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Life-cycle characteristics and energy practices in developing countries: the case of Mexico

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Abstract

Developing countries are characterized by slightly higher GDP growth rates that developed ones, are advancing towards universal energy access and many of them are yet to finish their demographic transition, which implies their fertility rate is higher than average and their population is still young. The previous socio-demographic and economic changes could make energy consumption patterns quite different from the ones observed in developed countries. Herein we use Mexico as a case study to estimate determinants of energy consumption as well as the importance that change in generational preferences has on such consumption. We find that results are in line with the few studies performed for developed countries but that the magnitudes are four times stronger. This means that younger generations in Mexico increase their consumption at a much faster rate as they grow older than households in developed countries, which may become a concern for policymakers deciding on investments to meet future energy demand, particularly in the context of the energy transition.

Keywords: energy consumption, electricity, residential, life-cycle, generation, Mexico

JEL Classification: C3, D12, Q4

1. Introduction

Following the UN Sustainable Development Goals, universal energy access has become a priority and, as from 2018, on average 90% of the world's population has access to electricity services (World Bank, 2021). This increase in energy access is excellent news for living conditions of the world's population but will certainly make it more difficult to meet increasing energy demand in the future, particularly considering the changes that must take place in the energy matrix to comply with the Paris Agreement objective of zero-net-emissions by 2050.

Developing countries are characterized by slightly higher GDP growth rates and many of them are yet to finish their demographic transition (Easterlin, 2019). These two characteristics, together with changing energy consumption patterns due to cultural and generational changes, make it even more difficult to predict their energy demand growth as well as to design the right policies to increase energy conservation and reduce energy poverty. To better understand 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. As many developing countries, Mexico has just reached universal electricity access in 2018 (World Bank, 2021) and residential consumption, being heavily subsidized[1] (Contreras Liesperguer, 2020), has been growing at an average annual rate of 4.37% (Escoto Castillo and Sanchez Pena, 2017).

However, electricity consumption is not only linked to energy access and price levels. Residential electricity consumption is expanding worldwide since new appliances are shaping energy practice and energy culture (WEO, 2017). Several studies – mostly 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). This is the first thing we do herein for the case of Mexico, distinguishing between rural and urban households. We find that, in line with the findings for developed countries, dwelling type, rural versus urban area, income and personal characteristics – among which age – are key factors explaining residential energy consumption. In a second step, we perform a study of generational cohort groups across time using repeated cross-sections with the purpose of disentangling 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. Differences in magnitude between rural and urban location are identified. 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 increase 25% every five-year cohort (and 18% for urban households). Moreover, when we study the generational impact per income

[1] According to Coady et al. (2015), only 7% of fuel subsidies in poor countries go to the bottom 20% of households.

quartile we observe that the rates of change in electricity expenditure per year of age and per cohort by quartiles are much larger for the poorest households (belonging to the first quartiles of income) while the effects are similar to the ones found for developed countries for the rich (last quartile of income). The fact that younger generations consume up to 25% more than older ones, together with the younger population of Mexico, still in the demographic transition, indicates energy consumption patterns markedly different from those of developed countries and could imply a great difficulty in the future to meet such fast-growing demand.

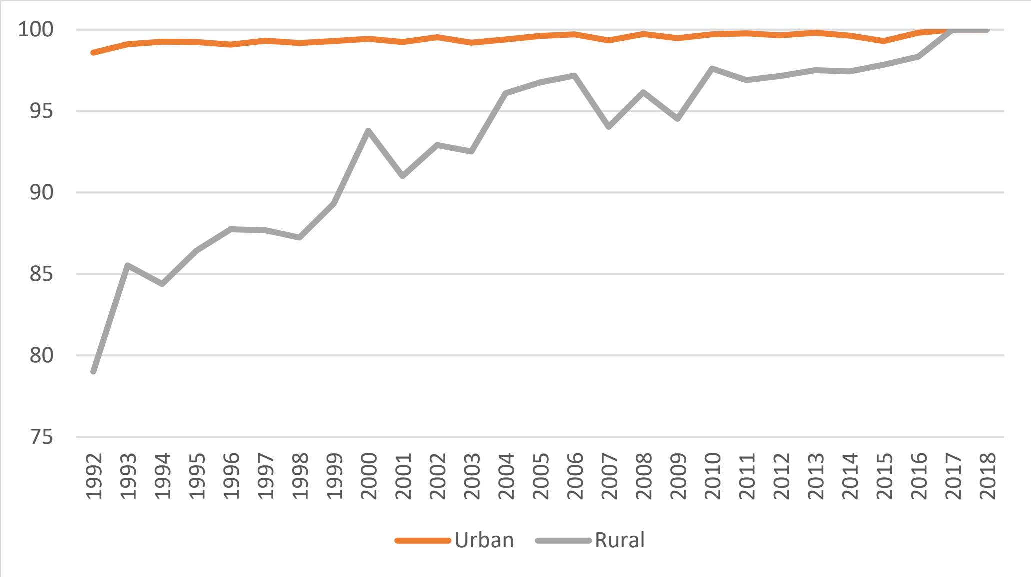
2. Using Mexico as a case study

Mexico ranks as the 10th most populated country in the world and third in the Americas after the US and Brazil (United Nations, 2021), its population is mostly concentrated in urban areas (84% behind Brazil with 88% but before the US with 83%) and together with most of the southern cone it can be considered as a developing country.[2] Most developed countries show a thin population pyramid's base due to aging population. Instead, Mexico's pyramid still shows a strong base and with a median age of population being under 30 years. However, in the next 30 years a fast-aging process is projected, with the median age approaching 40 years in 2050 (Un World Population Prospects, 2020). 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 be very different from developed countries and, more importantly, that if energy consumption increases with an aging population, energy demand growth for mid-century may be much stronger than in developed countries.

