



Energy practices and population cohorts: the case of Mexico

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Received: 31 August 2021 / Accepted: 5 September 2022
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Abstract

Developing countries are advancing towards universal energy access with high fertility rates and young population. Socio-demographic and economic evolutions will influence future energy consumption patterns. Herein, we use Mexico as a case study to estimate determinants of residential electricity consumption as well as the importance that a shift in generational preferences has on such energy demand. We build an original pseudo-panel of Mexican households to separately estimate generational and age effects on the use of electricity. Our findings are in line with the few studies performed for developed countries, but the magnitudes are four times stronger. This means that, as they grow older, younger generations in Mexico increase their electricity consumption at a much faster rate than in developed countries. This may represent a significant obstacle in the way of meeting future energy demand, particularly in the context of the energy transition.

Keywords Residential electricity demand · Cohort analysis · Pseudopanel · Energy cultures · Mexico

JEL Classification C2 · D12 · Q4

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Introduction

Developing countries are characterized by higher GDP growth rates than developed ones and many of them are yet to finish their demographic transition (Easterlin 2019). These two facts, together with changing energy consumption patterns due to cultural and generational changes over time, make it difficult to predict their energy demand growth as well as to design the right policies to increase energy conservation and reduce energy poverty. To assess the determinants of energy demand as well as whether energy usage practices are changing as compared to developed countries, we use the case of Mexico. Similar to other developing countries, Mexico has just reached universal electricity access in 2018 (World Bank 2021) and residential consumption, being heavily subsidized (Contreras Liesperguer 2020), has been growing at an average annual rate of 4.37% (Escoto Castillo and Sanchez Pena 2017).

Electricity consumption is not only linked to energy access and price levels. Residential electricity consumption is expanding worldwide as new appliances are shaping energy practice and energy culture (WEO 2017). Several studies—almost exclusively on developed countries—tried to assess the role of socio-demographic characteristics to disentangle households' energy practices (see Bardazzi and Pazienza 2017 and Jones et al. 2015 for a review). In this regard, we find that, in line with the evidence for developed countries, dwelling type, urbanization, income, and personal characteristics—among which age—are key factors explaining residential energy consumption. In a second step, we perform a study of cohort groups across time using an original longitudinal dataset built with repeated cross-section data to disentangle the pure age effect from the generational effect. Our results show that both determinants are significant and that, while electricity expenditure rises with age, cohort effects are increasing from older to younger generations: householders born up to the 1960s show a lower electricity consumption compared with householders of the same age born in more recent decades. We also identify differences in magnitude between rural and urban locations. To the best of our knowledge, this is the first time that the life-cycle effect is measured in a developing country and, even if the findings are in line with the literature that has studied this for European countries (Bardazzi and Pazienza 2017; Chancel 2014), the magnitude of the generational impact is four times larger for Mexico: expenditure of rural households increases 25% every 5-year cohort (and 18% for urban households). Moreover, when we study the generational impact per income quartile, we observe that the rates of change in electricity expenditure per year of age and per cohort are much larger for the poorest households (belonging to the first quartile), while the effects are similar to the ones found for developed countries for the rich (last quartile). The fact that younger generations consume up to 25% more than older ones, together with the fact that Mexican population is younger than developed countries population, implies a great difficulty to meet a fast-growing demand in the future.

Using Mexico as a case study

Mexico is a highly populated country and its population is largely concentrated in urban areas (84%, United Nations 2021). Together with most of the southern cone, it is a developing country.¹ In general, developed countries show a thin population pyramid's base due to aging population. Instead, Mexico's pyramid still shows a strong base and a median population age under 30. However, in the next decades, a fast-aging process is expected, with the median age approaching 40 years in 2050 (UN World Population Prospects 2021). This means that, as many other developing countries, Mexico is about to complete the last stages of its demographic transition (Pujol 1992) and this may imply that the life-cycle determinants of energy consumption will vary. If energy consumption increases with an aging population, energy demand growth for mid-century may be much stronger than in developed countries.

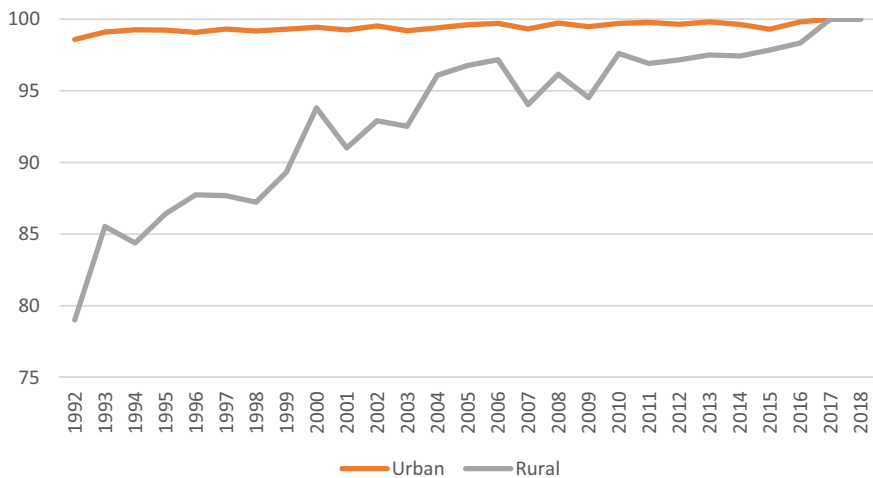
Over the last 3 decades (1980–2018), the country has underperformed in terms of growth (just above 2%), inclusion, and poverty reduction compared to similar countries narrowing its convergence to high-income economies. Despite the slow growth rate, income inequality (particularly between urban and rural population as well as between the rich Northern regions and the Southern ones) and concentration of energy use in the top quartile, standards of living have continuously improved.² Among these socio-demographic transformations, urbanization, education, and household size exhibit large changes (World Bank 2019), also thanks to universal access to electricity which has created a virtuous cycle between energy access, rise in per capita income, and general socio-demographic transformations. Figure 1 shows that all Mexican households have access to electricity, but the path to reach this target has been strongly differentiated between urban and rural areas.

