Energy efficiency programs in the context of increasing block tariffs: The case of residential electricity in Mexico

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January, 2019

Abstract

Increasing block pricing schemes represent difficulties for applied researchers who try to recover demand parameters, in particular, price and income elasticities. The Mexican residential electricity tariff structure is amongst the most intricate around the globe. In this paper, we estimate the residential electricity demand and use the corresponding structural parameter estimates to simulate an energy efficiency improvement scenario, as suggested by the Energy Transition Law of December 2015. The simulated program consists of a massive replacement of electric appliances (air conditioners, fans, refrigerators, washing machines, and lights) for more energy-efficient units. The main empirical findings are the following: in the main counterfactual scenario, the overall residential electricity consumption decreases 9.9% and the associated expenditure falls 11.3%. Additionally, the electricity subsidy decreases 7.5 billion of Mexican Pesos per year (i.e., 403 million of USD at the average exchange rate registered in 2017) and there is an annual cut in CO_2 emissions of 3.9 million of tons.

Keywords: increasing block pricing, energy efficiency, residential electricity users, electric appliances, energy subsidies, air pollution

JEL classification: D12, L50, L94, Q40, Q53

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We would like to thank seminar participants at CIDE for their helpful comments and suggestions. We are grateful for the much valuable help on data collection by the Subsecretaría de Electricidad at the Mexican Energy Ministry (SENER). All remaining errors are our own.

The Energy Transition Law was enacted in December 2015 (ETL-2015). It mandates the Mexican Ministry of Energy to undertake technical analysis to evaluate the potential effects that various energy efficiency measures would have on: (1) electricity subsidy reduction, (2) household welfare (due to the expected lower electricity bills), and (3) the environment –i.e., air pollution and water resources.[1] Although some hesitant, non-conclusive, engineering based reports have been written, there is no economic study that evaluates the potential performance of the proposed energy efficiency measures.

A very reduced number of papers study energy efficiency in Mexican households (Davis et al., 2014; Gutiérrez-Mendieta, 2016; Rosas-Flores et al., 2011). In particular, Davis et al. (2014) put under scrutiny and evaluate a large-scale appliance replacement program in Mexico during the 2009–2012 period.[2] Our paper goes beyond that historical point, and analyzes a set of potential future policy scenarios, which are expected to happen once the prospective regulations derived from the ETL-2015 become effective.

With the above objective in mind, we first specify and estimate a structural electricity demand model for residential users in Mexico. We use the corresponding estimates of price and income elasticities and the coefficients associated to electric appliances as well as other relevant variables in the demand function, to simulate different energy efficiency scenarios (programs) that go in line with the ETL-2015 requirements. Concretely, we follow the report by the Mexican Energy Ministry (SENER, 2017) to assume realistic improved energy efficiency levels for a selected group of sensible electric appliances: air conditioners, fans, refrigerators, washing machines, and lights. Notice that, unlike most existing studies that focus only on a single

[1]The ETL-2015 also requires the conduction of research to evaluate the potential impact of distributed photovoltaic generation on the same objective variables –i.e., electricity subsidy, household welfare, and pollution reduction. See Hancevic et al. (2017) for a complete analysis on this topic.

[2]Davis et al. (2014) find evidence that refrigerator replacement reduce electricity consumption by 8 percent (only one-quarter of what was predicted by ex-ante engineering-type analysis). Moreover, they find that air conditioning replacement actually increases electricity consumption due to a marked rebound effect. As a result, they conclude that the program was an expensive way to reduce carbon dioxide emissions, and estimate a program cost of over \$500 per ton of CO_2.

appliance, we simulate improvements in the efficiency of five of them. We then estimate the counterfactual electricity consumption levels, assuming each household re-optimizes its choice after the simulated energy efficiency measures are applied. Finally, using the results of the empirical exercise just described, we calculate the effects that improved energy efficiency would have on government savings and air pollution.

The residential electricity tariff structure in Mexico is very intricate.[3] There are seven different tariff classes across the country and eight tariff regions, which are linked to average temperatures in a subsidized scheme –i.e. high temperature zones afford lower marginal prices and have larger consumption blocks. Each tariff class consists of increasing block prices (IBP), which clearly invalidate any simple estimation strategy that relies on OLS or even traditional IV methods. In the presence of IBP, consumers face a piecewise-linear budget constraint. These pricing schemes present a serious simultaneity problem: prices and quantities consumed are endogenously and simultaneously determined (see, for example, Reiss and White (2005), Olmstead et al. (2007), or Olmstead (2009)). When the joint decision of marginal price and quantity is ignored in the demand estimation, price effects are likely to be positively biased.[4] Our structural model solves this endogeneity problem and allows us to identify the behavior of residential users. By the same token, we are able to simulate counterfactual scenarios for relevant energy efficiency programs.

Summarizing, the major contributions of this study are as follows. First, our structural model is useful to solve endogeneity problems that are typical to IBP schemes –an issue sometimes overlooked in the literature of electricity demand estimation. Second, the works on residential energy efficiency are quite scarce and very incomplete for the case of Mexico. Third, unlike most existing studies for other countries which only focus on a single electric appliance, we simulate improvements in the efficiency of five appliances. Finally, our structural model

[3] Mexico has one of the most complex tariff and subsidy structures in the world, see for example Komives et al. (2009) and Lopez-Calva and Rosellón (2002).

[4] They reveal the shape of the rate schedule rather than the demand curve.

based simulation exercise explicitly considers the re-optimization consumption decisions made by households once the energy efficiency improvements take place, generating more realistic outcomes.[5]

The main results of this paper are the following: on average, the residential electricity consumption and the associated expenditure in the main counterfactual scenario fall 9.9% and 11.3%, respectively. There is, however, significant heterogeneity with regards of the final effect across households. The reasons are threefold: the tariff structure differs across the country (i.e., distinct marginal prices and different consumption blocks), the electric appliances under study have uneven penetration levels, and their potential savings are dissimilar. AC units and refrigerators offer the best opportunities in terms of policy outcomes: they provide the largest consumption savings, 14.9% and 4.7%, respectively. Finally, the electricity subsidy burden is reduced in about 403 million USD/year, and there is an annual cut in CO_2 emissions of approximately 3.9 million of metric tons.

The rest of this paper is organized as follows. Section 1 develops the structural demand model to be estimated later. Section 2 illustrates the Mexican residential electricity sector and presents a description of the data used in the empirical analysis. Section 3 presents the estimation results. Section 4 describes the counterfactual scenarios and then presents the estimated impacts that improved energy efficiency would have on household electricity consumption and expenditure, the residential electricity subsidy, and the environment. Finally, section 5 concludes the paper.

[5] One of the major limitations of our empirical model is that it does not allow us to measure any sort of rebound effects. This limitation, however, is shared by all (structural) models that based their estimation on cross sectional data –with no possibilities to apply a diff-in-diffs sort of approach.

1 Structural model

In this section we present the structural model of electricity demand. The key feature of the model is the underlying piecewise linear budget constraint that emerges in the context of IBP. Figure 1 illustrates this point for a two-block tariff scheme. A consumer can choose a quantity of electricity in the first block (e.g., point A in the left panel of Figure 1), where the marginal price is p_1 (right panel). Another possibility is the consumer chooses a quantity in the second consumption block (e.g., point C in the left panel) and pays a higher marginal price p_2 (right panel). A third possibility is that the consumer chooses the quantity e_1, which is exactly the kink point. As noted by Hewitt and Hanemann (1995), though many households probably do not know the rate structure they face, the utility maximization-based discrete/continuous choice model can be used to estimate the demand relationship as if they did. Hence, the underlying idea is that consumers behave *as if* they were making a discrete–continuous choice: they first select the consumption block, and then, conditional on being in the selected block, they choose the quantity of electricity.[6] As it will become clear later, the idiosyncratic component of the compound error term in the demand function, ε, allows the researcher to capture the difference between actual consumption and that of the utility maximizing, perfectly informed household.