Moreover, over the last three decades (1980 to 2018) the country has underperformed in terms of growth (just above 2%), inclusion, and poverty reduction compared to similar countries limiting its convergence relative to high income economies. Despite the slow growth rate, income inequality (particularly between urban and rural regions as well as between the rich Northern regions and the poor in the South) and concentration of energy use in top deciles, standards of living have been improving year by year. [3] Among these sociodemographic transformations, urbanization, education and household size exhibit large changes (World Bank, 2019). It is evident that universal access to electricity has accelerated these transformations with a virtuous cycle between energy access, rise in per capita income and general sociodemographic transformations. Figure 1 highlights that since 2017 100% of Mexican population has access to electricity but the path to reach this target has been strongly differentiated between urban and rural areas of the country.

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

Figure 1: Evolution in access to electricity



Source: World Bank Database (2021)

The Mexican average tariff is 4.3 U$S cents/kWh for an average consumption of 125 kWh per month, only higher than Venezuela's and Paraguay but lower than most South-American countries (Contreras Liesperguer, 2020). [4] Despite relatively low prices and the good access rate, electricity demand for residential use still raises a question of economic affordability. Energy poverty, considering those households with high incidence of electricity bills on total income or with zero electricity expenditure, has been sharply increasing during the first decade of the century, as residential electricity prices increased and has only stared to improve after 2008 due to energy price dynamics, general income growth and universal energy access.

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 and to identify the optimal energy mix. 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, and a significant emission reduction. This is because beyond traditional drivers of energy use, such as population growth and GDP projections, energy practices 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

[4] In Mexico, residential electricity prices are based on the monthly energy consumed and in blocks of increasing consumption (there are seven consumption strata). Moreover, prices can vary depending on seasons in each region. For consumption above a certain limit, a Domestic High Consumption tariff is established. As for taxes, the fuels used to generate electricity are subject to the carbon tax, whereas electricity consumption is not taxed. The only tax applied to the household level is the value added tax (16%).

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), material culture (e.g. technologies, building form) and energy practices (e.g. activities, processes)."[5] As for developed countries, a significant generational effect in energy use has been found for France and Italy for both residential energy use and for mobility choice (Chancel, 2014, Bardazzi and Pazienza, 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 transitions 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 Yepez-Garcia (2014)). However, recent literature finds additional behavioural drivers. Davis et al. (2014) found 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 socioeconomic groups and marking a transformation in energy use behaviour among different generations of consumers. Herein, we analyse evidence of different energy practices among different Mexican generations.

3. The data

We use microdata from the National Income Expenditure Surveys (ENIGH) 2000-2016. These household surveys are carried out every two years and include several detailed data among which socio-demographic characteristics, income, consumption, dwelling characteristics and energy use. Energy use is surveyed as the total amount paid on energy bills during the observation period. The overall dataset is based on different sample sizes, with sample weights reflecting the Mexican population. In Table 1 we show some statistics for selected years: 2000 as the first observation period, then 2008 as the median year and the final year 2016. From the original dataset we excluded observations with householder age lower than 20 years and higher than 85 years. After this selection, we are 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 area.

Table 1: Households' frequencies by year and share of household with positive electricity expenditure

	Household frequencies		Total Population (weighted)			% of HH with zero electr. expend.		
	Unweighted	Weighted	Urban	Rural	Total	Urban	Rural	Total
2000	9,473	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%

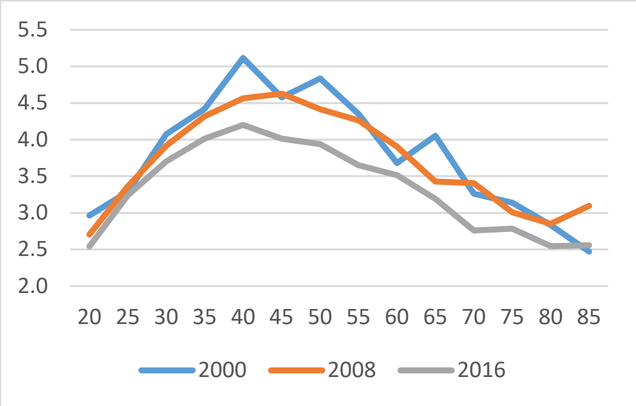
Source: Authors' elaboration based on ENIGH

[5] Stephenson et al. (2010), p. 6124.

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 shown in Table 1 is matched by a decrease in the average size, a trend that is also present in countries with higher living standards.

Figure 2: Average household size by householder age.



Source: Authors' elaboration based on ENIGH

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 higher per capita income inside the household resulting in more consumption within the family and, at the same time, a loss of economies of scale in overall energy use.

