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

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Abstract

This paper studies how one may overestimate the social cost of a corrective policy by neglecting the possibility of hysteresis, that corrective incentives in earlier periods may have lasting impacts in later periods. In a price-theoretic framework, we derive a lower bound for this bias that can be evaluated using one sufficient statistic: the long-term impacts of a similar but temporary policy that agents expected to be temporary. We then estimate such a statistic. In so doing, we provide evidence of the importance of hysteresis for a policy-relevant behavior, residential electricity use in a developing country context. We study the 10-year impacts 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 reduction in average electricity use of 11%, or about half of the short-run impacts. 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 persistence is a change in consumption habits. Incorporating our estimates into our theoretical framework implies that, neglecting the possibility of hysteresis, one could overestimate the social cost of maintaining such a corrective policy by 85%.

Policymakers may want to implement corrective policies (e.g. Pigouvian taxes) to change behaviors of economic agents that may be privately optimal but socially suboptimal. Such policies are desirable when the social gain from correcting the externality outweighs the social cost of the policy. In the standard Pigouvian framework, the social cost in any period is proportional to the size of the observed changes in behavior and the size of the associated corrective incentive. Therefore, inducing large and lasting changes in a behavior that presents a low price elasticity may not be desirable even when the associated externality is sizable. This influential argument rests on the assumption that agents' behaviors depend on concurrent incentives. It leaves out the possibility that the impacts of past incentives may persist in the long run. Yet, many changes in behaviors may be more costly to adopt than to maintain (e.g. new habits), potentially leading to some *hysteresis*.[1] This paper studies the social cost of corrective policies in the presence of hysteresis.

We consider the generic problem of a policymaker implementing an incentive scheme to change some behavior in the long run. Suppose that she could credibly measure the impacts of the policy in any given period compared to a situation in which the policy had never been enacted. In the standard Pigouvian framework, such estimates are assumed to result from agents' concurrent responses to concurrent incentives, and they are sufficient to measure the social cost of the policy. However, in any given period, the estimated impacts may also be due to past and concurrent responses in anticipation of future incentives, and to past responses to past incentives (hysteresis). We argue that separating this later case is critical. Intuitively, the social cost would be lower because past responses to past incentives are sunk from the agents' perspective and should not be double-counted as part of the social cost of concurrent incentives.

We proceed in three steps. First, we extend the standard Pigouvian framework to show how one would overestimate the social cost of a corrective policy by neglecting the possibility of hysteresis. The framework allows us to derive a lower bound for this bias that can be evaluated using one sufficient statistic: the long-term impacts of a similar but temporary policy that agents expected to be temporary. Second, we estimate such a statistic and provide evidence of the importance of hysteresis in a policy-relevant behavior: residential electricy use in a developing country context. Specifically, we estimate the 10-year impacts of a 9-month 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 impacts subsisted in the long run. Household level microdata suggest that the main mechanism of hysteresis was a change in electricity utilitization habits. Finally, we incorporate our estimates into our conceptual framework to illustrate implications for the social cost of corrective policies.

To the best of our knowledge, this paper is the first to show how one would overestimate the

[1] Hysteresis is defined as the failure of an effect to reverse itself as its underlying cause is reversed (Dixit, 1989).

social cost of a corrective policy by neglecting the possibility of hysteresis and to derive a lower bound for this bias that can be estimated empirically. Our empirical evidence serves as a way to illustrate the usefulness of our approach and is relevant in itself for two reasons. First, energy use (including from the residential sector) 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.[2] Yet, existing estimates of price elasticities are typically low. Thus, inducing large and persistent changes in residential electricity use is a typical example where the associated social cost may be considered too large despite sizable externalites. 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 in developing countries (IPCC, 2014). Yet, the energy saving potential of households in those countries, who are poorer, own fewer appliances, are more credit-constrained, and consume less energy to begin with, is largely unknown.

We begin by deriving our main theoretical result in an extension of a standard Pigouvian framework. Consider a partial-equilibrium two-period model (short vs. long run) where agents choose a behavior subject to a corrective incentive. When behaviors in the two periods are independent, as in the absence of hysteresis, the social cost of the policy is proportional to the size of the observed changes in behaviors compared to a situation where the incentive *had never been implemented*. One cannot derive such an approximation when behaviors in the two periods are not independent, as with habit formation à la Becker and Murphy (1988). Consider a slightly different policy where the incentive is introduced as temporary in the first period, but is then maintained in the second period. One can derive an approximation for the social cost of this policy even in the presence of hysteresis because choices in the first period are independent of future (unforeseen) incentives. Importantly, the social cost in the second period is now proportional to the size of the observed changes in behaviors compared to a situation where the incentive *had not been maintained*. Neglecting the possibility of hysteresis, one would thus overestimate the social cost by the difference in behaviors between situations where the incentive had not been maintained and had never been implemented. This is why an estimate of the persistent impact of a known-to-be temporary policy measures the bias. Moreover, one can show that the bias would be larger in the case of our main policy of interest. This is why such an estimate provides a lower bound. This result relies on simple price theory and is thus robust to relaxing many modeling assumptions.

We then study the long-term impacts 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

[2]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.

temporary and because we can study impacts up to ten years after the policy was suspended. The former rules out any persistence that would be due to past responses in anticipation of some future incentives. The latter rules out any persistence that would be due to a slow convergence towards a new equilibrium without hysteresis (e.g. when short- and long-run price elasticities differ).

Electricity generation capacity was severely reduced in some regions of Brazil in the beginning of 2001. A temporary shock to the streamflow level in the rivers that serves the hydroelectric powerplants 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 that aimed at reducing residential electricity use by 20%. Residential customers were subject to a series of incentives, including pecuniary incentives to consume below individually-assigned quotas, and non-pecuniary incentives from moral suasion due to conservation appeal campaigns.[3]

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 impacts (-23%), but our main contribution is to show that about half of the short-run impacts persisted in the long run (-11%). Consumption levels partially rebounded once temporary incentives were removed but point estimates are stable from 2005 onwards (see Figure 1b).

We present many empirical tests supporting our results. Our estimates are robust to controlling for a series of possible confounders such as changes in electricity tariffs or income levels. 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 within-customer correlation between changes in consumption levels during the crisis and consumption levels four years later. Average 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

[3]Because pecuniary incentives were nonlinear, they cannot be simply translated in a given increase in linear tariffs.

the main mechanism of persistence was the formation of new utilization habits. This evidence is suggestive because it is based on self-reported information and because the survey sampling limits our ability to draw statistical inference over point estimates.

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 possible importance of hysteresis for policies that aim at changing behaviors in the long run. In so doing, we show theoretically that one may largely overestimate the social cost of such corrective policies and we derive a lower bound for this bias based on an estimable "sufficient statistic". Moreover, our analysis of the 2001 Brazilian electricity saving program indicates that taking hysteresis into account can be quantitatively important in a policy-relevant context. Incorporating our estimates into our theoretical framework implies that, neglecting the possibility of hysteresis, one could overestimate the social cost of pursuing this corrective policy beyond the temporary period by over 85%.

This paper contributes to the literature in public economics more broadly. Its main argument is not specific to corrective policies. It is common to measure the social cost of a policy, e.g. a commodity tax, from observed changes in behaviors compared to a situation where the incentive had never been implemented (Harberger, 1964). In any such setting, our results imply that the social cost is overestimated in the presence of hysteresis (e.g. if there is habit formation in the taxed commodity), and that the bias could be evaluated using the same sufficient statistic.

This paper also contributes to the growing empirical literature that investigates the presence and mechanisms of path-dependence in various behaviors of interest. Several studies infer path-dependence from the persistence of some impacts after a policy was removed.[4] In contrast to our empirical setting, it is sometimes unclear whether their estimates actually capture hysteresis. The persistence is often observed for a relatively short period of time and agents may have expected the policy to continue with some probability. Moreover, to the extent that some do capture hysteresis, one could directly use our theoretical framework to evaluate the overestimation bias from neglecting hysteresis for the social cost of corrective policies in their context. Existing studies do not consider the implication of their results for the social cost of corrective policies.

Finally, this paper participates to a small but growing empirical literature that studies issues related to energy consumption in developing countries.[5] We show that a temporary shock that

[4]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).

[5]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 ap-

forced Brazilian households to rationalize their electricity use had lasting impacts on consumption levels in the long run. Moreover, the persistence seems to arise mostly from the formation of new habits rather than from physical investments.[6] Our results thus open up an exciting research agenda: how could policymakers foster energy-efficient habits at an early 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 results. 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 persistence. Section 6 illustrates the importance of hysteresis for the social cost of corrective policies by incorporating our estimates into our conceptual framework. Section 7 concludes.

1 Conceptual Framework

Consider the problem of a government wanting to change the level of a behavior of interest (e.g. reduce energy consumption) in the medium or long run by introducing some incentive (e.g. a tax). Assume that the government has already estimated the social benefit of correcting this behavior. It remains for the government to estimate the social cost or deadweight loss that the policy creates (e.g. distorting privately optimal energy choices) in order to evaluate its desirability. In this section, we use a simple price-theoretic framework to show how one would overestimate the deadweight loss of such corrective policies by neglecting the possibility of hysteresis in the behavior of interest. The framework allows us to derive a lower bound for this bias, which can be estimated empirically provided one design or exploit the right experimental setting. All derivations are in the Appendix.

1.1 Setup

We derive our results in a representative-agent two-period model of household electricity consumption. The model applies equally well to other behaviors of interest and the results easily generalize to a multi-period model.[7] The first period corresponds to the short run, after some incentives are introduced. The second period corresponds to the medium or long run, after all adjustments have been made. We adopt a standard partial-equilibrium Pigouvian setup to focus attention on the possibility of hysteresis. In particular, we assume away income effects and redistributive concerns,

pliances' 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.

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

[7]The model can be seen as a two-period simplification of Becker and Murphy (1988) fully dynamic model with infinitely lived households, where we allow for direct investments in consumption capital.

and we model the agent as fully rational and forward looking. We relax this last assumption in an extension of our model. For simplicity, we also assume that goods (e.g. electricity) are produced competitively at constant marginal costs, such that the consumer and the social surplus are equivalent. Our main results would be identical assuming an upward-sloping supply curve.

The household chooses electricity consumption e_i at price p_i and ordinary consumption c_i at normalized price 1 given income y_i in periods $i = 1, 2$.[8] The per-period utility is represented by $u_i(c_i, e_i, s_i) = c_i + v_i(e_i, s_i)$, where s_i is a stock variable that captures the household's propensity to consume electricity. This variable can be intepreted as a preference parameter – e.g., consumption habits – or as the technology of a home production function of services from electricity à la Dubin and McFadden (1984) – e.g., the energy efficiency of a stock of electrical appliances.

We assume that $v_i(e_i, s_i)$ is strictly increasing and concave in e_i and that $\frac{\partial v_i(e_i,s_i)}{\partial s_i} \leq 0$ for all $e_i, s_i \geq 0$. The household derives less utility from a consumption bundle (c_i, e_i) if her habits or technology require more electricity to provide the same services. The propensity to consume evolves according to $s_i = s(s_{i-1}, e_{i-1}, I_i)$ with $0 \leq \frac{\partial s(s_{i-1},e_{i-1},I_i)}{\partial s_{i-1}}, \frac{\partial s(s_{i-1},e_{i-1},I_i)}{\partial e_{i-1}} \leq 1$. It depends "passively" on past choices, but also "actively" on current efficiency investments I_i at convex costs $X_i(I_i)$, which do not have to be monetary (e.g. learning costs). These two channels capture very different mechanisms of persistence, but our results do not depend on the specific mechanism at play. Finally, we assume that $\frac{\partial^2 v_i(e_i,s_i)}{\partial e_i \partial s_i} > 0$ for all $e_i, s_i \geq 0$: the higher the propensity to consume (e.g. to use electrical appliances), the higher the marginal utility of 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 the following problem for a set of initial values (s_0, e_0):

$$\max_{c_1,c_2,e_1,e_2,I_1,I_2} U = U_1 + \beta U_2 = c_1 + v_1(e_1, s_1) + \beta\left[c_2 + v_2(e_2, s_2)\right] \tag{1}$$
$$\text{s.t.} \quad c_i + p_i e_i + X_i(I_i) \leq y_i; \quad s_1 = s(s_0, e_0, I_1); \quad s_2 = s(s_1, e_1, I_2)$$

Substituting in for c_i, we obtain the following first-order conditions:

$$\begin{aligned} &e_1 : \frac{\partial v_1}{\partial e_1} + \beta \frac{\partial v_2}{\partial s_2}\frac{\partial s_2}{\partial e_1} = p_1 \quad ; \quad e_2 : \frac{\partial v_2}{\partial e_2} = p_2; \\ &I_1 : \left[\frac{\partial v_1}{\partial s_1} + \beta \frac{\partial v_2}{\partial s_2}\frac{\partial s_2}{\partial s_1}\right]\frac{\partial s_1}{\partial I_1} = \frac{\partial X_1}{\partial I_1} \quad ; \quad I_2 : \frac{\partial v_2}{\partial s_2}\frac{\partial s_2}{\partial I_2} = \frac{\partial X_2}{\partial I_2}. \end{aligned} \tag{2}$$

The left- and right-hand sides of each first-order condition capture the benefit and the cost of marginal changes in the associated choice variable, respectively. These must be equal at an

[8] Our main results would carry on if households could save or borrow. Quantitatively, a credit market would allow households to make larger investments, increasing the possibility of persistent changes in behaviors.

optimum. As expected, the household will use less electricity and make larger investments in energy efficiency in period 1 if the propensity to consume electricity depends on past choices and the household is aware of this relationship. The first-order conditions then implicitly define demand curves for e_1 and e_2 that are function of prices in both periods.

1.2 Deadweight loss of our main policy of interest

We are interested in the deadweight loss of a policy aiming to reduce electricity consumption in the medium or long run by imposing some corrective incentive in both periods. For simplicity, let's consider a set of Pigouvian taxes (τ_1, τ_2), such that electricity prices increase from counterfactual prices $(\overline{p_1}, \overline{p_2})$ to $(\overline{p_1}+\tau_1, \overline{p_2}+\tau_2)$. In our framework, the welfare effect of this policy is: $\Delta W^{main} = \int_{(0,0)}^{(\tau_1,\tau_2)} \frac{dW}{dt} dt$, where welfare is defined as $W = U + t_1 e_1 + \beta t_2 e_2 + B(e_1, e_2)$. The social benefit of the policy is captured by $B(e_1, e_2)$ with $\frac{\partial B}{\partial e_i} < 0$ for all e_i in our case.[9] The social cost or deadweight loss is the change in welfare minus any such social benefit. Using the envelope theorem, we have:

$$| DWL^{main} | = - \int_{(0,0)}^{(\tau_1,\tau_2)} \left[t_1 \frac{de_1}{dt} + \beta t_2 \frac{de_2}{dt} \right] dt \tag{3}$$

Equation (3) reduces to a (discounted) sum of one-dimensional integrals if electricity use is independent of past or future prices. In particular, this is the case if one assumes that the propensity to consume is independent of past choices, neglecting the possiblity of hysteresis in electricity use. Define $e_i(\overline{p_1}+\tau_1, \overline{p_2}+\tau_2)$ the observed consumption level in period i and $e_i(\overline{p_1}, \overline{p_2})$ the counterfactual consumption level in absence of the policy. The deadweight loss in each period is then the usual integral under the partial demand curve $e_i(p_i)$ and above the counterfactual price between the observed and counterfactual consumption levels. Typically, we don't know the shape of demand curves, so we approximate the deadweight loss by assuming that they are locally linear.[10] The approximation leads to the familiar "Harberger" triangle in a partial-equilibrium setup:

$$\begin{aligned} | DWL^{main}_{noH} | &= - \int_0^{\tau_1} t_1 \frac{de_1}{dt_1} dt_1 - \beta \int_0^{\tau_2} t_2 \frac{de_2}{dt_2} dt_2 \\ &\simeq \frac{1}{2} \tau_1 \left[e_1(\overline{p_1}, \overline{p_2}) - e_1(\overline{p_1}+\tau_1, \overline{p_2}+\tau_2) \right] + \beta \frac{1}{2} \tau_2 \left[e_2(\overline{p_1}, \overline{p_2}) - e_2(\overline{p_1}+\tau_1, \overline{p_2}+\tau_2) \right] \end{aligned} \tag{4}$$

In contrast, equation (3) does not reduce to a sum of one-dimensional integrals if the propensity to consume depends on past choices. In this case, it is not possible to derive a simple approximation for the deadweight loss $\left(| DWL^{main}_{H} | \right)$, or for the bias if one were to neglect the possibility of

[9] Our consideration of the case of a negative externality is of course without loss of generality, as is our focus on Pigouvian taxes rather than subsidies (for reductions in electricity use).

[10] The approximation is likely worse with large changes in quantity, but there is no other preferable approximation.

hysteresis in electricity use $\left(\mid DWL_{noH}^{main} \mid - \mid DWL_{H}^{main} \mid\right)$. We address this problem by considering the deadweight loss of an alternative policy.

1.3 Deadweight loss of an alternative policy

Consider the following policy. The government introduces a tax τ_1 as a temporary policy in period 1. The government then decides to impose a tax τ_2 in period 2, even though households expected the tax in period 1 to be temporary. Households face the same incentives under this alternative policy and our main policy of interest. Yet, consumption levels may differ. Define $e_1\left(\overline{p_1}+\tau_1^{temp},\overline{p_2}\right)$ and $e_2\left(\overline{p_1}+\tau_1^{temp},\overline{p_2}+\tau_2\right)$ the observed consumption levels under the alternative policy. If electricity use exhibits hysteresis, consumptions levels will be higher in both periods because the household was unable to correctly anticipate the future incentives: $e_1\left(\overline{p_1}+\tau_1^{temp},\overline{p_2}\right) \geq e_1\left(\overline{p_1}+\tau_1,\overline{p_2}+\tau_2\right), e_2\left(\overline{p_1}+\tau_1^{temp},\overline{p_2}+\tau_2\right) \geq e_2\left(\overline{p_1}+\tau_1,\overline{p_2}+\tau_2\right)$.

We consider this alternative policy for two reasons. First, its deadweight loss reduces to a sum of one-dimensional integrals even if electricity use exhibits hysteresis. The household only responds to concurrent incentives in the first period and take the first period's consumption as given in the second period. We can thus derive a simple approximation for the deadweight loss $\left(\mid DWL_{H}^{alt} \mid\right)$ by assuming again locally linear demand curves:

$$\begin{aligned} \mid DWL_{H}^{alt} \mid &= -\int_{(0,0)}^{(\tau_1,0)} t_1 \frac{de_1}{dt_1} dt_1 - \beta \int_{(\tau_1,0)}^{(\tau_1,\tau_2)} t_2 \frac{de_2}{dt_2} \mid_{(e_1,I_1)fixed} dt_2 \qquad (5) \\ &\simeq \frac{1}{2}\tau_1 \left[e_1\left(\overline{p_1},\overline{p_2}\right) - e_1\left(\overline{p_1}+\tau_1^{temp},\overline{p_2}\right)\right] + \frac{1}{2}\beta\tau_2 \left[e_2\left(\overline{p_1}+\tau_1^{temp},\overline{p_2}\right) - e_2\left(\overline{p_1}+\tau_1^{temp},\overline{p_2}+\tau_2\right)\right] \end{aligned}$$

In period 1, the deadweight loss is the usual integral under the demand curve $e_1\left(p_1 \mid s_0, e_0, \overline{p_2}\right)$ and above the counterfactual price between the observed and counterfactual consumption levels. This is the case whether electricity use exhibits hysteresis or not. A similar measure, however, would overestimate the deadweight loss in period 2 if electricity use exhibits hysteresis. Consumption would have been lower in period 2 even if the tax had remained temporary $\left(e_2\left(\overline{p_1}+\tau_1^{temp},\overline{p_2}\right) \leq e_2\left(\overline{p_1},\overline{p_2}\right)\right)$. As a result, τ_2 distorts quantity to a lesser extent and creates a smaller deadweight loss. This is illustrated in Figure 2. The hatched area (discounted) approximates this overestimation bias:

$$\mid DWL_{noH}^{alt} \mid - \mid DWL_{H}^{alt} \mid \simeq \frac{1}{2}\beta\tau_2 \left[e_2\left(\overline{p_1},\overline{p_2}\right) - e_2\left(\overline{p_1}+\tau_1^{temp},\overline{p_2}\right)\right] \qquad (6)$$

The key statistic to estimate in order to evaluate the bias in equation (6) is the persistent impact of τ_1 had it remained temporary.

