]	[128–267]	(.021)	(.038)	(.048)
Main residential electricity	.152	.183	.164	.151	.15	-.093	-.001	-.083
tariff (R/kWh)	[.134–.171]		[.141–.188]	[.14–.171]	[.129–.165]	(.062)	(.065)	(.098)
Number of customers	360	2864	861	834	238	.014	.151***	.165***
(1000's)	[1.63–2200]		[17.7–4160]	[63–2405]	[12.2–857]	(.041)	(.044)	(.045)
Population size	1457	9025	3235	4323	1605	.031	.027	.164***
(1000's)	[12.1–9208]		[64.8–16661]	[193–13014]	[124–6122]	(.03)	(.028)	(.047)
Share of households	.982	.999	.984	.894	.83	-.002	.081***	.109***
with electricity	[.949–1]		[.896–1]	[.759–.989]	[.645–.989]	(.007)	(.028)	(.037)
Share of households	.795	.991	.861	.72	.734	-.02	-.01	-.003
in urban areas	[.587–.916]		[.654–.991]	[.613–.851]	[.414–.979]	(.017)	(.017)	(.025)
Median household income	624	800	645	290	420	-.104**	.081*	-.057
(R/month)	[430–800]		[381–1000]	[239–350]	[300–680]	(.045)	(.043)	(.082)
Share of households	.937	.972	.921	.646	.708	.009	.258***	.148***
with refrigerator	[.828–.994]		[.806–.985]	[.538–.758]	[.522–.916]	(.018)	(.037)	(.056)
Share of households	.436	.554	.366	.089	.199	-.008	.369***	.06
with washing machine	[.145–.661]		[.1–.618]	[.039–.137]	[.075–.311]	(.089)	(.092)	(.118)
Average temperature	18	21.9	21.5	25	26	-.032*	-.025	-.016
(degrees Celsius)	[16.7–19.5]		[19–24.5]	[23.1–26.4]	[25.2–26.5]	(.019)	(.02)	(.023)
Observations	17	1	26	11	8	86	56	50

Utility-level administrative data for distribution utilities in the four subsystems in 2000 and 2010 and census data matched to the concession area of these utilities in the same years. Columns (1)–(5) display descriptive statistics in 2000 (prior to the crisis) for the variables listed in the left–hand side column for distribution utilities in the South (column 1), in the Southeast/Midwest (LIGHT in column 2, all distribution utilities in column 3), in the Northeast (column 4), and in the North (column 5). Columns (6)–(8) display estimates of a long–term difference–in–difference estimator comparing the logarithm of these variables in 2010 vs. 2000 for distribution utilities in the Southeast/Midwest (column 6), in the Northeast (column 7), and in the North (column 8) compared to distribution utilities in the South. Significance levels: *10%, **5%, ***1% (s.e. clustered by utility). Regressions include fixed effects for each distribution utility and each year. The exchange rate in 2000 was about R$1.9 for US$1. A similar table with additional variables is provided in the Appendix. We argue in the text that the information in this table shows that distribution utilities in the South constitute a credible control group for distribution utilities in the Southeast/Midwest, but not for those in the other two subsystems.

Table 2: Long–term difference in difference results controlling for variables available in census data

Dependent variable: Log(yearly average household electricity consumption						
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment region	-.113***	-.117***	-.103***	-.121***	-.118***	-.116***
× Year2010	(.021)	(.026)	(.028)	(.026)	(.029)	(.041)
Log main		-.202***	-.152		-.215**	-.167
tariff (R)		(.071)	(.094)		(.089)	(.109)
Log median		.142	.318***		.15	.434**
household income (R)		(.095)	(.118)		(.126)	(.172)
Clusters	43	43	43	35	35	35
Restricted sample	No	No	No	Yes	Yes	Yes
Other controls	No	No	Yes	No	No	Yes

Utility-level administrative data for distribution utilities in the Southeast/Midwest and in the South in 2000 and 2010 and census data matched to the concession area of these utilities in the same years. Significance levels: *10%, **5%, ***1% (s.e. clustered by utility). The table displays estimates of the long-term impact of the electricity saving program, controlling for census data. The first row displays coefficients from regressing the logarithm of monthly average electricity consumption per customer for each utility on a year dummy for 2010 interacted with an indicator for utilities subject to the electricity saving program during the crisis (long-term difference–in–difference estimators). All regressions include a constant and utility fixed effects. Columns (4)-(6) restricts the sample to distribution utilities with overlapping support at baseline in average electricity use and in household median income. The estimated impact is similar when we don't include any control (columns 1 and 4), when we control for the main electricity tariff and median household income (columns 2 and 5), and when we additionally control for the logarithm of population size, the share of households living in urban areas, average household size, average dwelling size, the share of dwellings with a bathroom, the employment rate, and the average temperature (columns 3 and 6). The robustness of our results does not come from an absence of variation in these variables. We show graphically in the Appendix that long-term changes in consumption levels are systematically lower for utilities in the Southeast/Midwest than in the South for given baseline levels or long-term changes in all the variables in Table 1.

Table 3: Self-reported appliance usage after crisis (Southeast/Midwest)

	Main domestic appliances					Other domestic appliances		
	Electric shower	Refrigerator	Freezer	Light	TV	Air Conditioner	Laundry machine	Microwave
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. 1999 Survey								
Average (Quantity)	.97	.99	.20	8.45	1.39	.10	.53	.21
Average (kWh/month)	58.14	41.71	7.88	42.54	15.63	2.78	3.37	2.97
Panel B. 2005 Survey								
Share of households who owned appliance	.92	.97	.18	1	.96	.06	.68	.33
Conditional on prior ownership, share of households who:								
Use appliance as much as before crisis	.61	.90	.59	.5		.30	.44	.53
Use appliance less than before crisis	.39	.07	.20	.41		.56	.54	.39
Disconnected or disposed of appliance	.01	0	.16	0		.05	.01	.03
Substituted a more energy-efficient model	0	.03	.01	.08		.03	0	0

Household-level survey data for 8 distribution utilities in the Southeast/Midwest subsystem from Appliances and Habits of Use Survey (PPH) 1998/1999 and 2004/2005. *Panel A* displays the average number of appliances (in columns) per household and the inputed average monthly electricity use in 1999, before the crisis. kWh consumption calculated by multiplying quantity by average utilization in 1999 (share of appliances owned frequently in use) and by the kWh consumption of the average model of each appliance from PROCEL estimates – shown in R.1 in the Appendix. N=6482. *Panel B* reports the share of households who owened each major domestic appliance (in columns) at some point in time that answered, in 2005, each of four answers for each appliance: (1) households were currently using the appliance as much as before the crisis; (2) they were using it less than before the crisis; (2) they had disconnected or disposed of the appliance during or after the crisis; or (4) they had substituted a more energy-efficient model during or after the crisis. N=4579.

Table 4: Difference-in-difference results on appliances' quantity, characteristics, and utilization

Panel A. Quantity

	Index (KKL)	Shower	Refrigerators	Freezer	Light	TV
	(1)	(2)	(3)	(4)	(5)	(6)
$SE/MW \times Year2005$	**-.183**	**-.075**	**-.032**	**-.184**	**.669**	**-.329****
	(.248)	(.276)	(.042)	(.241)	(1.063)	(.153)
Average SE/MW 1999	-.020	.969	.994	.202	8.447	1.392
N	14,251	14,251	14,251	14,251	14,251	14,251

Panel B. Characteristics

	Index		Refrigerators		Freezer		Light		TV	
	Age (KKL)	Type (KKL)	Age	Size (Liters)	Age	Size (Liters)	CFLs (share)	Wattage (incand.)	Age	Size (Inches)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$SE/MW \times Year2005$	**.091**	**.034**	**.107**	**-38.373**	**.789**	**-2.706**	**-.263**	**-1.977**	**.230**	**-1.455**
	(.146)	(.111)	(.916)	(56.625)	(.728)	(28.849)	(.548)	(14.839)	(1.292)	(4.976)
Average SE/MW 1999	-.058	.198	7.501	304.793	5.193	239.519	.150	63.215	5.291	18.754
N	14,206	14,206	12,787	8,815	2,390	2,179	13,038	13,050	12,110	13,603

Panel C. Utilization

	Index (KKL)	Shower Thermostat	Appliance Always Switched On		Appliance Frequently Used	
		High Power	Refrigerator	Freezer	Light	TV
	(1)	(2)	(3)	(4)	(5)	(6)
$SE/MW \times Year2005$	**-.951**	**-.863****	**-.042**	**-.221**	**.595**	**-.473**
	(1.305)	(.425)	(.077)	(.270)	(1.401)	(.690)
Average SE/MW 1999	.212	.391	.973	.183	3.565	1.116
N	14,251	14,251	14,251	14,251	14,251	14,251

Household-level survey data for 10 distribution utilities in the South and Southeast/Midwest subsystems from Appliances and Habits of Use Survey (PPH) 1998/1999 and 2004/2005. This table displays the difference-in-differences estimates of the energy saving program effects on the quantity, characteristics and utilization of the five main electrical appliances, from equation (8) in Section 5. Each column corresponds to a regression of a different dependent variable and appliance. *Panel A* displayes the results on the quantity of appliances owned by household, *Panel B* displayes the results on the indicated characteristcs of appliances owned by households and *Panel c* displays quantity of appliances frequently used (as discribed in Section 3) or quantity of electric showers regulated on high power (winter mode). The *Indices (KKL)* shown in the first columns are the average of the dependent variables shown in the columns each normalized by the average and standard deviation of each variable in the South in 1999 as in Kling, Liebman and Katz (2007). To obtain these indices, we input missing values with the mean of the cell group the household belong (South/South-Midwest and 1999/2005). All regressions contain utility company fixed effects, year fixed effects, income, squared income, number of household members, floorplan area, and dummies for rich neighborhood and for proximity to "favelas". We missing values in two control variables (income and dwelling size) with a linear regression, for each year, of the variable on class of energy consumption and remaining controls. Significance levels: *10%, **5%, ***1% (s.e. estimated with wild-cluster bootstrap by utility level).

Table 5: Households' reported life quality during the crisis (Southeast/Midwest)

	Percentage of respondents
	(1)
How do you evaluate your change in life quality caused by the electricity saving program?	(N=4376)
I did not experience any change in life quality (*não houve variação*)	.48
I experienced some discomfort (*causou desconforto*)	.20
I experience some severe discomfort (*causou muito desconforto*)	.08
I learned to live with the same comfort while saving money (*aprendi a viver com o mesmo conforto economizando dinheiro*)	.24
If your consumption reduction was sufficient to meet your quota, how difficult was it?	(N=3375)
It was very difficult (*muito*)	.09
It was not so difficult (*pouco*)	.48
It was not difficult at all (*nenhuma*)	.43

Household-level survey data for 8 distribution utilities in the Southeast/Midwest subsystem from Appliances and Habits of Use Survey (PPH) 2004/2005. This table displays the percentage of households who answered each of the two questions indicated. These were not open questions and households had to choose one of the answers or "Others". The original text of the two questions are "*Como o(a) sr.(a) avalia a variação de qualidade de vida causada pelo racionamento?*" and "*As medidas adotadas para atingir as metas durante o período de racionamento foram suficientes ou mais que suficientes. Dificuldade?*", respectively and original answers in parenthesis.

Web Appendix (not for publication)

A Formal discussion of synthetic control methods

Formally, define T_0 as the first month of the crisis, index utilities in the South by $c = 1...C$, and define $W = \left(w_{d,1}, ...w_{d,C}\right)$, a vector of positive weights that sum to one. The synthetic control estimator of the impact of the electricity saving program in $t \geq T_0$ is given by:

$$\delta_{d,t} = Y_{d,t} - \sum_{c=1}^{c=C} w^*_{d,c} Y_{c,t} \tag{9}$$

where a weighted sum of the outcome for utilities in the South provides an estimate of the counterfactual for a given utility d in the South–East/Midwest. The weights are chosen to minimize:

$$\parallel Y_{d0} - Y_{c0}W \parallel = \sqrt{\left(Y_{d0} - Y_{c0}W\right)' V \left(Y_{d0} - Y_{c0}W\right)} \tag{10}$$

where Y_{d0} and Y_{c0} are vectors containing the values of the outcome in pre-crisis periods in the treated utility and in control utilities, respectively. An optimal choice of V minimizes the mean squared error of the synthetic control estimator.

B Model with "behavioral" agents

In this section, we extend our simple theoretical framework by relaxing the assumption of fully rational and forward looking agent. Agents may be unaware of the degree of hysteresis in their behavior: they might be myopic about the future gains from incurring learning costs tomorrow, or have biased beliefs about the impact of their current behavior on their future propensity to behave in certain ways.

Suppose for instance that the perceived effect of current electricity use on the future propensity to consume is: $\alpha \frac{\partial s(s_1,x_1)}{\partial x_1}$. The first-order condition from the agent's problem is now:

$$x_1 : \frac{\partial v_1 \left(x_1, s_1\right)}{\partial x_1} + \beta \frac{\partial v_2 \left(x_2, s(s_1, x_1)\right)}{\partial s} \alpha \frac{\partial s(s_1, x_1)}{\partial x_1} = p_1 \quad ; \quad x_2 : \frac{\partial v_2 \left(x_2, s(s_1, x_1)\right)}{\partial x_2} = p_2$$

If the parameter α is smaller (resp. greater) than 1, the agent underestimates (resp. overestimates) this effect. In the extreme case where $\alpha = 0$, the agent is fully myopic and does not take this effect into account. We evaluate welfare based on the true underlying effect and preferences. Therefore, the agent consumes too much (resp. too little) electricity to begin with if she understimates (resp. overestimates) the degree of hysteresis.

Define $\left(x^*_{10}, x^*_{20}\right)$ the optimal level of electricity use and $\left(x_{10}, x_{20}\right)$ the observed level of electricity use at baseline prices determined by the first-order conditions above. Note that given our simplification of a two-period model, the level of x_2 would be optimal as long as the level of x_1 is optimal. The social cost or deadweight loss of our corrective policy is still the change in the household's indirect utility: $DWL = V(\overline{x_1},\overline{x_2}) - V(x_{10},x_{20}) = \left[V(\overline{x_1},\overline{x_2}) - V(x^*_{10},x^*_{20})\right] + \left[V(x^*_{10},x^*_{20}) - V(x_{10},x_{20})\right]$. The first bracket accounts for the fact that consumption may have been suboptimal to begin with. Tracing the change in indirect utility by first moving x_1, we have:

$$\begin{aligned} DWL &= \int_{x_{10}}^{x^*_{10}} \frac{dV(x_1,x_2)}{dx_1}dx_1 + \int_{x^*_{10}}^{\overline{x_1}} \frac{dV(x_1,x_2)}{dx_1}dx_1 + \int_{x_2(\overline{x_1})}^{\overline{x_2}} \frac{dV(\overline{x_1},x_2)}{dx_2}dx_2 \\ &= \int_{x_{10}}^{x^*_{10}} \left[p_1(x_1) - p_{10}\right]dx_1 + \int_{x^*_{10}}^{\overline{x_1}} \left[p_1(x_1) - p_{10}\right]dx_1 + \int_{x_2(\overline{x_1})}^{\overline{x_2}} \left[p_2(x_2|\overline{x_1}) - p_{20}\right]dx_2 \end{aligned} \tag{11}$$

where the inverse demand curves are the same as in the paper. The first term accounts for the fact that x_{10} is suboptimal to begin with. If the agent was overconsuming to begin with ($\alpha < 1$), the difference in bracket is negative and we have $x_{10} > x^*_{10}$, so the first term is positive. If the agent was overconsuming to begin with ($\alpha > 1$), the difference in bracket is positive and we have $x_{10} < x^*_{10}$, so the first term is also positive. The second term and third terms are similar as in the paper. In both cases, the deadweight loss is thus smaller. Assuming away hysteresis, the social cost would still be measured as before:

$$DWL_{NoHysteresis} = \int_{x_{10}}^{\overline{x_1}} \left[p_{1,NoH}(x_1) - p_{10}\right]dx_1 + \int_{x_{20}}^{\overline{x_2}} \left[p_{2,NoH}(x_2) - p_{20}\right]dx_2$$

The bias is larger than the expression for the bias in the paper if the agent is myopic or underestimates the degree of hysteresis. This is because assuming away hysteresis, one would not take into account the first (positive) term in equation (11) and one would take the integral in the second term in equation (11) over a larger interval ($x_{10} > x^*_{10}$). This may not be the case if the agent overestimates the degree of hysteresis. This is because assuming away hysteresis one would not take into account the first (positive) term in equation (11), but one would take the integral in the second term in equation (11) over a smaller interval ($x_{10} < x^*_{10}$). We present suggestive evidence in the paper that, if anything, households were underestimating the degree of hysteresis. Of course, there is a limitation when trying to estimate the true deadweight loss if agents do not perceive the true degree of hysteresis: the relevant inverse demand curve $p_1(x_1)$ is not easily observed empirically. The difficulty, which is more severe with heterogenous agents, is raised and discussed in details in (Allcott and Rogers, 2012).

C Model with direct investments in the propensity to consume

In this section, we extend our simple theoretical framework by allowing for direct investments in the propensity to use electricity. Specifically, suppose that the propensity to consume is a function: $s_i = s_i(s_{i-1}, x_{i-1}, I_i)$, where I_i accounts for such investment, where $\frac{\partial s_i}{\partial I_i} < 0$ (investments in energy efficiency), and s_0 and x_0 are given. The idea behind this extension of our model is that households may have different ways to reduce electricity, some of them being more likely to lead to hysteresis. We assume that such investment has a convex cost $\kappa_i(I_i)$, which does not have to be monetary. The household now solves:

$$\max_{x_1,x_2,I_1,I_2} U = U_1+\beta U_2 = y_1 - p_1x_1 - \kappa_1(I_1) + v_1(x_1,s_1) + \beta\left[y_2 - p_2x_2 - \kappa_2(I_2) + v_2(x_2,s_2)\right]$$
$$s.t.\, s_i = s_i(s_{i-1},x_{i-1},I_i)$$

We obtain the following first-order conditions:

$$x_1 : \frac{\partial v_1(x_1,s_1)}{\partial x_1} + \beta\frac{\partial v_2(x_2,s_2)}{\partial s_2}\frac{\partial s_2}{\partial x_1} = p_1 \quad ; \quad x_2 : \frac{\partial v_2(x_2,s_2)}{\partial x_2} = p_2 \qquad (12)$$
$$I_1 : \left[\frac{\partial v_1(x_1,s_1)}{\partial s_1} + \beta\frac{\partial v_2(x_2,s_2)}{\partial s_2}\frac{\partial s_2}{\partial s_1}\right]\frac{\partial s_1}{\partial I_1} = \kappa_1'(I_1) \quad ; \quad I_2 : \frac{\partial v_2(x_2,s_2)}{\partial s_2}\frac{\partial s_2}{\partial I_2} = \kappa_2'(I_2) \qquad (13)$$

Define $(x_{10},x_{20},I_{10},I_{20})$, the optimal levels of electricity use and investments at baseline prices determined by the first-order conditions above. Define $I_1(\overline{x_1},\overline{x_2})$ and $I_2(\overline{x_1},\overline{x_2})$, the optimal levels of investments given the corrective policy. The social cost or deadweight loss of the policy is the change in the household's indirect utility: $DWL = V(\overline{x_1},\overline{x_2},I_1(\overline{x_1},\overline{x_2}),I_2(\overline{x_1},\overline{x_2})) - V(x_{10},x_{20},I_{10},I_{20})$. We can trace this change with the two same steps as before: first, we change x_1 to $\overline{x_1}$, then we change $x_2(\overline{x_1})$ to $\overline{x_2}$, holding constant choices in the first period, $\overline{x_1}$ and $I(\overline{x_1})$. However, the choice of I_1 would optimally adjust to the change in x_2 to $\overline{x_2}$ in the second period: $I(\overline{x_1},x_2(\overline{x_1})) \neq I(\overline{x_1},\overline{x_2})$. So we need to add a third step taking this into account. This third step can only increase the household's utility, thus reducing our measured social cost. Such a decomposition of the change in indirect utility allows us to show that the expression for the deadweight loss in the paper would be an upper bound for the social cost (in absolute values). Specifically, we have:

$$\begin{aligned}
DWL = &\int_{x_{10}}^{\overline{x_1}} \frac{dV(x_1,x_2,I_1,I_2)}{dx_1}dx_1 + \int_{x_2(\overline{x_1})}^{\overline{x_2}} \frac{dV(\overline{x_1},x_2,I_1(\overline{x_1}),I_2)}{dx_2}dx_2 + \int_{I_1(\overline{x_1})}^{I_1(\overline{x_1},\overline{x_2})} \frac{dV(\overline{x_1},\overline{x_2},I_1(\overline{x_1}),I_2)}{dI_1}dI_1 \\
= &\int_{x_{10}}^{\overline{x_1}} \left[\frac{\partial v_1(x_1,s_1)}{\partial x_1} + \beta\frac{\partial v_2(x_2,s_2)}{\partial s_2}\frac{\partial s_2}{\partial x_1} - p_1 + \underbrace{\frac{\partial V(x_1,x_2,I_1,I_2)}{\partial I_1}}_{=0}\frac{\partial I_1}{\partial x_1} + \underbrace{\frac{\partial V(x_1,x_2,I_1,I_2)}{\partial x_2}}_{=0}\frac{\partial x_2}{\partial x_1} + \underbrace{\frac{\partial V(x_1,x_2,I_1,I_2)}{\partial I_1}}_{=0}\frac{\partial I_2}{\partial x_1}\right] \\
&+ \int_{x_2(\overline{x_1})}^{\overline{x_2}} \left[\frac{\partial v_2(x_2,s_2(\overline{x_1},I_1(\overline{x_1},x_2(\overline{x_1}))))}{\partial x_2} - p_2 + \underbrace{\frac{\partial V(\overline{x_1},x_2,I_1(\overline{x_1},x_2(\overline{x_1})),I_2)}{\partial I_2}}_{=0}\frac{\partial I_2}{\partial x_2}\right]dx_2 \\
&+ \int_{I_1(\overline{x_1},x_2(\overline{x_1}))}^{I_1(\overline{x_1},\overline{x_2})} \left[\left[\frac{\partial v_1(\overline{x_1},s_1)}{\partial s_1} + \beta\frac{\partial v_2(\overline{x_2},s_2(\overline{x_1}))}{\partial s_2}\frac{\partial s_2}{\partial s_1}\right]\frac{\partial s_1}{\partial I_1} - \kappa_1'(I_1) + \underbrace{\frac{\partial V(\overline{x_1},\overline{x_2},I_1,I_2)}{\partial I_2}}_{=0}\frac{\partial I_2}{\partial I_1}\right]dI_1
\end{aligned}$$

where the third integral is not nil because $\left[\frac{\partial v_1(\overline{x_1},s_1)}{\partial s_1} + \beta\frac{\partial v_2(\overline{x_2},s_2(\overline{x_1}))}{\partial s_2}\frac{\partial s_2}{\partial s_1}\right]\frac{\partial s_1}{\partial I_1} \neq \kappa_1'(I_1(\overline{x_1},x_2(\overline{x_1})))$: in the second step, we changed x_2 without allowing I_1 to readjust. Finally, we have:

$$DWL = \int_{x_{10}}^{\overline{x_1}} \left[p_1(x_1) - p_{10}\right] dx_1 + \int_{x_2(\overline{x_1})}^{\overline{x_2}} \left[p_2\left(x_2 | \overline{x_1}, I_1\left(\overline{x_1}, x_2\left(\overline{x_1}\right)\right)\right) - p_{20}\right] dx_2$$
$$+ \int_{I_1(\overline{x_1}, x_2(\overline{x_1}))}^{I_1(\overline{x_1}, \overline{x_2})} \left[\left[\frac{\partial v_1\left(\overline{x_1}, s_1\right)}{\partial s_1} + \beta \frac{\partial v_2\left(\overline{x_2}, s_2\left(\overline{x_1}\right)\right)}{\partial s_2} \frac{\partial s_2}{\partial s_1}\right] \frac{\partial s_1}{\partial I_1} - \kappa_1'\left(I_1\right)\right] dI_1$$

where the inverse demand curves in the first two integrals are observationally equivalent to the inverse demand curves in the paper. They would also be recovered by observing changes in x_1 using price variation in period 1, and changes in x_2 using price variation once in period 2, respectively. In other words, demand curve will factor in any cost and benefit of endogenous changes in investments. The last term must be positive as we allow the household to reoptimize I_1 once in period 2. It will thus reduce the deadweight loss (in absolute values). Assuming away hysteresis, the deadweight loss would be measured as in the paper. Therefore, the expression in the paper for the deadweight loss with hysteresis is an upper bound (in absolute values) if the true model has direct investments in the propensity to use electricity. The expression in the paper for the bias from assuming away hysteresis would then be a lower bound (in absolute values).

D Model with heterogeneous agents

In this section, we extend our simple theoretical framework by allowing for heterogeneous agents. If the policy aims at correcting individual behaviors specifically, it is trivial that one should just apply the argument in the paper separately for each agent. To measure the deadweight loss, one would then need to know individual demand curves and individual degrees of hysteresis.

