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# What determines poverty in Mexico? A quantile regression approach

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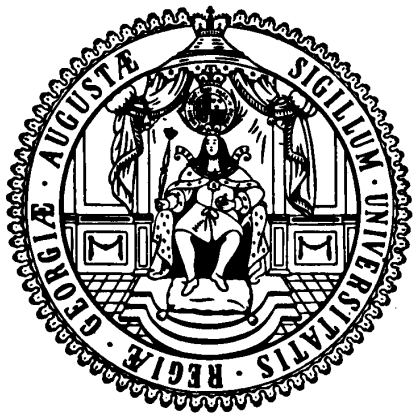



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## What Determines Poverty in Mexico? A Quantile Regression Approach


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# What Determines Poverty in Mexico? A Quantile Regression Approach

Juan Armando Torres-Munguía*

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***Abstract***

According to official poverty estimates in Mexico, more than 50 percent of the population was poor in 2016, half of which could not even afford the basic food basket. Whereas most of the existing research analyses poverty focusing exclusively on average income or on the expected probability of being poor, this paper departs from this approach by analyzing income differences between households in rural and urban settlements using boosting additive quantile models. The models are estimated using a cross-sectional dataset containing information of more that 50 thousand households for the year 2015. The main results highlight the importance of analyzing poverty from an individual, household, community and regional perspectives and the relevance of accounting for heterogeneity of the effects on female- and male-headed households. The results point towards the existence of a life-income cycle and the relevance of education, social networks, income equality and quality of government to fight poverty. The findings also indicate that economic empowerment of women matters for pro-poor income policies to be effective and point towards the need of introducing a gender approach in the study on poverty.

**Keywords:** Extreme poverty; Mexico; Quantile regression; Spatial effects; Boosting; Gender

**JEL**: C21, O10, O54

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## What Determines Poverty in Mexico? A Quantile Regression Approach

## 1. Introduction

Poverty is one of the greatest challenges facing humankind, which affects not only the ability of individuals to purchase basic goods and services that contribute to their wellbeing, but also the ability to exercise their rights. Although poverty is a multifaceted phenomenon, it has been largely viewed in monetary terms. Usually, income of an individual or a household is compared with a threshold below which a person is considered to live under poverty. Internationally, the extreme poverty threshold has been established in $1.25 American dollars in purchasing power parity terms a day.

Eradicating extreme poverty for all individuals globally is the first of the Sustainable Development Goals included in the 2030 Agenda. According to United Nation estimates, in 2017 almost 750 million people were living under extreme poverty in the world down from around 1.7 billion people in 1999 (United Nations, 2018). Despite the fact that significant progress has been made globally in the last 20 years, much still remains to be done to reach the target of ending extreme poverty by 2030. The uneven progress on poverty reduction between regions, sexes, age groups and rural and urban settlements are amongst the biggest challenges to face (United Nations, 2017).

In order to formulate measures to fight poverty more efficiently, it is of primary importance to analyze its underlying causes. In this paper the determinants of extreme income poverty in Mexico are analyzed. Even though Mexico is one of the top 20 world's largest advanced and emerging economies, according to the latest estimates of poverty, there were in 2016 around 62 million people whose income was below the well-being line -equivalent to 50.6% of total population-, of which nearly 21.4 million -17.5%- cannot even afford the basic food basket. Although poverty in Mexico has been widely investigated, previous research suffers from some important shortcomings. From the methodological point of view, most of the existent research

analyses poverty with the usual mean regression models and in consequence, they exclusively focus on income average or on the expected probability of being poor, disregarding the potential differentiated effect of covariates on the quantiles of the distribution of the dependent variable (Garza-Rodríguez, 2002; Székely & Rascón, 2005; World Bank, 2005; Esquivel & Huerta-Pineda, 2007; Ordaz Díaz, 2009; Garza-Rodríguez, 2016; Torres García & Hernández-Cantú, 2017). Furthermore, previous research uses models that do not flexibly incorporate both linear and nonlinear interactions, nor spatial effects. Additionally, the problem of variable selection and model choice is often overlooked. Finally, from a theoretical perspective, studies on poverty generally ignore the gender issue. Potential explanatory variables are neither sex-disaggregated nor incorporate concepts that capture the unequal experiences of females and males in other spheres of life, such as violence and political or economic participation.

The research strategy used in this paper aims to overcome the abovementioned shortcomings. In contrast to previous research on poverty in Mexico, this paper applies an additive quantile regression approach to study how the distribution of the households' per capita income is affected by a broad set of continuous and categorical covariates, including spatial information by municipalities and random effects. Proposed explanatory variables cover information on individual and household characteristics, as well as both features of the community and the region of residence, including gender related issues such as violence against females, use of time and political and economic participation. Information is mainly based on the 2016 National Survey of Household Income and Expenditure (ENIGH) provided by the Mexican Institute of Statistics and Geography (INEGI). Given that investigating covariate effects on the income of the poorest households is of great interest, this paper estimates regression models for the 5%-, 10%- and 50%-income quantiles (Koenker, 2005). With the goal of identifying gender specific inequalities faced between sexes, these models are separately estimated for female- and male-headed households both in rural and urban communities. Aiming to capture both linear and nonlinear processes, an additive quantile regression approach is applied (Hastie & Tibshirani,

1986; Hastie & Tibshirani, 1990; Koenker, 2010). Additive methods flexibly model and estimate the effect of continuous variables on the response without establishing *a priori* a specific functional form.

Finally, in order to achieve both model interpretability and goodness of fit, variable selection and model choice are applied by pursuing a boosting approach (Kneib, Hothorn & Tutz, 2009; Fenske, Kneib & Hothorn, 2011). This data-driven method allows to simultaneously perform automatic variable selection and model choice by deciding the amount of smoothness required for capturing covariate effects, that is, if the linear component of the model is enough to describe these relationships or if nonlinear effects should be introduced. The boosting proposal is then a regularization technique used to overcome the problems associated to models with a large number of potential covariates or even when it exceeds the number of observations (Fahrmeir, Kneib, Lang & Marx, 2013).

The rest of the paper is organized as follows. Section 2 goes through the theory of the determinants of poverty with particular emphasis on the Mexican case. Section 3 shortly reviews the framework for boosting geoadditive quantile models and how this approach is applied to this study. Section 4 provides information on the data used and presents the main results and a discussion of them. To conclude, section 5 presents the final comments and directions for future research.

## 2. Literature Review

Previous research indicates that poverty is shaped by a number of factors that can be classified into three main categories: individual and household characteristics, characteristics of the community and those of the region of residence. First, the individual and household characteristics such as age, sex, ethnicity, education and social cohesion have been found to have a strong inter-linkage with poverty. It is widely believed that the risk of poverty is higher for young and elderly people, for female-headed households, as well as for those people

belonging to an ethnic group and those with lower educational level (Haughton & Khandker, 2009; Andriopoulou & Tsakloglou, 2011; World Bank, 2013; OECD, 2015; Blau, 2016; Corsi, Botti & D'Ippoliti, 2016; Espinoza-Delgado & Klasen, 2017; Peng, et al., 2018). Although the association between poverty and social cohesion has been less explored, it could be expected that individuals excluded from social groups may have a more limited access to resources than individuals taking part in social networks (Montgomery, 1991; Fafchamps & Minten, 1999; Narayan, 1999; Rankin & Quane, 2000). Second, regarding the characteristics of the community of residence, household income tend to be lower in rural communities, in those characterized for having low infrastructure development, susceptibility to natural disasters or inhospitable climatic conditions, limited access to public services and goods and with an agriculture-oriented economy (Rodriguez & Smith, 1994; Coulombe & Mckay, 1996; Levernier, Partridge & Rickman, 2000; Geda, de Jong, Mwabu & Kimenyi, 2001; Rupasingha & Goetz, 2007; Peters, et al., 2008; World Bank, 2013; Hallegatte, Vogt-Schilb, Bangalore & Rozenberg, 2017). Finally, in addition to individual and community characteristics, regional features are also associated to poverty. Most common indicators at the regional level are related to the public sector and governance. Broadly speaking, a weak quality of government -high levels of corruption, low quality of public goods and services and weak governance- goes together with higher poverty levels (Moore, Leavy, Houtzager & White, 1999; Gupta, Davoodi & Alonso-Terme, 2002; Negin, Abd Rashid & Nikopour, 2010; World Bank, 2013).

