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

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Abstract

Increasing block pricing (IBP) structures represent difficulties for applied researchers who tried 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 (December 2015). The simulated program consists of a massive replacement of electric appliances (AC units, fans, refrigerators, washers, and light-bulbs) for more energy efficient units. The main empirical findings are the following: overall residential electricity consumption decreases by 8.9% and the associated expenditure falls 11.1%. Additionally, the electricity subsidy is reduced in 360 million USD/year and there is an annual cut in CO_2 emissions of 3.5 million of tons.

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The Energy Transition Law (ETL) was enacted in December 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; J. Rosas-Flores, D. Rosas-Flores and D. Morillón-Gálvez, 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, 2017b) to assume realistic improved energy efficiency levels for a selected group of sensible electric appliances: air conditioning (AC) units, fans, refrig-

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[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 analyses). Moreover, they find that air conditioning replacement actually increase 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.

erators, washing machines, and light-bulbs. 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 the different energy efficiency scenarios would have on government savings and the air pollution.

The residential electricity tariff structure in Mexico is very intricate.[3] There are seven different *tariff classes* across the country and eigth 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.

The main results of this study are the following: on average, the residential electricity consumption and the associated expenditure fall 9.7% and 13.3%, respectively. There is, however, significant heterogeneity with regards of the final effect across households. The reasons are threefold: the tariff structure differ substantially across the country (i.e., different marginal prices and different consumption blocks), the electric appliances under study have uneven penetration levels, and the potential savings of each appliance is different. AC units and refrig-

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[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.

erators offer the best opportunities in terms of policy outcomes: they provide the largest consumption savings, 13% and 5%, respectively. Finally, the electricity subsidy burden is reduced in about 360 million USD/year, and there is an annual cut in CO_2 emissions of approximately 3.5 million of 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. In section 4 we describe the counterfactual scenario and then calculate the impact that the proposed energy efficiency program would have on household electricity consumption, the residential electricity subsidy, and the environment. Finally, section 5 concludes the paper.

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 (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 (point C in the left panel) and pays a higher marginal price p_2 (right panel). A third possibility is that the consumer chooses e_1, which is exactly the kink point. The underlying idea is that consumers behave (as if) they where making a discrete/continuous choice. They first select the consumption block, and then, conditional on being in the the selected block, they choose the quantity of electricity.

FIGURE 1 ABOUT HERE

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 –typically, OLS and 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.[5]

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 the more specific context of consumer choice, the model was developed 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 Olmstead et al. (2007) for water demand, and incorporates two error terms: $\omega_j + \varepsilon_{jt}$. The first term, 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 context of IBP, one must distinguish between conditional and unconditional demand functions. The former is defined as the quantity the household consumes conditional on being

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[5] It is worth mentioning, however, that some authors have questioned whether consumers behave rationally and respond to marginal prices in IBP schemes. See, for example, Ito (2014) and Borenstein (2009). Here, we do not test the rationality assumption of our model.

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. [6]

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

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

where

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

and

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

$\Phi(.)$ 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 price and income elasticities.

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[6] 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 what the household would pay if all KWh were charged at the marginal price and what it actually pays.

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 different 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.[7] 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. 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 tariff classes and the associated marginal price differs over CFE tariff regions. 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.[8] Concretely, we retrieve monthly consumption for each household using the corresponding DAC tariff structure and then compare it to an imputed monthly consumption limit (based on the actual annual limit). All households exceeding this limit are considered to afford a DAC tariff and consequently, for these households we use this retrieved consumption instead of the one computed based on the original tariff.

The three cross sections used in this paper add up to 52,580 household observations. Our final sample comprises 41,779 observations. First, we discarded households that either were

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[7] Billing data reported in the ENIGH 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.

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

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.[9] 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.[10] Finally, we dropped 147 observations due to missing values in other sensible variables used in our estimations. Table 3 shows the final distribution of users and the average consumption by tariff classes, 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 presented later in this paper.

TABLE 3 ABOUT HERE

3 Electricity demand estimation

As described in section 2, our database provide us with detailed household-level electricity demand data. We exploit the substantial cross-sectional and time-series variation in prices that residential users face in order to estimate the structural DCC model of equation (2).