FIGURE 1 ABOUT HERE

The structural discrete/continuous choice (DCC) model was originally proposed by Burtless and Hausman (1978) and Hausman (1983) in the setting of labor supply and progressive income taxation. In a more specific context of consumer choice, the model was developed

[6] An alternative interpretation is that even without having a deep knowledge of the rates they pay, households purchase their equipment (electrical installations, lighting, heating, air conditioning, and the rest of appliances) in such a way that average usage of the equipment places them in some specific consumption block. The long-run approach of Dubin and McFadden (1984) introduced the choice of durables in the energy consumption decision but without considering any sort of IBP structure. Instead, the short-run approach of our paper does not model the equipment choice but incorporates the IBP structure explicitly. However, one can think of the short-run block choice as being closely matched to a (probably previous) long-run equipment choice. In that sense, both approaches are closely related.

by Hanemann (1984). The typical electricity demand function estimated in most empirical applications has the following log-log form:

$$\ln e_{jt} = \alpha \ln p_{jt} + \gamma \ln y_{jt} + X_{jt}\,\beta + v_{jt} \tag{1}$$

where e_{jt} is the quantity of electricity consumed by the household j in period t, p_{jt} is the marginal (or sometimes, the average) price of electricity, y_{jt} is the household income, and X_{jt} is a vector of variables that includes household characteristics, dwelling characteristics, weather variables, and several other control variables. Our model closely follows the model proposed by Hewitt and Hanemann (1995) for water demand, later extended by Olmstead et al. (2007). It incorporates a compounded error term $v_{jt} = \omega_j + \varepsilon_{jt}$. The first part of the error, ω_j, includes unobserved (to the econometrician) household preferences for electricity consumption, whereas ε_{jt} includes both optimization errors and the traditional measurement error. We assume that $\omega_j \sim N(0, \sigma^2_\omega)$ and that $\varepsilon_{jt} \sim N(0, \sigma^2_\varepsilon)$. We also assume that both error terms are independently distributed. Hence, the compounded error $v_{jt} \sim N\left(0, \sigma^2_\omega + \sigma^2_\varepsilon\right)$.

In the environment of IBP, one must distinguish between conditional and unconditional demand functions. The former is defined as the quantity the household consumes conditional on being in the m^{th} price block. This is reflected in equation (1) evaluated at the price p_m and the *virtual income* $\hat{y}_m = y + \delta_m$, where $\delta_m = 0$ if $m = 1$, and $\delta_m = \sum_{i=1}^{m-1} (p_{i+1} - p_i)\, e_i$ if $m > 1$. The term e_i refers to the the upper limit of the block (kink point) i. [7]

Each household has separate conditional demand functions, one for each block. On the other hand, there is only one unconditional demand function that characterizes the overall consumption choice. Omitting household and time subscripts, define e as the observed consumption, $\underline{e}^*_m$ as the optimal consumption on block m, and e_m as the consumption at the kink point

[7]Notice that the shaded area in Figure 1 represents δ_m evaluated at $m = 2$. This term constitutes the implicit subsidy that emerges from the difference between the amount the household would pay if all electricity consumed were charged at the marginal price and the amount it actually pays.

m. We estimate the unconditional demand function using a Maximum Likelihood approach. The log-likelihood function is as follows

$$\ln L = \sum \ln \left(\begin{array}{l} \sum_{m=1}^{M} \left[\frac{1}{\sqrt{2\pi\sigma_v^2}} \cdot \exp\left(\frac{-\left(\ln e - \ln \underline{e}_m^*\right)^2}{2\sigma_v^2} \right) \right] \cdot \Pr\left(\text{block}_m\right) \\ + \sum_{m=1}^{M-1} \left[\frac{1}{\sqrt{2\pi\sigma_\varepsilon^2}} \cdot \exp\left(\frac{-\left(\ln e - \ln e_m\right)^2}{2\sigma_\varepsilon^2} \right) \right] \cdot \Pr\left(\text{kink}_m\right) \end{array} \right) \tag{2}$$

where

$$\Pr\left(\text{block}_m\right) = \Phi\left(\frac{\frac{\ln e_m - \ln \underline{e}_m^*}{\sigma_\omega} - \rho \frac{\ln e - \ln \underline{e}_m^*}{\sigma_v}}{\sqrt{1-\rho^2}} \right) - \Phi\left(\frac{\frac{\ln e_{m-1} - \ln \underline{e}_m^*}{\sigma_\omega} - \rho \frac{\ln e - \ln \underline{e}_m^*}{\sigma_v}}{\sqrt{1-\rho^2}} \right)$$

and

$$\Pr\left(\text{kink}_m\right) = \Phi\left(\frac{\ln e_m - \ln \underline{e}_{m+1}^*}{\sigma_\omega} \right) - \Phi\left(\frac{\ln e_m - \ln \underline{e}_m^*}{\sigma_\omega} \right)$$

$\Phi(.)$ is the normal CDF and $\rho = \text{corr}(v, \omega)$. Notice that each observation in the likelihood function has positive probability of having occurred in any segment and any kink point of the budget constraint. We use the estimated parameters to calculate the expected unconditional demand, as well as unconditional price and income elasticities.

As pointed out in Olmstead (2009), there are two main advantages of structural models of the sort described above over the traditional reduced-form approaches –either OLS or IV models. First, structural models (potentially) produce unbiased and consistent estimates of parameters such as price and income elasticities. Second, they are consistent with a utility-maximizing behavior and allow the researcher to perform meaningful counterfactual analysis, such as measurement of welfare changes due to price adjustments or other policy changes.

We are aware of the fact that there is no consensus regarding which price consumers respond to. This issue is, in turn, part of a broader question of how electricity/natural gas/water users make their decisions and how price schemes enter into their decision processes. There is mixed evidence favoring (disfavoring) the idea of rational consumers responding to marginal prices in the context of IBP structures. Borenstein (2009) simply speculates with the idea that consumers respond to expected marginal prices. Ito (2014) goes further and finds some empirical evidence that consumers tend to respond to average prices (rather than marginal or expected marginal prices) in a small geographical area in Southern California. On the other hand, Nataraj and Hanemann (2011) uses billing data for Santa Cruz California and finds evidence that water consumers who face IBP do respond to changes in marginal prices. Zhang et al. (2017) analyzes residential electricity consumption in the Guangdong province in China and finds certain evidence that households respond differently to small and large marginal price changes under an IBP structure. Concretely, households tend to respond relatively more to larger increases in marginal prices.

The discrepancy among the results mentioned in the previous paragraph could be, in principle, due to some fundamental differences in the services (e.g., water and electricity satisfy different needs), structural differences in the set of consumers analyzed (e.g., high-density urban areas versus low-density urban or rural areas), or merely, due to differences in the price structures themselves. In any case, these pieces of evidence (both, in favor and against the use of marginal prices in the demand estimation) cannot be directly extrapolated to all settings, periods, and regions. A case by case investigation is the most appropriate manner of proceeding. In this study, we cannot formally test the rationality assumption made in our structural model. Therefore, a maintained assumption is that consumers respond to marginal prices. We believe, however, that our empirical strategy is still superior than linear OLS or IV models (often based on weak instruments) which use average prices but systematically ignore the multi-block price structure. Specifically, our approach addresses the endogeneity problem associated with the joint determination of marginal price and quantity that characterizes IBP schemes.

2 Data and context

Our main source of data is the National Survey of Household Income and Expenditure (ENIGH), which is collected every two years by the National Institute of Statistics and Geography (INEGI). Specifically, we make use of the surveys 2010, 2012 and 2014. The data collected in these surveys provide us with certain household and dwelling characteristics –including some information on the stock of electric appliances–, as well as monthly household expenditures. The ENIGH sample is representative of both rural and urban areas throughout the country. In Table 1 we provide the summary statistics for the relevant variables used in this research.

TABLE 1 ABOUT HERE

Aside socio-demographic and economic characteristics at the household level, the ENIGH data include each household electricity expenditure which corresponds to a single billing period. This fact allows us to avoid the problems resulting from aggregating consumption data across billing periods, typically an entire year (see Dubin and McFadden (1984) and Reiss and White (2005)). Based on household geographic location, we match each household in the ENIGH with the actual electric rate schedule the household faces. For that purpose, we use tariff data provided by the national electricity company that is in charge of electricity distribution all across the country (*Comisión Federal de Electricidad*, CFE). We therefore invert the corresponding tariff formula and retrieve the electricity consumption (in KWh) from the electricity expenditure data provided in the ENIGH.

There are seven regular residential tariff classes (i.e., categories): 1, 1A, 1B, 1C, 1D, 1E and 1F, which are set by the CFE based on average temperature during summer months at the municipality level. Each tariff class consists of three or four consumption blocks. The corresponding block lengths and marginal prices differ considerably across tariff classes for both summer and winter seasons. We use the month of payment reported by household to classify users between summer and winter tariff structures.[8] Another source of price heterogeneity comes from the fact that we use three different cross sections: 2010, 2012, and 2014, and the CFE adjusted block marginal prices in each of those years[9] Table 2 provides an example for the rate schedules during Summer 2014.