More interestingly, imagine a policy that aims at long-run *aggregate* changes in behavior and a situation in which one could only observe *aggregate* demand curves and degrees of hysteresis. For simplicity, assume that there are two households, $j = A, B$. Household j solves:

$$\max_{c_1^j, c_2^j, x_1^j, x_2^j} U^j = U_1^j + \beta U_2^j = c_1^j + v_1^j\left(x_1^j, s_1^j\right) + \beta\left[c_2^j + v_2^j\left(x_2^j, s^j(s_1^j, x_1^j)\right)\right] \quad \text{s.t. } c_i^j + p_i x_i^j \leq y_i^j$$

One can obtain the same first-order conditions as in the paper for each agent. Define X_1 and X_2 as the aggregate levels of electricity use in the two periods. Without government intervention, the first-order conditions and baseline electricity prices in the two periods, p_{10} and p_{20}, will determine baseline electricity use x_{10}^j and x_{20}^j for each agent j and aggregate baseline electricity use X_{10} and X_{20}. Now, suppose that the government wants to reduce aggregate electricity use to $\overline{X_1} < X_{10}$ and $\overline{X_2} < X_{20}$. Define $\left(\widetilde{x_1^A}, \widetilde{x_1^B}, \widetilde{x_2^A}, \widetilde{x_2^B}\right)$ an efficient allocation of $\left(\widetilde{X_1}, \widetilde{X_2}\right)$ such that:

$$\widetilde{X_i} = \widetilde{x_i^A} + \widetilde{x_i^B}$$

$$\frac{\partial v_1^A\left(\widetilde{x_1^A}, s_1^A\right)}{\partial x_1^A} + \beta \frac{\partial v_2^A\left(\widetilde{x_2^A}, s^A(s_1^A, \widetilde{x_1^A})\right)}{\partial s^A} \frac{\partial s^A(s_1^A, \widetilde{x_1^A})}{\partial x_1^A} = \frac{\partial v_1^B\left(\widetilde{x_1^B}, s_1^B\right)}{\partial x_1^B} + \beta \frac{\partial v_2^B\left(\widetilde{x_2^B}, s^B(s_1^B, \widetilde{x_1^B})\right)}{\partial s^B} \frac{\partial s^B(s_1^B, \widetilde{x_1^B})}{\partial x_1^B}$$

$$\frac{\partial v_2^A\left(\widetilde{x_2^A}, s^A(s_1^A, \widetilde{x_1^A})\right)}{\partial x_2^A} = \frac{\partial v_2^B\left(\widetilde{x_2^B}, s^B(s_1^B, \widetilde{x_1^B})\right)}{\partial x_2^B}$$

The initial allocation $\left(x_{10}^A, x_{10}^B, x_{20}^A, x_{20}^B\right)$ is clearly an efficient allocation of (X_{10}, X_{20}). We consider corrective policies $\left(\overline{X_1}, \overline{X_2}\right)$ implemented efficiently (e.g. with tradable quotas or pigouvian taxes or subsidies) because they minimize the deadweight loss. Importantly for our purpose, efficient allocations are those that can be traced along aggregate demand curves. Let's define the following three allocations: $\left(\widehat{X_1}, X_2\left(\widehat{X_1}\right)\right) = \left(\widehat{x_1^A}, \widehat{x_1^B}, x_2^A\left(\widehat{x_1^A}\right), x_2^B\left(\widehat{x_1^B}\right)\right)$, where $\widehat{X_1} = \overline{X_1}$ is allocated efficiently between the agents and $X_2\left(\widehat{X_1}\right) = x_2^A\left(\widehat{x_1^A}\right) + x_2^B\left(\widehat{x_1^B}\right)$ is determined endogenously by the first-order conditions for x_2^j given $\widehat{x_1^j}$; $\left(\widehat{X_1}, \widehat{X_2}\right) = \left(\widehat{x_1^A}, \widehat{x_1^B}, \widehat{x_2^A}, \widehat{x_2^B}\right)$, where the $\widehat{x_1^j}$ are defined as above and $\widehat{X_2} = \overline{X_2}$ is allocated efficiently for a given level of electricity use $\widehat{x_1^j}$ (we have $\frac{\partial v_2^A\left(\widehat{x_2^A}, s^A(s_1^A, \widehat{x_1^A})\right)}{\partial x_2^A} = \frac{\partial v_2^B\left(\widehat{x_2^B}, s^B(s_1^B, \widehat{x_1^B})\right)}{\partial x_2^B}$); and $\left(\overline{X_1}, \overline{X_2}\right) = \left(\overline{x_1^A}, \overline{x_1^B}, \overline{x_2^A}, \overline{x_2^B}\right)$, the efficient allocation of $\left(\overline{X_1}, \overline{X_2}\right)$. We potentially have $\left(\overline{X_1}, \overline{X_2}\right) \neq \left(\widehat{X_1}, \widehat{X_2}\right)$ because the allocation in period 1 is not allowed to be readjusted once changing aggregate levels of electricity use from $\widehat{X_2}$ to $\overline{X_2}$, and agents may differ in their degree of hysteresis in electricity use. The social cost or deadweight loss of our corrective policy is the change in the sum of the agents' indirect utility. We can trace it in three steps: from (X_{10}, X_{20}) to $\left(\widehat{X_1}, X_2\right)$, then to $\left(\widehat{X_1}, \widehat{X_2}\right)$, and finally to $\left(\overline{X_1}, \overline{X_2}\right)$:

$$\begin{aligned}
DWL =& \int_{X_{10}}^{\widehat{X_1}} \left[\sum_j \frac{dV^j(x_1^j, x_2^j)}{dx_1^j} \frac{dx_1^j}{dX_1}\right] dX_1 + \int_{X_2(\widehat{X_1})}^{\widehat{X_2}} \left[\sum_j \frac{dV^j(\widehat{x_1^j}, x_2^j)}{dx_2^j} \frac{dx_2^j}{dX_2}\right] dX_2 \\
&+ \sum_j \left[\int_{\widehat{x_1^j}}^{\overline{x_1^j}} \frac{\partial V^j(x_1^j, \widehat{x_2^j})}{\partial x_1^j} dx_1^j + \int_{\widehat{x_2^j}}^{\overline{x_2^j}} \frac{\partial V^j(\overline{x_1^j}, x_2^j)}{\partial x_2^j} dx_2^j\right] \\
=& \int_{X_{10}}^{\widehat{X_1}} \left[P_1\left(X_1\right) - p_{10}\right] dX_1 + \int_{X_2(\widehat{X_1})}^{\widehat{X_2}} \left[P_2\left(X_2 | \widehat{X_1}\right) - p_{20}\right] dX_2 \\
&+ \sum_j \left[\int_{\widehat{x_1^j}}^{\overline{x_1^j}} \frac{\partial V^j(x_1^j, \widehat{x_2^j})}{\partial x_1^j} dx_1^j + \int_{\widehat{x_2^j}}^{\overline{x_2^j}} \frac{\partial V^j(\overline{x_1^j}, x_2^j)}{\partial x_2^j} dx_2^j\right] \qquad (14)
\end{aligned}$$

The first two integrals are the aggregate versions of the two integrals in the comparable expression in the paper. The inverse demand curves correspond to the aggregate demand curves (because we focus on efficient allocations between the agents). The first aggregate demand curve would be recovered by observing aggregate changes in X_1 using price variation in period 1. The second aggregate demand curve would be recovered by observing aggregate changes in X_2 using price variation once in period 2 and after an efficient allocation of the constraint $\overline{X_1}$ in period 1. The third term is positive as we allow for a re-optimization of the allocations across agents ex-post, thus reducing the deadweight loss (in absolute values). Abstracting from this term, we thus overestimate the true deadweight loss (in absolute values). Assuming away hysteresis (and still considering an efficient corrective policy), we would measure the deadweight loss as:

$$\begin{aligned} DWL_{NoHysteresis} &= \int_{X_{10}}^{\overline{X_1}} \left[\sum_j \frac{dV^j(x_1^j, x_2^j)}{dx_1^j} \frac{dx_1^j}{dX_1} \right] dX_1 + \int_{X_{20}}^{\overline{X_2}} \left[\sum_j \frac{dV(\overline{x_1^j}, x_2^j)}{dx_2^j} \frac{dx_2^j}{dX_2} \right] dX_2 \\ &= \int_{X_{10}}^{\overline{X_1}} \left[P_{1,NoH}(X_1) - p_{10} \right] dX_1 + \int_{X_{20}}^{\overline{X_2}} \left[P_{2,NoH}(X_2) - p_{20} \right] dX_2 \end{aligned}$$

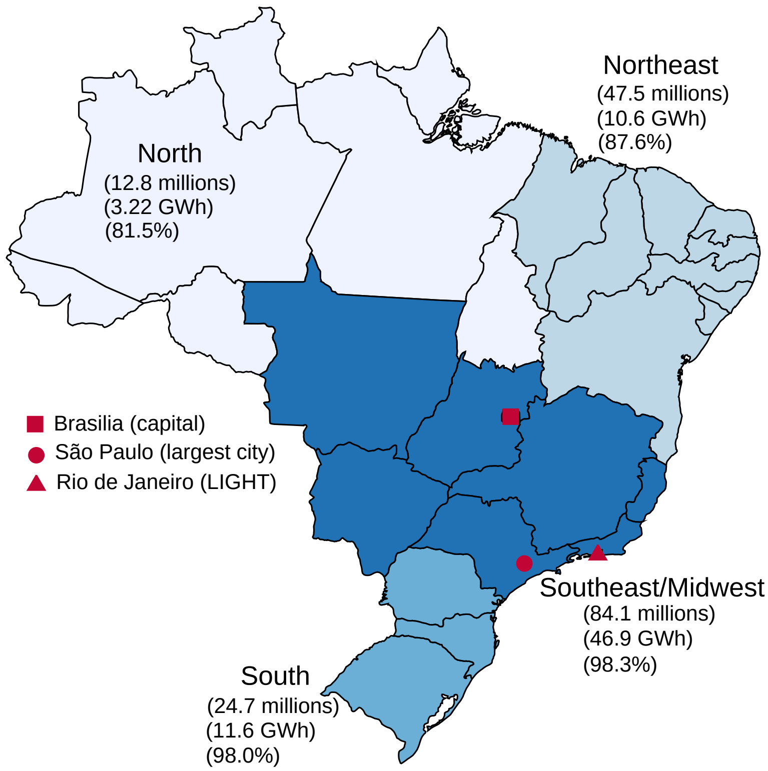
As discussed in the paper, the fact that one would assume that the aggregate demand curves are independent in each period may not lead to any bias in itself. The same variation identifying the relevant demand curves in equation (14) would be used to identify the demand curves here. However, there will be two sources of biases. First, as before, the second integral would be taken over a larger interval by neglecting the possibility of hysteresis. Only the aggregate degree of hysteresis, not the individual degrees of hysteresis, is necessary to evaluate this bias. Second, the third term in equation (14) would also be neglected. Abstracting from this second source of bias, and thus only using information from aggregate demand curves, we would thus underestimate the bias (in absolute values).

E The causes of the 2001 Brazilian electricity crisis

We present here additional information related to the causes of the 2001 Brazilian electricity crisis.

Figure E.1 presents the map of Brazil, highlighting the four subsystems of the National Interconnected System of Brazil with the population, total residential electricity demand and the share of households connected to electricity, all values of 2000.

Figure E.1: Map of Subsystems of the National Interconnected System of Brazil with Summary Statistics



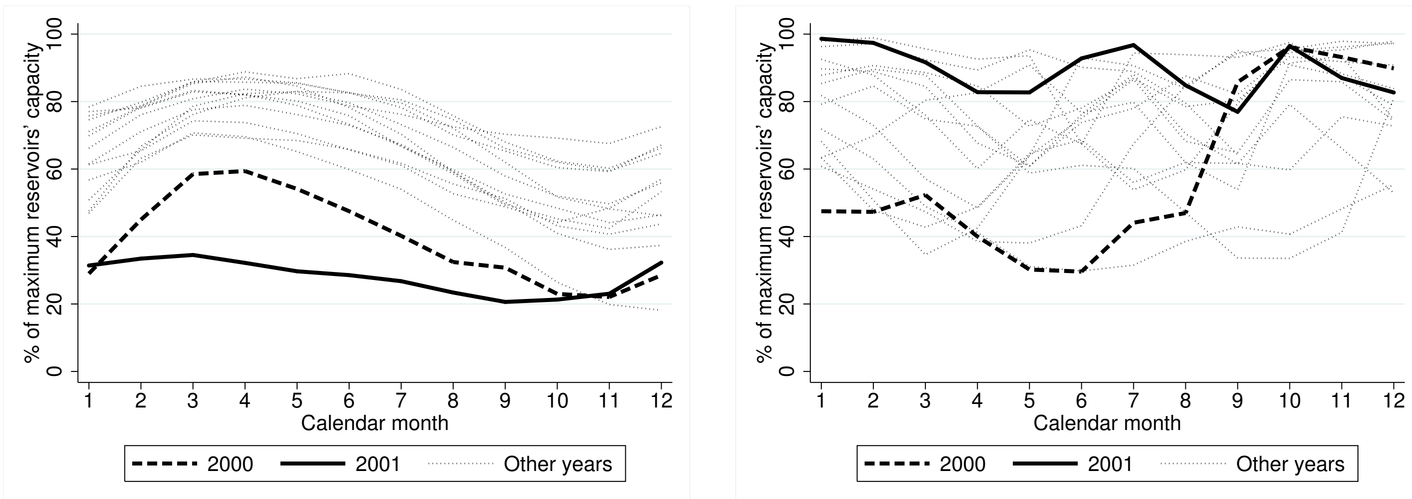
This map presents the four subsystems of the National Interconnected System of Brazil. The first number in parenthesis is the population, the second number is the total residential energy consumption in 2000, and the third is the percentage of households connected to electricity. The three red markers locate the three main cities in Brazil. Source: Censo 2000 and National System Operator (ONS).

Figure E.2 present the same information as Figure 1a in a different and useful format. It displays the evolution of hydro–reservoirs' capacity in percentage of their maximum capacity over calendar months within each year between 1991 and 2011 in the Southeast/Midwest (panel a) and in the South (panel b). In the same format, Figure E.3 displays the streamflow level of the rivers serving the reservoirs in the two regions between 1996 and 2010 in percentage of the long-term average of streamflow levels in each month in each region. The sold line corresponds to 2001, the year the 2001 Brazilian electricity crisis started; the dashed line to 2000; the dotted lines to all other years. Figure E.2 shows a clear seasonal pattern in the Southeast/Midwest, heavy rainfall upstream of the rivers serving the reservoirs replenishing them at the beginning of every year. The levels of the reservoirs were very low in both regions at the beginning of 2000. Figure E.3 then shows that the crisis and the differential treatment between regions was indeed due to a weather shock affecting streamflow levels (and not to a demand shock for instance). Streamflow levels were higher than average in both regions around September 2000. This is a period of low streamflow levels in the Southeast/Midwest but of high streamflow levels in the South. As a result, reservoirs were rapidly replenished in the South but not in the Southeast/Midwest. The beginning of every year is a period of high streamflow levels in the Southeast/Midwest. However, at the beginning of 2001, streamflow levels were much lower than average. As a result, the level of the reservoirs did not increase in the Southeast/Midwest, as they usually do at the beginning of every year. In contrast, streamflow levels were higher than average over the same period in the South, and the level of the reservoirs remained high.

Figure E.2: Stocked energy of the reservoirs by calendar month

(a) Southeast/Midwest

(b) South

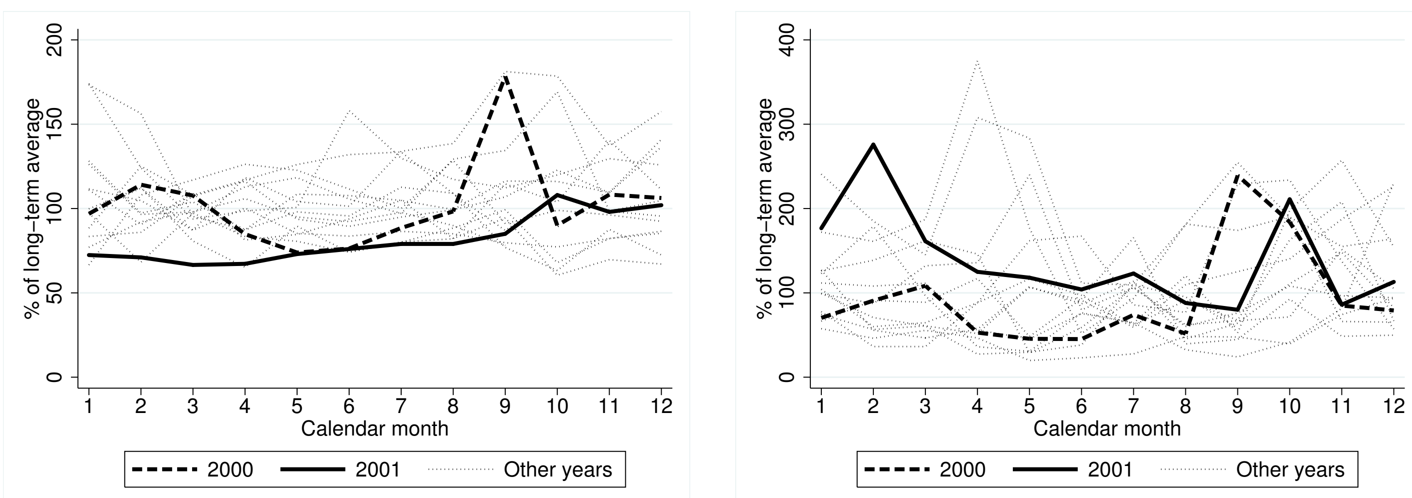


Official data from ONS, the National System Operator. The figure displays the evolution of hydro–reservoirs' capacity in percentage of their maximum capacity over calendar months within each year between 1991 and 2011 in the Southeast/Midwest (panel a) and in the South (panel b).

Figure E.3: Flow into the reservoirs by calendar month

(a) Southeast/Midwest

(b) South



Official data from ONS, the National System Operator. The figure displays the evolution of streamflow levels of the rivers serving the hydro–reservoirs in the Southeast/Midwest (panel a) and in the South (panel b) between 1996 and 2010 in percentage of the long-term average of streamflow levels in each month in each region.

Table E.1 presents the realized electricity demand in each subsystem and year as as a percentage of the demand forecast from the 1997-2007 Decennial Energy Plan (PDE) produced by the National System Operator along with the Mining and Energy Ministry. This is the main national plan that guide the medium- and long-run plan of expansion of energy infrastructure in the country.

We can see in the first cell in column (1) that the energy used in the Southeast in 1998 was 99.6 percent of the forecast demand (in PDE 1997) for that region and year. We can see in the table that the growth in demand never outpaced growth in projected demand. However, it systematically outpaced growth in generation capacity in the years prior to 2001. The crisis would have been avoided if generation capacity had been expanded adequately – e.g., several infrastructure projects were delayed or canceled. See Kelman (2001), Maurer, Pereira and Rosenblatt (2005), and Mation and Ferraz (2011) for more discussion on the cause of the crisis and the exogenous role of weather in the differential treatment across subsystems.

Table E.1: Realized Electricity Demand as Percentage of Demand Forecast (%)

	Southeast	**Midwest**	**South**	**Brazil**
	(1)	(2)	(3)	(4)
1998	99.6	98.5	97.9	99.4
1999	95.6	96.4	97.5	95.6
2000	96.2	95.7	98.5	95.6

Original calculations. Forecasts from 1997-2007 Decennial Energy Plan (PDE) produced by the National System Operator (ONS) along with the Mining and Energy Ministry. Realized demand from ONS.

F Timeline of the electricity crisis

Late 1999	The National System Operator (ONS) presents simulations of hydrological scenarios for 2000 based on the actual reserve levels in 30 November of 1999. The report concludes that the reservoir levels in some regions would hit zero (i.e., no electricity) in 13% of these scenarios. (*ONS-DPP 059/1999*)
Feb 2000	The Ministry of Mining and Energy (MME) creates the Priority Thermal Program (PPT) to increase the generation capacity of thermal power plants as the "unique solution" to a possible collapse of the system.
Early 2000	The Priority Thermal Program becomes the Emergency Thermal Program.
Jul 2000	In a meeting with the President and his economic advisors, the minister of the MME dismisses the chances of any energy crisis during 2000-2003.[51]
Dec 2000	ONS forecasts a scenario for 2001 with no energy crisis.
Feb 2001	Hydrological conditions reach 70% of the long run average, and ONS radically change the forecast for 2001.
Mar 2001	ONS officially requests that the federal government intervene to assure a 20% load reduction.
Mar 2001	*First time the regulatory agency (ANEEL) publicly addressed a possible imminent electricity shortage*. It proposes the Consumption Reduction and Supply Increase Plan (RECAO), which was abandoned shortly afterward.
Apr 2001	The Priority Thermal Program (PPT) fails and MME starts designing the load reduction program.[52]
May 2001	Government announces temporary electricity saving program to be implemented in June 4. This announcement receives a lot of attention from the media.[53]
Jun 2001	Household incentives are implemented.

[51] Based on documents from the National System Operator (ONS), the minister stated: "considering the Priority Thermal Program (PPT), even if we observe an increase in demand larger than expected, we will not face energy supply and peak problems during 2000-2003 as long as the hydrological conditions are above 85% of the long run average".

[52] "Plan to hold expenditure on electricity" aims to reduce consumption in three regions with 25 measures. In case these measures are not effective it is possible that these regions will have blackouts in June. (Folha de São Paulo, Front page, A1, 06/04/2001). "Plan to avoid energy saving program failed", only three of the planned measures were implemented. (Folha de São Paulo, B7, 05/05/2001)

[53] Folha de São Paulo: "Government is not decided between regular supply interruptions or higher tariffs" (Front page, A1, 15/05/2001); "Plan will affect households with electricity bill above R$29" [U$15.9] (Front page, A1, 18/05/2001); "Government imposes 'super tariffs' and will cut electricity of those who don't save" (Front page, A1, 19/05/2001); "Households should avoid storing food at home and shop for groceries more often" (B10, 29/05/2001); "Subsidies do not reduce lightbulbs' prices" (B7, 01/06/2001).

Feb 2002 Household fines and threat of electricity cuts are suspended.[54]

March 2002 Last billing cycle (February-March) bonuses were paid.

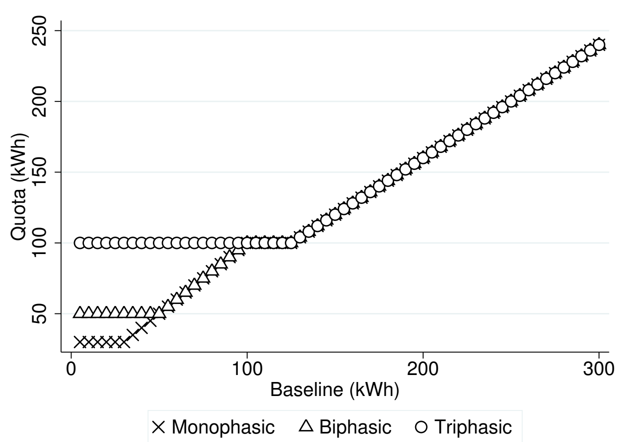
[54] "Rain brings relief to reservoirs" (Folha de São Paulo, B1, 03/01/2002).

G The electricity saving program

We present here additional information related to the electricity saving program of the 2001 Brazilian electricity crisis.

Figure G.1 explains the rule of the electricity saving program to assign individual quotas to customers at the beginning of the crisis. Customers' *baseline* was defined as the average billed monthly consumption from May to July 2000 (or the first three monthly bills for customers who moved in after May 2000). Quotas were set at 80% of the baseline 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, quotas were at least equal to these minimum levels. Figure G.1 illustrates the case of LIGHT, the distribution utility serving the city of Rio de Janeiro and surrounding municipalities, where minimum levels are 30 kWh, 50 kWh, and 100 kWh for monophasic, biphasic, and triphasic connections, respectively.

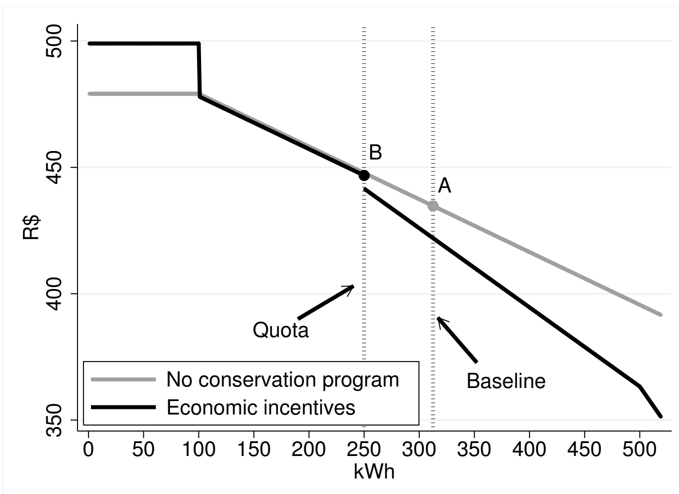
Figure G.1: Quota assignment rule of the electricity saving program



The figure explains the rule of the electricity saving program to assign individual quotas to customers at the beginning of the crisis.

Figure G.2 provides an example of how the pecuniary incentives of the electricity saving program modified the cost of consuming electricity during the crisis. The figure considers the case of customers with a quota of 250 kWh (80% of baseline in the first five months of the crisis, before any change in quotas). We assume a budget of R\$500 and a tariff of R\$.208/kWh (LIGHT, June 2001). The usual marginal cost of electricity is nil up to 100 kWh because of we assume a minimum consumption level of 100 kWh (triphasic connection). During the crisis, the total cost of electricity is nil if consuming below 100 kWh because of the guaranteed bonus. Conditional on exceeding the quota, the cost of electricity increases because of the fines paid for every kWh above 200. Above the quota, the fines (i) increase the marginal price (by 50% up to 500 kWh, then by 200%) and (ii) increase the cost discretely by $(250-200) \times .208 \times 50\%$ =R\$5.2.

Figure G.2: Example of the economic incentives of the electricity saving program



The figure displays the pecuniary incentives of the electricity saving program for customers with a quota of 250 kWh (80% of baseline).

H Additional descriptive statistics (end of Table 1)

Table H.1 displays the same information as in Table 1 in the paper, but it consider a different set of variables. Columns (1)-(5) compare initial values across distribution utilities in the four subsystems (and for LIGHT), namely the mean and range of relevant variables in 2000. Columns (6)-(8) present the differential trend in these variables between 2000 and 2010 comparing utilities in each of the three other subsystems to utilities in the South. The information in Table H.1 supports our key identification assumption of a common-trend for distribution utilities in the Southeast/Midwest and in the South. It also shows that such an assumption is unlikely to hold, especially in the long term, when considering distribution utilities in the other two subsystems subject to the electricity saving program.

