Promoting energy efficiency in emerging economies through consumer education: Results from a field experiment in Mexico

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Abstract

We undertake a field experiment that delivers information on electricity pricing to randomly-selected households in Puebla, Mexico. The 20-minute, in-person intervention educated households on how their electricity use translates into pesos on their electricity bill. Households receiving the treatment reduced electricity use, especially those that paid the highest marginal prices. The estimated impacts were durable, with no observed rebound for at least a year. In addition, those with less educational attainment reduced electricity use the most, suggesting that it was newly-acquired knowledge that led to this behavior. Our intervention was tailored for an emerging economy setting and had high acceptance rates. We also find that it is a cost-effective approach to overcoming information barriers that are likely to exist in developing countries that are restructuring their energy sectors.

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1 Introduction

Restructuring of state-owned utilities is usually motivated by the potential to unlock efficiency gains. For example, transitioning from a state-owned electricity sector to a competitive market structure may improve load management practices and investment decisions. The success of reforms on the retail side of electricity markets hinges on the engagement of a utility's customers. If end-users do not understand and adapt to policy changes and price signals, then restructured retail markets are unlikely to function well.

In the case of residential electricity customers (households), this means that they need to have at least a basic understanding of how they are being billed for their electricity use. If consumers simply view their bills as coming from a utility's mysterious "black box," then they cannot respond to the pricing signals the utility or policymakers may wish to send. By contrast, if customers are able to relate their own household's electricity use habits to the pricing system they are subject to, they can make self-interested decisions to increase or curtail use, as appropriate.

This challenge of consumer engagement is heightened in emerging economies. In many countries, households have traditionally interacted with electric utilities simply as government agencies rather than as counterparts to a commercial transaction to purchase electricity. In those settings, the "electricity bill as a black box" problem might be especially difficult to overcome, but the benefits from overcoming it could also be amplified. That is, the factors that make it desirable to undertake energy reforms in developing countries in the first place (the traditional lack of market-based transactions, financial incentives, and information exchange between a utility and its customers) are the same ones that make them difficult to implement in practice. Improving consumer informedness and engagement in low- and middle-income countries may therefore significantly increase the extent to which the potential benefits of electricity sector reforms are realized.

In this paper we address two key policy questions. First, what is an effective way to communicate complex topics on electricity pricing in a straightforward manner that many (previously unengaged) consumers will understand? Second, will consumers be motivated and/or able to adjust their electricity use habits to take advantage of any new knowledge they acquire? We undertake a first step toward answering these questions through a field experiment in the city of Puebla, Mexico, that tested an actionable information treatment on increasing block pricing tariffs (IBT). These are non-linear pricing schemes that many electricity, gas, and water utilities throughout the world use to sell their services to end-user households. IBTs are designed to provide highly affordable base amounts of a service while also incentivizing resource conservation in higher levels of consumption. Instituting an IBT pricing mechanism is also often among the first reforms undertaken by developing countries seeking to invigorate a stagnant electricity monopoly.[1]

Our experiment probes the extent to which improved consumer education in an emerging economy might improve the effectiveness of an IBT pricing system (and, by extension, other more complex reforms) as a policy tool. We provided randomly-selected households with a 20-minute interactive explanation of the way in which electricity bills are calculated and the manner and extent to which each individual household might be able to change their bill by making different electricity use choices. We find that households tended to use less electricity following this simple information exchange, which did not have any additional normative or peer group context. We did not appeal to consumers' emotions regarding environmental responsibility, global warming, resource conservation or the like. Nor did we compare households' electricity use with their neighbors or others in an attempt to encourage what the household might perceive as socially desirable behaviors. We also find that our implementation strategy – delivering the treatment in person on the doorsteps of households – was cost-effective and resulted in high penetration rates. Of households in which we found someone at home, 60% chose to participate in the research and receive the information-based treatment. These high take-up rates, along with low labor costs (relative to electricity bill savings), drove the cost-effectiveness of the intervention.

On average, households that we *attempted* to provide this information intervention to (regardless of whether we were successful in doing so) reduced their electricity use by more than 1%. These results were driven by those households that faced the highest marginal prices for electricity – they reduced use, on average, by nearly 3%. Those results, in turn, appear to be due to high-consuming households that actually accepted our treatment (as opposed to those where we did not find anybody home or those who declined to participate), who lowered their electricity consumption by an average of over 6%. The impact of the information intervention was durable, as the reductions in electricity use among the treatment group continued for more than one year. Our findings that those facing the highest marginal prices responded the most to the study's intervention underscores the importance of aligning electricity pricing mechanisms with the overall policy goals of a utility or regulator. These results are consistent with the theory that there are basic price and consumption thresholds below which consumers will simply be unmotivated and/or unable to adjust electricity use.

In addition, we observed that households where less educated respondents accepted the treatment

[1]Under IBT volumetric pricing, it is hoped that even poor households can afford to purchase a necessary minimum of the relevant service; but the cost of consuming one more unit of the service (the "marginal price") becomes increasingly higher once a household goes above certain thresholds of consumption. It is common to set much higher marginal prices for households with high levels of consumption relative to the basic users. This is especially important in developing countries with high income inequalities, where it is hoped that the wealthier households paying the much higher marginal prices will help the utility recover costs and enable subsidies to poor households that may not be able to pay for even basic levels of electricity at the utility's cost of generation.

reduced their consumption more than those where we interacted with a more educated member of the household. This link between the electricity use reductions and lower levels of education, combined with the markedly high participation rates in our study, suggests that consumers in emerging economies are eager to receive actionable information and that similarly simple information campaigns could meaningfully raise the level of energy education across a broad demographic in Mexico and other emerging economies.

Overall, the results of this research demonstrate the potential to successfully reach and educate utility customers in an emerging economy about the "black box" of electricity pricing and the financial consequences of their behaviors. At conservative estimates of costs and energy savings, the cost of saving energy under a program similar to the intervention we tested is less than the average cost of generation in Mexico. Indeed, undertaking and scaling such consumer education programs in emerging economies with low labor costs and Internet penetration rates might provide certain advantages and greater impacts that could not be replicated in more industrialized settings. Rather than struggling to repeat the energy sector reform experiences of the highest income countries, Mexico and other transitioning economies could have cost advantages for overcoming problems with consumer education and engagement during reforms.

The paper proceeds with a review of the literature that we build upon concerning consumer education, IBTs, and their applications in emerging economies. We then detail the electricity billing system in Puebla, Mexico, before describing the details of our randomized controlled trial. The empirical strategy and results follow. Finally, the discussion and concluding remarks emphasize the broader implications and relevance of our findings.

2 Consumer education, non-linear prices and emerging economies

This research builds upon several foundational studies that probed whether utility customers accurately understand and respond to marginal prices. Amongst these are Shin (1985), Borenstein (2009) and Ito (2014), which suggest that customers are broadly unaware of the pricing system they are subject to, that they do not understand how much electricity their daily activities use, or are unable to anticipate shocks to their demand over the course of a billing period. More recently McRae and Meeks (2016) show that many customers do not understand how consumption relates to prices even in a very simple two-step IBT mechanism. This has motivated research into overcoming information frictions in markets with similar pricing structures.

Our field experiment was designed to have three key elements, 1) contain a detailed educational treatment with actionable information; 2) be tailored to an emerging economy setting; and 3) be free of normative or peer comparison content. Most of the prior field work on information-based strategies for incentivizing energy conservation has focused on industrialized countries (See Delmas, Fischlein and Asensio, 2013, for a meta-analysis). An exception, 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 had no additional effect.[2] Although peer comparison might be effective in reducing energy consumption, policymakers may seek to develop a more educated consumer base (that can serve as a foundation to further improve pricing policies and efficiencies), something normative appeals do not address. To this end, McRae and Meeks (2016) show that customers in Kyrgyzstan with accurate perceptions of prices were more responsive to later tariff changes, with larger responses observed for those that perceived themselves to be directly affected by pricing changes. We therefore attempt to deeply engage respondents on the complex subject of electricity use and pricing through a highly visual and interactive 20-minute educational workshop. We provide a detailed lesson in how electricity bills are calculated and then give customized information on the estimated financial impacts of different actions by our respondents.

The content of our intervention is most related to Kahn and Wolak (2013), who undertake a similar randomized controlled trial that targeted electricity customers in California. Their web-based intervention shows that out of the customers who received information about their marginal prices and potential financial savings associated with conservation, those facing the lowest marginal price increased their consumption (perhaps because they learned that it was cheap to use more electricity) while those facing higher marginal prices decreased use.