TABLE 2 ABOUT HERE

In addition, each of the seven IBP tariff classes has an associated annual maximum consumption threshold. When the threshold is crossed, the corresponding household is automatically classified as a High-Consumption User (DAC). Analogously, when the sum of consumption in the last 12 months falls below the threshold, a DAC user returns to its original tariff class. The DAC users afford a two-part tariff that is composed of a fixed charge and a uniform marginal price, which is applicable to any consumption level and substantially more expensive than the regular IBP tariffs mentioned before. The consumption limit to become a DAC user differs across the seven regular tariff classes and the associated marginal price differs over CFE tariff regions.[10] Since the ENIGH data do not identify the exact tariff class each household belongs to, we need to make some additional assumptions in order to establish which households are considered as DAC users in our sample.[11] Concretely, for each household in our sample, we retrieve the monthly consumption that would emerge if it were a DAC user and then compare that figure with an imputed monthly limit (based on the actual annual limit). All users who exceed the monthly threshold are considered as DAC users. That is, we assume they have

[8]Billing data reported in the ENIGH typically correspond to the preceding two months. November to January are the only unequivocally winter months across the whole country, so we assumed that only bills paid between December and February were winter-season bills. It is worth mentioning that ENIGH data is collected between August and November, and correspondingly, 94% of households in our sample reported to have paid their bills between July and October. It is therefore possible (and natural) to assume they afford summer tariffs.

[9]In particular, block lengths and the number blocks substantially changed between 2010 and 2012 for some tariff classes.

[10]It is worth mentioning that the intricate Mexican tariff structure, and particularly, the DAC selection mechanism, could exacerbate the uncertainty of consumers in terms of the electricity price they pay. See section 1 for the justifications of the structural estimation method used in this work.

[11]Recall we recover electricity consumption from expenditure data.

the DAC consumption computed as described before, instead of the consumption that would result from using the regular tariff class in the calculation.

The three cross sections used in this paper add up to 52,580 household observations. Our final sample comprises 41,780 observations [12]. First, we discarded households that either were not connected to the electricity grid (3,661) or did not have electricity meter (1,468). Second, we dropped 2,359 households for which it was impossible to identify their actual one-period electric bill.[13] For other 3,166 cases, it was troublesome to retrieve electricity consumption because they reported to have non-standard billing periods, paid their last bill long time ago or reported an expenditure in electricity bellow the minimum possible outlay charged by CFE. Lastly, we dropped 147 observations due to missing values in other sensible variables used in our estimations.

In sum, our final sample consists of single-family households which report to pay electric bills on a bimonthly basis, that are under a metered payment system in the year in which the survey was collected, and that report an expenditure corresponding to a consumption level that is greater than or equal to 25 kWh. Table 3 shows the final distribution of users and the average consumption by tariff class, comparing the estimated values from the ENIGH data with the the corresponding figures from the CFE official report for the year 2015. The two set of numbers do not differ substantially, validating our empirical exercise to be presented later in this paper.

TABLE 3 ABOUT HERE

Finally, the demand equation to be estimated in the next section does not include any

[12] As shown in Table 1, the number of observations differ substantially among the three years. The reason is that the ENIGH performs certain oversampling for some particular set of states, and that set of oversampled states varies from year to year depending on the special information needs the survey tries to solve. However, when the sample weights are used, the total number of households across surveys is quite similar. Concretely, the percentage of total households in the original sample (respectively, in our clean final sample) are: 31.72% (31.80%) for the year 2010, 33.82% (33.49%) for 2012, and 34.45% (34.71%) for 2014.

[13] This problem typically emerges in the case of multi-family households. In those cases, it is not clear whether each family living in the home reports the share of the bill they actually pay or the total amount of the bill. Additionally, some households report paying electric bills for more than one family, or even they report paying more than one bill (several periods at once).

weather variable. Although we have data from all the stations of the National Meteorological Service, in many cases the information is lacking for several months, and in others the records start in 2013 or even later. Then, it is impossible to even try to construct meaningful summary measures –e.g., cooling/heating degree days. An imperfect alternative would be to rely on average monthly variables at the state level. However, we believe it is inappropriate given that in many situations weather variables differ considerably across municipalities within the same state.

3 Electricity demand estimation

As described in section 2, our database provides us with detailed household level electricity demand data. We exploit the substantial cross-sectional –and some time series– variation in prices that residential users face in order to estimate the structural DCC model of Equation (2). As a pure academic concern, we have to mention that the price schedule itself could be endogenous: the schedule changes over time and varies across tariff classes. While these price variation is very useful for identifying the price coefficient, using the structural model does not solve the potential endogeneity issue per se. The schedule changes could be correlated with unobserved demand shocks not captured in our model. There is, however, a clear fact in the case of Mexican residential sector that supports our exogeneity assumption. Historically, in a context of highly subsidized electricity prices, authorities have designed tariff schedules from a (partial) cost recovery perspective –see, for example, Scott (2011). Hence, tariff schedule changes are supply-side decisions which are not correlated with demand shocks. In addition, the inclusion of state fixed effects and year fixed effects helps mitigate this unlikely endogeneity problem by reducing, to some extent, the unobserved heterogeneity.

Table 4 presents the electricity demand models estimates. The first column corresponds to the simple OLS specification, where the price variable represents the marginal price paid by the households. As expected, the estimated price elasticity in this model is positive, confirming that there is a substantial simultaneity –endogeneity– problem, as explained in section 1. We present two specifications for the DCC model. One excludes the DAC users and the other makes use of the full sample. As can be seen, the estimates are relatively similar in both DCC model specifications, validating the procedure used to recover the consumption of DAC users explained in section 2. As a result, we will concentrate in the DCC full sample model for the rest of the paper, which is our baseline specification.

TABLE 4 ABOUT HERE

In the baseline specification all the estimated coefficients are statistically significant and have the expected sign, with the only exception being the dummy variable elderly, which is not significant at any conventional level. The variables that represent electric appliance holdings (i.e., water-pump, AC unit, fans, number of lights, TV sets, refrigerators, and washers) have a positive impact on household electricity consumption. In particular, refrigerators and AC units have sizable effects.

Table 5 presents the simulated unconditional price and income elasticities for the two DCC models described before. We depart from Olmstead et al. (2007) and calculate demand elasticities in the following manner. First, we simulate an 1% increment in all marginal prices and re-calculate household virtual income, $\hat{y}_m$, at each block in order to compute a new predicted consumption. We then compare the counterfactual predicted consumption with the original predicted consumption. The bootstrapped average difference across households is the reported price elasticity. We perform a similar routine to calculate the unconditional simulated income elasticity. This way, in the baseline model the estimated unconditional elasticities are approximately -.21 and .19 for price and income, respectively.[14] It is worth noting that Table 5 is

[14] Other short-run estimates of price elasticities in the Mexican residential sector are -0.14 for the State of Mexico (Ortíz-Velázquez et al., 2017) and -0.16 for Nuevo León (Morales-Ramírez et al., 2012), the two biggest states in terms of residential consumption. At the national scale and for the whole economy (not only the resi-

only informative for marginal changes in prices. Situations where consumers suffer large price jumps cannot be correctly inferred from our elasticity calculations –recall that some users shifting from a regular tariff to DAC can suffer bill increases of up to 200%. Such empirical exercise would require additional information on the observed consumption before and after the price change occurs. Consequently, the results in Table 5 should be only applicable to relatively small changes in prices.

TABLE 5 ABOUT HERE

4 Simulated energy efficiency scenario

In this section we simulate a massive energy efficiency program that is in line with the Energy Transition Law of December 2015. For that purpose, we select a group of energy-intensive appliances that are present in a significant number of Mexican households: air conditioners, washers, fans, refrigerators, and lights. Following the report by SENER (2017), for each appliance we assume potential savings in electricity consumption by comparing known values from the Mexican Official Norms (NOM) of Energy Efficiency –or estimated baselines– with minimum values of energy consumption from international standards or new technologies.[15] Table 6 presents the assumptions of improved energy consumption in the coming years for the set of selected appliances.

TABLE 6 ABOUT HERE

dential sector), Caballero-Güendolain and Galindo-Paliza (2007) find -0.19 and 0.60 long-run price and income elasticities, respectively. Notice that our estimates correspond to a short-run situation where households choose the quantity of electricity to be consumed given the stock of appliances. In that sense, our estimated elasticities are substantially larger than the ones obtained in previous studies. However, those estimates were obtained from aggregate data and used time-series estimation approaches. They clearly ignore the IBP structure of the market, which is properly incorporated in our DCC empirical model.

[15] In a majority of cases, the most efficient equipment is already available in Mexico, although sometimes at a higher cost and with a substantially lower market penetration than the equipment considered at the baseline.