Table H.1: Additional descriptive statistics for distribution utilities in the four subsystems

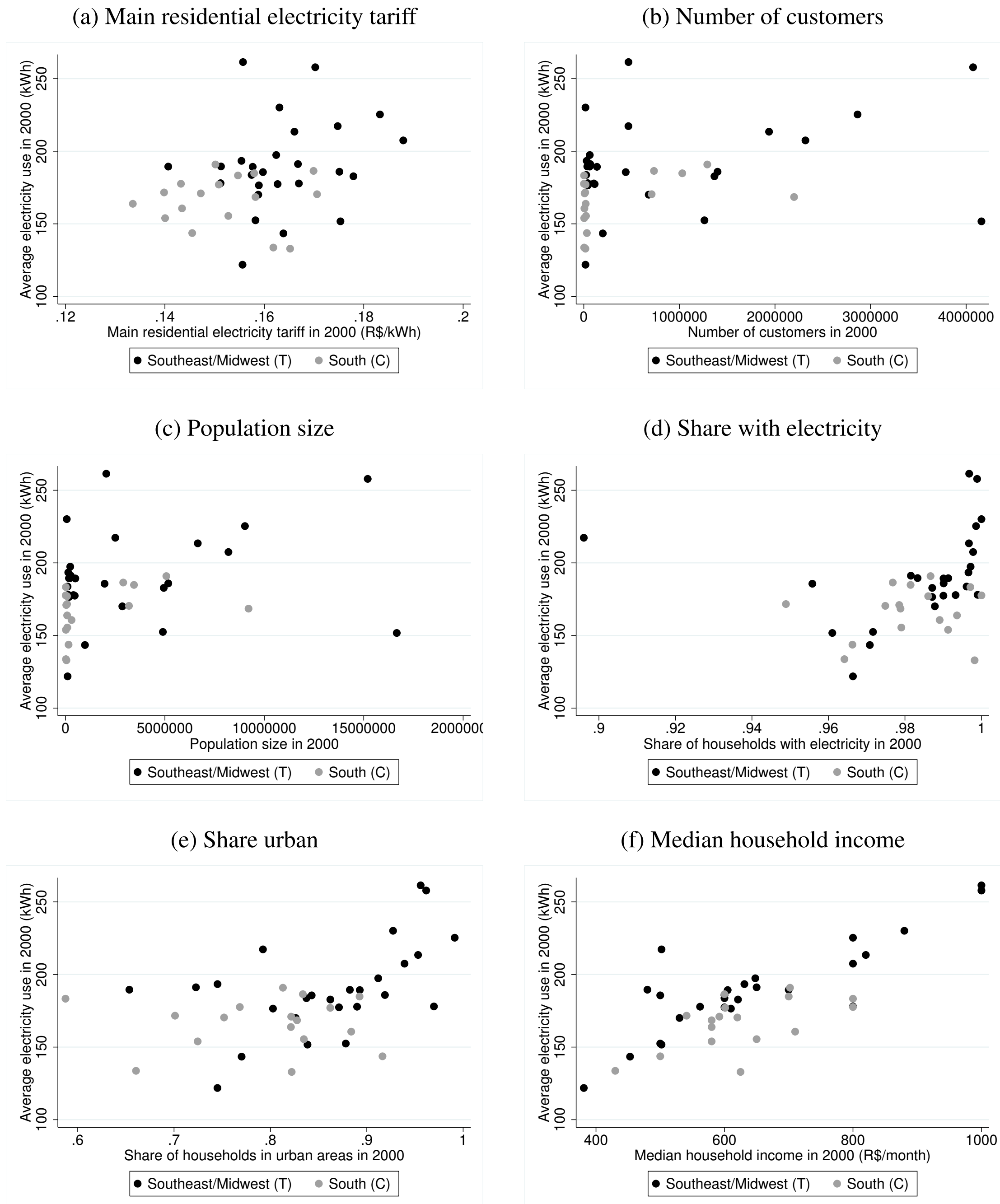
	Descriptive statistics in 2000 Mean [min-max]					**Differential trends 2010 vs. 2000** Coefficient, in logs (s.e.)		
	South (1)	LIGHT (2)	Southeast/Midwest (3)	Northeast (4)	North (5)	SE/MW vs. S (6)	NE vs. S (7)	N vs. S (8)
Average residential electricity	.144	.181	.159	.146	.145	-.113	-.144	-.133
price (R)	[.104–.168]		[.141–.181]	[.133–.16]	[.107–.166]	(.073)	(.094)	(.096)
Share of households	.584	.479	.58	.61	.543	.002	-.09*	-.041
with TV	[.477–.682]		[.45–.701]	[.511–.666]	[.436–.64]	(.053)	(.048)	(.047)
Share of households	.098	.179	.108	.043	.044	-.097	.103	.23
with computer	[.04–.155]		[.029–.234]	[.013–.07]	[.011–.078]	(.109)	(.141)	(.172)
Share of households	.071	.311	.06	.044	.125	n.a.	n.a.	n.a.
with air conditioner	[.005–.183]		[.008–.311]	[.014–.08]	[.047–.228]			
Average household	3.47	3.29	3.51	4.15	4.38	.005	-.028***	.001
size	[3.18–3.66]		[3.19–3.74]	[3.93–4.54]	[3.9–4.85]	(.006)	(.007)	(.013)
Average number of	6.22	5.47	5.81	5.57	4.53	.007	.019	.034*
rooms in dwelling	[5.73–6.71]		[5.27–6.41]	[5.02–5.77]	[4.01–5.27]	(.011)	(.012)	(.02)
Share of dwellings	.919	.974	.95	.656	.536	-.025	.222***	.341***
with bathroom	[.809–.971]		[.793–.994]	[.335–.855]	[.386–.76]	(.019)	(.067)	(.047)
Observations	17	1	26	11	8	86	56	50
Share of adults	.693	.614	.659	.579	.603	.004	-.104***	-.105**
with a job	[.633–.774]		[.614–.737]	[.55–.607]	[.567–.696]	(.015)	(.031)	(.053)
Share of adults	.306	.304	.293	.16	.149	-.016	.022	.181**
formally employed	[.251–.372]		[.17–.46]	[.091–.212]	[.068–.197]	(.041)	(.054)	(.089)
Share of adults	.129	.005	.1	.151	.131	.027	.03	.065
with agricultural job	[.041–.266]		[.002–.283]	[.051–.241]	[.03–.254]	(.077)	(.09)	(.101)
Observations	17	1	26	11	7	86	56	48

Utility-level administrative data for distribution utilities in the four subsystems in 2000 and 2010 and census data matched to the concession area of these utilities in the same years. Columns (1)–(5) display descriptive statistics in 2000 (prior to the crisis) for the variables listed in the left–hand side column for distribution utilities in the South (column 1), in the Southeast/Midwest (LIGHT in column 2, all distribution utilities in column 3), in the Northeast (column 4), and in the North (column 5). Columns (6)–(8) display estimates of a long–term difference–in–difference estimator comparing the logarithm of these variables in 2010 vs. 2000 for distribution utilities in the Southeast/Midwest (column 6), in the Northeast (column 7), and in the North (column 8) compared to distribution utilities in the South. Significance levels: *10%, **5%, ***1% (s.e. clustered by utility). Regressions include fixed effects for each distribution utility and each year. The exchange rate in 2000 was about R$1.9 for US$1.

I The joint distribution of average electricity use and relevant covariates before the crisis (2000) among distribution utilities

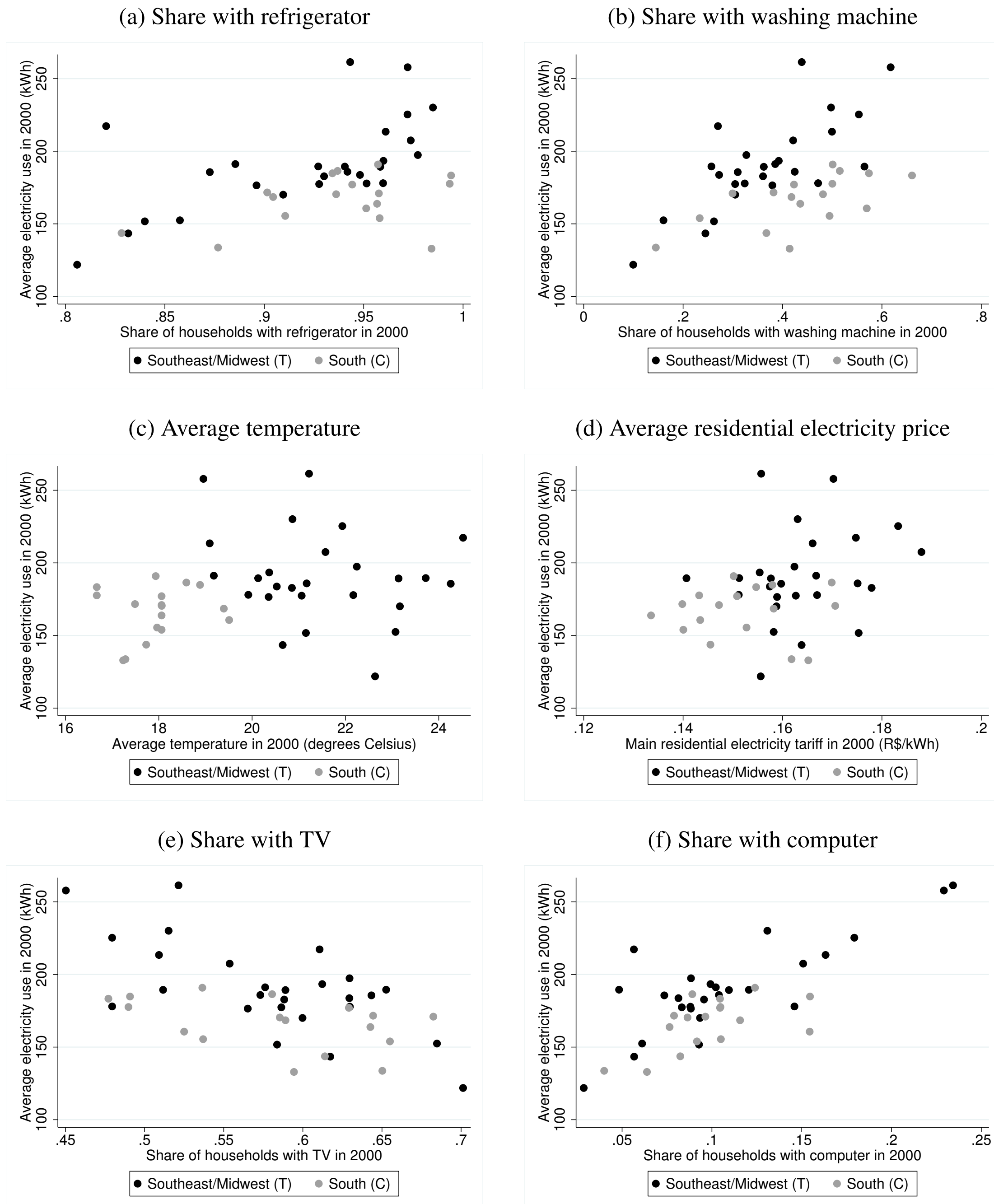
The following figures display the joint distribution of average residential electricity use per customer and relevant covariates before the crisis among distribution utilities in the Southeast/Midwest and in the South. We present figures for all the variables displayed in Tables 1 and H.1. The data come from either utility-level data from ANEEL or from the 2000 census matched to the concession area of each distribution utility. The figures show that there was some overlap in the distributions of average residential electricity use per customer in the Southeast/Midwest and in the South before the crisis. They also show that there was some overlap in the distributions of almost all covariates in the Southeast/Midwest and in the South before the crisis. The exception is for average temperatures, which are lower in the South.

Figure I.1: Joint distribution of average electricity use and relevant covariates before the crisis I (2000)



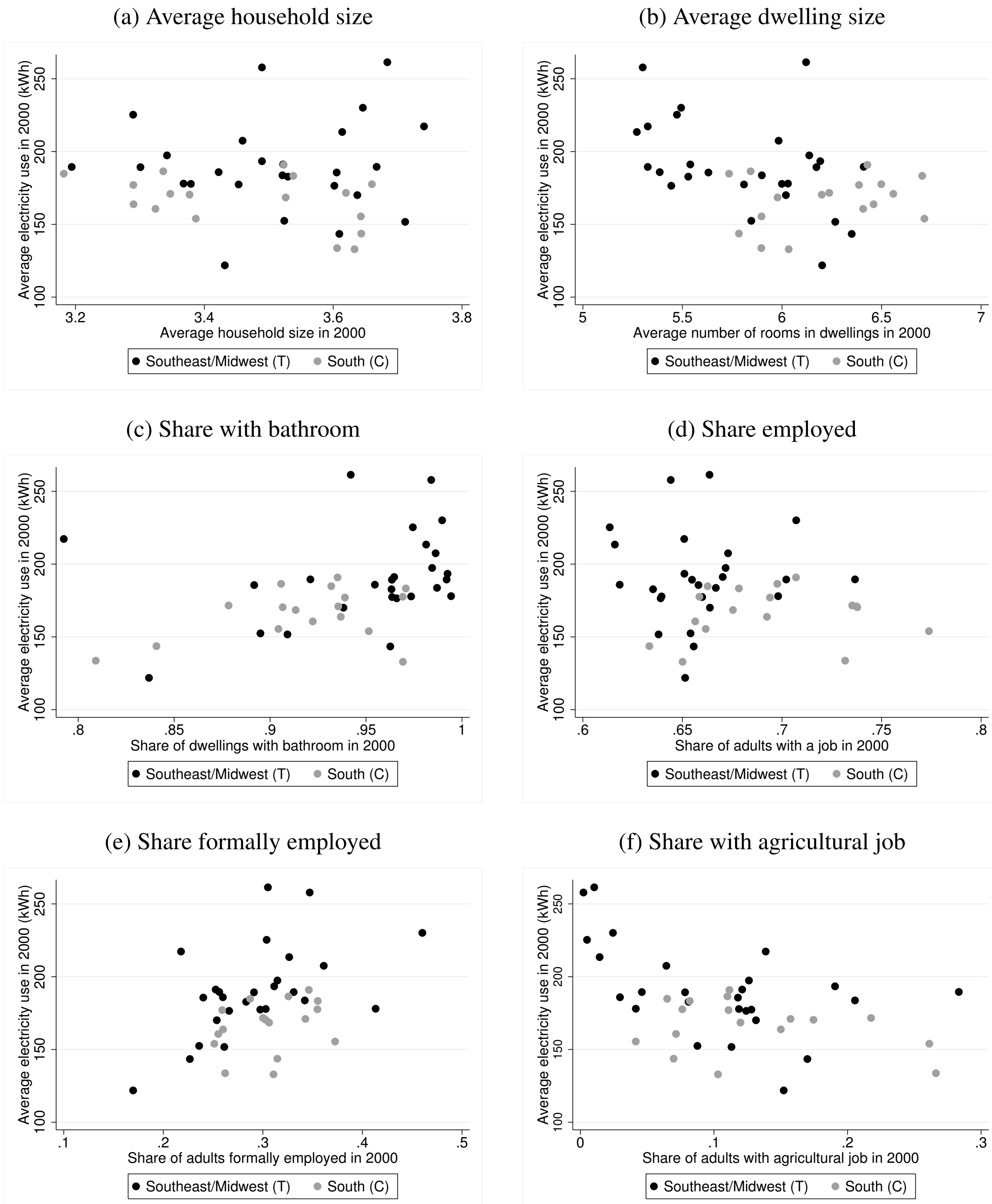
Each observation corresponds to a distribution utility and its concession area. The panels display the joint distribution of average residential electricity use per customer and relevant covariates before the crisis (2000) among distribution utilities in the Southeast/Midwest and in the South. In 2000, the exchange rate was about R$1.9≃US$1.

Figure I.2: Joint distribution of average electricity use and relevant covariates before the crisis II (2000)



Each observation corresponds to a distribution utility and its concession area. The panels display the joint distribution of average residential electricity use per customer and relevant covariates before the crisis (2000) among distribution utilities in the Southeast/Midwest and in the South. In 2000, the exchange rate was about R$1.9≃US$1.

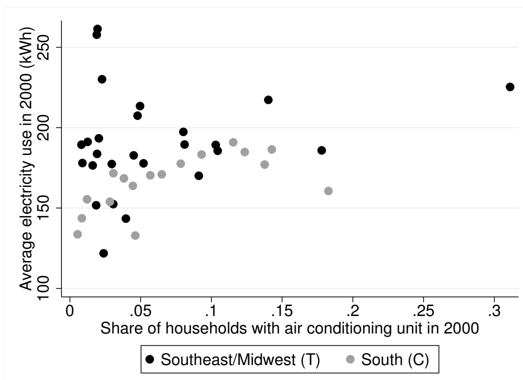
Figure I.3: Joint distribution of average electricity use and relevant covariates before the crisis III (2000)



Each observation corresponds to a distribution utility and its concession area. The panels display the joint distribution of average residential electricity use per customer and relevant covariates before the crisis (2000) among distribution utilities in the Southeast/Midwest and in the South. In 2000, the exchange rate was about R$1.9≃US$1.

Figure I.4: Joint distribution of average electricity use and relevant covariates before the crisis IV (2000)

(a) Share with air conditioning

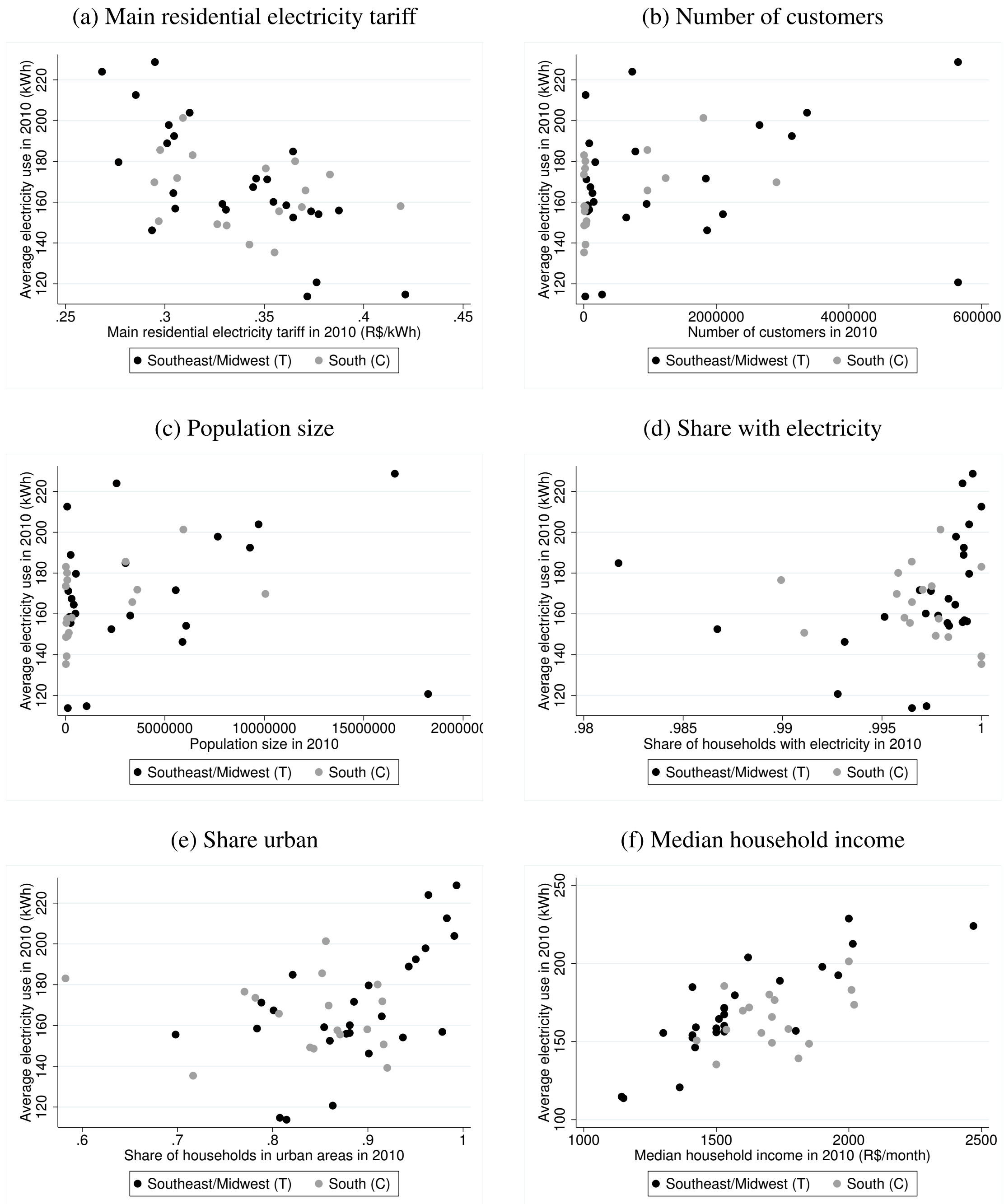


Each observation corresponds to a distribution utility and its concession area. The panels display the joint distribution of average residential electricity use per customer and relevant covariates before the crisis (2000) among distribution utilities in the Southeast/Midwest and in the South. In 2000, the exchange rate was about R$1.9≃US$1.

J The joint distribution of average electricity use and relevant covariates after the crisis (2010) among distribution utilities

The following figures display the joint distribution of average residential electricity use per customer and relevant covariates after the crisis among distribution utilities in the Southeast/Midwest and in the South. We present figures for all the variables displayed in Tables 1 and H.1. The data come from either utility-level data from ANEEL or from the 2010 census matched to the concession area of each distribution utility. The figures show that there is some overlap in the distributions of average residential electricity use per customer in the Southeast/Midwest and in the South after the crisis. They also show that there is some overlap in the distributions of almost all covariates in the Southeast/Midwest and in the South before the crisis. The exception is for average temperatures, which are lower in the South. Note that the 2010 census did not record ownership rates of air conditioning units.

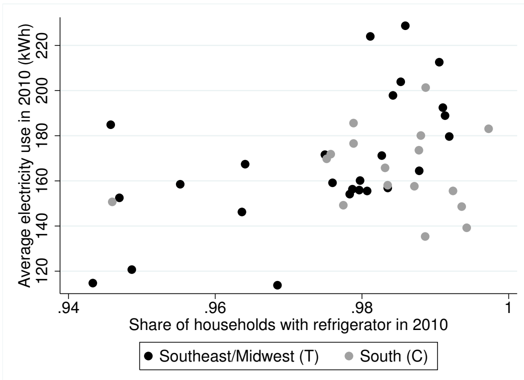
Figure J.1: Joint distribution of average electricity use and relevant covariates after the crisis I (2010)



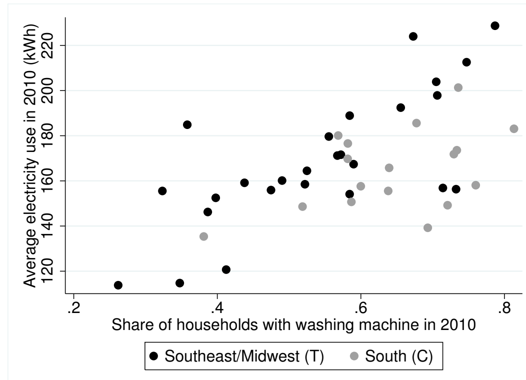
Each observation corresponds to a distribution utility and its concession area. The panels display the joint distribution of average residential electricity use per customer and relevant covariates before the crisis (2000) among distribution utilities in the Southeast/Midwest and in the South. In 2010, the exchange rate was about R$1.75≃US$1.

Figure J.2: Joint distribution of average electricity use and relevant covariates after the crisis II (2010)

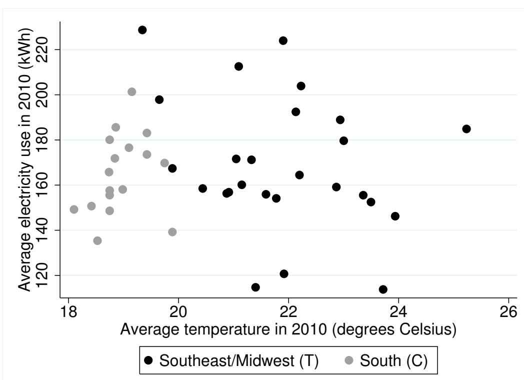
(a) Share with refrigerator



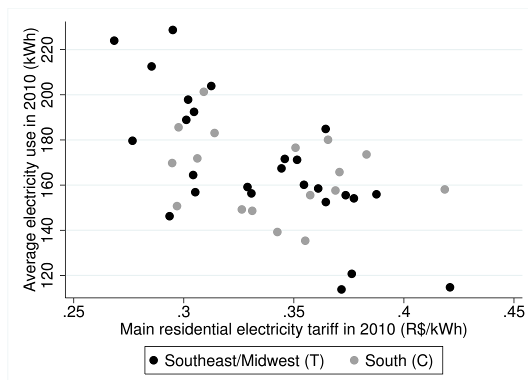
(b) Share with washing machine



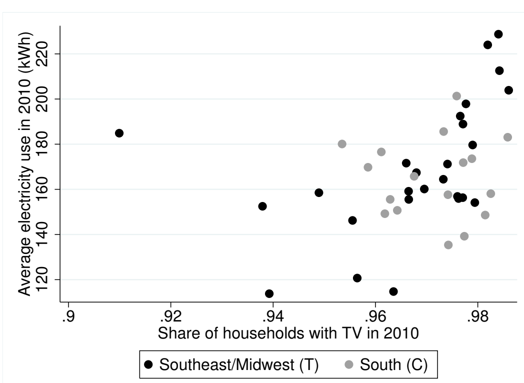
(c) Average temperature



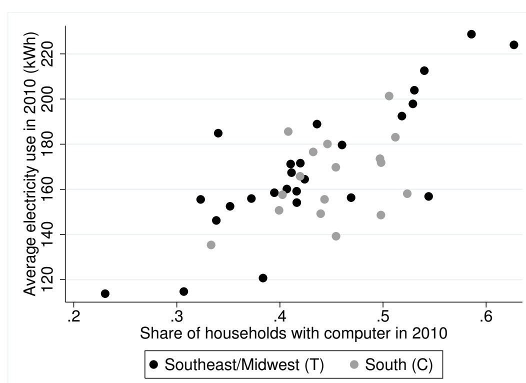
(d) Average residential electricity price



(e) Share with TV

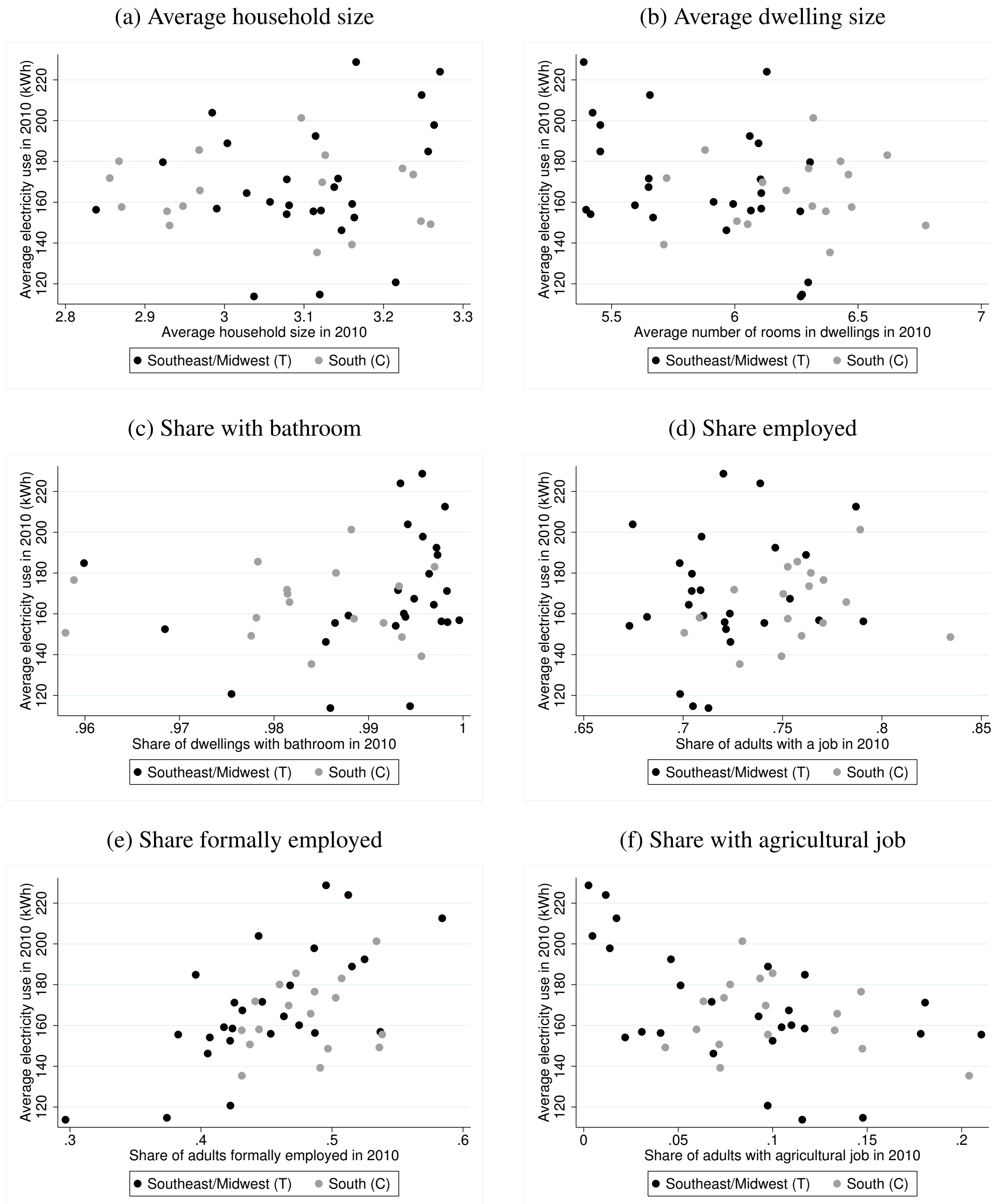


(f) Share with computer



Each observation corresponds to a distribution utility and its concession area. The panels display the joint distribution of average residential electricity use per customer and relevant covariates before the crisis (2000) among distribution utilities in the Southeast/Midwest and in the South. In 2010, the exchange rate was about R$1.75≃US$1.

