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DETERMINANTS OF POVERTY IN MEXICO: A QUANTILE REGRESSION ANALYSIS

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Determinants of poverty in Mexico:
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Abstract:

This article examines the determinants of poverty for Mexican households. It uses data from the Mexican National Household Income and Expenditure Survey (ENIGH) 2018 conducted by the Mexican National Institute of Statistics and Geography (INEGI). This study estimates two econometric models. First, a probit model was held to estimate the probability that a Mexican household finds itself in poverty given their socio-economic and demographic characteristics. Results from the probit model indicate that households with more than one member, having a female head, or speaker of a native ethnic group dialect are more likely to be poor. The variables negatively correlated with the probability of being poor were found to be: the age of the household head, if he or she is divorced, his or her educational level greater than unfinished primary school, if he or she does not work in basic support activities and that his or her occupational sector is not the primary one, also if the household is located in Central-North or North regions. Second, the quantile regression approach was used to examine the extent to which the determinants of poverty vary across the poverty spectrum. The sample is divided into five groups: *extremely poor*, *deeply poor*, *at the poverty line*, *near poverty* and *marginally poor*. With this model, it was found that most of the coefficients estimated by the OLS method do not explain the *extremely poor* household's situation in Mexico. The households in the categories *extremely poor* and *deeply poor* are most affected if they are located in the southern region, if the household head speaks a native ethnic group dialect or is an elderly age person. It is observed that achieving a higher educational level is an effective way to increase income across the poverty spectrum. This is the first study of its kind for Mexico, accomplishing a broader picture of the determinants of poverty.

I. Introduction

This article is aimed at analyzing the determinants of poverty in the different income quantiles of the Mexican population. The Mexican National Household Income and Expenditure Survey (ENIGH) 2018 database was used. Poverty is associated to life conditions that damage people's dignity, limit their fundamental rights and liberty, inhibit the satisfaction of basic needs and preclude their full social integration (CONEVAL, 2018b). According to World Bank (2018), 735.9 million people in the world live in an extreme poverty situation, of which 25.9 million live in Latin America and the Caribbean.

In accordance with CONEVAL (National Council for the Evaluation of Social Development Policies) (2018a), income has been used as an approximation of people's economic welfare for the development of poverty measurement in Mexico. From this perspective, a poverty line is usually defined that represents the minimum income necessary for acquiring a basket of goods and services to satisfy basic needs. In of the last ten years (2008 - 2018) the percentage of the population with income below the poverty line remained almost at the same level, from 49% in 2008 to 48.8% in 2018. However, in this same period, population with income below poverty line increased from 54.7 million to 61.1 million people (CONEVAL, 2019a). Even though the proportion of population in poverty decreased, the quantity of people with income below the poverty line increased.

Total current income *per capita* (ICTPC, for its initials in Spanish) of Mexican households was used to measure welfare and compare it to the poverty lines established by CONEVAL due to two principal reasons: the presence of capital market imperfections and the low saving levels of the population. Székely (1995) argues that the presence of these two elements restricts the possibilities for smoothing future consumption, specially for the poor (Garza-Rodriguez, 2000). For this research, the two poverty lines set by CONEVAL (2019b) were considered: a rural poverty line of $1,941.91 Mexican pesos monthly *per capita* and a urban poverty line of $3,001.17 Mexican pesos monthly *per capita*.

According to Heshmati, A., Maasoumi, E. and Wan, G. (2019), making judgments about poverty incidence across time and space, or categorize the poor in sub-groups according to their severity, needs a number of substantial methodology decisions. The present paper not only takes into consideration households with an income below the poverty line, but also households with income above, although close, to it. An income-to-poverty ratio was calculated for including households with income of up to 1.5 times the poverty line. The poverty phenomenon is thus recognized as more than a simple dichotomy of *poor* and *non-poor households*, being replaced by a more complete classification that is discussed in the results section.

The purpose of including a quantile regression approach in the analysis is to avoid the generalization of the determinants of poverty without considering the differences that exist between quantiles. By doing so, it will be possible to identify the variables that vary the most among quantiles. The determinants of poverty found in this research could be taken into consideration for future experimental economic studies aimed to alleviate poverty with a direct application to the Mexican case, such as those realized by the Economic Nobel Prize 2019 winners: Michael Kremer, Abhijit Banerjee and Esther Duflo.

El artículo está organizado de la siguiente manera. La sección II incluye una revisión de literatura, donde se da un panorama pertinente de la literatura sobre la pobreza y el análisis empleando distintos métodos. La sección III describe la base de datos empleada en este artículo y en la sección IV se describen los modelos econométricos empleados. Los resultados del análisis son presentados en la sección V y la sección VI concluye.

II. Literature Review

Research on the determinants of poverty has developed under three different categories: macro or structural level, micro or individual level, and contextual level (Peng et al., 2019). The structural level consists on the analysis of economic, political and social systems deficiencies, while the micro level holds that poverty can be explained by individual characteristics and behavior. The contextual level highlights the importance of neighborhoods, household groups, etc.

The methodology used in existing empirical studies is diverse. Over the past decades, different economic variables have been used as dependent variables to explain the determinants of poverty, such as income (Cortés, 1997; Garza-Rodriguez, 2002; Peng et al., 2019; Serratos, 2015; Székely, 1998), consumption (De Silva, 2008; Heshmati et al., 2019; Kedir & Sookram, 2013), and poverty status as a dichotomous variable (Cortés, 1997; De Silva, 2008; Garza-Rodriguez, 2002; Kedir & Sookram, 2013; Peng et al., 2019; Serratos, 2015; Székely, 1998). According to Sen (1982), the direct method for identifying the poor consists on taking the consumption baskets of basic needs as the dependent variable. Among the advantages of using this household consumption approach lies the tendency of households to underestimate their income and that, specially in regions with an important informal sector, consumption is the best measure for lifetime income (Kedir & Sookram, 2013). In contrast, the main advantage of the income approach, as Sen (1982) argues, is that it provides a metric of numerical distances from the poverty line in terms of income short-falls. The use of consumption as dependent variable cannot elucidate such information, because it only points out the short-fall for each type of need. Specifically for the Mexican case, as explained by Székely (1995), the presence of capital market imperfections and the low levels of savings in the country, restrict the possibilities of smoothing future consumption, specially for the poor (Garza-Rodriguez, 2000).