In the simulations, we only use the ENIGH 2014 and take advantage of three facts. First, this cross section distinguishes between incandescent (i.e., inefficient) and low-consumption lamps held by the households. Second, data from 2014 are more comparable to the 2015 CFE numbers that we use to calculate savings in the electricity subsidy and air pollution emissions. Third, for some of the appliances considered we can establish the year of purchase. Therefore for each household holding those appliances, we can assume more precise initial energy efficiency levels before the corresponding improvements occur.

Concretely, in the case of refrigerators, we calculate the number of equivalent units each household has using as reference the average efficiency level observed in 2010 (see Table 7). E.g., a household with a refrigerator purchased in 1993 could replace it with .55 refrigerator purchased in 2010. The assumption is that refrigerators purchased after 2010 comply with the U.S. standards established in 2010.[16] In the case of air conditioners, the ENIGH 2014 neither provides information regarding the year of purchase nor the type of unit –i.e., window, split, central, etc.[17] Then, we assume AC units purchased prior to 2010 have an energy efficiency of .93 (i.e., the weighted average efficiency of the previous years, see Table 7), whereas units purchased from 2010 onwards have an efficiency factor equal to 1. To determine which units were older/newer than 2010, we take the difference between the AC penetration rates in the ENIGH 2014 and ENIGH 2010, and randomly allocate the new (efficient) units to cover that difference. Unfortunately, we do not have reliable market data for washing machines and fans, so we directly use the energy efficiency improvements scenarios presented in Table 6, assuming the same initial energy efficiency levels for all households.

TABLE 7 ABOUT HERE

[16] The Mexican norm of 2012 was aligned to the 2010 US Standards. Moreover, brand and models are similar in both countries since a significant share of the market in U.S correspond to refrigerators made in Mexico and vice versa. It is also worth mentioning that the first minimum efficiency performing standard for refrigerators in Mexico was established in 1994. Then, all models previous to 1993 are assumed to have the same efficiency as the average observed in 1993.

[17] In 2011, however, less than 1% of AC units were central systems.

We consider two different scenarios of improved energy efficiency that resemble massive appliance replacement/adoption programs:

Counterfactual 1: no changes in appliance penetration rates. That means all improvements in technology have no effect on adoption –equivalently, all the effects come from appliance replacement.

Counterfactual 2: allows for changes in penetration rates. For the case of AC units, washing machines and refrigerators, we compare the corresponding penetration rates observed in the ENIGH 2010 and 2014 and calculate the annual adoption rates. Then, we assume a constant annual growth rate for a 15-year time horizon.[18] For the case of fans, there is no meaningful (i.e., statistically significant) change in penetration rates during the years 2010, 2012 and 2014. Hence, we assume fans penetration rate remains unchanged.

Finally, since all residential users possess some (positive) number of lights, the only possibility is replacement. We therefore suppose households replace all incandescent lights with CFL and assume a 75% improvement in lights energy efficiency.[19] As a result, the simulations for improved light efficiency is the same for Counterfatuals 1 and 2.

With all the above in mind, we now explain the simulation exercise which consists of the following stages:

- **S-0** (Only applicable to Counterfactual 2) Estimate a Probit model for the probability of having at least one AC unit (also a refrigerator and a washing machine) at home. Sort the predicted probabilities and impute equipment adoption accordingly so as to achieve the penetration rate that is expected in 15 years.[20] [21]

[18] Our choice of 15 years is based on LBNL and IIE (2011a) and LBNL and IIE (2011b) which assume a 15-year lifespan for both refrigerators and air conditioners.

[19] This is equivalent to assuming that a household replace a 60-watt incandescent lamp with a new 15-watt CFL that provides the same illumination services.

[20] The results of the ancillary Probit regressions are available upon request. The regressors used in each Probit specification are similar to the ones used in table 4 for the DCC model. Concretely, we include: income, rural, apartment, owner, number of rooms, age of head, household size, children, elderly, and variables related to appliance holding. In addition we include state and tariff class fixed effects.

[21] More specific data on the characteristics of household electric appliances would make it possible to estimate

S-1 Compute the predicted electricity consumption for each household using the conditional demand coefficients of our baseline specification –i.e, the DCC full-sample model in Table 4

S-2 Recover the compounded error term, $\tilde{v}_{jt}$, as the difference between the observed consumption and the predicted consumption from S-1

S-3 For each electric appliance considered separately modify the corresponding demand coefficient by imputing the energy efficiency starting level and the associated improvement factor –Tables 7 and 6, respectively– and then obtain the new predicted consumption

S-4 Add the estimated error term from S-2 to the new predicted consumption of S-3

S-5 Compare the original (observed) consumption with the predicted consumption of S-4

It is worth noting that the predicted consumption derived from the DCC baseline model (stage S-1 above) is, in fact, the expected unconditional consumption. As a result, the calculation of the predicted consumption involves a process of re-estimating the probabilities associated to each consumption block and each kink point, and that is the case for each household regardless of the original (observed) consumption level.

Our approach is not free of limitations. Since we do not have information on the exact brand and model of electric appliance held by each household, we do not know the ex-ante unit energy consumption (UEC). As mentioned before, in the case of refrigerators and AC units we palliate this problem by using the average energy efficiency level by year presented in Table 7. In the case of refrigerators, we go further and match this information with the date of purchase, as reported in the ENIGH 2014. In the case of AC units, we simply impute different energy efficiency levels contrasting the penetration rates observed in ENIGH 2010 and 2014. Finally,

a model that contemplates the adoption/replacement decision. See for example Rapson (2014) for a structural dynamic discrete choice model of demand for air conditioners.

for fans and washers we do not have additional information in terms of average UEC by year, and we simply suppose the improvements in energy efficiency affect uniformly all households holding the corresponding appliance (Table 6).

In brief, the energy efficiency improvements to be presented in the next subsection of this work are a combination of two things: the estimates obtained from our structural DCC model, and average-type measures based on technical reports by SENER (2017), LBNL and IIE (2011a) and LBNL and IIE (2011b), which are matched with the ENIGH 2014 household data, when possible. In that sense, having more detailed data on household appliance holding would substantially improve the quality of this research.[22] Nevertheless, we believe our simulation exercise represents a very valuable effort to measure the potential impacts of the ETL-2015.

4.1 Impact on household consumption and expenditure

Table 8 presents the impact of the simulated energy efficiency scenario for each appliance individually considered –i.e., assuming energy efficiency is improved for one appliance at a time– when no new adoption is allowed (Counterfactual 1). The table shows the average savings per month in terms of electricity consumption and expenditure for affected households only –i.e., households that have at least one unit of the appliance under analysis.[23] AC units has the lowest penetration rate (14.8%) but the highest impact on electricity consumption and expenditure savings (14.9% and 18.8%, respectively). Refrigerators, in turn, have the largest penetration rate (89.6%) and the second highest savings in consumption and expenditure (4.7% and 6.0%, respectively).

[22]A great deal of relevant literature on residential energy efficiency is about interventions through frame field experiments. See for example Gandhi et al. (2016) or Hahn and Metcalfe (2016) for a review on this topic. We recognize the advantages of such experimental approaches. However, field experiments are beyond the scope of this research and the comparisons of outcomes are meaningless given the totally different contexts.

[23]Recall that we do not consider alternative adoption scenarios, that is to say the current level of appliance penetration is not affected in this counterfactual analysis.

TABLE 8 ABOUT HERE

Table 9 presents the results of Counterfactual 2: the impact of the simulated energy efficiency scenario for each appliance individually considered, but now assuming higher penetration rates. Concretely, 19.8% for AC units, 95.3% for refrigerators, and 74.6% for washers (versus the previous 14.8%, 89.6%, and 70.4%, respectively, observed in Counterfactual 1). The fact that a set of users purchase new appliances implies there is some additional electricity consumption that did not exist before. In some cases, that extra consumption cannot be counterbalanced by the increased efficiency of the equipment. This is particularly important for the case of AC units. Its penetration rate increased 33% so the total consumption and expenditure savings in Counterfactual 2 are considerably lower than those in Counterfactual 1. On the contrary, in the case of refrigerators and washers, current and expected penetration rates do not differ that much. This fact explains the similarity between results presented in tables 8 and 9 for washers and refrigerators.