Figure J.3: Joint distribution of average electricity use and relevant covariates after the crisis III (2010)

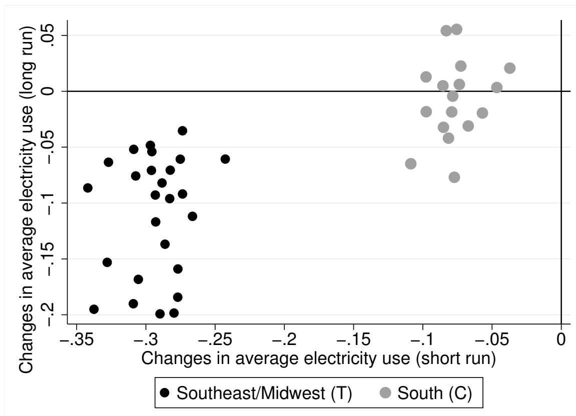


Each observation corresponds to a distribution utility and its concession area. The panels display the joint distribution of average residential electricity use per customer and relevant covariates before the crisis (2000) among distribution utilities in the Southeast/Midwest and in the South. In 2010, the exchange rate was about R$1.75≃US$1.

K Changes in average electricity during and after the crisis

Figure K.1 displays the changes in average residential electricity use per customer in every distribution utility in the Southeast/Midwest and in the South during the crisis (June 2001-February 2002) and long after the crisis (June 2010-February 2011) compared to before the crisis (June 2000-February 2001). Changes in average residential electricity use per customer y are calculated as follows: $\Delta y = \left(y_{during/after} - y_{before}\right)/y_{before}$. The figure shows that changes in average residential electricity use were lower for every distribution utility in the Southeast/Midwest during the crisis. The figure shows that changes in average residential electricity use were lower for almost every distribution utility in the Southeast/Midwest long after the crisis.

Figure K.1: Changes in average electricity use during and long after the crisis w.r.t before the crisis

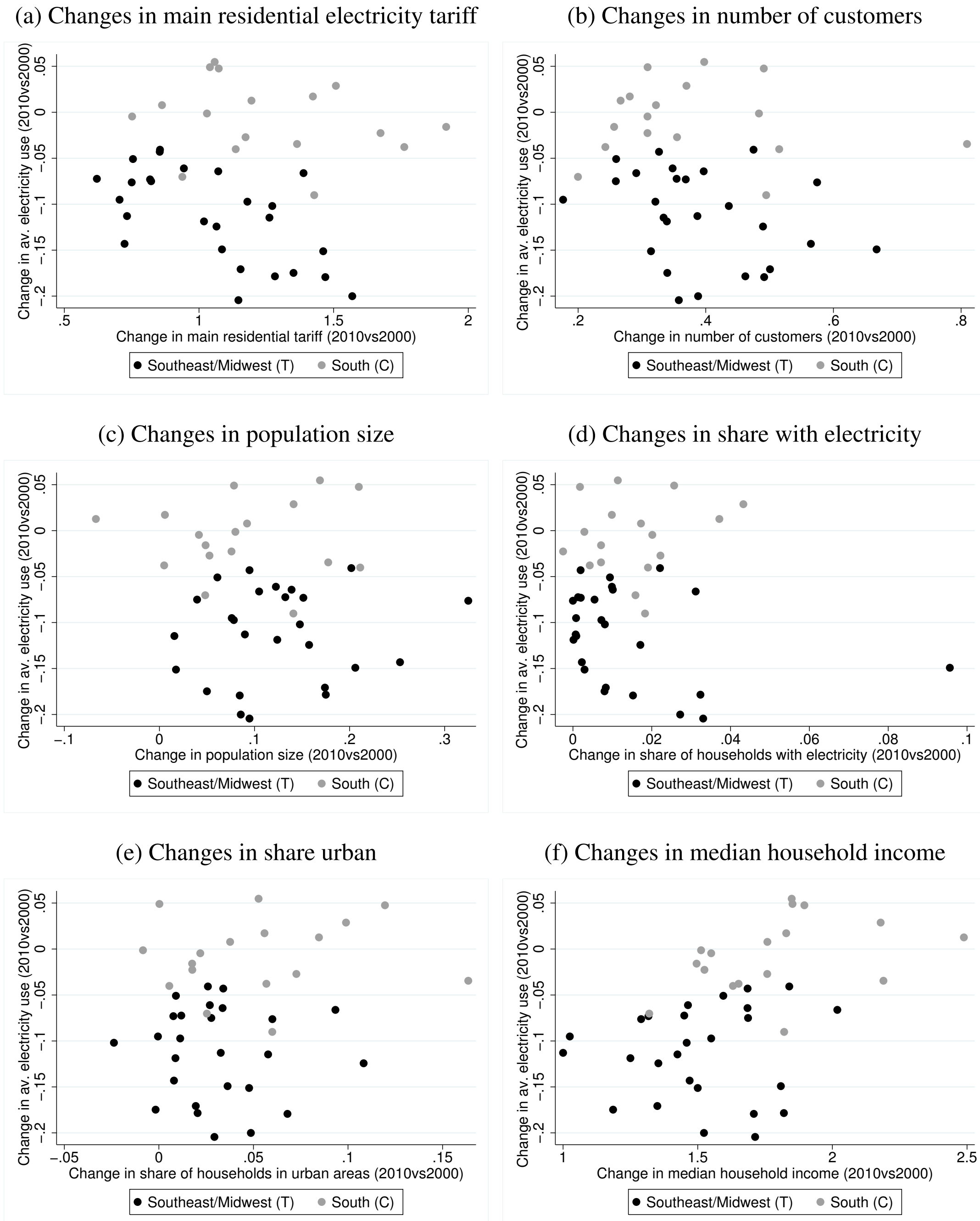


The figure displays the changes in average residential electricity use per customer in every distribution utility in the Southeast/Midwest and in the South during the crisis (June 2001-February 2002) and long after the crisis (June 2010-February 2011) compared to before the crisis (une 2000-February 2001). Changes in average residential electricity use per customer are calculated as follows: $\Delta y = \left(y_{during/after} - y_{before}\right)/y_{before}$.

L The joint distribution of long-run changes in average electricity use and relevant covariates (2010 vs. 2000) among distribution utilities

The following figures display the joint distribution of long-run changes in average residential electricity use per customer and in relevant covariates between 2010 (after the crisis) and 2000 (before the crisis) among distribution utilities in the Southeast/Midwest and in the South. Long-run changes for a variable y are calculated as follows: $\Delta y = \left(y_{2010} - y_{2000}\right)/y_{2000}$. We present figures for all the variables displayed in Tables 1 and H.1. The data come from either utility-level data from ANEEL or from the 2000 and 2010 censuses matched to the concession area of each distribution utility. The figures show that there is some overlap in the distributions of long-run changes in all covariates in the Southeast/Midwest and in the South. They also show that there is a lot of variation in terms of long-run changes in those covariates among distribution utilities. Importantly, the figures show that long-run changes in average electricity use per customer are systematically lower in the Southeast/Midwest than in the South for given long-run changes in those covariates. This explains why our results are robust to controlling for relevant covariates in Table 2.

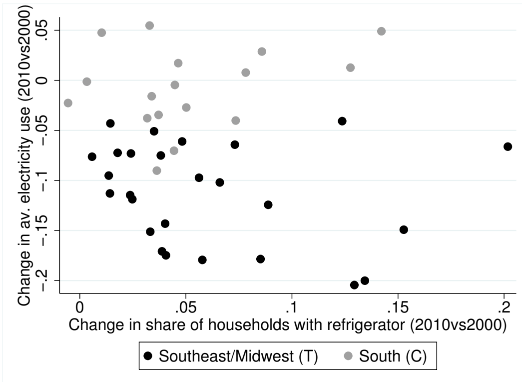
Figure L.1: Long-run changes in average electricity use and in relevant covariates I



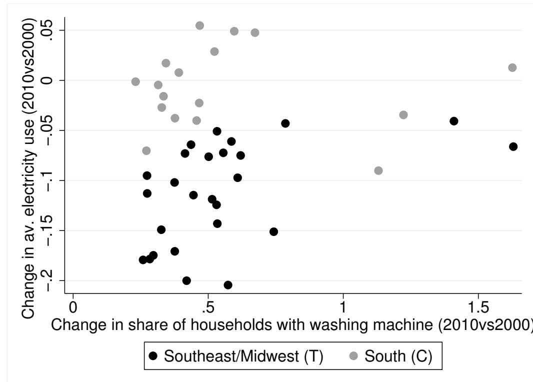
The panels display the joint distribution of long-run changes in average residential electricity use per customer and in relevant covariates between 2010 (after the crisis) and 2000 (before the crisis) among distribution utilities in the Southeast/Midwest and in the South. Long-run changes for a variable y are calculated as follows: $\Delta y = (y_{2010} - y_{2000})/y_{2000}$.

Figure L.2: Long-run changes in average electricity use and in relevant covariates II

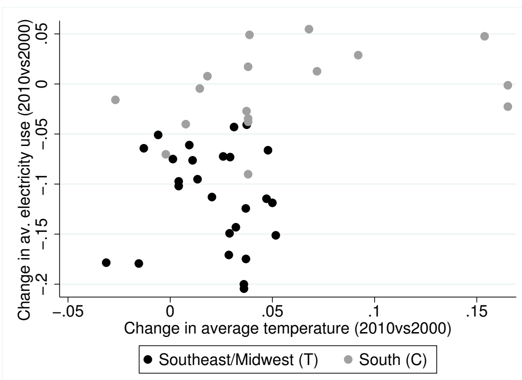
(a) Changes in share with refrigerator



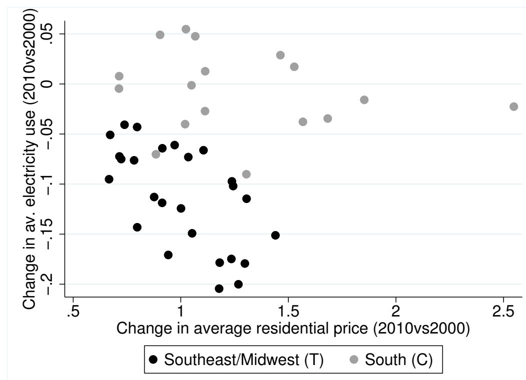
(b) Changes in share with washing machine



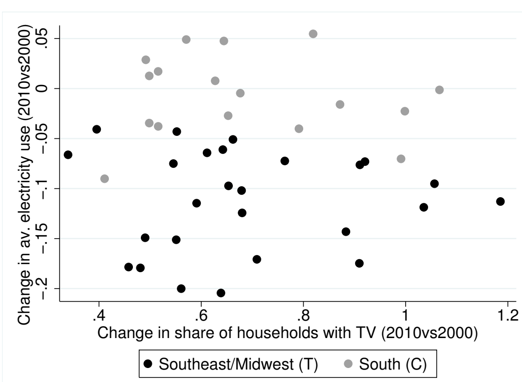
(c) Changes in average temperature



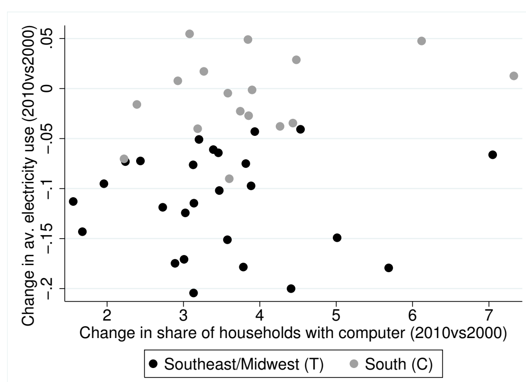
(d) Changes in average residential elecitricity price



(e) Changes in share with TV

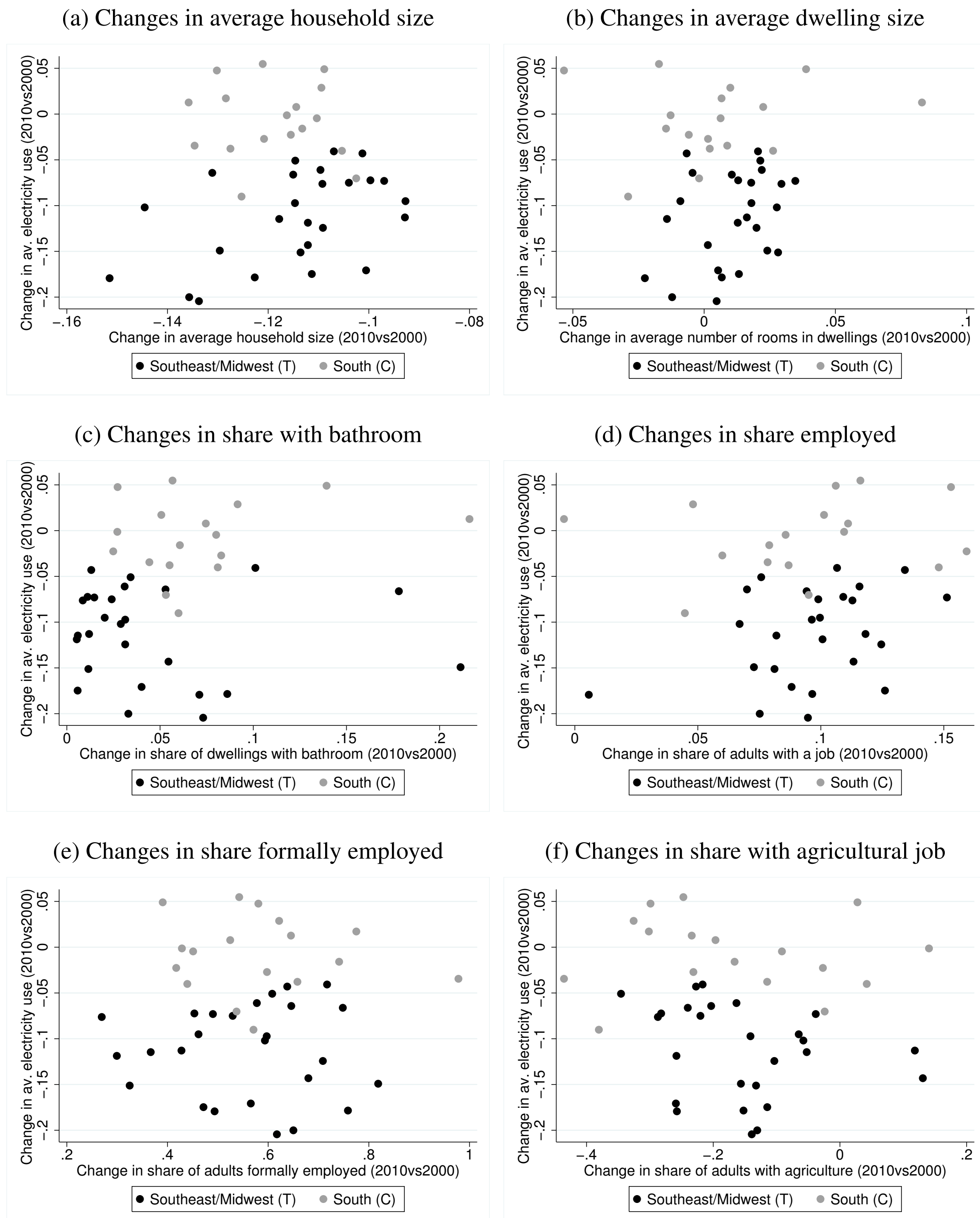


(f) Changes in share with computer



The panels display the joint distribution of long-run changes in average residential electricity use per customer and in relevant covariates between 2010 (after the crisis) and 2000 (before the crisis) among distribution utilities in the Southeast/Midwest and in the South. Long-run changes for a variable y are calculated as follows: $\Delta y = (y_{2010} - y_{2000})/y_{2000}$.

Figure L.3: Long-run changes in average electricity use and in relevant covariates III



The panels display the joint distribution of long-run changes in average residential electricity use per customer and in relevant covariates between 2010 (after the crisis) and 2000 (before the crisis) among distribution utilities in the Southeast/Midwest and in the South. Long-run changes for a variable y are calculated as follows: $\Delta y = (y_{2010} - y_{2000})/y_{2000}$.

M Tables with coefficient estimates and standard errors for Figures 3 and 4a

The following tables display coefficient estimates and standard errors for the regressions behind the results presented graphically in Figures 3 and 4a. All specifications include distribution utility and and calendar month per region fixed effects. Each table has the same format. Column (1) displays coefficients on time-period dummies (reference period: Early 2001) from a regression that only includes distribution utilities in the South. Column (2) displays difference-in-difference estimators in every time-period comparing utilities in the Southeast/Midwest and the South. The results in column (2) are the ones presented graphically in Figures 3 and 4a. Column (3) displays a robustness check for the results in column (2) by restricting the sample to distribution utilities with overlapping values for average electricity use, the main residential tariff, and median income levels in 2000. Tables vary in the sample years considered and the set of controls available in these years, and in using specifications in logs and levels. Difference-in-difference estimates in column (2) in Tables M.1 and M.2 are those presented in Figures 3. Difference-in-difference estimates in column (2) in Tables M.1, M.3, M.5, M.7, and M.9 are those presented in Figure 4a.

Table M.1: Difference–in–difference results in logs (1999–2010)

	Control region (1)		Treatment region dummy (2)		(3)	
1999	-.0018	(.0164)	.0099	(.0119)	.0069	(.0128)
2000	-.0021	(.0086)	.0025	(.0081)	.0018	(.0088)
Crisis	-.0813***	(.0042)	-.2581***	(.0079)	-.2573***	(.0087)
Rest of 2002	-.0528***	(.0077)	-.1695***	(.0089)	-.1705***	(.0103)
2003	-.0669***	(.0155)	-.1301***	(.0097)	-.1255***	(.0115)
2004	-.0604***	(.0211)	-.1281***	(.0115)	-.1282***	(.0138)
2005	-.0532**	(.022)	-.1154***	(.0117)	-.1129***	(.0143)
2006	-.054**	(.0235)	-.1145***	(.0123)	-.1129***	(.0144)
2007	-.0266	(.0257)	-.1252***	(.0135)	-.1267***	(.0158)
2008	-.0312	(.0291)	-.118***	(.0137)	-.1218***	(.0159)
2009	-.0086	(.0306)	-.113***	(.0134)	-.1171***	(.0153)
2010	.0115	(.0326)	-.1103***	(.0136)	-.1146***	(.015)
Log main tariff (R)	-.0597*	(.0351)	-.138***	(.0277)	-.1366***	(.0338)
Log population (1000's)	-.1851*	(.1056)	-.1514*	(.0877)	-.1194	(.1108)
Log formal employment (1000's)	.1069**	(.0517)	.121***	(.0445)	.1024*	(.055)
Log GDP per capita (R)	-.021	(.0302)	-.0335	(.028)	-.0317	(.034)
Log average temperature (C)	.1489*	(.0808)	.1439*	(.0788)	.141*	(.0797)
Regions	South		S/SE/MW		S/SE/MW	
Restricted sample	No		No		Yes	
Observations	2425		6169		5017	
Clusters	17		43		35	

Units of observation: distribution utilities as of 1999. Significance levels: *10%, **5%, ***1% (s.e. clustered by utility). Data from 1999 to 2010. Results from specifications including utility and calendar month per region fixed effects. Regressions also control for the main electricity tariff (monthly, log), total population, total formal employment, GDP per capita, and average temperature (yearly, log) for each utility. Column (1) reproduces coefficients on time–period dummies in the South (reference period: Early 2001). Column (2) presents difference–in–difference estimators in every time–period comparing utilities in the Southeast/Midwest and the South. Column (3) restricts the sample in column (2) to utilities with overlapping values for average electricity use, the main residential tariff, and median income levels in 2000.

Table M.2: Difference–in–difference results in levels (1999-2010)

	Control region		Treatment region dummy			
	(1)		(2)		(3)	
1999	1.224	(1.91)	1.274	(1.635)	1.204	(1.745)
2000	.0214	(1.155)	.0992	(1.271)	.4208	(1.446)
Crisis	-13.6***	(.9153)	-41.5***	(2.484)	-37.96***	(1.992)
Rest of 2002	-9.245***	(1.16)	-29.5***	(1.97)	-27.16***	(1.871)
2003	-11.82***	(2.408)	-22.99***	(2.225)	-19.74***	(2.192)
2004	-10.84***	(3.27)	-21.86***	(2.343)	-19.72***	(2.359)
2005	-9.832***	(3.54)	-19.72***	(2.309)	-17.48***	(2.299)
2006	-10.07***	(3.818)	-19***	(2.412)	-17.11***	(2.355)
2007	-6.234	(4.084)	-20.32***	(2.447)	-18.8***	(2.615)
2008	-6.764	(4.828)	-19.54***	(2.386)	-18.41***	(2.646)
2009	-3.803	(5.165)	-18.49***	(2.343)	-17.86***	(2.58)
2010	-.6471	(5.75)	-19.01***	(2.354)	-18.26***	(2.522)
Main tariff (R)	-24.97	(21.3)	-77.63***	(14.62)	-82.15***	(17.75)
Population (1000's)	-.0202***	(.0073)	-.0108***	(.0033)	-.0035	(.0062)
Formal employment (1000's)	.03***	(.0097)	.0098**	(.0043)	.0015	(.0099)
GDP per capita (R)	.0202	(.2037)	-.0983	(.1886)	.0814	(.3042)
Average temperature (C)	2.056**	(.831)	1.739**	(.7404)	1.338*	(.7525)
Regions	South		S/SE/MW		S/SE/MW	
Restricted sample	No		No		Yes	
Observations	2425		6169		5017	
Clusters	17		43		35	

Units of observation: distribution utilities as of 1999. Significance levels: *10%, **5%, ***1% (s.e. clustered by utility). Data from 1999 to 2010. Results from specifications including utility and calendar month per region fixed effects. Regressions also control for the main electricity tariff (monthly, levels), total population, total formal employment, GDP per capita, and average temperature (yearly, levels) for each utility. Column (1) reproduces coefficients on time–period dummies in the South (reference period: Early 2001). Column (2) presents difference–in–difference estimators in every time–period comparing utilities in the Southeast/Midwest and the South. Column (3) restricts the sample in column (2) to utilities with overlapping values for average electricity use, the main residential tariff, and median income levels in 2000.

Table M.3: Difference–in–difference results in logs (1991-2011)

	Control region		Treatment region dummy			
	(1)		(2)		(3)	
1991	-.141***	(.0215)	.021	(.0223)	.0222	(.0223)
1992	-.1613***	(.0195)	.0236	(.0208)	.0289	(.0205)
1993	-.1628***	(.018)	.0134	(.0196)	.0193	(.019)
1994	-.1576***	(.0157)	.0118	(.0179)	.0187	(.0181)
1995	-.0766***	(.0119)	.0186	(.0138)	.0217	(.0149)
1996	-.0206*	(.0105)	.0085	(.0126)	.0095	(.0135)
1997	-.0187***	(.0059)	.0353***	(.0081)	.0365***	(.0094)
1998	-.0054	(.0068)	.0438***	(.0091)	.0443***	(.0101)
1999	-.0046	(.007)	.0254***	(.0079)	.0237***	(.0084)
2000	-.0128***	(.0046)	.0202***	(.0055)	.0189***	(.0061)
Crisis	-.0937***	(.004)	-.2508***	(.0088)	-.2487***	(.0095)
Rest of 2002	-.0652***	(.0057)	-.1639***	(.0086)	-.1663***	(.0096)
2003	-.0966***	(.0077)	-.1242***	(.0106)	-.1228***	(.0123)
2004	-.0945***	(.0086)	-.1314***	(.0126)	-.1331***	(.0149)
2005	-.0824***	(.0083)	-.1233***	(.0128)	-.1265***	(.0155)
2006	-.0892***	(.0081)	-.1144***	(.0141)	-.1192***	(.0169)
2007	-.0679***	(.0104)	-.1094***	(.0165)	-.1177***	(.0199)
2008	-.0667***	(.0119)	-.1028***	(.0176)	-.1115***	(.0208)
2009	-.0393***	(.0135)	-.1036***	(.0183)	-.1121***	(.0211)
2010	-.0205	(.013)	-.0983***	(.0173)	-.1073***	(.0197)
2011	-.0012	(.0109)	-.1112***	(.0176)	-.1215***	(.0205)
Regions	South		S/SE/MW		S/SE/MW	
Restricted sample	No		No		Yes	
Observations	2772		8820		7056	
Clusters	11		35		28	

Units of observation: distribution utilities as of 1991. Significance levels: *10%, **5%, ***1% (s.e. clustered by utility). Data from 1991 to 2011. Results from specifications including utility and calendar month per region fixed effects. Column (1) reproduces coefficients on time–period dummies in the South (reference period: Early 2001). Column (2) presents difference–in–difference estimators in every time–period comparing utilities in the Southeast/Midwest and the South. Column (3) restricts the sample in column (2) to utilities with overlapping values for average electricity use, the main residential tariff, and median income levels in 2000.

