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Increasing the energy cognizance of electricity consumers in Mexico: Results from a field experiment☆

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A B S T R A C T

We report on the results of a field experiment in Puebla, Mexico that informed randomly-selected households facing a nonlinear price schedule about how different electricity-consuming actions might change their electricity bills. Households that received this 20-minute, in-person intervention reduced their electricity use, with much of this reduction driven by those that paid the highest marginal price for electricity. The estimated impacts were durable with no observed rebound for at least a year. Households with less educational attainment reduced use the most, consistent with the conclusion that the intervention imparted new knowledge to consumers that led to this observed behavior change. The high rate at which customers accepted the intervention, the resulting consumption decrease, and low implementation costs make this intervention cost-effective relative to several previous energy conservation campaigns in Mexico.

1. Introduction

Many electric utilities around the world attempt to communicate information to customers about their usage patterns, the tariffs they face, and their total expenditure using monthly or bi-monthly bills or periodic information campaigns.[1] There is little empirical evidence that utility customers understand how specific energy consuming actions translate into changes in their bills (see McRae and Meeks, 2016; Brent and Ward, 2019, for recent surveys examining electricity and water price perceptions). Educating consumers about the costs of their individual energy consuming actions is complicated by the fact that residential customers often face a nonlinear price schedule, where the total amount consumed up to any point in the billing cycle determines the marginal price the customer pays for an additional unit of consumption.

☆ The study protocol was approved by the Stanford IRB (protocol number 34234).

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[1] See Darby (2006) for an extensive review of customer feedback methods used by utilities.

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A utility rolling out a program to improve energy cognizance would aim for its customers to respond in a way that is both consistent with the goals of the utility and of a magnitude that makes the program worthwhile. For example, households may increase or decrease their consumption after improving their energy cognizance, and this may be a temporary or more permanent response. Observing *any* consumption response is important to the utility if it reflects an increase in the customer's ability to respond to price changes, because this could improve the effectiveness of subsequent changes in the utility's tariff policy.[2] This paper uses results from a field experiment in Puebla, Mexico, to evaluate the consumption responses to an intervention designed to improve energy cognizance. The intervention was a 20-minute workshop tailored to the household's typical monthly consumption that explains how usage of different electrical appliances owned by that household translates into marginal changes in the household's electricity bill given its typical position on the nonlinear tariff.

We find that in aggregate, households taking our intervention subsequently used less electricity. This result was driven by a subset of households that were heavy users before the intervention and consequently faced the highest marginal prices for electricity under the non-linear tariff structure in Puebla. These high-consuming households that randomly received the offer to take our workshop reduced energy use, on average, by nearly 3%. We estimate an average reduction in energy use of more than 6% for the high-consuming households that actually accepted our offer and took the workshop. The impact of our intervention was durable with the reductions in electricity use among the treatment group observed one year after the intervention, which was the end of our sample period.

Our study demonstrates that programs designed to improve the energy cognizance of customers can be a useful policy tool for utilities. Such educational interventions can offer a different response duration, magnitude, and mechanism relative to the more commonly studied utility interventions involving peer comparisons of consumption and normative appeals to conserve energy. Peer comparisons or normative appeals can be faster and easier messages to convey than developing energy cognizance. Ferraro and Price (2013) conclude from their study of non-pecuniary messages in a residential water experiment that "conservation strategies based on social comparisons or appeals to social norms …are best reserved for situations where immediate but short-lived conservation efforts are desired." Our intervention on the other hand might provide a more persistent consumption impact but perhaps is less suitable when instant conservation efforts are required.

We demonstrate that the scale of the consumption response in this study was large enough to make the program cost-effective, if the goal of the program was to conserve energy. We also present descriptive evidence consistent with improved energy cognizance being the mechanism behind these consumption responses. First, we find that younger households and those with less formal education had larger changes in their consumption following the intervention when compared to other households. Further, although not precisely estimated, households facing the lowest marginal price on the nonlinear tariff schedule on average increased their consumption, in contrast to the large consumption reductions observed among those facing higher marginal prices. These observations, for an intervention design that focused on information provision without normative appeals or peer-group comparisons, are consistent with less informed customers decreasing their consumption after discovering that the marginal cost for some of their electricity-consuming actions was higher than they previously thought. These results are also consistent with less informed consumers increasing their consumption upon discovering the marginal cost of their electricity-consuming actions was lower than they thought.

Three key elements characterize our field experiment and form the basis of comparison with existing studies of information provision in utility settings: 1) our intervention provides quantitative information through a personalized workshop on how a customer's bill changes in response to changes in their use of major electricity-consuming appliances relative to their typical monthly consumption level, 2) it is free of any normative or peer-comparison appeals, and 3) it is conducted in an emerging economy setting. Prior research has contained subsets of these characteristics, but we consider this study the first that has contained all three elements.

The primary aim of our intervention was to create more informed electricity consumers by providing the personalized energy workshop. Similar information to what we provide is included in some studies that also contain goal setting, normative appeals or peer comparisons, making it difficult to separately identify whether such information provision is useful.[3] The content in our intervention addresses the concern first expressed in Shin (1985) that residential customers are broadly unaware of the nonlinear price schedules they face (more recent studies in both electricity and water settings include Borenstein, 2009; Wichman, 2014; Ito, 2014; McRae and Meeks, 2016; Brent and Ward, 2019). We attempt to increase the sophistication of households by explaining how their bill is computed for the nonlinear price schedule they face and then demonstrating how changes in the use of different electricity-consuming appliances they own would change their electricity bill at their typical level of monthly consumption. This personalized educational invention differs from other approaches to improving the salience of electricity usage and consequent expenditures through varying the format of the bill (Wilhite and Ling, 1995), the frequency/time since last bill (Wilhite and Ling, 1995; Gilbert and Graff Zivin, 2014; Wichman, 2017) or transitioning to an electronic delivery method

[2] McRae and Meeks (2016) demonstrate in their field study in Kyrgyzstan that better informed customers were more responsive to a later tariff change.

[3] See Allcott (2011) for an example of the Opower home energy reports that have been studied primarily for their display of peer comparison information in utility bills. These reports also contain some suggestions for "quick fixes," "smart purchases," and "great investments," to reduce consumption with an unexplained estimate of the bill saving. A non-exhaustive list of utility programs or field experiments containing peer-comparison, norm-based interventions or goal setting includes Reiss and White (2008), Jacobsen et al. (2012), Ferraro and Price (2013), Ito et al. (2018), Harding and Rapson (2019) (norms), Allcott (2011), Ferraro and Price (2013), Allcott and Rogers (2014), Byrne et al. (2018) (peer comparison) and Harding and Hsiaw (2014) (goal setting).Pellerano et al. (2017) finds electricity consumers in Ecuador that had a social comparison letter attached to their electricity bills reduced their consumption, but those given an additional note with information mentioning their intrinsic financial incentive to reduce consumption did not in fact reduce their consumption any further.

(Sexton, 2015). Each of these other approaches has been shown to impact consumption levels.[4]

Our intervention is most closely related to Kahn and Wolak (2013), who administered a similar randomized controlled trial that targeted residential electricity customers in California. Their web-based intervention shows customers historical information about their marginal price – the highest price on the increasing block price schedule with positive consumption during the billing cycle – and the potential changes in their monthly electricity bill associated with changes in use of different electricity-consuming appliances.[5] Kahn and Wolak (2013) found that those customers facing the lowest marginal price increased their consumption slightly, while those facing higher marginal prices decreased use, with larger absolute decreases associated with higher marginal prices.

However, our study necessarily departs from Kahn and Wolak (2013) – and many prior studies that incentivize more informed energy consumption – by tailoring the workshop for households in an emerging economy setting, where energy use for larger segments of the population might be closer to subsistence levels, and where web-based delivery of information is less feasible.[6] Instead, our workshops were conducted in person, on the doorsteps of residences. Of the households in which we found someone at home, 60% chose to participate in the research and receive the information-based treatment, far exceeding response rates seen in similar information provision studies undertaken in more industrialized country settings. These high take-up rates, along with low labor costs to implement the treatment (relative to the bill savings from the observed electricity use reductions), can make education interventions in emerging economies cost-effective despite the need to deliver the information in person.

The findings and design of this intervention may be of particular relevance to utility policy makers in developing countries. The first reason relates to the information content; education may be a more appropriate policy goal than strict conservation, empowering households to make informed and financially self-interested decisions about how to increase or curtail their use of electricity-consuming appliances.[7]

Second, our study design and in-person delivery method is more implementable in developing country settings. Finding methods to engage effectively with customers in these settings can be challenging as they generally lack modern infrastructure for efficient load management or technologies such as “smart meters” that can allow utilities to send real-time price signals and consumption feedback to customers.[8] Therefore, promising real-time information provision tools such as those examined in Connecticut (Jessoe and Rapson, 2014) and Singapore (Wolak, 2015) are not yet applicable to virtually all developing country environments.[9]

Finally, electricity services in most developing countries have been provided by a monopoly state-run utility for generations, potentially resulting in less engaged and informed customers. In contrast, utilities in the US have attempted to engage customers by administering a wide variety of energy efficiency programs since the 1970s (Gillingham et al., 2006), whereas such programs have only recently become more common in low- and middle-income countries (Davis et al., 2014). As a result, the baseline level of engagement with a utility or knowledge about electricity in a typical household might be different in developing countries, and the lessons from studies aiming for more informed energy consumption in industrialized settings might be less relevant.[10] Although the questions we tackle and the applicability of our intervention are not unique to low- and middle-income countries, the ability to implement and scale consumer education programs in settings with low labor costs and low Internet penetration rates might provide certain advantages and greater impacts that could not be replicated in more industrialized settings. Rather than struggling to replicate the kinds of energy education and conservation programs used by the highest income countries, Mexico and other emerging economies could leverage their own cost and cultural advantages to overcome problems with consumer education and engagement.

The remainder of the paper proceeds to explain the electricity billing system in Puebla, Mexico, before describing the details of our randomized controlled trial and the specific information conveyed to customers through our intervention. A description of the empirical results follows, along with a discussion of several caveats associated with these results and then a comparison

[4] Wilhite and Ling (1995) also included energy saving tips in one of their treatment groups, combined with the higher frequency and additional information that formed the other treatment groups. The listed studies are not exhaustive, and we refer to Darby (2006) for a review of salience topics in electricity billing.

[5] Brent and Ward (2019) reveal similar information but in the format of a quiz, where they elicit responses from water customers about the prices they face and the water usage associated with different actions, revealing the correct answer after the fact.

[6] Most of the prior field work on strategies for incentivizing more informed energy consumption has focused on industrialized countries (See Delmas et al. (2013), for a meta-analysis). One exception is Szabó and Ujhelyi (2015), where researchers found that water utility customers in South Africa only briefly altered behavior following an information campaign aimed at decreasing customer nonpayment of bills.

[7] The directives to many utilities in wealthier jurisdictions to administer energy conservation programs has faced scrutiny on economic efficiency grounds (see, for example Brennan, 2013). Gillingham et al. (2018) provide a recent review of research findings on energy efficiency and energy audit programs.

[8] A notable exception is the adoption of pre-paid meters, where customers load a dollar amount of credit into their meter which is then converted to a kWh amount based on a flat rate of electricity consumption. The price structures are not advancing beyond those used for mechanical meters, but the technology change appears to impact behavior in some cases. See Jack and Smith (2015) for an evaluation of an introduction of pre-paid meters in parts of South Africa.

[9] Chen et al. (2017) found substantial energy responses to real-time feedback for a small trial in an Indian apartment block. However, technological barriers mean that such feedback is not scalable in many developing country settings.

[10] Engagement levels almost certainly differ across countries but not necessarily with higher income countries being uniformly more engaged. For example, many utilities in more developed settings now have automated billing services, where customers might not even view a bill in order to pay it (Sexton, 2015). In any case, it is unclear whether lower customer engagement and lower formal education levels in the developing country context is a clear disadvantage, if, for example, it means that it is especially difficult to educate consumers effectively in developing countries about the complexities of energy pricing, or if it may actually be an advantage, if low baseline education and frustration with the level of their electricity bills makes consumers especially eager for and receptive to new information.

to previous research. We provide an estimate of the cost-effectiveness of our intervention both in absolute terms and relative to previous energy conservation campaigns in Mexico. Finally, our concluding remarks emphasize the broader implications and relevance of our findings.

2. Setting: billing method and tariff structure in Puebla

The city of Puebla, Mexico is typical of locations in the developing world where our information-based intervention is likely to be effective. Electricity meters in the city, as in nearly all developing countries, are mechanical, and meter reading and billing are done every two months by the nation's electricity provider, Comisión Federal de Electricidad (CFE). Therefore, like in most developing countries, pricing schemes can only be designed to influence aggregate consumption over an entire billing cycle. Consequently, electricity (like water, natural gas and other utility services) is typically priced according to increasing block tariffs (IBT), where subsistence levels of electricity consumption are relatively cheap, and higher levels are increasingly expensive.[11]

The relative prosperity of Puebla means that there are a significant number of households that are expected to use more than just subsistence levels of electricity and so are theoretically able to respond to pricing signals. Because electricity bills are a significant fraction of total monthly expenditures, these households are likely to be economically motivated to understand how their electricity-using actions translate into changes in their electricity bill.