Second, the deadweight loss of this alternative policy provides an upper bound for the deadweight loss of our main policy of interest. The household must be worse off when she is unable to

anticipate future incentives ($\mid DWL_H^{alt} \mid \geq \mid DWL_H^{main} \mid$). In contrast, the deadweight loss of this alternative policy will be measured as smaller than the deadweight loss of our main policy of interest if one neglects the possibility of hysteresis in electricity use ($\mid DWL_{noH}^{alt} \mid \leq \mid DWL_{noH}^{main} \mid$). Observed changes in consumption levels will be smaller if there is in fact hysteresis in electricity use. The bias under this alternative policy thus provides a lower bound for the bias under our main policy of interest: $\mid DWL_{noH}^{alt} \mid - \mid DWL_H^{alt} \mid \leq \mid DWL_{noH}^{main} \mid - \mid DWL_H^{main} \mid$.

In sum, we are interested in the deadweight loss of a policy that imposes a corrective incentive in both periods, such as a tax τ. We are also interested in the bias when one approximates this deadweight loss by neglecting the possibility of hysteresis in the behavior of interest. We cannot derive simple approximations of these quantities. However, we could approximate meaningful bounds for these quantities by designing or exploiting the right empirical setting. For instance, estimating the persistent impact in period 2 of a policy that imposes the incentive as a temporary measure in period 1 would allow us to approximate a lower bound for our bias of interest.

1.4 Connecting the theory to the data

A few comments must be made before connecting the theory to any empirical setting.

In practice, the persistent impact of a temporary policy could be due to past responses to past incentives, but also to past responses in anticipation of future incentives if agents expected the policy to apply in the future with some probability. It is crucial to separate the relative impact of these two causes for welfare purposes: the latter is part of the deadweight loss of the policy, but the former is not (hysteresis). Accordingly, the persistent effect a temporary policy that was not known to be temporary carries limited information from a welfare point of view. To make this point clear, let's consider an extreme case where $\tau_1 = 0$ and $\tau_2 > 0$. Using the envelope theorem, we have:

$$\begin{aligned} \mid DWL \mid &= -\int_{(0,0)}^{(0,\tau_2)} \left[\beta t_2 \frac{de_2}{dt_2}\right] dt = -\int_{(0,0)}^{(0,\tau_2)} \beta t_2 \left(\left[\frac{\partial e_2}{\partial e_1}\frac{\partial e_1}{\partial t_2} + \frac{\partial e_2}{\partial I_1}\frac{\partial I_1}{\partial t_2}\right] + \left[\frac{\partial e_2}{\partial I_2}\frac{\partial I_2}{\partial t_2} + \frac{\partial e_2}{\partial t_2}\right] \right) dt \\ &\simeq \frac{1}{2}\beta\tau_2 \left(\left[e_2\left(\overline{p_1}, \overline{p_2}\right) - e_2\left(e_1\left(\tau_2\right), I_1\left(\tau_2\right)\right)\right] + \left[e_2\left(e_1\left(\tau_2\right), I_1\left(\tau_2\right)\right) - e_2\left(\overline{p_1}, \overline{p_2} + \tau_2\right)\right] \right) \end{aligned} \quad (7)$$

The deadweight loss can be decomposed into two components. First, consumption levels in period 2 may be lower because of choices made in period 1 in anticipation of future incentives ($e_1\left(\tau_2\right), I_1\left(\tau_2\right)$). Second, consumption levels in period 2 may be lower because of further responses to concurrent incentives. In this context, suppose that the government unexpectedly suspends the policy at the start of period 2. Any persistent impact would simply estimate the first component of the deadweight loss and not a bias from neglecting the possibility of hysteresis.

The ideal experiment to provide evidence of hysteresis and discuss welfare implications would then have the following features. First, it would randomize simple corrective incentives, such as a

Pigouvian tax, that are *known to be temporary* to isolate the persistence of past responses to past incentives. Second, researchers would estimate the empirical analog of $e_2\left(\overline{p_1},\overline{p_2}\right)-e_2\left(\overline{p_1}+\tau_1^{temp},\overline{p_2}\right)$ in equation (6) from the *long* persistence of a difference in behavior between treatment and control groups. This is important because short- and long-run price elasticities are likely to differ for many behaviors of interest. As a result, the persistence of an impact in the direct aftermath of a policy may simply result from the slow convergence towards counterfactual consumption levels rather than from true hysteresis. It is obvious that the deadweight loss of a policy that aims at changing behaviors in the medium or long run should be based on medium- or long-run elasticities even if one neglects the possibility of hysteresis. Finally, it would randomize incentives that are relatively large and for a temporary period that is relatively long. Intuitively, hysteresis is less likely to occur if agents do not have to make significant adjustments to their behavior in the short run or do not have the time to form new habits.

1.5 Extensions

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

First, we can allow for *discrete* choice variables. Individual demand curves for the behavior of interest may not be smooth in this case. However, our results still apply as long as the aggregate demand curve is smooth, e.g. if thresholds triggering discrete changes in behavior are smoothly distributed in the population.

Second, agents could be *naive* about the effect of their current choices on their future propensity to consume. A corrective policy would then reduce consumption levels that are suboptimally high from a private perspective. In our framework, such an "internality" would be captured in the social benefit of the policy, $B(e_1,e_2)$, together with other internalities and externalities. In terms of the social cost, this naiveté assumption would imply that the deadweight loss of our main policy of interest and of our alternative policy are identical. The persistent impact of a temporary policy would thus provide a direct approximation of the deadweight loss, rather than an upper bound, whether or not the policy was known to be temporary. Of course, this is only true if all agents are naive. In contrast, our approach provides valid bounds irrespective of the share of naive agents.

Finally, we have adopted a standard Pigouvian setup by assuming that the social cost of the policy comes only from distorting quantities. The direct effects of Pigouvian policies on agents' utility, from paying taxes or receiving subsidies, do not matter because they constitute transfers between agents and the government rather than welfare gains or losses. This would not be the case, however, if there were, e.g., equity concerns or if incentives had direct effects that were non-pecuniary and thus not transferable. These aspects are beyond the scope of the present paper. We thus limit social cost considerations to quantity distortions when interpreting our empirical

estimates in the light of our conceptual framework below.

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 impacts 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 is that the policy was not a simple Pigouvian tax. It included a set of (nonlinear) incentives that were both pecuniary and non-pecuniary, that changed over time, and that may have affected different households differently. We have little to say about the design of incentives in our empirical setting and its optimality. Our interest is that the policy allows us to provide clear evidence of hysteresis in electricity use. We then illustrate welfare implications as follows. First, we back out an average "perceived tax" ($\simeq \tau$) to summarize the magnitude of the incentives at play. Next, we incorporate our estimates in our conceptual framework to quantify how one would overestimate the deadweight loss of pursuing this policy by neglecting the possibility of hysteresis. Our context and evidence are relevant in themselves, but also to illustrate the usefulness of our approach for future empirical work on the social cost of corrective policies.[11]

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

[11] Our approach abstracts from possible allocative inefficiencies from the policy. Allocative inefficiencies would increase the size of the deadweight loss of the policy, but it is unclear how it would affect the bias from neglecting the possibility of hysteresis. The fact that some incentives were non-pecuniary does not constitute a problem for the applicability of our conceptual framework as long as the social cost of non-pecuniary (and pecuniary) incentives comes only from distorting quantities. In practice, any Pigouvian tax that aims at changing behavior in such a large scale would likely stimulate a set of non-pecuniary incentives, such as peer pressure, at least endogenously.

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 the following decade 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 (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).[12]

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 (more information is provided in the next section). Water levels follow a clear 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 at the time such that the South could not supply much electricity to the other subsystems. Moreover, while growth in demand had never

[12]The price-cap mechanism is aimed at encouraging distribution utilities to address electricity theft. Price revisions and adjustments occur at different times for different utilities. In June 2001, the main tariff was R$.208/kWh (US$.08) in Rio de Janeiro. Marginal prices in the alternative tariff were R$.073 (up to 30 kWh), R$.125 (up to 100 kWh), R$.188 (up to 140 kWh), and R$.208 (above 140 kWh). Minimum consumption levels are also charged, and local taxes increase what customers eventually pay.

outpaced growth in projected demand in the years prior to 2001 (as shown in the Appendix), it systematically outpaced growth in generation capacity. This was a nationwide issue, and in fact, 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).[13] 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.[14]As expected, the crisis officially ended in February 2002. The electricity saving program was fully suspended in March 2002, but according to a specialized periodical, "people were giving signals that they 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 a set of incentives for residential customers that was complicated, nonlinear, and changed more than once.[15] Therefore, it is unclear what customers were exactly responding to, even though rules were frequently repeated in the media and on electricity bills. However, we are not interested in the specificities of these measures. Our interest is that households reduced electricity use dramatically in response to these incentives, which were known to be temporary, and that they were responding to these incentives at the margin throughout the crisis (electricity use rebounded after the crisis).

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

[14]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.

[15]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.

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.[16]

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.[17]

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 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. This "strong national commitment to conservation" has been considered a main component of the Brazilian electricity saving program in the specialized literature (Meier, 2005).

All these elements increased the utility cost of electricity use for residential customers. They are not easily summarized into a single price change, but we later estimate an average "perceived" incentive for our calibrations. 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

[16]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.

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

outlets are national in Brazil. 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 used that information because they were subject to some incentives. In fact, we would argue that any incentive that aims at changing behavior in such a large scale would spur a market for information.

Other factors could be affecting 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.[18] Some policies were implemented nationally and are thus part of our counterfactual. Taxes on efficient light bulbs were reduced, and taxes on electric showers, water heaters, and incandescent light bulbs were temporarily increased (Decreto 3827, May 21, 2001). Efficiency standards for domestic appliances were adopted (Lei 10295, October 17, 2001). Finally, the rainfall pattern during the 2000-2001 summer was a unique outlier, so there was no rational reason for customers in different subsystems to differentially update their beliefs about the risk of future shortages.[19] Even if they did, it is unclear that they would have consumed less electricity in response, especially after the electricity saving program used grandfathering to assign individual quotas.

2.2 Data

Our analysis mostly relies on three sets of data.

A. Utility level administrative data (ANEEL).

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 the some concession areas being split). We match our panel of distribution utilities to decen-

[18] 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.

[19] 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.

nial 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.

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).

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 thus cannot be matched to the concession area of each distribution utility.

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), 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.[20] 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 (about R$.15/kWh or US$.165/kWh in US$ of 2012) 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. 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. Specifically, it increased 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. Strong economic growth and poverty alleviation, as experienced in Brazil in the years following the crisis, can have very different effects on residential electricity consumption when initial ownership rates are so different. Indeed, there is a "S–curve" relationship between income and appliance ownership (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.[21]

[20] 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.

[21] There is also a data limitation preventing us to study outcomes in the North subsystem. Many customers there are

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 the subsequent growth in ownership rates were comparable. Fourth, initial electricity tariffs were also comparable and did not evolve differentially. If anything, tariffs decreased relatively more in the Southeast/Midwest.

Distribution utilities in the South and in the Southeast/Midwest differ in some respects. For instance, average electricity consumption and median income 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 consumption 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. One factor that differs more 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 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 changes in 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:

$$log\left(Av_kWh_{d,r,m,t}\right) = \alpha_d + \beta_{r,m} + \gamma_p + \delta_p \, \mathbb{1}\left\{d \in \text{SE/MW}\right\} + log\left(X_{d,r,m,t}\right) + \nu_{d,r,m,t} \qquad (8)$$

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.

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.[22]

Estimates of δ_p during the crisis and for subsequent time periods can be interpreted as the average treatment effect of the electricity saving program 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 the long-run effects of the electricity saving program, 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 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 (8) with different samples years and the controls available in those years. Second, we show that our estimated average impacts are 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

[22] 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.

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 weights are 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 impacts are 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:

$$log(Av_kWh_{d,t}) = \alpha_d + \gamma \, \mathbb{1}(t = 2010) + \delta \, \mathbb{1}(t = 2010 \,\&\, d \in \text{SE/MW}) + log\left(X_{d,t}\right) + \nu_{d,t} \quad (9)$$

where $\nu_{d,t}$ is an error term for utility d in census year t clustered by 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*.[23] Finally, we investigate other dimensions of the distribution of 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.

[23] We cannot estimate the causal effect of some variation in incentives among LIGHT customers during the crisis. First, all customers were subject to some incentives and incentives were complicated and uncertain. Second, we don't know how non-pecuniary incentives varied among customers and they may have played a major role. Third, there is no discontinuity or bunching in electricity consumption where customers faced discontinuities or kinks in their budget set. This is consistent with the existing literature on residential electricity consumption (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).

4.1 Utility-level data

Difference-in-difference coefficients $\widehat{\delta}_p$ from estimating our preferred specification of equation (8) 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.

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 impact of the electricity saving program 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 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 impacts are large for all the distribution utilities subject to the electricity saving program, between -.19 and -.40 log points. Importantly, the long-run impacts are also negative for all those utilities. Our estimated average

impacts are 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. 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 both the Southeast/Midwest and in the South (see Appendix). Tariffs did not evolve differentially after the crisis.

Table 2 displays estimates of the long-term impacts of the electricity saving program from using equation (9) 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 in household median income. The estimated impacts are 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 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.

4.2 Customer-level data

Figure 5 presents additional robustness checks using the longitudinal microdata for LIGHT customers. Panel (a) shows that the time-series in average electricity use for LIGHT is almost identical when (i) we use 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 the balanced panel by construction, are unlikely to drive our results, at least until 2005 (our estimated coefficients $\widehat{\delta_p}$ are very stable after 2005 in Figure 3).[24] It also implies that our estimates are not due to electricity theft responses 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.[25]

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

[25]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

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 by the other ones. Almost all customers (92%) reduced electricity use compared to before the crisis; the median customer reduced electricity use by 31%. Densities one year and four years after the crisis are very similar and they fall exactly between the crisis and pre-crisis densities. Four years after the crisis, 69% were still consuming less than before the crisis; the median customer was consuming 16.5% less electricity. Average changes in electricity use thus came from sizable reductions at every level of consumption.[26]

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 pecuniary incentives. 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 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 in individual responses to the temporary electricity saving program. Yet, we have not shown any persistence at the individual level. This is done in panel (d). There is a strong correlation between electricity use during the crisis and four years after the crisis for customers with the same baseline consumption

and, if anything, point estimates suggest that non-technical losses (a neasure 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.

[26] 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, 2012).

levels (same sample as in panel c). This suggests that our results are indeed due to the persistence of individual changes in electricity use. We provide evidence on the mechanisms of persistence in the next section.

5 Mechanisms of persistence

There are three main mechanisms that could explain a persistent reduction in household electricity use. Households may have persistently 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.[27] Conveniently, our estimated long-term impacts on household electricity use are 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 who 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 less after the crisis. This is true for electric showers (39%),[28] lights (41%), and freezers (21%),[29] 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 reas-

[27] 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.

[28] 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).

[29] 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.

suring 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:

$$Y_{h,d,t} = \alpha_d + \gamma \, \mathbb{1}(t = 2005) + \delta \, \mathbb{1}(t = 2005 \,\&\, d \in \text{SE/MW}) + log\left(X_{h,d,t}\right) + \nu_{h,d,t} \qquad (10)$$

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.[30] 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.

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 3, 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

[30] 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").

measures the number of TVs per household.[31]

5.3 Appliances' characteristics

The PPH surveys recorded characteristics correlated with electricity use for some appliances. We use the specification in equation (10) to investigate any differential trend in each of 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 such that 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.[32] 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.[33]

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 the crisis (by about 10%), but it increased again after the crisis.[34]

[31] 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 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 share of households with refrigerators and TV, and a negative (and larger in magnitude) point estimate for the quantity of freezers.

[32] In 2001, Brazil had the highest real interest rate out of 150 countries present in the World Development Indicators (WDI) from the World Bank. The real interest rate in Brazil was 44.65 percent, compared to an average of 8.34 percent for the OECD countries, for example.

[33] We obtain those data 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. 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% (based on census data).

[34] 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.

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% 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.[35]

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 (10) 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 negative for our index (and large) 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 freezers unit permanently switched on in the Southeast/Midwest after the crisis, which is consistent with the information in Table 3. Households were also less likely to regulate the thermostat of their electric shower to the warmest setting; this result is statistically signifant even using our large standard errors. A back-of-the-envelope calculation suggests that this behavior alone could have generated almost enough savings to explain our long-term impacts (22 kWh per month).[36]

In sum, the main stated mechanism of persistence is a change in utilization habits. We found suggestive evidence that households changed their utilization habits persistently in the Southeast/Midwest. However, we cannot reject that some changes in appliances' quantity (living with fewer appliances is another type of habit formation) and characteristics may have also played a role. Note that our conceptual framework applies independently of the specific mechanisms as long as the persistence was due to the temporary incentives.[37]

[35] If we consider that this 52% national increase in adoption consisted of the substitution of an average 60W incandencent light bulb (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 light bulb on average. In 1999, households in the South used on average 5 incandescent light bulbs, such that CFL substitution would accound for a reduction of around 20 kWh/month in the South. This has the same order of magnitude of the drop in average electricity use in the South as we can see on Figure 1.

[36] 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).

[37] The second round of PPH surveys (but not the first round) also asked households about the information that they

6 Implications for the social cost of corrective policies

We established that households reduced electricity use persistently 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.

Consider a policy that would have implemented the incentives of the electricity saving program permanently. As discussed in Section 1, one would overestimate the deadweight loss of pursuing this policy after the crisis by neglecting the possibility of hysteresis in electricity use. An upper bound for the bias can be approximated as: $\mid DWL_{noH}^{main} \mid - \mid DWL_{H}^{main} \mid \geq \mid DWL_{noH}^{alt} \mid - \mid DWL_{H}^{alt} \mid \simeq \frac{1}{2}\beta\tau\left[e_2\left(\overline{p_1},\overline{p_2}\right) - e_2\left(\overline{p_1}+\tau^{temp},\overline{p_2}\right)\right]$, where τ measures the magnitude of the incentives. The "alternative" policy would have introduced the incentives as a temporary policy, but maintained them after the crisis. The term in brackets corresponds to the persistent impact if it had not been maintained beyond the temporary period. This is what we estimated in our empirical analysis.

We use two approaches to illustrate the magnitude of the bias in our case. First, we can express the bias as a percentage of the deadweight loss of maintaining the incentives beyond the temporary period. We do not know what the overall impacts of the policy would have been if it had been maintained. We thus assume that they would have been similar to the average impacts during the crisis.[38] Using estimates for 2010 as the persistent impacts of the temporary policy, we have:

$$\frac{\mid DWL_{noH}^{alt} \mid - \mid DWL_{H}^{alt} \mid}{\mid DWL_{H}^{alt} \mid} \simeq \frac{e_2\left(\overline{p_1},\overline{p_2}\right) - e_2\left(\overline{p_1}+\tau^{temp},\overline{p_2}\right)}{e_2\left(\overline{p_1}+\tau^{temp},\overline{p_2}\right) - e_2\left(\overline{p_1}+\tau^{temp},\overline{p_2}+\tau\right)} = \frac{1-e^{-.1103}}{e^{-.1103}-e^{-.2581}} = 84.9\%$$

One would overestimate the deadweight loss of pursuing this policy by about 85%. Taking into account hysteresis may thus severely affect the cost-benefit analysis of corrective policies. Of course, part of the observed reduction in electricity use during the crisis (after the first few weeks) must have also been due to hysteresis, thus reducing the social cost of the electricity saving program itself. Accordingly, we show in Table 5 that many households from the Southeast/Midwest reported in PPH surveys to not have experienced severe welfare losses during the crisis. When asked about changes to their life quality, only 24% of households reported a decrease in life quality, 48% reported no changes in life quality, and 28% reported to have "learned to live comfortably while

dispose 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).

[38] The bias would be even larger if the impacts of pursuing the policy would have been smaller after the crisis: in the extreme case where customers would not have reduced usage below the persistent effect that we estimate ($e_2\left(\overline{p_1}+\tau^{temp},\overline{p_2}\right) - e_2\left(\overline{p_1}+\tau^{temp},\overline{p_2}+\tau\right) = 0$), the bias in percentage terms would be infinite. As discussed previously, our approach abstracts from the fact that different households faced different incentives during the crisis, which may have lead to allocative inefficiencies. Taking into account allocative inefficiencies would certainly affect the size of the deadweight loss, but it is unclear how it would affect the bias.

saving money." 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".

Second, we obtain a nominal value for the bias. We recover an average "perceived" incentive (τ) as follows. Average residential electricity use rebounded by .128 log points after the crisis (by 2003). This corresponds to households' concurrent responses to the perceived incentives of the electricity saving program. We can then back out the implied magnitude of the incentives using $d\log(p) = \frac{d\log(kWh)}{\eta}$, where η is a medium-run price elasticity of average residential electricity use. In the Appendix, we obtain an estimate of $\eta \in (-.2911, -.2274)$, using quasi-exogenous variation in yearly residential electricity tariffs post-crisis across distribution utilities in the Southeast/Midwest. Using this estimate, the average perceived incentive during the crisis was equivalent to a 55.3%-75.6% (.44-.563 log points) increase in residential electricity tariffs. Assuming a yearly discount factor of $\beta = .95$, the same persistent impact as above, and a 10-year horizon, the bias from neglecting hysteresis amounts to a net present value of R$4.44-R$6.08 billions (in R$ of 2012, or US$2.44-US$3.34 in US$ of 2012). This is of course a lower bound because the impact persisted beyond the 10-year horizon. To put this figure in perspective, it corresponds to 2.9%-3.9% of the discounted value of household electricity bills in the Southeast/Midwest, or 6.7-9.2 times the discounted budget of the energy efficiency program of the Brazilian government (PROCEL), over the same period.