Table M.4: Difference–in–difference results in levels (1991-2011)

	Control region		Treatment region dummy			
	(1)		(2)		(3)	
1991	-22.72***	(3.501)	.9331	(3.831)	2.629	(3.682)
1992	-25.57***	(3.266)	.7361	(3.775)	3.257	(3.51)
1993	-25.71***	(3.041)	-.9454	(3.63)	1.771	(3.302)
1994	-24.91***	(2.744)	-1.269	(3.434)	1.446	(3.263)
1995	-12.83***	(2.095)	1.493	(2.559)	2.74	(2.661)
1996	-3.822**	(1.838)	.9914	(2.266)	1.294	(2.424)
1997	-3.457***	(1.022)	6.099***	(1.433)	5.971***	(1.657)
1998	-1.25	(1.219)	8.302***	(1.67)	7.788***	(1.793)
1999	-1.083	(1.227)	4.778***	(1.453)	3.999***	(1.523)
2000	-2.448***	(.8676)	3.396***	(1.09)	2.988**	(1.219)
Crisis	-15.35***	(1.092)	-39.91***	(2.783)	-36.4***	(2.213)
Rest of 2002	-10.86***	(1.152)	-27.97***	(2.149)	-26.06***	(1.949)
2003	-15.74***	(1.72)	-22.02***	(2.604)	-19.54***	(2.486)
2004	-15.49***	(1.659)	-23.01***	(2.687)	-20.93***	(2.664)
2005	-13.58***	(1.568)	-21.71***	(2.573)	-20.1***	(2.676)
2006	-14.48***	(1.432)	-20.33***	(2.609)	-19.02***	(2.734)
2007	-11.03***	(1.672)	-19.36***	(2.715)	-18.91***	(3.073)
2008	-11.02***	(1.942)	-18.15***	(2.909)	-17.89***	(3.27)
2009	-6.66***	(2.22)	-18.25***	(3.037)	-18.22***	(3.383)
2010	-3.531	(2.147)	-17.49***	(2.914)	-17.7***	(3.186)
2011	-.4998	(1.784)	-19.43***	(2.94)	-19.88***	(3.268)
Regions	South		S/SE/MW		S/SE/MW	
Restricted sample	No		No		Yes	
Observations	2772		8820		7056	
Clusters	11		35		28	

Units of observation: distribution utilities as of 1991. Significance levels: *10%, **5%, ***1% (s.e. clustered by utility). Data from 1991 to 2011. Results from specifications including utility and calendar month per region fixed effects. Column (1) reproduces coefficients on time–period dummies in the South (reference period: Early 2001). Column (2) presents difference–in–difference estimators in every time–period comparing utilities in the Southeast/Midwest and the South. Column (3) restricts the sample in column (2) to utilities with overlapping values for average electricity use, the main residential tariff, and median income levels in 2000.

Table M.5: Difference–in–difference results in logs (1996-2011)

	Control region (1)		Treatment region dummy (2)		(3)	
1996	-.0327***	(.0107)	.0245*	(.0144)	.0239	(.0154)
1997	-.0255***	(.0094)	.0448***	(.0121)	.045***	(.0127)
1998	-.0089	(.007)	.0463***	(.0108)	.0467***	(.0117)
1999	-.0059	(.0065)	.0265***	(.009)	.0245**	(.0096)
2000	-.0105***	(.004)	.0197***	(.0061)	.0181***	(.0069)
Crisis	-.086***	(.004)	-.2551***	(.0084)	-.253***	(.0089)
Rest of 2002	-.0579***	(.0056)	-.1658***	(.0083)	-.1679***	(.0091)
2003	-.0886***	(.0079)	-.1254***	(.0095)	-.1235***	(.011)
2004	-.088***	(.0092)	-.1303***	(.0118)	-.1313***	(.0138)
2005	-.0739***	(.0092)	-.1234***	(.0121)	-.1256***	(.0143)
2006	-.0801***	(.0077)	-.1158***	(.0136)	-.1191***	(.0158)
2007	-.0571***	(.0073)	-.113***	(.0159)	-.1196***	(.0187)
2008	-.0573***	(.0087)	-.1065***	(.0164)	-.1133***	(.0191)
2009	-.0317***	(.01)	-.1052***	(.0169)	-.1118***	(.0192)
2010	-.0103	(.0096)	-.1026***	(.0169)	-.1096***	(.0184)
2011	.0095	(.0101)	-.115***	(.0176)	-.1233***	(.0196)
Log main tariff (R)	-.0128***	(.0023)	-.0247**	(.0125)	-.022**	(.0105)
Log population (1000's)	.0287	(.0952)	.0369	(.0861)	.0225	(.0915)
Regions	South		S/SE/MW		S/SE/MW	
Restricted sample	No		No		Yes	
Observations	2496		7104		5760	
Clusters	13		37		30	

Units of observation: distribution utilities as of 1996. Significance levels: *10%, **5%, ***1% (s.e. clustered by utility). Data from 1996 to 2011. Results from specifications including utility and calendar month per region fixed effects. Regressions also control for the main electricity tariff (monthly, log) and total population (yearly, log) for each utility. Column (1) reproduces coefficients on time–period dummies in the South (reference period: Early 2001). Column (2) presents difference–in–difference estimators in every time–period comparing utilities in the Southeast/Midwest and the South. Column (3) restricts the sample in column (2) to utilities with overlapping values for average electricity use, the main residential tariff, and median income levels in 2000.

Table M.6: Difference–in–difference results in levels (1996-2011)

	Control region		Treatment region dummy			
	(1)		(2)		(3)	
1996	-4.999***	(1.877)	2.434	(2.358)	2.968	(2.493)
1997	-3.964**	(1.76)	6.862***	(1.903)	6.943***	(2.031)
1998	-1.156	(1.406)	8.631***	(1.742)	8.281***	(1.83)
1999	-.7298	(1.256)	4.832***	(1.43)	4.176***	(1.486)
2000	-1.72**	(.7684)	3.06***	(1.002)	2.736**	(1.11)
Crisis	-14.29***	(.9333)	-40.52***	(2.676)	-37.07***	(2.082)
Rest of 2002	-10.04***	(1.01)	-28.23***	(2.035)	-26.4***	(1.823)
2003	-15.24***	(1.498)	-22.11***	(2.378)	-19.76***	(2.253)
2004	-15.59***	(1.418)	-22.53***	(2.515)	-20.65***	(2.481)
2005	-13.5***	(1.355)	-21.42***	(2.412)	-20.06***	(2.496)
2006	-14.45***	(1.25)	-20***	(2.47)	-19***	(2.557)
2007	-10.77***	(1.452)	-19.24***	(2.607)	-19.1***	(2.901)
2008	-10.98***	(1.619)	-17.8***	(2.754)	-17.86***	(3.058)
2009	-6.961***	(1.796)	-17.57***	(2.891)	-17.88***	(3.161)
2010	-3.332*	(1.836)	-17.25***	(2.868)	-17.82***	(3.058)
2011	-.2635	(1.609)	-19.16***	(2.989)	-20***	(3.224)
Main tariff (R)	-.3327***	(.0546)	-.2589***	(.0415)	-.2612***	(.0521)
Population (1000's)	.0032	(.0031)	-.0025	(.0015)	-.0022	(.0026)
Regions	South		S/SE/MW		S/SE/MW	
Restricted sample	No		No		Yes	
Observations	2496		7104		5760	
Clusters	13		37		30	

Units of observation: distribution utilities as of 1996. Significance levels: *10%, **5%, ***1% (s.e. clustered by utility). Data from 1996 to 2011. Results from specifications including utility and calendar month per region fixed effects. Regressions also control for the main electricity tariff (monthly, level) and total population (yearly, level) for each utility. Column (1) reproduces coefficients on time–period dummies in the South (reference period: Early 2001). Column (2) presents difference–in–difference estimators in every time–period comparing utilities in the Southeast/Midwest and the South. Column (3) restricts the sample in column (2) to utilities with overlapping values for average electricity use, the main residential tariff, and median income levels in 2000.

Table M.7: Difference–in–difference results in logs (1996-2010)

	Control region		Treatment region dummy			
	(1)		(2)		(3)	
1996	-.0053	(.0136)	.0156	(.0145)	.0143	(.0157)
1997	-.0041	(.0103)	.0379***	(.0118)	.038***	(.0124)
1998	.0145	(.0097)	.0296**	(.0131)	.029**	(.0139)
1999	.0173	(.0113)	.0133	(.012)	.0092	(.013)
2000	.0063	(.0072)	.0067	(.0082)	.0045	(.0093)
Crisis	-.0859***	(.0043)	-.2584***	(.0087)	-.257***	(.0094)
Rest of 2002	-.0614***	(.0072)	-.1742***	(.0099)	-.1781***	(.0113)
2003	-.0925***	(.011)	-.1345***	(.0114)	-.1351***	(.0138)
2004	-.0959***	(.0142)	-.1362***	(.0132)	-.1394***	(.016)
2005	-.0903***	(.0141)	-.1296***	(.0132)	-.1333***	(.0159)
2006	-.0985***	(.013)	-.1243***	(.0139)	-.1289***	(.0165)
2007	-.0778***	(.0135)	-.1283***	(.0164)	-.1364***	(.0192)
2008	-.0855***	(.0157)	-.1147***	(.0162)	-.1223***	(.0186)
2009	-.0667***	(.0167)	-.1108***	(.0168)	-.1182***	(.0192)
2010	-.0547***	(.0182)	-.1061***	(.0171)	-.114***	(.0187)
Log main tariff (R)	-.0108***	(.0021)	-.0225*	(.0116)	-.0202**	(.0095)
Log population (1000's)	-.0042	(.0899)	.0023	(.0807)	.0184	(.0937)
Log formal employment (1000's)	.106***	(.0297)	-.0225*	(.0116)	-.0202**	(.0095)
Log average temperature (C)	.1693	(.1065)	.0023	(.0807)	.0184	(.0937)
Regions	South		S/SE/MW		S/SE/MW	
Restricted sample	No		No		Yes	
Observations	2340		6660		5400	
Clusters	13		37		30	

Units of observation: distribution utilities as of 1996. Significance levels: *10%, **5%, ***1% (s.e. clustered by utility). Data from 1996 to 2010. Results from specifications including utility and calendar month per region fixed effects. Regressions also control for the main electricity tariff (monthly, log), total population and total formal employment (yearly, log) for each utility. Column (1) reproduces coefficients on time–period dummies in the South (reference period: Early 2001). Column (2) presents difference–in–difference estimators in every time–period comparing utilities in the Southeast/Midwest and the South. Column (3) restricts the sample in column (2) to utilities with overlapping values for average electricity use, the main residential tariff, and median income levels in 2000.

Table M.8: Difference–in–difference results in levels (1996–2010)

	Control region		Treatment region dummy			
	(1)		(2)		(3)	
1996	-2.705	(2.732)	-.0804	(2.571)	1.346	(2.692)
1997	-2.879	(1.787)	4.886**	(1.911)	5.691***	(2.075)
1998	1.4	(2.021)	5.108**	(2.16)	5.475**	(2.259)
1999	3.153	(2.067)	1.795	(1.996)	1.645	(2.153)
2000	.9916	(1.309)	.5413	(1.437)	.6054	(1.646)
Crisis	-14.01***	(.8975)	-41.1***	(2.7)	-37.66***	(2.165)
Rest of 2002	-9.466***	(1.042)	-29.78***	(2.207)	-27.91***	(2.236)
2003	-13.14***	(1.493)	-23.76***	(2.57)	-21.47***	(2.672)
2004	-12.65***	(1.71)	-23.43***	(2.667)	-21.76***	(2.772)
2005	-11.94***	(1.265)	-22.29***	(2.526)	-21.08***	(2.725)
2006	-12.86***	(.9221)	-21.08***	(2.557)	-20.23***	(2.796)
2007	-9.429***	(1.201)	-21.53***	(2.79)	-21.25***	(3.262)
2008	-9.833***	(1.273)	-19.32***	(2.682)	-18.83***	(3.107)
2009	-7.279***	(1.829)	-18.56***	(2.828)	-18.4***	(3.214)
2010	-4.828**	(2.272)	-18.41***	(2.85)	-18.07***	(3.109)
Main tariff (R)	-.2718***	(.0376)	-.2311***	(.0388)	-.2421***	(.0459)
Population (1000's)	-.0112***	(.0032)	-.0104***	(.003)	-.0078	(.0054)
Formal employment (1000's)	.0205***	(.0063)	.0126***	(.0042)	.0092	(.01)
Average temperature (C)	51.64***	(19.56)	41.85**	(16.31)	38.9**	(17.15)
Regions	South		S/SE/MW		S/SE/MW	
Restricted sample	No		No		Yes	
Observations	2340		6660		5400	
Clusters	13		37		30	

Units of observation: distribution utilities as of 1996. Significance levels: *10%, **5%, ***1% (s.e. clustered by utility). Data from 1996 to 2010. Results from specifications including utility and calendar month per region fixed effects. Regressions also control for the main electricity tariff (monthly, levels), total population and total formal employment (yearly, levels) for each utility. Column (1) reproduces coefficients on time–period dummies in the South (reference period: Early 2001). Column (2) presents difference–in–difference estimators in every time–period comparing utilities in the Southeast/Midwest and the South. Column (3) restricts the sample in column (2) to utilities with overlapping values for average electricity use, the main residential tariff, and median income levels in 2000.

Table M.9: Difference–in–difference results in logs (1999–2011)

	Control region (1)		Treatment region dummy (2)		(3)	
1999	-.0127	(.0104)	.0167*	(.01)	.0143	(.0108)
2000	-.0128**	(.0053)	.0136**	(.0066)	.0126*	(.0073)
Crisis	-.0831***	(.0048)	-.2552***	(.0077)	-.2541***	(.0083)
Rest of 2002	-.0544***	(.0092)	-.1649***	(.0078)	-.1657***	(.0086)
2003	-.0767***	(.0169)	-.1239***	(.0086)	-.1186***	(.0098)
2004	-.0708***	(.0229)	-.127***	(.0109)	-.1257***	(.0127)
2005	-.057**	(.0249)	-.1153***	(.0113)	-.1118***	(.0128)
2006	-.0597**	(.0257)	-.1112***	(.0125)	-.1089***	(.0139)
2007	-.0363	(.0278)	-.1126***	(.0136)	-.1138***	(.0156)
2008	-.0378	(.0322)	-.1115***	(.0142)	-.1145***	(.0163)
2009	-.0119	(.0333)	-.1087***	(.0138)	-.1122***	(.0155)
2010	.0121	(.0352)	-.1101***	(.014)	-.114***	(.0151)
2011	.0299	(.0389)	-.1178***	(.0149)	-.1236***	(.0163)
Log main tariff (R)	-.0576*	(.0314)	-.1359***	(.0265)	-.138***	(.0318)
Log population (1000's)	-.0629	(.0798)	-.0394	(.0768)	-.0244	(.0804)
Log GDP per capita (R)	.0173	(.0307)	.0073	(.0252)	.0025	(.0282)
Regions	South		S/SE/MW		S/SE/MW	
Restricted sample	No		No		Yes	
Observations	2629		6685		5437	
Clusters	17		43		35	

Units of observation: distribution utilities as of 1999. Significance levels: *10%, **5%, ***1% (s.e. clustered by utility). Data from 1999 to 2011. Results from specifications including utility and calendar month per region fixed effects. Regressions also control for the main electricity tariff (monthly, log) and total population and GDP per capita (yearly, log) for each utility. Column (1) reproduces coefficients on time–period dummies in the South (reference period: Early 2001). Column (2) presents difference–in–difference estimators in every time–period comparing utilities in the Southeast/Midwest and the South. Column (3) restricts the sample in column (2) to utilities with overlapping values for average electricity use, the main residential tariff, and median income levels in 2000.

Table M.10: Difference–in–difference results in levels (1999–2011)

	Control region		Treatment region dummy			
	(1)		(2)		(3)	
1999	-1.693	(1.387)	3.582**	(1.435)	2.695*	(1.478)
2000	-2.028**	(.7909)	2.192**	(1.031)	1.808	(1.123)
Crisis	-13.87***	(.948)	-40.84***	(2.465)	-37.33***	(1.952)
Rest of 2002	-9.544***	(1.266)	-28.04***	(1.914)	-25.91***	(1.705)
2003	-12.86***	(2.474)	-21.55***	(2.174)	-18.37***	(1.986)
2004	-12.19***	(3.287)	-21.3***	(2.353)	-18.82***	(2.267)
2005	-10***	(3.55)	-19.11***	(2.378)	-16.58***	(2.254)
2006	-10.26***	(3.77)	-18.31***	(2.505)	-16.06***	(2.324)
2007	-6.257	(4.029)	-18.42***	(2.524)	-16.88***	(2.528)
2008	-6.442	(4.675)	-18.49***	(2.521)	-17.37***	(2.633)
2009	-2.386	(4.871)	-17.83***	(2.436)	-17.05***	(2.548)
2010	1.891	(5.299)	-18.15***	(2.505)	-17.58***	(2.571)
2011	4.959	(6.012)	-19***	(2.654)	-18.77***	(2.628)
Main tariff (R)	-37.75**	(17.19)	-83.45***	(13.24)	-83.34***	(15.63)
Population (1000's)	.0038	(.0036)	-.0034*	(.0018)	-.0025	(.0023)
GDP per capita (R)	.0769	(.2302)	-.017	(.2087)	.15	(.2707)
Regions	South		S/SE/MW		S/SE/MW	
Restricted sample	No		No		Yes	
Observations	2629		6685		5437	
Clusters	17		43		35	

Units of observation: distribution utilities as of 1999. Significance levels: *10%, **5%, ***1% (s.e. clustered by utility). Data from 1999 to 2011. Results from specifications including utility and calendar month per region fixed effects. Regressions also control for the main electricity tariff (monthly, levels) and total population and GDP per capita (yearly, levels) for each utility. Column (1) reproduces coefficients on time–period dummies in the South (reference period: Early 2001). Column (2) presents difference–in–difference estimators in every time–period comparing utilities in the Southeast/Midwest and the South. Column (3) restricts the sample in column (2) to utilities with overlapping values for average electricity use, the main residential tariff, and median income levels in 2000.

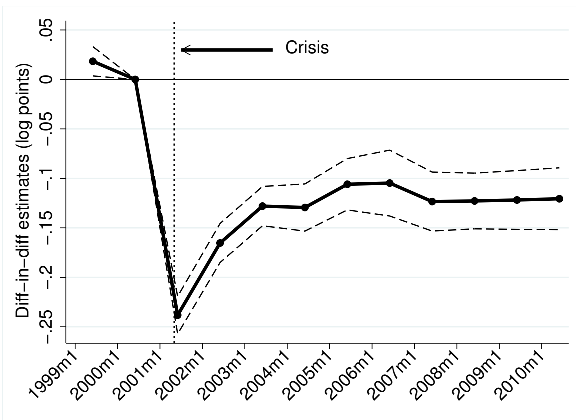
N Robustness of difference-in-difference results

The following figures and tables present some robustness checks for our difference-in-difference results.

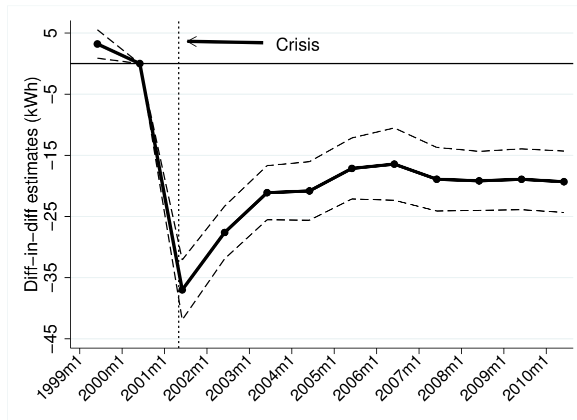
Figure N.1 and Tables N.1, N.2, N.3, and N.4 display similar results as in Figure 3 and Tables M.1 and M.2, splitting the sample between winter and summer months. The reference periods are the winter of 2000 and the summer of 2000-2001 (starting in 2000), respectively. We obtain similar effects across seasons.

Figure N.1: Robustness of difference–in–difference results (by season)

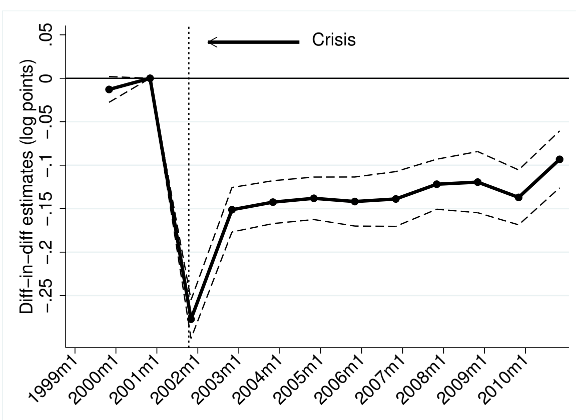
(a) in logs, winter



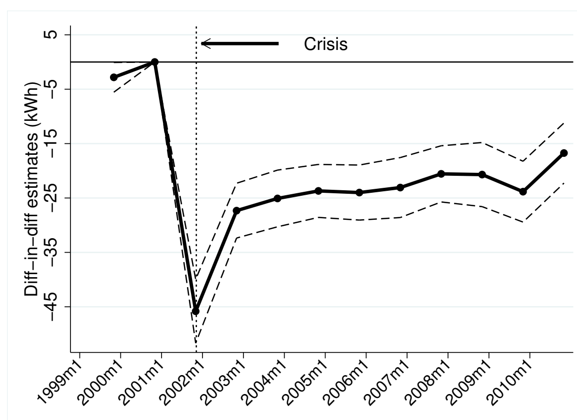
(b) in levels, winter



(c) in logs, summer



(d) in levels, summer



The figure displays similar results as in Figure 3 in the paper, splitting the sample between winter and summer months. Omitted periods: winter 2000, summer 2000-2001, respectively.

Table N.1: Difference–in–difference results for winter months in logs (1999–2010)

	Control region		Treatment region dummy			
	(1)		(2)		(3)	
1999	-.0015	(.0088)	.0184**	(.0074)	.0148**	(.0075)
Crisis	-.0865***	(.0084)	-.2382***	(.0095)	-.2384***	(.0105)
Rest of 2002	-.0575***	(.0106)	-.1653***	(.0099)	-.1657***	(.0105)
2003	-.0781***	(.0202)	-.128***	(.0099)	-.125***	(.0113)
2004	-.0632***	(.0216)	-.1294***	(.0119)	-.1298***	(.0134)
2005	-.0503**	(.022)	-.1059***	(.013)	-.1053***	(.0151)
2006	-.0588**	(.0237)	-.1047***	(.0166)	-.1013***	(.0186)
2007	-.035	(.0285)	-.1234***	(.0149)	-.1222***	(.0171)
2008	-.0368	(.0318)	-.1228***	(.0141)	-.1288***	(.0154)
2009	-.0067	(.0336)	-.1218***	(.0149)	-.1253***	(.0169)
2010	.0123	(.0363)	-.1206***	(.0156)	-.1249***	(.0175)
Log main tariff (R)	-.078***	(.0268)	-.1499***	(.0283)	-.1462***	(.0329)
Log population (1000's)	-.1344	(.1075)	-.1354	(.0906)	-.1009	(.1138)
Log formal employment (1000's)	.1165**	(.0471)	.1117**	(.0448)	.0918*	(.0541)
Log GDP per capita (R)	-.0079	(.0329)	-.0302	(.0282)	-.0249	(.0335)
Log average temperature (C)	-.0088	(.0631)	.0717	(.0906)	.0696	(.0948)
Regions	South		S/SE/MW		S/SE/MW	
Restricted sample	No		No		Yes	
Observations	808		2056		1672	
Clusters	17		43		35	

Units of observation: distribution utilities as of 1999. Significance levels: *10%, **5%, ***1% (s.e. clustered by utility). Data from 1999 to 2010, restricted to winter months. Results from specifications including utility and calendar month per region fixed effects. Regressions also control for the main electricity tariff (monthly, log), total population, total formal employment, GDP per capita, and average temperature (yearly, log) for each utility. Column (1) reproduces coefficients on time–period dummies in the South (reference period: winter 2000). Column (2) presents difference–in–difference estimators in every time–period comparing utilities in the Southeast/Midwest and the South. Column (3) restricts the sample in column (2) to utilities with overlapping values for average electricity use, the main residential tariff, and median income levels in 2000.

Table N.2: Difference–in–difference results for winter months in levels (1999–2010)

	Control region		Treatment region dummy			
	(1)		(2)		(3)	
1999	.4994	(1.049)	3.206***	(1.163)	2.6**	(1.085)
Crisis	-14.54***	(1.354)	-36.99***	(2.45)	-34.09***	(2.03)
Rest of 2002	-10.23***	(1.841)	-27.61***	(2.149)	-25.42***	(1.722)
2003	-13.85***	(3.241)	-21.11***	(2.213)	-18.39***	(2.005)
2004	-11.06***	(3.525)	-20.82***	(2.393)	-18.95***	(2.008)
2005	-9.08**	(3.819)	-17.14***	(2.493)	-15.56***	(2.228)
2006	-10.32**	(4.143)	-16.43***	(2.955)	-14.51***	(2.734)
2007	-6.872	(4.804)	-18.91***	(2.6)	-17.18***	(2.496)
2008	-6.547	(5.382)	-19.17***	(2.411)	-18.71***	(2.442)
2009	-2.353	(5.749)	-18.92***	(2.486)	-18.34***	(2.627)
2010	.6001	(6.357)	-19.32***	(2.51)	-18.72***	(2.629)
Main tariff (R)	-33.25*	(18.33)	-77.25***	(13.56)	-81.16***	(15.93)
Population (1000's)	-.0168**	(.008)	-.0097***	(.003)	-.0021	(.0055)
Formal employment (1000's)	.0253***	(.0088)	.009**	(.0037)	-.001	(.0092)
GDP per capita (R)	.1209	(.1999)	-.0256	(.1923)	.1827	(.2723)
Average temperature (C)	.7363	(.7039)	1.067	(.7558)	.7504	(.8024)
Regions	South		S/SE/MW		S/SE/MW	
Restricted sample	No		No		Yes	
Observations	808		2056		1672	
Clusters	17		43		35	

Units of observation: distribution utilities as of 1999. Significance levels: *10%, **5%, ***1% (s.e. clustered by utility). Data from 1999 to 2010, restricted to winter months. Results from specifications including utility and calendar month per region fixed effects. Regressions also control for the main electricity tariff (monthly, levels), total population, total formal employment, GDP per capita, and average temperature (yearly, levels) for each utility. Column (1) reproduces coefficients on time–period dummies in the South (reference period: winter 2000). Column (2) presents difference–in–difference estimators in every time–period comparing utilities in the Southeast/Midwest and the South. Column (3) restricts the sample in column (2) to utilities with overlapping values for average electricity use, the main residential tariff, and median income levels in 2000.