On the other hand, the necessity of separating the effects of each determinant or correlate is problematic for the study of poverty. A poverty status method might be used to split these effects through the use of a binary model, applying the *poor* (1) or *not poor* (0) dichotomy as the dependent variable. The binary regression method (Cortés, 1997; De Silva, 2008; Garza-Rodriguez, 2002; Kedir

& Sookram, 2013; Peng et al., 2019; Serratos, 2015; Székely, 1998) is used to analyze which factors define the probability of being poor. These types of models have the advantage to suppress the effect of atypical values in the distribution of the dependent variable (Kedir & Sookram, 2013).

Several research papers about the determinants of poverty use the multidimensional poverty approach: Dewilde (2008), Montoya and Teixiera (2017) and Chen, Leu and Wang (2019). This method takes poverty as a phenomenon that can take different shapes and severity levels in one or more scopes of the individual's' life through certain periods of time (Dewilde, 2008). Likewise, as Montoya and Teixiera (2017) show, the use of multidimensional measures of deprivation has increased recently, which has made important contributions to strengthen social programs to eradicate poverty. However, Ravallion (2011) criticizes the use of the multidimensional approach, specifically the Multidimensional Poverty Index, developed by Alkire and Foster (2010). According to this author, to compare compensations between deprivations is more complex and not so intuitive as comparing the compensations that arise from the consumption aggregates under the poverty-line approach.

The quantile regression model is another approach used to understand the determinants of poverty. This model allows the analysis of the effect of poverty determinants in the different quantiles in the distribution of the dependent variable, thus showing the full picture of the relationships between variables (Habyarimana, Zewotir, & Ramroop, 2015). Additionally, this method avoids the use of constant parameters in the whole distribution (De Silva, 2008) and can determine the existence of asymmetric effects in household's well-being (Kedir & Sookram, 2013). The differential effects of the determinants of poverty across its spectrum can then be compared (Peng et al., 2019).

For Sri Lanka, De Silva (2008) uses *per capita* consumption as dependent variable in a quantile regression. Household head sex, education, age, and employment status are among the key factors that explain poverty. Similarly, Kedir and Sookram (2013) use the same model for Trinidad and Tobago, finding that the poverty level is even greater than past measurements. The authors discovered a more significant relationship between poverty and household overcrowding for the lowest quantiles.

Research for Rwanda (Habyarimana et al., 2015) and Hong Kong (Peng et al., 2019) also analyze poverty through the quantile regression model. For the case of Rwanda, the authors focused in three different quantiles: the lower 40% for the poor population, the next 40% for the middle class and the last 20% for the non-poor. On the other hand, a ratio of income to poverty line (I/P ratio) was applied for the Hong Kong analysis. This ratio allows the analysis of the parameters of the independent variables according to the severity of poverty. Rwanda's research most relevant findings includes that key elements to reduce poverty are education and urbanization (Habyarimana et al., 2015). For Hong Kong, the main determinants of poverty are age, marital status and the educational level of the household head.

For the analysis of poverty determinants in India (Heshmati et al., 2019) household monthly *per capita* consumption was held as the dependent variable, and household head's age, marital status, occupation, and education, among other sociodemographic variables, as possible determinants of poverty. One of the findings was the household head age's inverse U-shape effect to consumption levels. These effects become stronger as poverty severity decreases, from the lowest quantiles to the highest quantiles.

For the case of Mexico, Lustig (1992), Székely (1995) and CONEVAL (2014), among others, have focused their efforts in the measurement of poverty. Lustig (1992) measured the incidence of poverty based on the ENIGH of 1984. Székely (1995) analyzed the changes in poverty levels after the stabilization of the Mexican economy in the 80's, concluding that poverty increased 35% because of the losses of the poorest 8%, which also increased economic inequality. Even though that in a first glance it could be thought that economic stabilization in the mid 80's decreased poverty levels in Mexico, Székely (1995) discovered that this was not true: poverty increased among the poorest, in other words, in the lower quantiles.

For research on the determinants of poverty in Mexico, four main papers stand out. Cortés (1997) uses the ENIGH 1992 data and applies a logit model, finding a direct relationship between poverty and household location in rural areas. Moreover, the author identifies an inverse relation between education and poverty. Based on the ENIGH database for 1984, 1989 and 1992, Székely (1998) concludes that lack of education is the most significant factor explaining poverty in Mexico. Household size, rural location, and household head's employment quality are variables that hold a positive relation with poverty. Garza-Rodriguez (2002) estimated a logit model with the probability of being extremely poor as dependent variable, and a set of demographic factors as explanatory variables. The author finds that overcrowding, location, and rural employment have a positive relation with poverty, while education of household head and age have a negative relation.

Serratos (2015) uses a logistic regression model to find the determinants of poverty in Mexican households and their evolution between the years 1996 and 2012. This author segments different intensities of poverty using three lines: alimentary, capacities and patrimonial. He finds that education, working in industrial or services occupations, living in an urban zone and the age of the household head are variables that decrease the probability for the house to be catalogued as poor. Considering the evolution of the determinants of poverty' through time, the results of the logit model applied show that the effect of household head's age and urban location as determinants of poverty do not change comparing the time periods analyzed. However, the positive effect of the sector of occupation of the household head (secondary or tertiary) had an increase in its magnitude through time, while the negative effect of household size decreased.

Likewise, the evolution of poverty through time has been studied recently, distinguishing between chronic poverty and transient poverty, and their respective determinants (Fernández-Ramos, Garcia-Guerra, Garza-Rodriguez, & Morales-Ramirez, 2016). The authors utilized a logistic multinomial regression model applied to the "Encuesta Nacional sobre Niveles de Vida de los Hogares" (ENNVIH) database to compare and contrast both phenomena, observing that 64% of poor households suffer from transient poverty, while the remaining 36% live in chronic poverty. The variables with a positive relation with chronic poverty are: belonging to a native ethnicity group, living in a rural area, household size, having elders and young children in the household, and if the household head is female. On the other hand, the variables related negatively with poverty are household head's education, assets, age and access to basic services (such as electricity and water).