Although electricity sector reforms in emerging economies are almost always modeled on the experiences of the highest income countries, the extent to which consumer education and responsiveness in developing regions is likely to parallel the experiences of the most developed settings has mostly not been investigated. We hypothesized that there could be substantial differences between high income countries and emerging economies with respect to the delivery and impact of actionable information on electricity pricing.

First, the relationship between utilities and their customers differs across countries. Electricity services in most developing countries have been provided by a monopolistic 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, Newell and Palmer, 2006), whereas such programs have only

[2]See Allcott (2011) (Minnesota) and Byrne, La Nauze and Martin (2018) (Australia) for studies on the impact of electricity pricing and peer ranking information provision in industrialized economy settings.

recently become more common in low- and middle-income countries (Davis, Fuchs and Gertler, 2014). As a result, the baseline level of knowledge about electricity (and, indeed, the general level of education) in a typical household is much lower in developing countries. But it is not clear whether this lower baseline is a clear disadvantage (if, for example, it means that it is especially difficult to effectively educate consumers in developing countries about the complexities of energy pricing) or if it may actually be an advantage (for example, if low baseline education and frustration with the traditional "black box" makes consumers especially eager for and receptive to new information).

Second, the typical household in developing countries uses relatively little electricity. Therefore, a large proportion of households might not be able to respond to pricing signals (even if we assume they could understand them) simply because they cannot afford any consumption beyond subsistence levels. Indeed, making it affordable for these households to *increase* their use of electricity in an efficient way would be a positive outcome in many emerging economies. This stands in sharp contrast to the most industrialized regions where the overriding goal of pricing and efficiency initiatives is strict conservation through reduced electricity use by the vast majority of households. Education rather than conservation may well be a better policy goal for developing countries, empowering households to make informed and financially self-interested decisions about how to efficiently increase or curtail their use of electricity.

Third, developing settings generally lack modern infrastructure for efficient load management or technologies such as “smart meters” that may make it easier for utilities to send real-time price signals to customers. 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 developing environments.[3]

Finally, Internet penetration – especially at the household level – is much lower in developing countries. As a result, the Internet-based methods that many prior studies have evaluated for communicating pricing information to end-users (eg Kahn and Wolak, 2013), along with programming automation for appliance use to respond to prices (Bollinger and Hartmann, 2017), do not readily extend to developing environments.

3 Setting: Billing method and tariff structure in Puebla

The city of Puebla, Mexico, lends itself as a favorable location for examining the impact of an information-based intervention in an emerging economy.

[3] 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 settings.

Electricity meters in the city (like in nearly all developing settings) are mechanical and meter reading and billing usually occurs 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 period. Consequently, electricity prices (along with water, natural gas and other utility services) tend to be designed to be increasing block tariffs (IBT), where subsistence levels of electricity consumption are relatively cheap, and high levels are more expensive.[4] The price tariff in Puebla has three pronounced blocks.

In addition, the relative prosperity of Puebla means that there are a significant number of households that could be expected to use more than just subsistence levels of electricity and so are theoretically able to respond to pricing signals. As a major urban and economic center and Mexico's fourth largest city, Puebla is also large enough to be able to draw more generalizable conclusions from our study.

Finally, 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 newly formed markets.[5] CFE is a legacy provider to households that has not faced competition since being established in 1937.[6] Therefore, identifying ways to improve consumer engagement in Mexican electricity markets could impact the success of the latest reforms or, at the very least, foster an environment where consumers would be interested and receptive to learning more about the energy sector and how it impacts their daily lives.

At the time of our intervention in July 2015, Puebla residents were subject to the following pricing structure (common to temperate regions in Mexico),[7] as depicted in figure 1:

- MX$0.809 per kilowatt-hour (kWh) for the first 150kWh consumed in a billing period. (The "basic" rate)

[4]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 electricity utilities had all customers facing a linear tariff structure.

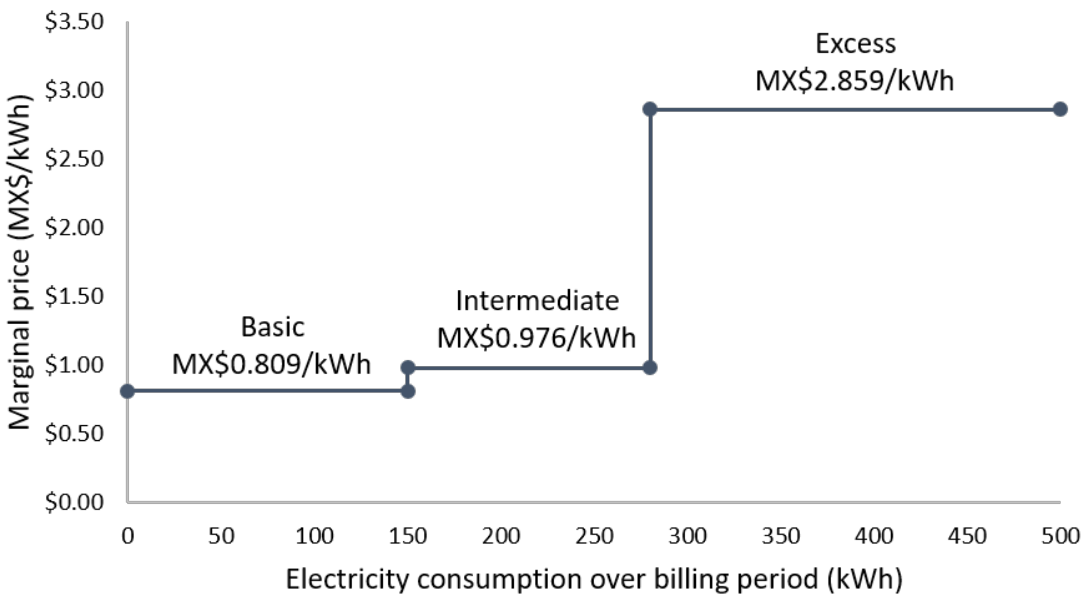
[5]Electricity reforms are often highly politicized, especially in developing countries, and the Mexican reforms at the time of our fieldwork were heavily covered by the national media. Consumers were therefore likely broadly aware that changes were forthcoming and may even have noticed their own bills becoming higher or lower after certain reforms. But if they lack a more detailed understand of why they are seeing changes in their electricity bills, then they will struggle to evaluate the success of the reforms and, more importantly, will lack an opportunity to become active participants that can make informed decisions and capture potential benefits of the reforms for their own households.

[6]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 privately-owned firms would be able to compete to generate electricity, supply electricity to industrial customers.

[7]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.

- MX$0.976 per kWh for the next 130kWh (exceeding the initial 150kWh) in the billing period. (The "intermediate" rate)
- MX$2.859 per kWh for all subsequent kWh of use (exceeding the first 280kWh) in the billing period. (The "excess" rate)

Figure 1: Increasing block pricing tariff (IBT) for household electricity in Puebla, Mexico



The differences in marginal prices means that the same electricity consuming actions (such as watching two hours of TV) cost 3.5 times as much for households that surpass 280kWh of use in the billing period (and so pay the "excess" marginal price) as compared to those that keep their consumption under 150kWh per period (and pay the "basic" rate). This tariff structure was stable throughout the two year period of June 2014 – July 2016 that is included in our analysis.[8] The amount (in MX$) that a CFE customer pays for their use during a billing period can be visualized as being the area under the graph of figure 1 that would be formed if one were to draw a straight vertical line from the amount consumed (in kWh) along the x-axis to the point of intersection with the line demarking the tiered marginal prices.[9]

[8]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.

[9]All bills incur a 16% value added tax and a minimum charge equivalent to 50kWh of use. Meanwhile, households that had used an average of 250kWh 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 "high consumption" or "DAC" rate). Less than 2% of households are billed under DAC. Although we explained

4 Field experiment design and implementation

4.1 The intervention: Electricity pricing educational workshop and actionable information provision

We designed our study to test the theory that explaining complex electricity pricing mechanisms in an engaging and straightforward manner could encourage electricity users to make (self-interested) decisions to change their electricity consumption. We began with an assumption that most Mexican consumers had only a cursory understanding of how electricity use, in general, is measured, as well as how the magnitude of their own electric bills was influenced by the electricity use choices they made.[10] We then designed an informational intervention that proceeded as follows.