The ongoing transformations in Mexican society triggered by urbanization, income growth and universal electricity access, make it difficult to forecast future changes in energy demand. This is crucial to plan investments and adequate policies to reach a general rise in living standards, a decline in energy poverty and in inequality. This is because beyond traditional drivers of energy use, such as population growth and GDP projections, energy practices linked to societal transformations play a key role, especially concerning the attitude of different Mexican generations towards new appliances, mobility, electrification and environmental concerns.

The empirical literature has highlighted that energy consumption choices vary greatly between apparently similar types of households (for income, education, area and dwellings characteristics): this heterogeneity can only partially be attributed to a different perception of price signals, and can be better explained by looking at how social drivers interplay to shape energy related behaviour. According to the approach of energy culture (Stephenson et al. 2010), energy choices can be understood by looking at the interactions between “cognitive norms, (e.g., beliefs, understandings),

¹ Meaning a country with less-developed industrial base and a low Human Development Index (HDI) relative to other countries (see O'Sullivan and Sheffrin 2003).

² Tornarolli et al. (2018) stress that Mexico enjoyed an improvement in both average income and income inequality over the first 2 decades of the century, although the magnitude of income growth was lower than the one reached by other South-American countries.



Source: World Bank Database (2021)

Fig. 1 Evolution in access to electricity in Mexico

material culture (e.g., technologies, building form), and energy practices (e.g., activities, processes).³ As for developed countries, a significant generational effect in energy use has been found for France and Italy, for both residential energy use and mobility choice (Chancel 2014; Bardazzi and Paziienza 2017, 2018). To the best of our knowledge, these effects have not been studied for developing countries, where such effects could be more important due to the transformations that such economies are living in terms of socio-demographic and economic conditions.

As for Mexico, the most relevant factors to analyse energy use have been traditionally limited to income constraints, household size, and geographic area (Rodriguez-Oreggia and Yopez-Garcia 2014).⁴ However, recent literature finds additional behavioural drivers. Davis et al. (2014) find that several energy efficiency programs—implemented by the Mexican government—have been effective in reducing electricity consumption, but that the rebound effect (according to which consumers tend to use energy-efficient appliances more intensively to increase comfort levels) can cause adverse overall results in terms of energy conservation. According to Escoto Castillo and Sanchez Pena (2017), intensive energy practices spread among Mexican households, expanding from high to lower socio-economic groups and marking a transformation in energy use behaviour among different generations of consumers. Herein, we analyse evidence of different energy practices among Mexican generations.

³ Stephenson et al. (2010), p. 6124.

⁴ The empirical literature on the drivers of residential energy expenditure in Mexico is rather limited. For further references, see Labeaga et al (2021).

Table 1 Households' frequencies by year and share of household with positive electricity expenditure. Source: Authors' elaboration based on ENIGH

	Household frequencies		Total population (weighted)			% of HH with zero electr. expend		
	Unweighted	Weighted	Urban	Rural	Total	Urban (%)	Rural (%)	Total (%)
2000	9473	21,988,755	55,740,115	35,527,852	91,267,967	26.2	36.7	30.3
2008	27,581	25,966,844	65,207,059	39,367,108	104,574,167	33.1	30.8	32.2
2016	65,947	31,183,542	87,122,107	26,662,630	113,784,737	10.7	14.8	11.6

The data

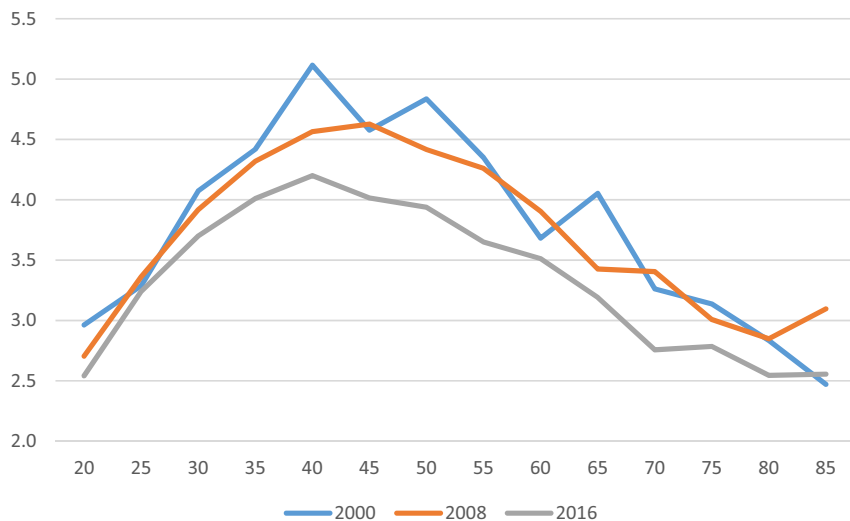
We use microdata from the National Income Expenditure Surveys (ENIGH) 2000–2016. These household surveys are carried out every 2 years and include several detailed data among which socio-demographic characteristics, income, consumption, dwelling characteristics, and energy use.⁵ The overall dataset is based on different sample sizes, with sample weights reflecting the Mexican population. In Table 1, we show summary statistics for selected years: 2000 as the first observation period, 2008 as the median year, and 2016 as the final year. We excluded observations with householder age lower than 20 years and higher than 85 years. We are then left with more than 200,000 cumulative observations, representing in 2016 more than 31 million families and 113 million people, 77% of whom is located in urban areas.

Table 1 also highlights important demographic changes in the observed period: total population exhibits a 25% growth, whereas population in urban areas grew by 56% leaving in 2016 only 23% of total population in rural areas. The data also show that even in 2016, despite a supposed universal access to the grid, around 15% of households in rural areas do not use electricity.

The increase in the number of households is matched by a decrease in the average size, a trend that is also present in countries with higher living standards.

Figure 2 displays the historical evolution of the link between the age of the householder and average family size. We observe that, besides the usual inverted u-shaped pattern—peaking between an age of 40 and 50 years—it is very clear that the whole 2016 curve is significantly lower than the 2000 curve. The steady decline in family size (from 4.19 in 2000 to 3.65 in 2016) implies a loss of economies of scale in overall energy use.

⁵ Energy use is surveyed as the total amount paid on energy bills during the observation period.