7 Conclusion

This paper showed how one may overestimate the social cost of a corrective policy in the presence of hysteresis. We derived a lower bound for this bias that can be evaluated using one sufficient statistic: the long-term impacts of a similar but temporary policy that agents expected to be temporary. We estimated such a statistic by studying the 10-year impacts of a temporary policy in Brazil. In so doing, we provided evidence of the importance of hysteresis in a policy-relevant behavior: residential electricity use in a developing country context. Finally, incorporating our estimates into our theoretical framework illustrated that taking into account hysteresis may dramatically affect the cost-benefit analysis of corrective policies.

A limitation of our empirical analysis is that we cannot relate the impacts of the electricity saving program that we studied to one specific easily-replicable incentive scheme. Moreover, policymakers may not be interested in implementing permanently a similar policy. Yet, there is a lot of interest in reducing energy use and the main argument against implementing sizable corrective incentives 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 early 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 approach can be used to discuss the social cost of corrective policies in any context where hysteresis may be relevant. For instance, Bryan, Chowdhury and Mobarak (2014) experimentally 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. Let's suppose that the effect does not dissipate in later years. Incorporating these estimates into our theoretical framework then implies that, neglecting the possibility of hysteresis, one could overestimate the social costs of maintaining the migration incentives by 46.6%. 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. Using our framework, their estimates imply that, neglecting the possibility of hysteresis, one could overestimate the social cost of maintaining an incentive that would lead to similar short-run impacts by 900%. Policies that incentivize voter turnout in many countries may thus have a relatively low social cost.

References

Abadie, Alberto, Alexis Diamond, and Jens Hainmueller. 2010. "Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program." *Journal of the American Statistical Association*, 105(490): 493–505.

Acland, Dan, and Matthew R Levy. 2015. "Naiveté, projection bias, and habit formation in gym attendance." *Management Science*, 61(1): 146–160.

Allcott, Hunt, Allan Collard-Wexler, and Stephen D O'Connell. 2014. "How do electricity shortages affect productivity? Evidence from India." *NBER Working Paper 19977*.

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

ANEEL. 2005. "Tarifas de fornecimento de energia elétrica." *Agência Nacional de Energia Elétrica, Cadernos Temáticos ANEEL*, 4.

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

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

Bryan, Gharad, Shyamal Chowdhury, and Ahmed Mushfiq Mobarak. 2014. "Underinvestment in a Profitable Technology: The Case of Seasonal Migration in Bangladesh." *Econometrica*, 82(5): 1671–1748.

Cameron, C., J. Gelbach, and D. Miller. 2008. "Bootstrap-Based Improvements for Inference With Clustererd Errors." *Review of Economics and Statistics*, 90(3): 414Ð–427.

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

Davis, Lucas W, Alan Fuchs, and Paul Gertler. 2014. "Cash for coolers: evaluating a large–scale appliance replacement program in Mexico." *American Economic Journal: Economic Policy*, 6(4): 207–238.

Dixit, Avinash. 1989. "Entry and Exit Decisions under Uncertainty." *Journal of Political Economy*, 97: 620–638.

Dubin, Jeffrey, and Daniel McFadden. 1984. "An econometric analysis of residential electric appliance holdings and consumption." *Econometrica*, 345–362.

Dupas, Pascaline. 2014. "Short-Run Subsidies and Long-Run Adoption of New Health Products: Evidence From a Field Experiment." *Econometrica*, 82(1): 197–228.

Ferraro, Paul J, and Michael K Price. 2013. "Using nonpecuniary strategies to influence behavior: evidence from a large-scale field experiment." *Review of Economics and Statistics*, 95(1): 64–73.

Fisher-Vanden, Karen, Erin T Mansur, and Qiong Juliana Wang. 2015. "Electricity Shortages and Firm Productivity: Evidence from ChinaÕs Industrial Firms." *Journal of Development Economics*.

Fujiwara, Thomas, Kyle Meng, and Tom Vogl. 2014. "Estimating Habit Formation in Voting." *mimeo*.

Gerard, François. 2013. "What Changes Energy Consumption, and for How Long? New Evidence from the 2001 Brazilian Electricity Crisis." *RFF Discussion Paper 13–06, E3 Working Paper WP-050*.

Giné, Xavier, Dean Karlan, and Jonathan Zinman. 2010. "Put your money where your butt is: a commitment contract for smoking cessation." *American Economic Journal: Applied Economics*, 213–235.

Harberger, A. 1964. "The measurement of waste." *American Economic Review*, 54(3): 58Ð–76.

IPCC. 2014. "Climate Change 2014: IPCC Fifth Assessment Report."

Ito, Koichiro. 2012. "Do Consumers Respond to Marginal or Average Price? Evidence from Nonlinear Electricity Pricing." *Working Paper, Energy Institute @ Haas*, 210R.

Ito, K., T. Ida, and M. Tanaka. 2015. "The Persistence of Moral Suasion and Economic Incentives: Field Experimental Evidence From Energy Demand." *NBER Working Paper*, 20910.

Kelman, Jerson. 2001. "Desequilíbrio entre Oferta e Demanda de Energia Elétrica." *Relatório da Comissão de Análise do Sistema Hidrotérmico de Energia Elétrica*.

Kling, J., J. Liebman, and L. Katz. 2007. "Experimental Analysis of Neighborhood Effects." *Econometrica*, 75(1): 83–119.

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

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

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

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

Miller, Conrad. 2014. "The Persistent Effect of Temporary Affirmative Action." *Mimeo, Massachussets Institute of Technology*.

ONS. 2011. "Plano Decenal de Energia." *Technical report, Operador Nacional do Sistema Eletrico.*

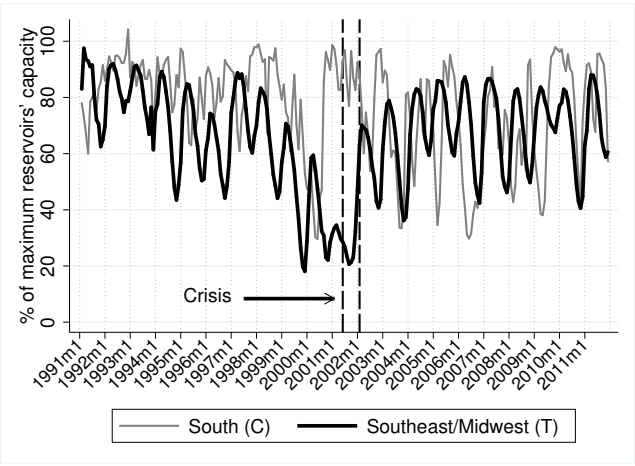
Pigou, Arthur. 1920. *The Economics of Welfare.* London: McMillan & Co.

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

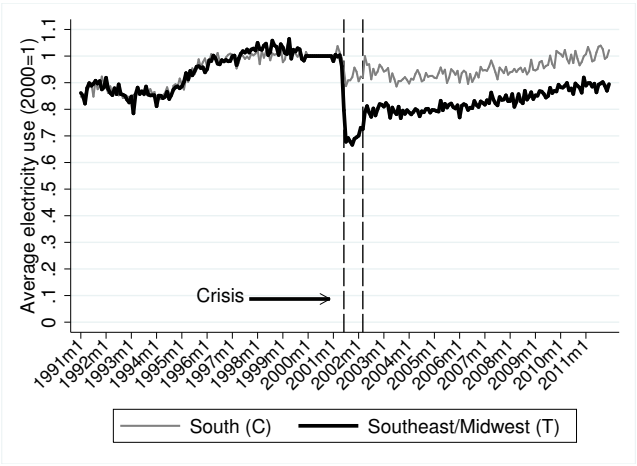
Zhou, Nan, David Fridley, Michael McNeil, Nina Zheng, Virginie Letschert, Jing Ke, and Yamina Saheb. 2011. "Analysis of potential energy saving and CO2 emission reduction of home appliances and commercial equipments in China." *Energy Policy*, 39(8): 4541–4550.

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

(a) Stocked energy of the hydroelectric reservoirs



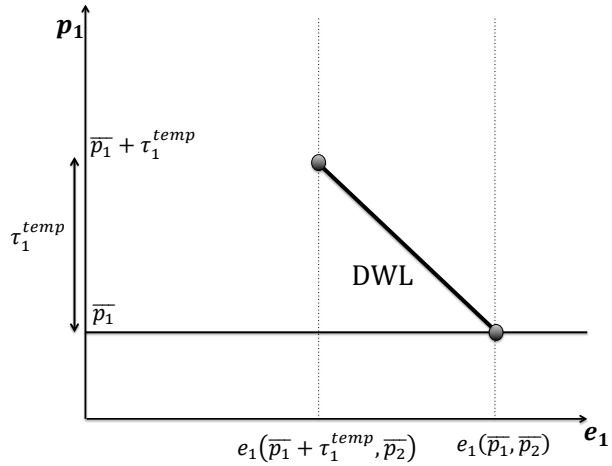
(b) Average residential electricity use



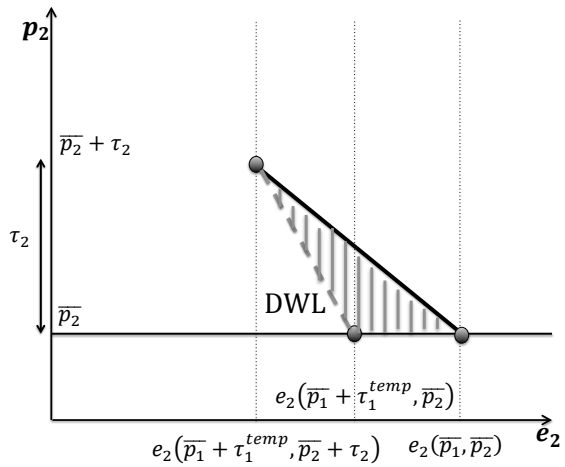
Panel (a) displays the evolution of hydro–reservoirs' capacity in the Southeast/Midwest and in the South (dotted lines indicate January; official data from ONS, the National System Operator). In the summer of 2000–2001, exceptionally low rainfall upstream of the reservoirs lead to dangerously low levels 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 impacts 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 impacts 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



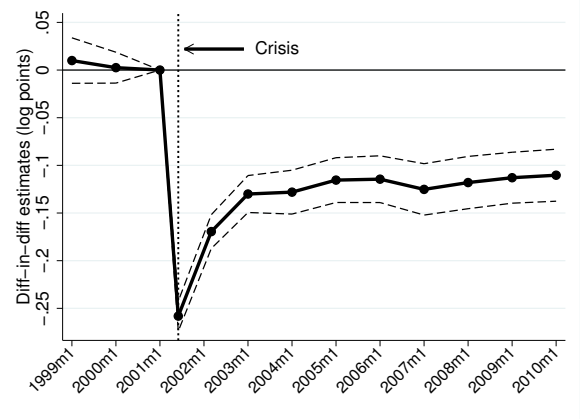
(b) Period 2



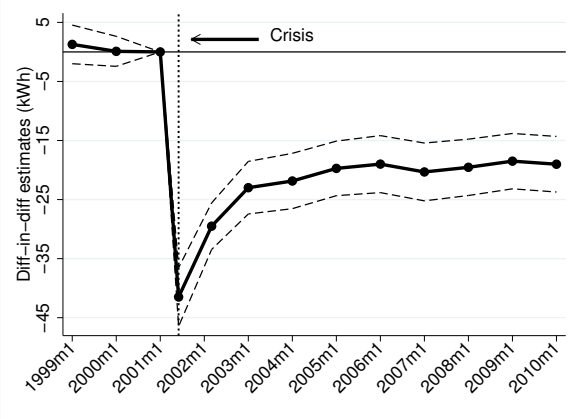
This figure illustrates how one would overestimate the deadweight loss of corrective policies in the presence of hysteresis. It considers our "alternative" policy where the government introduces a tax τ_1 as a temporary policy in period 2. The government then decides to impose a tax τ_2 in period 2, even though households expected the tax in period 1 to be temporary. Panel (a) displays the observed consumption level in period 1 under the policy, $e_1\left(\overline{p_1} + \tau_1^{temp}, \overline{p_2}\right)$, and the counterfactual consumption level had the policy never been implemented, $e_1\left(\overline{p_1}, \overline{p_2}\right)$. Panel (b) displays the same information for period 2, but also the counterfactual consumption level had the policy remained temporary, $e_2\left(\overline{p_1} + \tau_1^{temp}, \overline{p_2}\right)$. This level is lower than the counterfactual consumption level had the policy never been implemented because of hysteresis. In a standard Pigouvian framework, one would neglect the possibility of hysteresis and compute deadweight losses in both periods as the integral under the demand curves between observed consumption levels and counterfactual consumption levels had the policy never been implemented. However, in the presence of hysteresis, the deadweight loss in period 2 should be computed as the integral under the demand curves between observed consumption levels and counterfactual consumption levels had the policy remained temporary. The hatched area corresponds to the overestimation bias (using linear approximations for the unknown demand curves). As explained in the text, this is a lower bound for the equivalent bias in the case of our main policy of interest, in which incentives τ_1 and τ_2 are known since the beginning.

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

(a) in logs



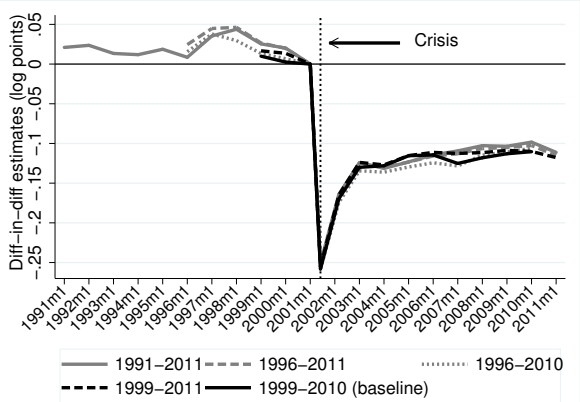
(b) in levels



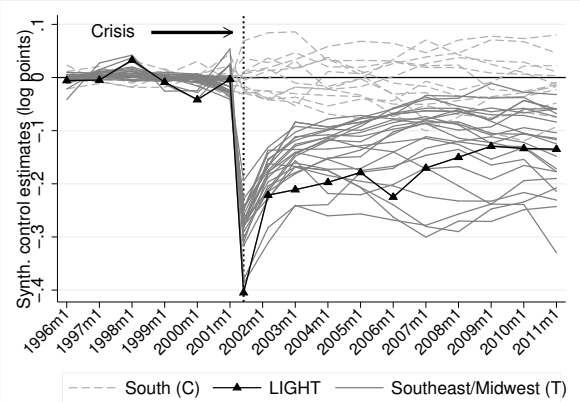
95% confidence interval in dash (s.e. clustered by utility). Utility-level administrative data for distribution utilities in the Southeast/Midwest and in the South from 1999 to 2010. The figures display coefficients from regressing the logarithm (panel a) or the level (panel b) of monthly average electricity 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)



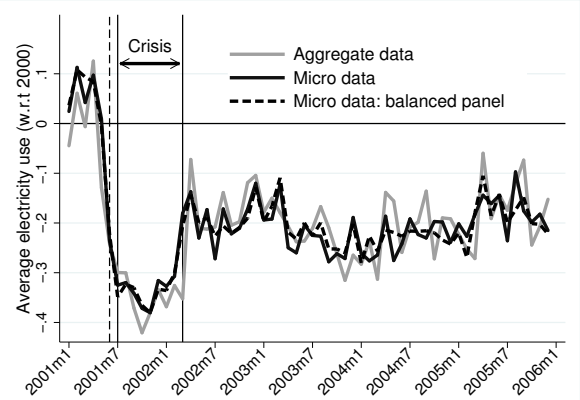
(b) Synthetic control estimates of utility–specific impacts (in logs)



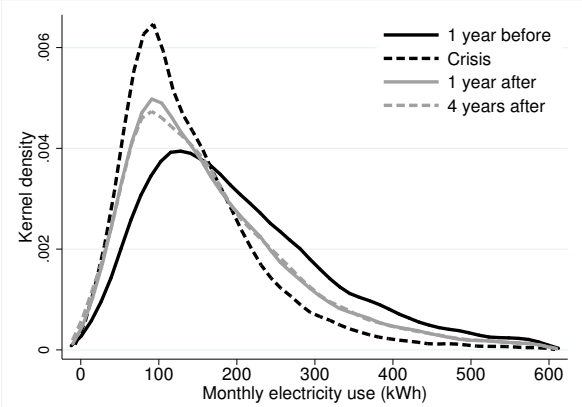
Panel (a) shows that our difference–in–difference estimates in Figure 3a are almost identical if we consider all the possible combinations of sample years determined by the availability of our yearly controls: 1991-2011 (no controls), 1996-2011 (tariffs and population), 1996-2010 (tariff, population, 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 impacts are large for all the distribution utilities subject to the electricity saving program, between -.19 and -.40 log points. Importantly, the long-run impacts are also negative for all those utilities. Our estimated average impacts are thus not driven by outliers. 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.

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

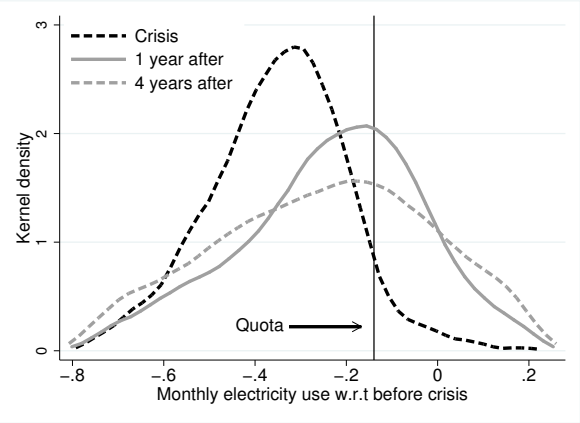
(a) Comparing time–series in average electricity using the utility-level data and the microdata



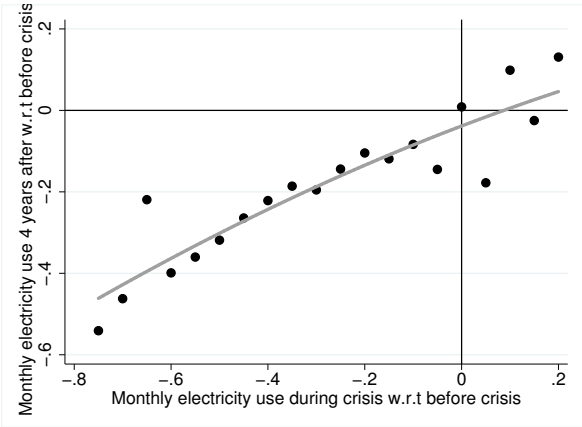
(b) Distribution of monthly electricity use over time for a balanced panel of customers



(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 impacts are 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

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

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: Log(yearly average household electricity consumption						
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 impacts 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 impacts are 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 Q.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 High Power	Appliance Always Switched On		Appliance Frequently Used	
			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 (10) 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:

$$\delta_{d,t} = Y_{d,t} - \sum_{c=1}^{c=C} w_{d,c}^{*} Y_{c,t} \tag{11}$$

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:

$$\| Y_{d0} - Y_{c0}W \| = \sqrt{(Y_{d0} - Y_{c0}W)' V (Y_{d0} - Y_{c0}W)} \tag{12}$$

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 discrete choice variable

We now show how our derivations based on a model with continuous variables hold with discrete choice variables instead.

For simplicity, we assume that there are only two choice variables in each period, ordinary consumption c and electricity consumption e. Moreover, we assume that e is now discrete. In particular, it can take two values: high ($e = 1$) or low ($e = 0$). Household k attaches value V^k to a high level of electricity consumption. Let $F(V)$denote the distribution of households' valuations. To allow for hysteresis in electricity use, we allow for the valuations in period 2 to depend on the level of electricity consumption in period 1. There are thus three possible valuations, V_1^k, V_{21}^k, and V_{20}^k, which are the valuations in period 1, in period 2 conditional on $e_1 = 1$, and in period 2 conditional on $e_1 = 1$.