Teams of three Stanford and UPAEP university student researchers knocked on the doors of randomly-selected households.[11] They offered free, 15-minute "workshops" to any adult member of a household that answered the door. These workshops explained how electricity bills are calculated, as well as customized simple tips for managing electricity bills.[12] Individuals who accepted this offer were then handed a tablet computer on which they completed a highly-visual "electricity education workshop" with the assistance of the students, as shown in figure B1.[13] Any adult household member that answered the door and agreed to participate in the study was eligible to complete the workshop, which was conducted right away by the home's front door. In practice, the mean and median workshop took 21 minutes to complete and all participants were given a MX$100 (US$5 equivalent) gift card to Walmart in gratitude. Figure B2 outlines the process by which certain 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 explained how electricity is measured in kWh, the relative rankings of various common household appliances by energy intensity, and a basic summary

DAC to the "treatment" group in our field experiment, we excluded the handful of households in our research sample that were subject to it from the final analysis.

[10]The bills that the CFE utility 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 overall pricing system or how users' behaviors are reflected in the amounts they are billed.

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

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

[13]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 savings for each household if the tips were to be implemented. These handouts were left behind with the study respondents as part of the intervention.

of Puebla's IBT electricity pricing system. The customized sections showed customers how their own household fit within this pricing regime. This helped demonstrate the effective price customers were paying to use their electric appliances. We also asked a series of appliance ownership and usage questions that were then converted to personalized information (tips) on how changes in appliance use habits would translate to changes in that particular household's bill. The most frequent tips given to our study sample were to replace incandescent lightbulbs with CFL or LED bulbs (estimated bill savings varied with the number of bulbs in the home), watch 30 minutes 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 to turn off computers/laptops when not in use. Finally, we asked respondents several questions on household demographics and questions that we thought may reveal their pre-existing energy efficiency awareness. Our experiment's workshop treatment is further detailed in appendix B.

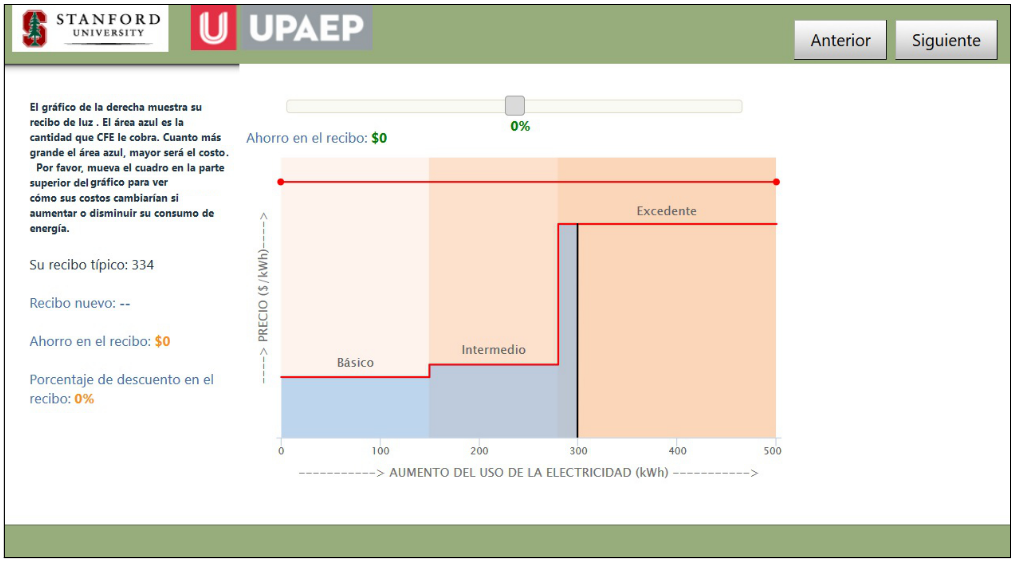
Anecdotal reports from our student researchers indicated that the most engaging part of the workshop treatment was an interactive "slider" graphic that respondents could play with on the tablet (figure 2). This graphic plotted the particular household's most recent consumption during a billing period on a visualization of the IBT mechanism (similar to what we showed in this paper in figure 1).[14] Respondents could then drag a slider bar that showed numerically and graphically by how much their household's bill would increase or decrease for given variations in electricity use. The greatest potential impact on bills are from changes in consumption levels near the large discontinuity between the intermediate and excess rates where marginal prices triple. Figure 2 shows a sample screenshot of the tablet. In this example, for customers just beyond 280kWh of consumption, a 10% reduction in electricity use would result in a bill drop of over 20%. Conversely, for customers just below the 280kWh excess threshold, a 10% increase in consumption would increase bills by more than 20%. A second version of this "slider" graphic was presented to respondents at the end of the workshop, with savings from the personalized efficiency tips subtracted from the household's baseline consumption levels. This gave participants a way to visualize and more fully understand the potential bill savings associated with the energy efficient actions we recommended.

4.2 Data and randomization

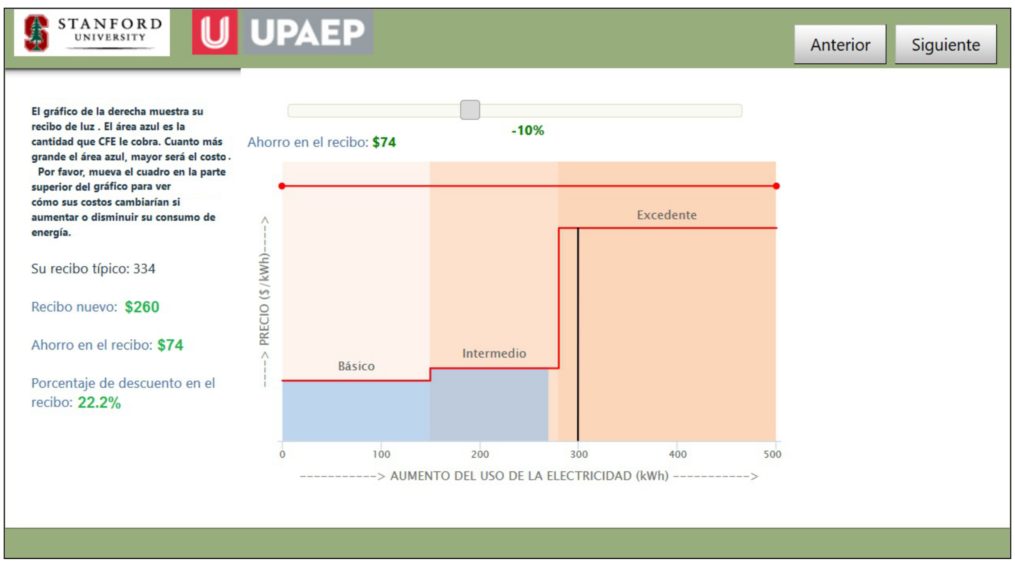
The outcome of interest is the electricity consumption by households in the city of Puebla, Mexico. We study the two year period from June 2014 through July 2016, which spans one year before and one year after our workshop was offered to randomly-selected households. We obtained this data

[14] If a recent household bill was not on hand, the respondent provided a best guess for their most recent electricity bill amount, which we then automatically converted to the corresponding kWh of consumption.

Figure 2: 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

directly from CFE after the interventions were complete. We also collected additional demographic data from the households that completed the education workshop. This was in order to gain more insights into factors that might drive any observed impacts of the 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.[15] We focused on these census blocks because they were good locations in which to find households with meaningful amounts of non-subsistence electricity use. These are the consumers who would theoretically be motivated to save money by making relatively simple energy efficiency decisions with respect to 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.[16] 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.[17] 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 efficiency tips, and received the gift certificate in gratitude for their participation.[18] The 14 census blocks corresponded to 28 neighborhoods listed in the CFE database that uses different regions to the census maps. All remaining households in these 28 neighborhoods formed our control group.[19]

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

[15]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.

[16]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.

[17]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 4.4 provides evidence that random assignment was maintained for our analysis sample.

[18]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.

[19]Census blocks were randomly assigned a number and we visited them in ascending order. The size of our study was determined by time, with our student enumerators in Puebla for a fourteen day research trip, ultimately resulting in 14 census blocks.

occupied[20]), 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. 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, used the home as a seasonal one, or may indicate that people had moved and the dwelling was either vacant or occupied by different households during the analysis window. It was also a general data cleaning measure to remove administrative anomalies.[21] In sum, we consider the sample as consisting of consistently occupied houses, with the same residents, who were subject to regular billing schedules and methods.[22]

Table 1 summarizes the final experimental samples. There were 472 households in the intent-to-treat 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 implies 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. We make a case in section 4.4 that random assignment was preserved in our analysis sample.