During our fieldwork in the summer of 2015, Mexico was in the early stages of implementing a new round of energy reforms, the success of which could be contingent upon the engagement and participation of electricity consumers in the newly reformed industry.[12] CFE was a legacy provider to households that had not faced competition since being established in 1937.[13] Therefore, improving the understanding of households in Mexico of how their electricity-consuming actions translate into their bi-monthly bill could impact the success of the latest reforms or, at the very least, foster an environment where consumers would be receptive to learning more about the energy sector.

At the time of our intervention in July 2015, Puebla residents were subject to a three-tier IBT structure (common to temperate regions in Mexico), as depicted in Fig. 1.[14] During this month, the average exchange rate was roughly 16 Mexican pesos per US dollar. The three tiers are defined as follows:

- MX$0.809 per kilowatt-hour (kWh) for the first 150 kWh consumed in a billing period. (The "basic" rate)
- MX$0.976 per kWh for the next 130 kWh (exceeding the initial 150 kWh) in the billing period. (The "intermediate" rate)
- MX$2.859 per kWh for all subsequent kWh of use (exceeding the first 280 kWh) in the billing period. (The "excess" rate)[15]

The above differences in marginal prices mean that the same electricity consuming actions (such as watching 2 hours of TV) cost 3.5 times as much for households that surpass 280 kWh of use in the billing period (and so pay the "excess" marginal price) as compared to those that keep their consumption under 150 kWh per period (and pay the "basic" rate). This tariff structure was relatively stable throughout the two-year period from June 2014 to July 2016 that is included in our analysis.[16] The amount (in MX$) that a CFE customer pays for their usage during a billing cycle is the area under the nonlinear price schedule in Fig. 1 up to the point of their total electricity consumption over the billing cycle in (kWh) as shown on the x-axis.[17]

Fig. 2 displays the empirical distribution of household-level consumption for the household's first billing cycle in our sample and marks the quantity thresholds of the increasing block tariff. There is no obvious bunching of billing cycle-level electricity consumption at the thresholds of the non-linear tariff. This contrasts with the literature on labor supply and nonlinear tax schedules, where individuals often have significant control over their hours of work. Potential explanations for Fig. 2 include: 1) electricity demand is derived from a household's demand for the services provided by the electricity-consuming appliances they own and it is difficult for consumers to predict how much electricity an appliance uses to provide a given quantity of services; 2) households received no feedback on their electricity consumption during the billing cycle that would allow them to adjust

[11] See Appendix H of Komives et al. (2005) for a list of water and electricity tariff structures in selected utility regions in Latin America, Asia and Africa. Only 4 of the 68 electric utilities had all customers facing a linear tariff structure.

[12] Electricity reforms are often highly politicized, especially in developing countries, and the Mexican reforms at the time of our fieldwork were heavily covered by the national media. Consumers were broadly aware that changes were forthcoming and may even have noticed their own bills becoming higher or lower after certain reforms.

[13] Although retail services for households are still provided by CFE, retail electricity for larger users of electricity is now contestable and new retailers may provide services to all consumers in the future (Vietor and Sheldahl-Thomason, 2017, pp.11–12). At the time of our fieldwork, Mexico was starting to create a wholesale electricity market in which government-owned and privately-owned firms would be able to compete to supply electricity.

[14] In Mexico, a region's climate determines the number of tiers in the applicable IBT mechanism, the thresholds of consumption that define each tier, the marginal prices for each tier, and whether or not there are seasonal adjustments. Many hotter locations have "summer" and "non-summer" seasons that set rates low enough to subsidize extended air conditioner and refrigerator use.

[15] Households that had used an average of 250 kWh per month over the previous year (calculated on a rolling average basis) were not subject to the IBT system described above. They instead paid a flat rate of MX$3.423 per kWh for every kWh used (the "Domestic High Consumption" or "DAC" rate). Approximately 1% of households are billed under the DAC. We were unable detect such households pre-intervention, and therefore we were unable tailor the marginal price information for their circumstances. For completeness, we did explain the DAC tariff criteria to each participating household. Those that we learned (subsequent to the intervention and during data analysis) were billed under the DAC were removed from the research sample. However, including these observations in our sample does not noticeably change the results of our analysis.

[16] The Basic, Intermediate and Excess rates were MX$0.810, MX$0.981, MX$2.871 in July 2014 and MX$0.793, MX$0.956, MX$2.802 in July 2016.

[17] All bills incur a 16% value added tax and a minimum charge equivalent to 50 kWh of use.

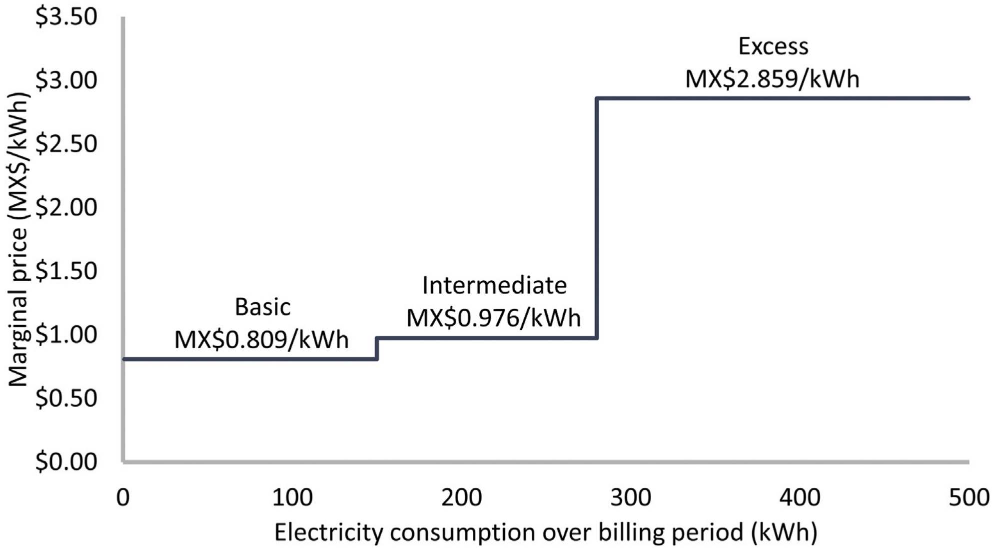


Fig. 1. July 2015 Increasing block pricing tariff (IBT) for household electricity in Puebla, Mexico.

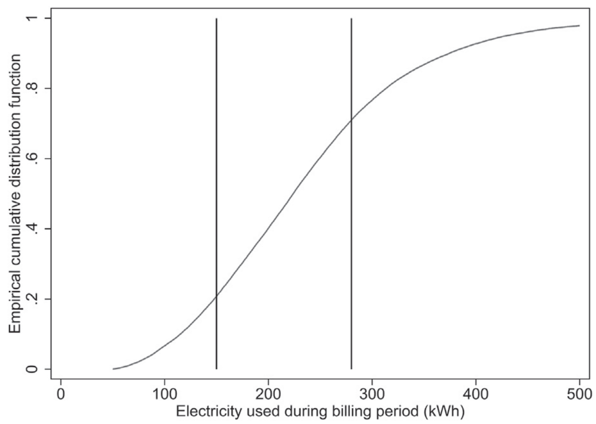


Fig. 2. Distribution of consumption in Puebla study sample for July 2014 billing period.

consumption to stay at or just below a given price threshold; 3) electricity consumption within the household is the result of the appliance-using decisions of individual members of the household where only one or two members (the ones that pay the bill) face the financial consequences for the entire household's electricity consumption.

3. Field experiment design and implementation

We designed our experiment to provide quantitative information on how the use of different electricity-consuming appliances translates into changes in a household's bi-monthly electricity bill in an engaging and straightforward format that would encourage electricity users to make self-interested decisions to change their electricity consumption. This approach necessitates some tailoring of information to ensure personal relevance, just as one would expect from a targeted policy campaign. We began with an assumption that most Mexican consumers had only a cursory understanding of how electricity use is measured, as well as how the magnitude of their own electric bills is influenced by the electricity use choices they make.[18]

[18] The bills that CFE sent households did include a small graphic that explained how the final marginal price users pay for each kWh compares to other potential prices. But it did not explain the nonlinear price schedule and computation of the household's bill or how marginal changes in the use of different electricity-consuming appliances impacts the household's bill.

3.1. The intervention: electricity pricing educational workshop and actionable information provision

A simple economic model is useful to explain our intervention. Let $S_t = (s_{1t}, s_{2t}, \dots s_{Kt})'$ equal the K-dimensional vector of energy services demanded by the household during billing cycle t, where s_{kt} is the household's demand for services from electricity-consuming appliance k in hours-of-use during the billing cycle. Examples of electricity-using appliances and services are lighting, cooling, cell phone charging, and television watching. Let E_t equal the household's consumption of electricity during billing cycle t. It is related to S_t through the following "electricity production function," $E_t = \sum_{k=1}^{K} A_{kt} s_{kt} + \epsilon_t$, where A_{kt} is the average kilowatt-hours of energy consumed by an hour of use of appliance k during billing cycle t and ϵ_t accounts for variation on the weather and other background conditions during the billing cycle. Let $p(E)$ equal the nonlinear price schedule given in Fig. 1 including the value-added tax. In terms of this notation, the household's monthly bill is equal to:

$$Bill(S_t) = \int_0^{[\sum_{k=1}^{K} A_{kt} s_{kt} + \epsilon_t]} p(x)dx$$

Let $E^* = \sum_{k=1}^{K} A_k^* s_k^*$ equal the household's typical electricity consumption during a billing cycle, S_t^* the vector of typical hours of use of the K electricity consuming appliances by the household, and A_k^* is the typical rate at which kilowatt-hours are consumed for an hour of use of appliance k. In terms of this notation, our intervention attempts to teach the household how $Bill(S_t)$ is determined and the values of $\frac{\partial Bill(S_t^*)}{\partial s_k^*}$ for the major electricity-consuming appliances owned by the household. Specifically, it conveys how the household's typical electricity bill will change as a result of changes in the use of the major electricity-consuming appliances owned by the household.

Teams of three university student researchers knocked on the doors of randomly-selected households.[19] They offered free, 20-min "workshops" to any adult member of a household that answered the door. These workshops explained how electricity bills are calculated, and they also provided customized simple explanations of the values of the $\frac{\partial Bill(S_t^*)}{\partial s_k^*}$ for the major electricity-consuming appliances owned by the household.[20] Individuals who accepted the offer to participate were handed a tablet computer on which they completed a highly-visual "electricity education workshop" with the assistance of the students, as shown in Fig. B1.[21] Any adult household member who answered the door and agreed to participate in the study was eligible to complete the workshop, which was conducted at the household's front door. The mean and median time to complete the workshop was 21 min and all participants were given a MX$100 (approximately equal to US$5) Walmart gift card as compensation. We recognize that in addition to the actionable information workshop, the empirical evaluation of the intervention includes both our educational intervention and the Walmart gift card, which we will address when interpreting the results in Section 4. Fig. B2 outlines the process by which households completed the electricity education workshop.

The workshop provided both general education about electricity pricing and customized information tailored to each household. The general portion communicated how electricity is measured in kWh, the relative rankings of various common household appliances by energy intensity, and a basic summary of Puebla's IBT electricity pricing system. The customized sections showed customers how their own bill was computed under the IBT pricing regime. We then asked a series of appliance ownership and usage questions that were then converted into personalized information on how changes in use for the household's major appliances would translate into changes in the household's electricity bill.