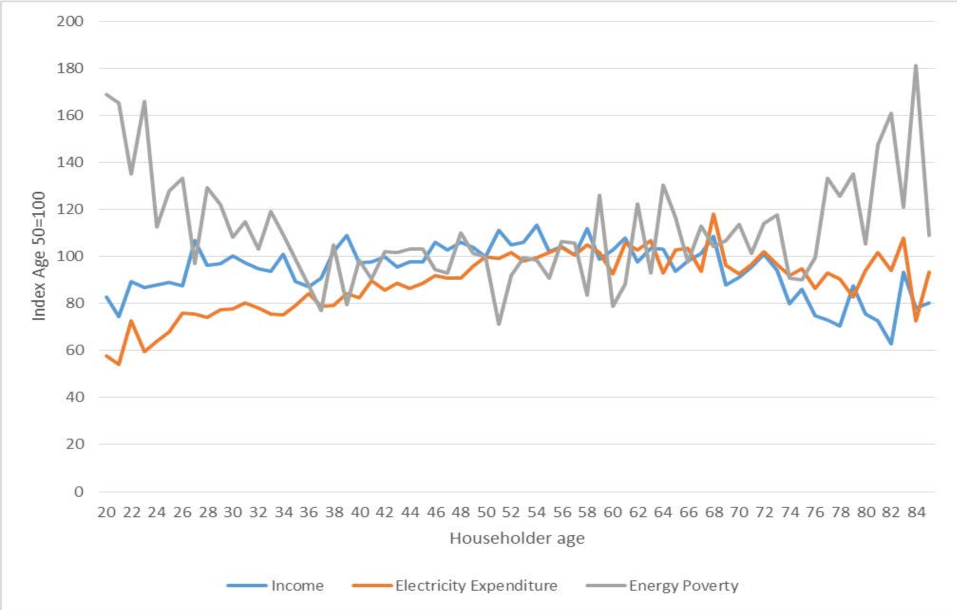
4. Determinants of residential energy expenditure

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 poverty[6] according to householder age that, on the contrary, has a clear U-shape.

[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. Table 2 shows 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 exceed 10% (ten per cent 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).

Figure 3: Household income, electricity expenditure and energy poverty by age of householder in 2016*



*Each of the three series of average values is transformed into an index that is equal to 100 for the 50 years old householder.
Source: Authors' elaboration based on ENIGH.

It's 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.

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	2,011	1,726			21.9%	20.1%	3.24%	2.59%
2	3,813	3,710			16.7%	17.7%	2.96%	2.53%
3	6,083	5,989			13.6%	16.6%	2.73%	2.48%
4	15,357	14,093			9.6%	12.5%	2.25%	2.36%
Total	7,880	4,110	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 are those with a share of electricity expenditure higher than 10% or equal to zero meaning they do not pay for electricity.
Source: authors' elaboration and CEDLAS -The World Bank for Gini index

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

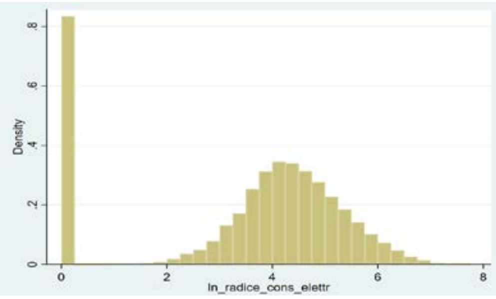
The empirical model can very generally be represented by the following equation

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

where the dependent variable ln (EE) is the logarithm of the household's deflated equivalent[7] 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 (Figure 4) hinders the use of estimation methods based on the hypothesis of normal distribution of the variables, and in particular parameters estimated with 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[8].

Figure 4: Electricity expenditure distribution (natural logarithm of the household equivalent expenditure)



Source: Authors' elaboration based on ENIGH

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), 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

[7] In order 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),

[8] 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 Humphreys (2013) and Pudney (1990).

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

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

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 becomes[9]:

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

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 3: Variable 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 lest 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

Source: Authors' elaboration on ENIGH

Table 4 presents the regression results for the whole period (2000-2016), considering urban and rural areas. The table show coefficients and marginal effects. This is due to the fact that, as the coefficient estimates in the two steps are not directly interpretable, to obtain the effect of the regressors 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.[10]

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 as well as Olaniyan et al., 2018 for the case of Nigeria and 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).

[9] In our empirical application, both hurdles are assumed to be linear in the parameters, with additive, independent and normally distributed error terms.
[10] For a formal derivation of the overall marginal effects and related elasticities on the dependent variable, see Eakins (2016).

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		

*Dwelling type is used in both of the estimation steps.
Source: Authors' elaboration on ENIGH

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 Figures 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[11]. 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 areas. The self-employed status of the householder has a negative impact, probably due to a related uncertainty in income.

As for the second step – the electricity expenditure behaviour – income has very similar impact in both rural and urban areas. The impact 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). Women householder and high education levels are associated with larger energy expenditure in rural areas. In urban areas, 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. 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 the ownership of the dwelling show a negative impact, which

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

denote better isolation and conservation practices in homes occupied by its owner, particularly in detached houses.

5. Life-cycle determinants of electricity consumption

In this section, household cohorts become the unit of analysis. We use this longitudinal perspective to estimate if there exists a combination of drivers on electricity consumption linked to a pure life-cycle factor as well as 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, pseudopanels built with repeated cross-sections – cohort data – are a good substitute. They preserve some heterogeneity of 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), who suggested forming cohort-level data if repeated cross sections are available. Bernard et al. (2011) used this methodology to study the residential electricity demand in the province of Québec (Canada) and Bardazzi and Pazienza (2017) used it for 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 results 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 pseudopanel 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 of the residential electricity use in Mexico.

In the cohort dataset, we include the household expenditure on electricity[12] and several demographic and economic control variables. Nominal expenditures are deflated using the consumer price index (CPI) with base year 2011.[13]

To construct the pseudo-panel for our analysis, firstly 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 five-year groups, except for the youngest cohort born between 1985 and 1992 to collect the largest number of observations. Using the householder's age and income quartile gives a total of 2189 cells for urban and 2176 for rural households, and it 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 lyfe-cycle and have different experiences, social and material influences. Therefore we compare the behaviour regarding the electricity consumption of a 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

$$y = \alpha + W\varphi + D_a\beta + D_c\delta + D_y\psi + \varepsilon \ , \tag{4}$$

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, D_y a matrix of year dummies to capture macro shocks that synchronously but temporarily move all cohorts away from their profiles[14] 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 equation (4) at the cohort level.