Source: Authors' elaboration based on ENIGH

Fig. 2 Average household size by householder age

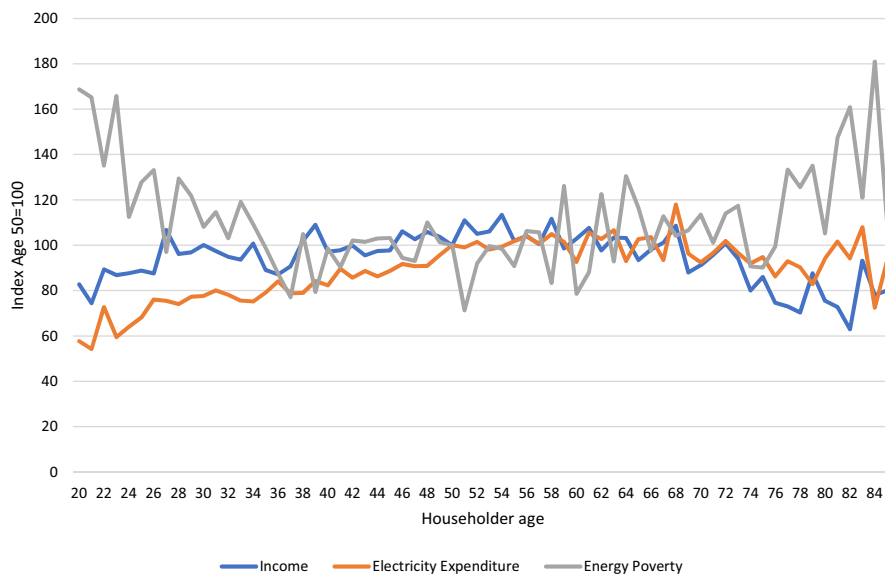


Fig. 3 Household income, electricity expenditure, and energy poverty by age of householder in 2016. Notes: each of the three series of average values is transformed into an index that is equal to 100 for the 50 year old householder. Source: Authors' elaboration based on ENIGH

Table 2 Income distribution and energy poverty incidence by quartiles and area (2016)

Quartiles	Average equivalent income		Gini Index		% Energy poor HH		% Electr. bills on total expenditure	
	Urban	Rural	Urban	Rural	Urban (%)	Rural (%)	Urban (%)	Rural (%)
1	2011	1726			21.9	20.1	3.24	2.59
2	3813	3710			16.7	17.7	2.96	2.53
3	6083	5989			13.6	16.6	2.73	2.48
4	15,357	14,093			9.6	12.5	2.25	2.36
Total	7880	4110	0.431	0.408	14.4	18.2	2.72	2.53

Average equivalent income refers to the income normalized by the number of members in the household using the transformation $(N)^{1/2}$ where N is the number of members (OECD 2013). Energy poor is those with a share of electricity expenditure higher than 10% or equal to zero meaning that they do not pay for electricity

Source: authors' elaboration and CEDLAS-The World Bank for Gini index

Determinants of residential energy expenditure

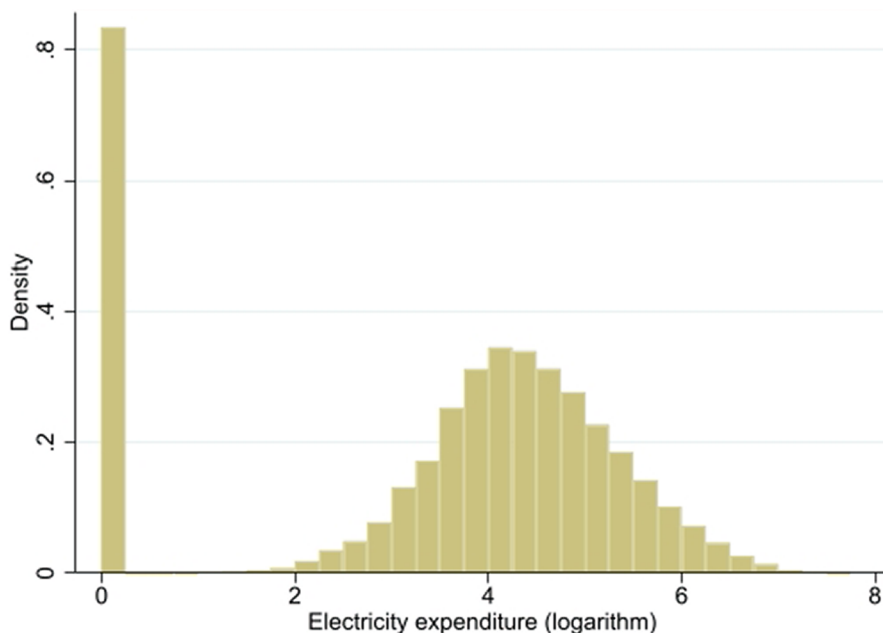
First, we use the pooled dataset to analyse the joint effect of demographic, social, and dwelling characteristics on electricity demand. Drawing from the international empirical literature (see for a review Jones et al. 2015), we expect a key role of income and socio-demographic variables.

Figure 3 shows the usual life-cycle pattern that is an inverted U-shape for electricity demand by age of householder: it is clear that this relation is driven by the evolution of household size and income during the life-cycle. The grey line highlights the incidence of energy poverty⁶ according to householder age that, on the contrary, has a clear U-shape.

It is worth highlighting that energy use has a slower decline with respect to income as age increase. This means that electricity bills weigh relatively more heavily on the budgets of elderly households with lower income levels and fewer family members.

Table 2 focuses on 2016 and shows that, besides energy poverty, also income levels, inequality, and the share of electricity expenditure on total expenditure differ between urban and rural areas. Notwithstanding higher income levels in urban areas, it is interesting to note that energy poor households or, more generally, those with zero consumption or a higher share of electricity expenditures are more numerous in the first quartile of urban areas, in part because of fewer opportunities for substitution between electricity and other energy sources. The considerable differences

⁶ Energy poverty here represents both aspects of lack of access to modern energy sources and lack of financial resources to adequately use energy services. Figure 3 and Table 2 show an expenditure-based metrics computed through a simplified combined indicator: a household is classified as energy poor if the share of energy expenditure on income exceeds 10% (ten percent rule) or if it shows zero expenditure. For a general discussion of energy poor metrics, see Bardazzi et al. (2021) and Sareen et al. (2020).