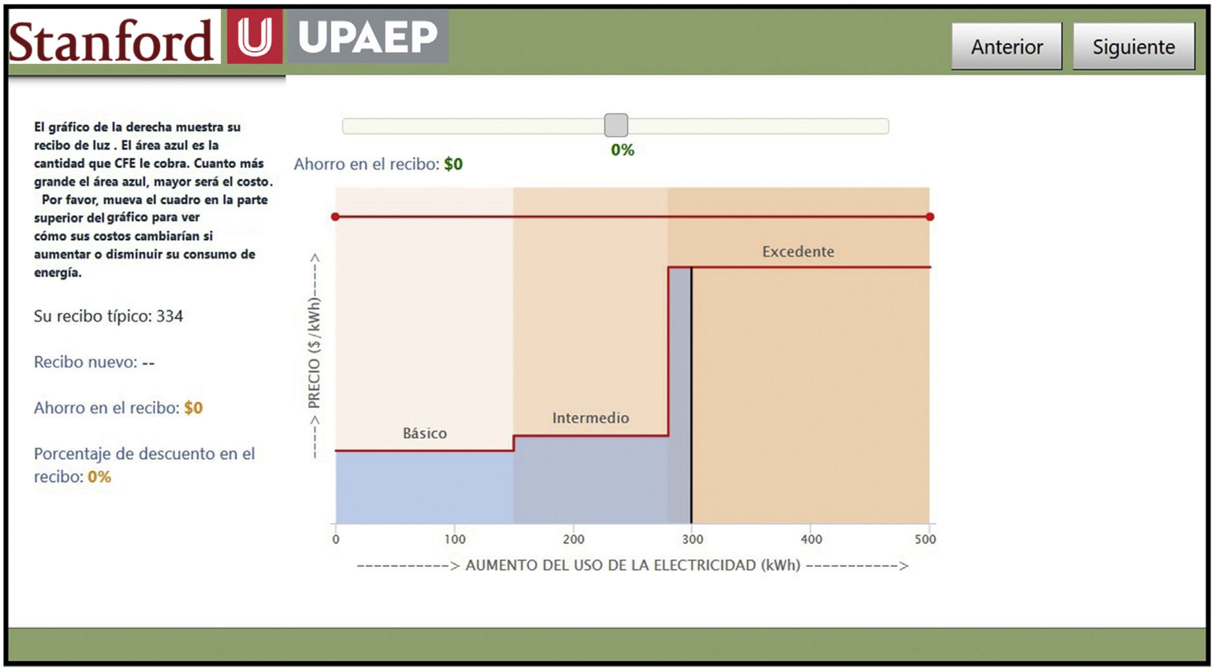
The most frequent changes in appliance use suggested to our study sample were to replace incandescent light bulbs with CFL or LED bulbs (estimated bill savings varied with the number of bulbs in the home), watch 30 min less TV each day or replace a TV with a more efficient model (estimated savings varied by TV size and type), replace or eliminate use of a second refrigerator (estimated savings varied by the size and vintage of the fridges in a household), and turn off computers/laptops when not in use. Finally, we asked respondents several questions on household demographics and questions that we thought might reveal their pre-existing energy efficiency awareness. Our experiment's workshop treatment is further detailed in appendix B.

Anecdotal reports from our student researchers indicated that the most engaging part of the workshop treatment was an interactive "slider" graphic that respondents could play with on the tablet (Fig. 3). This graphic plotted the particular household's most recent consumption during a billing period on a visualization of the IBT mechanism (similar to what is shown in Fig. 1). Respondents could then drag a slider bar that showed numerically and graphically how much their household's bill would increase or decrease for given changes in electricity use during the billing cycle. The greatest potential impact on bills were from changes in consumption levels near the large discontinuity between the intermediate and excess rates where marginal prices triple. Fig. 3 shows a sample screenshot of the tablet. In this example, for customers just beyond 280 kWh of consumption, a 10% reduction in electricity use would result in a bill drop of over 20%. Conversely, for customers just below the 280 kWh excess

[19] Details of the randomization and implementation are provided in the next section.

[20] The Spanish-speaking students identified themselves as students of UPAEP (Universidad Popular Autónoma del Estado de Puebla) and Stanford University and explained that the workshop was part of an academic study and not an initiative undertaken by either CFE or the government.

[21] The students walked respondents through the workshop and resolved any questions respondents had about the use of the tablet or data that respondents were asked to input regarding their household's characteristics. The students also filled in paper handouts where they circled the personalized tips for energy consumption and wrote down the estimated bill changes for each household if the tips were to be implemented. These handouts were left behind with the study respondents as part of the intervention.



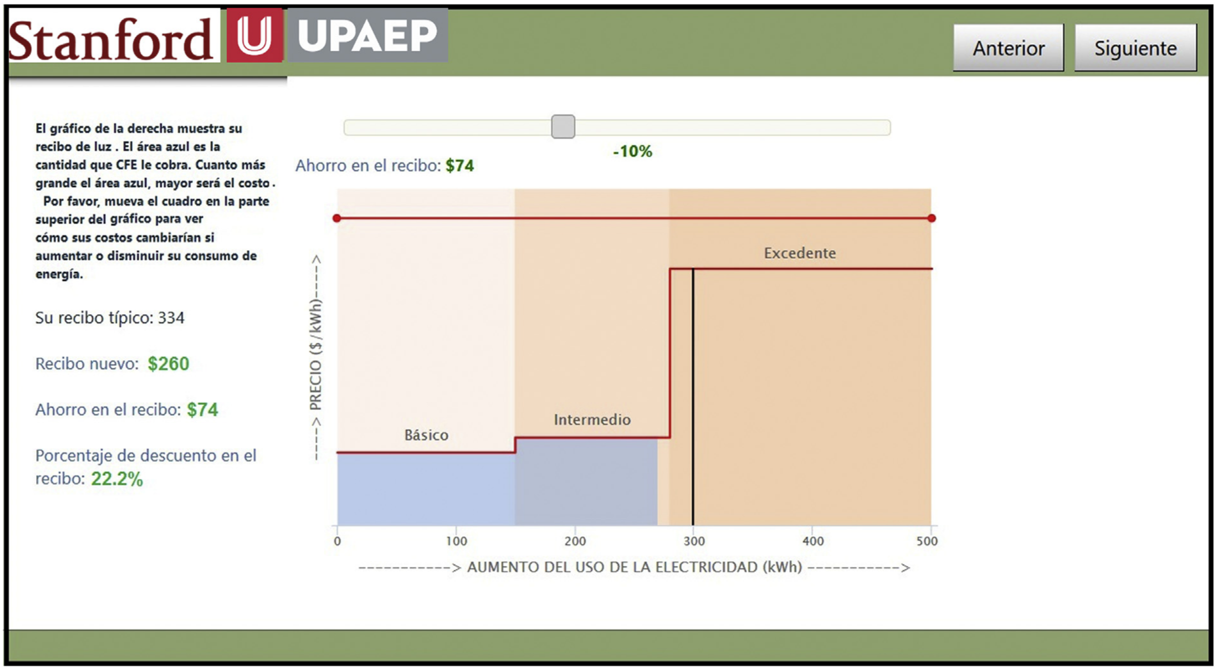


Fig. 3. Screenshot of intervention workshop's "slider" graphic. (a) Consumption and bill payment (shaded blue area): 300kWh baseline use in billing period. (b) Consumption and bill payment: 10% consumption reduction from baseline results in a >22% reduction in a bill. *Translation: The graph on the right shows your electricity bill. The blue area represents the amount the CFE charges you. When that area is larger, the cost is greater. Please slide the square in the top part of the image to see how your costs would change if you were to increase or reduce your electricity use. The listed numbers are: Your typical bill, New bill, Bill savings and Percentage savings on the bill.*

threshold, a 10% increase in consumption would increase bills by more than 20%. A second version of the "slider" graphic was presented to respondents at the end of the workshop, with personalized tips relative to the household's baseline consumption levels. This gave participants a way to visualize and more fully understand the potential bill changes associated with the changes in major electricity-consuming appliance use presented to the household.

3.2. Data and randomization

Our outcome variable is electricity consumption in each billing cycle for each household in the city of Puebla, Mexico. Our sample covers the two-year period from June 2014 through July 2016, which spans one year before and one year after our workshop was offered to randomly-selected households. We obtained this data directly from CFE after our interventions were complete. We also collected additional demographic data from the households that completed the education workshop in order to gain more insight into observable factors that might predict differences across households in the impact of our intervention.

To construct our research sample, we first began with all households in Puebla. We then used the Mexican national census maps and data to define a population of relatively affluent neighborhoods in the city. These were the 391 out of the 485 census blocks in Puebla that have been classified as middle class based on a commonly used measure of social welfare in Mexico.[22] We focused on these census blocks because they were good locations to find variation in the amount of non-subsistence energy consumption among households, so if the intervention did prove to be informative then some households would be motivated and able to adjust their discretionary use of electricity.

We randomly selected 14 census blocks from the pool of all candidate census blocks. We then further randomly selected specific residential street addresses to visit within each of these 14 census blocks. These were the individual households on whose doors we knocked in order to invite them to participate in the educational workshop intervention.[23] This multi-stage randomization approach was necessitated by logistical considerations; namely, we did not yet have access to the electric utility's customer database at the time the intervention was carried out.[24]

We assigned a household to the intent-to-treat group if their address was selected to be visited by our student researchers. Of those, the treated group was comprised of households that agreed to complete the workshop, received a handout summarizing the personalized energy conservation tips, and received the Walmart gift card in gratitude for their participation.[25] The 14 census blocks corresponded to 28 neighborhoods listed in the CFE database, which uses different regions from the census maps. All remaining households in these 28 neighborhoods formed our control group.

In total, we had 719 households in our intent-to-treat group, of which 37% accepted the treatment. We did not find anyone at home in 33% of the homes, and some of these may not have been occupied, while the remaining 30% either declined to participate or told us to come back at a later time or date, without us managing to do so.[26] Of the 265 interviewed households, 244 were matched to electricity consumption data provided by the utility. In the broader intent-to-treat group, we matched 592 of the 719 households.

We then undertook additional data cleaning to derive our final analysis sample. We restricted the sample to billing records that appeared to have had the same resident household for two years without any billing anomalies. Namely, we dropped households whose addresses had at least one billing period during which the utility's records indicated less than 50 kWh of use. This restriction removed households that may have vacationed for long periods or used the home as a seasonal one, as well as homes where people had moved and the dwelling was either vacant or occupied by different households during the analysis window. This restriction also served as a general data cleaning measure to remove administrative anomalies.[27] In summary, we consider the sample as consisting of continuously occupied houses, with the same residents, who were subject to regular billing schedules and methods.[28] Table 1 summarizes the final experimental samples. There were 472 households in the intent-to-treat

[22] The Council for Social Policy Evaluation (Coneval) is responsible for this social index (Rezago). This index is a composite of access to education, access to health, services, and housing where the social needs of each census block is classified as low (our focus), medium, or high. See https://www.coneval.org.mx/Medicion/MP/Paginas/Pobreza-2014-en.aspx for more information.

[23] Within each of the 14 census blocks, $\frac{1}{4}$ of street blocks were randomly selected. Of these street blocks, $\frac{1}{4}$ of property blocks were randomly selected. These steps were performed before interviewers entered the field. Finally, if our interviewers arrived and found that the property had multiple dwellings or apartments, they selected these units with $\frac{1}{4}$ probability using sheets of random numbers.

[24] A difficulty for analysis is that by randomly selecting households for intervention using a census map rather than the utility's administrative data, the selected street addresses then need to be matched to the utility's customer data to track consumption changes. This matching was done by hand on a case-by-case basis once we gained access to the CFE database post-intervention. Section 3.4 provides evidence that random assignment was maintained for our analysis sample.

[25] Interviewers knocked on each door in the intent-to-treat group. They wrote down the address of the household regardless of whether or not anyone opened the door or agreed to participate. This intent-to-treat address was then matched with an address in the utility's database using the neighborhood name, street name and house/unit number. We returned to the field to collect electricity meter numbers for households we were unable to match using this address method.

[26] If on arrival we found a selected address was an empty lot or clearly abandoned, it was not included in our intent-to-treat group because it would not be in the utility's database. Where it was ambiguous whether a house was occupied, they remained in the group. See Fig. B2.

[27] There were observations in the data that were clearly not reflective of consumption, including negative consumption values or very large values that appear to be administrative corrections given the billing windows were usually one to fifteen days, not two months.

[28] In addition, we removed the few households in our sample that had an average of more than 500 kWh in each billing period. This removed some clear administrative anomalies and also removed households that according to CFE should pay the DAC electricity tariff (households with long-term average electricity consumption greater than 250 kWh per month). This is a rate paid by less than 2% of Mexican households, Fig. 2 includes these households, but they make up less than 1% of the Puebla households.

Table 1
Sample sizes for treatment and control groups.

Group	N	N_{Matched}	N_{Sample}	$\frac{N_{\text{Sample}}}{N}$
Control	46,593	46,593	32,228	0.69
Intent-to-treat	719	593	472	0.67
Treated	265	245	208	0.78
Not treated - somebody home	215	170	132	0.61
Not treated - nobody home	239	178	132	0.55

N: Number of household dwellings recorded for each group. N_{Matched}: Number of household dwellings in group matched with CFE administrative data. N_{Sample}: Number of household dwellings in CFE data that have 11 billing periods of observations meeting the data cleaning rules (described in text).

group, 208 of which were actually treated, and 32,228 households in the control group. After the data cleaning measures, the proportion of households in the intent-to-treat group of the unrestricted sample that remained in the final analysis sample is 0.67. The corresponding figure for the control group is 0.69. This suggests that most of the intent-to-treat households that we were unable to manually match to the utility's data would nevertheless have been removed from the final analysis sample during data cleaning and validation. This is consistent with our observations in the field that many of the addresses where we found no one home appeared to be unoccupied, with their electricity disconnected, and therefore they would not appear in the database. We present statistical and graphical evidence in Section 3.4 that random assignment was preserved in our analysis sample and therefore a difference-in-differences estimation technique is suitable in this setting.