[12] This variable is calculated following the preliminary operations previously discussed in Section 2.

[13] 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.

[14] 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 year-olds) 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 normalisation 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, ... T $d_t^* = d_t - [(t-1)\, d_2 - (t-2)\, d_1]$.

Table 5: Descriptive statistics of the urban and rural pseudopanels

Variable	Obs	Mean	Std. Dev.	Min	Max
URBAN					
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
RURAL					
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: author's elaboration based on ENIGH.

Estimations results are presented in Table 6 and summarized in Figure 5.[15] First of all, we notice a similar pattern in coefficients between urban and rural notwithstanding some differences in magnitude. Parameters[16] of the income quartiles show the expected signs 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 youger age groups and cohorts contributes to explain the lower significance of coefficients and 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. [17]

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*

[16] As the model is log-linear, coefficients must be transformed and interpreted with respect to the reference categories.
[17] 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.

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*
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*
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	

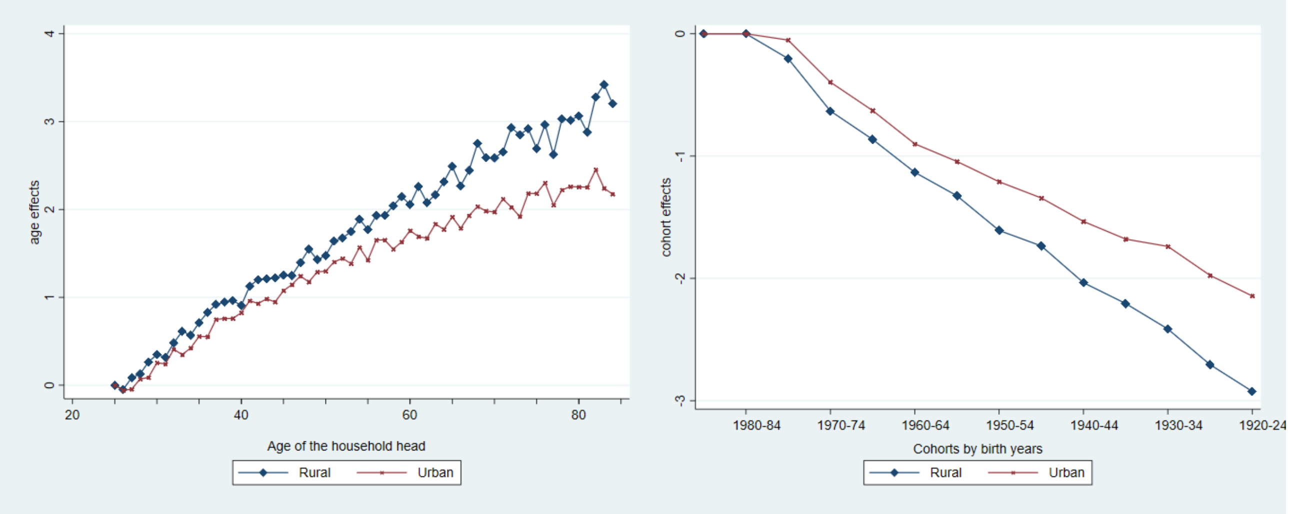
	F(82, 2092) 17.98	F(83, 2105) 22.57
R-squared	0.4164	0.4709
Adj R-squared	0.3932	0.4500
Root MSE	0.6486	0.5112

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

Age and cohorts effects are more effectively represented in Figure 7. The age estimated 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 age effect is stronger for rural households and the gap increases for the elderly. For 85-years old householders, the difference between the coefficients is more than 60 per cent. The cohort estimated coefficients are presented in the righ 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 rural and urban households as the age effects. New generation householders born in the 1990s have an electricity expenditure that is more than 80 per cent 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 our case, the electricity expenditure of urban households increases at about 18 per cent every five-year cohort (25 per cent for rural households) and at about 4 per cent per year of age for urban householders (5 per cent for rural). These results are four times larger than those in Bardazzi and Pazienza (2017). This difference in results could be explained partially by the very recent completion of the electricity grid 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.

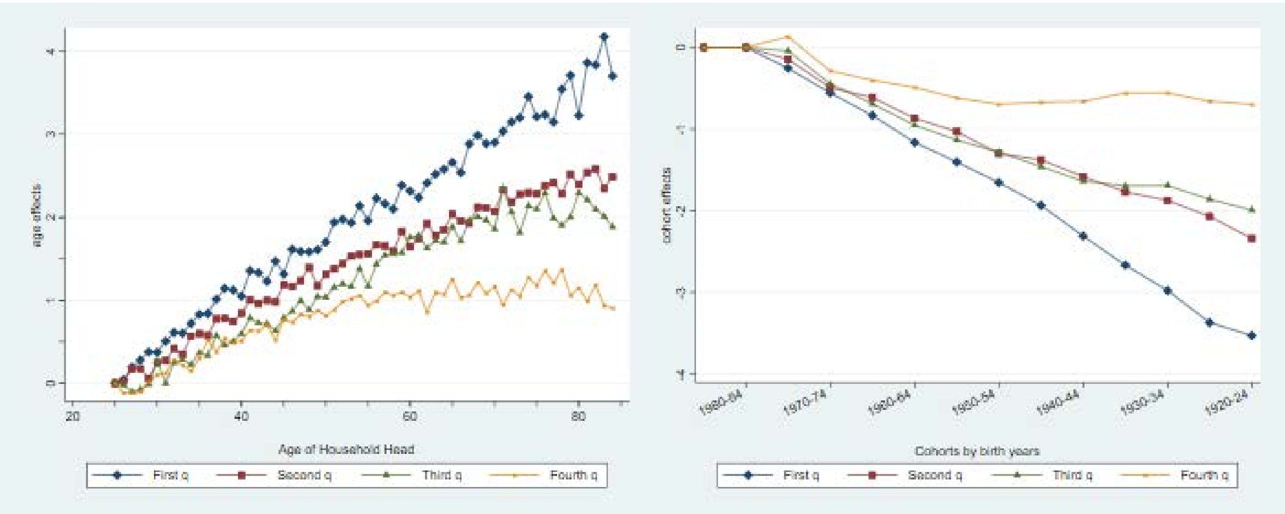
Figure 5: Age and cohort effects for electricity expenditure of Mexican households