Source: Authors' elaboration based on ENIGH

Fig. 4 Electricity expenditure distribution (natural logarithm of the household equivalent expenditure)

between urban and rural areas, therefore, suggest treating the two samples separately when looking for the determinants of electricity consumption.⁷

On the pooled dataset, we test the relevance of the main drivers of electricity demand in Mexico, by considering socio-demographic characteristics as well as some structural data.

The empirical model can very generally be represented by the following equation:

$$\text{Ln}(EE_{it}) = \alpha + \beta X_{it} + \gamma Y_{it} + u_{it}, \quad (1)$$

where the dependent variable $\text{Ln}(EE)$ is the logarithm of the household's deflated equivalent⁸ residential electricity expenditure, X_{it} is the set of non-human characteristics (such as geographical area and dwelling type), and Y_{it} is the set of socio-demographic factors (or human characteristics).

Unfortunately, the presence of several zero values in household electricity expenditure (Fig. 4) hinders the use of estimation methods based on the hypothesis of normal distribution of the variables, and in particular, parameters estimated with

⁷ Interestingly, Labeaga et al. (2021), when looking at elasticities for the several energy products, chose to split the Mexican dataset according to the ownership of a vehicle and to consider rural/urban location as independent variables.

⁸ To make expenditure comparable when considering different household size, we employ the simple Oecd equivalence scale which divides household income by the square root of household size (see OECD 2013),

OLS would be biased. In this sample, zero values cannot be considered only survey errors or truncated values and mostly arise from an affordability issue.⁹

When the zero value is the result of a specific choice and can be thought of as a corner solution due to a constrained utility maximization problem, the Tobit estimation is usually employed. However, this model rests on two strong assumptions of normality and homoscedasticity that were tested and failed on our data. Therefore, we decided to relax the strong Tobit assumption that the same mechanism generates both zeros and positive values and to consider electricity expenditure as the combination of two separate decisions: connecting or not to the electricity grid and deciding how much to consume. The double-hurdle model by Cragg (1971) is suitable for this case, also because it provides more flexibility compared with other censored or two stages techniques (as Tobit's and Heckman's models) as it allows zero expenditure to be generated at both decision levels and because different sets of explanatory variables can be used to build the two hurdles.

To sketch the double-hurdle model, let y_i be the observed expenditure of household i , while y_{ip}^* and y_{ic}^* are two latent variables respectively representing the household participation and consumption decisions. We define S_i as the binary variable for the participation decision, considering a set of factors w_i able to describe the latent variable y_{ip}^* . The selection model is therefore

$$p_i = P(y_{ip}^* > 0) = P(S_i = 1) = \Phi(w_i) = \Phi_i, \quad (2)$$

where Φ_i is a cumulative distribution function. The continuous latent variable y_{ic}^* is a function of a vector of explanatory variables x_i . Under the assumption that the process generating S_i is independent of y_i conditional on x_i , the specification of the observed dependent variable becomes¹⁰

$$y_i = S_i \max \{y_{ic}^*, 0\}. \quad (3)$$

The first decision is modelled using a probit model, while the consumption decision is modelled with a truncated regression model. Table 3 describes the variables used in the equations.

Table 4 presents the regression results for the whole period (2000–2016), considering urban and rural areas. The table shows coefficients and marginal effects. Indeed, as the coefficient estimates in the two steps are not directly interpretable, to obtain the effect of the covariates on the dependent variable, it is necessary to analyse the marginal effects which are a function of the parameters and explanatory variables in both tiers of the regression.¹¹

⁹ Zero values can be rationalized by three different alternatives: they can represent a choice made by the agents, they can represent either missing or non-response outcomes, or they can be the result of a structural characteristics, when the agents have no control over the decision. See also Pudney (1990).

¹⁰ In our empirical application, both hurdles are assumed to be linear in the parameters, with additive, independent, and normally distributed error terms.

¹¹ For a formal derivation of the overall marginal effects and related elasticities on the dependent variable, see Eakins (2016).

Table 3 Variables' definition

Variable name	Type	Notes	Mean	St. dev	Min	Max
Househ. equiv. electricity exp. (dep. var.)	Monetary	Log, deflated values	4.4	0.9	- 1.5	7.7
Householder age	Integer	Age > 20 years	47.4	15.0	20.0	85.0
Householder age ²	Integer	Age > 20 years	2474.8	1530.1	400.0	7225.0
Householder gender	Binary	female = 2	1.2	0.4	1.0	2.0
Presence of children	Binary	Yes = 1	0.3	0.5	0.0	1.0
Education level	Binary	At least 10 years of education	0.3	0.5	0.0	1.0
Total equivalent household income	Monetary	log, deflated values	8.4	0.8	- 0.7	14.3
Quartile	Integer	HH equivalent income quartiles			1.0	4.0
Poor area	Binary	HH located in poor area	0.4	0.5	0.0	1.0
Geographic area	Integer	North regions = 1; Centre = 2, South = 3			1.0	3.0
Property	Binary	Owner = 1	0.6	0.5	0.0	1.0
Household size	Integer	Integer	3.9	1.9	1.0	43.0
Air conditioning	Binary	Yes = 1	0.1	0.3	0.0	1.0
Self employment	Binary	Yes = 1	0.3	0.5	0.0	1.0
Dwelling type (flat, detached house)	Binary	Detached = 1	0.6	0.5	0.0	1.0

Table 4 Double hurdle regression results for electricity demand (coefficients and marginal effects)