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 similar household-level experiments carried out in the US and other countries. For example, Kahn and Wolak (2013) (California) report approximately 10% of their intent-to-treat group accepted treatment, while Jessoe and Rapson (2014) (Connecticut) report a 2% acceptance rate.[23] One likely reason why

[20] 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 figure B2.

[21] 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.

[22] In addition, we removed the few households in our sample that paid the DAC electricity tariff, as that is a rate paid by less than 2% of Mexican households. Households with long-term average electricity consumption greater than 250kWh per month face this tariff.

[23] Many participants in this study never opened the email invitation. Of those that actually opened the emails in this study, there was a 16% response rate.

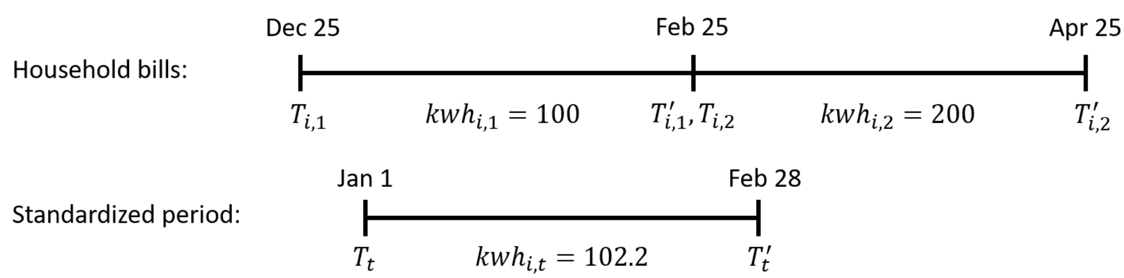
Table 1: Sample sizes for treatment and control groups

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).

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 billpayer. 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. Finally, 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.

Figure 3: Billing window standardization



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 figure 3, one household's billing period might be January 1 through February 28, while another 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 $T'_{i,1}$ bill 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 figure 3, 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. The first six periods are pre-intervention, early in the seventh period households received the intervention, and 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.

4.3 Empirical strategy

We use a difference-in-differences estimator 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.[24]

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

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

[24]We assume that the amount of electricity used by households where nobody answered the door, as well as ones who declined the invitation to participate in the workshop, was not impacted in any way simply by us attempting to offer the workshop. In other words, we assume that any observed ITT impacts are driven solely by changes in electricity consumption in households that actually took the workshop. To the extent this assumption is incorrect and there was spillover of electricity pricing knowledge or electricity use habits from our intent-to-treat group to the control group (for example, if a person that took the workshop told her neighbor in the control group about the lessons learned), then our ITT estimates can be interpreted as estimating a lower bound on the "true," larger impact of our intervention.

In this model $\text{kWh}_{i,t}$ is the amount of kWh of electricity used by household i during billing period t. We assign the values of the indicator variable $Z_{i,t}$ for all households and time periods. It is 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 period observations.[25] The variable α_i is a household-specific fixed effect, γ_t is a billing period fixed effect (for the entire sample) 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 $E[\epsilon_{i,t}|Z_{i,t}] = 0$. As such, ordinary least squares will give an unbiased estimate for the mean consumption difference households experience after being 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 also 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 differing reactions to the workshop, as well as differing abilities to curtail use and make energy efficient choices. 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. If the maximum amount of electricity used in any billing period was less than 150kWh, 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 150kWh and 280kWh, a household is classified as *intermediate*. Households that exceeded 280kWh 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 for 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

[25] 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.

actually treated the TOT is equal to:

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

In our context, the TOT estimator might provide guidance for two things. First, we provided tips to participants for the kWh they could save each billing period, so it provides a useful benchmark to relate the magnitude of any observed consumption reductions to the potential savings we identified. Second, it estimates the impact of the treatment on those that accepted it. 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, estimates of the TOT are not necessarily indicative of the magnitudes of impacts we could expect across the entire intent-to-treat group had more of those households accepted our invitation. Nevertheless, if we assume that we successfully reached those with the largest responses to the treatment, the TOT would then provide an upper bound on the magnitude of the response we could expect if we were able to reach more households with the treatment.

4.4 Tests for randomization

The logistics of this study necessitated that we select our intent-to-treat group before constructing our estimating sample. As a precaution, we present some evidence that supports our identifying assumption that the randomization strategy was successful for the estimating sample. 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). Graphically, in figure 4 we observe very close tracking between the control group and the treated group in our sample prior to the intervention. Similar trends can be seen for the intent-to-treat group and the not interviewed but offered treatment groups in figures A1 and A2.

More formally, we estimate the following model using the consumption data for households in our study for the six pre-intervention periods in the analysis sample.

$$\text{kWh}_{i,t} = \alpha_i + \gamma_1 1(t = 1) + \sum_{s=2}^{6} 1(t = s)(\gamma_s + \gamma_{itt,s} * Z_i) + \epsilon_{i,t} \tag{3}$$

As before, i is a household, t a billing period, α_i a household fixed effect and $Z_i = 1$ if a household was randomly assigned to the intent-to-treat group, while $Z_i = 0$ for the control group. The γ variables are time fixed effects, and these fixed effects are constructed such that they can differ for the households in our intent-to-treat group. If there were different electricity use trends between the intent-to-treat and control groups prior to our intervention, some or all $\gamma_{itt,s}$ 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 perform a joint test that $\gamma_{itt,2} = 0, \gamma_{itt,3} = 0, \gamma_{itt,4} = 0, \gamma_{itt,5} = 0, \gamma_{itt,6} = 0$ at a 5% significance level. We fail to reject this Wald test,[26] 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. 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[27] (rather than the intent-to-treat group), and the group offered the treatment but not interviewed[28]. 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).

5 Results

Our results suggest 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 figure 4, which graph the deviations in electricity consumption between our actually treated and control groups over the two year study horizon. Figure 4b 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 (since they are clearly above subsistence levels of electricity use). They are the electricity consumers who could save the most money by making relatively simple energy efficiency decisions. Indeed, the figures show that this sub-sample responded to the intervention in a more pronounced way than the full sample.

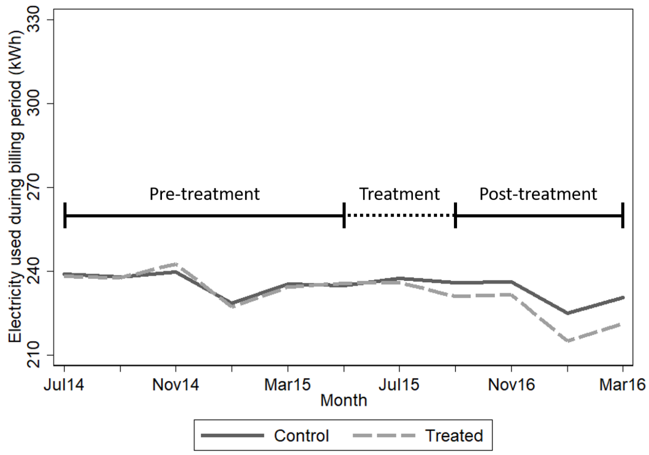
The ITT estimates for the average change in electricity use by those we randomly assigned to

[26] The distribution of the Wald test statistic is χ^2_5.

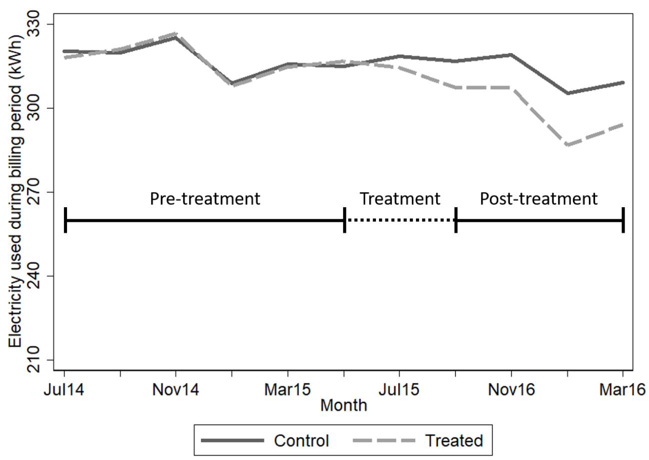
[27] We repeat the above test except we use $D_i = 1$ for those that actually completed the workshop rather than Z_i.