Research has also shown that the effect of some of these explaining variables on income poverty may follow a nonlinear relationship. An obvious example of these covariates is individuals' age. In general, highest risks of poverty are observed in the youngest and oldest ends of the age spectrum (Andriopoulou & Tsakloglou, 2011; Lekobane & Seleka, 2014; Espinoza-Delgado & Klasen, 2017). Additionally, it is also widely recognized that space plays a significant role when analyzing poverty (Palmer-Jones & Sen, 2006; Rupasingha & Goetz, 2007).

By using the abovementioned classification of individual, household, community and regional factors to examine the case of Mexico, research has identified a set of covariates whose effect on poverty is widely recognized. At the individual and household levels, there is a consensus that higher risks of poverty are linked to large-size households, low educational level of the household-head, economic participation in primary activities, indigenous origin and informal work (World Bank, 2005; Ordaz Díaz, 2009; Garza-Rodríguez, 2016; Torres García & Hernández-Cantú, 2017). At this individual and household level, there also exist some covariates whose effects on poverty are unexplored, unclear or even contradict international evidence. For instance, the World Bank (2005) found no significant effect of female headship on poverty in rural areas in 1992 but a negative effect in 1996 and 2002. With regard to age, Garza-Rodríguez (2002) found that it has a constantly decreasing linkage with poverty, however this conclusion came from using linear models that hamper testing the existence of a life-income cycle.

Regarding the community and regional characteristics, there is consensus in the literature that higher levels of poverty are observed in households living in areas with larger shares of migrants, social deprivation, lower levels of education, larger shares of indigenous population, overcrowded population and lower participation in industrial activities (Wodon, Angel-Urdinola, Gonzalez-Konig, Ojeda Revah & Siaens, 2003; Coneval, 2014).

To the best of our knowledge for the case of Mexico there is no study introducing heterogeneous effects by gender for the variables mentioned, nor indicators on women's economic, social and political empowerment to further investigate gender differences in poverty.

## 3. Methodology and empirical strategy

Consider the variable $y_i$ and the vectors $\mathbf{w_i} \coloneqq \left(1, \boldsymbol{w}_{i1}, \dots, \boldsymbol{w}_{ip}\right)'$ and $\mathbf{z_i} \coloneqq \left(\boldsymbol{z}_{i1}, \dots, \boldsymbol{z}_{iq}\right)'$ of $p$ categorical and $q$ continuous covariables for $i = 1, \dots, n$ observations. Recall an additive quantile model (Hastie & Tibshirani, 1986; 1990; Koenker, 2005, 2010), expressed as follows

$$y_i = \mathbf{w_i}'\boldsymbol{\beta}_\tau + \sum_{k=1}^{q} s_{k\tau}(\mathbf{z}_{ik}) + \varepsilon_{\tau i} \qquad [1]$$

This semiparametric model comprises a linear term for estimating the effect of categorical variables, $\mathbf{w_i}'\boldsymbol{\beta}_\tau$ with $\boldsymbol{\beta}_\tau$ as the quantile specific regression coefficients, and a nonlinear component for the continuous covariates, $\sum_{k=1}^{q} s_{k\tau}(\mathbf{z}_{ik})$. The smoothing parameters, $s_{k\tau}(\mathbf{z}_{ik})$, can also include among others, spatial, temporal and random effects, as well as varying coefficient terms (Wood, 2006; Lang, Umlauf, Wechselberger, Harttgen & Kneib, 2012; Fahrmeir, Kneib, Lang & Marx, 2013). $\epsilon_{\tau i}$ represents the quantile specific regression errors. Moreover, the cumulative distribution function of $\epsilon_{\tau i}$, $\boldsymbol{F}_{\epsilon_{\tau i}}$, fulfills $\boldsymbol{F}_{\epsilon_{\tau i}}(0) = \tau$. By using this approach, the model allows focusing on extreme poverty, i.e. on the lowest income quantiles. It is noteworthy to mention that quantile models are complete distribution-free regression methods and incidentally error terms can follow different distributions and they can even show non-constant variances across them (Fahrmeir, Kneib, Lang & Marx, 2013).

One approach to get the optimal solution of the proposed model consists on minimizing the difference between the observed data and the model via the loss function $\rho_\tau(y_i, \eta_{\tau i}) \in \mathbb{R}$, where $\eta_{\tau i} = \mathbf{w_i}'\boldsymbol{\beta}_\tau + \sum_{k=1}^{q} s_{k\tau}(\mathbf{z}_{ik})$ is a prediction function to be optimized. In practice, the loss function is typically minimized by least squares or likelihood methods. Alternatively, a component wise gradient boosting method could be applied (Friedman, Hastie & Tibshirani, 2000; Friedman, 2001). In this second approach, the goal is to iteratively solve the optimization function given by

$$\eta_{\tau i}{}^{*} = \arg min_{f_\tau} \mathbb{E}_{Y,W,Z}[\rho_\tau(y_i, \eta_{\tau i})] \qquad [2]$$

Since $\mathbb{E}_{Y,W,Z}[\rho_\tau(y_i, \eta_{\tau i})]$ is in practice unknown, it is then replaced by the observed mean $\sum_{i=1}^{n} \rho_\tau(y_i, \eta_{\tau i})\, n^{-1}$, also called the empirical risk, for $i = 1, \ldots, n$ observations. Broadly speaking, the component wise gradient boosting algorithm can be described as follows. First, let $\eta_{\tau i} = \mathbf{w_i}'\boldsymbol{\beta}_\tau + \sum_{k=1}^{q} s_{k\tau}(\mathbf{z}_{ik})$ be written as

$$\eta_{\tau i} = \boldsymbol{\beta}_{0\tau} + \mathbf{w}'_{i1}\boldsymbol{\beta}_{1\tau} + \cdots + \mathbf{w}'_{ip}\boldsymbol{\beta}_{p\tau} + s_{1\tau}(\mathbf{z}_{i1}) + \cdots + s_{q\tau}(\mathbf{z}_{iq}) \qquad [3]$$

where each of the $\boldsymbol{\beta}_{0\tau}, \boldsymbol{\beta}_{1\tau}, \ldots, \boldsymbol{\beta}_{p\tau}$ and $s_{1\tau}, \ldots, s_{q\tau}$ represent a vector related to a specific block of covariates, in the simplest case every block is related to only one covariate. These blocks are

disjoint subsets of the data and are utilized as base-learners, denoted as $\boldsymbol{b}_{0\tau}, \boldsymbol{b}_{1\tau}, \ldots, \boldsymbol{b}_{p\tau}$ and $\boldsymbol{g}_{1\tau}, \ldots, \boldsymbol{g}_{q\tau}$, respectively. In the case of continuous variables, every $\boldsymbol{g}_{1\tau}, \ldots, \boldsymbol{g}_{q\tau}$ combines all polynomials of the same covariate $s_{k\tau} = (s_{1k\tau}(\mathbf{z}_k), s_{2k\tau}(\mathbf{z}_k), \ldots)'$. Then, the following steps of the boosting algorithm are carried out:

1. Establish a maximum number of boosting iterations, $m_{stop}$, and set the iteration index $m = 1$. Then initialize all blocks $\boldsymbol{\beta}_{l\tau}$ and $s_{k\tau}$ with appropriate offset values $\boldsymbol{\beta}_{l\tau}^{[0]}$ and $s_{k\tau}^{[0]}$ for $l = 0, 1, \ldots, p$ and $k = 1, \ldots, q$. With these starting values compute the negative gradient of the empirical risk

$$u_i = -\frac{\partial L(y_i, \eta_\tau)}{\partial \eta_\tau}\Big|_{\eta_\tau = \hat{\eta}_{\tau i}^{[m-1]}}, \quad for\ i = 1, \ldots, n \qquad [4]$$

2. Obtain estimates for $\widehat{\boldsymbol{b}}_{l\tau}^{[m]}$ and $\widehat{\boldsymbol{g}}_{k\tau}^{[m]}$ for $l = 0, 1, \ldots, p$ and $k = 1, \ldots, q$ by separately fitting each of the base-learners to the negative gradient. Negative gradients can be obtained by inserting the check function for the loss function.