The importance of applying the quantile regression model in the study of poverty in Mexico lies in the fact that this type of research enriches household poverty knowledge. To the best of the authors' knowledge, this is the first study that applies the quantile regression approach for the analysis of poverty in Mexico.

III. Data

The data used in this study was obtained from the Mexican National Household Income and Expenditure Survey (ENIGH) 2018. The objective of this survey is to provide a statistical overview of the behavior of the households' income and expenditures in terms of amount, origin and distribution (INEGI, 2019). In addition, the information obtained presents households' occupational and sociodemographic characteristics, infrastructure, family composition and the economic activity of the members. The survey is conducted by the Mexican National Institute of Statistics and Geography (INEGI) since 1984, with a periodicity of two years since 2006. .The sample is representative at the state and national levels and consists of 87,826 households.

For the probit model the dependent variable is dichotomous, being *poor* or *non-poor* the result when evaluating each of the households. In contrast, for the quantile regression model, the dependent variable used will be the total current income *per capita* of each household. The poverty line used in the study is the one defined by CONEVAL, one for each type of locality: rural or urban.

The independent variables that will be used during the development of this research are found in *Table 1*, each of them with its respective statistical summary which includes its mean and standard deviation. Within the content of the table are variables related to the household's head, such as sex and if he/she belongs a native ethnic group (dichotomous variables), the level of education, marital status, employment's position and sector, the region of location of the household and the total

Table 1: Summary statistics of key variables

Variables	Mean	Standard Deviation
Sex of the household head (base category: male)	0.274	0.446
Age of the household head	49.796	16.033
Age squared of the household head	2736.692	1713.292
Marital status of the household head (base category: married)		
Consensual union	0.196	0.397
Separated	0.088	0.283
Divorced	0.034	0.182
Widowed	0.112	0.315
Single	0.075	0.263
Educational level of the household head (base category: unfinished primary school)		
Finished primary school	0.170	0.375
At least one year of secondary school	0.275	0.447
At least one year of high school	0.134	0.341
At least one year of teacher training college or technical career	0.040	0.197
At least one year of university or more	0.135	0.342
Location region of the household (base category: Central)		
Central-North	0.304	0.460
North	0.232	0.422
South	0.217	0.412
Speaks a native ethnic group dialect (base category: non speaker of a native ethnic group dialect)	0.083	0.276
Household size (base category: 1)		
2	0.189	0.392
3	0.196	0.397
4	0.221	0.415
5	0.146	0.353
6 or more	0.131	0.337
Occupational position of the household head (base category: basic support activities)		
Bureocrats, directors, heads	0.039	0.194
Professionists and technicians	0.120	0.325
Support employees in administrative activities	0.036	0.185
Salesman	0.097	0.296
Employees in personal services and surveillance	0.078	0.269
Agriculture, livestock, forestry, fishing and hunting	0.142	0.349
Craftsmen	0.121	0.326
Industrial machinery operators, assemblers and drivers	0.115	0.319
Occupational sector of the household head (base category: primary sector)		
Secondary sector	0.277	0.447
Tertiary sector	0.499	0.500

number of household members (categorical variables), and age and age squared (continuous variables).

IV. Methodology

A probit model was estimated to identify the variables that have a significant effect in the probability of being poor. Moreover, a quantile regression model was used to visualize and understand how the determinant effects vary across the poverty spectrum.

The probit model (Gujarati & Porter, 2009) is used to analyze the behavior of a dichotomous dependent variable by the regression with binary results, which estimates the probability that the variable takes one of the two possible values.

Thus, $P(y = 1|x) = E(y|x)$, the probability that the value of the dependent variable is 1 is given by the vector of independent variables. Furthermore, the mathematical expression of the probit $P(y = 1|x) = \beta_0 + \beta_i x_i$ shows that it consists on a constant β_0 and a parameter for each explanatory variable x_i.

To apply the model in this study, a value of 1 was assigned to household total current income per capita below the rural or urban poverty line calculated by CONEVAL (depending on the household location), and a value of 0 in the contrary. Therefore, having the dependent dichotomous variable: *poor households* (1) and *non-poor households* (0).

The explanatory variables chosen for the probit model were household head's sex, age and age squared, marital status, educational level, occupational position, occupational sector, speaking a native ethnic dialect, region and household size.

The quantile regression model (Koenker & Bassett, 1978) was used to examine the correlates of income at different points of its distribution. While a regression by the Ordinary Least Squares method (OLS) estimates how independent variables are related to the average value of the dependent variable, quantile regression allows the study of the impact of predictive variables on different quantiles of the response distribution, in this case income (Habyarimana et al., 2015). This enables us to find a better explanation of the relationship between the dependent variable and the independent variables of the model. Frequently, household poverty studies focus on the mean parameters of the regressions and do not examine the asymmetric effects of dependent variables on household income (Kedir & Sookram, 2013). To address this problem in the case of Mexico, the quantile regression model was used.

With the purpose of explaining the quantile regression model methodology, it will be contrasted with the OLS regression, which was also estimated for comparing results (Leeds, 2014). The OLS regression model can be expressed with the following:

$$y_i = \beta_0 + \beta_i x_i + \varepsilon_i$$

For $i = 1, \ldots, n$

In this model, the method for obtaining parameters is by using the minimization of squared errors:

$$min \sum_i (y_i - (\beta_0 + \beta_i x_i))^2$$

The quantile regression model can be expressed as follows:

$$y_i = \beta_0^{(\tau)} + \beta_i^{(\tau)} x_i + \varepsilon_i^{(\tau)}$$

Where τ represents the quantile and $0 < \tau < 1$, for $i = 1, \ldots, n$.

The quantile regression model estimates the coefficients by minimizing the weighted sum of absolute residuals of the estimation, which can be expressed as follows:

$$min \sum_{i=1}^{n} d_\tau(y_i, \hat{y}_i) = \tau \sum_{y_i \geq \beta_0^{(\tau)} + \beta_i^{(\tau)} x_i} |y_i - \beta_0^{(\tau)} - \beta_i^{(\tau)} x_i \,| + (1 - \tau) \sum_{y_i < \beta_0^{(\tau)} + \beta_i^{(\tau)} x_i} |y_i - \beta_0^{(\tau)} - \beta_i^{(\tau)} x_i|$$

Hao and Naiman (2007) establish that quantile regression is a natural extension of the linear regression model and is particularly useful when the research's interest resides in the full understanding of how the response distribution is affected by the predictor variables.