[28] Here we use $D'_i = 1$ for those that were in the intent-to-treat group but did not complete the workshop rather than Z_i

Figure 4: Mean electricity consumption of treated and control groups (1 year before to 1 year after intervention)



(a) Mean consumption of control and actually treated groups



(b) Mean consumption of *excess* sub-sample of control and actually treated groups (had pre-intervention consumption >280kWh during a billing period)

For easier visual comparison purposes, the actually treated series has subtracted the mean difference in pre-treatment consumption between the actually treated group and the control group. Invitations for the treatment were made during the standardized billing window of July 1 2015 to August 31 2015.

the intent-to-treat group (using equation 1) are reported in table 2 for levels and table 3 for logs.

Overall, we estimate an average 4.08kWh reduction (p-value[29] 0.013) or 1.2% reduction (p-value 0.073) in consumption for those in the intent-to-treat group. When estimating the impact by the sub-samples of pre-intervention levels of electricity use, it was only customers in the *excess* sub-sample (>280kWh) where 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 for tests of size 5%.

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 9.18kWh or 2.7% for all those who were actually treated. Once again, the result is driven by those in the *excess* sub-sample. In this case, we estimate an average 20.13kWh 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 31kWh. 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.

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	3,114	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.

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 could be from: 1) the financial incentive of households to reduce their consumption

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

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	3,114	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.

(financial incentive); 2) their non-subsistence consumption or their ability to reduce 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 allowing us to examine whether the magnitude of changes in electricity consumption by those who were actually treated can be predicted by their pre-intervention tariff level, the specific recommendations they received from the workshop or their demographic characteristics. To do so, 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-constant 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 variable:** Marginal price faced by household.
- **Ability variables:** Received specific tip (8 categories).
- **Financial incentive and/or ability variables:** Estimated savings from tips ($MX\$$), owns home (not renting), household income.

- **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) having higher potential bill savings from the tips; and, 3) having lower levels of educational attainment. The estimates of equation (4) predict that for every MX\$50 ($\approx$US\$3) of bill savings in our tips, households had approximately 1% less energy consumption post-intervention,[30] and that all else being equal, households facing the *excess* marginal price consumes 6.5% less than those on the basic marginal price post-intervention (one-sided p-value 0.043). It could be the case that both incentive and ability factors – higher marginal prices and greater pre-intervention non-subsistence consumption – contributed to why the treatment was only found to be effective in reducing consumption for the *excess* households. We are unable to identify any systematic differences between any of the tips as predictors for consumption reductions post intervention.

With regard to the energy education of the households, we did not have a prior hypothesis for 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 less educated households with the educational workshop if seeking to encourage more energy efficient behavior. However, given the overall lack of precision in these prediction regressions, further investigation is warranted before attempting to target particular demographic groups.

[30] The coefficient on total estimated savings from tips is -0.00034. After rounding, MX$50 times this value is -0.01. Note that same respondents had no tips, therefore the dollar savings entered the regression in levels instead of being transformed into logs. The p-value for a one-sided test for this coefficient being equal to zero is 0.0019.

Table 4: Estimates of consumption responses by workshop participants

Interactions with Interviewed variable (D_{it}):	kWh	log(kwH)
Financial incentive variables		
Intermediate marginal price	-4.602	-0.048
	(5.011)	(0.034)
Excess marginal price	-12.691	-0.065
	(6.720)	(0.038)
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 minutes 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)
Financial incentive and/or ability variables		
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$900 to MX$	-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)
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)
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.

5.1 Comparing the cost savings from our energy education workshop to other efficiency programs

Utility programs aimed at improving energy efficiency are often evaluated by their cost of a "negawatt hour" - the average cost of a kWh saving induced by the program. The long history of such programs in the U.S. has resulted in a wide range of cost estimates in the evaluations of appliance standards, financial incentive programs and information initiatives (See Gillingham, Newell and Palmer, 2006). Joskow and Marron (1992) raise 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 (referred to as "cash-for-coolers" in the academic literature) for replacing old refrigerators estimated to have cost US$0.28/kWh in Davis, Fuchs and Gertler (2014).[31] 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. In this section, we use the estimates from our randomized control trial to consider the costs and savings that could result from scaling and extending our energy education workshop.

On the cost side, we believe 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 minutes (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.[32] With our intervention also containing a $5 Walmart gift card, this gives a marginal cost of $10 per workshop. We also report cost scenarios of $15 and $20 per workshop to allow for recovery of supervisor and tablet computer costs (which would decrease as the scale of the program increases) and unexpected cost blowouts. Regarding the effectiveness of the program, we apply the TOT estimates in table 2 of 9.26kWh per billing cycle, and 20.13kWh if targeting the consumers on the excess tariff. Given our randomization strategy and sample selection, we expect similar results to be observed amongst those that would self-select 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 (which we would surely expect to the be the case). Given that the intervention is designed to provide education on a specific

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

[32] We expect our workshop could be streamlined to lower the time below our observed median 21 minute completion time. 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 like we did in this study).

topic, we would expect its impact to be long-lasting, which is consistent with the durability of the treatment effect we observed (see figure 4). We therefore consider cases where the effect lasts for 5, 10 or 20 years, applying a discount rate of 3%.[33]

Under these conservative assumptions, our energy education program compares favorably to estimates by Auffhammer, Blumstein and Fowlie (2008) for the costs incurred by historical energy efficiency programs in the US of $0.071-$0.196 (adjusted to 2016 US dollars). Table 5 reports the estimated cost per kWh of savings from our program under different scenarios of program cost and duration of impact. We see that if 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 cost is $0.012/kWh. However, if costs blow out and the effect is not long lasting, it becomes less cost-effective at $0.079/kWh, almost double the average wholesale price of electricity.

However, some of the exposure to cost blowouts could be mitigated if the program was designed to only target customers that are predicted to respond to the treatment. Indeed, our results suggest that a simple scale-up of our tablet-based educational workshop (without any further modifications) should only be targeted at those households that we would classify as falling in the *excess* sub-sample. When restricting participation only to those households, the best and worst case scenarios for the cost of achieving reductions in electricity use are $0.006 - $0.036/kWh. Despite the conservative cost estimates provided in this section, the results demonstrate the potential for educational programs to be used to improve energy efficiency in a low- or middle- income country. Further, utility companies could substantially lower program costs by effectively targeting their programs to the customers that are more likely to be responsive.

6 Discussion

Our results demonstrate that it is possible to effectively communicate the complexities of electricity pricing to residential electricity customers in Mexico. More broadly, the results are consistent with the theory that better informed consumers will make a choice to conserve energy once they understand the potential financial ramifications of doing so. In our study, this was especially true with customers that were paying the highest marginal prices. While our experiment cannot definitively address why the informational intervention was effective, and mostly so for the higher consumers of electricity, we put forward several potential explanations.

[33]The cost per kWh of savings is calculated as the assumed intervention cost per household, divided by the energy savings. The 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.

Table 5: Estimated costs per kWh of savings from the energy education workshop

Years of savings	Cost of program per household (US$/kWh)		
	10	15	20
	All households		
5	0.039	0.059	0.079
10	0.021	0.032	0.042
20	0.012	0.018	0.024
	Excess tariff households		
5	0.018	0.027	0.036
10	0.010	0.015	0.019
20	0.006	0.008	0.011

Estimates of consumption decreases apply the TOT estimates from table 2, applied for the number of years specified in the row, discounted by 3% each year. A discussion of the cost assumptions is in the text body.

First, the focus of our intervention was to explain how IBT pricing works and why the marginal price a household pays is important. Therefore, assuming that learning such information is valuable, it could be expected that those on the highest marginal price (which is three times the next lower tier) changed their behavior more than those facing marginal rates. For example, those *excess* sub-sample households may previously not have realized just how expensive their last kWh of electricity consumed is. On the other hand, households in the *intermediate* sub-sample may have discovered that their lower marginal price was as they expected or at a level that did not warrant behavior changes. The intermediate (and basic) tier of electricity is subsidized and so might be quite affordable. Even if households paying that low marginal price could curtail electricity use without affecting their quality of life, they may simply easily afford to be wasteful. If this is the case, then our results emphasize the importance of aligning pricing mechanisms with overall policy goals. Policymakers and the utility may reconsider how to balance the need to keep electricity affordable while still providing incentives for customers to be energy efficient. Adjusting the intermediate marginal price (which was only 20% more expensive than the basic one but three times cheaper than the excess one) as well as the thresholds of consumption at which the three prices are charged are policy levers that policymakers could adjust to better strike this balance.