For those meeting the criteria to be included in our sample, 44% of households in the intent-to-treat group accepted the treatment by taking our educational workshop. Of the households where someone was home and to whom our research staff managed to make the offer of the workshop, over 60% accepted the treatment. These response rates are much higher than in similar household-level experiments carried out in the US and other countries. For example, Kahn and Wolak (2013) (California) report that slightly more than 10% of their intent-to-treat group accepted treatment, while Jessoe and Rapson (2014) (Connecticut) report a 2% acceptance rate.[29] One likely reason why our treatment acceptance rates were so much higher was the in-person, immediate nature of the offer to treat. Ours was an on-the-spot offer that could be accepted by any adult member of the household, not just the primary bill payer. The treatment was highly interactive and convenient to accept and there was not an opportunity to procrastinate. We note anecdotal reports that some respondents seemed drawn to the fact that they were being invited to participate by university students rather than the utility itself, as well as by the medium of using a tablet computer, which seemed to be a novelty. In addition, most of the neighborhoods we visited were traditional in the sense that adult family members returned home for lunch. This made it possible to find a convenient time to conduct the workshop in the middle of the workday without intruding on evening or weekend leisure time that might be perceived as more scarce by respondents. Finally, it may also be the case that consumers in settings that have traditionally not had opportunities for meaningful interaction with their utilities have pent up demand for information and are especially receptive to it, something that would be consistent with the response rates observed by Szabó and Ujhelyi (2015) in South Africa.

In order to carry out our analysis, we needed to account for the different billing cycles of different households and the different lengths of months. A standardization is performed to ensure that any impacts detected from our intervention are not due to the composition of the sample. For example, as depicted in Fig. 4, one household's billing period might be January 1 through February 28, while another's might be December 25 through February 25. To derive directly comparable time periods of electricity consumption between different households, we select standardized billing windows and construct consumption in this window as a day-weighted average of the consumption during the household's actual billing periods that overlap the standardized window. The standardized windows are based on calendar months (January 1 - February 28, March 1 - April 30, …) and are each normalized to 60 days of consumption. That is, $kwh_{i,t}$, the consumption of household i in the standardized billing window t beginning at day T_t and ending at day T'_t, is constructed from the first bill overlapping this window with observed consumption of $kwh_{i,1}$ from $T_{i,1}$ to $T'_{i,1}$ and the second overlapping bill with observed consumption of $kwh_{i,2}$ from $T_{i,2}$ to $T'_{i,2}$ as:

$$kwh_{i,t} = \left[\frac{T'_{i,1} - T_t}{T'_{i,1} - T_{i,1}} \cdot kwh_{i,1} + \frac{T'_t - T_{i,2}}{T'_{i,2} - T_{i,2}} \cdot kwh_{i,2}\right] \cdot \frac{60}{T'_t - T_t}$$

In the example in Fig. 4, this apportions most of the consumption to the first overlapping bill:

$$kwh_{i,t} = \left[\frac{56}{62} \cdot 100 + \frac{3}{59} \cdot 200\right] \cdot \frac{60}{59} = 102.2$$

Our two-year balanced panel contains electricity consumption data for 11 of these standardized billing periods. This standardized billing cycle dataset allows us to include a fixed-effect for each billing cycle to account for differences in weather and

[29] Many participants in Jessoe and Rapson (2014) study never opened the email invitation. Of those that actually opened the emails in this study, there was a 16% response rate.

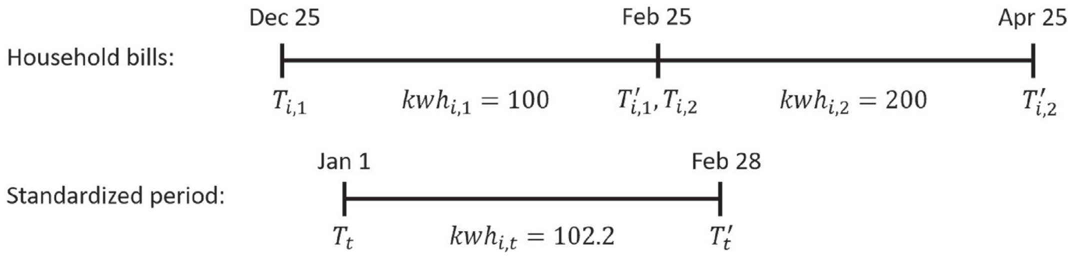


Fig. 4. Billing window standardization.

other background conditions impacting electricity consumption in each standardized billing cycle during our sample period. The first six periods are pre-intervention. Early in the seventh period households received the intervention. The final four periods are post-intervention. Overall, the analysis sample contains 11 periods for the 32,700 households, giving a total of 359,700 observations.

3.3. Empirical strategy

We use a difference-in-differences model to estimate the impact of the educational workshop on household electricity consumption. Because we randomized at the level of attempting to knock on doors in order to offer the intervention, we calculate an intent-to-treat (ITT) estimator.

The ITT estimator is calculated by an ordinary least squares regression using the following electricity consumption model, where the ITT effect is the coefficient on the variable $Z_{i,t}$.

$$\text{kWh}_{i,t} = ITT \cdot Z_{i,t} + \alpha_i + \gamma_t + \epsilon_{i,t} \tag{1}$$

In this model $\text{kWh}_{i,t}$ is the amount of kWh of electricity used by household i during billing period t. $Z_{i,t}$ is assigned a value equal to 1 for all households in the intent-to-treat group (regardless of whether anyone was home to consider the offer or whether someone took the workshop) during billing periods following our intervention. It is set to zero for all other household/billing cycle observations.[30] The variable α_i is a household-specific fixed effect, γ_t is a standardized billing period fixed effect (one for each standardized billing period of our sample time period, excluding the first period) and $\epsilon_{i,t}$ is an idiosyncratic variable unique to household i at billing period t. Because we randomly assigned households to the intent-to-treat group, we assume that $E[\epsilon_{i,t}|Z_{i,t} for\ i = 1, 2, \ldots, N, t = 1, 2, \ldots, T] = 0$ for N equal to the number of households and T the number of billing cycles. Under these assumptions, ordinary least squares yields an unbiased estimate of the mean consumption difference for households offered the intervention.

In addition to calculating the ITT estimator for the entire analysis sample, we also partition the sample into three sub-samples for which we estimate the ITT impacts. This partitioning allows for heterogeneity in responses to the educational workshop. Differences in households' pre-intervention levels of electricity use means they faced different marginal prices and might therefore have different reactions to the workshop as well as different abilities to curtail use. Reiss and White (2008) document how responses to price shocks and public conservation campaigns can vary significantly across households with different pre-period consumption levels, motivating such an analysis in our setting. The three sub-samples are mutually exclusive and are defined by the maximum consumption of a household during a billing period in the year prior to the intervention. Each billing period in Mexico is two months long. If the maximum amount of electricity used in any pre-intervention billing period was less than 150 kWh, then a household is classified as *basic* given the highest marginal tariff it ever faced was the "basic rate." Similarly, if the maximum electricity used was between 150 kWh and 280 kWh, a household is classified as *intermediate*. Households that exceeded 280 kWh in any billing period prior to the intervention are classified as *excess*. Because we purposefully designed the study to sample from census blocks that are in or above Mexico's middle class, only 6% of our intent-to-treat group is classified as *basic*, while 46% and 49% are classified as *intermediate* and *excess*, respectively.

Finally, we also estimate the average treatment effect on the treated (TOT) for those that accepted our offer and chose to take the educational workshop. The TOT is identified under the assumption that any observed ITT effects are driven by households that actually completed the workshop. Given that there was no way for households not in the intent-to-treat group to be treated, the estimate of the TOT is equal to the estimate of the ITT effect divided by the proportion of households in the intent-to-treat group that were actually treated. We set an indicator variable $D_{i,t} = 1$ for those actually treated, so the TOT is equal to:

$$TOT = \frac{ITT}{E(D_{i,t}|Z_{i,t} = 1)} \tag{2}$$

[30] If the workshop offer was made in the middle of a household's billing period, then the $Z_{i,t}$ value for that billing period is adjusted to be the fraction of billing period that occurred after our attempt to offer the household the workshop treatment. The treatments were delivered in late June and early July. Therefore, given the standardized bill window adjustment, Z was non-zero for some participants in the sixth billing period of May 1 - June 30 (mean value 0.02 for the ITT group), was close to one for the seventh billing period (mean value of 0.95 for the ITT group) and 1 thereafter.

In our context, the TOT estimator might provide guidance for two things. First, it estimates the impact of the treatment on those that accepted it.[31] Second, because we provided information to participants about the kWh they could save each billing period from changes in major appliance use, the TOT estimator provides a useful benchmark to relate the magnitude of any observed consumption reductions to the potential savings we identified.

3.4. Tests for randomization and impact persistence

The logistics of this study necessitated that we select our intent-to-treat group before constructing our estimation sample. Although there is no reason to expect differing trends between our treatment and control groups, as a precaution we present evidence that supports our identifying assumption that the randomization strategy was successful for the estimating sample.[32] An implication of a successful randomization strategy is that there should be no systematic differences in the consumption trends of the treatment or control groups in the periods *before* the intervention. In other words, we allow for the possibility that there might be systematic differences in mean levels of electricity use between the relevant treatment and control groups prior to our intervention, but we assume that if we had not carried out this study, then such mean differences would have persisted during the time period we analyze (the year before and year after our intervention). In Fig. 5 we observe very close tracking between the control group and treatment group in our sample prior to the intervention, usually a strong signal that a difference-in-difference framework is suitable for estimating the impact of the intervention. Similar trends can be seen for the intent-to-treat group and the not-interviewed-but-offered treatment groups in Figs. A1 and A2.

More formally, we also report the following period-by-period model specification using the consumption data for households in our study:

$$\begin{aligned}\text{kWh}_{i,t} =&\alpha_i + \gamma_1 1(t=1) + \underbrace{\sum_{s=2}^{6} 1(t=s)(\gamma_s + \gamma_{G,s} * G_i)}_{\text{Pre-treatment}} + \underbrace{\gamma_7 + \gamma_{G,7} * G_i}_{\text{Treatment}} \\ &+ \underbrace{\sum_{s=8}^{11} 1(t=s)(\gamma_s + \gamma_{G,s} * G_i)}_{\text{Post-treatment}} + \epsilon_{i,t}\end{aligned} \tag{3}$$

In this model $\text{kWh}_{i,t}$ is the amount of kWh of electricity used by household i in a billing period t, α_i a household fixed effect and $G_i = 1$ if a household was in the treatment category being studied and $G_i = 0$ otherwise. The three groups we examine are those that were randomly selected to receive an invitation for the workshop (the ITT group), those that accepted the treatment, and those that were in the ITT group but did not receive the treatment. Unlike equation (1), this group indicator does not vary with time, as it will be used to test for any confounding pre-treatment trends. The γ variables are time fixed effects, and these fixed effects are constructed such that they can differ for the households in the selected group. If there were different electricity use trends between the intent-to-treat and control groups prior to our intervention, some or all $\gamma_{G,s}$ parameters for periods 2 through 6 would be non-zero relative to the difference in mean consumption between the groups in the first period. We report the estimated coefficients of equation (3) in Table A1, along with a joint test that $\gamma_{G,2} = 0, \gamma_{G,3} = 0, \gamma_{G,4} = 0, \gamma_{G,5} = 0, \gamma_{G,6} = 0$ at a 5% significance level. We fail to reject this Wald test at 5% significance level (with a p-value of 0.092) and therefore maintain the assumption that the randomization was successful because we do not have evidence (in the pre-intervention data) against the assumption that the intent-to-treat and control groups had parallel trends in mean electricity consumption.[33] Nor do we have any reason to believe that these trends would not have persisted for at least another year had we not carried out our research. We repeat this test using both our actually treated group (rather than the intent-to-treat group), and the group offered the treatment but not interviewed. We similarly find no evidence of systematic pre-intervention differences in mean electricity consumption between these groups and the control group (p-values of 0.22 and 0.28). There is no obvious concern that our sample inclusion or exclusion rules are linked to time-varying unobservable components of household energy use. The assignment of the treatment and the statistical and graphical tests validate that there was no such linkage for the 6 pre-intervention consumption periods. We therefore maintain the assumption that this is the case for all consumption periods. Estimates for the remaining $\gamma_{G,s}$ coefficients will be discussed in the results section to supplement the results from estimating the average impact of the intervention across all periods in equation (1).

[31] We note that we could not randomly assign acceptance of the treatment (whether or not someone was home or accepted the offer of the workshop was beyond our control), therefore the TOT is not a projection of outcomes we would expect if more households in our intent-to-treat group accepted our invitation.

[32] Ideally, we would have liked to have had information beyond consumption levels for households in both the treatment and control groups, however such information is not available, and trying to elicit it from surveys would require full compliance to avoid selection bias issues.

[33] We also fail to reject individual t-tests for each $\gamma_{G,s}$ being equal to zero, see Table A1.