The individual household problem is now:

$$\begin{aligned}\max_{e_1,e_2} U^k =& e_1 \left[y_1 - p_1 + V_1^k + \beta e_2 \left(y_2 - p_2 + V_{21}^k \right) + \beta (1 - e_2) y_2 \right] \\ &+ (1 - e_1) \left[y_1 + \beta e_2 \left(y_2 - p_2 + V_{20}^k \right) + \beta (1 - e_2) y_2 \right]\end{aligned}$$

With Pigouvian taxes (t_1, t_2), welfare is now defined as:

$$
\begin{aligned}
W(t_1,t_2) = & \int_{V_1^k} e_1 \left[y_1 - p_1 - t_1 + V_1^k + \int_{V_{21}^k} \left[\beta e_2 \left(y_2 - p_2 - t_2 + V_{21}^k \right) + \beta (1-e_2) y_2 \right] dF\left(V_{21}^k\right) \right] dF\left(V_1^k\right) \\
& + \int_{V_1^k} (1-e_1) \left[y_1 + \int_{V_{20}^k} \left[\beta e_2 \left(y_2 - p_2 - t_2 + V_{20}^k \right) + \beta (1-e_2) y_2 \right] dF\left(V_{20}^k\right) \right] dF\left(V_1^k\right) \\
& + t_1 \int_{V_1^k} e_1 dF\left(V_1^k\right) + \beta t_2 \int_{V_1^k} e_1 \left[\int_{V_{21}^k} e_2 dF\left(V_{21}^k\right) \right] + (1-e_1) \left[\int_{V_{20}^k} e_2 dF\left(V_{20}^k\right) \right] dF\left(V_1^k\right) \\
& + B(E_1,E_2),
\end{aligned}
$$

where E_1 and E_2 capture the aggregate level of electricity consumption in both periods (the share of households with a high level of electricity consumption). The problem is not smooth at the individual level but we can recast the problem as a social planner problem choosing the threshold above which households should consume a high level of electricity consumption:

$$
\begin{aligned}
W(t_1,t_2) = & \max_{\overline{V_1},\overline{V_{21}},\overline{V_{20}}} \int_{\overline{V_1}}^{\infty} \left[y_1 - p_1 - t_1 + V_1^k + \int_{\overline{V_{21}}}^{\infty} \beta \left(y_2 - p_2 - t_2 + V_{21}^k \right) dF\left(V_{21}^k\right) + \int_{-\infty}^{\overline{V_{21}}} \beta y_2 dF\left(V_{21}^k\right) \right] dF\left(V_1^k\right) \\
& + \int_{-\infty}^{\overline{V_1}} \left[y_1 + \int_{\overline{V_{20}}}^{\infty} \beta \left(y_2 - p_2 - t_2 + V_{20}^k \right) dF\left(V_{21}^k\right) + \int_{-\infty}^{\overline{V_{20}}} \beta y_2 dF\left(V_{20}^k\right) \right] dF\left(V_1^k\right) \\
& + \int_{\overline{V_1}}^{\infty} \left[t_1 + \int_{\overline{V_{21}}}^{\infty} \beta t_2 dF\left(V_{21}^k\right) \right] dF\left(V_1^k\right) + \int_{-\infty}^{\overline{V_1}} \int_{\overline{V_{21}}}^{\infty} \beta t_2 dF\left(V_{21}^k\right) dF\left(V_1^k\right) \\
& + B(E_1,E_2)
\end{aligned}
$$

Applying the envelope theorem on the planner problem, we now have:

$$
\begin{aligned}
\frac{dW}{dt} = & -\left(1 - F\left(\overline{V_1}\right)\right) + \left(1 - F\left(\overline{V_1}\right)\right) + t_1 \frac{\int_{\overline{V_1}}^{\infty} dF\left(V_1^k\right)}{dt} \\
& - \beta \left(1 - F\left(\overline{V_1}\right)\right)\left(1 - F\left(\overline{V_{21}}\right)\right) + \beta \left(1 - F\left(\overline{V_1}\right)\right)\left(1 - F\left(\overline{V_{21}}\right)\right) + \beta t_2 \frac{\int_{\overline{V_1}}^{\infty} \int_{\overline{V_{21}}}^{\infty} dF\left(V_{21}^k\right) dF\left(V_1^k\right)}{dt} \\
& - \beta F\left(\overline{V_1}\right)\left(1 - F\left(\overline{V_{20}}\right)\right) + \beta F\left(\overline{V_1}\right)\left(1 - F\left(\overline{V_{20}}\right)\right) + \beta t_2 \frac{\int_{-\infty}^{\overline{V_1}} \int_{\overline{V_{20}}}^{\infty} dF\left(V_{20}^k\right) dF\left(V_1^k\right)}{dt} \\
& + \frac{dB(E_1,E_2)}{dt} \\
= & t_1 \frac{\int_{\overline{V_1}}^{\infty} dF\left(V_1^k\right)}{dt} + \beta t_2 \left[\frac{\int_{\overline{V_1}}^{\infty} \int_{\overline{V_{21}}}^{\infty} dF\left(V_{21}^k\right) dF\left(V_1^k\right)}{dt} + \frac{\int_{-\infty}^{\overline{V_1}} \int_{\overline{V_{20}}}^{\infty} dF\left(V_{20}^k\right) dF\left(V_1^k\right)}{dt} \right] + \frac{dB(E_1,E_2)}{dt} \\
= & t_1 \frac{dE_1}{dt} + \beta t_2 \frac{dE_2}{dt} + \frac{dB(E_1,E_2)}{dt}
\end{aligned}
$$

The social cost or deadweight loss is the change in welfare minus any social benefit. We thus obtain a similar formula for the deadweight loss with the integral taken over the aggregate demand curve:

$$\mid DWL^{main} \mid = -\int_{(0,0)}^{(\tau_1,\tau_2)} \left[t_1 \frac{dE_1}{dt} + \beta t_2 \frac{dE_2}{dt} \right] dt,$$

which is well-defined as long as the aggregate demand curve is smooth. The other results then apply similarly.

C Model with household naive about future propensity to consume electricity

We now show the same derivations as in the paper for the case of a representative household who would not be aware of the impact of her current choices on her future propensity to consume electricity.

For simplicity, we assume that there are only two choice variables in each period, ordinary consumption c and electricity consumption e. The representative household now solves in period 1:

$$\begin{aligned} \max_{c_1^N, c_2^N, e_1^N, e_2^N} U^N = U_1^N + \beta U_2^N = c_1^N + v_1\left(e_1^N, s_1\right) + \beta\left[c_2^N + v_2\left(e_2^N, s_2^N\right)\right] \\ \text{s.t.} \quad c_i^N + p_i e_i^N \leq y_i; \quad s_1 = s\left(s_0, e_0\right); \quad s_2^N = s\left(s_0, e_0\right), \end{aligned}$$

where N indexes the choices of the household in period 2 according to her plans in period 1. However, in period 2, the household actually solves:

$$\begin{aligned} \max_{c_{2,}^A, e_2^A, , I_2^A} U_2^A = & c_2^A + v_2\left(e_2^A, s_2\right) \\ \text{s.t.} \quad & c_2^A + p_2 e_2^A \leq y_i; \quad ; \quad s_2 = s\left(s_1, e_1^N\right). \end{aligned}$$

We thus have the following first-order conditions:

$$\begin{aligned} & e_1^N : \frac{\partial v_1\left(e_1^N, s_1\right)}{\partial e_1^N} = p_1 \quad ; \quad e_2^N : \frac{\partial v_2\left(e_2^N, s_2^N\right)}{\partial e_2^N} = p_2; \\ & e_2^A : \frac{\partial v_2\left(e_2^A, s_2\right)}{\partial e_2^A} = p_2. \end{aligned}$$

With Pigouvian taxes, welfare is still defined as $W\left(t_1, t_2\right) = U\left(t_1, t_2\right) + t_1 e_1 + \beta t_2 e_2 + B\left(e_1, e_2\right)$ where U is defined as:

$$U = c_1^N + v_1\left(e_1^N, s_1\right) + \beta\left[c_2^A + v_2\left(e_2^A, s_2\right)\right].$$

We thus have:

$$\begin{aligned}
\frac{dW}{dt} =& \frac{dU}{dt} + t_1 \frac{de_1}{dt} + e_1 + \beta t_2 \frac{de_2}{dt} + \beta e_2 + \frac{dB(e_1,e_2)}{dt} \\
=& -e_1 + \left(\frac{\partial v_1}{\partial e_1} + \beta \frac{\partial v_2}{\partial s_2} \frac{\partial s_2}{\partial e_1} - p_1 - t_1 \right) \frac{de_1}{dt} \\
& - \beta e_2 + \beta \left(\frac{\partial v_2}{\partial e_2} - p_2 - t_2 \right) \frac{de_2}{dt} \\
& + t_1 \frac{de_1}{dt} + e_1 + \beta t_2 \frac{de_2}{dt} + \beta e_2 + \frac{dB(e_1,e_2)}{dt} \\
=& \left(\frac{\partial v_1\left(e_1^N, s_1\right)}{\partial e_1} + \beta \frac{\partial v_2\left(e_2^A, s_2\right)}{\partial s_2} \frac{\partial s_2}{\partial e_1} - \frac{\partial v_1\left(e_1^N, s_1\right)}{\partial e_1} \right) \frac{de_1}{dt} \\
& + \beta \left(\frac{\partial v_2\left(e_2^A, s_2\right)}{\partial e_2} - \frac{\partial v_2\left(e_2^A, s_2\right)}{\partial e_2} \right) \frac{de_2}{dt} \\
& + t_1 \frac{de_1}{dt} + \beta t_2 \frac{de_2}{dt} + \frac{dB(e_1,e_2)}{dt} \\
=& t_1 \frac{de_1}{dt} + \beta t_2 \frac{de_2}{dt} + \frac{dB(e_1,e_2)}{dt} + \left(\beta \frac{\partial v_2\left(e_2^A, s_2\right)}{\partial s_2} \frac{\partial s_2}{\partial e_1} \right) \frac{de_1}{dt}
\end{aligned} \tag{13}$$

The social benefits of the policy now include the same social benefits as before $\frac{dB(e_1,e_2)}{dt}$, but also the last expression in equation (13). This expression captures the correction of an *internality*. The representative household was not choosing a privately optimal level of consumption to begin with, by not considering the impact of period 1 consumption on the propensity to consume in period 2. However, the social cost or deadweight loss of the policy is still the change in welfare minus any social benefits, so we still have:

$$\mid DWL^{main} \mid = -\int_{(0,0)}^{(\tau_1,\tau_2)} \left[t_1 \frac{de_1}{dt} + \beta t_2 \frac{de_2}{dt} \right] dt.$$

The main difference now is that the agent chooses consumption levels in both periods independently. So the above expression becomes:

$$\mid DWL^{main} \mid = -\int_{(0,0)}^{(\tau_1,0)} t_1 \frac{de_1}{dt_1} dt_1 - \beta \int_{(\tau_1,0)}^{(\tau_1,\tau_2)} t_2 \frac{de_2}{dt_2} \mid_{(e_1)fixed} dt_2 = \mid DWL^{alt} \mid$$

The deadweight loss of our main policy of interest and of our alternative policy are equivalent in this case. Naive households act as if the Pigouvian tax in period 1 was a temporary policy. In this case, we would still overestimate the deadweight loss by not considering the possibility of hysteresis in electricity use. However, the key statistic to approximate the actual bias (and not a bound anymore) is now the persistent impact of τ_1 whether it was known-to-be temporary or not.

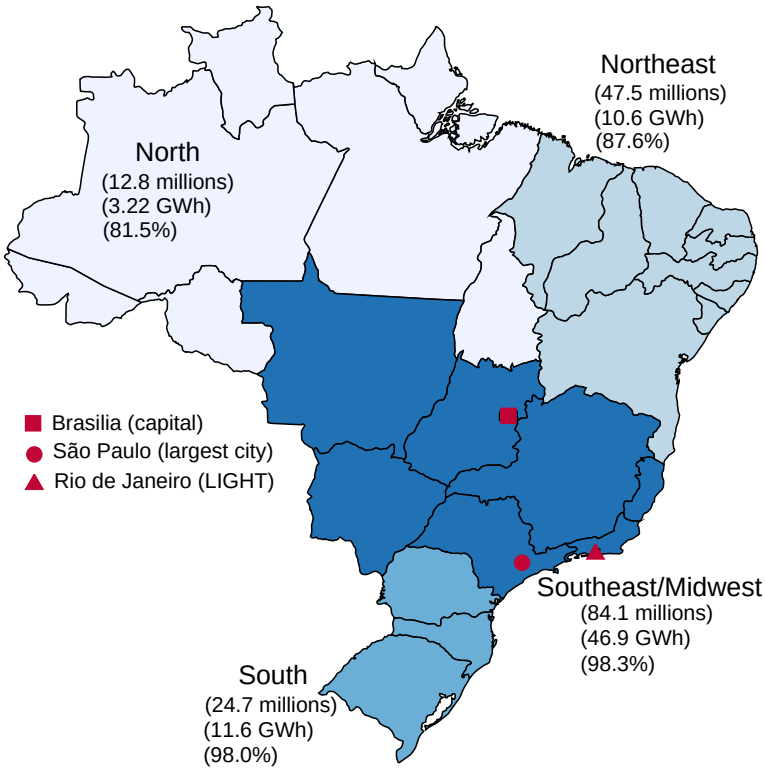
In practice, the need to consider a policy than was known-to-be temporary will arise as long as some households are not completely naive about the influence of their current choices on their future propensity to consume.

D The causes of the 2001 Brazilian electricity crisis

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

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

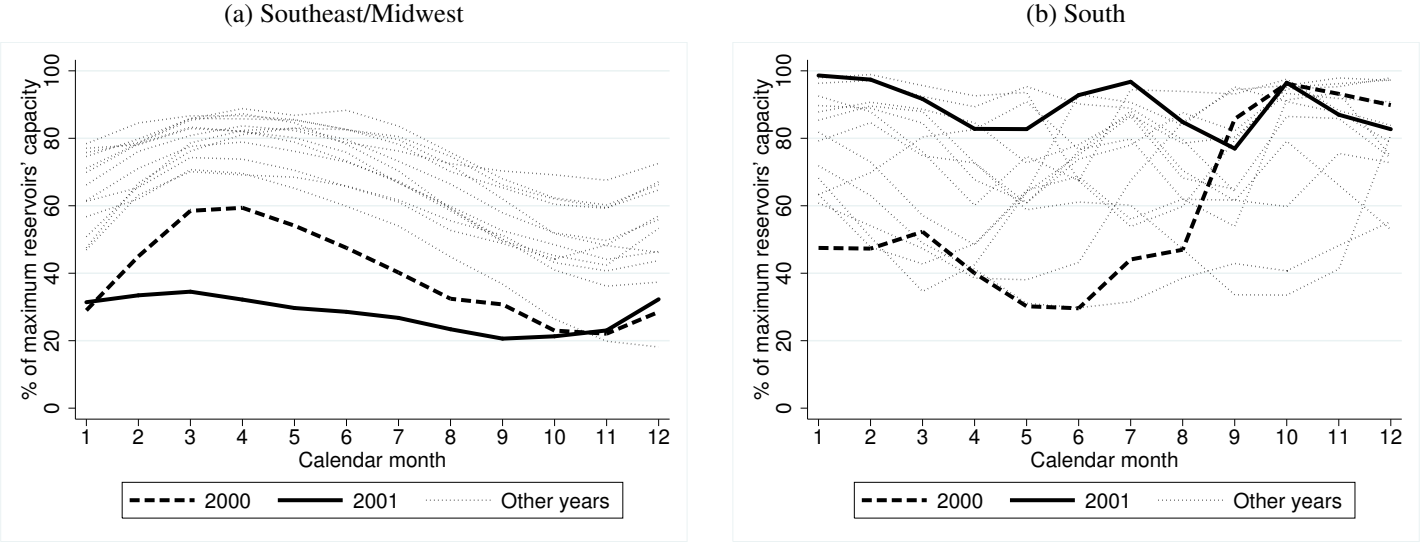


This map presents the four subsystems of the National Interconnected System of Brazil. The first number in parenthesis is the population, the second number is the total residential energy consumption in 2000, and the third is the percentage of households connected to electricity. The three red markers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

Figure D.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 D.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 D.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 D.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.

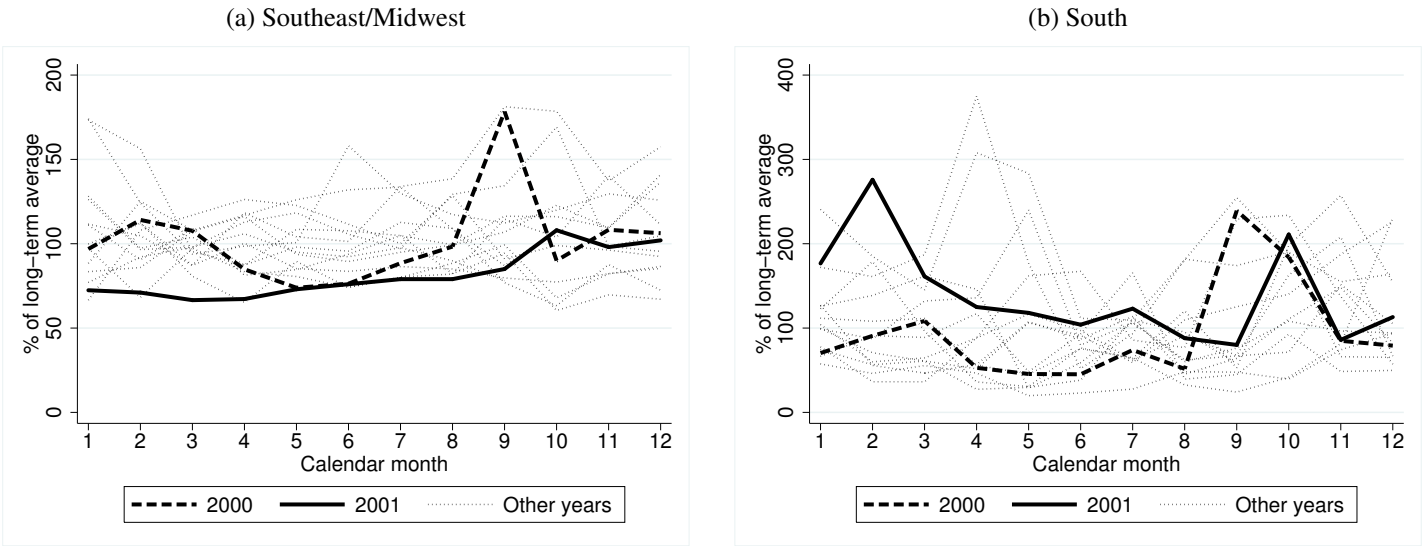
Figure D.2: Stocked energy of the reservoirs by calendar month



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).

Table D.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

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



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.

in the differential treatment across subsystems.

Table D.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.

E 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.[39]

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 afterwards.

Apr 2001 The Priority Thermal Program (PPT) fails and MME starts designing the load reduction program.[40]

May 2001 Government announces temporary electricity saving program to be implemented in June 4. This announcement receives a lot of attention from the media.[41]

Jun 2001 Household incentives are implemented.

[39] 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".

[40] "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)

[41] 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" (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 light bulb's prices" (B7, 01/06/2001).

Feb 2002 Household fines and threat of electricity cuts are suspended.[42]

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

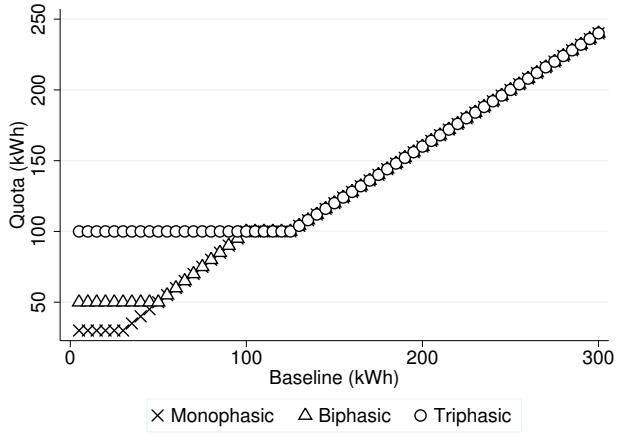
[42] "Rain brings relief to reservoirs" (Folha de São Paulo, B1, 03/01/2002).

F The electricity saving program

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

Figure F.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 F.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.

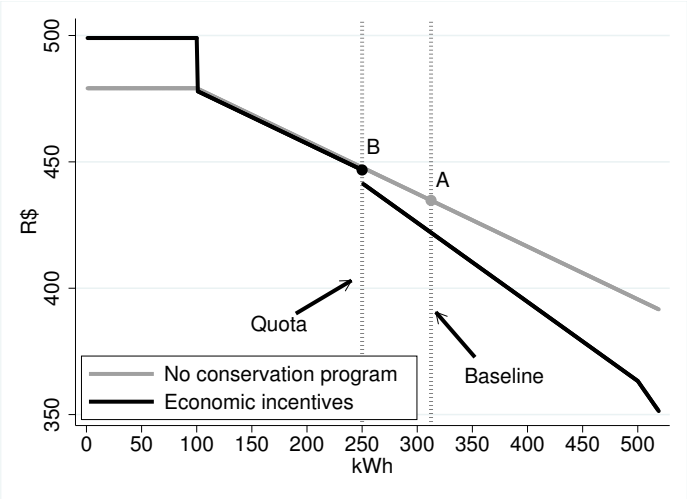
Figure F.1: Quota assignment rule of the electricity saving program



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

Figure F.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 F.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).