The dependent variable to be used in the quantile regression model is the natural logarithm of the ICTPC, while the explanatory variables are sex, age, age squared, marital status and educational level of the head of the household, if he/she speaks a native ethnic group dialect, his or her occupational sector and position. The household size and its location region were also included.

V. Analysis of Results

A probit model was estimated to identify the variables that have an effect on the probability of a household being poor. The results are shown in *Table 2*. It must be pointed out that all the variables are statistically significant at 99%, which indicates that the selected variables are important determinants of poverty in Mexico. Given that the dependent variable of the probit model denotes if a household is poor or not, the positive (+) coefficients increase the probability that the household is poor, and the negative (-) coefficients decrease it.

The results indicate that the household is more likely to be poor if the household head's sex is female. Barros et al. (1997) mention that male-headed households tend to have better lower poverty rates than those with a female household head. If the head of the household has any marital status different from being divorced, the likelihood of the household being in poverty is greater. If the household is located in the Southern region of the country, there is a greater probability that the household will be poor, compared to living in the Central region. In the case that the head of the household speaks a native ethnic dialect the probability of the household being poor also increases. When studying ethnicity through this model, Kedir and Sookram (2013) found the same result, indicating that it could be caused by past failed public policies. Likewise, the results indicate that if the size of the household is different from one, there is a greater probability that the household will be poor. The above is consistent with the findings made by Grootaert and Narayan (2001), Lanjouw and Ravallion (1995), Lipton and Ravallion (1995) and Garza-Rodriguez (2002), who find that a larger household size is positively related to the probability of being poor.

Variables that decrease the probability of household poverty are: if the household head is divorced, holds any educational level higher than unfinished primary school, if the location region is either Central-North or North, if the head is employed in any position of occupation except basic support activities, and if the occupation is in the secondary or tertiary sector. The household head's age is negatively related to the probability of being poor, reflecting the effect of experience on the income of the household head. The negative coefficient for the age squared of the household head is coherent with the life-cycle theory, which asserts that income through time has the shape of a downward parabola due to human resource capital depreciation of the worker, who takes longer to finish tasks as age increases (Hoffmann & Kassouf, 2005).

Based on the methodology used by Peng et al. (2019), five quantile regression models were estimated, one for each quantile determined according to the income-to-poverty line ratio (I/ P). On *Table 3* the classification of each of the I/P ratios is shown, as well as the percentage they represent in the total sample.

The results of the quantile regressions and OLS are presented in *Table 4*. The signs of the estimated parameters are as theoretically expected and in general are in line with those found by other authors in the relevan literature, in addition to the fact that, in the great majority, they agree with the results of the probit model shown before. The OLS's parameters are presented in the last column, with the aim of taking it as a basis to compare with the results of the quantile regression. *Figure 1* shows graphically the results of the estimated quantile regressions for each of the variables. The dotted black line indicates the value of the coefficients for each of the quantile regressions and the gray shaded area indicates the 95% confidence interval. The vertical lines indicate the I/P ratios that were applied to determine the quantiles of this study. The red solid horizontal line shows the regression coefficient value by the OLS method, with two horizontal dotted lines in the same color, which indicate the confidence interval of the regression at 95%. As De Silva (2008) suggests, there are significant

Table 2: Results of the probit model

Explanatory variables	
Sex of the household head (base category: male)	0.065 (0.001)***
Age of the household head	-0.037 (0.000)***
Age squared of the household head	0.0003 (0.000)***
Marital status of the household head (base category: married)	
Consensual union	0.137 (0.001)***
Separated	0.072 (0.001)***
Divorced	-0.021 (0.002)***
Widowed	0.023 (0.001)***
Single	0.020 (0.001)***
Educational level of the household head (base category: unfinished primary school)	
Finished primary school	-0.173 (0.001)***
At least one year of secondary school	-0.279 (0.001)***
At least one year of high school	-0.504 (0.001)***
At least one year of teacher training college or technical career	-0.612 (0.002)***
At least one year of university or more	-1.095 (0.001)***
Location region of the household (base category: Central)	
Central-North	-0.301 (0.001)***
North	-0.412 (0.001)***
South	0.214 (0.001)***
Speaks a native ethnic group dialect (base category: non speaker of a native ethnic group dialect)	0.266 (0.001)***
Household size (base category: 1)	
2	0.365 (0.001)***
3	0.604 (0.001)***
4	0.853 (0.001)***
5	1.112 (0.001)***
6 or more	1.162 (0.001)***
Occupational position of the household head (base category: basic support activities)	
Bureocrats, directors, heads	-0.964 (0.002)***
Professionists and technicians	-0.529 (0.001)***
Support employees in administrative activities	-0.450 (0.002)***
Salesman	-0.195 (0.001)***
Employees in personal services and surveillance	-0.429 (0.001)***
Agriculture, livestock, forestry, fishing and hunting	-0.107 (0.001)***
Craftsmen	-0.146 (0.001)***
Industrial machinery operators, assemblers and drivers	-0.367 (0.001)***
Occupational sector of the household head (base category: primary sector)	
Secondary sector	-0.238 (0.001)***
Tertiary sector	-0.177 (0.001)***
Constant	0.844 (0.003)***
Wald $\chi 2$	5911524.330
Pseudo R2	0.1989
Log likelihood	-14901237
Observations	27253381

Robust standard errors are reported in parentheses.
*Significant at 10%; **significant at 5%; ***significant at 1%

differences between the results of the models if those parameters estimated by the quantile regression are outside the confidence intervals of the OLS regression.

If the sex of the head of the household is female, a negative effect on poverty is observed in the studied quantiles, with the deepest effect on the quantile of *marginally poor* households. This is consistent with the corresponding result of the probit model. The World Bank (2019) presented a study with indicators measuring how laws affect women in their working lives, where Mexico has a 86.25 base 100 rating of labor equality. Among its lowest indicators are the laws regarding the salary of women, the possibility of getting married, receiving a pension and having children. This gender inequality in the laws may be in part cause for the negative coefficients in the quantile regression and OLS. The coefficient obtained from the OLS regression shows a consistent sign with the coefficients of the quantile regression, however, it is noteworthy that, in households in *extreme poverty* the effect of the presence of a female head of household is significantly different and less profound than in the OLS method.