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 it was previously explained. We present two specifications for the DCC model. One excludes the DAC users and the other

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

[10] Our final sample comprises only those observations that reported to pay electricity on a bimonthly basis, and to pay an amount corresponding to a consumption greater or equal than 25 kWh.

makes use of the full sample. As can be seen, the estimates are relatively similar in both DDC model specifications, validating the exercise we performed to retrieve consumption of DAC users (see section 2). As a result, we will concentrate in the DDC full sample model for the rest of the paper, which is our baseline specification.

TABLE 4 ABOUT HERE

Clearly, 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 light bulbs, 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. They are calculated in the following manner: we first simulate an increment of 1% in the prices of all blocks and recalculate the 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 -.23 and .19 for price and income, respectively.[11]

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[11] 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 residential 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 elasticities result substantially larger than the other studies estimates. However, those estimates were obtained from aggregate data and using time-series estimation approaches, which clearly ignore the IBP structure of the market that is properly incorporated in our DDC empirical model.

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. Following the report by SENER (2017b), for each appliance we assume *potential savings* in electricity consumption by comparing known values from the Mexican Official Norms of Energy Efficiency (MON) –or estimated baselines– with minimum values of energy consumption from international standards or new technologies. 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. Table 6 presents the assumptions of improved energy consumption for the set of selected electric appliances.

TABLE 6 ABOUT HERE

For the simulations, we only use the ENIGH 2014 and take advantage of two facts. First, this cross section distinguish between incandescent (inefficient) and low-consumption lamps held by the households. Second, data from ENIGH 2014 are more comparable to the 2015 CFE numbers we use to calculate savings in the electricity subsidy and air pollution emissions. The simulation exercise consists of the following steps:

1. Compute the predicted electricity consumption for each household using the conditional demand coefficients of the DCC full-sample model (table 4)

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

3. For each electric appliance considered separately (except for light-bulbs), modify the corresponding demand coefficient by imputing the associated energy efficiency factor (Table 6) and then obtain the new predicted consumption

4. Add the estimated error term from step 2 to the new predicted consumption of step 3

5. Compare the original (observed) consumption with the predicted consumption of step 4.

It is worth noting that the predicted consumption derived from the DCC baseline model (step 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.

In the case of light-bulbs, we simulate a massive adoption scenario of compact fluorescent lamps (CFL). We assume households replace the incandescent lights with CFL up to the point of reaching at least 50% CFL penetration, as well as an improvement in energy consumption of 75% of CFL with respect to the old incandescent lamps.[12] We then compute the counterfactual consumption.

There is a number of implicit assumptions (limitations) in the simulation exercise of this section. First, we do not allow for changes in appliance penetration rates. Hence, all improvements in technology has no effect on adoption.[13] Second, we consider the energy efficiency improvement in a given appliance affects uniformly all households holding the appliance. Third, since we do not have information on the brand and model of electric appliance held by the household, we do not know the ex-ante unit energy consumption (UEC). As a result, the imputed energy efficiency improvement factors are simply averaged measures based on technical

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[12] For instance, this is equivalent to assuming a household replace a 60-watt incandescent lamp with a new 15-watt CFL.

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

reports from CONUEE and SENER.[14] In that sense, having detailed data on household appliance holding would substantially improve the quality of this research. Unfortunately, we do not have such information.[15] Nevertheless, our simulation exercise represents a valuable effort to measure the potential impacts of the ETL-2015.

4.1 Impact on household consumption and expenditure

Table 7 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. 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.[16] AC units has the lowest penetration rate (14.8%) but the highest impact on electricity consumption and expenditure (13% and 16.7% savings, respectively). Refrigerators, in turn, have the largest penetration rate (89.6%) and the second highest savings (4.8% and 6.1%).

TABLE 7 ABOUT HERE

Table 8 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 savings will depend on the corresponding stock of appliances. The overall average consumption savings amount to 16.6 kWh per month, which in monetary terms represents a reduction of $27.3 in the electricity bill. As can be seen, the savings differ substantially

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[14] See SENER (2017b), LBNL and IIE (2011a) and LBNL and IIE (2011b)

[15] 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 an approach, however field experiments are beyond the scope of this research and the comparisons are, to some extent, meaningless given the totally different contexts.

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

among the different tariff classes, being 1F users the most benefited. At the other end of the spectrum, tariff 1 users have, on average, the lowest savings.

TABLE 8 ABOUT HERE

Notice that savings in expenditure are systematically larger than savings in consumption, as shown in Tables 7 and 8. In fact, that is a direct consequence of the re-estimation of probabilities associated to different consumption blocks.[17] 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 –i.e., they pay a lower marginal price. Table 9 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 more flexibility (and realism).