$$u_i = \rho_\tau'\left(y_i - \hat{\eta}_i^{[m-1]}\right) = \begin{cases} \tau, & y_i - \hat{\eta}_i^{[m-1]} \geq 0 \\ \tau - 1, & y_i - \hat{\eta}_i^{[m-1]} < 0 \end{cases} \qquad [5]$$

3. Compute $\left(\mathbf{u}^{[m]} - \hat{\mathbf{u}}^{[m]}\right)'\left(\mathbf{u}^{[m]} - \hat{\mathbf{u}}^{[m]}\right)$, where $\mathbf{u}^{[m]} = \left(u_1^{[m]}, \ldots, u_n^{[m]}\right)'$, by introducing every $\widehat{\boldsymbol{b}}_{l\tau}^{[m]}$ and $\widehat{\boldsymbol{g}}_{k\tau}^{[m]}$ into $\hat{\mathbf{u}}$, and find the best-fitting base learner. Then,

    a. If the base-learner with the most influential effect is $\widehat{\boldsymbol{b}}_{j^*\tau}^{[m]}$, then update $\widehat{\boldsymbol{\beta}}_{j^*\tau}^{[m]} = \widehat{\boldsymbol{\beta}}_{j^*\tau}^{[m-1]} + v\widehat{\boldsymbol{b}}_{j^*\tau}^{[m]}$, for $v \in (0, 1]$, and leave the rest unchanged, i.e., $\widehat{\boldsymbol{\beta}}_{l\tau}^{[m]} = \widehat{\boldsymbol{\beta}}_{l\tau}^{[m-1]}$, for $l \neq j^*$ and $\widehat{\boldsymbol{g}}_{k\tau}^{[m]} = \widehat{\boldsymbol{g}}_{k\tau}^{[m-1]}$, for $k = 1, \ldots, q$.

    b. If the base-learner with the most influential effect is $\widehat{\boldsymbol{g}}_{j^*\tau}^{[m]}$, then update $\hat{\boldsymbol{s}}_{j^*\tau}^{[m]} = \hat{\boldsymbol{s}}_{j^*\tau}^{[m]} + v\widehat{\boldsymbol{g}}_{j^*\tau}^{[m]}$ for $v \in (0, 1]$, and leave the rest unchanged, i.e., $\widehat{\boldsymbol{\beta}}_{l\tau}^{[m]} = \widehat{\boldsymbol{\beta}}_{l\tau}^{[m-1]}$, for $l = 0, 1, \ldots, p$ and $\widehat{\boldsymbol{g}}_{k\tau}^{[m]} = \widehat{\boldsymbol{g}}_{k\tau}^{[m-1]}$, for $k \neq j^*$.

4. The algorithm is repeated until $m = m_{stop}$ by using again the full set of base-learners, including the obtained in the previous steps.

To prevent overfitting, the optimal number of boosting iterations is chosen via cross-validated estimation of the empirical risk. By choosing the optimal number of iterations the boosting algorithm also enables variable selection and model choice since only the most influential variables are picked with the appropriate functional form.

The specification of the empirical model is obtained by incorporating into model [1] the determinants of poverty considered in this paper. It given by,

$$y_{\tau i} = \boldsymbol{\beta}_{0\tau} + \sum_{j=1}^{14} \mathbf{w}'_{\boldsymbol{ij}} \boldsymbol{\beta}_{j\tau} + \sum_{k=1}^{28} s_{k\tau}(\mathbf{z}_{ik}) + s_{29\tau}(\boldsymbol{mun_i}) + s_{30\tau}(\boldsymbol{ent_i}) + s_{31\tau}(\boldsymbol{lon_i}, \boldsymbol{lat_i}) + \boldsymbol{lon_i}\boldsymbol{\beta}_{lon\tau} + \boldsymbol{lat_i}\boldsymbol{\beta}_{lat\tau} + (\boldsymbol{lon_i} * \boldsymbol{lat_i})\boldsymbol{\beta}_{ll\tau} + \varepsilon_{\tau i} \quad [6]$$

where $y_{\tau i}$ is the gross per capita family income of the observation $i$. The covariates in the model are listed in Table 1. $\boldsymbol{\beta}_{j\tau}$ are the quantile specific regression coefficients of the 14 categorical variables included. All continuous covariates are zero-centered for convergence reasons (Hofner, Mayr, Robinzonov & Schmid, 2014). Smoothing functions $s_{k\tau}(\mathbf{z}_{ik})$ are decomposed into an unpenalized polynomial, $s_{k\tau}(\mathbf{z}_{ik}) = \alpha_{0\tau} + \alpha_{1\tau}\mathbf{z}_{ik}$, and a smooth deviation from this polynomial, $s_{k\tau}^{centered}(\mathbf{z}_{ik})$. Therefore, from the decomposition of $s_{k\tau}(\mathbf{z}_{ik})$ four potential effects of $\mathbf{z}_{ik}$ on $y_{\tau i}$ are considered: no significant effect, purely linear effect, zero-centered smooth effect or a linear and smooth deviation combinate effect (Kneib, Hothorn & Tutz, 2009). The $s_{k\tau}^{centered}(\mathbf{z}_{ik})$ are smooth P-spline base-learners with a second-order difference penalty and 20 equidistant inner knots (Eilers & Marx, 1996). Moreover, $s_{29\tau}(\boldsymbol{mun_i})$ and $s_{30\tau}(\boldsymbol{ent_i})$ are random effects base-learners that capture the unobserved heterogeneity across municipalities and states, respectively. Here, $s_{29\tau}(\boldsymbol{mun_i}) = \boldsymbol{Z\gamma}$, where

$$\boldsymbol{Z} = \begin{bmatrix} \mathbf{1_1} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \mathbf{1_h} \end{bmatrix} \quad \text{and} \quad \boldsymbol{\gamma} = \begin{bmatrix} \boldsymbol{\gamma_1} \\ \vdots \\ \boldsymbol{\gamma_h} \end{bmatrix} \quad [7]$$

with every $\mathbf{1_1}, \ldots, \mathbf{1_h}$ in $\boldsymbol{Z}$ is a vector of ones whose dimension corresponds to the number of observations for each of the $\boldsymbol{h}$ municipalities and every $\boldsymbol{\gamma_1}, \ldots, \boldsymbol{\gamma_h}$ in $\boldsymbol{\gamma}$ is the vector of random intercepts corresponding to each municipality. $s_{30\tau}(\boldsymbol{ent_i})$ is defined similarly for each of the 32 States in Mexico. Finally, spatial effects are introduced and decomposed in a parametric part

captured with the terms $\boldsymbol{lon_i\beta}_{lon\tau}$, $\boldsymbol{lat_i\beta}_{lat\tau}$ and $(\boldsymbol{lon_i} * \boldsymbol{lat_i})\boldsymbol{\beta}_{ll\tau}$, and a smooth deviation polynomial, $s_{31\tau}(\boldsymbol{lon_i}, \boldsymbol{lat_i})$, estimated by a bivariate tensor product P-spline for spatial effects (Kneib, Hothorn & Tutz, 2009).