Table 3: Income-to-poverty line ratio classification (I/P ratio)

Classification	I/P ratio	Sample percentage
Extremely poor	0.50 or lower	11.21%
Deeply poor	0.75 or lower	25.62%
At the poverty line	1.00 or lower	40.11%
Near poverty	1.25 or lower	52.32%
Marginally poor	1.50 or lower	61.06%

Age has a positive and significant association with the standard of living of households in all studied quantiles. The sign of this result is as expected and agrees with what was found by Kedir and Henry (2010), who argue that high youth unemployment rates could be one of the causes of a greater likelihood of a household being poor when it is led by young adults. On the other hand, the negative sign of the coefficients of the age squared variable reflects that, at a certain age, the ICTPC begins to decrease. This result is consistent with that obtained in the probit model. Making a descriptive analysis by deciles of the database, the average ICTPC of households increases as the age of the head of the household increases until he reaches sixty years old, where it begins to decrease. The results obtained for the marital status of the heads of the household suggest that the households where the head lives with his partner, is separated or is a widower, perceive a lower ICTPC in all quantiles, compared to the married ones. In the OLS regression, the status of single or widowed head of household does not have a statistically significant effect on poverty. Instead, being separated and living with his or her partner or in free union have significant differences between the OLS method and quantile regressions. For households in *extreme poverty* the effect of being separated is underestimated by the OLS. On the other hand, for the heads of household living with their partner or in free union in *deeply poor* status, the OLS method overestimates the effect of this conjugal state. The positive values of the coefficients of being single (except in households in *extreme poverty*) or divorced, could be attributed to supporting fewer people or receiving legal benefits of separation, respectively (Kedir & Sookram, 2013).

The only sign that contrasts with the probit model is the single marital status. The binary model indicates that being single increases the probability that the household is poor. Cheung (2015) suggests that this is due to factors related to participation in the labor market. Single household heads have difficulty balancing their time between being resource providers and leading the family . In contrast to the above, in the quantile regression it can be seen that households that are not in *extreme poverty* benefit from the single status of the head of the household.

As it was expected, any educational level higher than holding unfinished primary school increases the ICTPC of households. That is, a greater education of the head of the household significantly improves the welfare of Mexican households throughout the entire spectrum of poverty. In line with the results of the probit model, all levels of education decrease the likelihood of the household being poor. *Figure 1* shows an overestimation of the results of the OLS of household heads in the poverty line who have at least one year of secondary school. The same result is shown for households in *deeply poor* status, along the line of poverty and close to poverty in which the heads have at least one year of high school. This means that their condition harms them more than the method shows. The same is true for those who got to study at least one year of teacher training college or technical school and whose income is below the corresponding income line, where the results of the OLS again show a more favorable condition in terms of the ICTPC than the quantile regression results. When the household head reached at least one year of college or more, the OLS regression only explains *marginally poor* households. For households in *extreme poverty* and *deeply poor* status, having a

Table 4: Results of the quantile regression

Explanatory variables	Extremely poor I/P ratio = 0.5	Deeply poor I/P ratio = 0.75	At the poverty line I/P ratio = 1	Near poverty I/P ratio = 1.25	Marginally poor I/P ratio = 1.5	OLS
Sex of the household head (base category: male)	-0.0113 (0.000)***	-0.0282 (0.000)***	-0.0193 (0.000)***	-0.0297 (0.000)***	-0.0519 (0.000)***	-0.0404 (0.013)***
Age of the household head	0.0232 (0.000)***	0.0249 (0.000)***	0.0222 (0.000)***	0.0224 (0.000)***	0.0232 (0.000)***	0.0219 (0.002)***
Age squared of the household head	-0.0002 (0.000)***	-0.0002 (0.000)***	-0.0002 (0.000)***	-0.0002 (0.000)***	-0.0002 (0.000)***	-0.0002 (0.000)***
Marital status of the household head (base category: married)						
Consensual union	-0.0644 (0.000)***	-0.0453 (0.000)***	-0.0513 (0.000)***	-0.0502 (0.000)***	-0.0470 (0.000)***	-0.0654 (0.010)***
Separated	-0.0786 (0.000)***	-0.0370 (0.001)***	-0.0405 (0.000)***	-0.0406 (0.000)***	-0.0257 (0.001)***	-0.0386 (0.017)**
Divorced	0.0351 (0.000)***	0.0689 (0.000)***	0.0806 (0.001)***	0.0891 (0.000)***	0.0686 (0.001)***	0.0589 (0.026)**
Widowed	-0.0409 (0.000)***	-0.0428 (0.000)***	-0.0278 (0.000)***	-0.0163 (0.000)***	-0.0069 (0.001)***	-0.0260 (0.020)
Single	-0.0229 (0.001)***	0.0094 (0.001)***	0.0118 (0.000)***	0.0062 (0.000)***	0.0246 (0.001)***	0.0180 (0.020)
Educational level of the household head (base category: unfinished primary school)						
Finished primary school	0.1458 (0.000)***	0.1394 (0.001)***	0.1314 (0.000)***	0.1267 (0.000)***	0.1290 (0.000)***	0.1392 (0.012)***
At least one year of secondary school	0.2224 (0.000)***	0.2183 (0.000)***	0.2080 (0.000)***	0.2171 (0.000)***	0.2282 (0.000)***	0.2340 (0.012)***
At least one year of high school	0.3733 (0.000)***	0.3551 (0.001)***	0.3577 (0.001)***	0.3582 (0.000)***	0.3695 (0.000)***	0.3968 (0.015)***
At least one year of teacher training college or technical career	0.4045 (0.001)***	0.4084 (0.001)***	0.4146 (0.001)***	0.4533 (0.001)***	0.4807 (0.001)***	0.4657 (0.023)***
At least one year of university or more	0.7419 (0.001)***	0.7504 (0.001)***	0.7767 (0.000)***	0.7973 (0.001)***	0.8313 (0.001)***	0.8575 (0.018)***
Location region of the household (base category: Central)						
Central-North	0.0842 (0.000)***	0.1186 (0.000)***	0.1346 (0.000)***	0.1395 (0.000)***	0.1590 (0.000)***	0.1281 (0.010)***
North	0.1726 (0.000)***	0.2108 (0.000)***	0.2319 (0.000)***	0.2363 (0.000)***	0.2523 (0.000)***	0.2137 (0.010)***
South	-0.2980 (0.000)***	-0.2481 (0.000)***	-0.2071 (0.000)***	-0.1900 (0.000)***	-0.1642 (0.000)***	-0.2056 (0.011)***
Speaks a native ethnic group dialect (base category: non speaker of a native ethnic group dialect)	-0.2913 (0.001)***	-0.2644 (0.000)***	-0.2195 (0.001)***	-0.2144 (0.000)***	-0.1881 (0.001)***	-0.2310 (0.015)***