TABLE 9 ABOUT HERE

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. 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.

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

Table 10 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 553.5 million of Mexican Pesos (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 6.6 billion of MXP –i.e., 360 million of USD at the current exchange rate.

TABLE 10 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 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), and explains more than 20% of total GHG emissions. In particular, the residential sector accounts for 25% of total electricity consumed in the country.[18] In this section we calculate the environmental impact of the simulated energy efficiency scenario. Our analysis relies on the emission factors recently published by SENER (2017a), which were calculated assuming

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

the typical operation of an average thermal generator.[19] Table 11 presents the environmental outcomes of the massive energy efficiency scenario.

TABLE 11 ABOUT HERE

The technologies used for electricity generation are: 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 such as 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 11) to annual values.[20] The estimated annual cut in CO_2 emissions is approximately 3.5 million of metric tons. That figure represents 2.7% 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 60 MXP/ton. As a result, the environmental savings due to CO_2 emissions reduction amounts to 210 million of MXP per year.

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[19] 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.

[20] 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.

5 Conclusion

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 scenario. The simulated situation consists of massive replacements 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 (2017b), which follows the requirements of the Energy Transition Law of December 2015.

The main results of this study are the following: residential electricity consumption falls 8.9% and the associated expenditure decreases 11.1%, on average. The outcomes, 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. As a result, electricity consumption and expenditure once the energy efficiency improvements take place have a variety of responses. Users under 1F tariff are the most benefited in terms of monetary savings (19.9%), whereas users in the most numerous tariff class (1) save 8.6% in their electricity bill. In terms of electric appliances, AC units and refrigerators are probably the best candidates for future policy targets: they proportion, on average, consumption savings of approximately 13% and 5% on affected users, respectively. With regards of the residential electricity subsidy, the fiscal burden could be reduced in 360 million

USD per year. Finally, there would be an annual cut in CO_2 emissions of approximately 3.5 million of tons, which represents about 2.7% of the 2020-2030 emissions reduction goal for the electricity generation sector as it was committed in the COP-21 held in Paris.

There are some limitations in our simulation exercise that provide incentives for further research on this topic. The consumer decisions regarding the replacement of old appliances/adoption of new technologies were not considered in our model –we assume all households holding the selected appliance simply replace it for a more efficient unit. 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.[21] 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. Finally, detailed information on the actual household stock of appliances (e.g., price, operation and maintenance costs, UEC, etc.) and on conservation practices followed by users would be a plus.

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

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[21] An assumption difficult to support given the evidence from previous studies. See, for example, Davis et al. (2014)

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

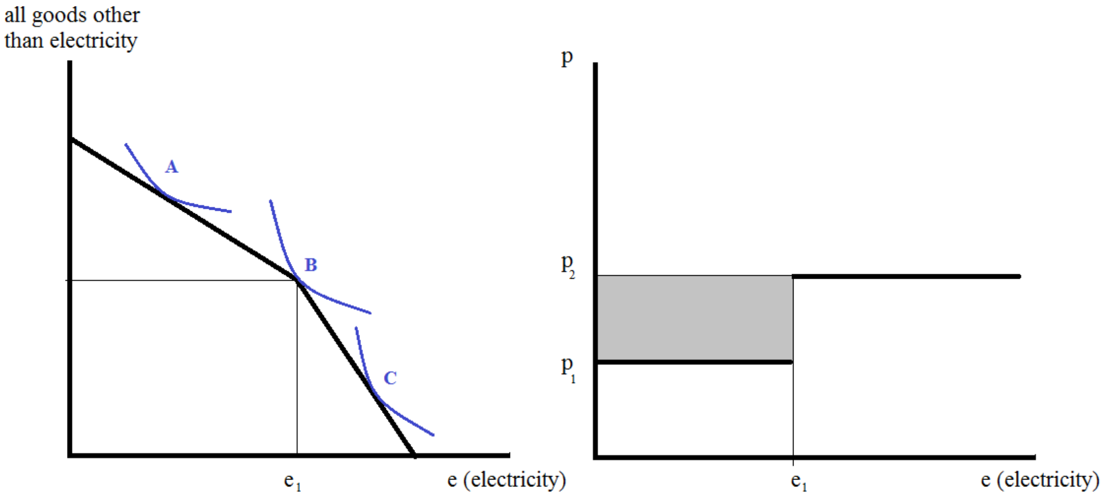

Table 1: Variable definitions and summary statistics

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)	8,863	9,567	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: 20,604 in year 2010; 6,649 in year 2012; and 14,526 in year 2014.