TABLE 9 ABOUT HERE

Table 10 displays the average savings in terms of consumption and expenditure when improvements in energy efficiency occur in all selected appliances simultaneously. In this case, the results are computed considering the full 2014 sample. In that context, the final impact on each household's savings will depend on the corresponding stock of electric appliances. In Counterfactual 1, the overall average consumption savings amount to 16.9 kWh per month which in turn represents, on average, a 9.9% reduction in consumption and a 11.3% reduction in the monthly electricity bill. As can be seen, the savings differ substantially among the different tariff classes, being 1F and DAC users the most benefited. In particular, 1F users correspond to households living in the warmest areas of the country –i.e., the areas more subsidized according to the IBP scheme. At the other end of the spectrum, tariff 1 users have, on average, the lowest savings. The users in this category live in areas of temperate climate, and they are not affected by extreme temperatures or excessive humidity. Although the effects of air conditioning and fans are captured by the corresponding coefficients in our model, other effects explaining these results might be present as well. Since table 10 considers the effects of all appliances simultaneously, the aggregated results across tariff classes do not differ substantially when contrasting Counterfactual 1 to Counterfactual 2.

TABLE 10 ABOUT HERE

Even though it is not the main objective of our study, it is important to analyze the distributional impacts of any prospective economic policy. This is clearly true in an emerging economy like Mexico. For that reason, we present the results of our simulations by household income decile in Appendix A.

In the remainder of this paper we base our analysis on Counterfactual 1 –i.e., we do not allow for the adoption of new appliances and only focus on replacement. Notice that savings in expenditure are systematically larger than savings in consumption (see Tables 8, 9, and 10). In fact, that is a direct consequence of the re-estimation of probabilities associated to different consumption blocks.[24] Once the improvements in efficiency take place, in a significant number of cases households not only consume less but also consume in a lower block, paying a lower marginal price. Table 11 presents the percentage of households switching to a lower block once improvements in efficiency occur. It also shows the cases where DAC users reduce consumption sufficiently to return to the original tariff class. This constitute a significant advantage of our structural model, which provide us with both more flexibility and more realism.

TABLE 11 ABOUT HERE

[24]That is a necessary step to recover the expected unconditional consumption levels, a point previously discussed in the text.

4.2 Impact on government savings

The federal government collects the value-added tax (VAT) which has a 16% rate on electricity sales. Additionally, most local governments collect a street lighting tax with rates ranging from 5% to 10%. However, the government fiscal outcome derived from the residential electricity sector operation is a large deficit. Household electricity consumption is heavily subsidized: more than 98% of households receive the electricity subsidy and pay, on average, only 45% of the overall electricity cost.[25] As a result, the fiscal burden associated to residential electricity consumption has consistently increased during the last decade and currently represents more than 0.5% of the Mexican GDP.

Table 12 displays the effect that the main energy efficiency scenario (i.e., improvements in energy efficiency occur in all selected appliances simultaneously) would have on federal government savings. We assume that local governments continue affording the street lighting costs. The results in the table are calibrated using the actual number of users in each tariff class according to the CFE official report for the year 2015. The total monthly reduction in the net subsidy account amounts to 627 million of MXP. Although electricity consumption differs during summer and winter months, a simple (arbitrary and imperfect) extrapolation of this result would imply annual savings of approximately 7.5 billion of MXP –i.e., 403 million of USD at the average exchange rate registered in 2017.

TABLE 12 ABOUT HERE

By decomposing the fiscal outcome into the distinct tariff classes, it is apparent that the bulk of savings come from the more numerous classes (1 and 1C). On the other hand, the changes in both consumption and composition of DAC users have a negative impact on the subsidy account. The reason is simple: DAC users pay for electricity approximately 50% above the

[25] A deep discussion of whether the current overall cost of generating, transmitting, distributing and commercializing electricity reflects the true opportunity cost is out of the scope of this paper.

real supply cost, and therefore cross-subsidize users in other tariff classes.

4.3 Impact on air pollution

Electricity generation in Mexico is heavily based on fossil fuels –approximately 80% of the total generation– and explains more than 20% of total GHG emissions. In particular, the residential sector accounts for 25% of total electricity consumed in the country.[26] In this section we calculate the environmental impact of the simulated energy efficiency scenario. Our measurement is an estimation of the long-run effects caused by the counterfactual appliance replacement situation. Nevertheless, it does not consider the negative short-run effects that might result from producing the new appliances needed to replace the old ones.

Our analysis relies on emission factors recently published by SENER (2017), which were calculated assuming the typical operation of an average thermal generator.[27] Table 13 presents the environmental outcomes of the massive energy efficiency scenario.

TABLE 13 ABOUT HERE

The technologies used for electricity generation in Mexico include: coal, combined cycle, internal combustion, turbo-gas and conventional steam (fuel-oil and gas). It is important to note that, since 2015, the higher availability of natural gas made it possible to reduce the consumption of more expensive and polluting fuels such as fuel-oil and diesel. Hence, the avoided emissions of local pollutants (mainly, SO_2 and NO_X) are important but not extremely significant since the country relies more on natural gas, which in this case could be considered a "cleaner" fuel. With regards of carbon dioxide emissions, it is interesting to put these numbers in context. In so doing, we transform the results obtained for summer months (shown in table

[26] Mexico is the 13th largest GHG emitter in the world and the second in Latin America, just behind Brazil. It contributes with 1.4% of the global GHG emissions (Damassa et al., 2015).

[27] Concretely, the emission factors used in our analysis are: 0.00283 kg/kWh for SO_2, 0.00186 kg/kWh for NO_X, and 0.47753 kg/kWh for CO_2.

13) to annual values.[28] The estimated annual cut in CO_2 emissions is approximately 3.9 million of metric tons. That figure represents 2.9% of the 2020-2030 emission reduction target for the electricity generation sector that was committed after COP-21 held in Paris (December 2015).

To provide a monetary metric, we make an additional effort and measure emission savings. Unfortunately, a market for emissions in Mexico does not exist. There is not a single price for each of these air pollutants, and no global agreement has been reached. In the case of Mexico, however, the government sets a tax of approximately 3 USD per ton of carbon emitted. In some developed countries such as Sweden, the corresponding price could be as high as 130 USD per ton (Ward et al., 2015). Here we assume an intermediate value of 13 USD/ton.[29] As a result, the environmental savings due to CO_2 emissions reduction are 50.6 million of USD per year.

5 Conclusions and Policy Implications

In this paper we propose and estimate a structural model of residential electricity demand to simulate the effects that a massive energy efficiency program in Mexico would have on household consumption and expenditure, government subsidies, and air pollution. The characteristics of the tariff structure all across the country make it difficult to rely on simple reduced form models. In that sense, our structural model, which builds on the model proposed by Olmstead et al. (2007) for water demand, allows us to recover sensible parameters of the electricity demand function to simulate a meaningful counterfactual energy efficiency scenarios. The simulated situations consist of massive replacement (and adoption) of electric appliances in Mexican households (AC units, refrigerators, fans, washing machines, and lights). It is based on the suggestions of a previous report by SENER (2017), which follows the requirements of

[28]Here the same disclaimers of section 4.2 apply: this is an imperfect and, to some extent, arbitrary exercise. However, given the limitations of the data, it is still a valuable contribution.

[29]That value is similar to the average price registered in the Californian cap and trade program during the 2016–2017 period.

the Energy Transition Law of December 2015.

The main results of our simulation when only appliance replacements are allowed (Counterfactual 1) are the following: residential electricity consumption falls 9.9% and the associated expenditure decreases 11.3%, on average. Those numbers, however, vary significantly across consumers because the tariff structure differs substantially depending on the geographical location of households. There are different marginal prices and different consumption blocks at the municipality level, which are linked to the average summer temperatures. Also, the electric appliances under study have very uneven penetration levels and different potential savings. Consequently, electricity consumption and expenditure once the energy efficiency improvements take place have a variety of responses. Users under 1F and DAC tariffs are the most benefited in terms of monetary savings (21.2% and 22.8 respectively), whereas users in the most numerous tariff category, tariff 1, save 8.8% in their electricity bill. In terms of electric appliances, AC units and refrigerators are probably the best candidates for future policy targets: consumers holding these appliances enjoys, on average, consumption savings of 15% and 5%, respectively. With regards of the residential electricity subsidy, the fiscal burden could be reduced in 7.5 billion of MXP (equivalently, 403 million of USD at the average exchange rate in 2017). Finally, there could be an annual cut in CO_2 emissions of approximately 3.9 million of tons, which represents about 2.9% of the 2020-2030 emissions reduction goal for the electricity generation sector as it was committed in the COP-21 held in Paris.

From a distributional perspective, the outcomes of our simulations suggest that, in absolute terms, richer households experience larger reductions in their electricity bills. However, when changes in expenditure are normalized by household income, poorer households are the most benefited. This result is an obvious consequence of two facts. First, the subsidy is received by almost all households –more than 98%. Second, the (slightly) increasing relationship between income and electricity consumption.