**Table 1.** List of variables used as covariates

| Covariate | Level | Description |
|---|---|---|
| **edu** | Individual / household | Formal education level of the household head (categorical: “low” if maximum complete primary education, “medium” if at least secondary education and a maximum of high school, “high”: at least university) |
| **etn** | Individual / household | Ethnic origin of the household head (categorical: “yes”=1, “no” =0) |
| **snt** | Individual / household | Perception of the household head on how ease would be to get support from social networks in some hypothetical situations, including whether the person needed money, care due to illness, help to get a job, to be accompanied to medical consultation, obtain cooperation to improve neighborhood conditions and child care assistance (categorical: “high”, “medium”, “low”) |
| **mrt** | Individual / household | Marital status of the household head (categorical: "open union", "married", "separated", "divorced", "widowed", "single") |
| **crd** | Individual / household | Holding of a credit card from a family member (categorical: “yes”=1, “no”=0) |
| **dsb** | Individual / household | Disability condition of the household head (categorical: “yes”=1, “no”=0) |
| **age** | Individual / household | Age in years of the household head (continuous) |
| **hhw** | Individual / household | Time in hours spent by the household head for undertaking housework per week (continuous) |
| **thh** | Individual / household | Type of household (categorical: "one-person", "nuclear", "extended", "other") |
| **fod** | Individual / household | Lack of access to food (categorical: “yes”=1, “no”=0) |
| **hlt** | Individual / household | Lack of access to health services (categorical: “yes”=1, “no”=0) |
| **qdw** | Individual / household | Dwelling with inadequate quality or insufficient space (categorical: “yes”=1, “no”=0) |
| **edl** | Individual / household | Educational lag (categorical: “yes”=1, “no”=0) |
| **bhs** | Individual / household | Lack of access to basic housing services (categorical: “yes”=1, “no”=0) |
| **sse** | Individual / household | Lack of access to social security (categorical: “yes”=1, “no”=0). |
| **mun** | Community | Random effects of the municipality |
| **lon, lat** | Community | Centroid coordinates: longitude, latitude (continuous) |

| | | |
|---|---|---|
| **wth** | Community | Number of yearly average declarations of emergency, disaster or contingency due to weather between 2010 and 2015 (continuous) |
| **hdi** | Community | Human Development Index in 2015 (continuous) |
| **fci** | Community | Municipal Functional Capacities Index in 2016 (continuous) |
| **fpp** | Community | Share of head positions in the Municipal Public Administration held by females in 2015 (continuous) |
| **mrg** | Community | Social marginalization level in 2015 (categorical: "very high", "high", "medium", "low", "very low") |
| **fmg** | Community | Share of the female population aged 5 and over that lived in another state / country in 2010 (continuous) |
| **mmg** | Community | Share of the male population aged 5 and over that lived in another state / country in 2010 (continuous) |
| **fhh** | Community | Share of the population living in female headed households in 2015 (continuous) |
| **gin** | Community | Gini index 2015 (continuous) |
| **fea** | Community | Share of the female population aged >=12 years economically active in 2015 (continuous) |
| **mea** | Community | Share of the male population aged >=12 years economically active in 2015 (continuous) |
| **rhw** | Community | Number of hours spent by females aged >=12 years for undertaking housework per hour spent by males aged 12 and over for undertaking housework in 2015 (continuous) |
| **fpr** | Community | Share of the female working population aged >=12 years employed in the primary sector in 2015 (continuous) |
| **mpr** | Community | Share of the male working population aged >=12 years employed in the primary sector in 2015 (continuous) |
| **fsc** | Community | Share of the female working population aged >=12 years employed in the secondary sector in 2015 (continuous) |
| **msc** | Community | Share of the male working population aged >=12 years employed in the secondary sector in 2015 (continuous) |
| **ftr** | Community | Share of the female working population aged >=12 years employed in the trade sector in 2015 (continuous) |
| **mtr** | Community | Share of the male working population aged >=12 years employed in the trade sector in 2015 (continuous) |
| **fsr** | Community | Share of the female working population aged >=12 years employed in the service sector in 2015 (continuous) |
| **msr** | Community | Share of the male working population aged >=12 years employed in the service sector in 2015 (continuous) |
| **ent** | Region | Random effects of the state |
| **cor** | Region | Share of the population aged >=18 years who considered corruption as a frequent and very frequent problem in their region in 2015 (continuous) |
| **sat** | Region | Share of the population aged >=18 years who are satisfied with the basic and on-demand public services provided in their region in 2015 (continuous) |

| | | |
|---|---|---|
| **vlc** | Region | Share of the female population >=15 years old who were victims of violence at the community level in 2015 (continuous) |
| **vls** | Region | Share of the female population >=15 years old who were victims of violence at the school in 2015 (continuous) |
| **vlw** | Region | Share of the female population >=15 years old who were victims of violence at the workplace in 2015 (continuous) |
| **vlp** | Region | Share of the female population >=15 years old who were victims of violence by an intimate partner in 2015 (continuous) |
| **vlf** | Region | Share of the female population >=15 years old who were victims of violence in family contexts in 2015 (continuous) |

## 4. Data sources and main results

This section describes the data used and main sources and presents the empirical results as well as a discussion and comparison with the literature.

### *4.1. Data description and sources*

Income data come from 2016 National Survey of Household Income and Expenditure (ENIGH) provided by the Mexican Institute of Statistics and Geography (INEGI). Information on covariates integrates data from the 2015 Intercensal Population Survey, the 2015 National Census of Municipal and Delegation Governments, the 2015 National Survey of Quality and Governmental Impact, the 2016 National Survey on the Dynamics of Household Relationships, the National Center for Prevention of Disasters (CENAPRED), the National Council for the Evaluation of Social Development Policy (CONEVAL), the National Population Council (CONAPO) and the Human Development Index developed by the United Nations Development Program (UNDP)[1]. A table with summary statistics is presented in the Appendix (available upon request from the authors). After checking plausibility and omitting missing cases, the datasets corresponding to female-headed households are composed of 4,434 observations in rural settlements and 10,503 in the urban context. Datasets on male-headed households consist of 14,877 observations in rural communities and 22,570 in urban settlements.

[1] All these datasets are freely available at www.coneval.org.mx, www.inegi.org.mx, www.mx.undp.org and www.datos.gob.mx.

*4.2. Main results*

Model [6] has been estimated using the described methodology outlined in section 3. The model was estimated separately for female- and male-headed household as well as distinguishing between urban and rural areas and in each case convergence was achieved after an iterative process[2]. The main results obtained from the estimation of model [6] presented in Section 3 are graphically displayed for the 5% and 50% quantiles of the income distribution[3]. Effects of the selected covariates at the individual/household level are shown in Figures 1 to 4 and in Figures 5 and 6 for the community and regional levels, respectively[4]. Spatial effects are displayed in Figures 7 and 8. Estimated effects on poverty are presented, distinguishing by sex of the household head and type of settlement -rural/urban-.

In general, findings show a significant difference between female- and male-headed households. These differences are shaped by individual/household characteristics, community and regional features. As expected, in comparison to urban communities, lower levels of income are observed in rural settlements.

In particular, regarding the first level of analysis -individual and household characteristics-, households with the less skilled heads -lower education level- are in general showing a lower income level (Figure 1, left part), this result is consistent across income quantiles in both female- and male-headed households and in both rural and urban contexts. The effect is particularly strong for the 50% income quantile (bottom of Figure 1). This finding is in accordance with those obtained in previous research both for the Mexican case and internationally and reinforce the view that education is one of the most important tools for fighting poverty. As shown in Figure

[2] The optimal number of iterations for the female-headed household models in rural communities was 788 at the 5% quantile, 603 at the 10% and 1,615 at the 50%, and in urban settlements were 2,094 at the 5%, 1,949 at the 10% and 2,600 at the 50%. In the case of the male-headed household models, the optimal number of boosting iterations in rural settlements was achieved at 2,012 for the 5% quantile, 1,803 at the 10% and 3,421 at the median, while for urban households the optimal number of iterations was 4,988, 4,993 and 4,980 at the 5%, 10% and 50% quantiles, respectively. All computations were implemented in the R package "mboost" (Hothorn, Buehlmann, Kneib, Schmid & Hofner, 2018).

[3] Results for the 10% quantile are included in Appendix (available upon request from the authors).

[4] All figures show the expected value and the 95% empirical bootstrap confidence intervals calculated from 1000 outer bootstrap replicates (Hofner, Kneib & Hothorn, 2016).

1 (left part), no significant statistical differences were found between female- and male-headed households concerning education level. That is, education is equally important as determinant of poverty for both type of households.