Household size (base category: 1)						
2	-0.2499 (0.001)***	-0.2927 (0.000)***	-0.3076 (0.001)***	-0.3153 (0.001)***	-0.3068 (0.001)***	-0.2974 (0.019)***
3	-0.3890 (0.001)***	-0.4725 (0.001)***	-0.4859 (0.001)***	-0.5062 (0.001)***	-0.5070 (0.001)***	-0.4849 (0.019)***
4	-0.5392 (0.001)***	-0.6113 (0.001)***	-0.6444 (0.001)***	-0.6526 (0.001)***	-0.6495 (0.001)***	-0.6230 (0.019)***
5	-0.6383 (0.001)***	-0.7392 (0.001)***	-0.7675 (0.001)***	-0.7931 (0.001)***	-0.7821 (0.001)***	-0.7504 (0.020)***
6 or more	-0.6643 (0.001)***	-0.7560 (0.001)***	-0.7865 (0.001)***	-0.8173 (0.001)***	-0.8208 (0.001)***	-0.7820 (0.020)***
Occupational position of the household head (base category: basic support activities)						
Bureocrats, directors, heads	0.6144 (0.000)***	0.6474 (0.000)***	0.6464 (0.001)***	0.6514 (0.001)***	0.6738 (0.001)***	0.7111 (0.027)***
Professionists and technicians	0.3427 (0.000)***	0.3448 (0.001)***	0.3544 (0.001)***	0.3537 (0.000)***	0.3467 (0.001)***	0.3493 (0.016)***
Support employees in administrative activities	0.3391 (0.001)***	0.2724 (0.000)***	0.2604 (0.001)***	0.2490 (0.000)***	0.2363 (0.000)***	0.2601 (0.020)***
Salesman	0.0673 (0.001)***	0.0894 (0.000)***	0.1129 (0.000)***	0.1181 (0.000)***	0.1392 (0.000)***	0.1264 (0.016)***
Employees in personal services and surveillance	0.2383 (0.000)***	0.2463 (0.001)***	0.2437 (0.000)***	0.2223 (0.000)***	0.2042 (0.001)***	0.2304 (0.015)***
Agriculture, livestock, forestry, fishing and hunting	-0.2221 (0.001)***	-0.1657 (0.001)***	-0.0858 (0.001)***	-0.0409 (0.001)***	0.0027 (0.001)***	-0.0283 (0.016)*
Craftsmen	0.0484 (0.000)***	0.0835 (0.000)***	0.0996 (0.000)***	0.0863 (0.000)***	0.0928 (0.000)***	0.0808 (0.014)***
Industrial machinery operators, assemblers and drivers	0.2301 (0.000)***	0.2035 (0.000)***	0.2066 (0.000)***	0.1856 (0.000)***	0.1743 (0.000)***	0.1932 (0.013)***
Occupational sector of the household head (base category: primary sector)						
Secondary sector	0.3542 (0.001)***	0.3077 (0.000)***	0.3203 (0.000)***	0.3110 (0.000)***	0.3154 (0.001)***	0.3233 (0.015)***
Tertiary sector	0.2907 (0.001)***	0.2820 (0.000)***	0.2923 (0.000)***	0.2892 (0.000)***	0.2970 (0.001)***	0.2912 (0.014)***
Constant	6.5697 (0.002)***	6.9141 (0.002)***	7.1820 (0.001)***	7.3614 (0.001)***	7.4209 (0.001)***	7.2784 (0.045)***

Robust standard errors are reported in parentheses.

*Significant at 10%; **significant at 5%; ***significant at 1%

complete primary education or at least one year of secondary school has a greater effect on their ICTPC than in the higher quantiles. On the contrary, in *marginally poor* and *near poverty* households, having at least one year of teacher training college or technical school or at least one year of university or more has a greater effect than in the rest of the quantiles. This suggests that public policies should focus on seeking that the population reach at least one level of basic education to improve the income levels of the poorest people in the country.