Second, our intervention also included personalized information for how a household's electricity use translates to their bill. It is possible that our tips were simply more applicable and attractive to those in the *excess* sub-sample. Indeed, the estimated savings from the personalized tips we recommended to those in the *intermediate* sub-sample were, on average, 35% less than the savings our algorithm was able to suggest to those in the *excess*. As a result, those in the *intermediate* sub-sample that may have wanted to save electricity in response to our intervention may simply not have discovered convenient and cost effective methods to do so relative to the financial savings they would achieve. (We note, also, that we did not expect households in the *basic* sub-sample to meaningfully curtail use, given that those households were, by definition, using less than 75kWh per month.) This underscores the importance of targeting energy efficiency programs in low- and middle-income countries only at those who can afford to respond to them rather than the entire population.[34]

Third, there may have been some effects that encouraged households to reduce electricity use simply by virtue of talking to university student researchers who told the respondents they were part of a study that hoped to encourage efficiency and save money. However, the intervention was not designed to be normative in nature, instead aiming simply to inform households of the relationship between their appliance use and their electricity bill. Moreover, the durable and consistent nature of our estimated impacts for a full year after the intervention suggests that our study did not induce a fleeting guilt or stimulus to conserve in respondents. This is consistent with Costa and Gerard (2015) which also found that in Brazil responses to electricity bill salience shocks that promote energy efficient investments and habit formation were long lasting. Finally, our finding that the magnitudes of the responses to the intervention may have been larger for less educated respondents suggests the possibility that the workshop helped overcome an energy pricing information friction for those households.

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 stable households in Puebla's above average income neighborhoods would be expected to yield similar average reductions in electricity use as our estimated ITT effects (which already account for the fact that only some households will accept the treatment). If CFE is required to deliver energy savings through off market programs, then the costs of delivering the program delivered in this study scale with the reduction in generating costs. Moreover, our intervention appears cost effective relative to other efforts to encourage energy efficiency undertaken by US utilities, at 0.01 - 0.04 US$/kWh, with lower costs likely if more effective targeting of the program were to occur.

Finally, we suggest that a program like our energy education workshop should not just be compared to energy efficiency 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

[34] That is why we targeted our intervention only at solidly middle class neighborhoods, which successfully resulted in the *basic* sub-sample comprising only 5% of our overall intent-to-treat group.

so-called "Internet of things" has been used in order to directly manage the amount of electricity used by 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.

Given the simplicity and low costs of delivering our educational workshop, there are no obvious practical barriers to cost-effectively scaling such a program beyond the pilot research phase. Further, if an electric utility like CFE faces a mandate or other pressure from the government to reduce electricity consumption (which has previously happened in Mexico and many other countries), then the opportunity cost to roll out an information campaign like the one we tested may be cheaper than other programs with a similar impact on consumption (for example, the Mexican subsidy program for replacing old appliances examined in Davis, Fuchs and Gertler (2014)).

More broadly, programs like ours could be a valuable first step in encouraging a more active demand side of the electricity market. This could complement other efforts by policymakers or a utility seeking to unlock further efficiency gains. In the case of Mexico, helping consumers understand the "black box" of electricity pricing and empowering them to make informed decisions about how much electricity to use could better prepare them for the recent, highly publicized energy reforms, which largely depend on having an informed and active demand. This is especially the case as more renewable energy and associated marginal cost volatility are introduced to the electric grid. 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.[35] Realizing such potential efficiency gains could be crucial for developing economies, as their middle classes and electricity consumption habits grow. In this respect, even simple informational interventions that engage residential electricity customers can only smoothen the transition and improve the long-term success of other energy reform programs.

[35] 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.

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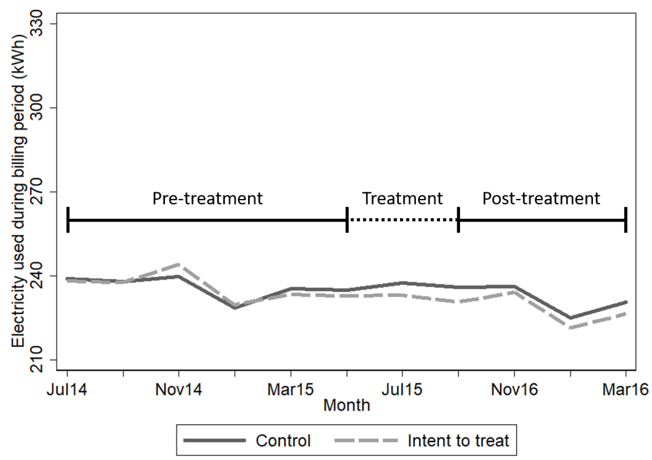
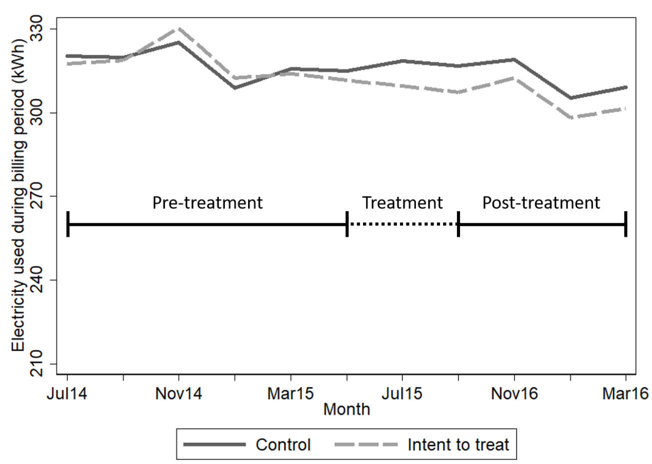
A Additional tables and figures

Figure A1: Mean electricity consumption of the intent-to-treat group and control group (1 year before to 1 year after intervention)



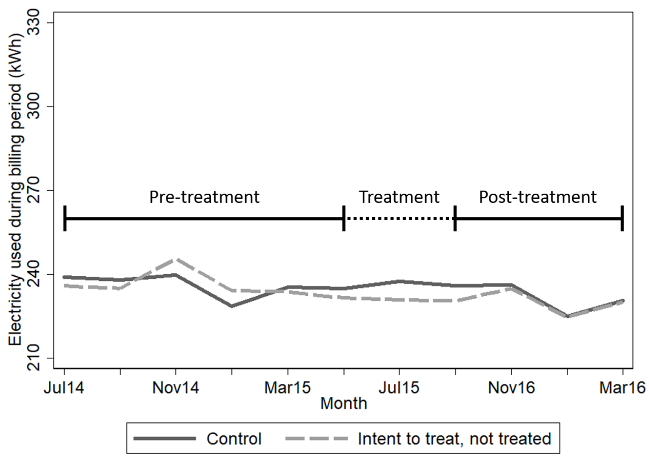
(a) Mean consumption of control and intent-to-treat groups



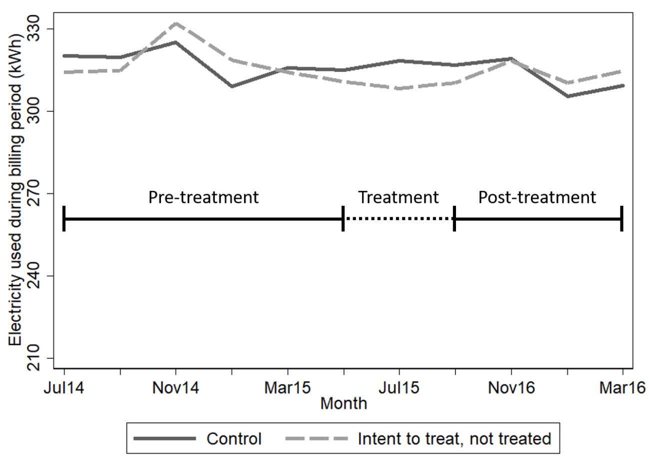
(b) Mean consumption of *excess* sub-sample of control and the intent-to-treat groups (had pre-intervention consumption >280kWh during a billing period)

For easier visual comparison purposes, the intent-to-treat series has subtracted the mean difference in pre-treatment consumption between the intent-to-treat group and the control group. Invitations for the treatment were made during the standardized billing window of July 1 2015 to August 31 2015.