	Urban areas						Rural areas					
	Selection step		Expenditure step		Marginal effects		Selection step		Expenditure step		Marginal effects	
	Coef	P values	Coef	P values	dy/dx	P values	Coef	P values	Coef	P values	dy/dx	P values
Age	0.0214	0.00	0.0201	0.00	0.042	0.00	0.0251	0.00	0.0185	0.00	0.047	0.00
Age ²	-0.0002	0.00	-0.0001	0.00	0.000	0.00	-0.0002	0.00	-0.0001	0.00	0.000	0.00
Gender	0.0207	0.15	-0.0059	0.52	0.021	0.28	-0.0241	0.35	0.0378	0.02	-0.005	0.89
Quartile_2	0.1180	0.00			0.161	0.00	0.0499	0.04			0.069	0.04
Quartile_3	0.1788	0.00			0.240	0.00	0.0997	0.00			0.135	0.00
Quartile_4	0.3084	0.00			0.393	0.00	0.1707	0.00			0.226	0.00
Center	-0.1653	0.00			-0.201	0.00	0.0897	0.00			0.124	0.00
South	-0.0734	0.00			-0.086	0.00	0.1742	0.00			0.235	0.00
Dwelling type	0.4128	0.00			0.206	0.00	0.4221	0.00			0.141	0.00
Self employed	-0.0944	0.00			-0.117	0.00	-0.0036	0.86			-0.005	0.86
Education			-0.0197	0.03	-0.016	0.03			0.0609	0.01	0.044	0.00
Poor area			-0.0338	0.00	-0.027	0.00			-0.0334	0.01	-0.024	0.00
Equivalent income			0.2980	0.00	0.238	0.00			0.3585	0.00	0.260	0.00
Children			-0.0247	0.02	-0.020	0.02			-0.0306	0.07	-0.022	0.00
Owner			-0.0761	0.00	-0.061	0.00			-0.2113	0.00	-0.153	0.00
HH size			-0.0320	0.00	-0.026	0.00			-0.0666	0.00	-0.048	0.00
Air conditioning			0.5464	0.00	0.436	0.00			0.5757	0.00	0.418	0.00
Dwelling type			-0.3814	0.00					-0.5916	0.00		
Constant	-0.2093	0.00	1.7361	0.00			-0.1916	0.00	1.5188	0.00		

The results show that the main findings of the international empirical literature are confirmed also for Mexican households [see Jones et al. (2015) for a review, Olaniyan et al. (2018) for the case of Nigeria, Taale and Keyermeh (2019) and Adusah-Poku and Takeuchi (2019) for the case of Ghana, which are two of the few papers on developing economies].

Regression results prove that age is a key determinant both for the participation step of grid connection and for the expenditure decision, with a nonlinear link, as discussed in Figs. 4 and 5. As for the decision to actually connect to the grid, householder gender has no relevance, whereas the higher income relative position of the household—proxied by the quartile dummies—and detached dwellings show positive influence.¹² As for geographic areas, a northern location increases the probability to connect to the grid in urban areas, while the reverse is true for rural locations. The self-employed status of the householder has a negative impact, probably due to a related uncertainty in income.

In the second step—the electricity expenditure behaviour—income has very similar impact in both rural and urban areas. The effect of gender in terms of expenditure is debated in the literature. Some find that women householders spend more (e.g., Besagni and Borgarello 2018 for Italy), while some others find they spend less (e.g., Permana et al. 2015 for Indonesia). Female householder and high education levels are associated with larger energy expenditure in Mexican rural areas. In urban locations, on the contrary, the gender is not statistically significant, whereas the education coefficient has a negative sign. Indeed, western countries generally show a negative link with education level because of its positive influence on energy saving behaviour, even if Mills and Schleich (2012) find that this impact widely varies among different areas. The presence of economies of scale shows its importance as household equivalent energy expenditure is lower the higher the household size, with a doubled effect in rural areas.¹³ Due to the different atmospheric temperature level, overall energy expenditure is higher in hotter areas, and coherently, the presence of air conditioning equipment shows a strong positive effect. Dwelling types and its ownership show a negative impact, which denote better isolation and conservation practices in homes occupied by its owner, particularly in detached houses.

Electricity consumption and population cohorts

In this section, household cohorts become the unit of analysis. We use a longitudinal perspective to estimate if there exists a combination of drivers on electricity consumption linked to a pure life-cycle factor and to a set of experiences and social influences which characterize the generations of the householders. To exploit this issue, neither cross-sectional nor time-series data are appropriate. The most suitable data are panel data, but, if not available, pseudopanel built with repeated cross-sections—cohort data—are a good substitute. They preserve some heterogeneity of

¹² For the role of the characteristics of the dwelling on energy consumption see Brounen et al. (2012).

¹³ The importance and the role of sociodemographic variables in Mexican residential electricity demand is also consistent with estimates by Labeaga et al. (2021).

the original microdata, allow to follow the agent behaviour across time, and make it possible to identify a cohort effect distinguished from a life-cycle pattern. This technique was introduced by Deaton (1985). Bernard et al. (2011) used this methodology to study the residential electricity demand in the province of Québec (Canada) and Bardazzi and Pazienza (2017) applied it to Italy. To the best of our knowledge, this methodology has never been used to study the residential energy consumption in a developing country like Mexico. As stated in the Introduction, there are numerous reasons to think that results and the magnitude of those results could be very different from the findings for developed countries.

Cohort data have both limitations and advantages, well discussed in the literature (Deaton 1997). First, a potential source of bias are population migration or death affecting cohort size and composition. Moreover, cohort data are defined by the age of the household head and the age composition of the other household members is not directly considered. Finally, the construction of a pseudo-panel involves a trade-off between the number of cohorts and the number of observations in each cohort. If the number of cohorts is too small, individuals with heterogenous behaviour risk to be in the same group. On the other hand, if a large number of cohorts preserve the variability within the pseudo-panel, it is likely to obtain cells with a very limited number of observations, thus leading to inconsistent estimators with inaccurate estimates of the true cohort population values (Verbeek 2008; Verbeek and Nijman 1992).

The main assumption behind the construction of a pseudo-panel is that units are defined as a group of agents sharing the same time-invariant characteristics and therefore having similar behaviour to be treated as a single unit. Household cohorts can be built according to different criteria. The simplest one is the date of birth of the household head, or more conveniently his/her age in 2000, which is the first year of our dataset. This assumption implies that the electricity consumption is determined by the age of the householder associated with other characteristics evolving during the individual life-cycle—such as the household size, the presence of children, the employment status, etc. In this paper, cohorts are built not only by the age of the householder and but also by the household income quartile, to consider the income distribution that has proven to be significant in the cross-sectional analysis shown in the previous section.