Table N.3: Difference–in–difference results for summer months in logs (1999–2010)

	Control region		Treatment region dummy			
	(1)		(2)		(3)	
1999	.0067	(.0061)	-.0129*	(.0074)	-.013	(.0079)
Crisis	-.0695***	(.0082)	-.2771***	(.011)	-.2725***	(.0117)
Rest of 2002	-.043***	(.0151)	-.1512***	(.0128)	-.1476***	(.0135)
2003	-.076***	(.0282)	-.1425***	(.0123)	-.1368***	(.0135)
2004	-.0672**	(.0314)	-.1381***	(.0122)	-.1364***	(.0143)
2005	-.0632**	(.0321)	-.1418***	(.0141)	-.1381***	(.0162)
2006	-.0375	(.0337)	-.1388***	(.0158)	-.1391***	(.0182)
2007	-.0409	(.0402)	-.1219***	(.0144)	-.1204***	(.0161)
2008	-.0363	(.0421)	-.1195***	(.0176)	-.1211***	(.0201)
2009	.0155	(.0419)	-.137***	(.0158)	-.1378***	(.0173)
2010	-.0176	(.0464)	-.0933***	(.0164)	-.0951***	(.018)
Log main tariff (R)	-.0277	(.0463)	-.1229***	(.0282)	-.1145***	(.0362)
Log population (1000's)	-.1627	(.1032)	-.1179	(.0819)	-.0629	(.1043)
Log formal employment (1000's)	.0489	(.0554)	.0956**	(.047)	.0669	(.0561)
Log GDP per capita (R)	-.0042	(.0273)	-.01	(.0257)	-.0066	(.0311)
Log average temperature (C)	.2597***	(.0629)	.2046***	(.0752)	.2033***	(.0767)
Regions	South		S/SE/MW		S/SE/MW	
Restricted sample	No		No		Yes	
Observations	809		2057		1673	
Clusters	17		43		35	

Units of observation: distribution utilities as of 1999. Significance levels: *10%, **5%, ***1% (s.e. clustered by utility). Data from 1999 to 2010, restricted to summer months. Results from specifications including utility and calendar month per region fixed effects. Regressions also control for the main electricity tariff (monthly, log), total population, total formal employment, GDP per capita, and average temperature (yearly, log) for each utility. Column (1) reproduces coefficients on time–period dummies in the South (reference period: summer 2000–2001, starting in 2000). Column (2) presents difference–in–difference estimators in every time–period comparing utilities in the Southeast/Midwest and the South. Column (3) restricts the sample in column (2) to utilities with overlapping values for average electricity use, the main residential tariff, and median income levels in 2000.

Table N.4: Difference–in–difference results for summer months in levels (1999–2010)

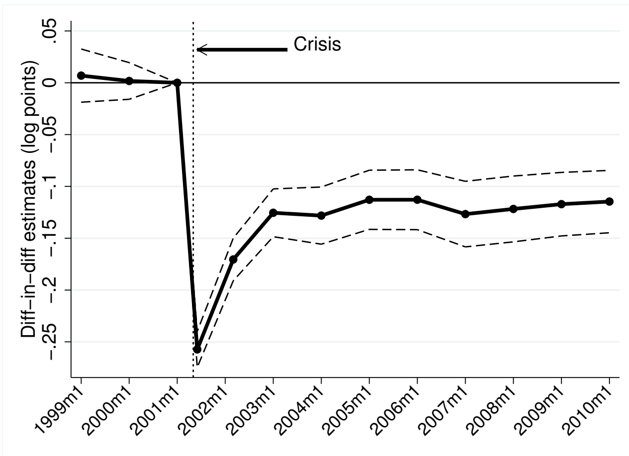
	Control region		Treatment region dummy			
	(1)		(2)		(3)	
1999	1.129	(1.013)	-2.817**	(1.367)	-2.459*	(1.372)
Crisis	-12.26***	(1.405)	-45.82***	(2.932)	-41.76***	(2.282)
Rest of 2002	-7.997***	(2.077)	-27.32***	(2.518)	-24.58***	(2.337)
2003	-13.75***	(3.711)	-25.08***	(2.605)	-21.82***	(2.263)
2004	-12.59***	(4.18)	-23.7***	(2.434)	-21.5***	(2.388)
2005	-12.2***	(4.471)	-24***	(2.529)	-21.62***	(2.441)
2006	-8.5*	(4.615)	-23.08***	(2.756)	-21.43***	(2.817)
2007	-9.612*	(5.468)	-20.56***	(2.582)	-18.74***	(2.54)
2008	-9.225	(6.072)	-20.69***	(2.946)	-19.41***	(3.116)
2009	-1.028	(5.818)	-23.84***	(2.796)	-22.64***	(2.761)
2010	-7.652	(7.059)	-16.74***	(2.762)	-15.54***	(2.964)
Main tariff (R)	-7.094	(26.43)	-78.45***	(16.28)	-78.98***	(21.42)
Population (1000's)	-.0264***	(.0066)	-.0117**	(.0046)	-.0051	(.0074)
Formal employment (1000's)	.0397***	(.0114)	.0111*	(.0062)	.0047	(.0118)
GDP per capita (R)	.0024	(.2387)	-.1029	(.165)	.1143	(.3103)
Average temperature (C)	2.742***	(.7515)	1.882***	(.699)	1.557**	(.7268)
Regions	South		S/SE/MW		S/SE/MW	
Restricted sample	No		No		Yes	
Observations	809		2057		1673	
Clusters	17		43		35	

Units of observation: distribution utilities as of 1999. Significance levels: *10%, **5%, ***1% (s.e. clustered by utility). Data from 1999 to 2010, restricted to summer months. Results from specifications including utility and calendar month per region fixed effects. Regressions also control for the main electricity tariff (monthly, levels), total population, total formal employment, GDP per capita, and average temperature (yearly, levels) for each utility. Column (1) reproduces coefficients on time–period dummies in the South (reference period: summer 2000–2001, starting in 2000). Column (2) presents difference–in–difference estimators in every time–period comparing utilities in the Southeast/Midwest and the South. Column (3) restricts the sample in column (2) to utilities with overlapping values for average electricity use, the main residential tariff, and median income levels in 2000.

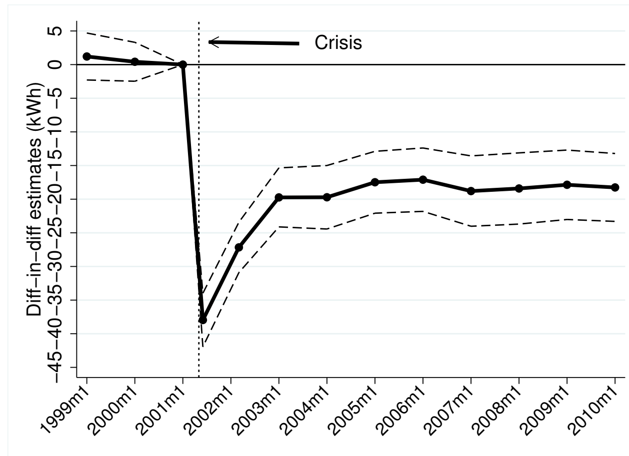
Figure N.2 displays similar results as in Figure 3 in the paper, limiting the sample to distribution utilities with common support in average electricity use, main residential tariff, and median household income between the Southeast/Midwest and the South in 2000 (before the crisis). We displayed above the distribution of these variables among distribution utilities in the Southeast/Midwest and in the South in 2000. Coefficients estimates and standard errors are presented in column (3) in Tables M.1 and M.2 above. Results are similar when we restrict the sample this way.

Figure N.2: Robustness of difference–in–difference results (distribution utilities with common support in average electricity use, main residential tariff, and median household income pre-crisis)

(a) in logs



(b) in levels



The figure displays similar results as in Figure 3 in the paper, limiting the sample to distribution utilities with common support in average electricity use, main residential tariff, and median household income between the Southeast/Midwest and the South in 2000 (before the crisis). Omitted periods: first few months in 2001.

Figure N.2 and Tables N.5, N.6 display similar results as in Figure 3 and Tables M.1 and M.2, weighting distribution utilities by their customer base in 2000 (before the crisis). Results are similar when we weight distribution utilities by their customer base at baseline. However, patterns are especially driven by the few very large utilities in this case. Figure N.4 also displays the overall impact of the electricity saving program as in Figure 1b, but presenting weighted averages in each month, normalized with respect to the same month in 2000 (seasonality). Trends were similar prior to June 2001, but they are more sensitive to patterns affecting the few very large utilities in this figure. For instance, differences in average consumption levels between the Southeast/Midwest and the South in preceding years compared to 2000 are a bit higher than in Figure 1b.

Table N.5: Difference–in–difference results in logs weighting distribution utilities by their customer base in 2000 (1999–2010)

	Control region		Treatment region dummy			
	(1)		(2)		(3)	
1999	.0315***	(.0096)	.0396***	(.0148)	.0405*	(.0222)
2000	.0174***	(.0051)	.0221*	(.0115)	.0241	(.0156)
Crisis	-.1032***	(.004)	-.2482***	(.0139)	-.2361***	(.0169)
Rest of 2002	-.0914***	(.0075)	-.1606***	(.011)	-.1583***	(.0143)
2003	-.1392***	(.0274)	-.1224***	(.0146)	-.102***	(.0198)
2004	-.1508***	(.0236)	-.1257***	(.0119)	-.1213***	(.0199)
2005	-.1557***	(.0243)	-.1082***	(.0146)	-.1101***	(.0171)
2006	-.17***	(.0273)	-.114***	(.0173)	-.1249***	(.0221)
2007	-.1552***	(.0322)	-.1219***	(.0153)	-.1459***	(.0212)
2008	-.1714***	(.0397)	-.123***	(.0152)	-.1491***	(.0193)
2009	-.1541***	(.0389)	-.1245***	(.018)	-.157***	(.0232)
2010	-.1547***	(.0438)	-.125***	(.0167)	-.1459***	(.0205)
Log main tariff (R)	-.0525***	(.0202)	-.1874***	(.0418)	-.1665***	(.0406)
Log population (1000's)	.281	(.1697)	-.1292	(.1243)	.1057	(.1856)
Log formal employment (1000's)	.1969**	(.0903)	.3448***	(.0701)	.4399***	(.0828)
Log GDP per capita (R)	.0754	(.0561)	-.1929***	(.0583)	-.1903**	(.0948)
Log average temperature (C)	.0875	(.12)	-.0282	(.2044)	-.0564	(.2068)
Regions	South		S/SE/MW		S/SE/MW	
Restricted sample	No		No		Yes	
Observations	2425		6169		5017	
Clusters	17		43		35	

Units of observation: distribution utilities as of 1999. Significance levels: *10%, **5%, ***1% (s.e. clustered by utility). Data from 1999 to 2010. Results from specifications including utility and calendar month per region fixed effects. Regressions also control for the main electricity tariff (monthly, log), total population, total formal employment, GDP per capita, and average temperature (yearly, log) for each utility. Distribution utilities are weighted by their customer base in 2000 (before the crisis). Column (1) reproduces coefficients on time–period dummies in the South (reference period: Early 2001). Column (2) presents difference–in–difference estimators in every time–period comparing utilities in the Southeast/Midwest and the South. Column (3) restricts the sample in column (2) to utilities with overlapping values for average electricity use, the main residential tariff, and median income levels in 2000.

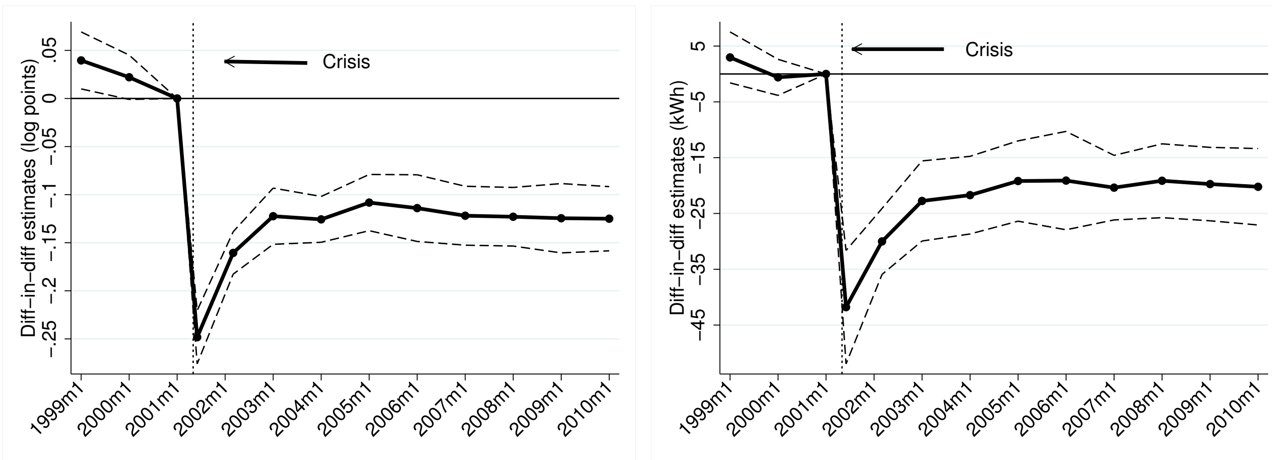
Table N.6: Difference–in–difference results in levels weighting distribution utilities by their customer base in 2000 (1999–2010)

	Control region		Treatment region dummy			
	(1)		(2)		(3)	
1999	6.241***	(1.647)	2.966	(2.284)	-.0327	(2.43)
2000	3.262***	(.933)	-.6067	(1.615)	-1.514	(2.181)
Crisis	-18.58***	(1.181)	-41.79***	(5.081)	-30.74***	(4.356)
Rest of 2002	-16.84***	(1.369)	-30.01***	(2.957)	-24.75***	(2.736)
2003	-25.64***	(4.162)	-22.76***	(3.59)	-15.4***	(2.744)
2004	-27.43***	(4)	-21.72***	(3.479)	-17.37***	(3.656)
2005	-28.88***	(4.714)	-19.19***	(3.596)	-14.55***	(3.85)
2006	-30.84***	(5.22)	-19.11***	(4.407)	-14.99***	(4.279)
2007	-29.65***	(5.682)	-20.37***	(2.893)	-19.61***	(3.996)
2008	-33.77***	(7.507)	-19.14***	(3.309)	-18.29***	(3.904)
2009	-32.5***	(7.66)	-19.73***	(3.29)	-21.2***	(4.602)
2010	-36.79***	(9.065)	-20.22***	(3.426)	-20.06***	(4.712)
Main tariff (R)	.1717	(16.52)	-86.58***	(20.99)	-92.32***	(21.75)
Population (1000's)	.0001	(.005)	-.0077**	(.0032)	.0004	(.0026)
Formal employment (1000's)	.0125***	(.0048)	.0043	(.0044)	-.0082	(.0053)
GDP per capita (R)	2.025***	(.4444)	-.1435	(.4655)	-.3833	(.7711)
Average temperature (C)	2.606***	(.8035)	3.949***	(1.417)	4.711***	(1.271)
Regions	South		S/SE/MW		S/SE/MW	
Restricted sample	No		No		Yes	
Observations	2425		6169		5017	
Clusters	17		43		35	

Units of observation: distribution utilities as of 1999. Significance levels: *10%, **5%, ***1% (s.e. clustered by utility). Data from 1999 to 2010. Results from specifications including utility and calendar month per region fixed effects. Regressions also control for the main electricity tariff (monthly, levels), total population, total formal employment, GDP per capita, and average temperature (yearly, levels) for each utility. Distribution utilities are weighted by their customer base in 2000 (before the crisis). Column (1) reproduces coefficients on time–period dummies in the South (reference period: Early 2001). Column (2) presents difference–in–difference estimators in every time–period comparing utilities in the Southeast/Midwest and the South. Column (3) restricts the sample in column (2) to utilities with overlapping values for average electricity use, the main residential tariff, and median income levels in 2000.

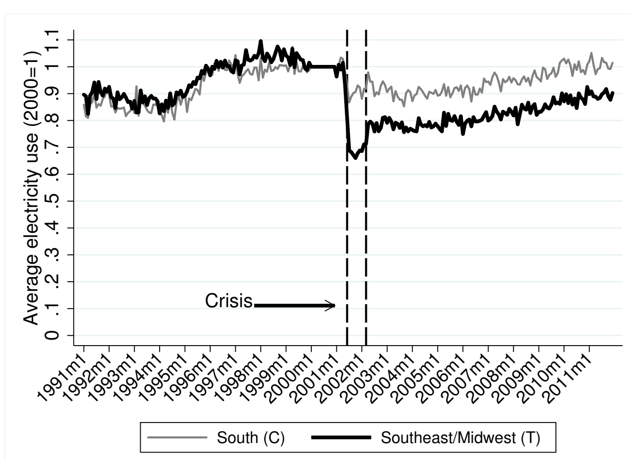
Figure N.3: Robustness of difference–in–difference results (distribution utilities weighted by their customer base pre-crisis)

(a) in logs (b) in levels



The figure displays similar results as in Figure 3 in the paper, weighting distribution utilities by their customer base in 2000 (before the crisis). Omitted periods: first few months in 2001.

Figure N.4: Consequence of the temporary electricity saving program (distribution utilities weighted by their customer base pre-crisis)



The figure displays the overall impact of the electricity saving program as in Figure **??**, but presenting weighted averages in each month, normalized with respect to the same month in 2000 (seasonality).

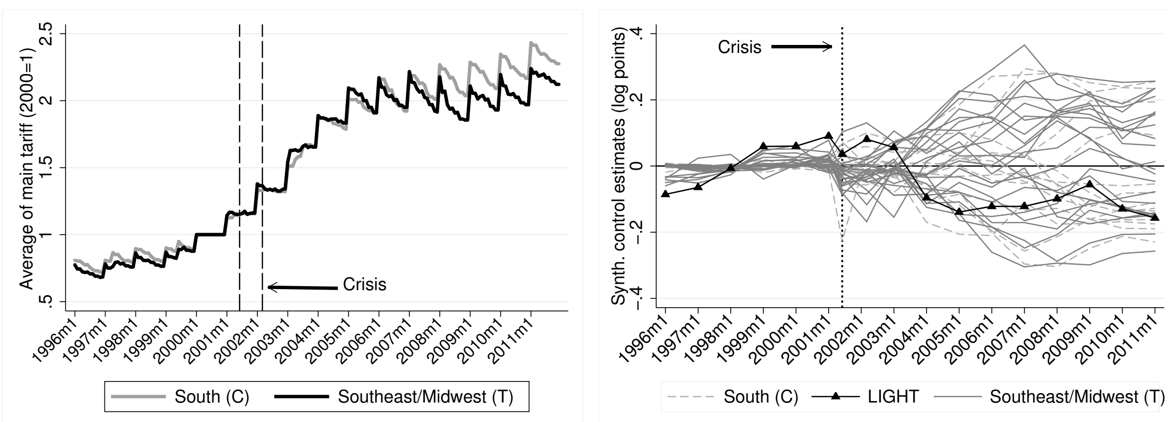
O Trends in the main residential electricity tariff

Figure O.1 shows that trends in the main residential electricity tariff did not evolve differentially for distribution utilities in the Southeast/Midwest compared to distribution utilities in the South after the crisis. Panel (a) is constructed similarly as Figure 1b, but it displays the average of the main residential electricity tariff for distribution utilities in the Southeast/Midwest and in the South, instead of the average residential electricity use per customer. It shows that electricity tariffs followed a similar trend in the two subsystems. If anything, electricity tariffs increased relatively less in the Southeast/Midwest (in later years). Panel (b) displays utility-specific impacts obtained by synthetic control methods as in Figure 4b, but for the main residential electricity tariff instead of the average residential electricity use per customer. It shows that the distributions of utility-specific impacts for the main residential electricity tariff completely overlap between distribution utilities in the Southeast/Midwest and in the South.

Figure O.1: Trends in the main residential electricity tariff

(a) Average of the main residential electricity tariff

(b) Synthetic control estimates for the main electricity tariff (in logs)



Panel (a) displays the average of the main residential electricity tariff for distribution utilities in the Southeast/Midwest and in the South, normalized with respect to the same month in 2000 (seasonality). Panel (b) displays utility-specific impacts obtained by synthetic control methods for the demeaned logarithm of the main residential electricity tariff. Monthly estimates are averaged into the same time periods as in Figure 3a. Darker lines correspond to distribution utilities in the Southeast/Midwest. Lighter lines correspond to placebo estimates in which we compare a given distribution utility in the South to a weighted average of the others.

P Difference-in-difference estimates using data on distribution losses

There is no good data on electricity theft in Brazil. Distribution utilities are supposed to report yearly information on distribution losses to the regulator, but many did not provide this information prior to 2000. Distribution losses are the share of the load not charged to particular customers. Distribution losses are divided into technical (engineering estimates) and non–technical (residual, a noisy proxy of theft) losses. It is unclear how companies separately identify the two categories and the resulting information is noisy. We use here yearly reports for 24 utilities in the Southeast/Midwest (13) and in the South (11) from 1998 to 2008. Table P.1 displays coefficients from regressing several outcomes (listed above each column) on year dummies interacted with an indicator for utilities subject to the electricity saving program during the crisis (difference–in–difference estimators in every year). The reference year corresponds to 2000. Regressions include an interacted year dummies and utility fixed effects, and control for the main electricity tariff, total population, total formal employment, and average temperature (log) for each distribution utility. Column (1) considers a specification similar to our main difference-in-difference results but looking at total residential consumption at the yearly level for this sample of utilities. The long–term effects on average residential electricity consumption are very similar. Columns (2)–(5) use the data from the yearly reports on distribution losses. Note that those data are for the whole distribution utility, and not specific to its residential customers The outcome in column (2) is the total load reported by the distribution utility; the outcome in column (3) are the total losses reported by the distribution utility; the outcome in column (4) are the total *technical* losses reported by the distribution utility; the outcome in column (5) are the total *non–technical* losses reported by the distribution utility. As expected, the total load decreased during and after the crisis. The effects are large and include other types of customers (e.g. industrial), so the long-term effects might include changes in the industrial composition of firms served by particular distribution utilities. Total losses were also reduced, which is not surprising if they are proportional to the total load, but the data are noisy so our estimates are not significant during and right after the crisis. Once we divide total losses into technical and non-technical losses, we find some evidence that technical losses decreases, although estimates are again noisy. We find no evidence that non-technical losses increased, which would be the case if electricity theft increased and non-technical losses were a good proxy for theft. The data are very noisy. For instance, point estimates imply that non-technical losses increased by .268 log points from 1999 to 2000 in the Southeast/Midwest compared to the South and then decreased by .243 log points the following year.

Table P.1: Difference–in–difference results for reported distribution losses

	Residential consumption (logs) (1)		Total load (logs) (2)		Total losses (logs) (3)		Technical losses (logs) (4)		Non–technical losses (logs) (5)	
1998	.0192	(.0143)	.03	(.0214)	-.081	(.0978)	-.0288	(.1008)	-.2451	(.2126)
1999	.0151	(.0125)	.0434**	(.0199)	-.0264	(.0947)	.0597	(.1214)	-.268**	(.1301)
2001	-.1194***	(.0189)	-.1362***	(.0235)	-.1725	(.2097)	-.1377	(.2044)	-.2427	(.3722)
2002	-.1724***	(.0091)	-.1647***	(.0198)	-.1422	(.119)	-.1597	(.1135)	-.2059	(.2473)
2003	-.1352***	(.0135)	-.1277***	(.0222)	-.148	(.093)	-.1829**	(.0836)	-.2198	(.2366)
2004	-.1421***	(.015)	-.1496***	(.0243)	-.1001	(.1596)	-.1167	(.1435)	-.2188	(.3258)
2005	-.1213***	(.0208)	-.154***	(.0342)	-.2131*	(.1243)	-.1937	(.1302)	-.3477	(.2367)
2006	-.1241***	(.0224)	-.1763***	(.0424)	-.2152**	(.091)	-.1776*	(.0918)	-.3932	(.2402)
2007	-.1465***	(.0205)	-.2062***	(.0457)	-.2289**	(.093)	-.2201**	(.0922)	-.4094**	(.1887)
2008	-.1259***	(.0211)	-.1881***	(.0399)	-.2873***	(.0967)	-.2589***	(.0903)	-.4276**	(.2179)
Log main tariff (R)	-.1524***	(.0541)	-.0608	(.0592)	-.2439	(.1977)	-.2348	(.1555)	-.2325	(.3227)
Log population (1000's)	.3926**	(.1744)	.6961**	(.3189)	.3423	(.7843)	-.241	(.6104)	2.897	(1.917)
Log formal employment (1000's)	.3482***	(.0781)	.7891***	(.1748)	.2796	(.2944)	.7233***	(.2005)	-.5474	(.5975)
Log average temperature (C)	.565**	(.223)	.4974*	(.2805)	1.312	(1.547)	1.681	(1.494)	2.342	(2.91)
Clusters	24		24		24		24		24	
Observations	3168		3168		3168		3168		3168	

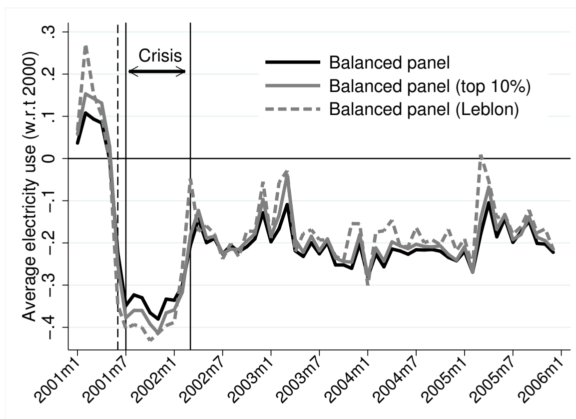
Significance levels: *10%, **5%, ***1% (s.e. clustered by utility in parentheses). Data for 24 distribution utilities in the Southeast/Midwest (13) and in the South (11) reporting technical and non–technical losses prior to 2000. Yearly data from 1998 to 2008. Distribution losses are the share of the load not charged to particular customers. Distribution losses are divided into technical (engineering estimates) and non–technical (residual, a noisy proxy of theft) losses. It is unclear how companies separately identify the two categories and the resulting information is noisy. The table displays coefficients from regressing several outcomes (listed above each column) on year dummies interacted with an indicator for utilities subject to the electricity saving program during the crisis (difference–in–difference estimators in every year). The reference year corresponds to 2000. Regressions include uninteracted year dummies and utility fixed effects. Column (1) considers a specification similar to our main difference-in-difference results but looking at total residential consumption at the yearly level for this sample of utilities. Columns (2)–(5) use the data from the yearly reports on distribution losses.

Q Robustness of the patterns based on the individual billing data

The following figures support the robustness of the patterns based on the household-level billing data in Figure 5 in the paper.