G Additional descriptive statistics (end of Table 1)

Table G.1 diplays 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 distibution 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 G.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 G.1: Additional descriptive statistics for distribution utilities in the four subsystems

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

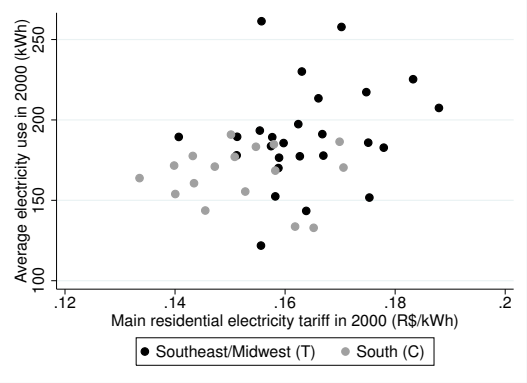
Utility-level administrative data for distribution utilities in the four subsystems in 2000 and 2010 and census data matched to the concession area of these utilities in the same years. Columns (1)–(5) display descriptive statistics in 2000 (prior to the crisis) for the variables listed in the left–hand 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 North–East (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 South–East/Midwest (column 6), in the North–East (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.

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

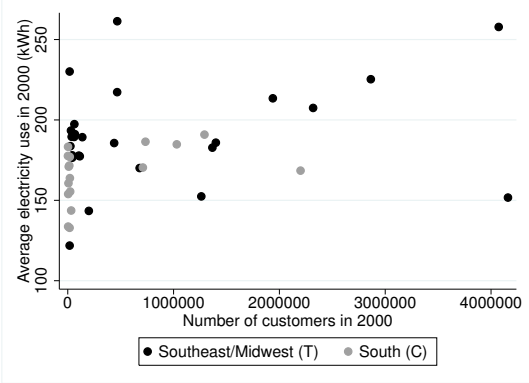
The following figures diplay the joint distribution of average residential electricity use per customer and relevant covariates before the crisis among distribution utilities in the Southeast/Midwest and in the South. We present figures for all the variables displayed in Tables 1 and G.1. The data come 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 H.1: Joint distribution of average electricity use and relevant covariates before the crisis I (2000)

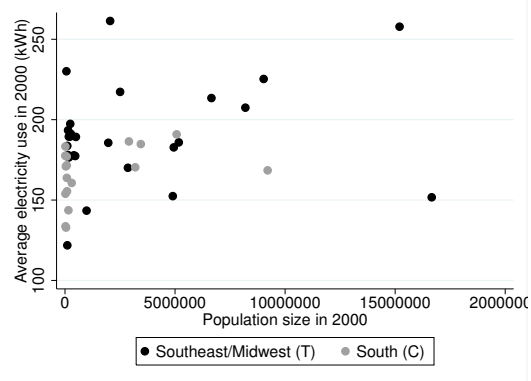
(a) Main residential electricity tariff



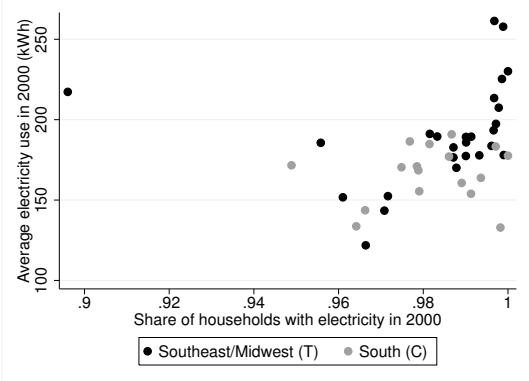
(b) Number of customers



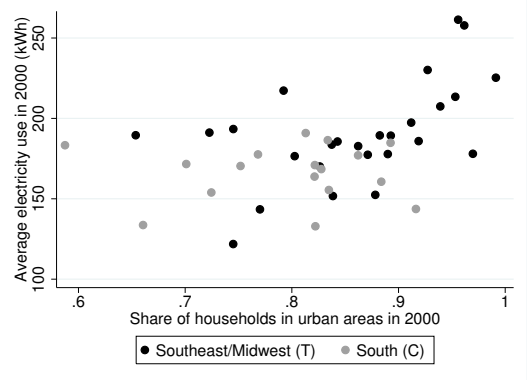
(c) Population size



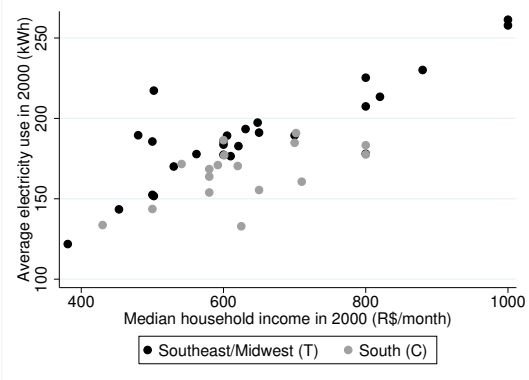
(d) Share with electricity



(e) Share urban



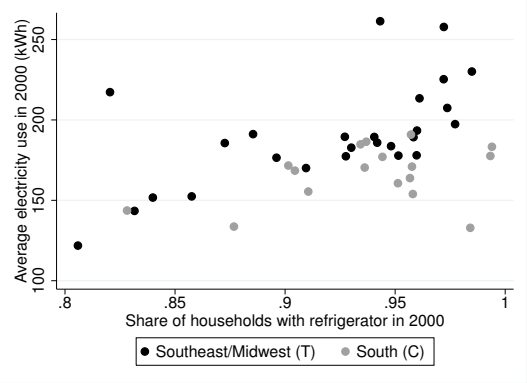
(f) Median household income



Each observation corresponds to a distribution utility and its concession area. The panels diplay 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 H.2: Joint distribution of average electricity use and relevant covariates before the crisis II (2000)

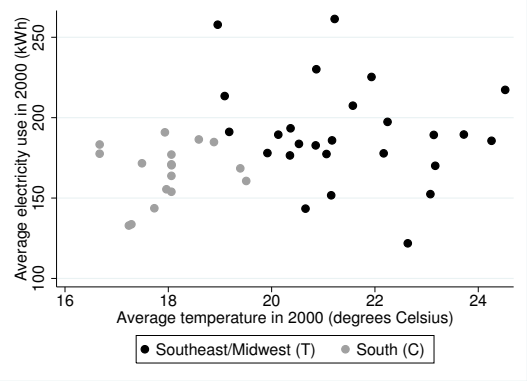
(a) Share with refrigerator



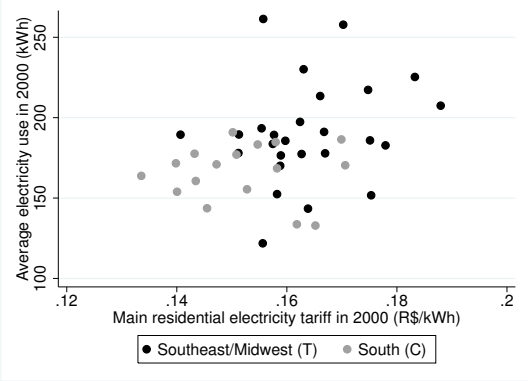
(b) Share with washing machine



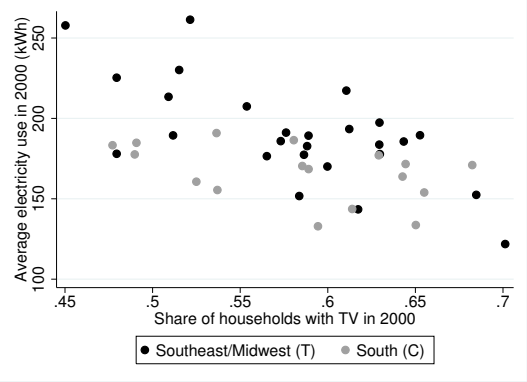
(c) Average temperature



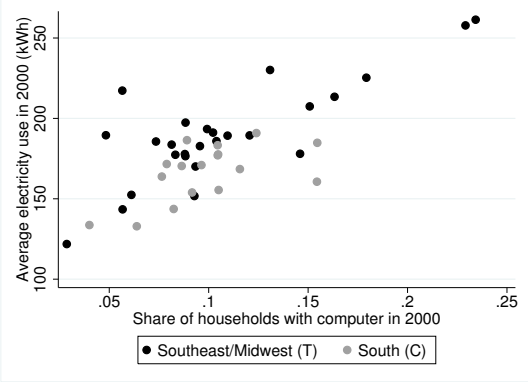
(d) Average residential electricity price



(e) Share with TV



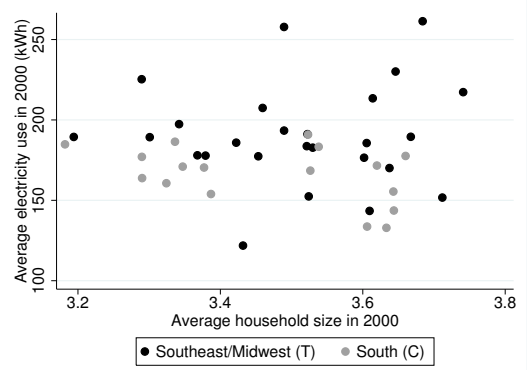
(f) Share with computer



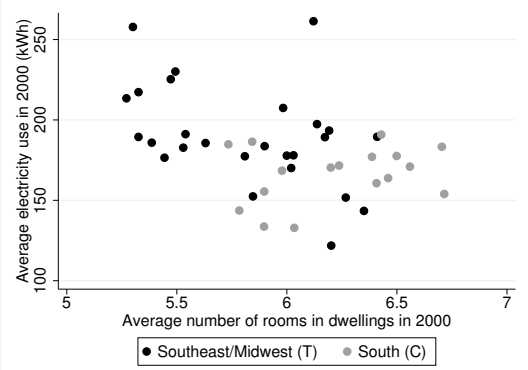
Each observation corresponds to a distribution utility and its concession area. The panels diplay the joint distribution of average residential electricity use per customer and relevant covariates before the crisis (2000) among distribution utilities in the Southeast/Midwest and in the South. In 2000,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

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

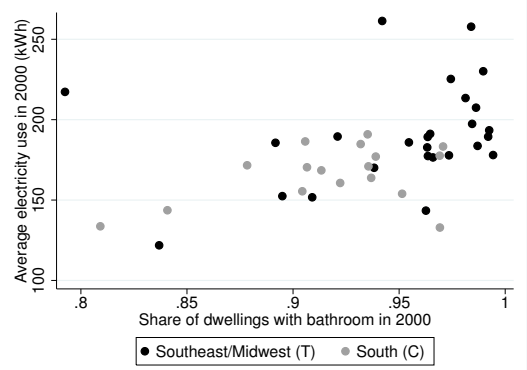
(a) Average household size



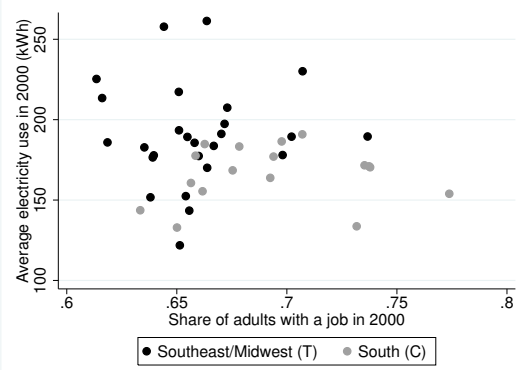
(b) Average dwelling size



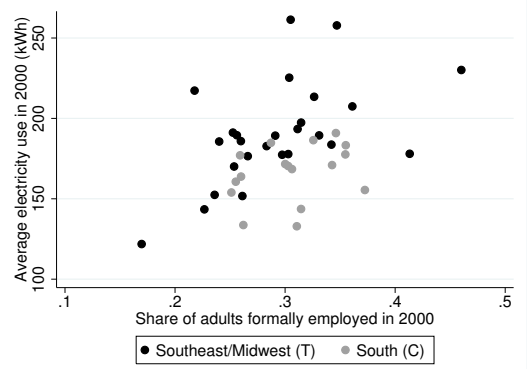
(c) Share with bathroom



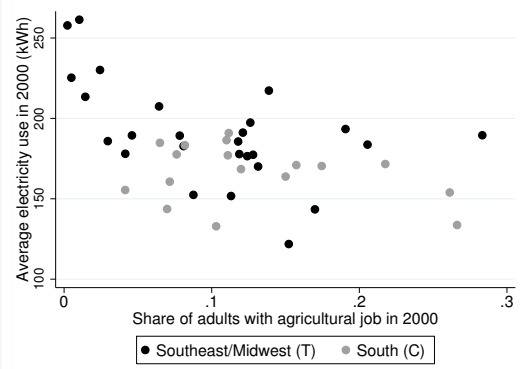
(d) Share employed



(e) Share formally employed



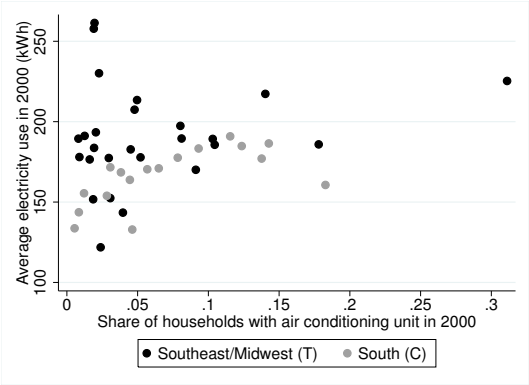
(f) Share with agricultural job



Each observation corresponds to a distribution utility and its concession area. The panels diplay 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 H.4: Joint distribution of average electricity use and relevant covariates before the crisis IV (2000)

(a) Share with air conditioning



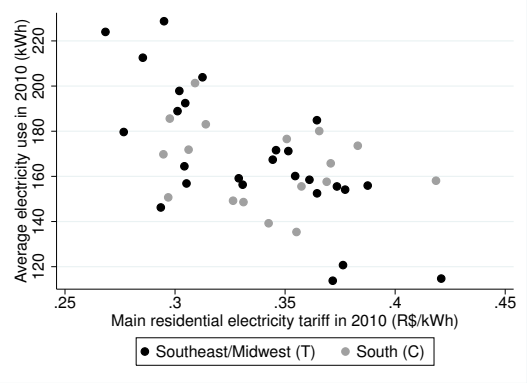
Each observation corresponds to a distribution utility and its concession area. The panels diplay the joint distribution of average residential electricity use per customer and relevant covariates before the crisis (2000) among distribution utilities in the Southeast/Midwest and in the South. In 2000,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

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

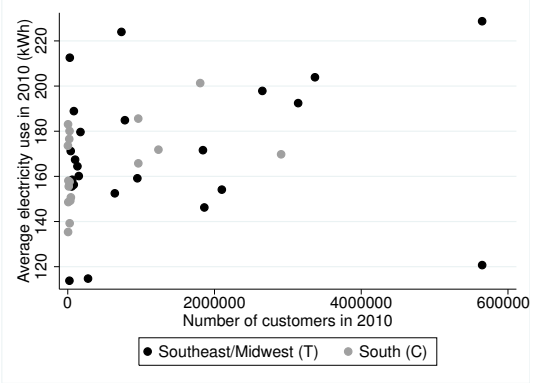
The following figures display the joint distribution of average residential electricity use per customer and relevant covariates after the crisis among distribution utilities in the Southeast/Midwest and in the South. We present figures for all the variables displayed in Tables 1 and G.1. The data come 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 I.1: Joint distribution of average electricity use and relevant covariates after the crisis I (2010)