In the cohort dataset, we include the household expenditure on electricity¹⁴ and several demographic and economic control variables. Nominal expenditures are deflated using the consumer price index (CPI) with base year 2011.¹⁵

To construct the pseudo-panel, first, we distinguish the sample between urban and rural households, following the analysis of the previous sections. Then, we only keep households in which the head is 25–85 years old. This truncation aims to avoid a selectivity problem. The birth cohorts are defined in 5-year groups, except for the youngest cohort born between 1985 and 1992 to collect the largest number

¹⁴ This variable is calculated following the preliminary operations previously discussed in Sect. 2.

¹⁵ In addition, extreme and unreliable values are cleaned from the dataset through a trimming procedure that excludes observations falling outside the first and last percentiles.

of observations. Using the householder's age and income quartile gives a total of 2189 cells for urban and 2176 for rural households, that is a reasonable compromise between accuracy (given the homogeneity in unobservable characteristics affecting energy demand linked to the birth year) and statistical significance (Verbeek 2008).

We observe cohorts at several points in time—the survey years—as they progress throughout the life-cycle and have different experiences, social, and material influences. Basically, we compare the behaviour regarding the electricity consumption of a say 30-year-old householder at a particular time with other 30-year-old householders at earlier or later points in time.

Our primary model can be written as

$$y = \alpha + W\varphi + D_a\beta + D_c\delta + D_y + \varepsilon, \quad (4)$$

where y is the stacked vector of cohort mean observations in terms of electricity consumption, D_a is a matrix of age dummies, D_c a matrix of cohort dummies, and D_y a matrix of year dummies to capture macro shocks that synchronously but temporarily move all cohorts away from their profiles¹⁶ Finally, W is a matrix of time-varying covariates, which in our case includes only dummies for household income quartile. The β and δ parameters will then represent the age and cohort effects that are not captured by movements in the W variables.

Table 5 presents the descriptive statistics of the variables used in the estimation of Eq. (4) at the cohort level.

Estimations results are presented in Table 6 and summarized in Fig. 5.¹⁷ First of all, we notice a similar pattern in coefficients between urban and rural notwithstanding some differences in magnitude. Parameters¹⁸ of the income quartiles show the expected sign and have statistical significance. The increase in magnitude of coefficients as household's income is placed in higher quartiles confirms the findings of the cross-sectional analysis. Age effects are statistically significant starting from 30 years old and they are monotonically increasing. Cohort effects are negative and decreasing from younger to older generations: householders born in decades up to the 1960s show a lower electricity consumption compared with householders of the same age born in more recent decades. The smaller cell size for the younger age groups and cohorts contributes to explain the lower significance of coefficients and

¹⁶ In our case, all the matrices have m rows, which is the number of cohort-year pairs. The number of columns is 61 (the number of ages) for matrix D_a , 14 (the number of cohorts) for D_c and 9 for D_y (the number of survey years). To avoid singularity, we must drop one reference category for each matrix of dummies. We choose as reference categories the group of individuals in the first equivalent income quartile, in the first age class (25 years old) and those born in the youngest cohort (1985–1999). Moreover, to solve the identification problem due to the linear relationship across age, cohort, and period, we apply the normalization by Deaton and Paxson (1994) and impose the constraint that year dummy coefficients are orthogonal to a time-trend and sum to zero. In particular, considering d_t as the usual zero-one dummy, to enforce this restriction, we use a set of $T - 2$ year dummies, d_t^* , defined as follows, from $t=3, \dots, T$ $d_t^* = d_t - [(t-1)d_2 - (t-2)d_1]$.

¹⁷ In Figure 5 age and cohort effects for urban and rural households are estimated with respect to the reference categories (25 years-old household head).

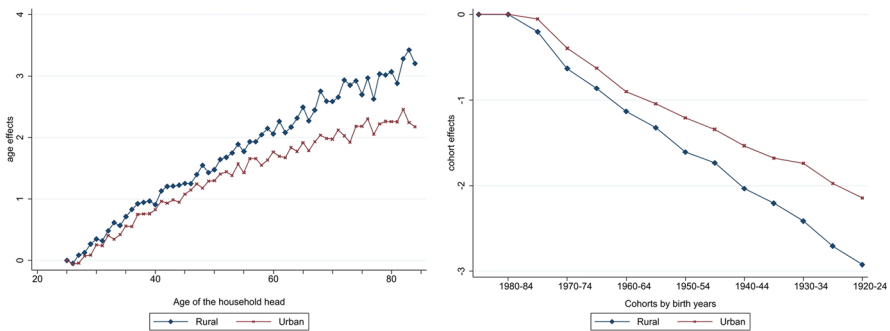
¹⁸ As the model is log-linear, coefficients must be transformed and interpreted with respect to the reference categories.

Table 5 Descriptive statistics of the urban and rural pseudopanel

Variable	Obs	Mean	Std. dev.	Min	Max
<i>Urban</i>					
Electricity expenditure (real equivalent, log)	2,189	3.58	0.69	0	5.83
Age	2,189	54.91	17.57	25	85
Cohort	2,189	7.76	3.63	1	14
Household income (real equivalent, log)	2,189	8.39	0.72	6.958	9.88
<i>Rural</i>					
Electricity expenditure (real equivalent, log)	2,176	3.19	0.83	0	7.28
Age	2,176	54.75	17.5	25	85
Cohort	2,176	7.73	3.62	1	14
Household income (real equivalent, log)	2,176	8.31	0.76	6.68	10.52

Household income is deflated by the CPI 2011

Source: authors' elaboration based on ENIGH



Source: Authors' elaboration based on ENIGH

Fig. 5 Age and cohort effects for electricity expenditure of Mexican households

it is simply due to the fact that 25-year-olds are less likely to be household heads than older individuals. However, all age and cohort effects are jointly statistically significant.¹⁹

Age and cohorts effects are more effectively represented in Fig. 5. The age coefficients are plotted as a function of the age in the left panel. We can see that equivalent electricity expenditure rises with age for both rural and urban households, but the effect is stronger for rural households and the gap increases for the elderly. For 85 year old householders, the difference between the coefficients is more than 60%. The cohort coefficients are presented in the right panel as a function of the householder birth year. Cohort effects decrease from the younger to the older generations and show, in absolute value, the same magnitude and the same difference between

¹⁹ *F*-values for age and cohort effects for urban households are 6.9 and 24.04, respectively. For rural households, they are 7.43 and 30.97.