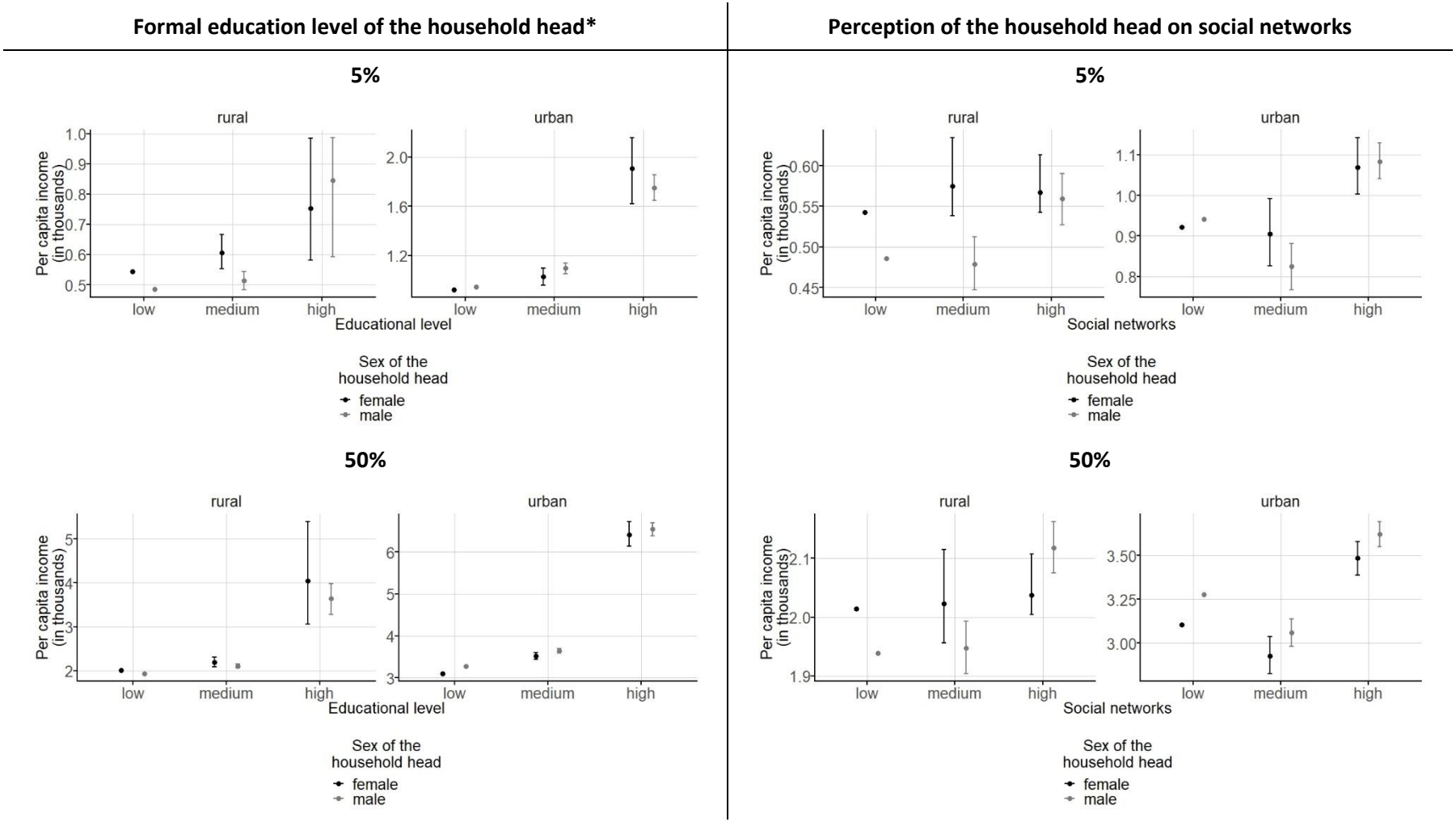
Overall, concerning perception of social networks, it is observed that having close links and connections with other people may help households to improve their expected income (Figure 1, right part). This effect varies by gender of the household head, type of settlement (rural versus urban) and income quantile. While for female-headed households located in rural areas, both at the 5%- and 50%-income quantiles, there is no significant effect of social networks on income, in urban communities having a high level of perception on social networks is associated to a higher income. In this context, the effect of social networks for male-headed households is always related to a higher income and it is particularly evident for urban households at the 50% income quantile.

Holding of a credit card from a family member positively impacts household income (Figure 2, left part) except for the case of rural female-headed households in the 5% quantile. Concerning disability condition of the household head (Figure 2, right part), the effect on expected income tends to be lower in male-headed households than in female-headed ones at the 5% quantile. However, for households located in urban communities and at the 50% income quantile, the income effect is larger for male-headed households, in comparison to those headed by a female. Furthermore, there is also a clear indication that the multiple faces of poverty are interlinked. From the selected effects, lacking access to food and to social security (Figure 3) is consistently related to lower household income levels across all types of settlements and quantiles. Gender differences are observed in households with access to food in rural communities at the 5% quantile, where male-headed households show a lower income level than female-headed households. However, this pattern reverses for households with access to social security (Figure 3, right), in which male-headed households both in rural and urban communities at the 5% and 50% quantiles show a higher expected income than households with a female head.

A consistent finding across quantile levels is an inverted u-shaped relationship between age of the household head and income (Figure 4, left), i.e., households experience lower income levels in the youngest and oldest ends of the age spectrum, reaching a maximum approximately between 40 and 60 years. The curve also indicates the existence of gender differences in relation to poverty, highlighting the specific income inequalities between female- and male-headed households throughout all life stages. When we compare the estimated effects among quantiles and type of settlements, both in female- and male-headed households in rural communities it is observed an almost constant effect until the age of 50 years -without gender differences- followed by an income fall, which is sharper for male-headed households. In urban communities for the 5% quantile, male-headed households tend to exhibit a higher income level at the youngest life stage, but this effect is reversed at the rightest side of the curve. The curve is much more marked for urban households at the 50% and slightly higher for households with a male head.

A key variable on gender issues is weekly time spent by the head for undertaking housework (Figure 4, right). As can be seen in the range of observed values of this variable (x-axis of Figure 4, right), female-heads tend to allocate much more time to unpaid domestic activities than male-heads, regardless of the type of settlement. This unequal time distribution reflects gender social norms and stereotypes, which represent the importance of including this variable as an indicator of the dissimilar situation faced between sexes. For male-headed households both in rural and urban communities at 5% and 50% quantiles the link is described by an inverted u-shaped curve. Differentiated effects for female-headed households among quantiles and type of community were found. In urban communities, the more weekly hours spent by the female-head, the lower income. At the 50% an effect described by a smooth decay linkage was found, this curve seems to be much more pronounced for households in the lowest income levels. The opposite effect was found in rural female-headed households in the 5% quantile, whose relationship is described by a slightly increasing line.

**Figure 1.** Expected value and 95% empirical bootstrap confidence intervals of Household-head education (left) and Perception on social networks (right)




* “low” if maximum complete primary education, “medium” if at least secondary education and a maximum of high school, “high”: at least university.

**Figure 2.** Expected value and 95% empirical bootstrap confidence intervals of Holding a credit card (left) and disability (right)