Figure 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 of control and the intent-to-treat-but-not-treated groups



(b) Mean consumption of *excess* sub-sample of control and the intent-to-treat-but-not-treated groups (had pre-intervention consumption >280kWh during a billing period)

For easier visual comparison purposes, the intent-to-treat-but-not-treated series has subtracted the mean difference in pre-treatment consumption between the intent-to-treat-but-not-treated group and the control group. Invitations for the treatment were made during the standardized billing window of July 1 2015 to August 31 2015.

B Workshop offer and contents

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

Figure 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 figure B4.

The tips offered were constructed from the appliance usage questions. 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 minutes 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 the suggestion 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. If no savings can be identify, we used an overflow suggestion not derived from the survey responses to iron more efficiently, with a saving of 3kWh per billing period.

Figure B2: Flowchart of sample selection and overviews of the randomized control trial's treatment

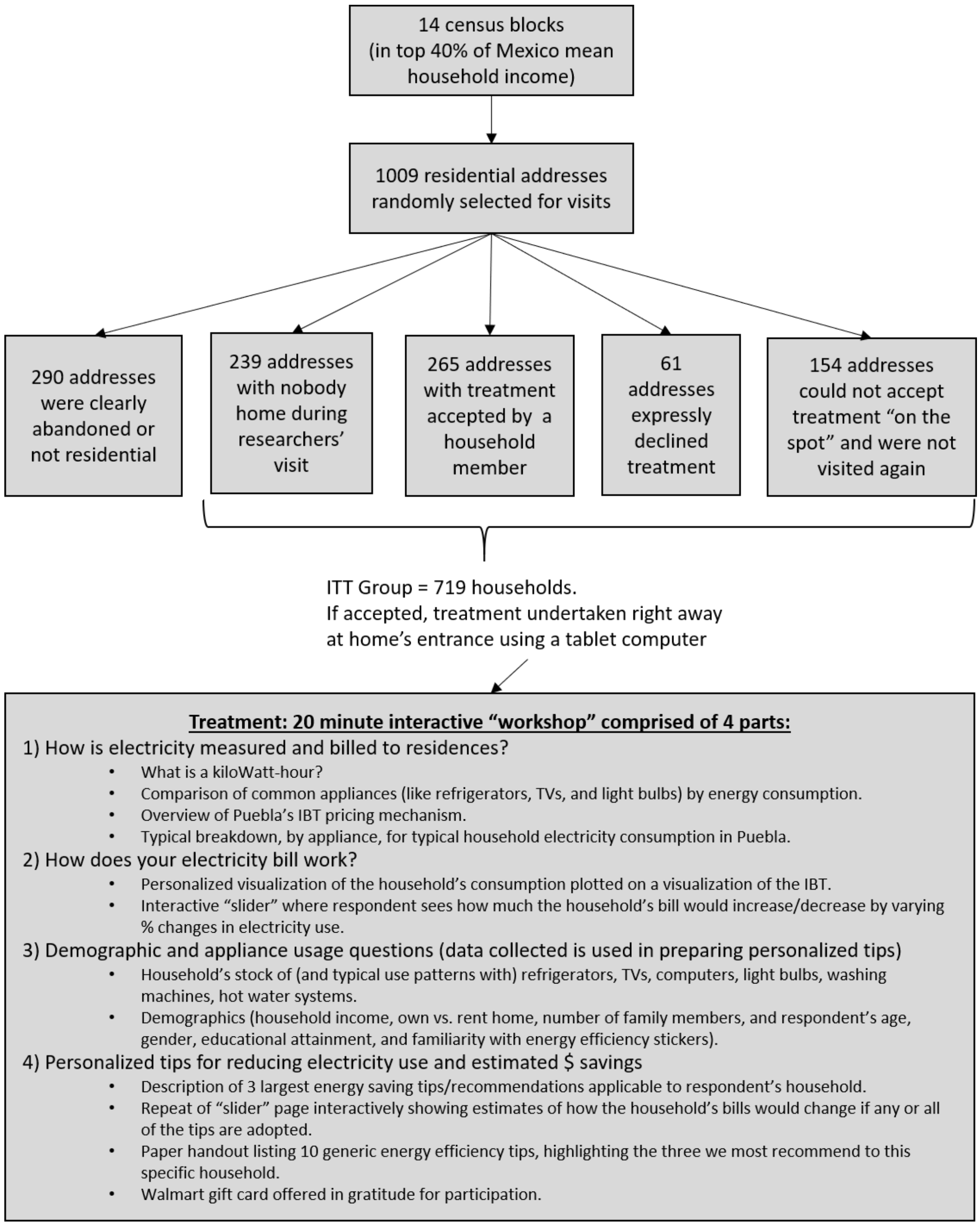
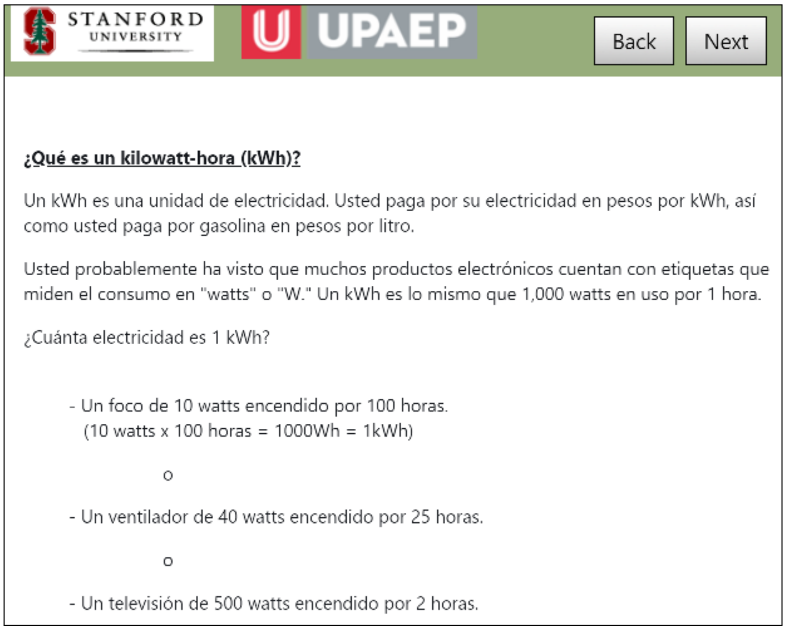
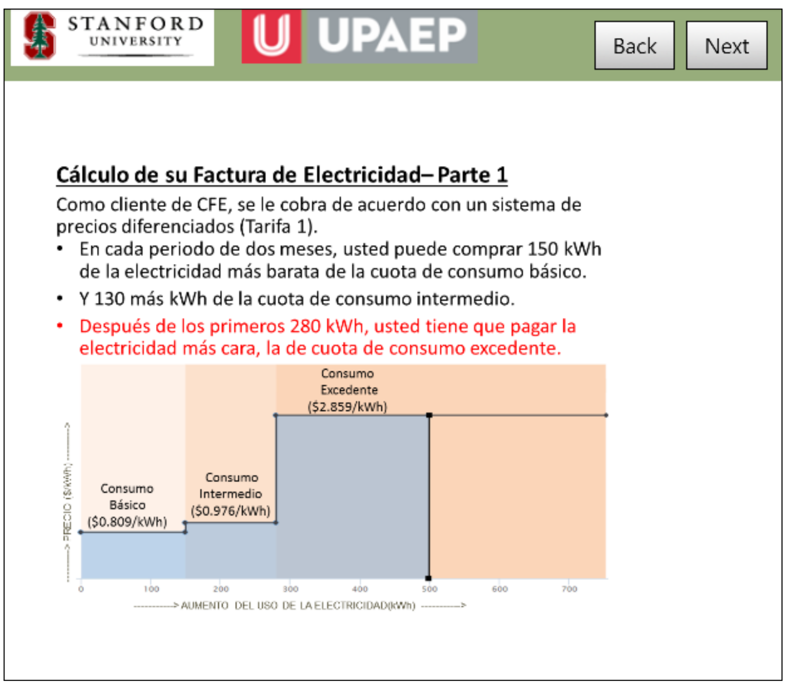