Table 2: Residential tariff schedules for Summer 2014

Tariff		1^{st} block	2^{nd} block	3^{rd} block	4^{th} 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.

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		CFE (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	294.45	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	169.62	100	157.44

Source: Own elaboration using ENIGH 2010, 2012 and 2014, and CFE.

[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)	0.5404***	0.0001	-0.2889***	0.0117	-0.2655***	0.0110
ln(income)	0.0906***	0.0001	0.2167***	0.0073	0.2186***	0.0075
rural	-0.0439***	0.0001	-0.0469***	0.0108	-0.0471***	0.0120
apartment	-0.0139***	0.0002	-0.0485**	0.0179	-0.0446*	0.0203
owner	0.0230***	0.0001	0.0601***	0.0099	0.0618***	0.0100
ln(num. of rooms)	0.0335***	0.0002	0.0765***	0.0114	0.0767***	0.0119
age of head	0.0074***	0.0000	0.0117***	0.0017	0.0119***	0.0017
(age of head)^2	-0.0001***	0.0000	-0.0001***	0.0000	-0.0001***	0.0000
ln(household size)	0.1147***	0.0001	0.1959***	0.0097	0.1942***	0.0092
children	-0.0106***	0.0001	-0.0321***	0.0105	-0.0295**	0.0107
elderly	0.0185***	0.0002	-0.0013	0.0121	0.0035	0.0136
waterpump	0.0044***	0.0001	0.0438***	0.0099	0.0478***	0.0104
num. of light bulbs	0.0014***	0.0000	0.0090***	0.0011	0.0090***	0.0011
num. of TVs	-0.0038***	0.0001	0.0290***	0.0053	0.0271***	0.0048
AC unit	0.4306***	0.0002	0.4727***	0.0145	0.4695***	0.0144
num. of refrigerators	0.1905***	0.0002	0.2067***	0.0136	0.2041***	0.0152
num. of washers	0.0365***	0.0001	0.0608***	0.0091	0.0601***	0.0090
fans	0.1245***	0.0001	0.1040***	0.0092	0.1053***	0.0101
constant	0.6709***	0.0009	3.3117***	0.0727	3.1860***	0.0742
σ_ε			0.1747***	0.0082	0.1649***	0.0079
σ_ω			0.4910***	0.0047	0.4927***	0.0046
σ_ν			0.5212***	0.0036	0.5196***	0.0036
ρ			0.9420***	0.0056	0.9481***	0.0051
Num. of observations	41,779		41,608		41,779	

Notes: *** significant at $\alpha = 0.01$. ** significant at $\alpha = 0.05$. *** significant at $\alpha = 0.10$. 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 DDC model are bootstrapped with 200 replications.

Table 5: Unconditional simulated price and income elasticities

Elasticity	DAC not included		Full sample	
Price	-0.2439^{***}	(0.0088)	-0.2263^{***}	(0.0084)
Income	0.1819^{***}	(0.0061)	0.1857^{***}	(0.0063)

Bootstrapped standard errors in parentheses (200 replications).

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 MON	Meets MEPS in US (potential savings: 25%)
AC units	Comply with the 2012 MON	Inverter technology (potential savings: 30%)
Fans	Voluntary standard	Blade and motor design (potential savings: 30%)
Washers	Comply with the 2012 MON	(potential savings: 25%)

Source: SENER and CONUEE.

Table 7: Impact of improved energy efficiency by electric appliance:
% change on consumption and expenditure per month (affected households only)

	Light-bulbs		AC units		Refrigerators		Washers		Fans	
Tariff Class	Cons.	Expend.	Cons.	Expend.	Cons.	Expend.	Cons.	Expend.	Cons.	Expend.
1	-1.60	-2.04	-18.27	-27.25	-4.73	-6.22	-1.41	-1.93	-2.98	-4.30
1A	-1.39	-1.89	-16.01	-26.25	-4.69	-6.70	-1.36	-2.13	-2.80	-4.31
1B	-1.45	-1.71	-13.29	-20.65	-4.67	-6.03	-1.34	-1.91	-2.89	-3.78
1C	-1.79	-2.00	-12.91	-16.00	-4.95	-5.82	-1.44	-1.74	-3.06	-3.61
1D	-1.87	-2.11	-12.51	-14.78	-4.99	-5.65	-1.47	-1.71	-3.14	-3.57
1E	-1.73	-1.87	-12.34	-14.14	-4.78	-5.40	-1.34	-1.56	-3.01	-3.40
1F	-1.64	-1.79	-12.43	-13.83	-4.74	-5.31	-1.37	-1.56	-2.93	-3.28
DAC	-14.46	-19.27	-10.27	-31.21	-3.15	-5.17	-1.22	-1.13	-2.53	-3.25
Total	-1.63	-2.01	-13.05	-16.70	-4.76	-6.10	-1.40	-1.88	-2.98	-3.89
Affected Households	8,276,794 (34.4%)		3,562,778 (14.8%)		21,541,641 (89.6%)		16,915,838 (70.4%)		11,555,314 (48.1%)	