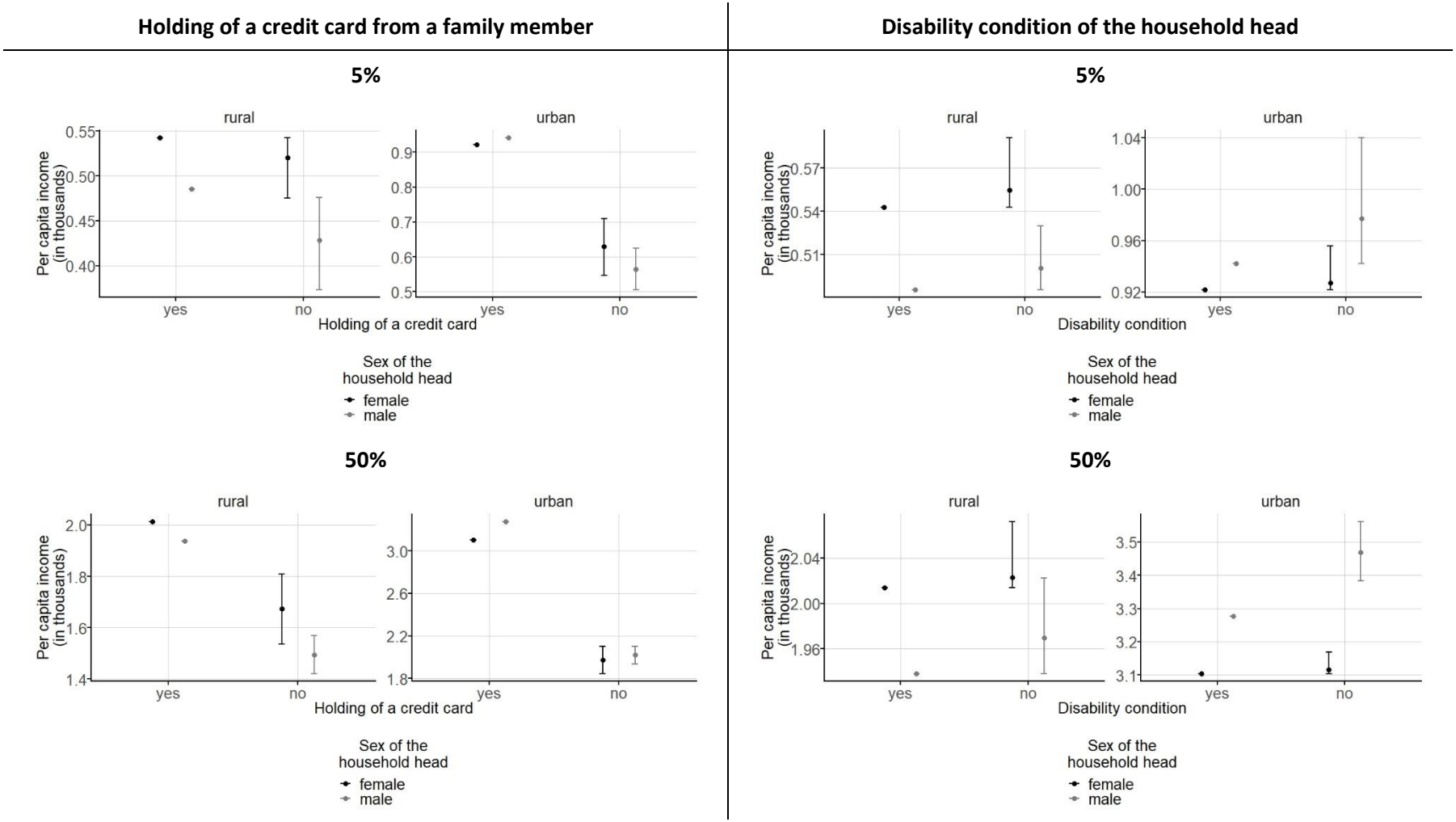


**Figure 3.** Expected value and 95% empirical bootstrap confidence intervals of Lack of access to food (left) and Social security (right)

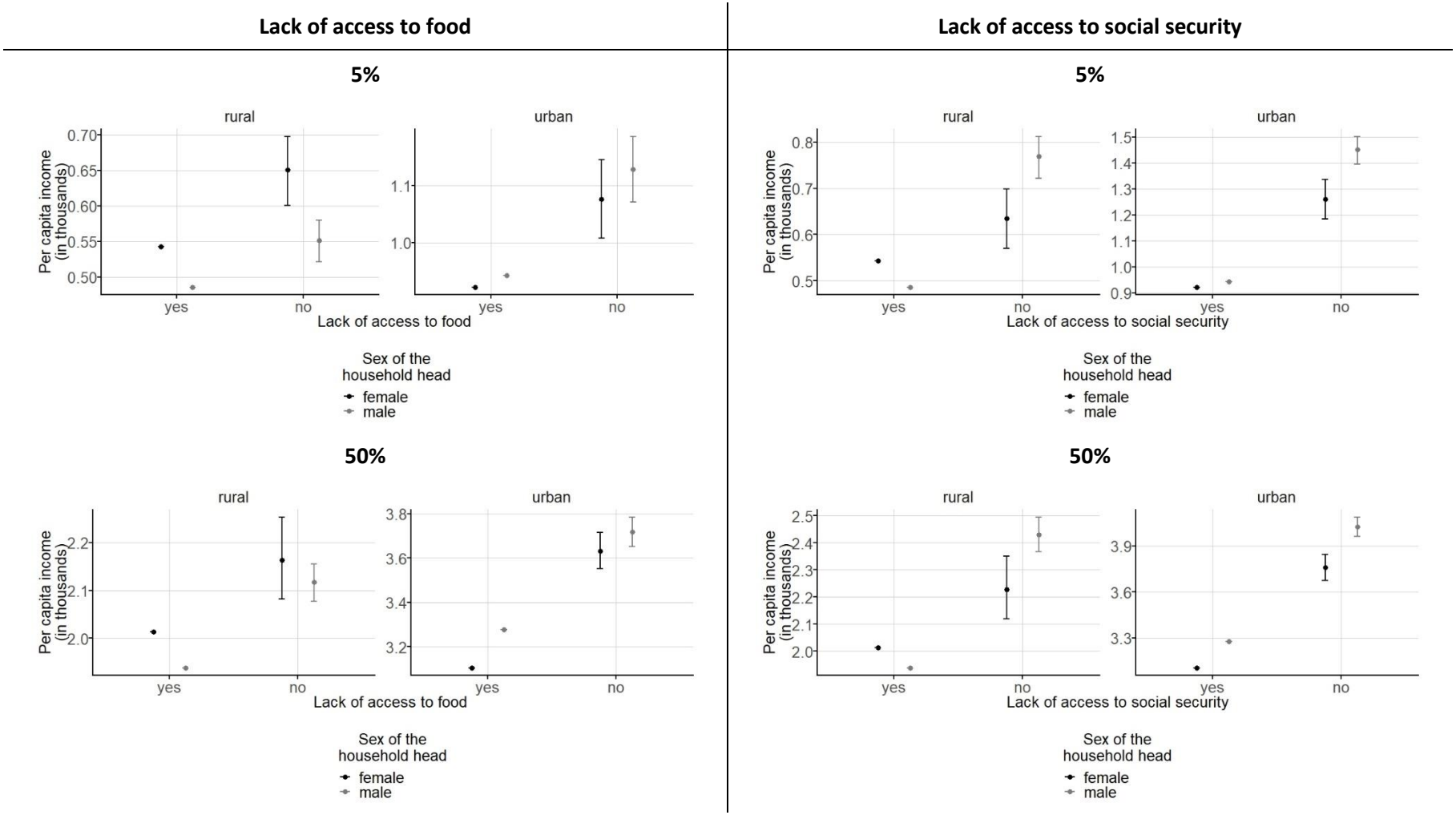
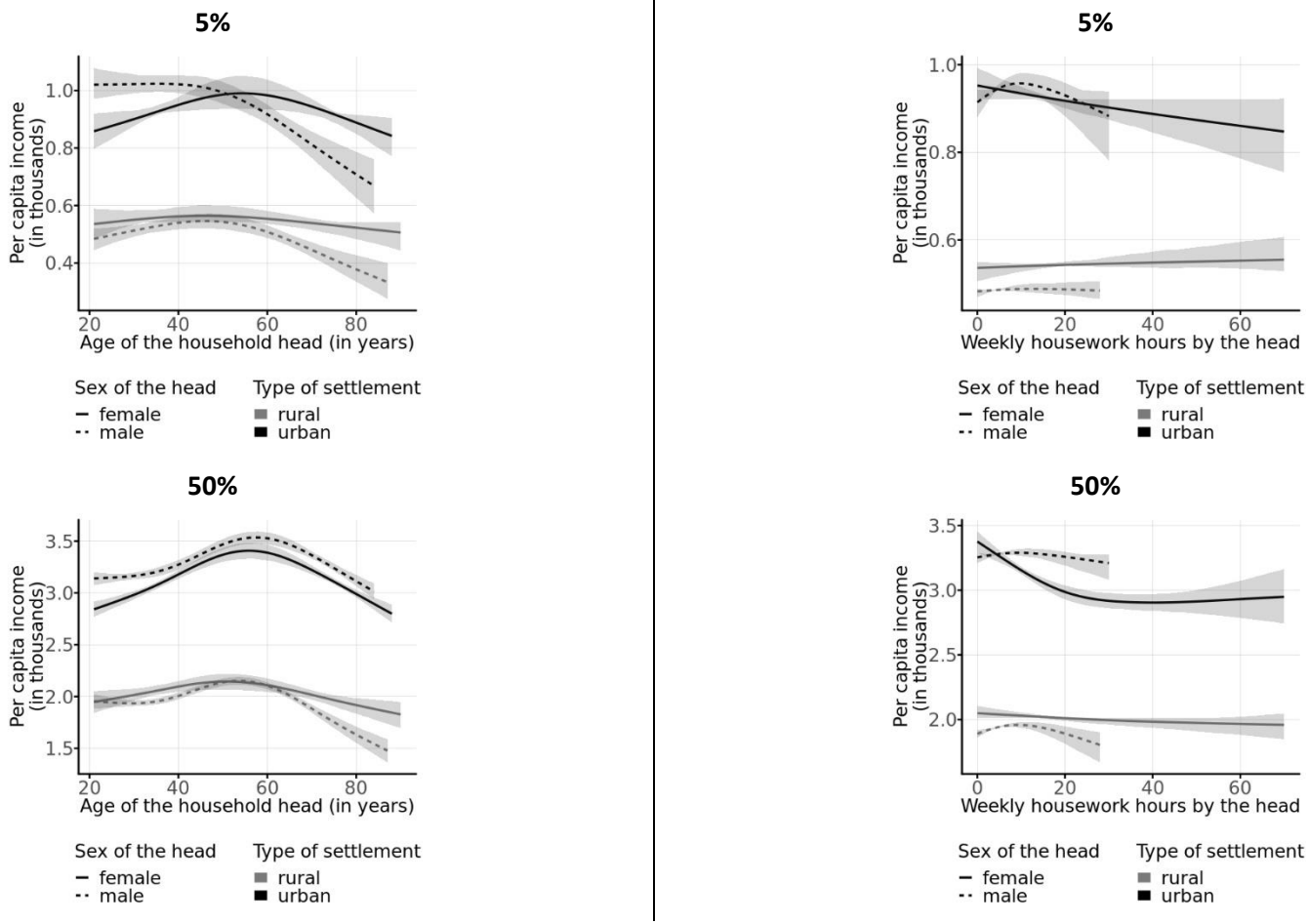