Figure Q.1 displays average electricity use for LIGHT customers in each month compared to the same month in 2000 as in Figure 5a. It shows that the time–series is almost identical (i) when we use microdata from a random sample of customers observed in every month from 2000 to 2005 (same balanced panel as in Figure 5a; 44,817 customers), (ii) when we only consider the top decile of users (highest consumption) in this balanced panel in each month, and (iii) when we use a similar balanced panel restricted to Leblon, a very wealthy neighborhood of Rio de Janeiro (12,054 customers). This provides additional evidence that electricity theft is unlikely to drive our results: electricity theft is more prevalent among smaller users and poorer neighborhoods in Rio de Janeiro.

Figure Q.1: Comparing time–series in average electricity using household–level billing data (robustness of Figure 5a)

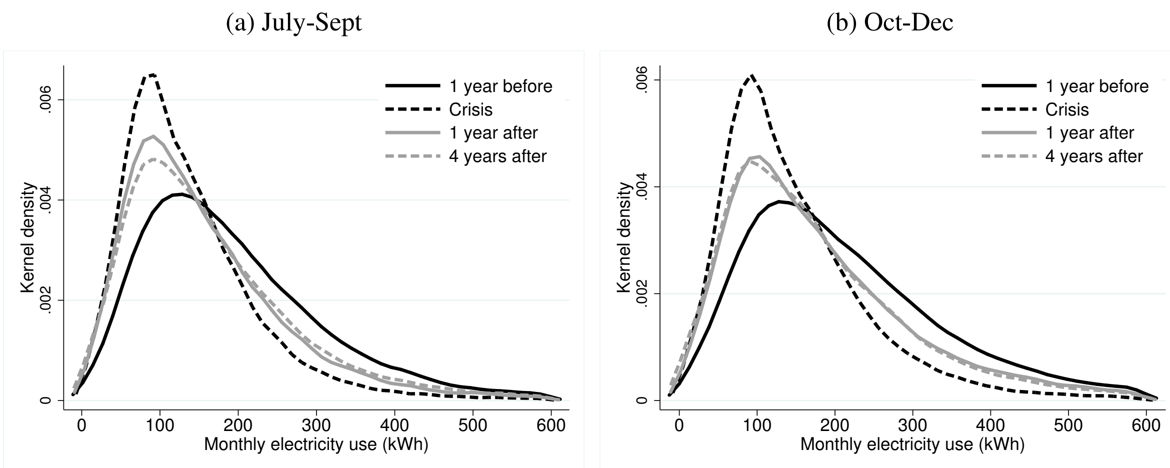


The figure displays average electricity use for LIGHT customers in each month compared to the same month in 2000. It shows that the time–series is almost identical (i) when we use microdata from a random sample of customers observed in every month from 2000 to 2005 (same balanced panel as in Figure 5a in the paper; 44,817 customers), (ii) when we only consider the top decile of users (highest consumption) in this balanced panel in each month, and (iii) when we use a similar balanced panel restricted to Leblon, a very wealthy neighborhood of Rio de Janeiro (12,054 customers).

Figure Q.2 displays Kernel densities for monthly electricity use before, during, and after the crisis as in Figure 5b in the paper. Kernel densities are based on the same balanced panel of customers observed in every month between January 2000 and December 2005. It shows that we obtain similar patterns when we split the sample months (June to December) between colder months (July to September) and warmer months (October to December).

Figure Q.3 displays the distribution of changes in average electricity use during and after the crisis compared to the same months before the crisis, for subsets of the same balanced panel of customers. The panels consider customers who had about the same baseline for quota assignment, and thus faced the same pecuniary incentives during the crisis, as in 5c but for different baseline levels. In particular, we consider customers with baseline levels 10% above and below 100 kWh/month (2,973 customers), 200 kWh/month (5,546 customers), 400 kWh/month (2,628 customers), and

Figure Q.2: Distribution of monthly electricity use over time for a balanced panel of customers (robustness of Figure 5b

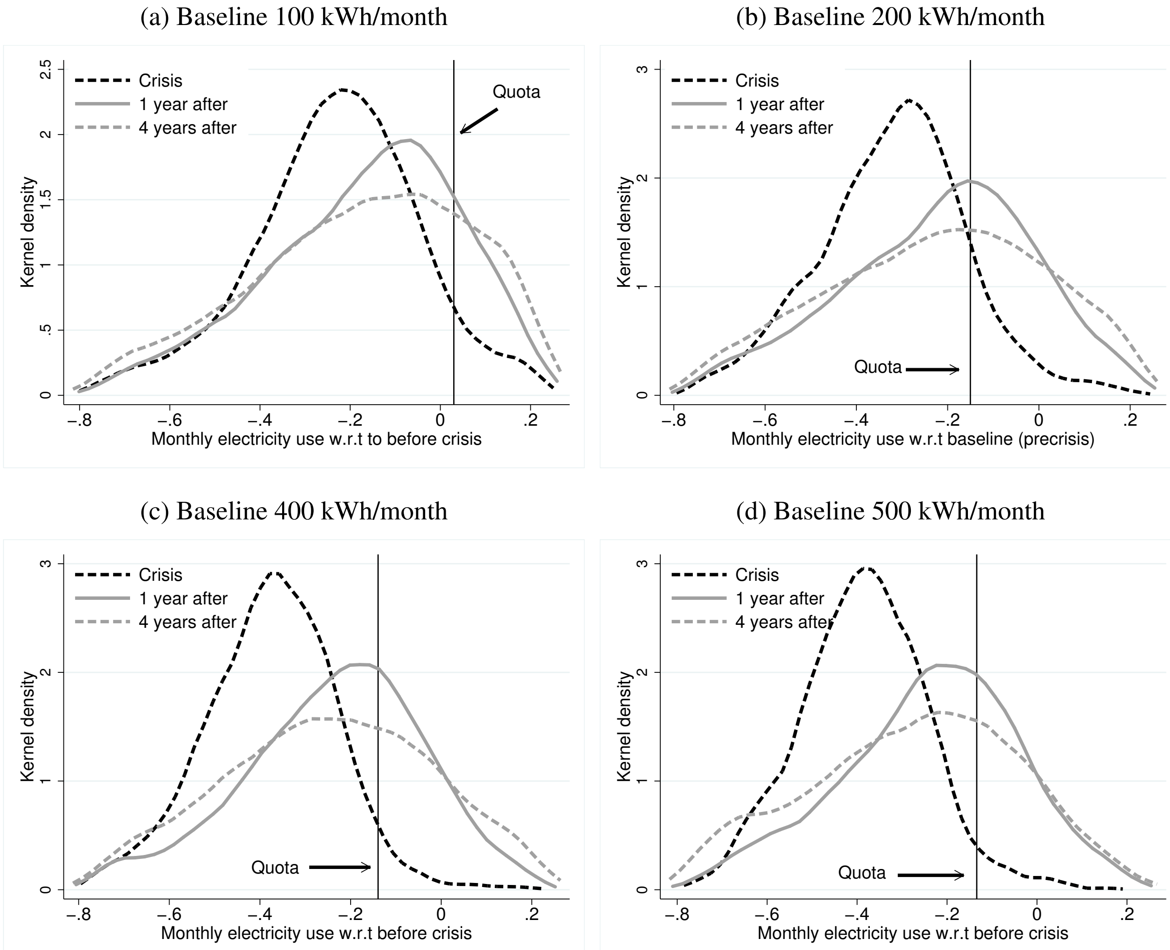


The figures uses the same balanced panel of customers observed in every month between January 2000 and December 2005. It displays Kernel densities for monthly electricity use before, during, and after the crisis as in Figure 5b in the paper. It shows that we obtain similar patterns when we split the sample months (June to December) between colder months (July to September) and warmer months (October to December). Kernel densities use Epanechnikov kernels and optimal bandwidths.

500 kWh/month (1,478 customers). Kernel densities are based on electricity use during the first five months of the crisis (and in the same months in other years), before any change in quotas. We find no evidence of bunching at the quota. During the crisis, 85%, 96%, 99%, and 99% reduced electricity use and the median customer reduced usage by 21%, 31%, 37%, and 39% among customers with baseline levels around 100 kWh/month, 200 kWh/month, 400 kWh/month, and 500 kWh/month, respectively. Four years after the crisis, 54%, 70%, 81%, and 84% were still using less electricity than before the crisis and the median customer was using 4%, 17%, 24%, and 25% less electricity among customers with baseline levels around 100 kWh/month, 200 kWh/month, 400 kWh/month, and 500 kWh/month, respectively. Changes in consumption levels were thus large at every baseline consumption level, but they were larger at customers with higher baseline levels. This is shown graphically in Figure Q.4. The figure displays average electricity use during and after the crisis compared to before the crisis for the same balanced panel of customers, as a function of *baseline* consumption levels. The figure displays averages by baseline bins and uses data on the first five months of the crisis (and in the same months in other years), before any change in quotas. The minimum baseline level is 30 kWh (minimum consumption level charged for LIGHT customers). On average, customers at every baseline level severely reduced electricity use in the short and the long run, except at the very bottom of the baseline consumption distribution.

Figure Q.5 displays the correlation between individual changes in electricity use during the crisis and four years after the crisis compared to the same months before the crisis as in Figure 5d in the paper, but for the same samples as in Figure Q.3. Customers are averaged by bins of 5% changes in electricity use during the crisis. There is a clear correlation at every baseline consumption level, suggesting that the long-term impact is due to the persistence of individual changes in electricity use. Figure Q.6 present similar patterns but only looking at one year after the crisis.

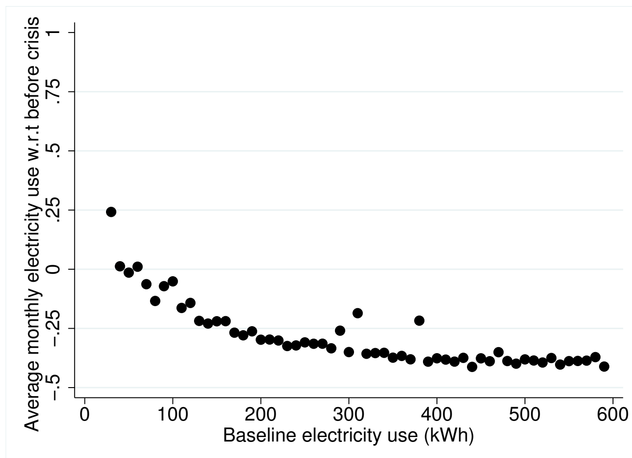
Figure Q.3: Distribution of changes in monthly electricity use for a balanced panel of customers with the same baseline level/quota (robustness of Figure 5c)



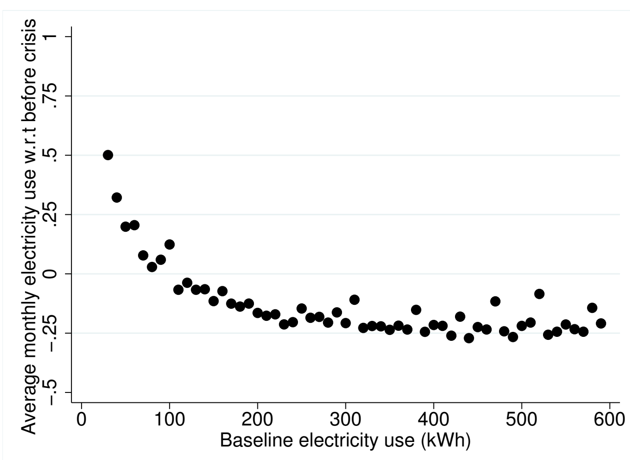
The panels display the distribution of changes in average electricity use during and after the crisis compared to the same months before the crisis, for subsets of the same balanced panel of customers. The panels consider customers who had about the same baseline for quota assignment, and thus faced the same pecuniary incentives during the crisis, as in Figure 5c in the paper, but for different baseline levels. In particular, we consider customers with baseline levels 10% above and below 100 kWh/month (2,973 customers), 200 kWh/month (5,546 customers), 400 kWh/month (2,628 customers), and 500 kWh/month (1,478 customers). Kernel densities use Epanechnikov kernels and optimal bandwidths.

Figure Q.4: Changes in monthly electricity use during and after the crisis by baseline consumption level

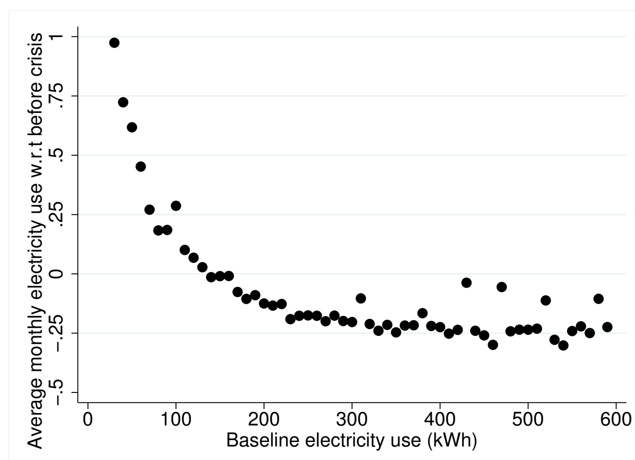
(a) During the crisis



(b) 1 year after the crisis

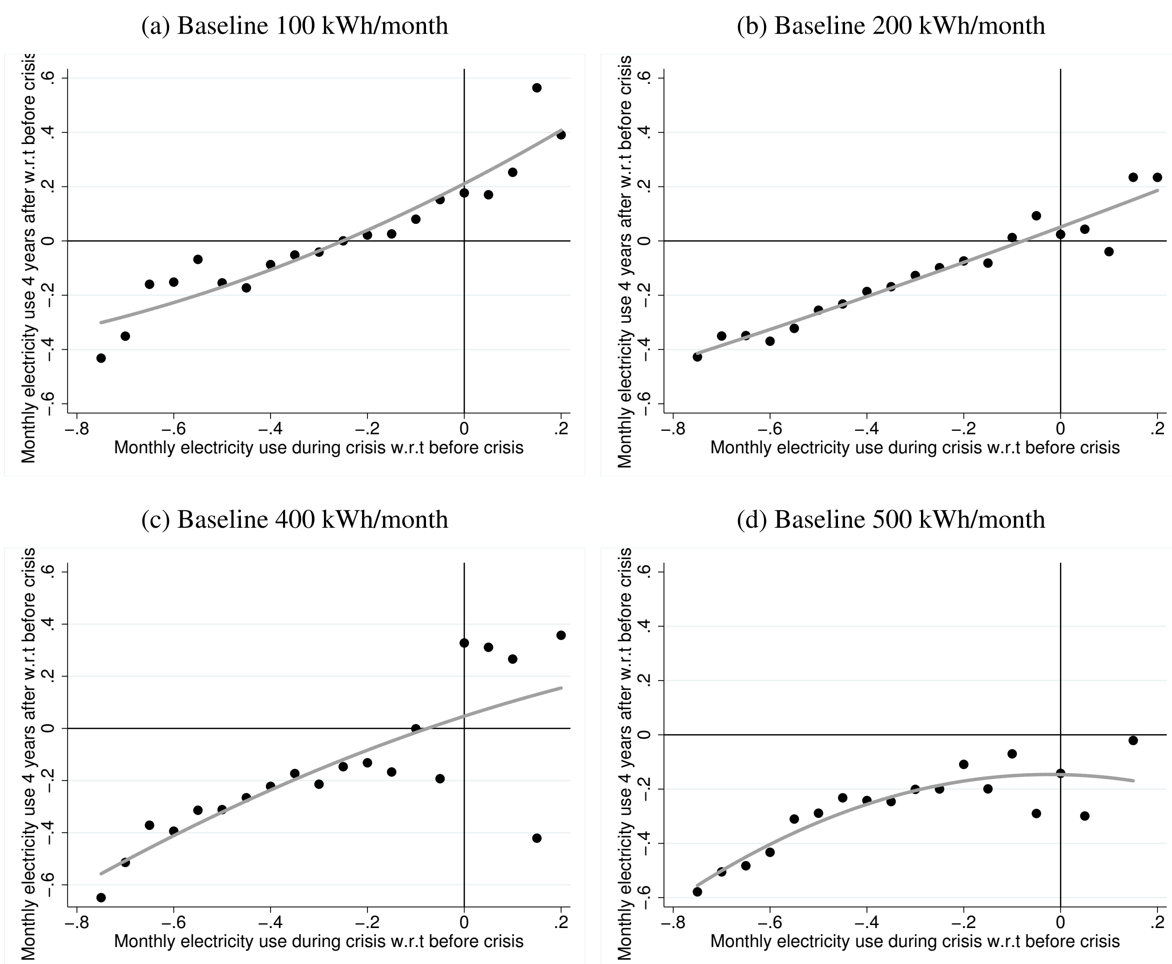


(c) 4 years after the crisis



The figure displays average electricity use during and after the crisis compared to before the crisis for the same balanced panel of customers, as a function of *baseline* consumption levels. The figure displays averages by baseline bins and uses data on the first five months of the crisis (and in the same months in other years), before any change in quotas. The minimum baseline level is 30 kWh (minimum consumption level charged for LIGHT customers).

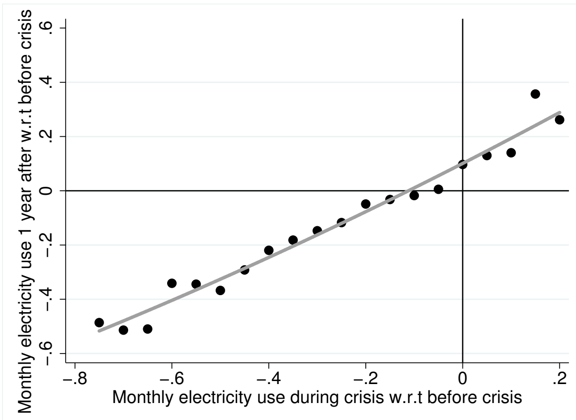
Figure Q.5: Correlation between changes in electricity use during the crisis and four years after the crisis for a balanced panel of customers with same baseline level/quota (robustness of Figure 5d)



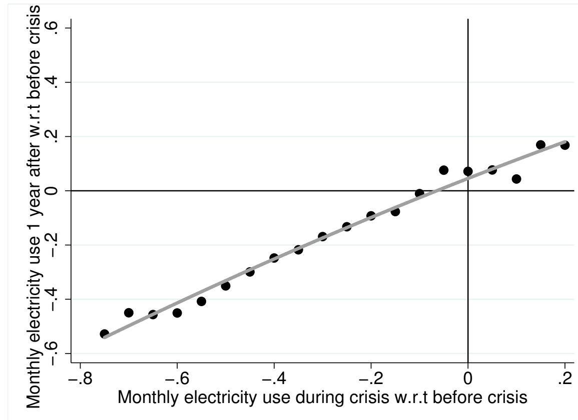
The panels display the correlation between individual changes in electricity use during the crisis and four years after the crisis compared to the same months before the crisis as in Figure 5d in the paper, but for the same samples as in Figure Q.3. Customers are averaged by bins of 5% changes in electricity use during the crisis.

Figure Q.6: Correlation between changes in electricity use during the crisis and one year after the crisis for a balanced panel of customers with same baseline level/quota (robustness of Figure 5d)

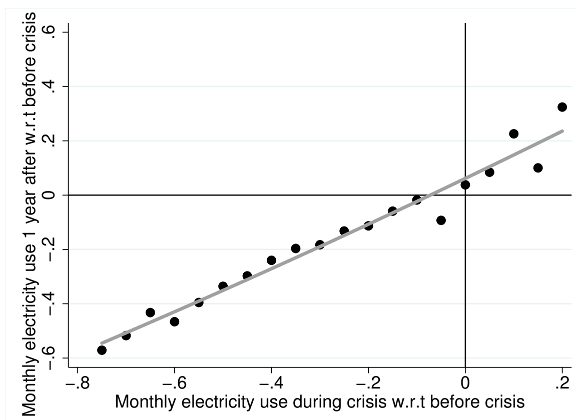
(a) Baseline 100 kWh/month



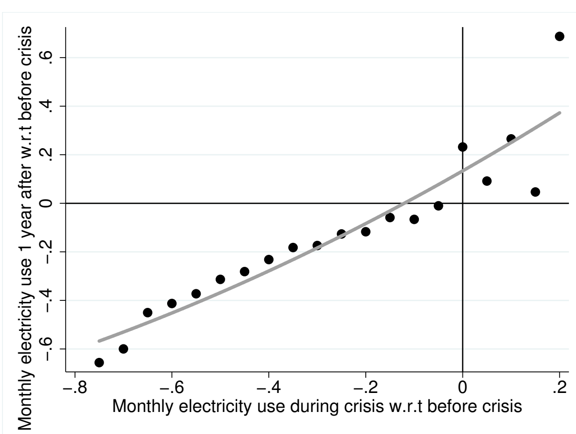
(b) Baseline 200 kWh/month



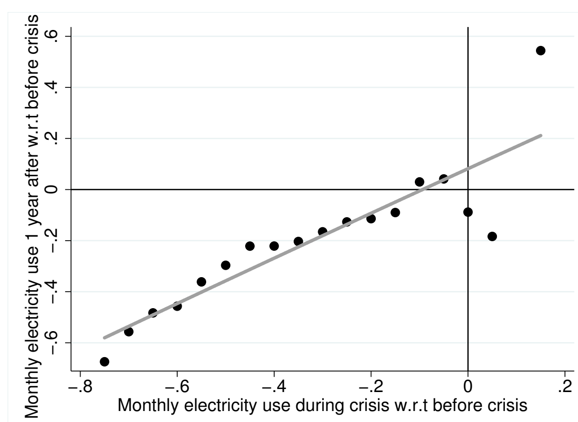
(c) Baseline 400 kWh/month



(d) Baseline 400



(e) Baseline 500 kWh/month



The panels display the correlation between individual changes in electricity use during the crisis and one year after the crisis compared to the same months before the crisis as in Figure 5d in the paper, but for the same samples as in Figure Q.3. Customers are averaged by bins of 5% changes in electricity use during the crisis.

R Further evidence from the Survey of Appliances and Utilization Habits (PPH)

The following tables present further evidence based on the two Survey of Appliances and Utilization Habits (PPH) 1998/1999 and 2004/2005. First, Table R.1 presents the average kWh/month consumption of the main appliances as calculated by PROCEL. We use these values to perform back-of-the-envelope calculations of appliances consumption in Section 5.

Table R.2 is similar to Table 3 Panel B in the paper and reports the share of households who answered how they changed their utilization of“Other Appliances” and “Stand By” mode. Table R.3 shows how households in the Southeast/Midwest reported adoption of CFL lamps during the crisis and if they kept using it afterward. These tables corroborate the pattern discussed in the main text that households adopted new habits that persisted afterward.

Table R.4 is similar to Table 4 in the paper and presents the difference-in-differences estimates of the energy saving program effects on the quantity, characteristics and utilization of the remaining electrical appliances present in PPH. Note that the indices (KKL) are calculated including all appliances and variables presented in the two tables. Overall, we find similar coefficients for the indices of quantity, appliances' type and utilization. We find a zero coefficient to the index of appliances age (Panel B, column 1). In Panel A column (4), we find a statistically significant reduction in the average quantity of iron owned by households, but no difference in appliance utilization of this appliance (Panel C). Interestingly, the only appliance that we find a meaningful and statistically significant increase in utilization is fans, the closer substitute for air conditioners.

Table R.5 presents suggestive evidence of access to information about energy efficient appliances in the South and Southeast/Midwest in 2005. The differences between the two groups are small and, if anything, households in the Southeast/Midwest reported they used to receive more information than households in the South, but know less what that information is good for. Unfortunately, the 1999 survey did not ask these questions.

Table R.1: Inputted Average Electricity Consumption by Appliance

	Appliance Specification	Utilization (1)	Average Monthly Consumption (kWh) (2)
Electric Shower	Low Power	18 minutes/person/day*	61.0
	High Power	18 minutes/person/day*	87.1
Refrigerator	1 Door, Frost Free	24 hours/day	42.8
Freezer		24 hours/day	43.5
Lightbulbs	Incandescent 60 Watts	5 hours/day	10.2
	Fluorescent 15 Watts	5 hours/day	2.25
TV		5 hours/day	13.5
Air Conditioner	Wall, 9001-14000 BTU	24 hours/week	69.0
Washing M.		12 loads/month	30.9
Microwave		20 minutes/day	14.0

Notes. This table presents the hypothetical average electricity use of appliances, calculated by the Brazilian energy efficiency program PROCEL. Thes figures are based on technical characteristics of appliances and hypothetical utilization draw from PPH Survey. (*) The shower calculation is based on 3.25 household members using the shower (number obtained from PPH 1998). The complete table can be found in the website www.eletrobras.com/procel.

Table R.2: Self-reported appliance usage after crisis – 2005 Survey (Southeast/Midwest)

	Other Appliances	Stand By
	(1)	(2)
Use appliance as much as before crisis	.24	.68
Use appliance less than before crisis	.71	.27
Disconnected or disposed of appliance	.03	.05
Substituted a more energy-efficient model	.02	0
Obs.	63	3325

Household-level survey data for 8 distribution utilities in the Southeast/Midwest subsystems from Appliances and Habits of Use Survey (PPH) 2004/2005. The table reports the share of households who owened each major domestic appliance (in columns) at some point in time that answered, in 2005, each of four answers for each appliance: (1) households were currently using the appliance as much as before the crisis; (2) they were using it less than before the crisis; (2) they had disconnected or disposed of the appliance during or after the crisis; or (4) they had substituted a more energy-efficient model during or after the crisis.

Table R.3: Adoption of more efficient lightbulbs around the crisis (Southeast/Midwest)

	All	Some	None	N
	(1)	(2)	(3)	(4)
Did you substitute incandescent lightbulbs with fluorescent ones?	.29	.14	.51	4648
Do you still use fluorescent lightbulbs?	.60	.09	.26	1963

Household-level survey data for 8 distribution utilities in the Southeast/Midwest subsystems from Appliances and Habits of Use Survey (PPH) 2004/2005. This table displays the percentage of answers (in columns) for two questions about adoption of CFL lamps (rows). Column 4 reports the number of households who asnwered each question.