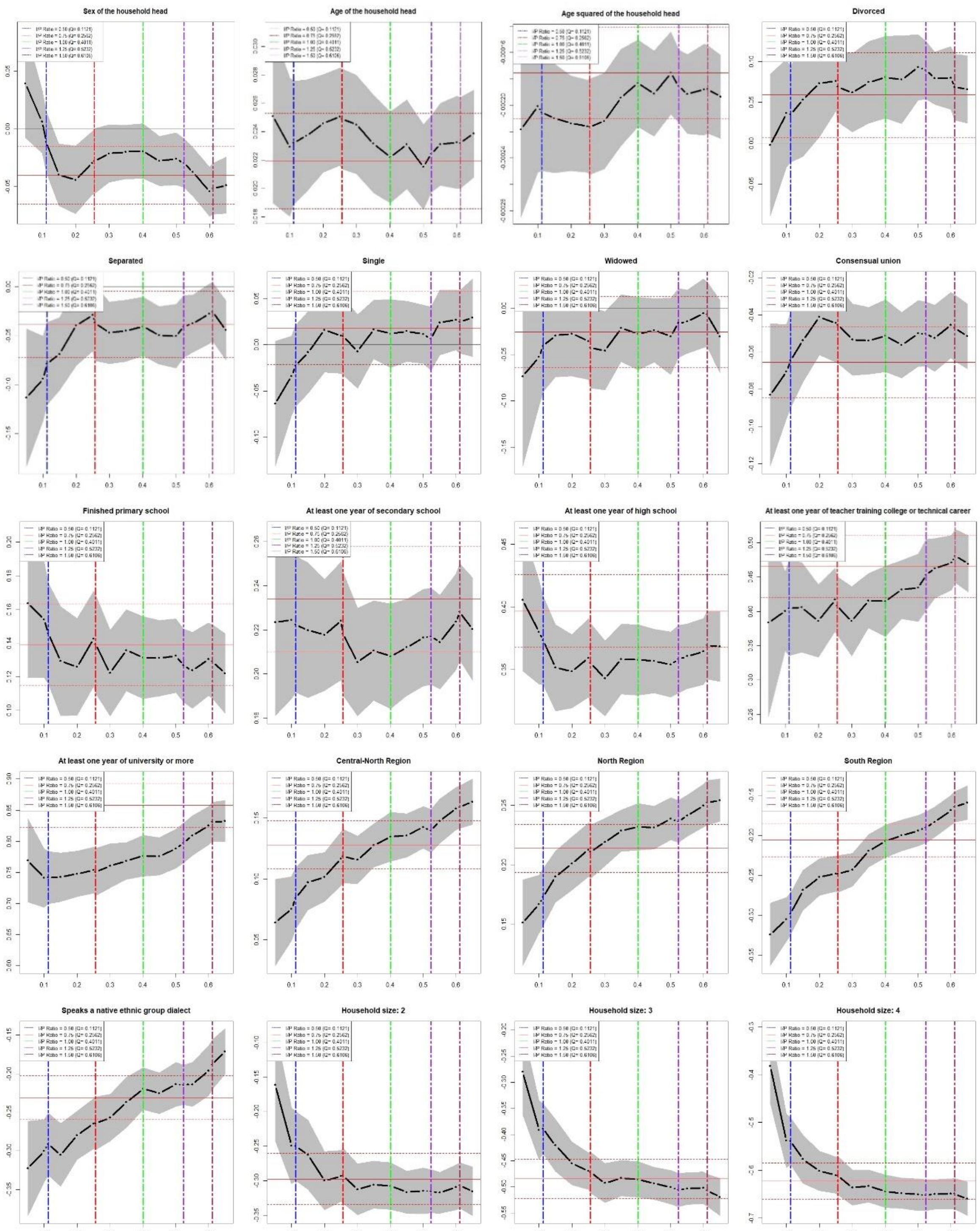
In terms of the region of location of the home and in comparison with the ones located in the Central region, the results show strong regional patterns of lower poverty levels in the Central-North and North regions. However, in the South region there is a negative effect. According to Galindo and Bolívar (2013), among the causes that have prevented the reduction of poverty is the segmentation of development in the country, since the southeast region of Mexico is the most marginalized. The situation described above may partly explain the negative coefficients in the quantile regressions and OLS for households located in the South. This result is consistent with that obtained in the probit model. In line with the results of the OLS regression, location is important for well-being, considering that the results for all quantiles are statistically significant at 99% confidence. It is interesting to observe how in the three regions the extremes of the poverty spectrum (households in *extreme poverty* and *marginally poor*) show a difference between the OLS estimate and the quantile regression. For the Central-North and North regions, first the effect is overestimated and then underestimated, respectively. In the South region the effect in the households in *extreme poverty* is underestimated and for *marginally poor* households it is overestimated. Other differences between the methods occur in households *near poverty* located in the North region and those in *deeply poor* status in the South of the country, which report a smaller effect on the OLS than in the quantile regression.

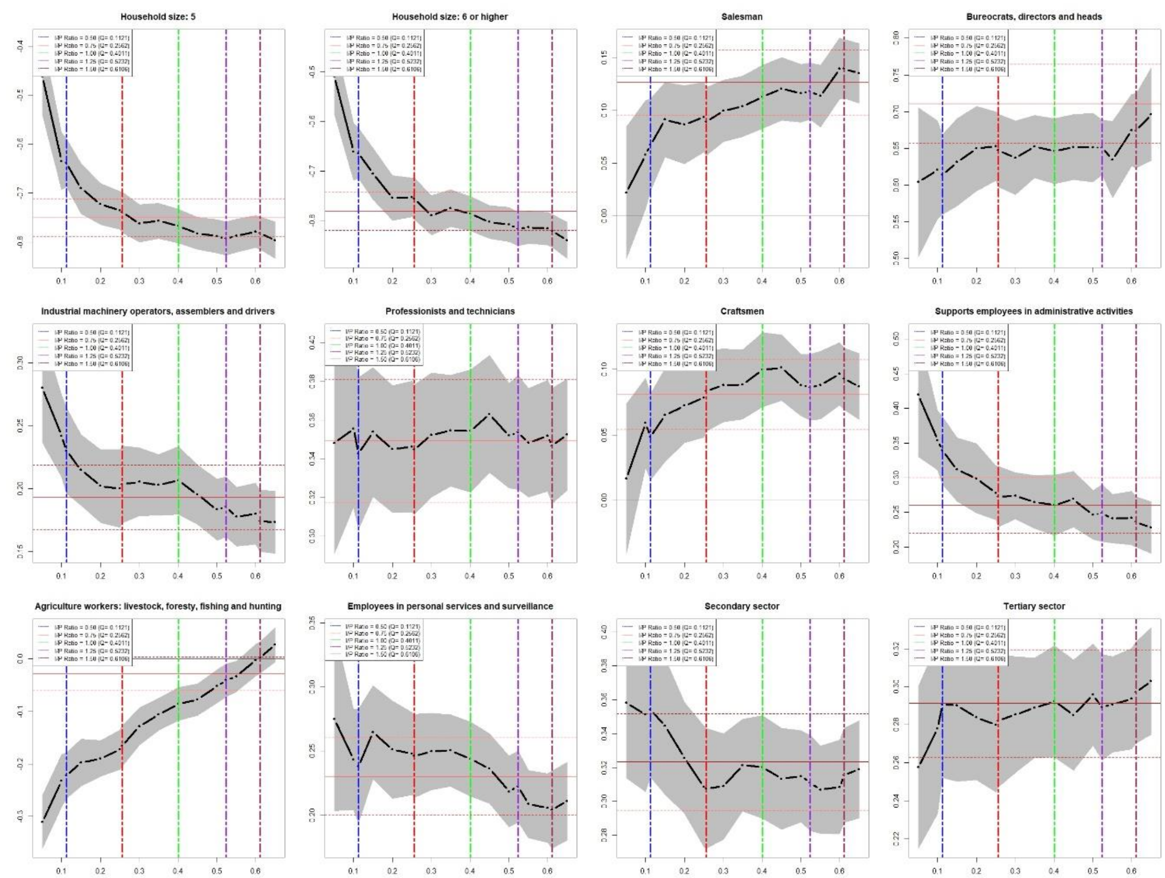
Speaking a native ethnic group language has a negative statistically significant effect on poverty. De Alba (2017) mentions that the indigenous population is discriminated against in the labor market and that they need to work harder to compensate for the low wages they receive. The OLS method underestimates the condition in which households are in *extreme poverty* and in *deeply poor* status, while for *marginally poor* households the estimate by the OLS method is greater than that found by quantile regression.