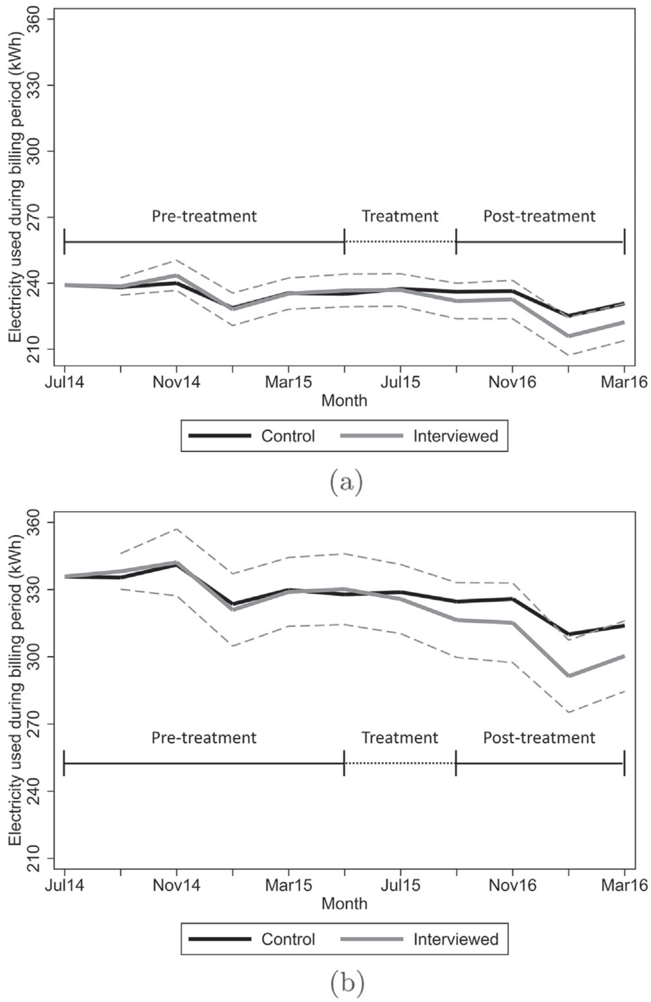


Fig. 5. Mean electricity consumption of treated and control groups (1 year before to 1 year after intervention). (a) Mean consumption for the control group, with estimated deviation from the actually treated group. (b) Mean consumption of excess sub-sample for the control group, with estimated deviation from the actually treated group (had pre-intervention consumption >280kWh during a billing period). The interviewed series is constructed by adding the estimates of equation (3) (displayed in tables A1 and A2) to the control series, with a 95% confidence interval plotted. The first observation does not have standard errors as the omitted category due to linear dependence arising from the inclusion of household fixed effects. Invitations for the treatment were made during the standardized billing window of July 1 2015 to August 31 2015.

4. Results

Our results imply that the informational electricity pricing workshop meaningfully lowered the amount of electricity used by customers in the intent-to-treat group. This reduction was driven by households who chose to take the workshop and, prior to the intervention, used the most electricity. These results are shown graphically in Fig. 5, which graphs the deviations in electricity consumption between our actually treated and control groups over the two year study horizon. The change in consumption levels is maintained until the end of our sample window, which is confirmed statistically in Table A1.[34] Fig. 5b presents average consumption levels for households in our *excess* sub-sample (as defined in the previous section). These are the customers likely have both a greater incentive to reduce consumption (because they pay a much higher marginal price), as well a greater ability to reduce consumption without affecting their overall quality of life, because their electricity use is clearly above the subsistence level. Indeed, the figures show that this sub-sample responded to the intervention in a much more pronounced way than the full sample.

[34] In Table A1 we estimate equation (3), where our estimate of $\gamma_{G,11}$ for the treated column shows that those that accepted the treatment had consumption levels 8.53 kWh less than all other households in the final sample period, statistically different from zero at a 5% test size.

Table 2
ITT and TOT estimates (electricity consumption in kWh).

Group	All	Basic Max < 150	Intermediate 150 < Max < 280	Excess Max > 280
$\widehat{ITT}$	−4.08	2.87	0.25	−8.84
	(1.83)	(2.82)	(1.91)	(3.25)
$\widehat{TOT}$	−9.26	7.75	0.55	−20.13
	(4.15)	(7.61)	(4.23)	(7.40)
Obs.	359,700	34,551	165,869	159,280
Households Invited	472	27	215	230
Households Treated	208	10	97	101
Households Control	32,228	3114	14,864	14,250

Standard errors clustered at the household level reported in parentheses. There are 11, 2-month time periods. $\widehat{ITT}$ reports the average intent-to-treat estimate from equation (1) and $\widehat{TOT}$ reports the local average treatment effect estimate from equation (2), where $E(D_{i,t}|Z_{i,t} = 1)$ is set at the ratio of households treated to households invited and standard errors are adjusted using the Delta method.

Table 3
ITT and TOT estimates (electricity consumption in log(kWh)).

Group	All	Basic Max < 150	Intermediate 150 < Max < 280	Excess Max > 280
$\widehat{ITT}$	−0.012	0.030	−0.001	−0.027
	(0.008)	(0.028)	(0.011)	(0.013)
$\widehat{TOT}$	−0.027	0.081	−0.002	−0.062
	(0.019)	(0.076)	(0.024)	(0.030)
Obs.	359,700	34,551	165,869	159,280
Households Invited	472	27	215	230
Households Treated	208	10	97	101
Households Control	32,228	3114	14,864	14,250

Standard errors clustered at the household level reported in parentheses. There are 11, 2-month time periods. $\widehat{ITT}$ reports the average intent-to-treat estimate from equation (1) and $\widehat{TOT}$ reports the local average treatment effect estimate from equation (2), where $E(D_{i,t}|Z_{i,t} = 1)$ is set at the ratio of households treated to households invited and standard errors are adjusted using the Delta method.

The ITT estimates for the average change in electricity use by those we randomly assigned to the intent-to-treat group from equation (1) are reported in Table 2 for levels and Table 3 for logs. Overall, we estimate an average 4.08 kWh reduction (p-value[35] 0.013) or 1.2% reduction (p-value 0.073) in consumption for those in the intent-to-treat group. The significance and magnitude of these figures are supported in the period-by-period specification reported in Table A1, where a joint test of the post-intervention periods detects consumption differences for the treated households (p-value 0.02) but not the households in the ITT group that did not receive the treatment (p-value 0.18). When applying equation (1) to estimate the impact by the sub-samples of pre-intervention levels of electricity use, it was only customers in the *excess* sub-sample (>280 kWh) for whom we detected a meaningful reduction in electricity use (8.84 kWh or 2.7% decrease, with associated p-values of 0.003 and 0.016). We do not detect a non-zero ITT effect for the *intermediate* or *basic* sub-samples using 5% size tests.

Estimates for the TOT are also reported in Table 2 for levels and Table 3 for logs. Mechanically, this estimator is larger in magnitude than the ITT estimator because all changes in mean consumption for the intent-to-treat group are attributed to those that actually took the educational workshop. In this case, we estimate an overall average reduction of 9.26 kWh or 2.7% for all those who were actually treated. Further, the treated households are seen in Table A1 to have the reduction in their consumption maintained over the post-intervention sample window, with statistically lower levels of consumption detected in the final billing intervals.[36] Once again, the result is driven by those in the *excess* sub-sample. In this case, we estimate an average 20.13 kWh or 6.2% reduction in electricity consumption for the consumers that actually took the workshop. For scale, the average consumption reduction attached to the primary energy saving tip we gave the *excess* consumption households in our study was 31 kWh. Although we do not know whether the tips were acted upon and to what extent, it demonstrates that the actionable suggestions we gave participants were somewhat in the range of the realized consumption reductions resulting from the workshop.

Finally, we attempt to further investigate the drivers of the observed electricity consumption reductions resulting from our educational workshop. We anticipated that the key drivers for the response to the workshop would be: 1) the financial incentive of households to reduce their consumption (financial incentive); 2) their non-subsistence consumption or their ability to reduce

[35] P-value for a one-sided test of the null hypothesis that ITT = 0 against the one-sided alternative that ITT <0.

[36] Although the point estimates reflect a response consistent with nearly immediate consumption reductions, only the coefficients for the final two intervals are precisely estimated, which may suggest a slight delay in responsiveness to the intervention (consistent with the information in our invention being utilized by households after receiving their next bill, or after accruing sufficient savings to invest in an energy efficient appliance). However, we cannot reject the null hypothesis that later periods had the same consumption response as earlier periods – a joint test that all consumption responses post-intervention are equal for the invited and treated samples in the tables is not rejected at a 5% level. Similar results are found when restricting the sample to households in the *excess* pre-intervention consumption category in Table A2.

consumption (ability); and, 3) their pre-existing understanding of electricity consumption and their bills (energy education). Therefore, we collected additional information from the treated households during our workshop that allowed us to examine whether the magnitude of changes in electricity consumption by those that were actually treated can be predicted by their pre-intervention tariff level, the specific recommendations they received from the workshop or their demographic characteristics. We estimate the following model:

$$\text{kWh}_{i,t} = \beta \cdot D_{i,t} \cdot X_i + \alpha_i + \gamma_t + \epsilon_{i,t} \tag{4}$$

Here, the indicator variable of actually being treated ($D_{i,t}$) is interacted with a vector X_i that contains time-invariant variables of interest that may be correlated with the extent to which a household might decrease electricity use in response to our intervention. The characteristics of households contained in X_i are listed loosely by how they might fall in the three drivers of consumption responses:

- **Financial incentive and/or ability variables:** Marginal price faced by household, estimated savings from tips (*MX$*), owns home (not renting), household income.
- **Ability variables:** Received specific tip (8 categories).
- **Energy education variables:** Recalls energy efficiency stickers on appliances, understood the stickers, educational attainment.
- **Other variables:** Gender of respondent, age of respondent.

Table 4 reports the functional form of the variables in X_i and the coefficients from estimating equation (4) using ordinary least squares. We find consumption reductions following the workshop were largest for 1) those facing higher marginal prices; 2) those having higher potential bill savings from the tips; and, 3) those having lower levels of educational attainment. The estimates of equation (4) predict that for every MX$50 (≈US$3) of bill savings in our tips,[37] households had 1.7% less energy consumption post-intervention,[38] and that all else being equal, households facing the *excess* marginal price consumed 6.5% less than those on the basic marginal price post-intervention (one-sided p-value 0.043). Although we expect more overlap between households on the excess tariff and those with higher levels of identified bill savings from tips, the model shows that both factors predict lower consumption following the intervention, even when conditioning on the other factor. Our earlier finding that only households facing the *excess* tariff reduced consumption from our intervention could be because these households both faced a higher marginal price than other households (and therefore had a stronger incentive to reduce consumption) and had more discretionary consumption (and therefore had greater ability or lower inconvenience costs to reduce consumption).

We did not have a prior hypothesis about how demographic characteristics would interact with our treatment and therefore report p-values for a two-sided hypothesis test. We observe that respondents that had no post-secondary education are predicted to have 5.7% lower post-intervention consumption than those with tertiary education (p-value 0.065). Further, those less than 55 years old are predicted to have 4.8% less consumption post-intervention than the more elderly (p-value 0.044). However, reporting an understanding of the energy efficiency labels attached to appliances was not found to predict different levels of post-intervention consumption (p-value 0.676). Although demographic information would need to be obtained for the control group to compare the causal impact of the workshop across these demographic groups, a policy to scale up this program might use these predictions to consider targeting households with less formal education for this workshop. However, given the lack of precision in many of the coefficient estimates in these regressions, further research is warranted before attempting to target particular demographic groups with this intervention.

4.1. Caveats and comparisons to similar interventions

Although the interpretation of our empirical results has focused on the educational content of our intervention, we acknowledge that in addition to this key feature of the intervention, respondents also completed a small survey and received a MX$100 (≈US$5 equivalent) Walmart gift card. Below we discuss how we believe our results should be interpreted given these facts. This section also re-considers the interpretation of the results and compares them with Kahn and Wolak (2013), a similar non-normative, non-peer-comparison, actionable-information intervention in an electric utility setting.

The core component of the intervention is the calculation of the household's bill using the nonlinear price schedule and the quantitative information on how changes in major appliance-specific electricity-consuming actions impact the household's bill. In contrast, the survey was a brief component of the workshop and largely focused on collecting household-level demographic characteristics. The gift card provision was a brief exchange at the end of the workshop, but there could be an income effect that flows through to energy use. If this small amount of income raises general consumption (of which energy use is a component), then we would expect the impact of the information component of the intervention to be slightly lower than the estimated program impacts reported above, assuming that electricity-consuming appliance use is a normal good.

[37] We are unable to identify any systematic differences between any of the individual tips as predictors for consumption reductions post intervention.

[38] The coefficient on total estimated savings from tips in the log(kWh) specification is −0.00034. After rounding, MX$50 times this value is −0.017. The p-value for a one-sided test for this coefficient being equal to zero is 0.017.

Table 4
Estimates of consumption responses by workshop participants.