Source: Authors' elaboration based on ENIGH

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 pseudopanel by income quartiles, not considering the rural/urban categorisation. Estimated age and cohort effects are plotted in Figure 6 that show that both effects have a similar shape as those shown in the previous figure: effects are increasing as the householder gets older and belongs to younger generations. [18]

Figure 6: Cohort and age effects by income quartile



Source: Authors' elaboration based on ENIGH

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 plays a role in the magnitude of the

[18] Estimated parameters are presented in the Appendix. ADD APPENDIX

estimeated effects which are polarized at the two extremes.[19] The rates of change per year of age and per cohort by quartiles are shown in Table 7. For the households belongin 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 Pazienza (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.

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

Concluding remarks

In this paper we follow the intuition that energy consumption patterns in developing countries could be different from the ones observed in developed ones and that generational aspects in countries with younger populations and in the middle of a demographic and economic transition could have an important role. With this purpose we study determinants of energy consumption putting an accent on age and generational effects in a developing country like Mexico. We find that, on the side from other socio-economic determinants, age effects are statistically significant starting from 30 years-old and they are monotonically increasing. Regarding the generational impact: 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 the previous two effects are in line with what was found by previous litterature for developed countries but the size of the effect is very different: the increase in electricity expenditures from young to older ages is 4 times higher in Mexico than in Italy (Bardazzi and Pazienza, 2017). This result could derive from the faster economic gowth observed in developing countries and, in the case of Mexico, to the recent completion of the electricity grid giving access to 100 per cent of the population.

Inequality is stronger in developing countries. Therefore, income growth affects differently rich from poor households. 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 by quartiles are much larger for the poorest households (belongin to the first quartiles of income) while the effects are similar to

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

the ones found for developed countries for the rich (last quartile of income). Indeed, for these rich households, results are closer to the estimated average rate of expenditure change found for developed countries, as seen for the Italian case in Bardazzi and Pazienza (2020) and similar to what was found in France by Chancel (2014).

Our finding supports 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 determinants have on such consumption. Given that developing countries are the ones that will drive energy demand growth in the following decades, understanding these differences and considering them to decide on investment and policies to meet such demand is crucial.

References

Adusah-Poku, F., & Takeuchi, K. (2019). Household energy expenditure in Ghana: A double-hurdle model approach. *World Development, 117, 266-277*.

Bardazzi, R., Bortolotti, L., and Pazienza, M. G. (2021). To eat and not to heat? Energy poverty and income inequality in Italian regions. *Energy Research & Social Science*, *73*, 101946.

Bardazzi R. and M.G. Pazienza, (2017), Switch off the light, please! Energy use, aging population and consumption habits, *Energy Economics* 65 (2017) 161–171.

Bardazzi, R., and M.G. Pazienza, (2018), Ageing and private transport fuel expenditure: Do generations matter? *Energy Policy*, *117*, 396-405.

Bernard, J. T., Bolduc, D., & Yameogo, N. D. (2011). A pseudo-panel data model of household electricity demand. *Resource and Energy Economics*, *33*(1), 315-325.

Besagni, G., Borgarello, M., 2018. The determinants of residential energy expenditure in Italy. *Energy 165, 369–386.*

Brounen, D., Kok, N. and Quigley, J.M. (2012) Residential Energy Use and Conservation: Economics and Demographics. *European Economic Review* 56: 931-945.

Escoto Castillo, A., and Sánchez Peña, L. (2017). Diffusion of Electricity Consumption Practices in Mexico. *Social Sciences*, *6*(4), 144.

Chancel, L. (2014), "Are younger generations higher carbon emitters than their elders? Inequalities, generations and CO2 emissions in France and in the USA", *Ecological Economics* 100 (2014) 195–207.

Contreras Lisperguer, R. (2020). Análisis de las tarifas del sector eléctrico: los efectos del COVID-19 y la integración energética en los casos de la Argentina, Chile, el Ecuador, México y el Uruguay. *Recursos Naturales y Desarrollo 199, CEPAL, United Nations*.

Coady D., V. Flamini and L. Sears (2015), "The unequal benefits of fuel subsidies revisited: evidence for developing countries", *IMF Working paper WP/15/250.*

Cragg, J. G. (1971), "Some statistical models for limited dependent variables with application to the demand for durable goods", *Econometrica,* 829-844.

Davis L., Fuchs A. and P. Gertler (2014), Cash for Coolers: Evaluating a Large-Scale Appliance Replacement Program in Mexico, *American Economic Journal: Economic Policy*, V. 6, N.4

Deaton, A. (1985), "Panel data from time series of cross-sections", *Journal of econometrics*, 30(1), 109-126.