For the results of the household size variable, the coefficients are negative in any quantile and in any of the categories. In other words, any household size larger than a person has a detrimental effect on the ICTPC of households. It can be noticed that, for households in *extreme poverty*, the results of the OLS regression overestimate the effect it has on the ICTPC, that is, the size of the household is less negative than shown. Additionally, in households *near poverty* and *marginally poor*, with five and six or more members, respectively, the results of the OLS underestimate the effect. This means that the size of the household affects in a greater extent by significantly reducing its ICTPC. Given this, since the dependent variable used is the natural logarithm of the ICTPC, it is logical that there is an inverse relationship with the size of the household, because the income is divided into a greater number of people, which is consistent with the findings of Lanjouw and Ravallion (1995).

In terms of the occupational position of the head of the household and in comparison with the heads of household who are workers in elementary and support activities, the results show a positive relationship with the ICTPC for all positions, except for agricultural workers in livestock, forestry, hunting and fishing activities, in which there is a negative effect on the studied quantiles. Huesca (2009) points out that in Mexico a large number of informal workers are employed in agricultural activities. These workers present an important salary gap with formal employees, who receive a higher remuneration for the work performed (Rodríguez Pérez, Castro Lugo, & Mendoza López, 2019). Significant differences were found between the results of the methods for households in *extreme poverty*, except for the occupations of professionals and technicians, and workers in personal services and surveillance. For the positions of salesmen and workers in agricultural, livestock, forestry, hunting and fishing activities, the value of the coefficient increases as the studied quantile increases. However, in the categories of support employees in administrative activities and operators of industrial machinery and transport drivers, the effects on the ICTPC are greater and are underestimated by the OLS regression exclusively for households in *extreme poverty*. The coefficients

Figure 1: Quantile regression and OLS coefficients





estimated for officials, directors and managers show that the OLS method overestimates the effect for all quantiles, except for the *marginally poor*. As for the results of the probit model, all are consistent with those of the quantile regressions, except for the heads of household employed in agricultural, livestock, forestry, hunting and fishing activities.

Regarding the sector of occupation of the household head in comparison with households heads working in the primary sector, the results show a positive effect in the ICTPC both for the secondary and the tertiary sectors. This result is coherent with the result obtained in the probit model, where it is shown that if a household head works in the secondary or tertiary sectors, the probability of poverty diminishes. Considering the coefficients of the quantile regressions, it can be seen that the values are higher for the secondary sector rather than the tertiary sector. Coll-Hurtado and Córdoba y Ordoñez (2006) found that in Mexico two contrasting realities exist in the tertiary sector, one with a high level of professionalization and another one where banal, of limited qualification, and underpaid services are predominant. Activities such as elderly care, fast food delivering, small business clerks, domestic and unprofessional hotel services, are the type of activities within tertiary sector that members of the poorest households usually perform. For the case of the secondary sector, the effect is higher and even underestimated by the OLS in *extremely poor* households. The estimates obtained for the tertiary sector from the quantile regressions and from the OLS, do not show significant differences. This indicates that the positive effect on ICTPC for the households where the head works in a tertiary sector is persistent throughout the income distribution.

VI. Conclusions

This study, the first of its kind for the case of Mexico, analyses the determinants of poverty in five quantiles of the income distribution: *extremely poor, deeply poor, at the poverty line, near poverty and* *marginally poor* households. A probit and a quantile regression model were estimated using the ENIGH 2018 database to understand with more clarity the characteristics of the poverty spectrum in Mexico.

A probit model was applied to estimate the probability that a Mexican household finds itself in poverty given its socio-economic and demographic characteristics. It was found that among the variables related to the household head that decrease the probability for the household being poor are: household head's age, divorced marital status, educational level higher than incomplete primary school, not being employed in basic support activities nor primary sector, and that the region where the household is located is different from South. In contrast, the variables that increase the probability of being poor are: if the household head is female, speaks a native ethnic group language and if the household size is higher than one.

The quantile regression model was used to examine the correlates at different points of the income distribution. With the results obtained, it can be observed that the OLS method cannot explain adequately the situation of households in *extreme poverty*. The location region of the households shows contrasting results with households in *extreme poverty* and *marginally poor*. These are overestimated and underestimated by the OLS method, respectively. Poverty is more severe than the OLS estimations for households in *extreme poverty* and *deeply poor* for the South region, and households with heads that are speakers of a native ethnic group language. The quantile regression results across the poverty spectrum show that achieving a higher educational level is an effective way of increasing household income. On the contrary, age of the household head, if he or she is divorced or widowed, has complete primary school degree, if his or her position of occupation is professionalt or technician, personal service or surveillance, or if he or she works in the tertiary sector, do not present significant differences in results with the quantile regression and the OLS estimates. Households in *extreme poverty* have more severe needs, and have higher differences between the OLS and the quantile regression coefficient estimates.

For future research it is recommended to include in the analysis the interaction between variables and show the evolution of poverty determinants over time through a quantile regression methodology. Another interesting issue to analyze would be to contrast the analysis using consumption and income as dependent variables. Finally, it would be worthwhile to to use experimental economics in the analysis of the most relevant determinants of poverty.

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