Interactions with Interviewed variable (D_{it}):	kWh	log(kWh)
Financial incentive and/or ability variables		
Intermediate marginal price	−4.602	−0.048
	(5.011)	(0.034)
Excess marginal price	−12.691	−0.065
	(6.720)	(0.038)
Total estimated savings from tips ($MX)	−0.090	−0.00034
	(0.041)	(0.00016)
Owns home	−1.325	0.022
	(6.778)	(0.033)
Monthly income < MX$900	−5.808	−0.013
	(12.449)	(0.059)
Monthly income MX$901 to MX$1500	0.383	0.013
	(10.908)	(0.049)
Monthly income MX$1501 to MX$2300	0.940	0.007
	(12.655)	(0.056)
Monthly income MX$2301 to MX$3600	5.058	0.025
	(9.642)	(0.045)
Monthly income MX$3601 to MX$12300	0.930	0.016
	(8.307)	(0.037)
Ability variables		
Tip: Replace incandescent lightbulbs with CFLs/LEDs	5.945	0.029
	(6.289)	(0.027)
Tip: Put computer/laptop in sleep mode or turn off	4.939	−0.006
	(11.639)	(0.050)
Tip: Iron more efficiently	−7.349	−0.012
	(7.639)	(0.035)
Tip: Watch 30 min less TV per day	11.165	0.053
	(5.734)	(0.025)
Tip: Wash full- not half-loads of laundry	9.473	0.034
	(12.041)	(0.048)
Tip: Replace refrigerator with more efficient model	1.394	−0.000
	(7.101)	(0.031)
Tip: Use only one refrigerator	5.401	0.026
	(14.232)	(0.078)
Energy education variables		
Understood energy efficiency labels	−3.873	−0.016
	(8.350)	(0.037)
Knew about energy efficiency labels	8.994	0.024
	(13.183)	(0.058)
No higher education (secondary school or below)	−13.021	−0.057
	(7.139)	(0.031)
Other variables		
Male	0.940	0.015
	(5.791)	(0.026)
Age > 55	8.874	0.048
	(5.533)	(0.024)
Constant	−19.082	−0.152
	(50.150)	(0.185)
Observations	2265	2265

Estimates of equation (4). Standard errors clustered at the household level reported in parentheses. There are 11, 2-month time periods. Time and household fixed effects are not reported. The tip to replace the TV with a more efficient model is the omitted category. Demographic information collected during workshops.

It is also possible that some portion of the income effect from the gift card was put toward the purchase of an energy-efficient appliance suggested by our workshop.[39] However we stress that the value of the gift card was small in the context of the appliance information we delivered; it could only go a tiny way toward upgrading televisions or refrigerators, and could have at most covered the cost of an LED light bulb.[40] We cannot isolate the exact channels behind the energy saving responses we observed, but the estimated consumption reduction following the workshop for households on the excess tariff was 6%, far more than the contribution we expect a single light bulb would contribute to total energy use. If *every* household purchased a 10 Watt LED light bulb that replaced a 40 Watt incandescent bulb, and it was used for 5 h per day, this would account for

[39] We thank an anonymous reviewer for highlighting this point.
[40] The cheapest LED light bulbs in Mexico were approximately US$5 each during our intervention window, approximately equal to the value of the gift voucher.

9 kWh (less than half) of the estimated impact of the program for consumers on the excess tariff. We cannot rule out that one possible response to the educational intervention was the purchase of an LED light bulb, because for many households, this was one of the ways they were told that they could lower their electricity bill. However, if the household decided to use their income to purchase an energy efficient appliance, the choice to spend the voucher in such a way could very well be motivated by the information gained from our workshop. Finally, even if a household that took our treatment used the Walmart gift card to purchase an LED bulb, we have no way of knowing that the household would not have still purchased this LED bulb if we had not given them a Walmart gift card. For these reasons, we believe that a significant fraction of the estimated treatment effect is due to the information content of our intervention.[41]

The reward and intervention format closely followed that of Kahn and Wolak (2013), with their intervention being web-based and self-guided (in English) in more affluent California. Participants in the California study generally had much higher levels of baseline energy consumption and were offered an Amazon gift card to participate in the workshop with a value randomly assigned to be between 2 and 10 times larger than in the Puebla study. They report increasing rates of accepting the intervention with the size of the gift card, but do not find that the magnitude of the treatment effect of their intervention depended on the gift card amount.

Despite differences in the settings, our study and Kahn and Wolak (2013) find an aggregate intervention impact of a decline in energy use driven by the customers on the highest marginal price tier of the increasing block tariff. Kahn and Wolak (2013) also find that customers facing the lowest marginal price increased their consumption. Brent and Ward (2019) find an increase in consumption from an intervention where the marginal prices are revealed to water users in Melbourne, Australia and customers discover that the marginal cost of water is cheaper than they had previously thought. In our study, point estimates for the consumption response by households facing the lowest marginal price are also positive but lack significant statistical precision (see the *Basic* column in Tables 2 and 3). Collectively, our study and these others suggest that in both higher- and lower-income countries consumers might adjust their consumption of energy or water up or down following a tariff-salience information intervention similar to ours. Further, our survey allowed us to highlight a potential link between the magnitude of the consumption reduction from our intervention and lower levels of formal education that could indicate that it was newly-acquired knowledge that led to a consumption response. This finding may motivate further work to understand whether people with different education levels respond better to face-to-face or web-based informational interventions.

5. Evaluating cost-effectiveness

Our results suggest that our electricity pricing workshop resulted in an overall decrease in energy usage by the participants. Policy makers often seek to reduce energy use, motivated by the potential to delay infrastructure upgrades, improve service reliability, lessen environmental damages or other reasons. Although we do not evaluate the advisability of undertaking any particular conservation program, or applying the intervention presented in this study as a conservation program, we can demonstrate the scale of the consumer education program costs by comparing the cost-effectiveness our intervention had in reducing electricity use relative to other energy conservation programs.

The usual evaluation method that utilities apply to evaluate conservation programs is the levelized cost of a “negawatt-hour,” which is the average cost of the discounted present value of the kWhs of energy savings induced by the program. The long history of such programs in the United States has resulted in a wide range of levelized cost estimates in the evaluations of appliance standards, financial incentive programs and information initiatives (See Gillingham et al., 2006). Joskow and Marron (1992) raise the concern that many programs are not as cost-effective as utilities might claim, and perhaps much worse if some program costs are not fully accounted for. This concern has also been raised in Mexico with the National Appliance Replacement Program subsidy for replacing old refrigerators (referred to as “cash-for-coolers” in the academic literature) that is estimated to have a levelized cost of US$0.28/kWh in Davis et al. (2014).[42] This greatly exceeded the average wholesale electricity price in central Mexico in 2016 of US$0.048/kWh (Irastorza, 2017) and the average retail price paid by customers in our study of US$0.067/kWh. When applying environmental costs from carbon, assuming an emissions intensity of 0.538tCO_2/MWh and $36/t of damages, as in Davis et al. (2014), this adds an additional externality of US$0.018/kWh. We use the estimates from our randomized control trial to estimate the energy savings that could result from scaling and extending our energy education workshop.

On the cost side, we believe, based on our fieldwork, that a team of two students or market researchers, working at the wage of US$5 per hour, could successfully complete at least one workshop every 30 min (including time spent to knock on doors where nobody is home or where someone declines to participate). This assumed wage rate is slightly above market research wage rates, and the workshop completion time is conservative given our experience in the field.[43] With our intervention also including a $5 Walmart gift card, this gives a cost of $10 per workshop. In assessing the effectiveness of the program, we apply the TOT estimates in Table 2 of 9.26 kWh per billing cycle, and 20.13 kWh if the intervention is targeting consumers on the excess tariff. Given our randomization strategy and sample selection, we expect treated households in a scaled-up program to

[41] A more conclusive statement regarding the precise actions behind the estimated impact of our intervention would require the collection of detailed information on appliance holdings and energy-consuming actions before and after the intervention which we were unable to collect.

[42] All monetary references in this section are converted to 2016 US dollars.

[43] We believe our workshop could be streamlined to lower the time below our observed median 21 min completion time by eliminating our demographic survey. In addition, a program roll-out would likely go from door-to-door, so we do not expect large time breaks between workshops (as opposed to going several blocks at a time between randomly selected addresses as we did in this study).

Table 5
Comparing doorstep energy education workshop costs to energy savings.

Target group	Years of consumption response following workshop			
	1	2	5	10
	Levelized cost of energy savings (US$/kWh)			
All households	0.185	0.094	0.039	0.021
Excess tariff households	0.085	0.043	0.018	0.010
	Break-even overhead per household (US$)			
All households	−7.41	−4.90	2.21	12.75
Excess tariff households	−4.37	1.09	16.56	39.48
	Break-even overhead per household (incl. carbon cost, US$)			
All households	−6.42	−2.95	6.87	21.42
Excess tariff households	−2.23	5.32	26.67	58.30

Estimates of consumption decreases apply the TOT estimates from Table 2, applied for the number of years specified in the column, discounted by 3% each year. Estimates for the top panel divide the program delivery cost by the estimated consumption decrease to give the levelized cost of energy savings. Estimates for the middle panel apply the average wholesale electricity price in central Mexico in 2016 of US$0.048/kWh (Irastorza, 2017) to the estimated consumption decrease each year, then subtract the marginal program delivery cost to give the break-even overhead per household (US$). The final panel applies the assumptions used in Davis et al. (2014) of emissions intensity 0.538tCO_2/MWh and social cost of carbon of $34/t. A discussion of the cost assumptions is in the text.

be similar to those that self-selected to accept the workshop treatment in middle class neighborhoods in Puebla (and perhaps other temperate regions in Mexico). We also note that it would be straightforward to target only those households that would be classified as falling in our *excess* sub-sample if we had access to the utility's billing records in advance of implementing a scaled-up program. Given that the intervention is designed to provide education on a specific topic, we would expect its impact to be long-lasting, which is consistent with the durability of the treatment effect we observed (see Fig. 5). We therefore consider cases where the effect lasts for 1, 2, 5 or 10 years, applying a discount rate of 3%.[44] The 1-year estimates are likely to be overly conservative, as Fig. 5 and Table A1 shows that households receiving the energy workshop consumed less energy through to the end of following year, with no indication that this would not continue to persist to some degree. However, caution must be taken when extrapolating to periods of time outside of our sample window, because we do not have empirical guidance beyond that point, as our ability to track households ended after twelve months. These estimates therefore represent projections assuming the treatment impact follows a 3% discount rate and ends after either 2, 5 or 10 years.

Under these conservative per workshop cost assumptions, our energy education program compares favorably to estimates by Auffhammer et al. (2008) for the costs incurred by historical conservation programs in the US of $0.071-$0.196 per kWh (adjusted to 2016 US dollars). The top panel of Table 5 reports the estimated cost per kWh of savings from our program under different scenarios of program cost and duration of the impact. Delivering this program to all households in our sample of 14 middle-class census blocks in Puebla, under the most generous assumptions (lowest cost, longest lasting consumption effect), the levelized cost is $0.021/kWh. However, if the effect were to abruptly end at the end of our 1 year sample window, the levelized cost is $0.185/kWh, almost four times the average wholesale price of electricity.

Clearly, there are fixed costs associated with rolling out an energy education workshop program, including supervisor and tablet computer costs (which are unlikely to increase as rapidly as the scale of the program increases), and unexpected cost overruns. The middle panel of Table 5 displays the break-even overhead cost per household. This represents the maximum fixed workshop costs that could be incurred such that the wholesale energy cost savings from the estimated consumption reduction is greater than the implementation costs of the workshop. We see that there is no opportunity to break even if the consumption response to the workshop only lasts one year, but with enough scale the program could deliver net savings if the consumption effect is 5 years, with a margin of $2.21 per household to protect against unexpected program costs. Further, if the program were to internalise a social cost of carbon into the consumption impacts at the rates used in Davis et al. (2014) (in the bottom panel of Table 5), this break-even margin triples to $6.87 per household.

Some of the exposure to cost overruns could be mitigated if the program was designed to target only the customers that are predicted to respond to the treatment. Indeed, under this objective, our results suggest that a simple scale-up of our tablet-based educational workshop (without any further modifications) should only target households that we would classify as falling in the *excess* sub-sample. When restricting participation only to these households, the best to worst case range for the levelized cost of achieving reductions in electricity use is $0.010 - $0.085 per kWh, with the break-even calculations substantially improving, such that we only require 2 years of consumption responses to break even. These results demonstrate the potential for educational programs to improve energy efficiency in a low- or middle- income country. They also show that by effectively targeting the intervention to customers that are most likely to deliver the largest consumption reductions, the levelized cost of the intervention can be reduced.

[44] The levelized cost of a kWh of savings is calculated as the assumed intervention cost per household, divided by the discounted energy savings. The discounted annual energy savings are the assumed to be 6 times the estimated *TOT* value, summed over the number of years specified, discounted at a rate 1.03^t where t is the year.

Overall, we believe it could be cost-effective to use actionable information interventions to empower high-consuming households to make self-interested choices to save electricity and money in this setting. It is plausible that households make the decision to curtail usage after receiving the information because they expect to benefit financially from using less electricity relative to the pre-intervention level. Whether it is desirable for the utility to empower these consumers to make more informed electricity consuming choices is a policy decision. After all, these high consuming households pay the greatest amount in electricity bills and so are critical to the utility's ability to recover its costs or subsidize low-income customers. On the other hand, if the financial viability of the electricity sector relies upon high-intensity users not being fully-informed about how their electricity-consuming actions impact their bills, then it might indicate a problem with the long-term financial viability of the sector rather than a reason to avoid undertaking this sort of information campaign.

6. Conclusion

The observed impact from our intervention suggests that it is possible to communicate to residential consumers in Mexico the complexities of how changes in a household's use of its major electricity-consuming appliances impacts its typical electricity bill. Households could increase or decrease their consumption after improving their energy cognizance, and this could be a temporary or more permanent response. In our study, we found that the average response to our intervention was a consumption decrease. The careful intervention design that focused on information provision without normative appeals or peer-group comparisons, plus supplementary evidence that includes less educated and younger households being more responsive to the intervention, is consistent with the mechanism behind the consumption changes being improved energy cognizance.