Deaton, A. (1997), The analysis of household surveys: a microeconometric approach to development policy, *World Bank Books, Washington DC, USA.*

Deaton and Paxson (1994), "Intertemporal Choice and Inequality", *Journal of Political Economy*, Vol. 102, No. 3 (June), 437-467.

Easterlin, R. A. (Ed.). (2019). Population and economic change in developing countries. *University of Chicago Press.*

Eakins, J. (2016), “An application of the double-hurdle model to petrol and diesel household expenditures in Ireland”, *Transport Policy*, *47*, 84-93.

Grottera, C., Barbier, C., Sanches-Pereira, A., Abreu, M.W. de, Uchôa, C., Tudeschini, L.G., Cayla, J.-M., Nadaud, F., Pereira Jr, A.O., Cohen, C., Coelho, S.T., (2018), Linking electricity consumption of home appliances and standard of living: A comparison between Brazilian and French households. *Renewable and Sustainable Energy Review* 94, 877–888.

Humphreys, B. R. (2013). Dealing with zeros in economic data. *University of Alberta, Department of Economics*, *1*, 1-27.

Jones, R.V., Fuertes, A., Lomas, K.J., (2015). The socio-economic, dwelling and appliance related factors affecting electricity consumption in domestic buildings. *Renewable and Sustainable Energy Review*, 43, 901–917.

Mills, B., Schleich, J., (2012). Residential energy-efficient technology adoption, energy conservation, knowledge, and attitudes: an analysis of European countries. *Energy Policy* 49, 616–628.

OECD, (2013). Framework for statistics on the distribution of household income. *Consumption and Wealth. OECD, Paris*.

Olaniyan, K., McLellan, B., Ogata, S., Tezuka, T., (2018). Estimating Residential Electricity Consumption in Nigeria to Support Energy Transitions. *Sustainability* 10, 1440.

O'Sullivan A, Sheffrin SM (2003). Economics: Principles in Action. *Upper Saddle River, New Jersey 07458: Pearson Prentice Hall*. p. 471. ISBN 978-0-13-063085-8.

Permana, A.S., Aziz, N.Abd., Siong, H.C., (2015). Is mom energy efficient? A study of gender, household energy consumption and family decision making in Indonesia. *Energy Resources and Social Science* 6, 78–86.

Pujol JM. (1992), La poblacion de Mexico de 1950 a 2025. Indicadores demograficos para 75 anos [The population of Mexico from 1950 to 2025. Demographic indicators for 75 years]. *Demos*.;(5):4-5.

Pudney, S., (1990), “The estimation of Engel curves”, in Myles, G. D. (ed.), *Measurement and Modelling in Economics*, North-Holland, Amsterdam, 267–323.

Rodriguez-Oreggia E. and Yepez-Garcia R. A. (2014), Income and Energy Consumption in Mexican Households, *Policy Research Working Paper 6864*, The World Bank.

Sareen S., Thomson H., Tirado Herrero S., Gouveia J. P., Lippert I. and A. Lis, “European energy poverty metrics: Scales, prospects and limits,” *Global Transitions*, vol. 2, pp. 26–36

Stephenson, J., Barton, B., Carrington, G., Gnoth, D., Lawson, R., Thorsnes, P., (2010). Energy cultures: a framework for understanding energy behaviours. *Energy Policy* 38, 6120–6129.

SIELAC-OLADE (2021) retrived from https://sielac.olade.org/ on April 2021.

Taale, F., Kyeremeh, C., (2019). Drivers of households’ electricity expenditure in Ghana. *Energy Building*. 205, 109546. https://doi.org/10.1016/j.enbuild.2019.109546

Tornarolli, L., Ciaschi, M., & Galeano, L. (2018). Income distribution in latin america: The evolution in the last

20 years: A global approach (No. 234). *Documento de Trabajo*.

United Nations (2021), Population Division, retrieved from https://www.worldometers.info/world-population/population-by-country/ on April 2021.

Verbeek, M., (2008). Pseudo-panels and repeated cross-sections. In: Mátyás, L., Sevestre, P. (Eds.), The Econometrics of Panel Data. *Advanced Studies in Theoretical and Applied Econometrics* Vol. 46.

Verbeek, M., & Nijman, T. (1992). Can cohort data be treated as genuine panel data?, In *Panel data analysis* (pp. 9-23). Physica-Verlag HD.

World Energy Outlook (WEO) (2017), International Energy Agency (IEA), Paris, France.

World Bank (2019), Systematic country diagnostic, retrieved from http://documents1.worldbank.org/curated/es/588351544812277321/pdf/Mexico-Systematic-Country-Diagnostic.pdf Washington DC.

World Bank Database (2021) retrieved from https://databank.worldbank.org/home.aspx on April 2021.