Table 8: Estimated average effect of improved energy efficiency on household consumption and expenditure per month: all appliances involved (all sample)

		Initial situation		Counterfactual			
		Consumption	Expenditure	Consumption		Expenditure	
Tariff	Users	(kWh)	($)	(KWh)	(% change)	($)	(% change)
1	14,229,968	109.5	145.4	102.7	-6.6%	131.7	-8.6%
		(53.8)	(128.6)	(51.4)	(5.0%)	(115.5)	(6.4%)
1A	1,682,899	125.9	154.8	116.6	-7.6%	134.6	-10.7%
		(60.0)	(142.2)	(55.3)	(8.2%)	(116.9)	(10.0%)
1B	2,503,712	158.9	189.3	144.0	-9.5%	160.5	-12.1%
		(90.4)	(196.7)	(82.1)	(8.0%)	(161.2)	(10.5%)
1C	3,271,032	262.0	314.2	229.5	-14.1%	262.1	-16.5%
		(165.8)	(342.4)	(153.9)	(11.0%)	(291.3)	(11.5%)
1D	752,057	291.2	327.2	253.2	-14.4%	273.3	-16.2%
		(198.6)	(350.3)	(181.8)	(11.5%)	(296.7)	(11.8%)
1E	825,343	411.4	362.1	357.4	-15.8%	303.5	-17.5%
		(254.8)	(299.1)	(236.9)	(17.0%)	(249.8)	(17.0%)
1F	671,115	615.1	558.4	527.1	-18.0%	466.0	-19.9%
		(371.3)	(437.6)	(350.4)	(13.7%)	(383.4)	(13.6%)
DAC	103,364	355.3	1751.3	326.3	-8.3%	1434.1	-19.6%
		(118.6)	(521.3)	(115.7)	(8.6%)	(666.6)	(25.5%)
Total	24,039,490	167.7	205.2	151.5	-8.9%	177.9	-11.1%
		(159.8)	(252.2)	(142.5)	(8.7%)	(215.2)	(9.8%)

Standard deviations in parenthesis.

Table 9: Household re-optimization process: block changes within regular tariffs and DAC re-categorization (percentage 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	3.8%	4.8%		8.6%
1A	4.8%	9.8%		14.6%
1B	6.3%	7.5%		13.8%
1C	10.4%	8.2%	3.6%	18.7%
1D	7.4%	9.5%	3.8%	16.9%
1E	7.7%	2.7%	4.7%	10.4%
1F	7.9%	3.4%	0.0%	11.3%
DAC	–	–	–	23.5%

Table 10: Government savings in the proposed energy efficiency scenario

Tariff	CFE users	Subsidy reduction (1)	VAT not collected (2)	Net savings (1) - (2)
1	19,264,114	241.7	42.4	199.3
1A	2,051,397	35.0	6.6	28.4
1B	3,910,140	88.5	18.0	70.5
1C	5,432,016	208.0	45.3	162.7
1D	1,127,508	50.0	9.7	40.2
1E	1,156,322	75.3	10.8	64.5
1F	1,247,839	121.2	18.5	102.8
DAC	419,678	-93.6	21.3	-114.9
Total	34,609,015	726.1	172.6	553.5

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

Table 11: Emissions reduction in the proposed energy efficiency scenario

Tariff	CFE users	SO_2	NO_X	CO_2
1	19,264,114	366	241	61,823
1A	2,051,397	54	35	9,064
1B	3,910,140	165	109	27,895
1C	5,432,016	501	329	84,473
1D	1,127,508	121	80	20,478
1E	1,156,322	176	116	29,769
1F	1,247,839	311	204	52,434
DAC	419,678	35	23	5,831
Total	34,609,015	1,729	1,136	291,768