Regardless of the exact mechanisms driving our results, the economic implications may be substantial. In particular, assuming that we were successful in randomly selecting our intent-to-treat group (and we have no evidence to the contrary), then extending our educational workshop to all households in Puebla's above average income neighborhoods would be expected to yield similar average reductions in electricity use as our estimated intent-to-treat effects (which already account for the fact that only some households will accept the treatment). Under a range of plausible administrative cost assumptions, we find that the cost per kWh saved is less than a previous appliance-upgrade program studied in Davis et al. (2014). Moreover, if the effects we estimated continue to persist beyond our sample window, our intervention appears cost-effective relative to efforts to encourage conservation by US utilities, especially if customers are targeted effectively.

We suggest that a program like our energy education workshop should not just be compared to programs in the United States or other high income countries. That is because less developed countries may have an advantage in implementing and scaling programs like our intervention. Analogous studies in the United States and other advanced economies rely on Internet connectivity as the means through which to engage consumers, and also tend to face much lower response rates than our study (Kahn and Wolak, 2013; Jessoe and Rapson, 2014). More recently, the so-called "Internet of things" has been used to directly manage the amount of electricity used by Internet-connected household appliances rather than relying upon individuals in the household to alter their behavior (Bollinger and Hartmann, 2017). By contrast, our intervention is a more personal and participatory one that helps respondents more fully engage with and understand the information being presented. While such an approach would be cost-prohibitive (and quite likely culturally not appropriate) to scale in more advanced economies, developing regions may be different. In Mexico, for example, labor is relatively cheap, and it was not culturally strange or intrusive for our team of student researchers to knock on doors, even in affluent neighborhoods, to recruit participants for the study.

More broadly, programs like ours could be a valuable first step in encouraging a more active demand side of the electricity market. It could complement other efforts by policymakers or utilities seeking to unlock efficiency gains. In the case of Mexico, helping consumers understand how their electricity-consuming actions and the price schedule they face impact their electricity bill can empower them to make more informed decisions about how much electricity to consume. It can also help prepare them for the recent, highly publicized energy reforms, which are likely to yield more benefits to Mexican consumers if there is an informed and active demand side of the market. This is especially the case as more renewable energy (and associated wholesale price volatility) is introduced. For example, a competitive retail market can improve total market efficiency if customers actively search for plans that are best for them, with retailers offering cheaper plans for those that consume at times when wholesale electricity prices are low.[45] Realizing such potential efficiency gains could be crucial for developing economies as their middle classes and electricity consumption grow. Even simple informational interventions that engage residential electricity customers may help smooth this transition and increase the likelihood that electricity reform programs will be successful.

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[45] Given that the marginal cost of electricity generation varies with system demand, tariffs that charge higher prices when total demand is higher will encourage energy efficient behavior at the most valuable times.

support of UPAEP, including the use of the campus and resources in Puebla, thanks in large part to Herberto Rodríguez Regordosa. Additional funding for follow-on research was provided by Stanford's Institute for Innovation in Developing Economies and Program on Energy and Sustainable Development. Leslie acknowledges dissertation support received during this research project from the Alfred P. Sloan Foundation Pre-doctoral Fellowship on Energy Economics (awarded by the National Bureau of Economic Research) and the Gale and Steve Kohlhagen Fellowship in Economics (awarded by the Stanford Institute for Economic Policy Research). Michael Miller provided excellent research support. The paper benefited from comments at NC State University's Camp Resources (8/4/16), the Monash Environmental Economics Workshop (11/20/18) and from Jim Savage. Last but certainly not least, the project was the result of months of hard work by Stanford students enrolled in the Economics 121 course and their peers at UPAEP: Humberto Alba, Annelise Dillon, Albert Gehami, Antonio Hernandez, Ireri Hernandez, Jocelyne Juarez, Gyu Rim Kim, Rosa Maria Lechuga, Cesar Martinez, Kevin Martinez, Luis Arturo Medina, Ana Sophia Mifsud, and Emmanuel Perez. The views expressed in this article are solely those of the authors, none of whom have an affiliation with CFE, CONUEE, or the government of Mexico.

A. Additional tables and figures

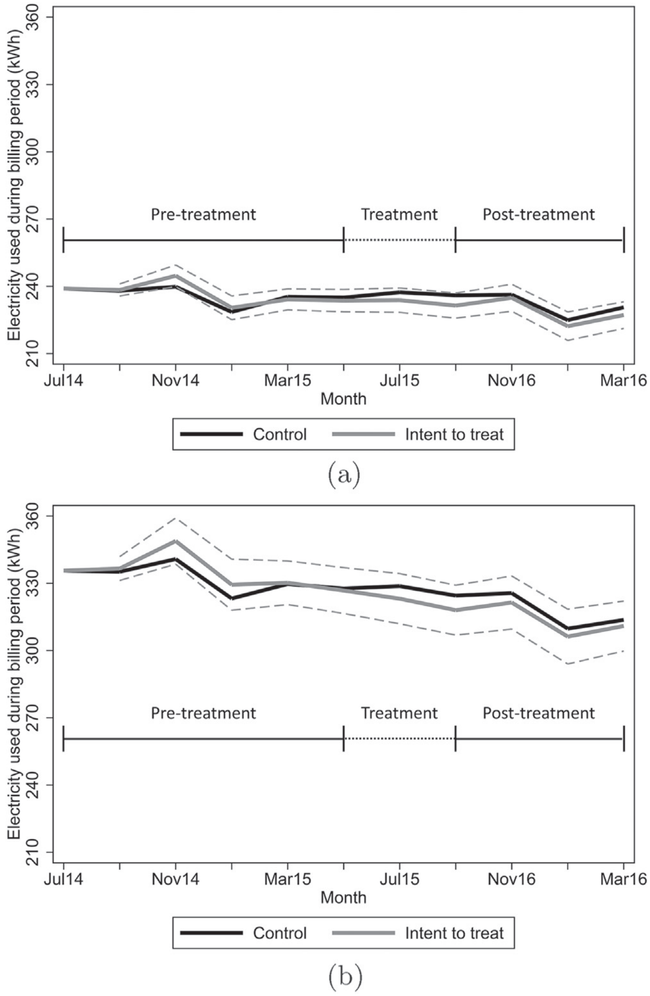
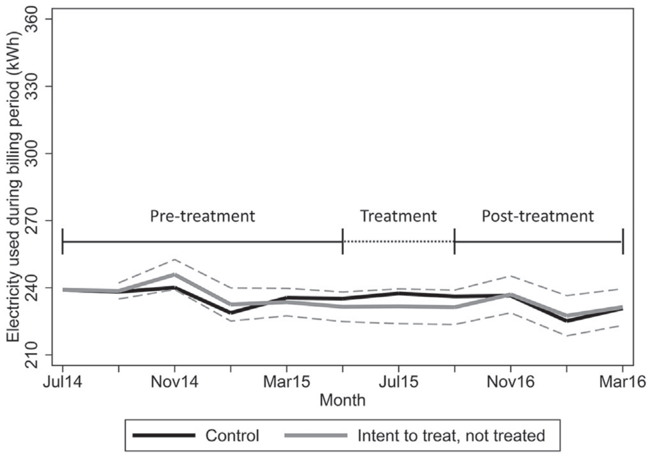
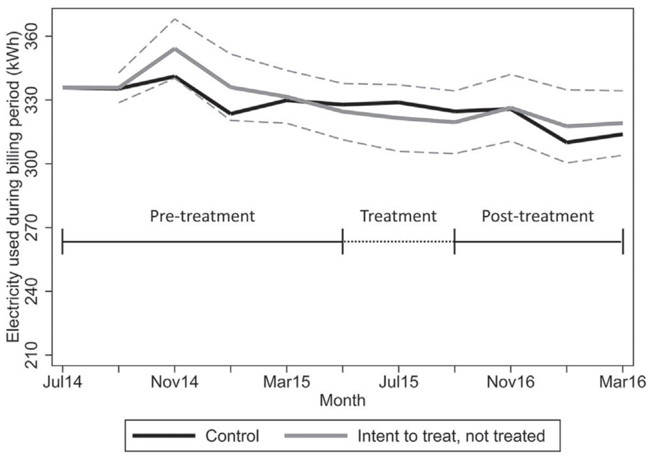


Fig. A1 Mean electricity consumption of the intent-to-treat group and control group (1 year before to 1 year after intervention). (a) Mean consumption for the control, with estimated deviation from the intent-to-treat group. (b) Mean consumption of excess sub-sample for the control group, with estimated deviation from the intent-to-treat group (had pre-intervention consumption >280kWh during a billing period). The intent-to-treat series is constructed by adding the estimates of equation (3) (displayed in tables A1 and A2) to the control series, with a 95% confidence interval plotted. The first observation does not have standard errors as the omitted category due to linear dependence arising from the inclusion of household fixed effects. Invitations for the treatment were made during the standardized billing window of July 1 2015 to August 31 2015.



(a)



(b)

Fig. A2 Mean electricity consumption of the intent-to-treat-but-not-treated group and control group (1 year before to 1 year after intervention). (a) Mean consumption for the control group, with estimated deviation from the intent-to-treat-but-not-treated group. (b) Mean consumption of excess sub-sample for the control group, with estimated deviation from the intent-totreat- but-not-treated group (had pre-intervention consumption >280kWh during a billing period). The intent-to-treat-but-not-treated series is constructed by adding the estimates of equation (3) (displayed in tables A1 and A2) to the control series, with a 95% confidence interval plotted. The first observation does not have standard errors as the omitted category due to linear dependence arising from the inclusion of household fixed effects. Invitations for the treatment were made during the standardized billing window of July 1 2015 to August 31 2015.

Table A1
Bimonthly consumption estimates by treatment category - full sample.

Group	Invited	Treated	Inv., not treated
Pre-intervention periods			
$\gamma_{G,2}$	0.37	0.34	0.39
	(1.37)	(2.02)	(1.84)
$\gamma_{G,3}$	4.87	3.52	5.85
	(2.46)	(3.49)	(3.41)
$\gamma_{G,4}$	1.88	−0.62	3.79
	(2.70)	(3.77)	(3.78)
$\gamma_{G,5}$	−1.20	−0.24	−1.92
	(2.39)	(3.62)	(3.14)
$\gamma_{G,6}$	−1.37	1.56	−3.63
	(2.54)	(3.79)	(3.38)
Period where intervention occurred			
$\gamma_{G,7}$	−3.49	−0.54	−5.74
	(2.78)	(3.76)	(3.96)
Post-intervention periods			
$\gamma_{G,8}$	−4.59	−4.20	−4.84
	(2.86)	(4.11)	(3.92)
$\gamma_{G,9}$	−1.38	−3.86	0.57
	(3.08)	(4.44)	(4.20)
$\gamma_{G,10}$	−2.72	−9.23	2.38
	(3.24)	(4.38)	(4.59)
$\gamma_{G,11}$	−3.44	−8.53	0.56
	(3.03)	(4.29)	(4.17)
P-value ($\gamma_{G,2} = \gamma_{G,3} = \gamma_{G,4} = \gamma_{G,5} = \gamma_{G,6} = 0$)	0.09	0.22	0.28
P-value ($\gamma_{G,8} = \gamma_{G,9} = \gamma_{G,10} = \gamma_{G,11} = 0$)	0.07	0.02	0.18
P-value ($\gamma_{G,8} = \gamma_{G,9} = \gamma_{G,10} = \gamma_{G,11}$)	0.10	0.11	0.08
Observations	359,700	359,700	359,700
Households	32,700	32,700	32,700
Households in treatment category	472	208	264

Standard errors clustered at the household level reported in parentheses, with each column a separate regression. There are 11, 2-month time periods. $\gamma_{G,s}$ reports the coefficient on the interaction variable between the treatment category denoted in column and time period s, as described in equation (3). The Wald test-statistic for the pre-treatment trends test is distributed χ^2_5 and for the post-treatment trends test is χ^2_4. Household and time fixed effects are included but not reported.

Table A2
Bimonthly consumption estimates by treatment category - excess consumption group.