Figure B3: Sample educational slides from workshop



(a) Explanation of a kWh



(b) Introductory explanation of increasing block tariffs

Figure B4: Unfolded handouts given to respondents after the workshop

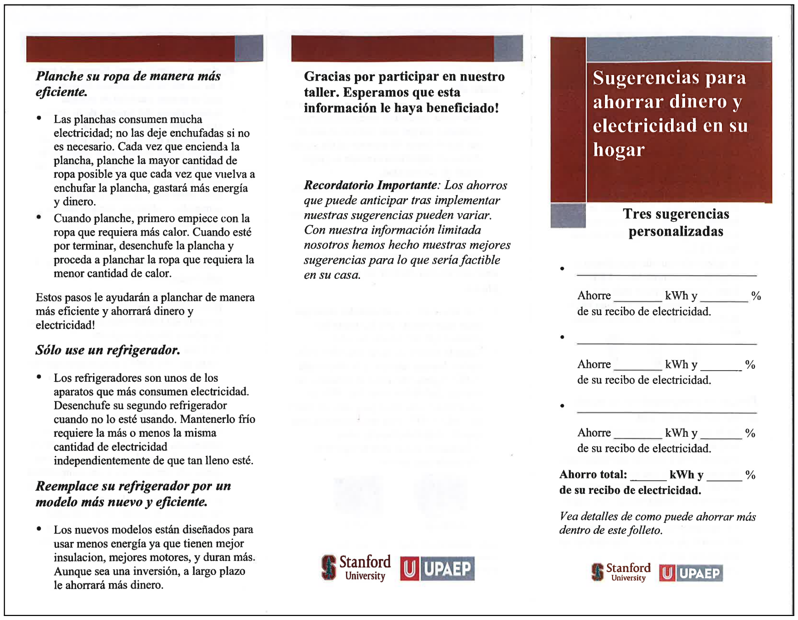


Planche su ropa de manera más eficiente.

- Las planchas consumen mucha electricidad; no las deje enchufadas si no es necesario. Cada vez que encienda la plancha, planche la mayor cantidad de ropa posible ya que cada vez que vuelva a enchufar la plancha, gastará más energía y dinero.
- Cuando planche, primero empiece con la ropa que requiera más calor. Cuando esté por terminar, desenchufe la plancha y proceda a planchar la ropa que requiera la menor cantidad de calor.

Estos pasos le ayudarán a planchar de manera más eficiente y ahorrará dinero y electricidad!

Sólo use un refrigerador.

- Los refrigeradores son unos de los aparatos que más consumen electricidad. Desenchufe su segundo refrigerador cuando no lo esté usando. Mantenerlo frío requiere la más o menos la misma cantidad de electricidad independientemente de que tan lleno esté.

Reemplace su refrigerador por un modelo más nuevo y eficiente.

- Los nuevos modelos están diseñados para usar menos energía ya que tienen mejor insulacion, mejores motores, y duran más. Aunque sea una inversión, a largo plazo le ahorrará más dinero.

Gracias por participar en nuestro taller. Esperamos que esta información le haya beneficiado!

Recordatorio Importante*: Los ahorros que puede anticipar tras implementar nuestras sugerencias pueden variar. Con nuestra información limitada nosotros hemos hecho nuestras mejores sugerencias para lo que sería factible en su casa.*

Stanford University UPAEP

Sugerencias para ahorrar dinero y electricidad en su hogar

Tres sugerencias personalizadas

- ____________________

Ahorre _______ kWh y _______ % de su recibo de electricidad.

- ____________________

Ahorre _______ kWh y ______ % de su recibo de electricidad.

- ____________________

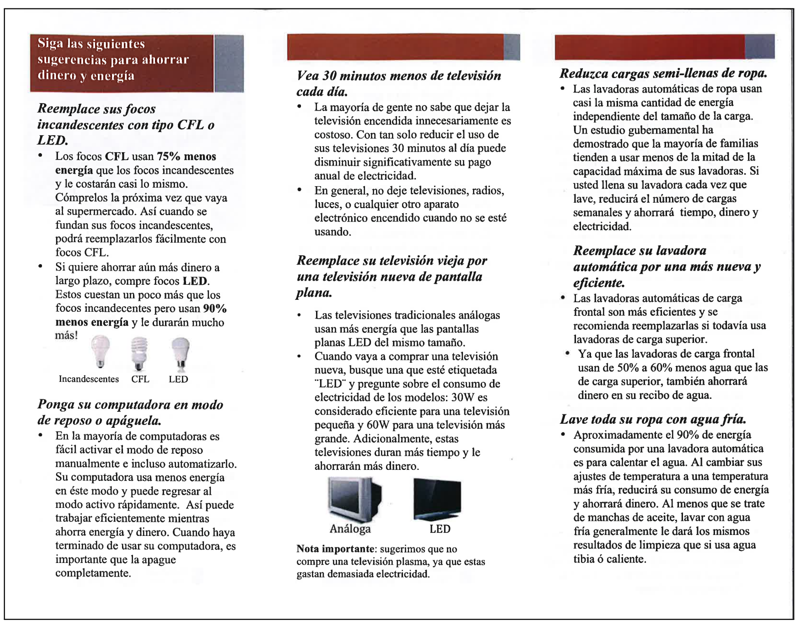
Ahorre _______ kWh y ______ % de su recibo de electricidad.

Ahorro total: ______ kWh y ______ % de su recibo de electricidad.

Vea detalles de como puede ahorrar más dentro de este folleto.

Stanford University UPAEP

(a) Unfolded handout, pages 5, 6 and 1



Siga las siguientes sugerencias para ahorrar dinero y energía

Reemplace sus focos incandescentes con tipo CFL o LED.

- Los focos **CFL** usan **75% menos energía** que los focos incandescentes y le costarán casi lo mismo. Cómprelos la próxima vez que vaya al supermercado. Así cuando se fundan sus focos incandescentes, podrá reemplazarlos fácilmente con focos CFL.
- Si quiere ahorrar aún más dinero a largo plazo, compre focos **LED**. Estos cuestan un poco más que los focos incandescentes pero usan **90% menos energía** y le durarán mucho más!

Incandescentes CFL LED

Ponga su computadora en modo de reposo o apáguela.

- En la mayoría de computadoras es fácil activar el modo de reposo manualmente e incluso automatizarlo. Su computadora usa menos energía en éste modo y puede regresar al modo activo rápidamente. Así puede trabajar eficientemente mientras ahorra energía y dinero. Cuando haya terminado de usar su computadora, es importante que la apague completamente.

Vea 30 minutos menos de televisión cada día.

- La mayoría de gente no sabe que dejar la televisión encendida innecesariamente es costoso. Con tan solo reducir el uso de sus televisiones 30 minutos al día puede disminuir significativamente su pago anual de electricidad.
- En general, no deje televisiones, radios, luces, o cualquier otro aparato electrónico encendido cuando no se esté usando.

Reemplace su televisión vieja por una televisión nueva de pantalla plana.

- Las televisiones tradicionales análogas usan más energía que las pantallas planas LED del mismo tamaño.
- Cuando vaya a comprar una televisión nueva, busque una que esté etiquetada "LED" y pregunte sobre el consumo de electricidad de los modelos: 30W es considerado eficiente para una televisión pequeña y 60W para una televisión más grande. Adicionalmente, estas televisiones duran más tiempo y le ahorrarán más dinero.

Análoga LED

Nota importante: sugerimos que no compre una televisión plasma, ya que estas gastan demasiada electricidad.

Reduzca cargas semi-llenas de ropa.

- Las lavadoras automáticas de ropa usan casi la misma cantidad de energía independiente del tamaño de la carga. Un estudio gubernamental ha demostrado que la mayoría de familias tienden a usar menos de la mitad de la capacidad máxima de sus lavadoras. Si usted llena su lavadora cada vez que lave, reducirá el número de cargas semanales y ahorrará tiempo, dinero y electricidad.

Reemplace su lavadora automática por una más nueva y eficiente.

- Las lavadoras automáticas de carga frontal son más eficientes y se recomienda reemplazarlas si todavía usa lavadoras de carga superior.
- Ya que las lavadoras de carga frontal usan de 50% a 60% menos agua que las de carga superior, también ahorrará dinero en su recibo de agua.

Lave toda su ropa con agua fría.

- Aproximadamente el 90% de energía consumida por una lavadora automática es para calentar el agua. Al cambiar sus ajustes de temperatura a una temperatura más fría, reducirá su consumo de energía y ahorrará dinero. Al menos que se trate de manchas de aceite, lavar con agua fría generalmente le dará los mismos resultados de limpieza que si usa agua tibia ó caliente.

(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.