Table 6 Estimation results for electricity consumption of rural and urban Mexican households (Cohort Analysis)

	Rural		Urban	
	Coefficient	Std.error	Coefficient	Std. error
Income quartiles (ref. first quartile)				
Second income quartile	0.429***	0.039	0.388***	0.031
Third income quartile	0.632***	0.039	0.649***	0.031
Fourth income quartile	0.913***	0.039	1.031***	0.031
Householder age (ref. 25 years-old)				
26 years-old	- 0.048	0.154	- 0.058	0.121
27 years-old	0.085	0.153	- 0.045	0.121
28 years-old	0.128	0.155	0.070	0.122
29 years-old	0.266*	0.155	0.089	0.122
30 years-old	0.349**	0.158	0.256**	0.124
31 years-old	0.319**	0.157	0.242*	0.124
32 years-old	0.482***	0.161	0.409***	0.127
33 years-old	0.614***	0.161	0.348***	0.127
34 years-old	0.570***	0.162	0.424***	0.128
35 years-old	0.714***	0.163	0.556***	0.128
36 years-old	0.829***	0.164	0.551***	0.129
37 years-old	0.921***	0.165	0.748***	0.130
38 years-old	0.945***	0.166	0.758***	0.131
39 years-old	0.965***	0.167	0.760***	0.131
40 years-old	0.907***	0.169	0.825***	0.133
41 years-old	1.129***	0.169	0.962***	0.133
42 years-old	1.203***	0.171	0.930***	0.135
43 years-old	1.210***	0.173	0.983***	0.136
44 years-old	1.224***	0.173	0.947***	0.136
45 years-old	1.252***	0.175	1.076***	0.138
46 years-old	1.248***	0.175	1.145***	0.138
47 years-old	1.395***	0.177	1.243***	0.140
48 years-old	1.547***	0.178	1.176***	0.140
49 years-old	1.428***	0.179	1.290***	0.141
50 years-old	1.476***	0.180	1.298***	0.142
51 years-old	1.642***	0.181	1.403***	0.143
52 years-old	1.676***	0.183	1.444***	0.144
53 years-old	1.748***	0.184	1.384***	0.145
54 years-old	1.888***	0.184	1.568***	0.145
55 years-old	1.773***	0.186	1.424***	0.147
56 years-old	1.930***	0.187	1.653***	0.147
57 years-old	1.931***	0.188	1.653***	0.148
58 years-old	2.043***	0.189	1.548***	0.149
59 years-old	2.147***	0.190	1.632***	0.150
60 years-old	2.057***	0.191	1.760***	0.151

Table 6 (continued)

	Rural		Urban	
	Coefficient	Std.error	Coefficient	Std. error
61 years-old	2.262***	0.192	1.692***	0.151
62 years-old	2.079***	0.194	1.673***	0.153
63 years-old	2.169***	0.195	1.835***	0.153
64 years-old	2.313***	0.195	1.774***	0.154
65 years-old	2.491***	0.197	1.915***	0.155
66 years-old	2.270***	0.197	1.787***	0.155
67 years-old	2.445***	0.199	1.931***	0.157
68 years-old	2.751***	0.200	2.035***	0.158
69 years-old	2.589***	0.200	1.983***	0.158
70 years-old	2.586***	0.202	1.972***	0.159
71 years-old	2.655***	0.202	2.119***	0.159
72 years-old	2.933***	0.204	2.026***	0.161
73 years-old	2.849***	0.205	1.921***	0.162
74 years-old	2.920***	0.205	2.183***	0.162
75 years-old	2.696***	0.207	2.182***	0.163
76 years-old	2.967***	0.208	2.303***	0.163
77 years-old	2.625***	0.209	2.050***	0.165
78 years-old	3.031***	0.211	2.222***	0.165
79 years-old	3.015***	0.213	2.261***	0.166
80 years-old	3.067***	0.213	2.257***	0.167
81 years-old	2.879***	0.215	2.255***	0.167
82 years-old	3.279***	0.216	2.453***	0.169
83 years-old	3.424***	0.216	2.242***	0.170
84 years-old	3.202***	0.220	2.175***	0.170
85 years-old	3.286***	0.219	2.353***	0.173
Householder cohort (ref. 1985–1999)				
Cohort 1980–84	– 0.203*	0.110	– 0.052	0.087
Cohort 1975–79	– 0.631***	0.106	– 0.395***	0.084
Cohort 1970–74	– 0.863***	0.113	– 0.627***	0.089
Cohort 1965–69	– 1.132***	0.123	– 0.900***	0.097
Cohort 1960–64	– 1.324***	0.131	– 1.044***	0.103
Cohort 1955–59	– 1.608***	0.138	– 1.210***	0.109
Cohort 1950–54	– 1.735***	0.145	– 1.342***	0.115
Cohort 1945–49	– 2.035***	0.152	– 1.534***	0.120
Cohort 1940–44	– 2.206***	0.159	– 1.679***	0.125
Cohort 1935–39	– 2.414***	0.165	– 1.739***	0.130
Cohort 1930–34	– 2.705***	0.171	– 1.975***	0.135
Cohort 1925–29	– 2.924***	0.179	– 2.144***	0.141
Cohort 1920–24	– 3.485***	0.186	– 2.542***	0.146
Year 2004	0.061	0.038	0.180***	0.030
Year 2006	– 0.281***	0.039	– 0.191***	0.031

Table 6 (continued)

	Rural		Urban	
	Coefficient	Std.error	Coefficient	Std. error
Year 2008	0.157***	0.039	- 0.110***	0.031
Year 2010	0.599***	0.039	0.184***	0.031
Year 2012	- 0.045	0.038	0.007	0.030
Year 2014	- 0.196***	0.036	0.007	0.028
Year 2016	- 0.126***	0.033	- 0.031	0.026
Constant	2.447***	0.129	2.920***	0.102
Number of obs	2,176		2,189	
<i>F</i> Statistic	<i>F</i> (82, 2092) 17.98		<i>F</i> (83, 2105) 22.57	
<i>R</i> -squared	0.4164		0.4709	
Adj <i>R</i> -squared	0.3932		0.4500	
Root MSE	0.6486		0.5112	

Source: Authors' elaboration based on ENIGH

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

rural and urban households as the age effects. New generation householders born in the 1990s have an electricity expenditure that is more than 80% higher than individuals born in the 1920s.