Group	Invited	Treated	Inv., not treated
Pre-intervention periods			
$\gamma_{G,2}$	1.42	2.78	0.40
	(2.71)	(4.07)	(3.58)
$\gamma_{G,3}$	8.05	1.04	13.06
	(5.25)	(7.61)	(7.11)
$\gamma_{G,4}$	6.16	−2.61	12.48
	(5.81)	(8.24)	(7.96)
$\gamma_{G,5}$	0.57	−0.89	1.63
	(4.96)	(7.83)	(6.34)
$\gamma_{G,6}$	−0.91	2.33	−3.27
	(5.21)	(8.06)	(6.76)
Period where intervention occurred			
$\gamma_{G,7}$	−4.88	−6.12	−4.14
	(5.36)	(7.60)	(7.37)
Post-intervention periods			
$\gamma_{G,8}$	−5.98	−9.78	−3.24
	(5.39)	(7.89)	(7.24)
$\gamma_{G,9}$	−2.77	−9.44	2.17
	(5.59)	(8.19)	(7.50)
$\gamma_{G,10}$	−4.11	−14.81	3.98
	(5.59)	(7.79)	(7.70)
$\gamma_{G,11}$	−4.83	−14.11	2.16
	(5.40)	(7.62)	(7.38)
P-value ($\gamma_{G,2} = \gamma_{G,3} = \gamma_{G,4} = \gamma_{G,5} = \gamma_{G,6} = 0$)	0.64	0.85	0.34
P-value ($\gamma_{G,8} = \gamma_{G,9} = \gamma_{G,10} = \gamma_{G,11} = 0$)	0.08	0.01	0.22
P-value ($\gamma_{G,8} = \gamma_{G,9} = \gamma_{G,10} = \gamma_{G,11}$)	0.75	0.10	0.22
Observations	159,280	159,280	159,280
Households	14,581	14,581	14,581
Households in treatment category	230	101	129

Standard errors clustered at the household level reported in parentheses, with each column a separate regression. There are 11, 2-month time periods. Sample restricted to the group classified as the excess consumption group based on their pre-intervention consumption levels. $\gamma_{G,s}$ reports the coefficient on the interaction variable between the treatment category denoted in column and time period s, as described in equation (3). The Wald test-statistic for the pre-treatment trends test is distributed χ^2_5 and for the post-treatment trends test is χ^2_4. Household and time fixed effects are included but not reported.

B. Workshop offer and contents

Fig. B1 displays a photograph of a workshop being undertaken. Fig. B2 outlines the sample selection, raw response rates and the contents of the workshop. Fig. B3 displays two of the educational slides in the workshop.

Fig. B1 The delivery of a workshop. In the workshops, the tablet computer often changed hands between the student and the household member, with two of the Spanish speaking students taking the lead reading through the contents of the slides, and a third student managing the logistics by documenting whether a respondent answered the door, ensuring the households offered the treatment matched the households selected at random, and filling in the first page of the handout depicted in Fig. B4.

The tips offered were constructed from the appliance ownership and usage questions administered during the intervention. The list of possible savings tips and inputs to the calculations were:

1. Replace incandescent lightbulbs with CFLs/LEDs
   - Counting lightbulbs in the house for each type (visual aids presented for lightbulb types).
2. Put computer/laptop in sleep mode or turn off when not being used
   - How many laptops or desktops are used in the house and how often are they turned off or put to sleep when not in use (0, 25, 50, 75 or 100% of the time)
3. Watch 30 min less TV per day
   - 16 discrete bins by size and technology of TV (CRT, LCD, LED, Plasma) collected for the most used TV in the house, along with the number of hours each day it is used.
4. Wash full- not half-loads of laundry
   - Number of loads of washing run each week, water temperature and three types (front-loading, top-loading with agitator and top-loading without agitator (visual aids presented for classification).
5. Replace refrigerator with more efficient model
   - 9 discrete bins by size and vintage of model collected for up to 3 refrigerators in the house (visual aids presented for classification).
6. Disconnect second refrigerator (uses inputs from above)
7. Disconnect third refrigerator (uses inputs from above)
8. Replace TV with more efficient model (uses inputs from above)
9. Replace washing machine with more efficient model (uses inputs from above)
10. Iron clothes more efficiently
    - Only used if none of the other tips apply - no appliance information gathered

Using the survey responses, the code calculates how much a user could save (in kWh) by pursuing each tip. The code first rounds all kWh savings values to the closest integer. Then it checks that no suggestion is more than 1/4 of the users total bill. Finally, we sort the suggested tips by the calculated kWh savings in descending order. These suggestions are displayed, along with their savings value. We only show suggestions with calculated kWh savings greater than 0.

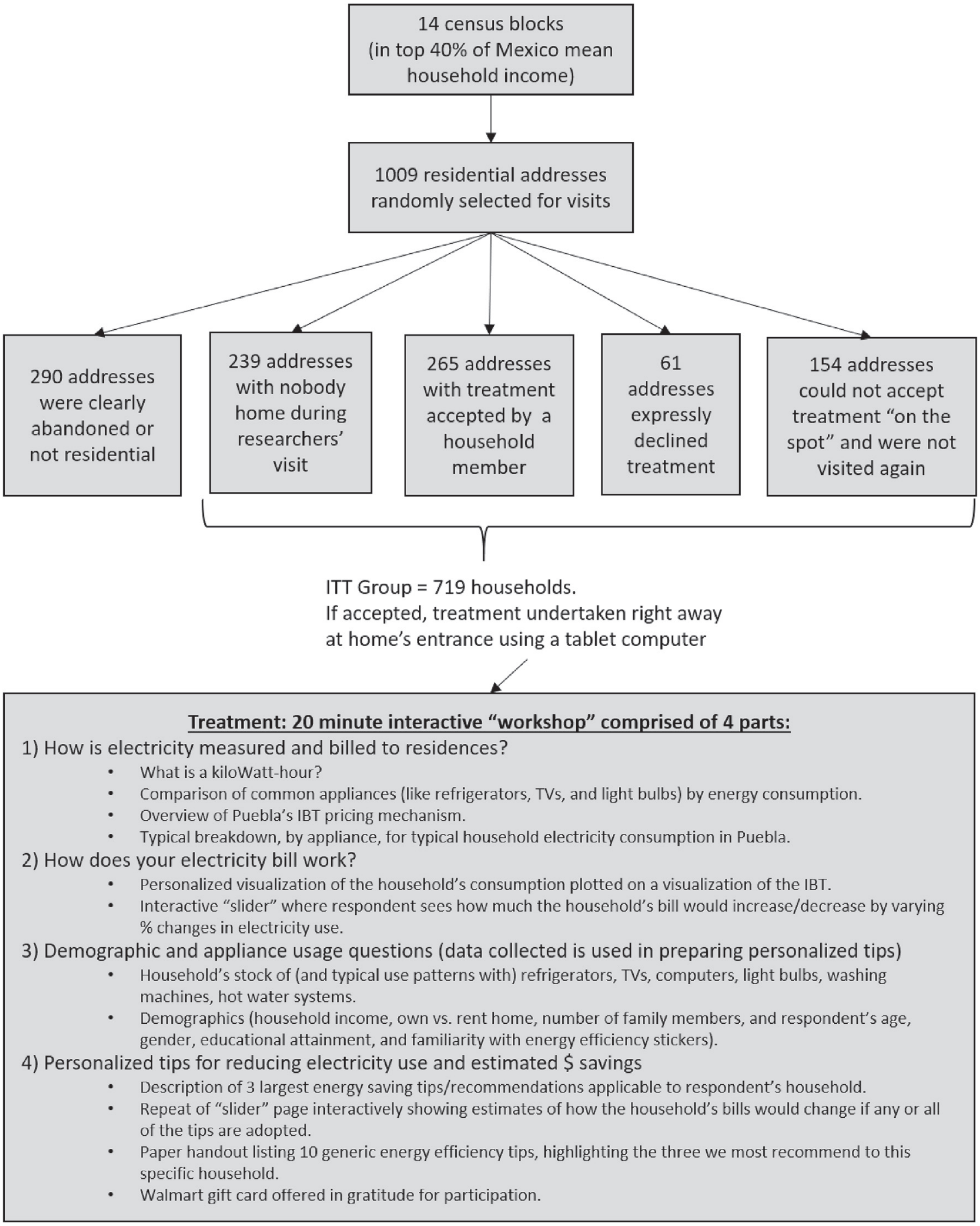
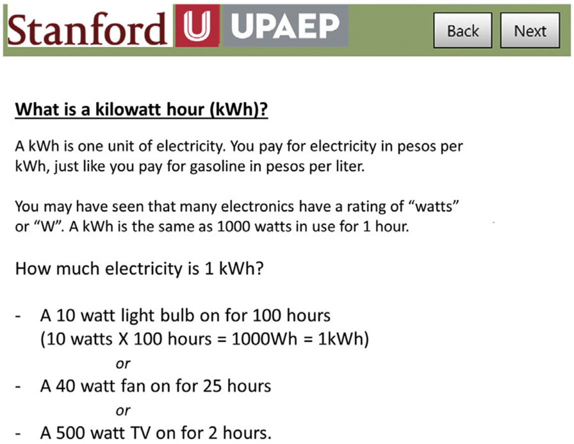
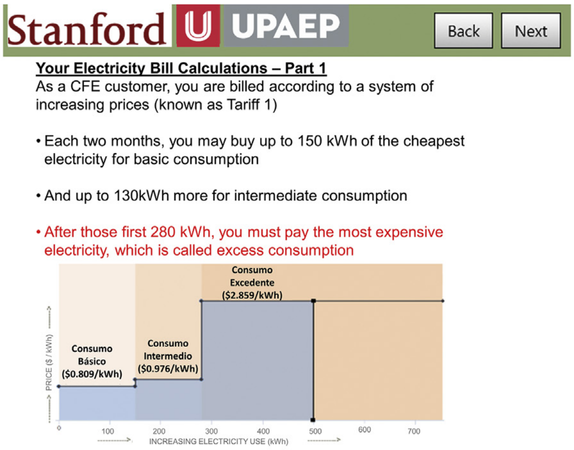


Fig. B2 Flowchart of sample selection and overviews of the randomized control trial's treatment.



(a)



(b)

Fig. B3 Sample educational slides from workshop (English translation). (a) Explanation of a kWh. (b) Introductory explanation of increasing block tariffs.

Iron your clothes more efficiently

•Irons use up lots of electricity; do not leave them turned on unnecessarily. Each time you use it, iron as many clothes as posible at once. In this way, you will sabe energy and money each time you use your iron.
•When you iron, begin with the clothes that requires most heat. As you get closer to finishing, unplug the iron and continue ironing the clothes that require less heat to press.

Use only one refrigerator

•Fridges are among the appliances that use the most electricity. Unplug your second refrigerator when you are not using it. Keeping it cold requires more or less the same electricity regardless of how full it is.

Replace your refrigerator with a newer and more efficient model

•The new models are designed to use less electricity by having better insulation and improved motors, and they are also more durable. Although this requires an investment, in the long run it will save you money.

Thanks for participating in our workshop. We hope that this information will be useful!

Important Reminder: *The actual savings you may get by implementing our suggestions may vary. These tips represent our best estimates for your household based on the limited information we have gathered.*

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Suggestions for saving money and electricity in your household

Three personalized suggestions

• ______________________

Save ________ kWh and ______ % on your electricity bill.

• ______________________

Save ________ kWh and ______ % on your electricity bill.

• ______________________

Save ________ kWh and ______ % on your electricity bill.

Total savings: _____ kWh and ____ % on your electricity bill.

See inside for detailed tips on how you could potentially save even more.

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(a)

Follow these tips to save money and electricity

Replace your incandescent light bulbs with CFL or LED types.

•**CFL** bulbs use **75% less energy** than incandescent bulbs and they cost about the same. Buy those the next time you go to the supermarket. That way the next time your bulbs burn our, you can replace them easily with CFL ones.
•If you want to save even more money in the long run, buy LED bulbs. These cost more than incandescent bulbs but they use **90% less energy** and also last much longer!

Place your computer in sleep mode or turn it off

•In most computers it is easy to actívate sleep mode or adjust settings to do it automatically. Your computer will use less energy but can still return to being active very quickly. This way you can continue to work efficiently while saving energy and money. When you finish using the computer, it is important to turn it off completely.

Watch 30 minutes less TV each day

•Most people don't realize that leaving the TV on unnecessarily is costly. Reducing TV use by just 30 minutes per day could significantly reduce your annual electricity costs.
•In general, do not leave TVs, radios, lights or any other electric appliance turned on when not using it.

Replace your old TV with a new flat screen one

•Traditional analogue televisions use more electricity than the flat screen LED ones of the same size.
•When you go to buy a new TV, look for the label "LED" and ask about the electriciy use of the different models: 30W is considered efficient for a small TV and 60W for a larger one. In addition, these TVs will likely last longer and save you more money.

Important note: We do not recommend purchasing a plasma TV, since these types use lots of electricity.

Reduce partial loads of laundry

•Washing machines use up about the same amount of electricity regardless of the load size. A government study found that most families tend to use less than half the maximum capacity of their washing machines. If you fill up your washing machine each time that you use it, you will reduce your number of weekly loads and save time, money and electricity.

Replace your washing machine with a newer and efficient one

•Front-loading machines are more efficient and its recommended that you replace top-loading models.
•And since front-loading machines also use 50-60% less water than top-loading ones, you will also save money on your water bills.

Wash all clothes in cold water

•Approx. 90% of the electricity used by washing machines is for heating water. By lowering your water temperature settings you will save energy and money. Other than for oily stains, washing with cold water generally cleans clothes the same as washing them in warm or hot water.

(b)

Fig. B4 Unfolded handouts given to respondents after the workshop (English translation). (a) Unfolded handout, pages 5, 6 and 1. (b) Unfolded handout, pages 2, 3 and 4. The handouts were a single sheet of paper folded into thirds. The cover sheet with the three personalized energy saving tips were filled in by a student enumerator.

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