There are some limitations in our simulation exercise that provide incentives for further research on this topic. The consumer decision process regarding replacement of old appliances and/or adoption of new technologies was not considered in our model. Instead, we simply assume all households holding the selected appliance replace it for a more efficient unit (Counterfactual 1), or also assume a higher appliance penetration rate based on a probabilistic model (Counterfactual 2). Also, more flexibility in terms of consumer behavior would be welcome: our empirical exercise assumes a uniform effect for all households holding the appliances under consideration, and we only allow for minor variations in terms of the ex-ante energy efficiency levels for AC units and refrigerators.[30] Therefore, all the heterogeneity we obtain in our results comes from the differential tariff structure, the household stock of appliances, and the imputed energy efficiency improvement factors for each appliance. Clearly, more detailed information on the actual household stock of appliances (e.g., price, operation and maintenance costs, UEC, etc.) and on conservation practices followed by residential users would be a plus. Finally, the implementation of simulations using our DCC model do not allow us to compute any sort of rebound effects. However, this limitation will be shared by all cross-sectional approaches, regardless of the (structural) model specification.

The discussion in the above paragraph points in the direction of suggesting a concrete piece of advice for interested researchers and policymakers: collection of detailed consumers data which ideally should be combined with interventions through field experiments to evaluate concrete measures of energy-efficiency and conservation policies. In this line of thoughts, we could think of a three-step empirical strategy. Hence, engineering-type studies constitute the first (necessary) step to evaluate the current situation of buildings materials, facilities, equipment and appliances, and the potential new technologies that could be introduced in the market. Structural economic studies that used observational micro-data are the second (intermediate) step. Our contribution to the literature, and more specifically, to the Mexican case, clearly be-

[30]An assumption that is probably unrealistic given the evidence from previous studies. See, for example, Davis et al. (2014)

longs to this second step. The final step is the gold standard in the energy efficiency literature: field experiments. They should be performed to evaluate the complex interactions between economic agents, information problems, market failures, and behavioral biases. As a result, different policy options can be properly implemented depending on the specific context.

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Figures and Tables

Figure 1: Utility maximization under a two-block increasing price structure

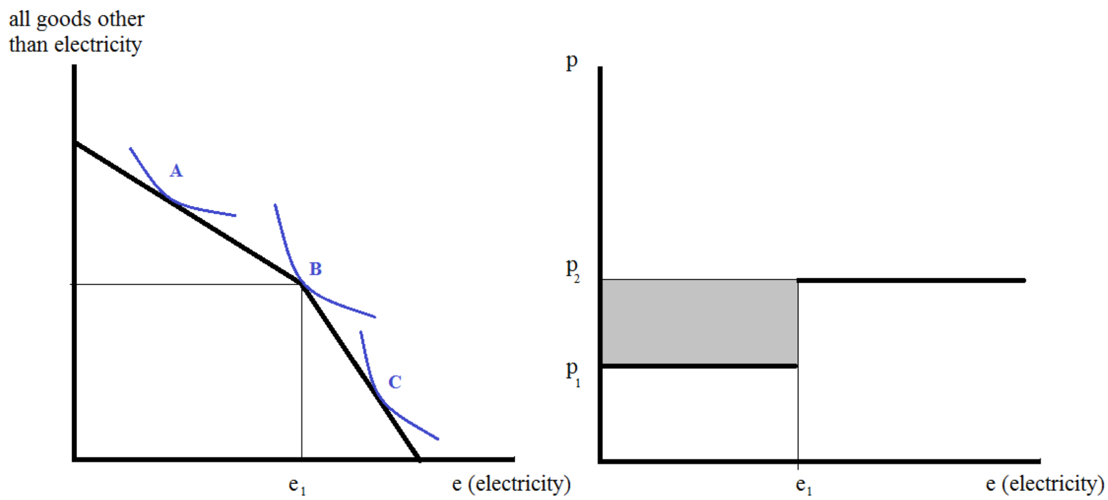

Table 1: Variable definitions and summary statistics

Variable	Definition	Mean	Std. Dev.	Min	Max
Household size	Number of household members at home	3.84	1.89	1	21
Children	=1 if at least one child living at home	0.48	0.50	0	1
Elderly	=1 if at least one person age 65 or older living at home	0.22	0.41	0	1
Age of head	Age of the head of household (in years)	49.30	15.37	15	97
Rural	=1 if the home is located in a rural area	0.14	0.35	0	1
Apartment	=1 if the home is located in an apartment	0.06	0.24	0	1
Owner	=1 if the home is owned by any member of household	0.76	0.42	0	1
Number of rooms	Number of rooms, excluding kitchen and bathrooms	3.99	1.63	1	21
Number of lights	Number of lights of any kind in the home	7.43	5.57	1	130
Number of TVs	Number of TV sets in the home	1.58	0.95	0	14
Number of refrigerators	Number of refrigerators in the home	0.90	0.35	0	5
Number of washers	Number of washing machines in the home	0.71	0.48	0	4
Fans	=1 if there is at least one fan in the home	0.49	0.50	0	1
AC unit	=1 if there is at least one AC unit in the home	0.14	0.34	0	1
Waterpump	=1 if there is at least one waterpump in the home	0.28	0.45	0	1
Income	Monthly total income (in MXP)*	9,029	10,206	91	258,947
Electricity expenditure	Monthly electricity expenditure (in MXP)*	219	298	21	12,922
Electricity consumption	Monthly electricity consumption (in KWh)	170	161	25	2,775

Source: Own elaboration, based on ENIGH 2010, 2012 and 2014.
Number of observations: 20,603 in year 2010; 6,650 in year 2012; and 14,527 in year 2014.
*The average exchange rate in 2014 and 2015 was 14.6 MXP/USD.

Table 2: Residential tariff schedules for Summer 2014

Tariff		1st block	2nd block	3rd block	4th block
1	range (KWh)	0 – 75	76 – 140	$\geq$ 141	
	marginal price ($)	0.719	0.847	2.889	
1A	range (KWh)	0 – 100	101 – 150	$\geq$ 151	
	marginal price ($)	0.719	0.847	2.889	
1B	range (KWh)	0 – 125	126 – 225	$\geq$ 226	
	marginal price ($)	0.719	0.847	2.889	
1C	range (KWh)	0 – 150	151 – 300	301 – 450	$\geq$ 451
	marginal price ($)	0.719	0.847	1.081	2.889
1D	range (KWh)	0 – 175	176 – 400	401 – 600	$\geq$ 601
	marginal price ($)	0.719	0.847	1.081	2.889
1E	range (KWh)	0 – 300	301 – 750	751 – 900	$\geq$ 901
	marginal price ($)	0.601	0.750	0.978	2.889
1F	range (KWh)	0 – 300	301 – 1200	1201 – 2500	$\geq$ 2501
	marginal price ($)	0.601	0.750	1.823	2.889

Source: CFE. Average exchange rate in 2014 was 13.3 MXP per USD.

Table 3: Percentage of users and average monthly consumption by tariff class: own calculation based on ENIGH data versus CFE users in 2015

	ENIGH 2010, 2012, 2014		Official CFE data for 2015 [a]	
Tariff	% of users	avg. cons. (KWh)	% of users	avg. cons. (KWh)
1	56.99	112.14	55.66	88.69
1A	6.73	125.90	5.93	98.48
1B	11.99	160.89	11.30	138.35
1C	14.91	252.29	15.70	228.39
1D	3.35	294.60	3.26	276.74
1E	2.83	414.64	3.34	386.23
1F	2.68	615.04	3.61	663.00
DAC	0.51	439.85	1.21	500.12
Total	100	169.63	100	157.44

Source: Own elaboration based on ENIGH 2010, 2012 and 2014, and CFE tariffs.
[a]CFE figures correspond to the months from June to September