Appendix

Table A1 – Estimated age, cohort and period effects by income quartile

	First quartile	Second quartile	Third quartile	Fourth quartile
Householder age 26 years-old	0.061	0.024	0.016	-0.104
	(0.146)	*(0.165)*	*(0.170)*	*(0.177)*
27 years-old	0.191	0.182	-0.102	-0.092
	(0.145)	*(0.164)*	*(0.170)*	*(0.176)*
28 years-old	0.262*	0.193	-0.041	0.007
	(0.147)	*(0.166)*	*(0.171)*	*(0.178)*
29 years-old	0.358**	0.069	0.065	0.075
	(0.147)	*(0.166)*	*(0.171)*	*(0.178)*
30 years_old	0.326**	0.266	0.358**	0.187
	(0.149)	*(0.169)*	*(0.174)*	*(0.181)*
31 years_old	0.472***	0.299*	0.123	0.229
	(0.149)	*(0.169)*	*(0.174)*	*(0.181)*
32 years_old	0.582***	0.439**	0.348*	0.383**
	(0.152)	*(0.172)*	*(0.178)*	*(0.185)*
33 years_old	0.546***	0.374**	0.401**	0.383**
	(0.152)	*(0.172)*	*(0.178)*	*(0.185)*
34 years_old	0.667***	0.570***	0.375**	0.292
	(0.153)	*(0.173)*	*(0.179)*	*(0.186)*
35 years_old	0.790***	0.610***	0.515***	0.469**
	(0.154)	*(0.174)*	*(0.180)*	*(0.187)*
36 years_old	0.790***	0.590***	0.477***	0.669***
	(0.155)	*(0.175)*	*(0.181)*	*(0.188)*
37 years_old	0.961***	0.805***	0.737***	0.520***
	(0.156)	*(0.177)*	*(0.182)*	*(0.189)*
38 years_old	1.117***	0.822***	0.631***	0.700***
	(0.157)	*(0.178)*	*(0.184)*	*(0.191)*
39 years_old	1.096***	0.782***	0.686***	0.652***
	(0.158)	*(0.179)*	*(0.184)*	*(0.192)*
40 years_old	1.000***	0.873***	0.758***	0.674***
	(0.160)	*(0.181)*	*(0.186)*	*(0.194)*
41 years_old	1.367***	1.046***	0.975***	0.790***
	(0.160)	*(0.181)*	*(0.187)*	*(0.195)*
42 years_old	1.336***	1.007***	0.883***	0.763***
	(0.163)	*(0.184)*	*(0.190)*	*(0.197)*
43 years_old	1.246***	1.052***	0.887***	0.860***
	(0.163)	*(0.185)*	*(0.191)*	*(0.198)*
44 years_old	1.473***	1.045***	0.811***	0.681***
	(0.164)	*(0.186)*	*(0.191)*	*(0.199)*
45 years_old	1.376***	1.257***	0.911***	0.947***
	(0.166)	*(0.187)*	*(0.193)*	*(0.201)*
46 years_old	1.666***	1.247***	0.960***	0.865***
	(0.166)	*(0.188)*	*(0.194)*	*(0.202)*
47 years_old	1.639***	1.321***	1.120***	0.991***
	(0.168)	*(0.190)*	*(0.196)*	*(0.204)*
48 years_old	1.676***	1.475***	1.013***	0.969***
	(0.169)	*(0.191)*	*(0.197)*	*(0.205)*
49 years_old	1.671***	1.269***	1.142***	1.027***
	(0.170)	*(0.192)*	*(0.198)*	*(0.206)*
50 years_old	1.806***	1.432***	1.098***	0.972***
	(0.171)	*(0.193)*	*(0.199)*	*(0.207)*
51 years_old	2.061***	1.520***	1.209***	1.062***
	(0.172)	*(0.194)*	*(0.200)*	*(0.208)*
52 years_old	2.121***	1.590***	1.220***	1.176***
	(0.173)	*(0.196)*	*(0.202)*	*(0.210)*
53 years_old	2.129***	1.668***	1.179***	1.222***
	(0.174)	*(0.197)*	*(0.203)*	*(0.211)*
54 years_old	2.296***	1.690***	1.365***	1.200***
	(0.175)	*(0.198)*	*(0.204)*	*(0.212)*
55 years_old	2.140***	1.714***	1.144***	1.104***
	(0.176)	*(0.199)*	*(0.206)*	*(0.214)*
56 years_old	2.441***	1.823***	1.374***	1.193***
	(0.177)	*(0.200)*	*(0.206)*	*(0.214)*
57 years_old	2.376***	1.834***	1.469***	1.268***
	(0.179)	*(0.202)*	*(0.208)*	*(0.217)*
58 years_old	2.312***	1.782***	1.495***	1.240***
	(0.179)	*(0.203)*	*(0.209)*	*(0.218)*