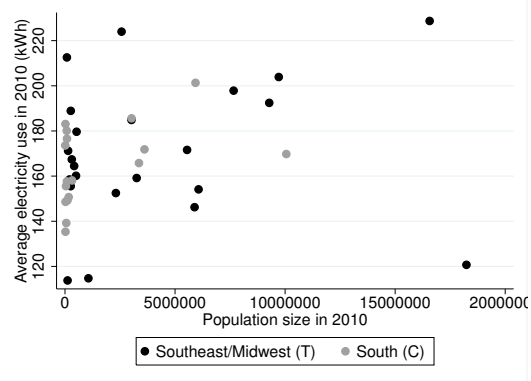
(a) Main residential electricity tariff



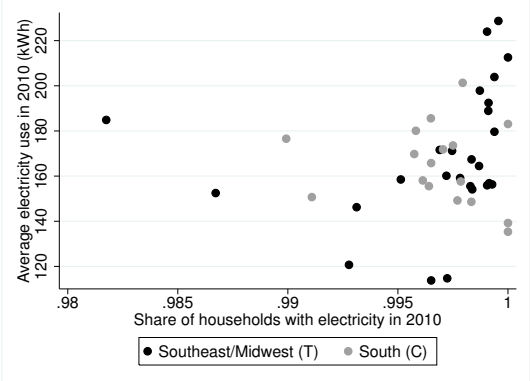
(b) Number of customers



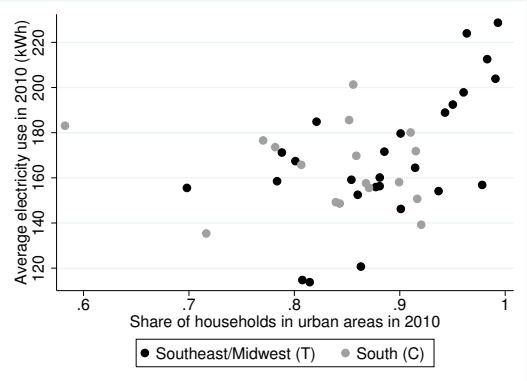
(c) Population size



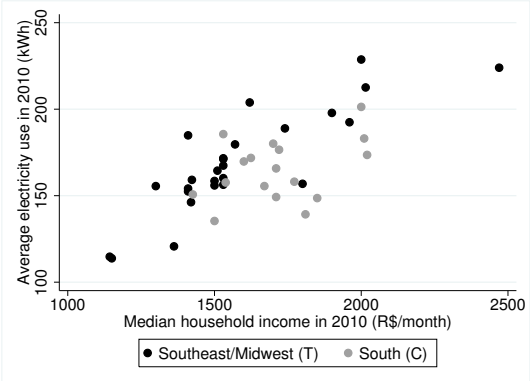
(d) Share with electricity



(e) Share urban

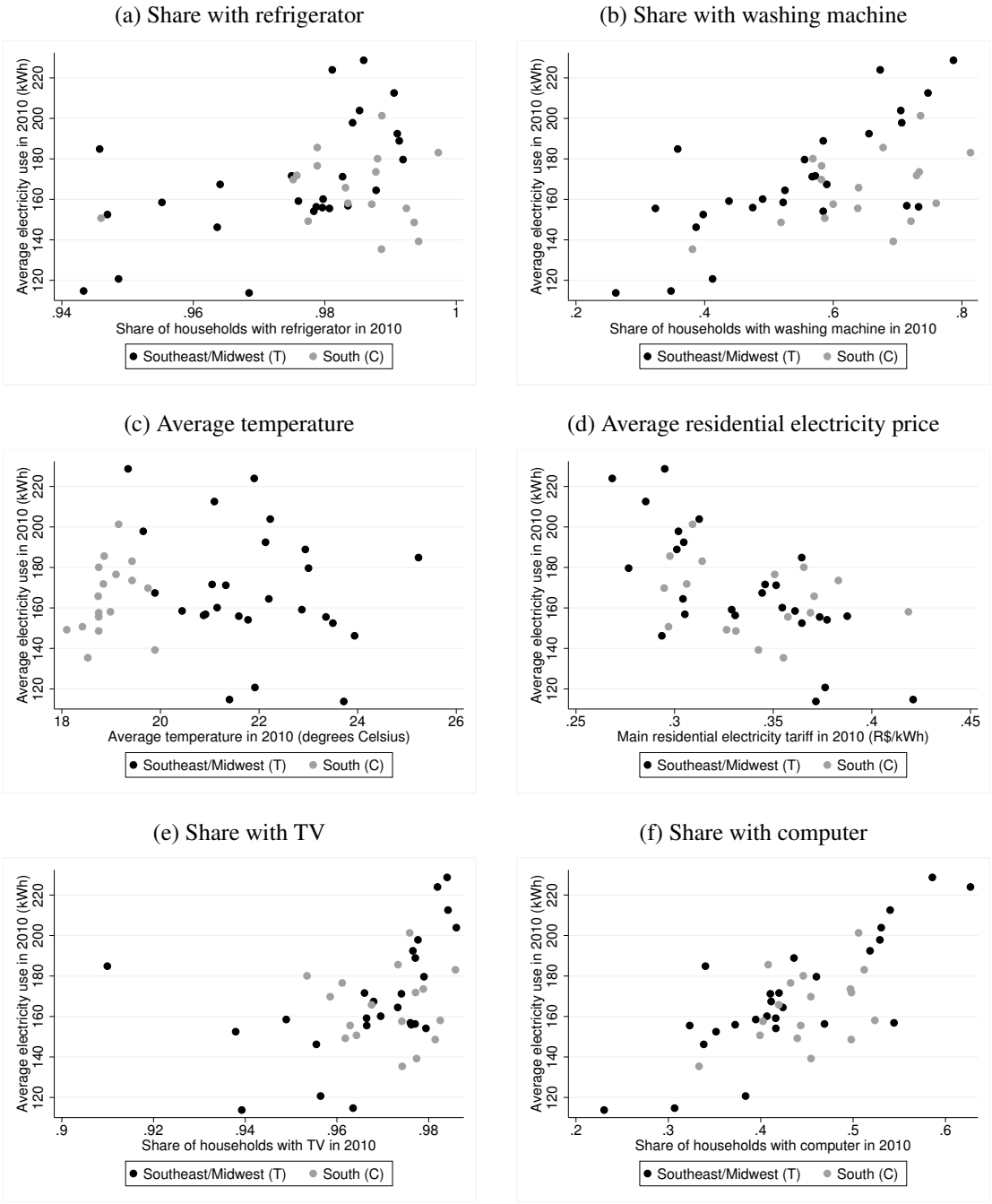


(f) Median household income



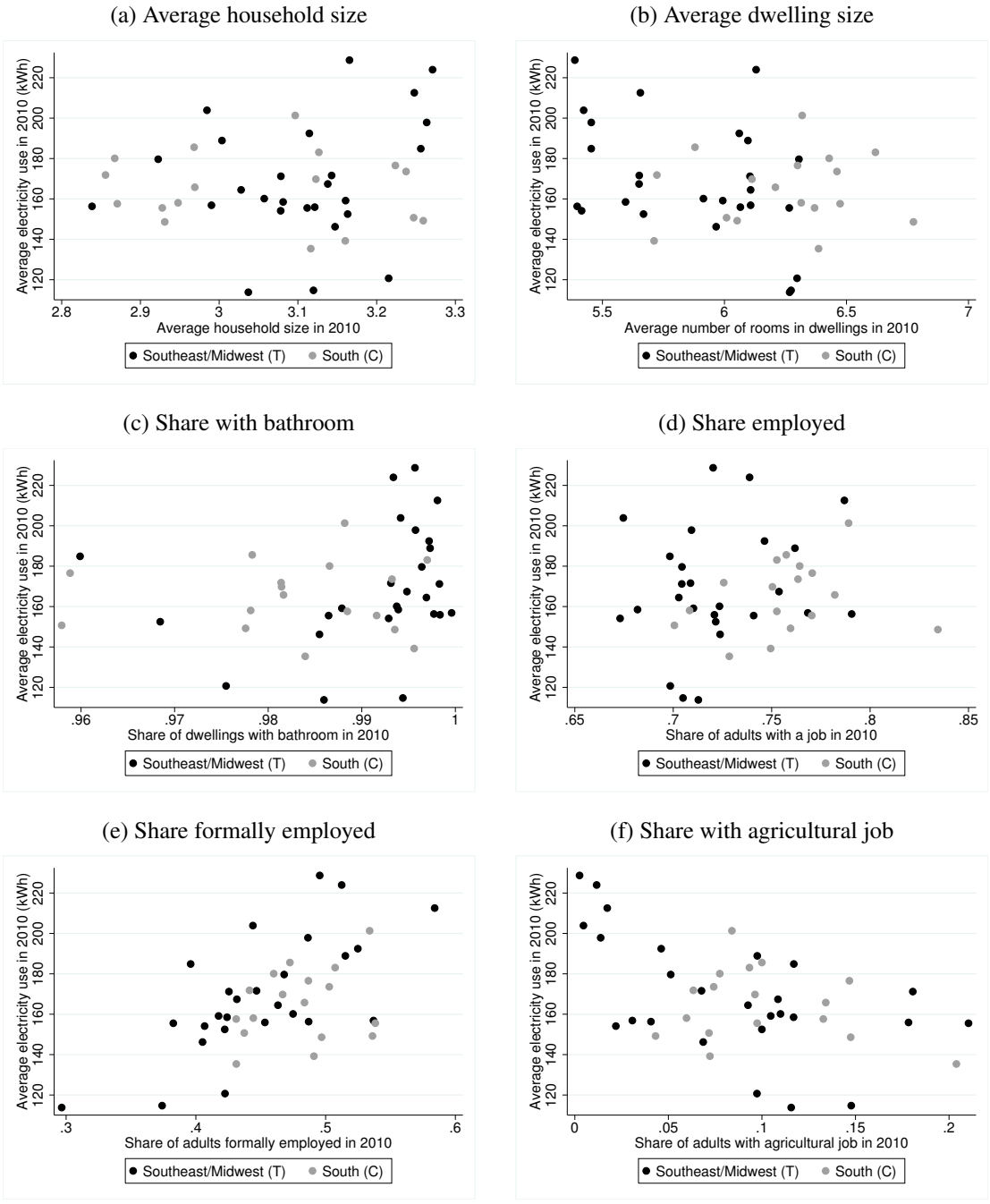
Each observation corresponds to a distribution utility and its concession area. The panels diplay the joint distribution of average residential electricity use per customer and relevant covariates before the crisis (2000) among distribution utilities in the Southeast/Midwest and in the South. In 2010,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

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



Each observation corresponds to a distribution utility and its concession area. The panels diplay 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 I.3: Joint distribution of average electricity use and relevant covariates after the crisis III (2010)

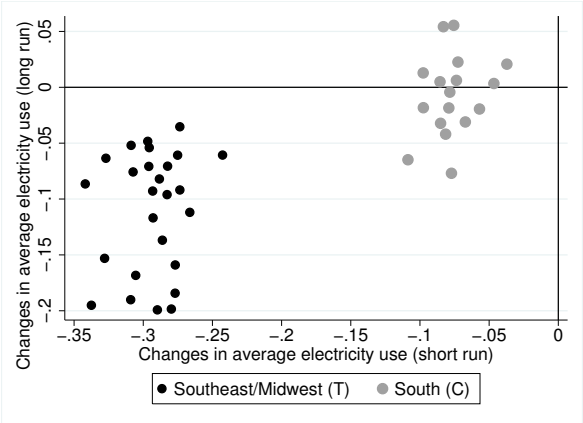


Each observation corresponds to a distribution utility and its concession area. The panels diplay the joint distribution of average residential electricity use per customer and relevant covariates before the crisis (2000) among distribution utilities in the Southeast/Midwest and in the South. In 2010,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

J Changes in average electricity during and after the crisis

Figure J.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 J.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: $\Delta y = \left(y_{during/after} - y_{before}\right)/y_{before}$.

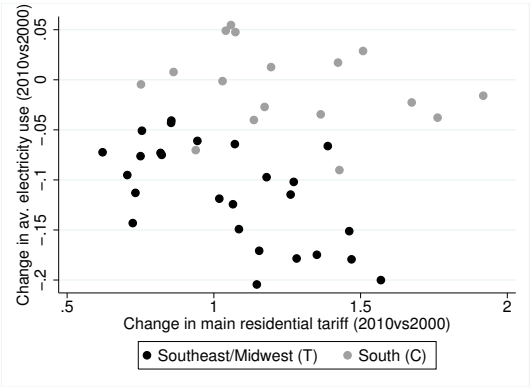
K The joint distribution of long-run changes in average electricity use and relevant covariates (2010 vs. 2000) among distribution utilities

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 G.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

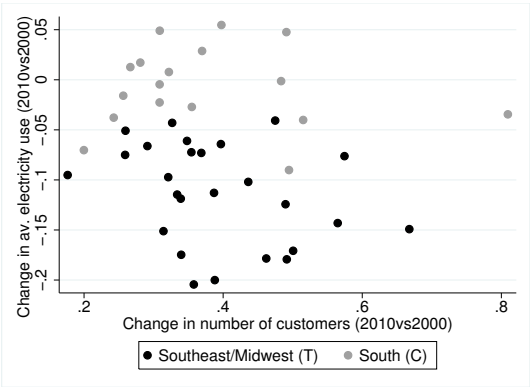
lower in the Southeast/Midwest than in the South for given long-run changes in those covariates. This explains why our results are robust to controlling for relevant covariates in Table 2.

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

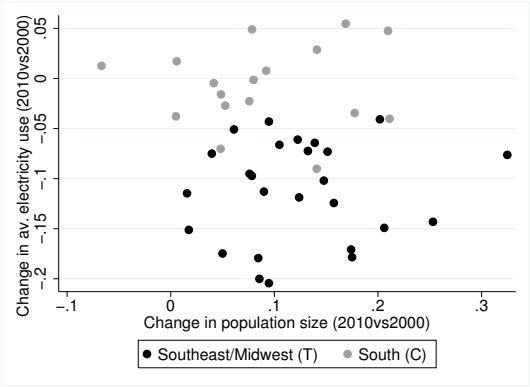
(a) Changes in main residential electricity tariff



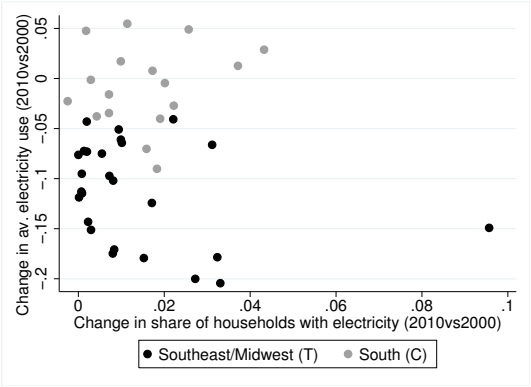
(b) Changes in number of customers



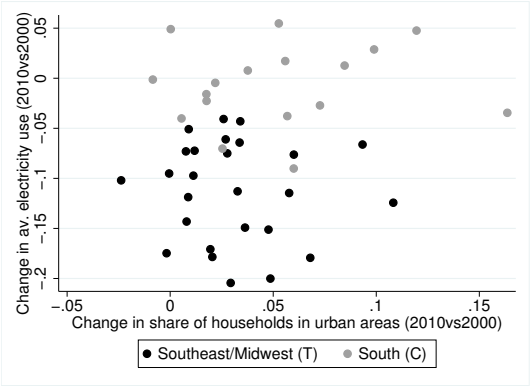
(c) Changes in population size



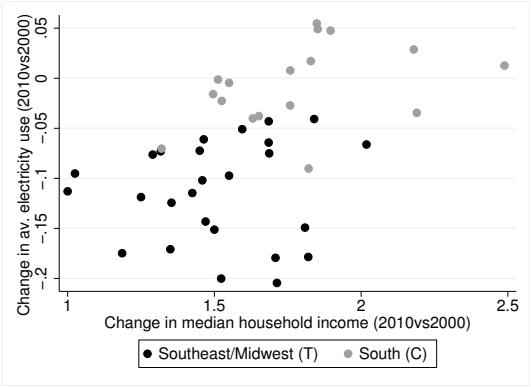
(d) Changes in share with electricity



(e) Changes in share urban



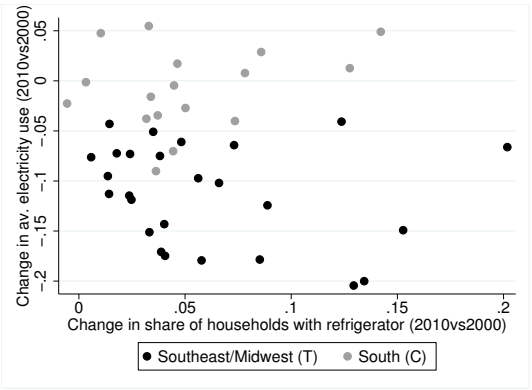
(f) Changes in median household income



The panels diplay 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 K.2: Long-run changes in average electricity use and in relevant covariates II

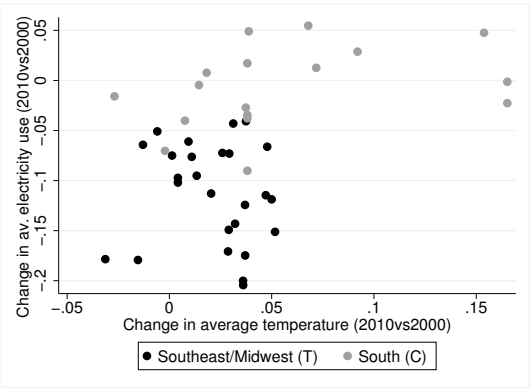
(a) Changes in share with refrigerator



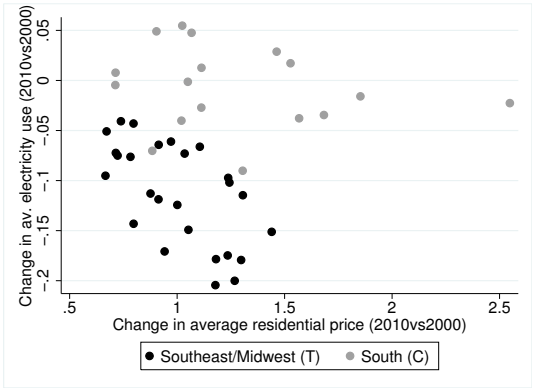
(b) Changes in share with washing machine



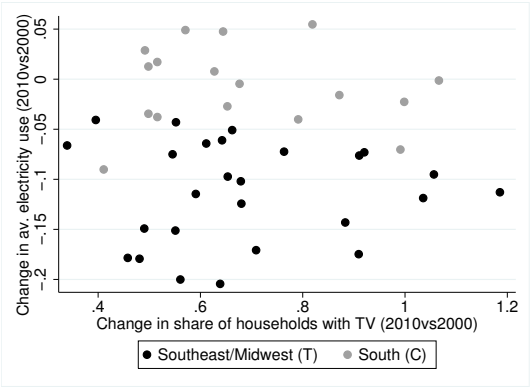
(c) Changes in average temperature



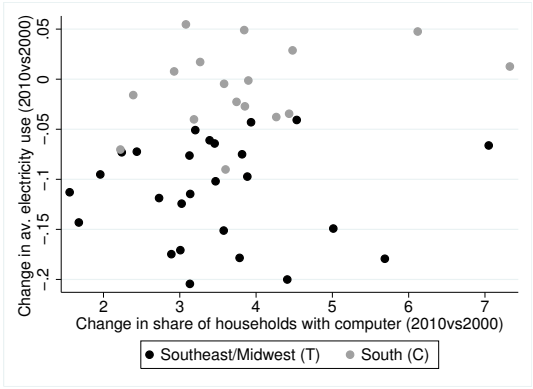
(d) Changes in average residential elecitricity price



(e) Changes in share with TV



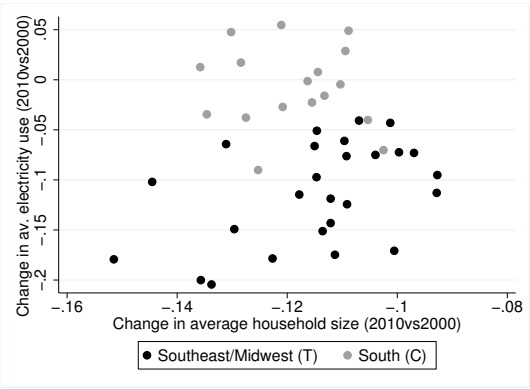
(f) Changes in share with computer



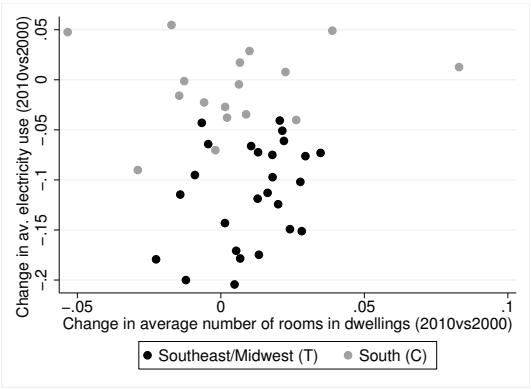
The panels diplay the joint distribution of long-run changes in average residential electricity use per customer and in relevant covariates between 2010 (after the crisis) and 2000 (before the crisis) among distribution utilities in the Southeast/Midwest and in the South. Long-run changes for a variable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

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

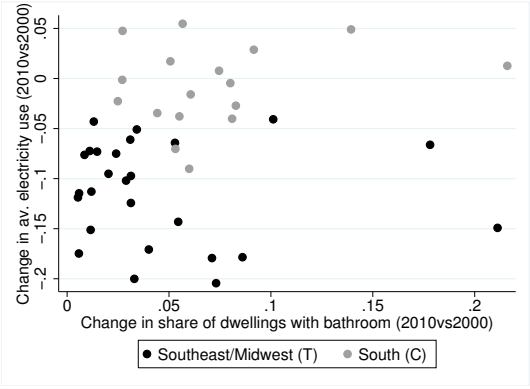
(a) Changes in average household size



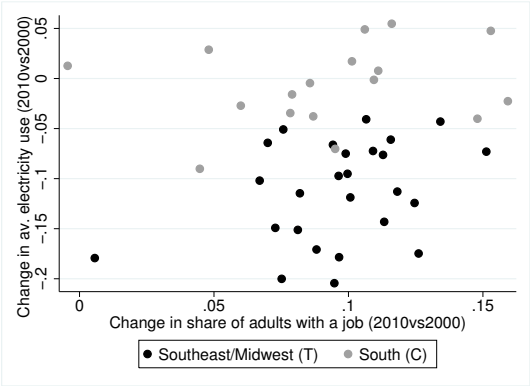
(b) Changes in average dwelling size



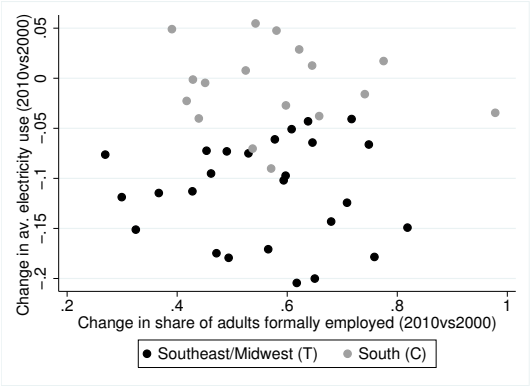
(c) Changes in share with bathroom



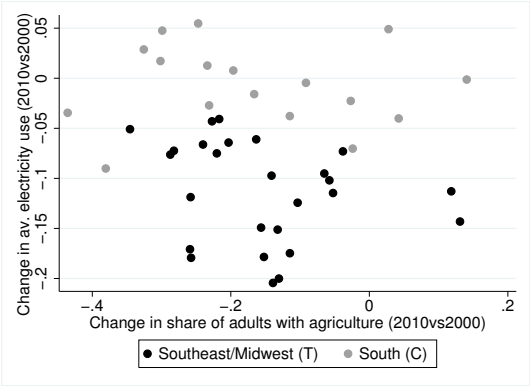
(d) Changes in share employed



(e) Changes in share formally employed



(f) Changes in share with agricultural job



The panels diplay 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: $\Delta y = (y_{2010} - y_{2000})/y_{2000}$.

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

The following tables diplay 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 L.1 and L.2 are those presented in Figures 3. Difference-in-difference estimates in column (2) in Tables L.1, L.3, L.5, L.7, and L.9 are those presented in Figure 4a.

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

	Control region		Treatment region dummy			
	(1)		(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 L.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 L.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 L.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 L.5: Difference–in–difference results in logs (1996-2011)

	Control region		Treatment region dummy			
	(1)		(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 L.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 L.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 L.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 L.9: Difference–in–difference results in logs (1999–2011)

	Control region		Treatment region dummy			
	(1)		(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 L.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.