Table R.4: Difference-in-difference results on appliances' quantity, characteristics, and utilization

Panel A. Quantity

	Index (KKL)	Air Conditioner	Laundry	Iron	Dish Washer	Dryer	Microwave	Electric Oven	Fan	Heater
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$SE/MW \times Year2005$	**-.395**	**-.227**	**-.040**	**-.082***	**-.114**	**-.281**	**-.066**	**-.007**	**-1.077**	**-.031**
	(.542)	(.360)	(.057)	(.045)	(.167)	(.387)	(.102)	(.028)	(1.335)	(.053)
Average SE/MW 1999	-.005	.099	.532	.954	.049	.040	.212	.087	.811	.019
N	14,251	14,251	14,251	14,251	14,251	14,251	14,251	14,251	14,251	14,251

Panel B. Characteristics

	Index		Air conditioner	
	Age (KKL)	Type (KKL)	Age	Power (BTUs)
	(1)	(2)	(3)	(4)
$SE/MW \times Year2005$	**-.004**	**.082**	**-.234**	**1058.2**
	(.046)	(.119)	(.895)	(1259.3)
Average SE/MW 1999	-.018	.118	5.873	7823.043
N	14,206	14,206	888	805

Panel C. Utilization

	Index (KKL)	Appliance Frequently Used								
		Air Conditioner	Laundry	Iron	Dish Washer	Dryer	Microwave	Electric Oven	Fan	Heater
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$SE/MW \times Year2005$	**-.427**	**-.049**	**-.022**	**.008**	**-.014*****	**-.002**	**-.056**	**.010**	**.190*****	**.001**
	(.586)	(.036)	(.044)	(.064)	(.004)	(.007)	(.072)	(.008)	(.074)	(.007)
Average SE/MW 1999	.095	.040	.083	.130	.010	.004	.099	.014	.149	.002
N	14,251	14,251	14,251	14,251	14,251	14,251	14,251	14,251	14,251	14,251

Household-level survey data for 10 distribution utilities in the South and Southeast/Midwest subsystems from Appliances and Habits of Use Survey (PPH) 1998/1999 and 2004/2005. This table displays the difference-in-differences estimates of the energy saving program effects on the quantity, characteristics and utilization of all electrical appliances available, from equation (8) in Section 5. Each column corresponds to a regression of a different dependent variable and appliance. *Panel A* displayes the results on the quantity of appliances owned by household, *Panel B* displayes the results on the indicated characteristcs of appliances owned by households and *Panel c* displays quantity of appliances frequently used (as discribed in Section 3) or quantity of electric showers regulated on high power (winter mode). The *Indices (KKL)* shown in the first columns are the average of the dependent variables shown in the columns of each Panel including the main appliances in Table 4. When calculating the indices, each dependent variable is normalized by the average and standard deviation of each variable in the South in 1999 as in Kling, Liebman and Katz (2007). To obtain these indices, we input missing values with the mean of the cell group the household belong (South/South-Midwest and 1999/2005). All regressions contain utility company fixed effects, year fixed effects, income, squared income, number of household members, floorplan area, and dummies for rich neighborhood and for proximity to "favelas". We missing values in two control variables (income and dwelling size) with a linear regression, for each year, of the variable on class of energy consumption and remaining controls. Significance levels: *10%, **5%, ***1% (s.e. estimated with wild-cluster bootstrap by utility level).

Table R.5: Average Information Level Southeast/Midwest and South - PPH

	Mean		Difference
	Southeast/Midwest	South	= (1) - (2)
	(1)	(2)	(3)
Do you receive information about energy efficient appliances and energy saving measures?	.73	.62	.11
			(.33)
Do you know the label for energy efficient appliances (PROCEL)?	.46	.50	-.04
			(.11)
Do you know what the PROCEL label represents?	.34	.40	-.06
			(.14)
Do you know how much you can save by using labeled appliances?	.21	.21	0
			(.01)

Household-level survey data for 10 distribution utilities in the South and Southeast/Midwest subsystems from Appliances and Habits of Use Survey (PPH) 2004/2005. The table reports the share of households who responded in a positive the questions about access to information (rows) in the Southeast/Midwest (column 1) and in the South (column 2). Column 3 presents the difference between these two columns. N=3364. Significance levels: *10%, **5%, ***1% (s.e. estimated with wild-cluster bootstrap by utility level).

S Evidence from the Household Budget Surveys (POF)

The following tables present evidence based on the three last rounds of the Household Budget Surveys (POF) 1996/1997, 2002/2003 and 2008/2009. This is a repeated cross-section household-level microdata from a national survey conducted by the Brazilian Geography & Statistics Institute (IBGE), which is also responsible for the National Census. We use this data to assess appliance holdings and ages, as well as a proxy for energy theft. We use the household level microdata from the three most recent surveys, which are from 1996/1997, 2002/2003 and 2008/2009. All surveys were conducted between July of the base year and June of the following year. The 1996/1997 survey covered only the main metropolitan areas of fewer states, while the two subsequent surveys covered rural areas and more states. We restrict attention to the urban areas of the 7 states present in the 1996/1997 survey. The microdata contains the quantities of different types of appliances owned by the households and the year these appliances were bought. It does not have details about the model of these appliances, or whether the appliance were bought new or second-hand.

Finally, there is a relevant difference between the sampling of this survey and the sampling of the two datasets presented so far. The official records from the Electricity Regulatory Agency (ANEEL), and the Appliances and Habit of Use Survey (PPH) only contain households regularly connected to electricity. The Household Budget Survey (POF), however, aims to be representative of all households, including those who have irregular connections to electricity. Consequently, some households in POF own electrical appliances, but claim to have no expenses on electricity and not to own a generator. First, we use this information to investigate the share of households who are likely irregularly connected to the electricity grid (energy theft). Second, since these households who do not pay for electricity were not subject to the energy saving program's incentives, we exclude them from the main specifications.[55]

We use the different round of POF surveys to investigate any differential trend in the share of households paying for electricity (non-theft) and in appliances' quantity and age using a difference-in-difference strategy as in Section 5. Since We have three rounds of the survey, one just after the end of the energy saving program (2002/2003) and one more than six years later, we regress

$$Y_{h,d,t} = \alpha_d + \sum_{t' \in \{2002,2008\}} \left\{ \delta_{t'} \, \mathbb{1}(t = t' \,\&\, d \in \text{SE/MW}) \right\} + \gamma_t + X_{h,d,t} + \nu_{h,d,t} \tag{15}$$

where $Y_{h,d,t}$ is an outcome for household h from state d in survey round t. We control for state fixed effects α_d and a survey round fixed effect γ_t. The coefficients δ_{2002} and δ_{2008} are the short- and long-run difference-in-difference estimator under a common-trend assumption. We control for household characteristics, $X_{h,d,t}$, which may be correlated with different trends in appliance ownership.[56] We also construct an appliance quantity index to avoid multiple-inference problems, as in the main text.

First, Table S.1 presents the difference-in-difference results of the energy saving program on

[55] In the Household Budget Survey (POF), a household may declare having more than one house, we discard second houses and restrict attention to the main domicile. As discussed in the text, we restrict the sample of the regressions to the households who pay for electricity. We define a household who do not pay for electricity as a household who own at least one electrical appliance and claim no expenses on electricity or own an electricity generator. We truncate appliances' *age* at 20 years, because the year an old appliance was bought is subject to severe measurement errors.

[56] The vector of household characteristics include income, squared income, number of household members and number of rooms.

the share of households who report paying for electricity. We find close to zero point estimates both in the short and long run.

Second, Table S.2, similar to Table 4, presents the difference-in-differences estimates of the energy saving program on the quantity (Panel A) and age (Panel B) of all electrical appliances present in POF. We find close to zero long-run effects on the quantity of refrigerators and TV. We find negative long-run effect on the quantity of freezers, similarly to the results with PPH. We find small point estimates for the long-run effects on appliances ages except for air conditioners. We find a large increase on the average age of air conditioners, that is, air conditioners tended to get on average 1.7 year older in the Southeast/Midwest relative to the South in this period according to POF. This figure is substantially different from the one found using the PPH survey, but should be interpreted with caution because the small number of non-missing values for this variable in both surveys.

Table S.1: Difference-in-difference results on households paying for electricity (non-theft) – POF

	Share of Households Paying for Electricity
	(1)
$SE/MW \times Year2002$	**-.002**
	(.044)
$SE/MW \times Year2008$	**.009**
	(.025)
Average SE/MW 1996	.901
N	34493

Household-level survey data for 7 states (urban area only) in the South and Southeast/Midwest subsystems from Household Budget Survey (POF) 1996/1997, 2002/2003 and 2008/2009. This table displays the difference-in-differences estimates of the energy saving program effects on the share of households that pay for electricity, from equation (15). The dependent variable is a dummy equal to zero those households who own at least one electrical appliance and claim no expenses on electricity or own an electricity generator. All regressions contain utility company fixed effects, year fixed effects, income, squared income, number of household members and number of rooms. We input missing values in income with a linear regression, for each year, of income on the remaining controls. Significance levels: *10%, **5%, ***1% (s.e. estimated with wild-cluster bootstrap by state level).

Table S.2: Difference-in-difference results on appliances' quantity and age from Household Budget Surveys (POF)

Panel A. Quantity

	Index (KKL)	Refrigerator	Freezer	TV	AC	Laundry	Iron	Dish Washer	Dryer	Microwave	Hair dryer	Sound System	Computer
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
$SE/MW \times Year2002$	**.019**	**.013**	**-.026**	**.044**	**.048**	**-.151**	**.025**	**.005**	**.055**	**.024**	**.028**	**.038**	**.019**
	(.016)	(.049)	(.027)	(.052)	(.031)	(.131)	(.120)	(.038)	(.080)	(.026)	(.214)	(.085)	(.029)
$SE/MW \times Year2008$	**-.019**	**.006**	**-.035**	**-.007**	**-.009**	**-.088**	**-.001**	**.020**	**.089**	**-.031**	**-.025**	**-.031**	**-.021**
	(.022)	(.011)	(.042)	(.084)	(.023)	(.097)	(.017)	(.055)	(.086)	(.020)	(.046)	(.027)	(.018)
Average SE/MW 1996	-.086	.982	.207	1.299	.132	.554	1.139	.077	.092	.196	.483	.755	.083
N	31113	31113	31113	31113	31113	31113	31113	31113	31113	31113	31113	31113	31113

Panel B. Age

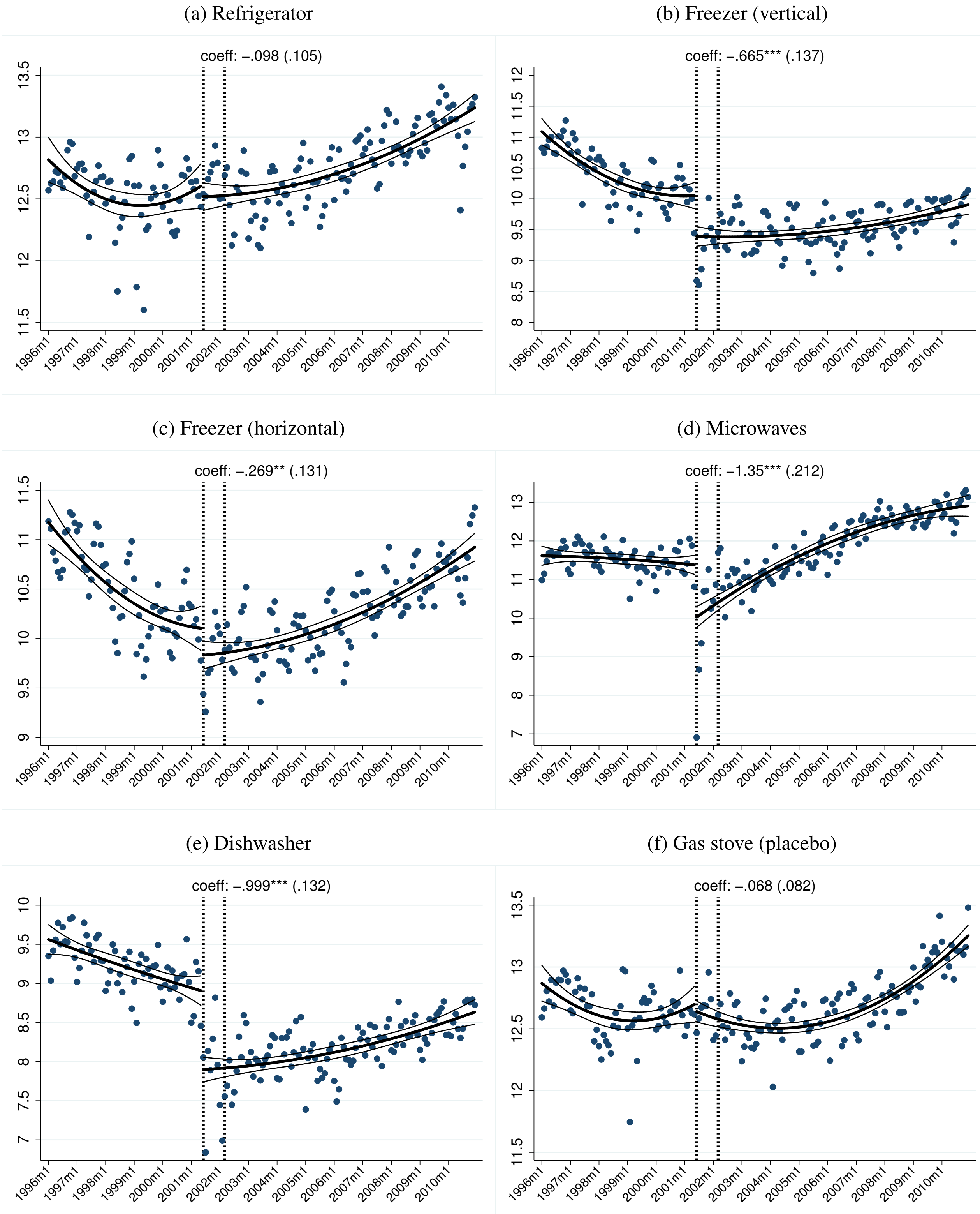
	Index (KKL)	Refrigerator	Freezer	TV	AC	Laundry	Iron	Dish Washer	Dryer	Microwave	Hair dryer	Sound System	Computer
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
$SE/MW \times Year2002$	**.155****	**-.874**	**-.270**	**-.612***	**1.560****	**-.258**	**-.266**	**-14.999**	**.214**	**.469**	**.242**	**-.538*****	**-.057**
	(.069)	(.643)	(1.466)	(.332)	(.781)	(.251)	(.334)	(1994.2)	(1.139)	(.520)	(.487)	(.203)	(.343)
$SE/MW \times Year2008$	**.014****	**-.039**	**-.073**	**-.303**	**1.798**	**-.820**	**-.386**	**-1.712**	**-.143**	**.663**	**.137**	**.259**	**.227**
	(.006)	(.132)	(.905)	(.210)	(1.661)	(.567)	(.431)	(1365.9)	(4.372)	(.518)	(.641)	(.233)	(.318)
Average SE/MW 1996	-.026	8.024	5.336	4.378	6.46	7.038	5.119	6.032	6.215	3.257	5.76	4.687	1.784
N	31113	28908	5516	28198	2185	16018	27178	1460	2382	8093	10955	18544	7107

Household-level survey data for 7 states (urban area only) in the South and Southeast/Midwest subsystems from Household Budget Survey (POF) 1996/1997, 2002/2003 and 2008/2009. This table displays the difference-in-differences estimates of the energy saving program effects on the quantity and age of all electrical appliances available, from equation (15). Each column corresponds to a regression of a different appliance. *Panel A* displayes the results on the quantity of appliances owned by household, and *Panel B* displayes the results on the age of appliances owned by households. The *Indices (KKL)* shown in the first columns are the average of the appliances shown in the columns. When calculating the indices, each dependent variable is normalized by the average and standard deviation of each variable in the South in 1996 as in Kling, Liebman and Katz (2007). To obtain these indices, we input missing values with the mean of the cell group the household belong (South/South-Midwest and 1996/2002/2008). We include only households who pay for electricity (non-theft). All regressions contain utility company fixed effects, year fixed effects, income, squared income, number of household members and number of rooms. We input missing values in income with a linear regression, for each year, of income on the remaining controls. Significance levels: *10%, **5%, ***1% (s.e. estimated with wild-cluster bootstrap by state level).

T Time-series in national sales of domestic appliances in Brazil (Whirlpool data)

The following figures display the time-series in national sales of several domestic appliances in Brazil. The data are estimates that we obtained from Whirlpool, a leading manufacturer, which produces those estimates for its own market strategy. The manufacturer did not share with us the estimation methodology used. In each figure, we plot the raw data (in logs), estimate a quadratic fit on each side of the start of the crisis (June 2001), and display the estimate of the change in sales at the time of the crisis from a regression discontinuity design using those quadratic fits. The Southeast/Midwest is by far the largest market for domestic appliances in Brazil (more than 50%). We find no evidence of an increase in sales for any of the domestic appliances. In contrast, we find evidence of a decrease in national sales for several of them.

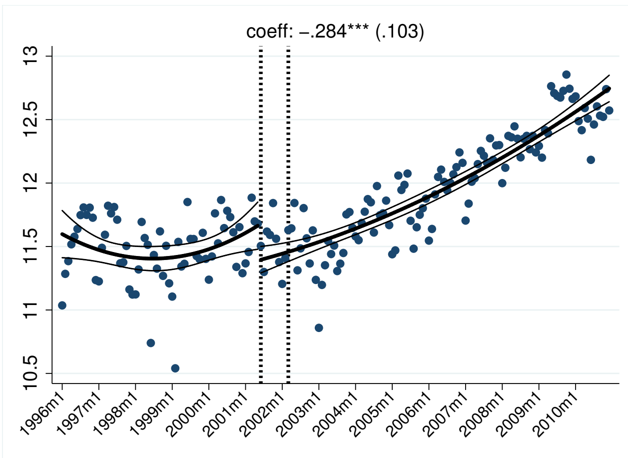
Figure T.1: Log sales of different domestic appliances I (all Brazil, Whirlpool estimates)



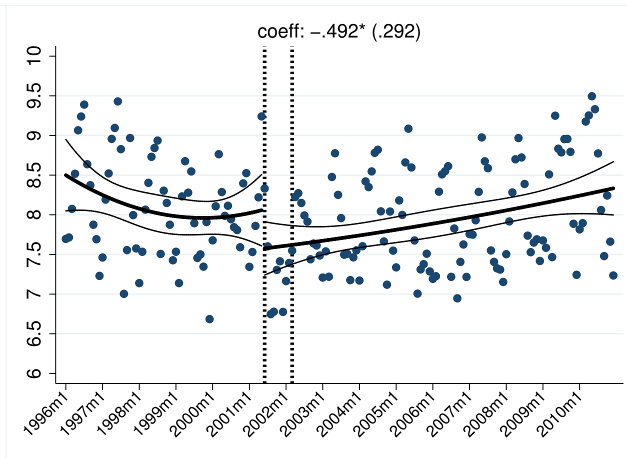
The panels display the time-series in national sales of several domestic appliances in Brazil. The data are estimates that we obtained from Whirlpool, a leading manufacturer, which produces those estimates for its own market strategy. The manufacturer did not share with us the estimation methodology used. In each figure, we plot the raw data (in logs), estimate a quadratic fit on each side of the start of the crisis (June 2001), and display the estimate of the change in sales at the time of the crisis from a regression discontinuity design using those quadratic fits. The Southeast/Midwest is by far the largest market for domestic appliances in Brazil (more than 50%).

Figure T.2: Log sales of different domestic appliances II (all Brazil, Whirlpool estimates)

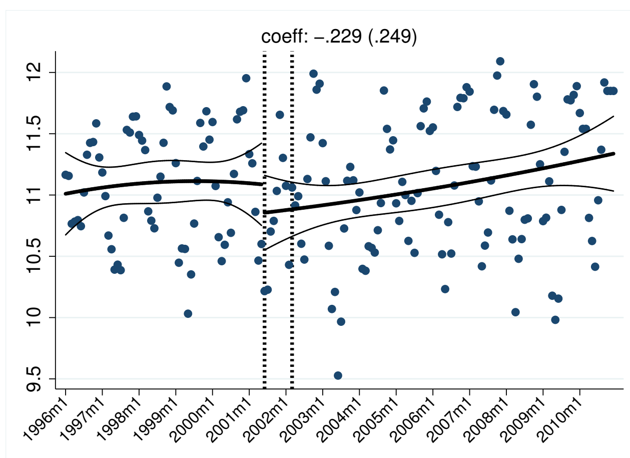
(a) Washing machine



(b) Dryer



(c) Air conditioning

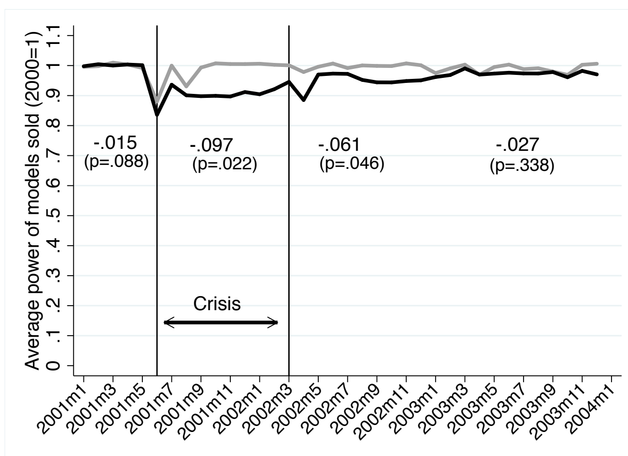


The panels display the time-series in national sales of several domestic appliances in Brazil. The data are estimates that we obtained from Whirlpool, a leading manufacturer, which produces those estimates for its own market strategy. The manufacturer did not share with us the estimation methodology used. In each figure, we plot the raw data (in logs), estimate a quadratic fit on each side of the start of the crisis (June 2001), and display the estimate of the change in sales at the time of the crisis from a regression discontinuity design using those quadratic fits. The Southeast/Midwest is by far the largest market for domestic appliances in Brazil (more than 50%).

U Changes in the average power of electric showers sold in the Southeast/Midwest and in the South (Fame data)

Figure U.1 uses data on the monthly sale of all the models of electric showers sold by Fame, a leading manufacturer, in each Brazilian state between January 2000 and December 2003. The data include the power (wattage) of each model, which is the only relevant measure of electric showers' propensity to use electricity. Figure U.1 displays the average power of electric showers sold in each month in the Southeast/Midwest and in the South, normalized to the same months in 2000. Figure U.1 also displays difference-in-difference estimates in each time period (early 2001, crisis, rest of 2002, 2003) from regressing the logarithm of average power on dummies for each state, dummies for each time period, and those later dummies interacted with an indicator for weather distribution utilities in a given state were subject to the electricity saving program during the crisis. Standard errors are obtained by using the wild cluster bootstrap-t clustered by state (10 clusters). The average power of electric showers sold decreased by about 10% during the crisis in the Southeast/Midwest compared to the South. We do not find any evidence of persistence. Note that Fame also started to sell relatively less in the Southeast/Midwest compared to the South (not shown; coefficient estimates are not significantly different from 0 during and after the crisis).

Figure U.1: Average power of electric showers sold (one manufacturer, Fame)



The figure displays the average power of electric showers sold by Fame in each month in the Southeast/Midwest and in the South, normalized to the same months in 2000. It also displays difference-in-difference estimates in each time period (early 2001, crisis, rest of 2002, 2003) from regressing the logarithm of average power on dummies for each state, dummies for each time period, and those later dummies interacted with an indicator for weather distribution utilities in a given state were subject to the electricity saving program during the crisis. Standard errors are obtained by using the wild cluster bootstrap-t clustered by state (10 clusters).

V Estimating a price elasticity of average residential electricity use

In Section 6 in the paper, we use estimates of the price elasticity of average residential electricity use in the Southeast/Midwest to recover an average "perceived" incentive during the crisis. We detail here how we obtain such estimates.

We use the same utility-level panel as in the paper for distribution utilities in the Southeast/Midwest. We are interested in a medium-run elasticity (demand typically responds with a lag), so we average all variables at the yearly level. We are interested in a price elasticity after the crisis, so we only consider data from 2003 onward. We then regress the logarithm of average residential use on the logarithm of the main residential tariff:

$$\log(kWh_{d,t}) = a_d + \beta_t + \eta \log(tariff_{d,t}) + \log(X_{d,t}) + \nu_{d,t} \tag{16}$$

where a_d and β_t are fixed effects for distribution utility d, and year t. $\nu_{d,t}$ is an error term clustered by utility. $X_{d,t}$ are yearly controls for total population, total formal employment, GDP, and average temperature for each distribution utility. η capture our price elasticity.

There are two major concerns with an equation such as equation (16). 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 main tariff. Therefore, percentage changes in the main tariff capture percentage changes in every marginal price.

Second, changes in prices may be endogenous to changes in quantities. The price-cap mechanism limits such a concern in Brazil. Between *revision* years, demand risk falls entirely on distribution utilities and yearly price *adjustments* are not endogenous to changes in quantities by design (ANEEL, 2005). Price revisions every four to five years may still create some endogeneity, biasing estimates of η away from 0. We directly assess the extent of endogeneity in two ways. First, we run the same regression instrumenting the main tariff by its cost-of-energy component (exogenous to the firm on a yearly basis) available for every utility since 2005. Second, we estimate equation (16) 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 V.1. We estimate $\widehat{\eta}$ at $-.2079$ (column 1) and $-.1812$ (column 4) with the full variation in tariffs from 2003 and 2005, respectively. Estimates using only the variation from price adjustments (column 3) are similar (because sample years are different in column 3, we also show results from a similar specification as in column 1 for those samples years in column 2). Estimates are larger with the IV strategy (column 5), at $-.2911$ (the first stage is strong). In the paper, we use estimates from columns (3) and (5).

Table V.1: Price elasticity estimates using yearly variation in the South-East/Midwest post-crisis

Dependent variable: Log(yearly mean of average residential consumption)					
	(1)	(2)	(3)	(4)	(5)
Log(yearly mean of main residential tariff)	-.2079***	-.2047***	-.2274**	-.1812***	-.2911**
	(.04332)	(.04249)	(.09434)	(.0414)	(.1307)
First stage dependent variable: Log(yearly mean of main residential tariff)					
Log(yearly mean of the cost of energy in the main residential tariff)					.2142***
					(.07327)
Model	OLS	OLS	OLS	OLS	IV-2SLS
First year	2003	2003	2003	2005	2005
Exclude variation from revision years	No	Yes	Yes	No	No
Between-revision FE	No	No	Yes	No	No
Observations	216	161	161	162	162
Clusters	27	27	27	27	27

s.e. clustered by distribution utility. Significance levels: *10%, **5%, ***1%. We use the same utility-level panel as in the paper for distribution utilities in the Southeast/Midwest. We average all variables at the yearly level and we only consider data from 2003 onward. We present coefficient estimates from regressing the logarithm of average residential use on the logarithm of the main residential tariff. All regressions control for year and utility fixed effects, as well as population, formal employment, GDP per capita, and average temperature (yearly, logs) for each utility. Column (1) uses the full variation in tariffs. Column (2) excludes years of price revisions. Column (3) includes utility-specific fixed effects for each between-revision period. The only variation left comes from price *adjustments*. Column (4) uses the full variation in tariffs from 2005 onward. Column (5) then instrument the residential electricity tariff in those years by its cost-of-energy component (exogenous to the firm on a yearly basis and available for every utility since 2005).