59 years_old	2.642***	2.006***	1.460***	1.254***
	(0.180)	*(0.204)*	*(0.210)*	*(0.218)*
60 years_old	2.597***	1.835***	1.643***	1.242***
	(0.181)	*(0.205)*	*(0.212)*	*(0.220)*
61 years_old	2.502***	1.927***	1.637***	1.336***
	(0.182)	*(0.206)*	*(0.212)*	*(0.221)*
62 years_old	2.690***	2.147***	1.456***	1.065***
	(0.184)	*(0.208)*	*(0.214)*	*(0.223)*
63 years_old	2.840***	2.005***	1.566***	1.261***
	(0.184)	*(0.209)*	*(0.215)*	*(0.224)*
64 years_old	2.884***	2.064***	1.512***	1.259***
	(0.185)	*(0.209)*	*(0.216)*	*(0.224)*
65 years_old	2.986***	2.276***	1.673***	1.442***
	(0.186)	*(0.211)*	*(0.217)*	*(0.226)*
66 years_old	2.850***	2.170***	1.502***	1.233***
	(0.187)	*(0.211)*	*(0.218)*	*(0.227)*
67 years_old	3.237***	2.177***	1.737***	1.289***
	(0.189)	*(0.213)*	*(0.220)*	*(0.229)*
68 years_old	3.357***	2.372***	1.742***	1.452***
	(0.189)	*(0.214)*	*(0.221)*	*(0.230)*
69 years_old	3.243***	2.374***	1.671***	1.332***
	(0.190)	*(0.215)*	*(0.221)*	*(0.230)*
70 years_old	3.301***	2.358***	1.600***	1.408***
	(0.191)	*(0.216)*	*(0.223)*	*(0.232)*
71 years_old	3.401***	2.602***	2.030***	1.130***
	(0.192)	*(0.217)*	*(0.224)*	*(0.233)*
72 years_old	3.534***	2.461***	1.765***	1.390***
	(0.193)	*(0.219)*	*(0.225)*	*(0.235)*
73 years_old	3.614***	2.557***	1.517***	1.261***
	(0.194)	*(0.220)*	*(0.226)*	*(0.236)*
74 years_old	3.856***	2.558***	1.790***	1.540***
	(0.195)	*(0.220)*	*(0.227)*	*(0.236)*
75 years_old	3.630***	2.558***	1.831***	1.417***
	(0.196)	*(0.222)*	*(0.229)*	*(0.238)*
76 years_old	3.684***	2.677***	1.957***	1.566***
	(0.196)	*(0.222)*	*(0.229)*	*(0.238)*
77 years_old	3.580***	2.706***	1.665***	1.475***
	(0.198)	*(0.224)*	*(0.231)*	*(0.240)*
78 years_old	4.016***	2.624***	1.544***	1.678***
	(0.199)	*(0.225)*	*(0.232)*	*(0.241)*
79 years_old	4.162***	2.859***	1.658***	1.308***
	(0.199)	*(0.225)*	*(0.232)*	*(0.242)*
80 years_old	3.680***	2.722***	1.922***	1.371***
	(0.201)	*(0.227)*	*(0.234)*	*(0.243)*
81 years_old	4.313***	2.899***	1.832***	1.318***
	(0.201)	*(0.228)*	*(0.235)*	*(0.244)*
82 years_old	4.300***	2.950***	1.733***	1.527***
	(0.203)	*(0.230)*	*(0.237)*	*(0.246)*
83 years_old	4.647***	2.711***	1.650***	1.200***
	(0.204)	*(0.230)*	*(0.237)*	*(0.250)*
84 years_old	4.114***	2.809***	1.539***	1.197***
	(0.205)	*(0.231)*	*(0.238)*	*(0.248)*
85 years_old	3.951***	3.014***	2.062***	1.599***
	(0.205)	*(0.232)*	*(0.239)*	*(0.249)*
Cohort 1980-84	-0.265**	-0.183	-0.037	0.064
	(0.104)	*(0.118)*	*(0.121)*	*(0.126)*
Cohort 1975-79	-0.591***	-0.552***	-0.408***	-0.409***
	(0.101)	*(0.114)*	*(0.118)*	*(0.122)*
Cohort 1970-74	-0.895***	-0.699***	-0.630***	-0.571***
	(0.107)	*(0.121)*	*(0.125)*	*(0.130)*
Cohort 1965-69	-1.252***	-0.975***	-0.854***	-0.681***
	(0.116)	*(0.132)*	*(0.136)*	*(0.141)*
Cohort 1960-64	-1.546***	-1.166***	-0.984***	-0.802***
	(0.124)	*(0.140)*	*(0.144)*	*(0.150)*
Cohort 1955-59	-1.851***	-1.479***	-1.111***	-0.927***
	(0.131)	*(0.148)*	*(0.153)*	*(0.159)*
Cohort 1950-54	-2.165***	-1.586***	-1.232***	-0.946***
	(0.138)	*(0.156)*	*(0.161)*	*(0.167)*
Cohort 1945-49	-2.586***	-1.824***	-1.385***	-0.999***
	(0.144)	*(0.163)*	*(0.168)*	*(0.175)*
Cohort 1940-44	-2.976***	-2.029***	-1.409***	-0.955***
	(0.151)	*(0.170)*	*(0.176)*	*(0.183)*

Cohort 1935-39	-3.299***	-2.166***	-1.422***	-1.023***
	(0.157)	*(0.177)*	*(0.183)*	*(0.190)*
Cohort 1930-34	-3.722***	-2.378***	-1.584***	-1.222***
	(0.162)	*(0.184)*	*(0.189)*	*(0.197)*
Cohort 1925-29	-3.871***	-2.666***	-1.748***	-1.261***
	(0.169)	*(0.191)*	*(0.197)*	*(0.205)*
Cohort 1920-24	-4.464***	-3.220***	-2.147***	-1.447***
	(0.175)	*(0.198)*	*(0.204)*	*(0.213)*
Year 2004	-0.060*	0.206***	0.201***	0.264***
	(0.036)	*(0.040)*	*(0.042)*	*(0.043)*
Year 2006	-0.331***	-0.247***	-0.103**	-0.150***
	(0.037)	*(0.042)*	*(0.043)*	*(0.045)*
Year 2008	0.437***	0.092**	-0.152***	-0.417***
	(0.037)	*(0.042)*	*(0.043)*	*(0.045)*
Year 2010	0.869***	0.484***	0.129***	-0.162***
	(0.037)	*(0.042)*	*(0.043)*	*(0.045)*
Year 2012	-0.260***	-0.085**	-0.055	0.090**
	(0.036)	*(0.040)*	*(0.042)*	*(0.043)*
Year 2014	-0.199***	-0.094**	0.038	0.165***
	(0.034)	*(0.038)*	*(0.039)*	*(0.041)*
Year 2016	-0.215***	-0.136***	-0.000	0.088**
	(0.031)	*(0.035)*	*(0.036)*	*(0.038)*
Constant	2.787***	3.245***	3.565***	3.882***
	(0.115)	*(0.130)*	*(0.134)*	*(0.140)*
R^2	0.79	0.58	0.42	0.44
N	549	549	549	548

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