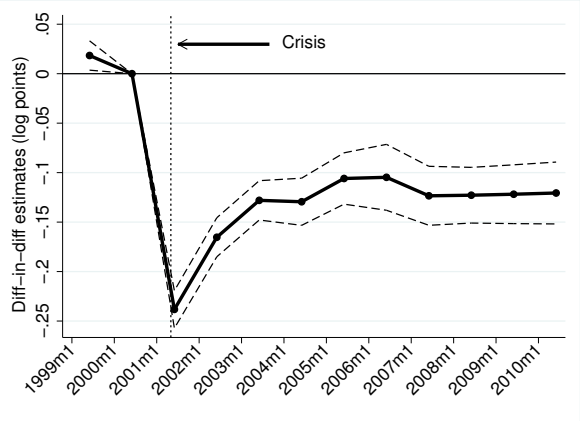
M Robustness of difference-in-difference results

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

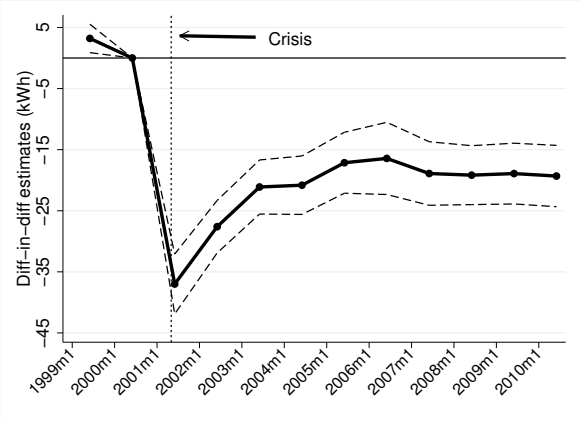
Figure M.1 and Tables M.1, M.2, M.3, and M.4 display similar results as in Figure 3 and Tables L.1 and L.2, splitting the sample between winter and summer months. The reference periods are the winter of 2000 and the summer of 2000-2001 (starting in 2000), respectively. We obtain similar effects across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

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

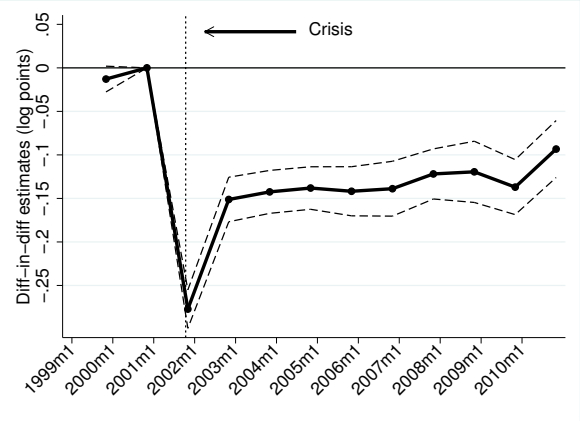
(a) in logs, winter



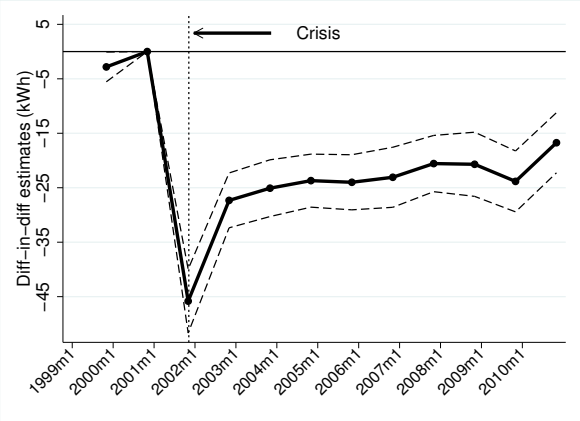
(b) in levels, winter



(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 M.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 M.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 M.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.

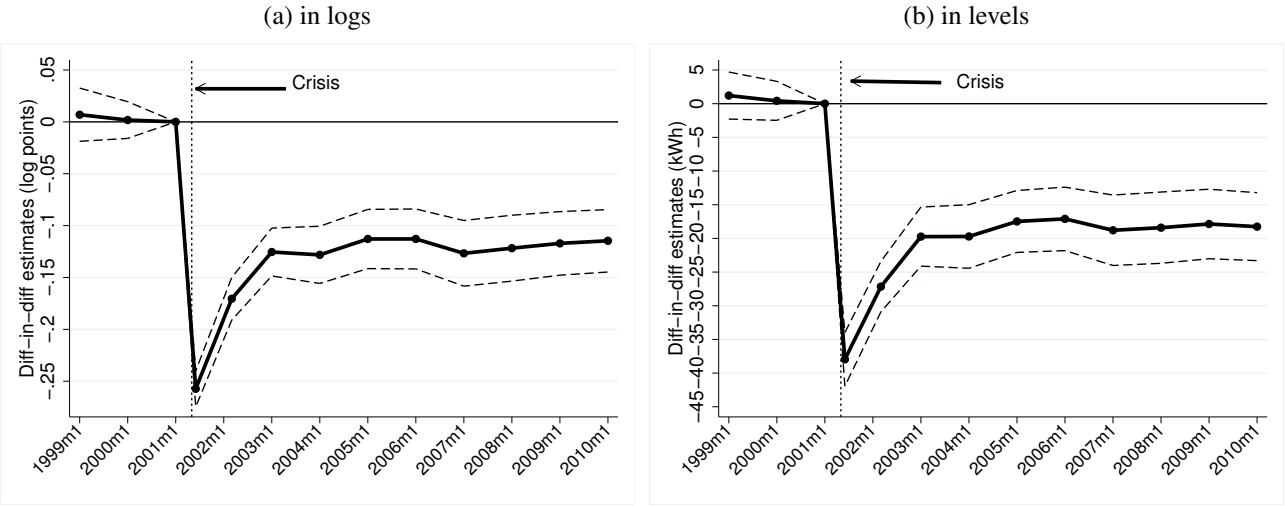
Table M.4: Difference–in–difference results for summer months in levels (1999–2010)

	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 M.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 L.1 and L.2 above. Results are similar when we restrict the sample this way.

Figure M.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)



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 M.2 and Tables M.5, M.6 display similar results as in Figure 3 and Tables L.1 and L.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 M.4 also displays the overall impacts 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 M.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	

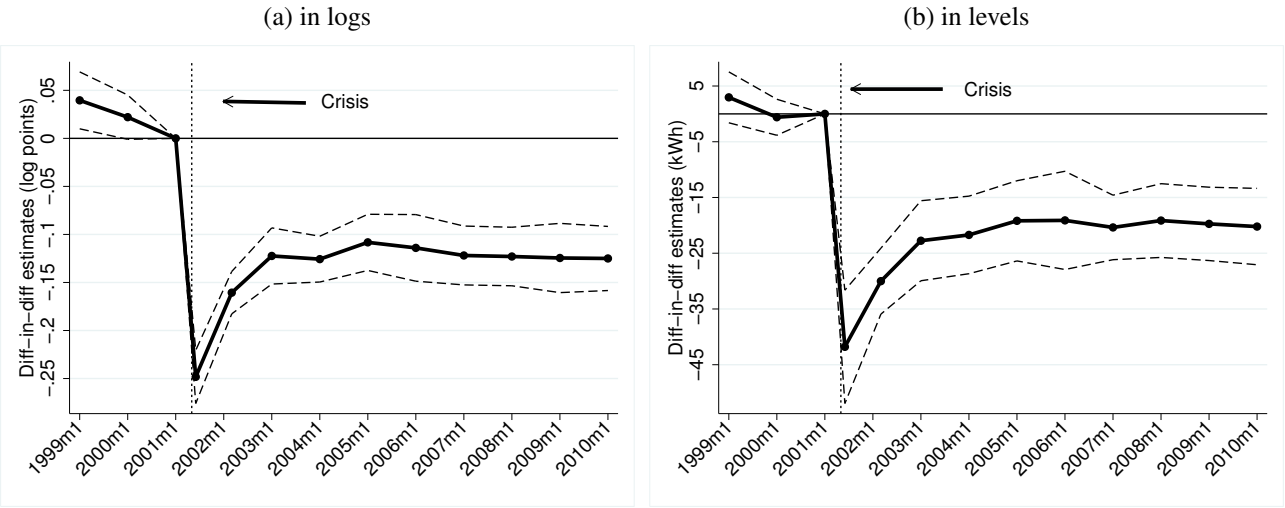
Units of observation: distribution utilities as of 1999. Significance levels: *10%, **5%, ***1% (s.e. clustered by utility). Data from 1999 to 2010. Results from specifications including utility and calendar month per region fixed effects. Regressions also control for the main electricity tariff (monthly, 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 M.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	

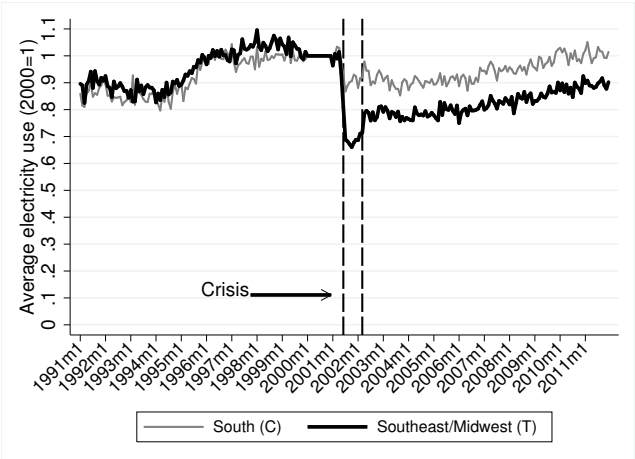
Units of observation: distribution utilities as of 1999. Significance levels: *10%, **5%, ***1% (s.e. clustered by utility). Data from 1999 to 2010. Results from specifications including utility and calendar month per region fixed effects. Regressions also control for the main electricity tariff (monthly, 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 M.3: Robustness of difference–in–difference results (distribution utilities weighted by their customer base pre-crisis)



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



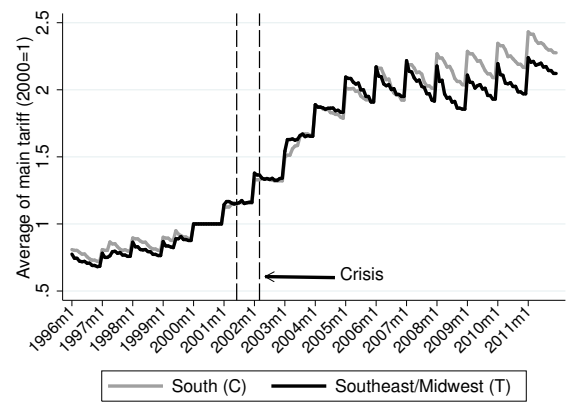
The figure displays the overall impacts of the electricity saving program as in Figure **??**, but presenting weighted averages in each month, normalized with respect to the same month in 2000 (seasonality).

N Trends in the main residential electricity tariff

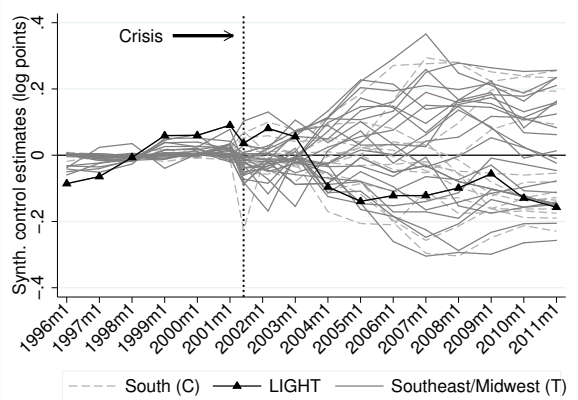
Figure N.1 shows that trends in the main residential electricity tariff did not evolve differentially for distribution utilities in the Southeast/Midwest compared to distribution utilities in the South after the crisis. Panel (a) is constructed similarly as Figure 1b, but it displays the average of the 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 N.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.

O 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 O.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 O.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	

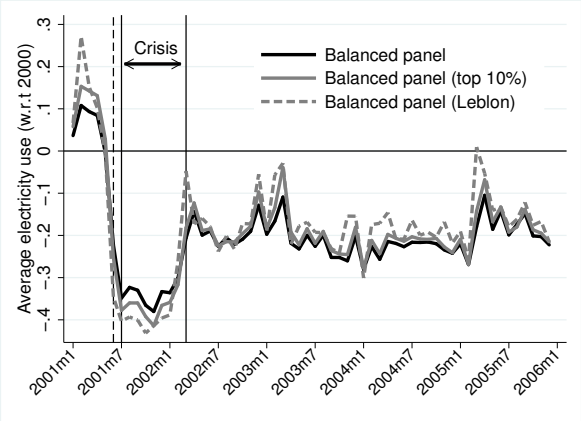
Significance levels: *10%, **5%, ***1% (s.e. clustered by utility in parentheses). Data for 24 distribution utilities in the South–East/Midwest (13) and in the South (11) reporting technical and non–technical losses prior to 2000. Yearly data from 1998 to 2008. Distribution losses are the share of the 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.

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

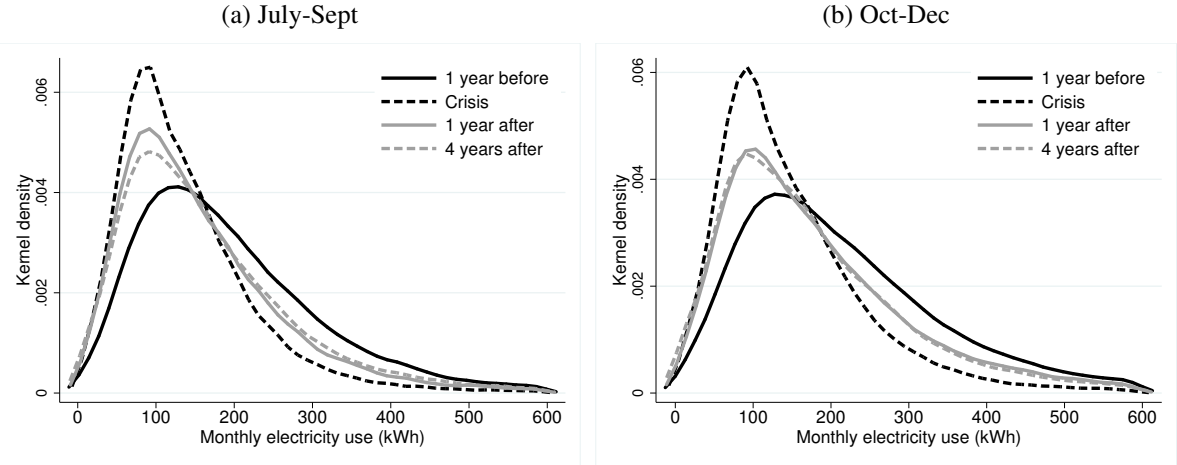


The figure displays average electricity use for LIGHT customers in each month compared to the same month in 2000. It shows that the time–series is almost identical (i) when we use microdata from a random sample of customers observed in every month from 2000 to 2005 (same balanced panel as in Figure 5a 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 P.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 P.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 P.2: Distribution of monthly electricity use over time for a balanced panel of customers (robustness of Figure 5b



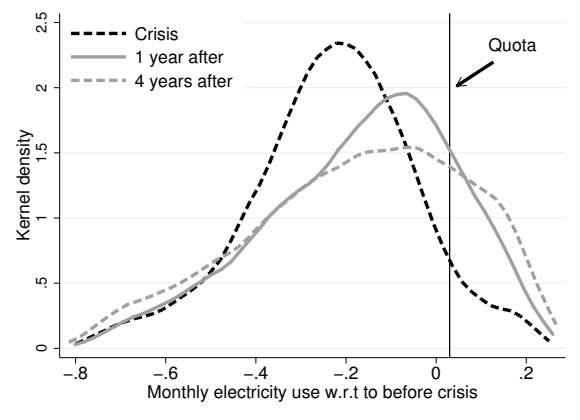
The figures uses the same balanced panel of customers observed in every month between January 2000 and December 2005. It displays Kernel densities for monthly electricity use before, during, and after the crisis as in Figure 5b in the paper. It shows that we obtain similar patterns when we split the 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 P.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 severly reduced electricity use in the short and the long run, except at the very bottom of the baseline consumption distribution.

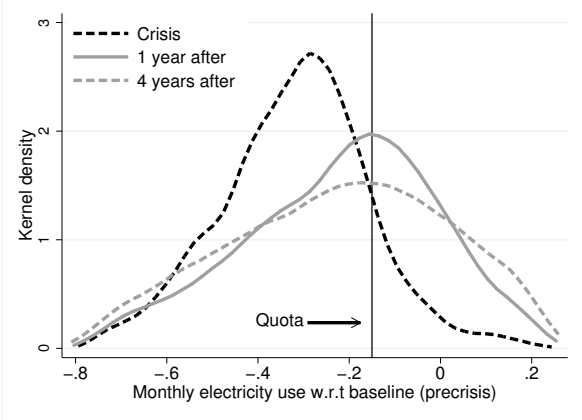
Figure P.5 displays the correlation between individual changes in electricity use during the crisis and four years after the crisis compared to the same months before the crisis as in Figure 5d in the paper, but for the same samples as in Figure P.3. Customers are averaged by bins of 5% changes in electricity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

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

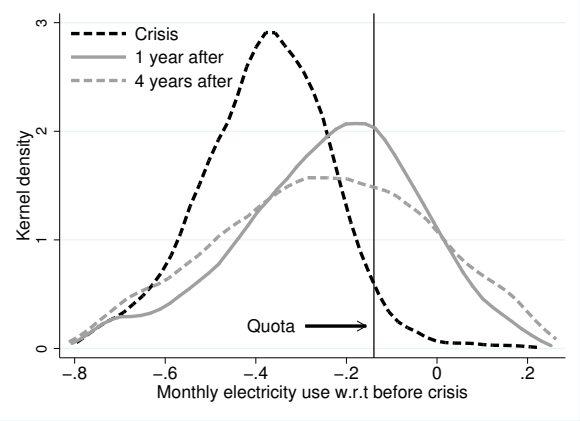
(a) Baseline 100 kWh/month



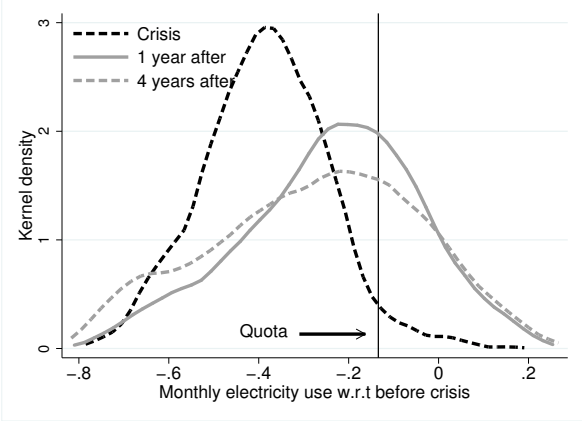
(b) Baseline 200 kWh/month



(c) Baseline 400 kWh/month



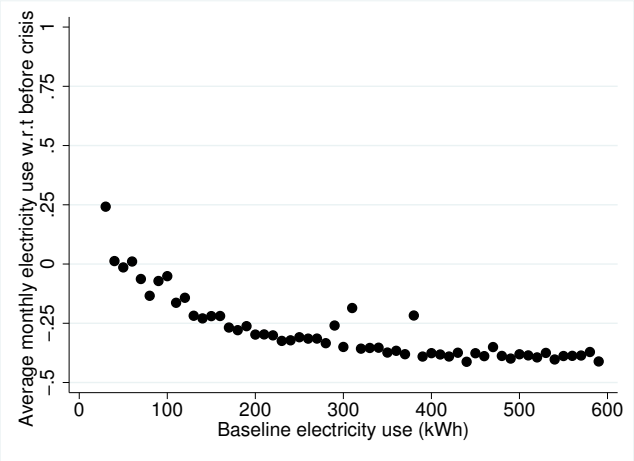
(d) Baseline 500 kWh/month



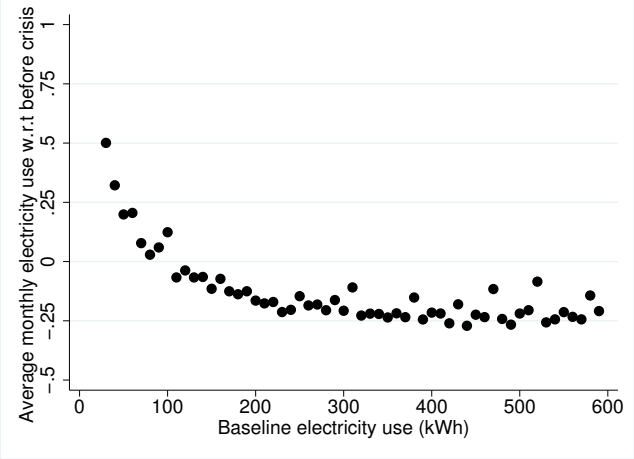
The panels display the distribution of changes in average electricity use during and after the crisis compared to the same months before the crisis, for subsets of the same balanced panel of customers. The panels consider customers who had about the same baseline for quota assignment, and thus faced 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