Table 4: Residential electricity demand model estimates

	OLS		DCC			
	Full sample		DAC not included		Full sample	
Variable	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error
ln(price)	0.5403***	0.0001	-0.2702***	0.0119	-0.2449***	0.0118
ln(income)	0.0906***	0.0001	0.2138***	0.0073	0.2164***	0.0066
rural	-0.0439***	0.0001	-0.0471***	0.0110	-0.0471***	0.0102
apartment	-0.0139***	0.0002	-0.0520**	0.0192	-0.0457*	0.0217
owner	0.0230***	0.0001	0.0599***	0.0096	0.0643***	0.0087
ln(num. of rooms)	0.0335***	0.0002	0.0776***	0.0111	0.0766***	0.0112
age of head	0.0074***	0.0000	0.0120***	0.0017	0.0120***	0.0017
$(\text{age of head})^2$	-0.0001***	0.0000	-0.0001***	0.0000	-0.0001***	0.0000
ln(household size)	0.1147***	0.0001	0.1952***	0.0099	0.1949***	0.0087
children	-0.0106***	0.0001	-0.0326**	0.0111	-0.0303**	0.0112
elderly	0.0185***	0.0002	-0.0016	0.0143	0.0038	0.0134
waterpump	0.0043***	0.0001	0.0426***	0.0111	0.0451***	0.0105
num. of light bulbs	0.0014***	0.0000	0.0089***	0.0010	0.0087***	0.0011
num. of TVs	-0.0038***	0.0001	0.0281***	0.0057	0.0269***	0.0052
AC unit	0.4306***	0.0002	0.4750***	0.0144	0.4724***	0.0149
num. of refrigerators	0.1905***	0.0002	0.2078***	0.0141	0.2059***	0.0143
num. of washers	0.0365***	0.0001	0.0624***	0.0096	0.0604***	0.0086
fans	0.1245***	0.0001	0.1034***	0.0092	0.1065***	0.0099
constant	0.5451***	0.0009	2.9445***	0.0785	2.8058***	0.0758
σ_ε			0.1750***	0.0089	0.1652***	0.0078
σ_ω			0.4911***	0.0048	0.4927***	0.0044
σ_ν			0.5214***	0.0036	0.5197***	0.0035
ρ			0.3356***	0.0171	0.3179***	0.0149
Num. of observations	41,780		41,607		41,780	

Significance levels: ***p< 0.01; **p< 0.05; and *p< 0.10. Dependent variable is natural log of monthly electricity consumption. For the OLS model, the variable price refers to the marginal price at the consumption block. All models include state fixed effects and year fixed effects. Standard errors in the DCC model are bootstrapped with 200 replications.

Table 5: Unconditional simulated price and income elasticities

Elasticity	DAC not included		Full sample	
Price	-0.2314^{***}	(0.0089)	-0.2124^{***}	(0.0091)
Income	0.1832^{***}	(0.0062)	0.1879^{***}	(0.0057)

Bootstrapped standard errors in parentheses (200 replications).
Significance levels: $^{***}p< 0.01$; $^{**}p< 0.05$; and $^{*}p< 0.10$.

Table 6: Energy efficiency assumptions for main electric appliances in the Mexican residential sector

Appliance	Baseline	Potential savings
Lighting	Some incandescent lamps, low LED penetration	50% of CFL, and 50% of LED
Refrigerators	Comply with the 2012 NOM	Meets MEPS in US (potential savings: 25%)
AC units	Comply with the 2012 NOM	Inverter technology (potential savings: 30%)
Fans	Voluntary standard	Blade and motor design (potential savings: 30%)
Washers	Comply with the 2012 NOM	(potential savings: 25%)

Source: SENER and CONUEE.

Table 7: Average energy efficiency measures and equivalent units by year for refrigerators and air conditioner units

	Refrigerators		Air conditioners
Year	avg. UEC	equiv. units	avg. EER
1993	767	0.55	1.95
1994	615	0.69	–
1995	464	0.91	–
1996	453	0.93	2.62
1997	430	0.98	2.66
1998	493	0.86	2.69
1999	475	0.89	2.73
2000	457	0.92	2.76
2001	440	0.96	2.80
2002	422	1.00	2.83
2003	405	1.04	2.87
2004	430	0.98	2.92
2005	417	1.01	2.96
2006	380	1.11	2.90
2007	359	1.17	2.94
2008	360	1.17	3.00
2009	371	1.14	3.03
2010	422	1.00	2.98

Source: UEC and EER were obtained from LBNL and IIE (2011a,b)
Notes: Residential appliance unit energy consumption (UEC) is measured in kWh/year. The energy efficiency ratio (EER) is the ratio of cooling capacity to power input and it is measured in watt thermal by watt electrical, W_t/W_e. Higher EER values correspond to more efficient appliances. EER figures presented are for split and window air conditioners. Averages are weighted using market shares by class of refrigerators and AC, respectively.

Table 8: Impact of improved efficiency on monthly consumption and expenditure by appliance
– Counterfactual 1: no change in adoption –

	Light-bulbs		Air Conditioners		Refrigerators		Washers		Fans	
Tariff Class	Cons.	Expend.	Cons.	Expend.	Cons.	Expend.	Cons.	Expend.	Cons.	Expend.
1	-2.53%	-3.27%	-20.91%	-30.81%	-4.85%	-6.34%	-1.42%	-1.95%	-3.03%	-4.38%
1A	-2.12%	-2.96%	-18.29%	-29.46%	-4.49%	-6.37%	-1.36%	-2.14%	-2.83%	-4.36%
1B	-2.18%	-2.70%	-15.12%	-23.19%	-4.38%	-5.65%	-1.34%	-1.91%	-2.91%	-3.80%
1C	-2.59%	-2.98%	-14.66%	-18.07%	-4.60%	-5.41%	-1.43%	-1.74%	-3.08%	-3.63%
1D	-2.77%	-3.12%	-14.13%	-16.63%	-4.64%	-5.26%	-1.46%	-1.70%	-3.15%	-3.58%
1E	-2.78%	-3.05%	-13.96%	-15.93%	-4.42%	-4.99%	-1.33%	-1.55%	-3.02%	-3.40%
1F	-2.37%	-2.62%	-14.21%	-15.76%	-4.55%	-5.10%	-1.36%	-1.56%	-2.95%	-3.30%
DAC	-12.18%	-9.54%	-13.46%	-33.57%	-2.84%	-4.92%	-1.24%	-1.15%	-2.46%	-3.21%
Total	-2.51%	-3.13%	-14.85%	-18.84%	-4.70%	-6.01%	-1.41%	-1.89%	-3.00%	-3.93%
Affected households	13,505,785 (56.2%)		3,562,778 (14.8%)		21,539,061 (89.6%)		16,915,345 (70.4%)		11,555,314 (48.1%)	

Source: own calculations based on data from ENIGH-2014 and CFE.

Table 9: Impact of improved efficiency on monthly consumption and expenditure by appliance
– Counterfactual 2: allow for changes in adoption –

	Air Conditioners		Refrigerators		Washers	
Tariff Class	Cons.	Expend.	Cons.	Expend.	Cons.	Expend.
1	-6.43%	-3.83%	-3.46%	-4.68%	-0.59%	-0.75%
1A	-4.21%	1.28%	-3.18%	-4.67%	-0.73%	-1.22%
1B	-3.79%	-2.73%	-2.73%	-3.82%	-0.78%	-1.12%
1C	-0.61%	-0.82%	-3.78%	-4.51%	-1.06%	-1.24%
1D	0.82%	0.88%	-3.36%	-3.92%	-0.54%	-0.71%
1E	-0.79%	-1.58%	-3.17%	-3.67%	-1.54%	-1.76%
1F	-7.98%	-8.84%	-4.02%	-4.54%	-1.74%	-1.97%
DAC	-9.72%	-28.89%	-2.84%	-4.92%	1.02%	0.94%
Total	-2.25%	-2.37%	-3.41%	-4.50%	-1.08%	-1.46%
Affected households	4,766,937 (19.8%)		22,898,046 (95.2%)		17,928,635 (74.6%)	

Source: own calculations based on data from ENIGH-2014 and CFE.

Table 10: Estimated average effect of improved energy efficiency on household consumption and expenditure per month: all appliances involved (all sample)