The signs of age and cohort effects are in line with what was found by Bardazzi and Pazienza (2017) for Italy, but the size of the effect is very different. In the case of the European country, equivalent electricity expenditure increases at a much lower rate from young to older ages and from older to younger generations compared with the case of Mexico. In this case, the electricity expenditure of urban households increases at about 18% every 5-year cohort (25% for rural households) and at about 4% per year of age for urban householders (5% for rural). These results are four times larger than those in Bardazzi and Pazienza (2017). This difference could be partially explained by the very recent completion of the electricity grid in Mexico, but could also derive from the fact that economic growth is stronger in developing countries. Coupled with the younger population in such countries, this could generate some stress in the system in the future, as energy demand grows.

The income growth in Mexico has affected inequality in different areas and different age groups. Therefore, to ease the interpretation of the results, we estimate the same model by dividing the pseudo-panel by income quartiles, not considering the rural/urban categorisation. Estimated age and cohort effects are plotted in Fig. 6 that show that both effects have a similar shape as those in the previous figure: effects are increasing as the householder gets older and belongs to younger generations.²⁰

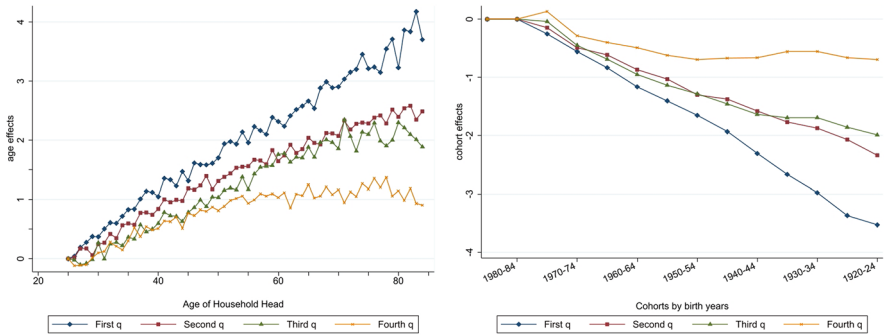
However, we observe a steeper pattern for the poorer households, which are similar in size for the second and third quartiles and show a slow down for households in the richest part of the distribution. This means that household income distribution

²⁰ Estimated parameters are presented in the Appendix.

Table 7 Estimated demographic effects by quartile

Income quartile	Age effects: annual average change (%)	Cohort effects: annual average change per cohort (%)
Q1	6.4	- 31.9
Q2	4.9	- 23.0
Q3	3	- 15.3
Q4	2.6	- 10.3

Source: Authors' elaboration based on ENIGH



Source: Authors' elaboration based on ENIGH

Fig. 6 Cohort and age effects by income quartile

plays a role in the magnitude of the estimated effects which are polarized at the two extremes.²¹ The rates of change per year of age and per cohort by quartiles are shown in Table 7. For the households belonging to the top of income distribution, these results are closer to the estimated average rate of change for developed countries, as seen for the Italian case in Bardazzi and Paziienza (2017). This finding supports the idea that the state of development of the economy plays a major role in explaining energy expenditure and the influence of age and generation on such expenditure.

Concluding remarks

In this paper, we explore if energy consumption patterns in developing economies are different from those observed in developed ones and if generational aspects in countries with younger populations and in the middle of a demographic and economic transition have an important role. With this purpose, we study determinants

²¹ This is in line with Grottera et al.'s (2018) results that, using another methodology, finds that the 1st French decile consumes more than the 8th Brazilian decile, but that, at the same time, the 10th Brazilian decile consumes more than the 10th French decile.

of residential electricity consumption, putting an accent on age and generational effects in a developing country like Mexico. We first use a double-hurdle model to study the main drivers of electricity consumption, including income, education, gender, characteristics of the dwelling, and age. We then look closely into demographic effects through a cohort approach.

We find that, among other socio-economic determinants, age effects are statistically significant starting from 30 years old and are monotonically increasing. Regarding the generational impact, estimations show that householders born in decades up to the 1960s show a lower electricity consumption compared with householders of the same age born in more recent decades. The signs of these two effects are in line with what was found by previous literature for developed countries, but the size of the effect is very different: the increase in electricity expenditures from young labtto older ages is four times higher in Mexico (Bardazzi and Pazienza 2017).

Inequality is stronger in developing countries, and to assess its role in this case, we study the generational impact per income quartile. We find that the rates of change in electricity expenditure per year of age and per cohort are four times larger for the first quartiles of income, while the effects for the last quartile are similar to the ones found for the few studies undertaken for developed countries [see Bardazzi and Pazienza (2020) for Italy and Chancel (2014) for France].

Our findings support the idea that the state of development of the economy is crucial to understand the determinants of energy consumption and the impact that age and generational factors have on such consumption. These findings are particularly relevant given that developing countries will drive energy demand growth in the following decades.

Supplementary Information The online version contains supplementary material available at <https://doi.org/10.1007/s43546-022-00332-0>.

Acknowledgements Maria Eugenia Sanin acknowledges financial support from the Chair Energy and Prosperity at Fondation du Risque, ANR/Investissements d'avenir (ANR-11-IDEX-0003-02). Rossella Bardazzi and Maria Grazia Pazienza acknowledge the support from the Erasmus+ Programme of the European Union, Jean Monnet Chair HOPPER (HOUSEHOLDS' energy Poverty in the EU: PERSpectives for research and policies) (610775-EPP-1-2019-1-IT-EPPJMO-CHAIR).

Funding Open access funding provided by Università degli Studi di Firenze within the CRUI-CARE Agreement.

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