**Figure 4.** Expected value and 95% empirical bootstrap confidence intervals of Household head's age (left) and Household head's housework (right)

| Age in years of the household head | Time spent by the household head for undertaking housework per week |
|---|---|



Concerning the selected effects of characteristics of the community (Figure 5), it was found that the municipal human development index is positively associated with income and it comparably improves both female- and male-headed households (Figure 5, left). This effect is particularly larger in urban communities. Similarly, another consistent relationship was found with the Gini index (Figure 5, center). Households in more unequal communities tend to exhibit lower income levels. At the median of income gender differences are observed. In comparison to female-headed households, male-headed households tend to show higher income levels in more equal urban settlements. On the other hand, the opposite is found in more equal rural communities, female-headed households show a higher income than households headed by a male. Moreover, it is worth to mention the effect of the share of females economically active on income (Figure 5, right). As more females incorporate in the economy not only female-headed households show a higher income level, but also male-headed households. This finding may reinforce the idea that economic empowerment of women matters for pro-poor income policies.

**Figure 5.** Expected value and 95% empirical bootstrap confidence intervals of selected estimated effects at the community level: Human development (left), inequality (center) and female participation (right)

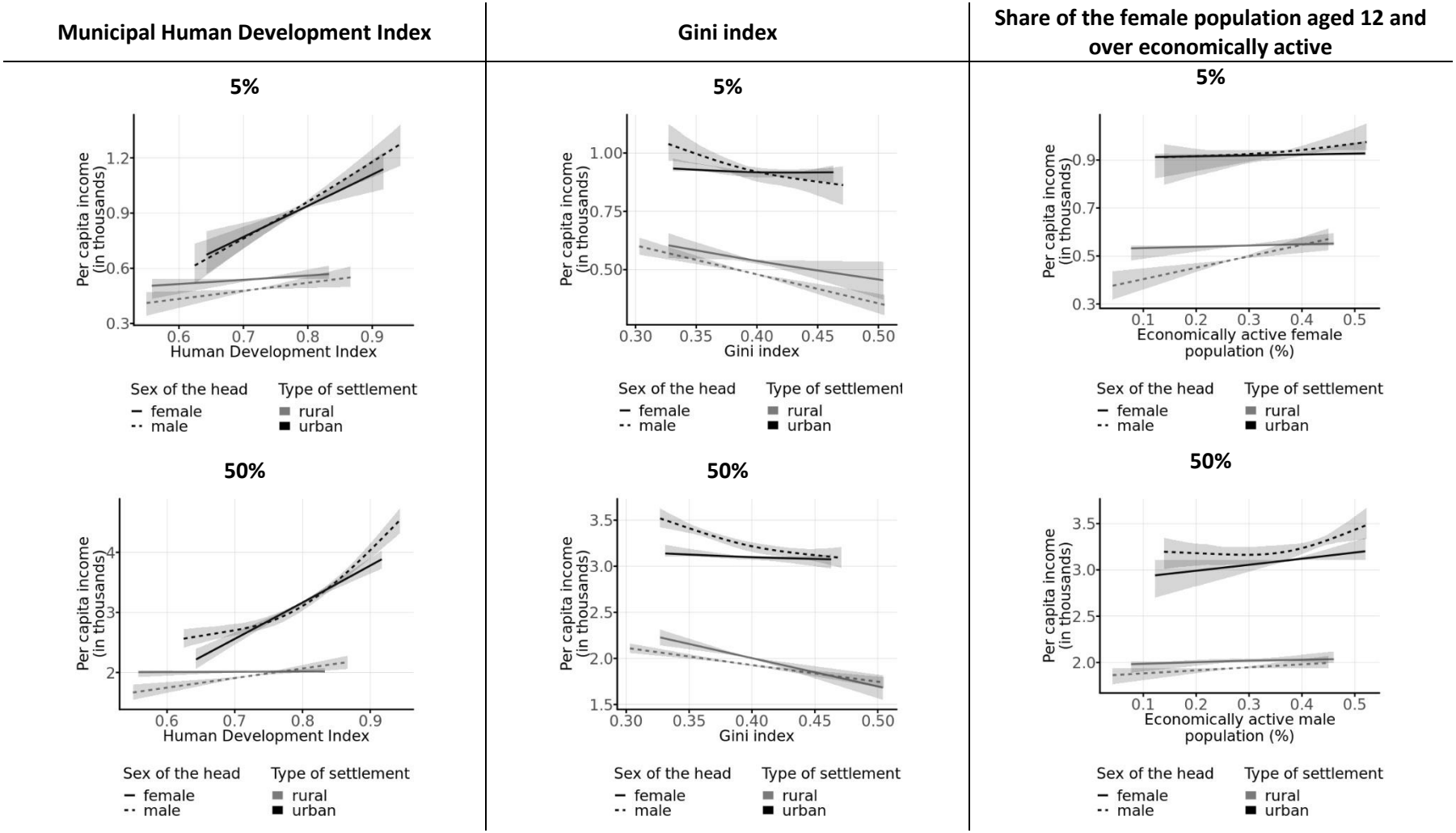
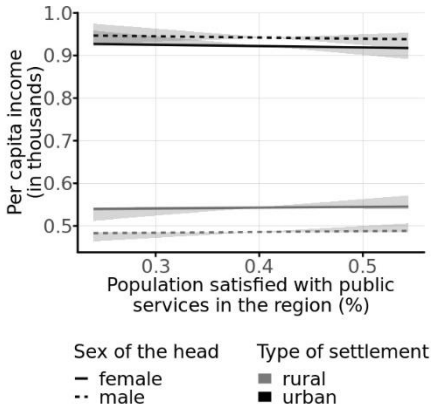
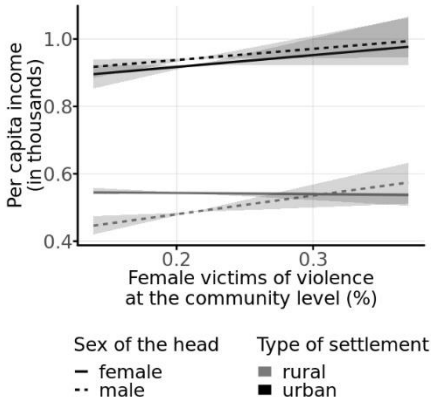
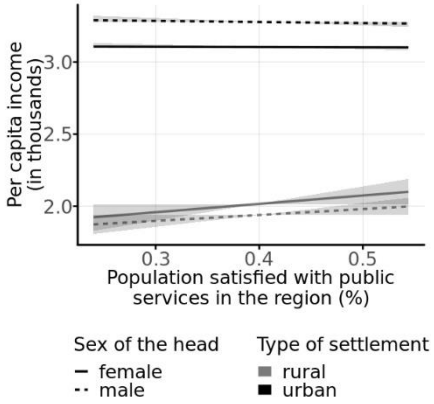
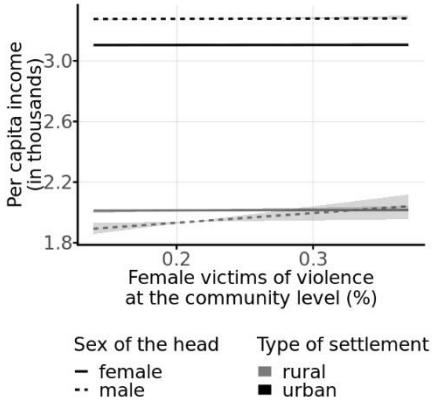


Figure 6 shows the findings from selected effects of variables at the regional level. There is a positive relationship between share of the population satisfied with public services and income in rural communities for households in the 50% quantile (Figure 6, left), which highlights the idea that income poverty can be related to the quality of the public provision of services and goods. There seems to be almost no effect for households in the 5% income quantile and those in the median of income in urban communities.