		Initial situation		Counterfactual 1: no adoption				Counterfactual 2: with adoption			
		Consumption	Expenditure	Consumption		Expenditure		Consumption		Expenditure	
Tariff	Users	(kWh)	($)	(KWh)	(% change)	($)	(% change)	(KWh)	(% change)	($)	(% change)
1	14,230,594	109.4	145.4	101.8	-7.6%	131.4	-8.8%	102.8	-6.3%	132.1	-8.2%
		(53.8)	(128.6)	(51.2)	(6.0%)	(115.0)	(6.8%)	(51.7)	(8.2%)	(117.6)	(10.2%)
1A	1,682,899	125.9	154.8	115.8	-8.3%	134.4	-10.6%	117.7	-6.7%	137.6	-9.2%
		(60.0)	(142.2)	(55.0)	(9.2%)	(115.9)	(10.3%)	(57.0)	(11.1%)	(125.6)	(14.9%)
1B	2,503,712	158.9	189.3	142.8	-10.2%	159.8	-12.1%	146.7	-7.4%	166.6	-9.0%
		(90.4)	(196.7)	(81.5)	(9.0%)	(159.7)	(11.3%)	(84.4)	(12.5%)	(170.0)	(17.2%)
1C	3,271,032	262.0	314.2	226.6	-15.3%	259.9	-17.0%	238.7	-8.7%	274.7	-10.1%
		(165.8)	(342.4)	(152.9)	(12.3%)	(288.9)	(12.4%)	(155.5)	(20.5%)	(296.9)	(22.8%)
1D	752,057	291.2	327.1	249.7	-15.6%	271.1	-16.7%	264.0	-7.9%	285.5	-9.0%
		(198.6)	(350.3)	(180.3)	(12.8%)	(293.6)	(12.6%)	(180.9)	(21.4%)	(295.2)	(23.2%)
1E	825,343	411.3	362.1	352.0	-17.4%	300.8	-18.2%	370.3	-9.0%	315.0	-10.3%
		(254.8)	(299.1)	(235.3)	(19.0%)	(247.1)	(17.4%)	(232.9)	(26.7%)	(250.9)	(27.6%)
1F	671,115	615.1	558.4	517.4	-20.0%	459.9	-21.2%	530.3	-15.6%	469.3	-17.1%
		(371.3)	(437.6)	(348.3)	(15.1%)	(380.9)	(14.5%)	(346.1)	(21.7%)	(383.8)	(22.6%)
DAC	103,364	355.3	1751.3	309.9	-13.3%	1382.3	-22.8%	301.5	-16.1%	1375.1	-23.2%
		(118.6)	(521.3)	(155.4)	(32.6%)	(719.0)	(30.3%)	(167.8)	(37.5%)	(755.4)	(34.2%)
All users	24,040,116	167.7	205.2	149.7	-9.9%	176.8	-11.3%	153.9	-7.2%	181.3	-9.0%
		(159.8)	(252.2)	(141.1)	(9.9%)	(213.2)	(10.4%)	(144.4)	(13.5%)	(218.9)	(15.6%)

Source: own calculations based on data from ENIGH-2014 and CFE. Standard deviations are shown in parenthesis.

Table 11: Household re-optimization process: block changes within regular tariff classes and DAC re-categorization (% of users by tariff class)

	Block changes within tariff class			
Tariff	from 2 to 1	from 3 to 2	from 4 to 3	Total changes
1	4.6%	5.5%		10.0%
1A	5.6%	10.0%		15.6%
1B	6.6%	8.3%		14.9%
1C	11.4%	8.7%	3.8%	23.9%
1D	7.6%	10.1%	3.9%	21.6%
1E	9.3%	3.0%	4.7%	17.0%
1F	10.2%	3.9%	0.0%	14.1%
DAC				25.0%

Source: own calculations based on data from ENIGH-2014 and CFE.

Table 12: Government savings in the proposed energy efficiency scenario (millions of MXP per month)

Tariff	CFE users	Subsidy reduction (1)	VAT not collected (2)	Net savings (1) - (2)
1	19,264,114	275.8	47.6	228.2
1A	2,051,397	38.0	7.1	30.9
1B	3,910,140	95.6	19.3	76.3
1C	5,432,016	226.1	49.0	177.1
1D	1,127,508	54.5	10.5	43.9
1E	1,156,322	83.0	11.8	71.1
1F	1,247,839	134.5	20.4	114.2
DAC	419,678	-90.2	24.1	-114.4
Total	34,609,015	817.2	190.0	627.3

Source: own calculations based on data from CFE and ENIGH-2014.

Table 13: Emissions reduction in the proposed energy efficiency scenario (metric tons per month)

Tariff	CFE users	SO_2	NO_X	CO_2
1	19,264,114	418	275	70,545
1A	2,051,397	58	38	9,836
1B	3,910,140	179	117	30,131
1C	5,432,016	544	358	91,794
1D	1,127,508	132	87	22,319
1E	1,156,322	194	128	32,795
1F	1,247,839	345	227	58,198
DAC	419,678	54	35	9,109
Total	34,609,015	1,924	1,265	324,726

A Appendix: Distributional analysis of improved energy efficiency scenarios

Table 14 presents the estimated effects of improved energy efficiency by household income decile. The first thing we should mention is that income elasticity is rather low –see table 5. But consumption is still increasing in income and, in absolute terms, policies that generate adoption or replacement of electric appliances will benefit more the non-poor households. For instance, in Counterfactual 1 households in decile 10 reduce their expenditure 13.9%, on average, whereas users in decile 1 only 8%. However, things are different when analyzed in relative terms. The expenditure-income ratio in decile 1 falls from 5.4% to 5%, whereas in decile 10 it falls from 1.3% to 1.0%. In sum, for richer households, the reduction in the electricity bill due to improved energy efficiency is larger in absolute terms, but lower in relative terms. Such result is not surprising at all. The electricity subsidy is present in practically all Mexican households: more than 98% of users pay some regular tariff (and not the DAC). As a result, the exclusion error is minimized at the cost of maximizing the inclusion error.

Table 14: Estimated average effect of improved energy efficiency on household consumption and expenditure per month: all appliances involved (all sample)

		Initial situation		Counterfactual 1: no adoption				Counterfactual 2: with adoption			
	Average	Consumption	Expend.	Consumption		Expend.		Consumption		Expend.	
Decile	income	(kWh)	($)	(KWh)	(% change)	($)	(% change)	(KWh)	(% change)	($)	(% change)
1	1,795	96.6	97.3	89.3	-7.5%	89.3	-8.0%	90.9	-5.5%	90.9	-6.0%
	(548)	(76.2)	(82.2)	(70.1)	(7.1%)	(75.1)	(7.3%)	(71.4)	(10.2%)	(76.2)	(10.6%)
2	3,154	124.4	128.3	112.9	-8.7%	114.9	-9.8%	115.8	-6.2%	117.9	-7.0%
	(310)	(103.8)	(107.5)	(92.6)	(8.7%)	(95.3)	(8.9%)	(95.2)	(12.1%)	(99.3)	(12.8%)
3	4,180	137.1	143.7	124.1	-9.0%	127.9	-10.3%	127.8	-6.3%	132.5	-7.4%
	(299)	(111.5)	(123.1)	(99.6)	(8.8%)	(109.8)	(9.1%)	(104.2)	(12.2%)	(120.2)	(13.0%)
4	5,150	143.4	153.0	129.0	-9.6%	134.7	-11.1%	132.9	-6.7%	139.4	-7.8%
	(276)	(121.7)	(132.0)	(108.5)	(9.6%)	(114.9)	(9.9%)	(112.4)	(13.6%)	(119.6)	(14.9%)
5	6,133	158.3	173.0	142.6	-9.4%	152.2	-11.2%	147.2	-6.3%	157.7	-7.7%
	(296)	(141.1)	(160.0)	(125.7)	(8.4%)	(140.0)	(8.7%)	(129.5)	(12.6%)	(145.0)	(14.0%)
6	7,254	161.8	192.9	145.0	-9.7%	169.1	-11.8%	149.0	-7.2%	174.2	-8.9%
	(363)	(138.2)	(216.4)	(122.6)	(8.7%)	(197.7)	(9.4%)	(126.0)	(12.3%)	(202.5)	(13.7%)
7	8,741	185.3	216.3	165.6	-10.5%	187.4	-13.0%	171.7	-7.1%	196.0	-8.9%
	(512)	(173.1)	(231.8)	(154.7)	(12.6%)	(205.8)	(12.9%)	(159.7)	(16.3%)	(217.6)	(18.0%)
8	10,853	192.8	240.4	171.3	-10.6%	206.2	-13.5%	176.2	-7.9%	213.0	-10.1%
	(758)	(173.3)	(258.1)	(152.2)	(10.6%)	(222.3)	(11.2%)	(155.0)	(13.9%)	(226.9)	(15.7%)
9	14,533	218.0	286.6	191.8	-11.4%	238.4	-15.4%	197.5	-8.5%	248.5	-11.5%
	(1,532)	(189.2)	(299.1)	(165.9)	(9.8%)	(249.8)	(11.1%)	(169.6)	(14.0%)	(260.5)	(17.7%)
10	31,642	259.7	420.0	225.7	-12.6%	331.6	-18.7%	230.8	-10.0%	344.1	-14.7%
	(21,842)	(237.1)	(472.9)	(209.4)	(12.3%)	(390.3)	(13.9%)	(211.1)	(15.9%)	(396.9)	(21.1%)
Total	9,344	167.7	205.2	149.7	-9.9%	175.2	-12.3%	154.0	-7.2%	181.5	-9.0%
	(10,781)	(159.8)	(252.2)	(141.1)	(9.9%)	(212.2)	(10.8%)	(144.4)	(13.5%)	(219.1)	(15.6%)

Source: own calculations based on data from ENIGH-2014 and CFE. Standard deviations are shown in parenthesis.