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

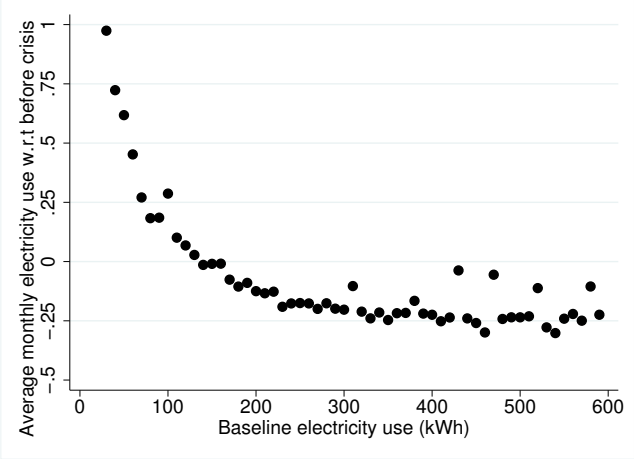
(a) During the crisis



(b) 1 year after the crisis



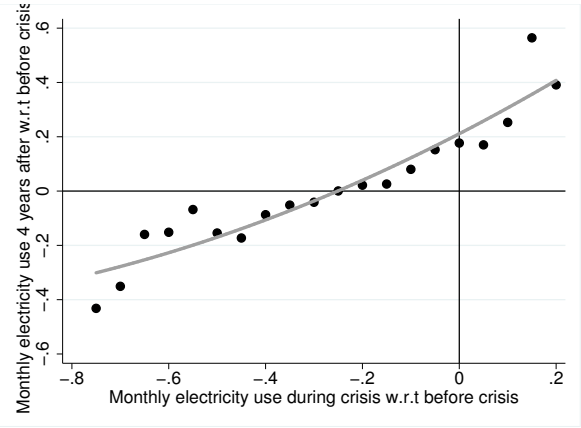
(c) 4 years after the crisis



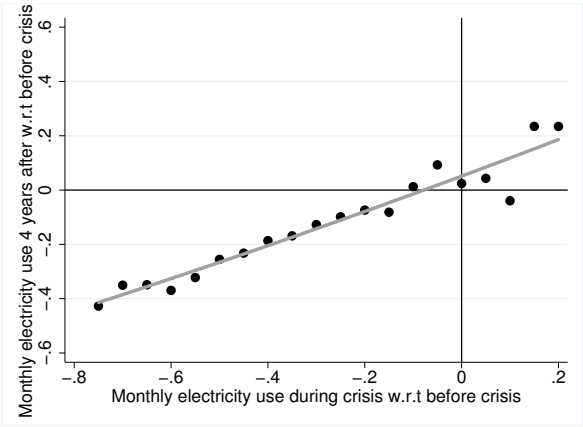
The figure displays average electricity use during and after the crisis compared to before the crisis for the same balanced panel of customers, as a function of *baseline* consumption levels. The figure displays averages by baseline bins and uses data on the first five months of the crisis (and in the 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 P.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)

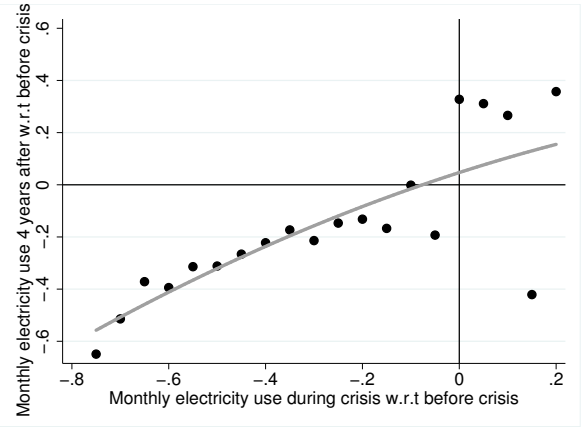
(a) Baseline 100 kWh/month



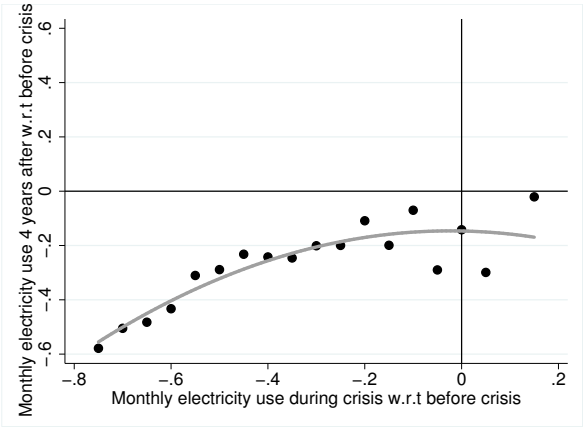
(b) Baseline 200 kWh/month



(c) Baseline 400 kWh/month



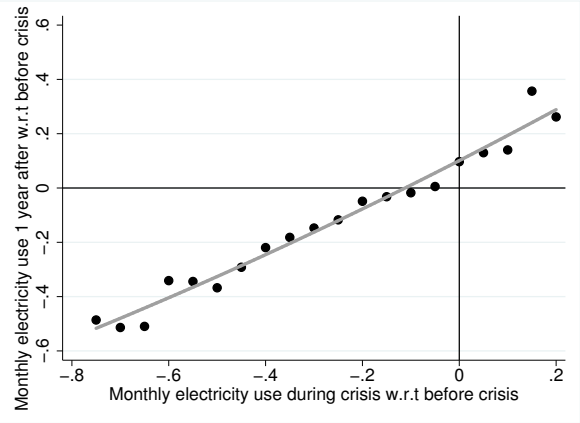
(d) Baseline 500 kWh/month



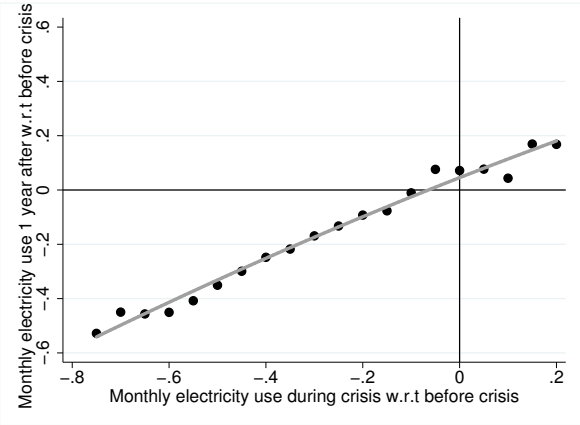
The panels display the correlation between individual changes in electricity use during the crisis and four years after the crisis compared to the same months before the crisis as in Figure 5d in the paper, but for the same samples as in Figure P.3. Customers are averaged by bins of 5

Figure P.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)

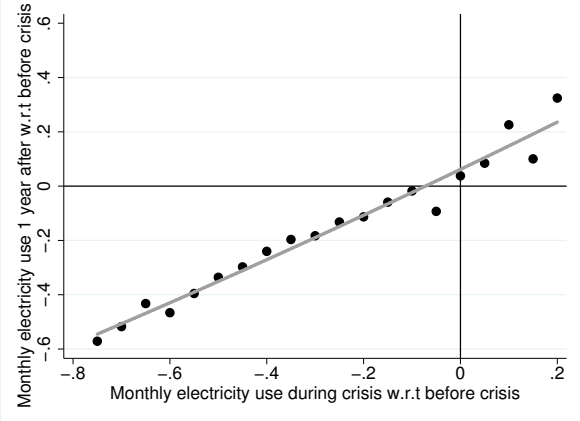
(a) Baseline 100 kWh/month



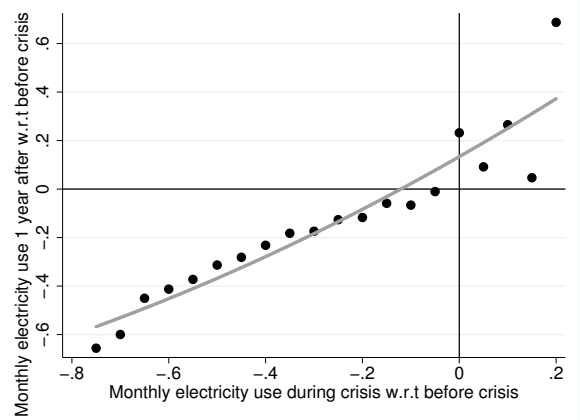
(b) Baseline 200 kWh/month



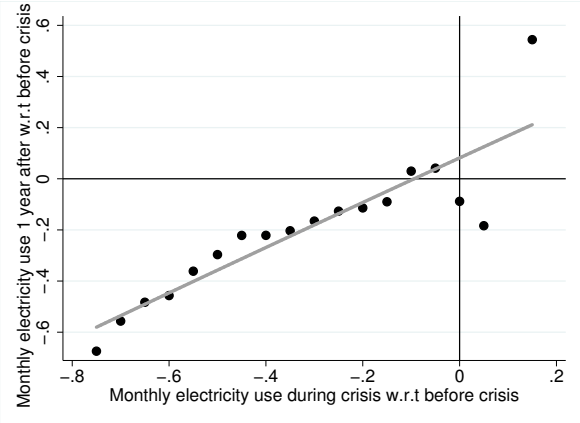
(c) Baseline 400 kWh/month



(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 P.3. Customers are averaged by bins of 5

Q 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 Q.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 Q.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 Q.3 shows how households in the Southeast/Midewest 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 Q.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 Q.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 Q.1: Inputted Average Electricity Consumption by Appliance

	Appliance Specification	Utilization	Average Monthly Consumption (kWh)
		(1)	(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
Light Bulbs	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 Q.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 Q.3: Adoption of more efficient light bulbs around the crisis (Southeast/Midwest)

	All	Some	None	N
	(1)	(2)	(3)	(4)
Did you substitute incandescent light bulbs with fluorescent ones?	.29	.14	.51	4648
Do you still use fluorescent light bulbs?	.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.

LIX

Table Q.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 (10) 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 Q.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).

R 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.[43]

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

$$Y_{h,d,t} = \alpha_d + \sum_{t' \in \{2002,2008\}} \left\{ \delta_{t'} \, \mathbb{1}(t = t' \,\&\, d \in \text{SE/MW}) \right\} + \gamma_t + X_{h,d,t} + \nu_{h,d,t} \tag{14}$$

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.[44] We also construct an appliance quantity index to avoid multiple-inference problems, as in the main text.

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

[43] 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.

[44] 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 R.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 R.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 (14). 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 R.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

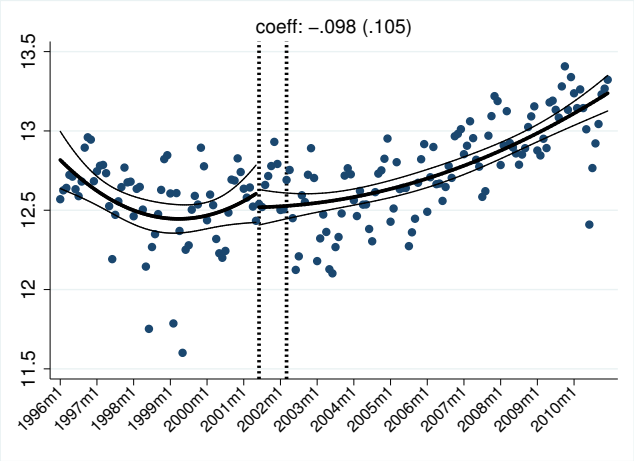
Household-level survey data for 7 states (urban area only) in the South and Southeast/Midwest subsystems from Household Budget Survey (POF) 1996/1997, 2002/2003 and 2008/2009. This table displays the difference-in-differences estimates of the energy saving program effects on the quantity and age of all electrical appliances available, from equation (14). 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).

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

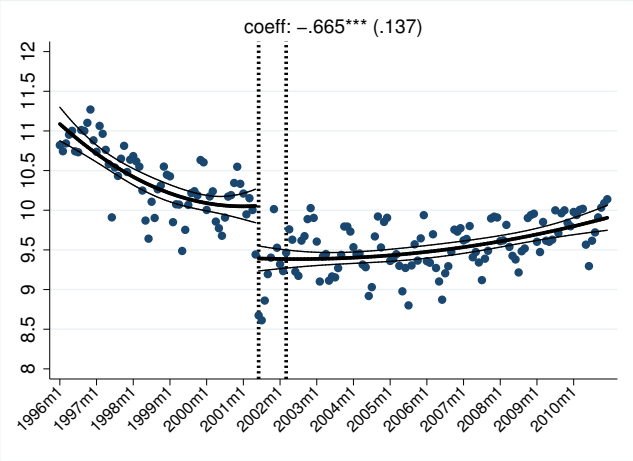
The following figures diplay the time-series in national sales of several domestic appliances in Brazil. The data are estimates that we obtained from Whirlpool, a leading manufacturer, which produces those estimates for its own market strategy. The manufacturer did not share with us the estimation methodology 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 S.1: Log sales of different domestic appliances I (all Brazil, Whirlpool estimates)

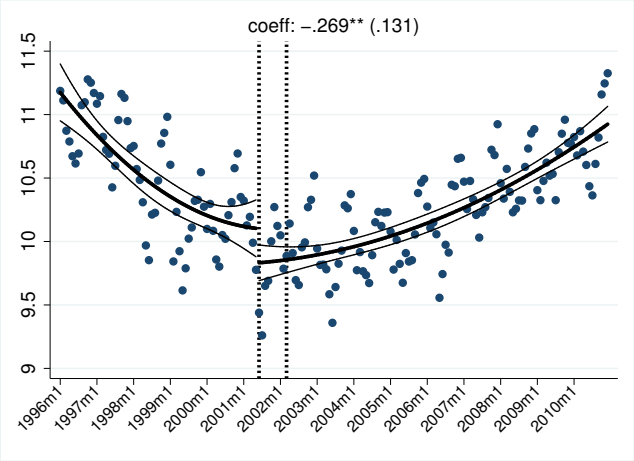
(a) Refrigerator



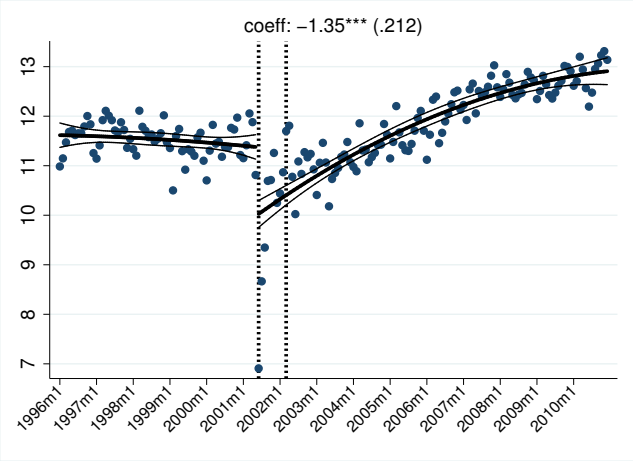
(b) Freezer (vertical)



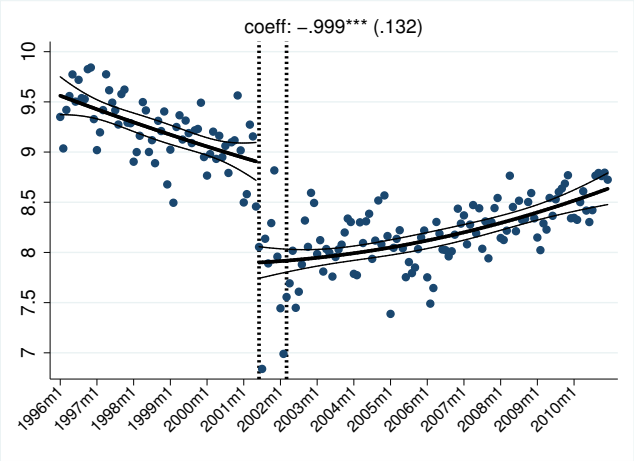
(c) Freezer (horizontal)



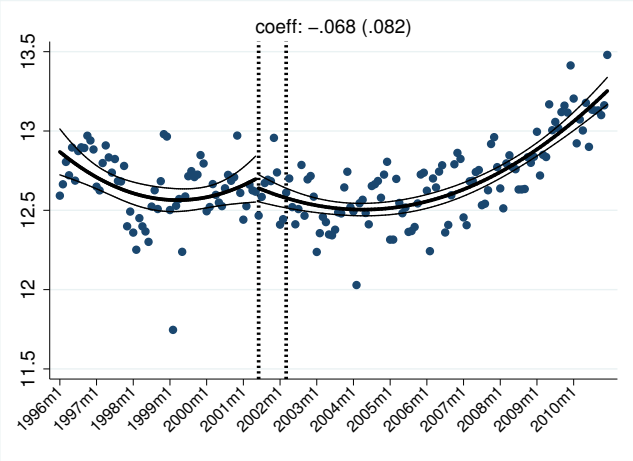
(d) Microwaves



(e) Dishwasher



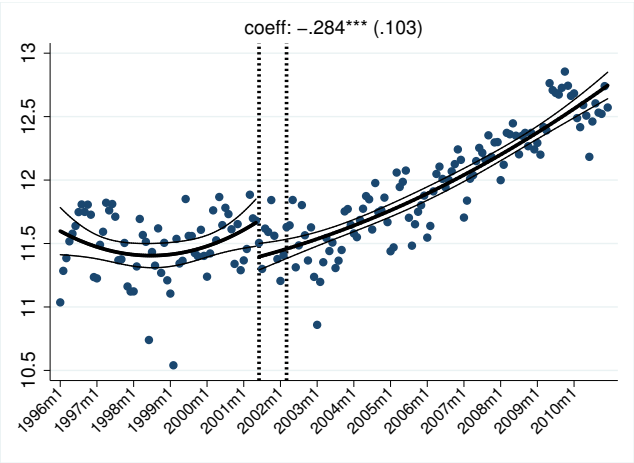
(f) Gas stove (placebo)



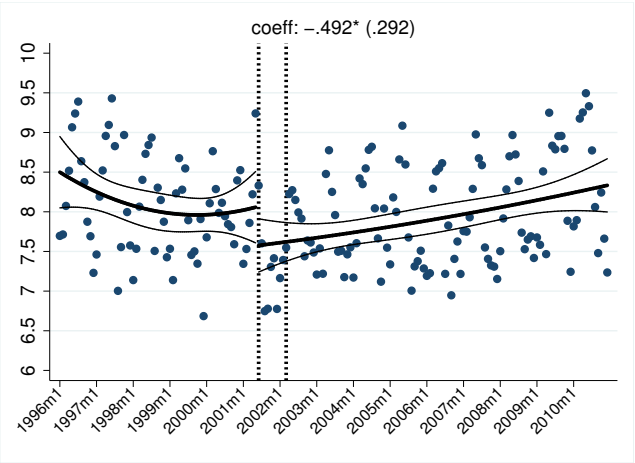
The panels diplay the time-series in national sales of several domestic appliances in Brazil. The data are estimates that we obtained from Whirlpool, a leading manufacturer, which produces those estimates for its own market strategy. The manufacturer did not share with us the estimation methodology used. 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 S.2: Log sales of different domestic appliances II (all Brazil, Whirlpool estimates)

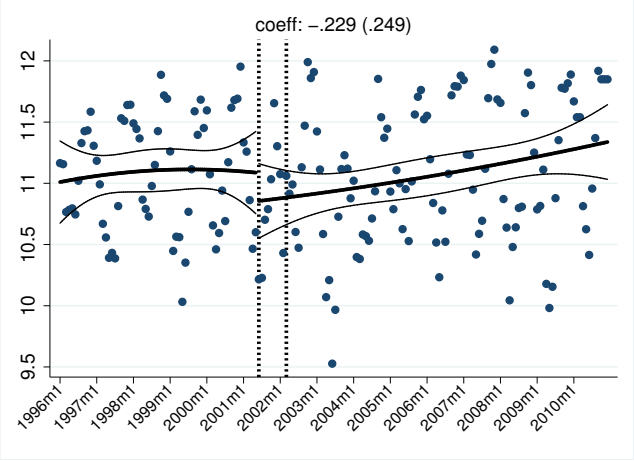
(a) Washing machine



(b) Dryer



(c) Air conditioning

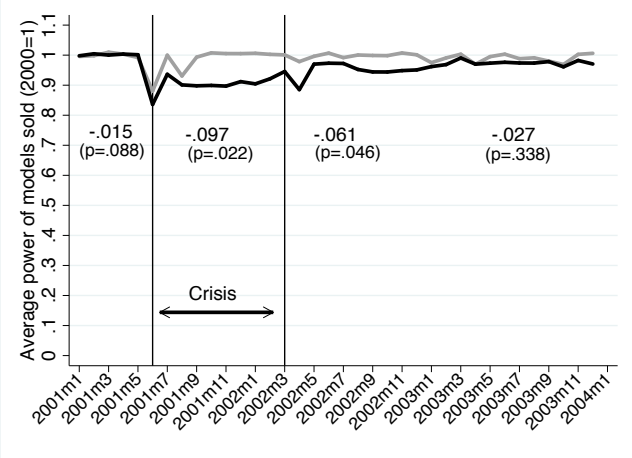


The panels diplay the time-series in national sales of several domestic appliances in Brazil. The data are estimates that we obtained from Whirlpool, a leading manufacturer, which produces those estimates for its own market strategy. The manufacturer did not share with us the estimation methodology used. 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

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

Figure T.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 T.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 T.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 T.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).

U 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:

$$\log(kWh_{d,t}) = a_d + \beta_t + \eta \log(tariff_{d,t}) + \log(X_{d,t}) + \nu_{d,t} \tag{15}$$

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 (15). 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 (15) 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 U.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 U.1: Price elasticity estimates using yearly variation in the South-East/Midwest post-crisis

	(1)	(2)	(3)	(4)	(5)
Dependent variable: Log(yearly mean of average residential consumption)					
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).