Similarly, another key result on gender issues was found regarding the linkage between violence against females and income (Figure 6, right). An increase in the percentage of women victims of violence in the community is associated to higher income levels in male-headed households in the 5% quantile living in urban and rural communities, and rural male-headed households in the 50% quantile. This could be indicating that the higher income of male-headed households increases the domination of females by males, including manifestations of violence. It is important to notice that results show correlations, but causality cannot be clearly established. A somewhat controversial result was found in the case of urban female-headed households in the 5% quantile, in which income seems to be positively associated to higher shares of female victims of violence in the community. As before, this could show reverse causality. It is well known that violence is mainly perpetrated by family members and partners (UNODC, 2019). Then, it could be that higher income per capita in female-headed households fosters women' empowerment and hence generates more gender violence by increasing female's risks from an additional source of violence, victimization from people outside the family and partners. Another potential explanation could be that despite this greater economic empowerment of women, in these societies obstacles to gender equality conditions still persist in other spheres of public life, such as stereotypes and traditional gender roles, that are manifested in acts of violence against females in the community. A more detailed analysis on this matter should be desirable, however it is outside the scope of this paper.

**Figure 6.** Expected value and 95% empirical bootstrap confidence intervals of selected estimated effects at the regional level: Satisfaction with public services (links) and females' victims of violence at the community level (right)

| Share of the population aged 18 and over who are satisfied with the basic and on-demand public services | Share of the female population aged 15 and over who were victims of violence at the community level |
|---|---|
| **5%** | **5%** |
|  |  |
| **50%** | **50%** |
|  |  |

Finally, space also seems to significantly contribute to explain income poverty. Spatial patterns vary across income quantiles, sex of the household-head and type of community, as shown in figures 7 and 8. On one hand, Figure 7 shows that for female-headed households both in rural and urban communities, extreme poverty -5% quantile- was mainly located in southwest and northwest Mexico. For the median, lowest income levels for rural female-headed households were concentrated in southwest and both in southwest and northwest for urban settlements. On the other hand, for male-headed households, as shown in Figure 8, spatial patterns are less consistent. While the lowest income levels for extreme poor households in rural communities are observed in west, central and southwest Mexico, for the median in rural communities, lower income is found in northern central and east regions and in southwest for urban settlements. At the 5% quantile, for the households in urban regions there is no clear spatial pattern. In female-headed households at any income quantile, higher income levels were mainly shown in southeast and northeast Mexico. When comparing to male-headed households, highest levels of income were observed in southeast and northwest of the country.

**Figure 7.** Expected value and 95% empirical bootstrap confidence intervals of selected spatial effects in female-headed households

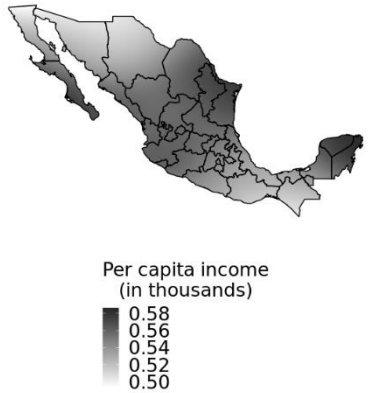
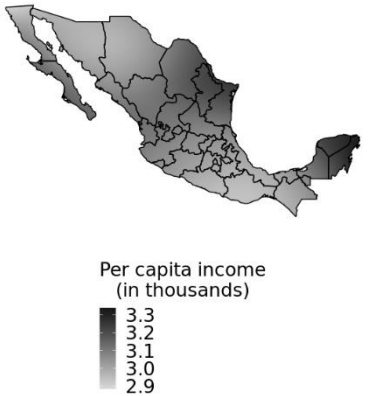
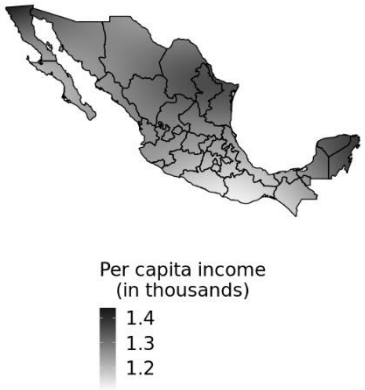
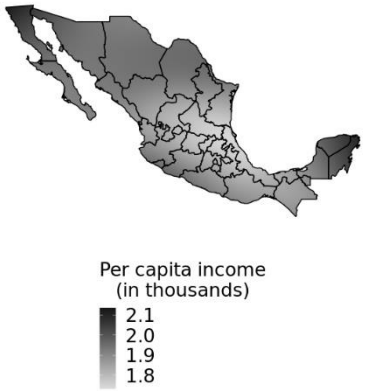
| Spatial effects of income in female-headed households in rural communities | Spatial effects of income in female-headed households in urban communities |
|---|---|
| **5%** | **5%** |
|  | |
| **50%** | **50%** |
| |  |

**Figure 8.** Expected value and 95% empirical bootstrap confidence intervals of selected spatial effects in male-headed households

| Spatial effects of income in male-headed households in rural communities | Spatial effects of income in male-headed households in urban communities |
|---|---|
| **5%** | **5%** |
| |  |
| **50%** | **50%** |
|  | |

## 5. Conclusions

In this paper, aiming at investigating the determinants of extreme income poverty, twelve different quantile models have been estimated. These models are used to identify how and to what extent a set of covariates have different impacts on female- and male-headed households in rural and urban settlements according to their per capita household income level.

From a methodological point, by using the boosting method it was possible to identify both the significance of each covariate and their functional form. The results confirm the importance of introducing data-driven methods into the study of complex social problems with multiple causes, such as poverty. Findings also emphasize the significance of moving out of the traditional linear models and considering nonparametric approaches.

By using variable selection and model choice, it was possible to consistently find patterns across different income quantiles both for rural and urban female- and male-headed households. Moreover, it was also found that analyzing poverty from a multilevel approach is key for determining the factors that affect poverty at the individual, community and regional level. By estimating specific models both by sex of the household-head and type of settlement, results allowed us to identify specific issues related to income poverty faced by women and men household-heads, and to what extent living in a rural or urban community makes a significant difference. In addition, by using a quantile model, it was not only possible to identify how the covariates are associated to the median income of the population, but also, how these variables are unequally linked to different poverty levels, especially to those households facing extreme poverty. The differential impact is particularly evident when analyzing the effects of education level, perception of social networks, age, weekly hours of housework, inequality, economic participation of women, quality of public services, violence against females and spatial effects.

The obtained results are also relevant for public policy purposes. Significant covariates point out the importance of targeting pro-poor policies with a gender perspective, and promoting in

consequence, associated factors such as social cohesion, education, access of females to a violence-free life, and economic empowerment of women.

The main limitation of our results is that the models provide estimated correlations between the covariates used and income, which do not necessarily imply causality, in particular, for independent variables that could be endogenously determined. A second limitation regards the fact that the analysis is done for a single year and hence we leave for further research an analysis including other points in time to investigate the dynamics of poverty in Mexico. We leave for further research the analysis of endogeneity issues and the dynamics of poverty in Mexico.

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