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ORIGINAL ARTICLE

Geography of Income and Education Inequalities in Mexico: Evidence from Small Area Estimation and Exploratory Spatial Analysis

Matthieu Clément[1] · **Lucie Piaser**[1]

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Abstract
This article examines the spatial distribution of income and education inequalities and their association in Mexico, focusing on the municipal level. We rely on a small area estimation methodology to construct measures of income inequality that are representative at the municipal level. We also construct variables accounting for education inequality. Based on these variables and on an exploratory spatial analysis, we emphasize a negative association between income and education inequalities, particularly salient among the poor and ethnically diverse municipalities from the southern states such as Oaxaca. Moreover, results from spatial econometrics analyses reveal the existence a U-inverted association between these two types of inequalities. Our results are discussed in relation to education returns, employment opportunities and migration.

Keywords Income inequality · Education inequality · Ethnic diversity · Small area estimation · Exploratory spatial analysis · Mexico

JEL Classification O15 · O54 · D31 · I24

Résumé
Cet article analyse la distribution spatiale des inégalités de revenu et d'éducation ainsi que leur association à l'échelle des municipalités du Mexique. Nous mobilisons les méthodes de small area estimation afin de construire des mesures d'inégalité de revenu représentatives à l'échelle municipale. Nous construisons également une mesure d'inégalité d'éducation. A partir de ces variables et d'une analyse spatiale exploratoire, nous mettons en évidence une association négative entre les inégali-

✉ Matthieu Clément
matthieu.clement@u-bordeaux.fr

Lucie Piaser
lucie.piaser@u-bordeaux.fr

1 GREThA (CNRS), University of Bordeaux, Avenue Léon Duguit, 33608 Pessac Cedex, France

tés de revenu et d’éducation, particulièrement marquée dans les municipalités pauvres et ethniquement fragmentées des états du sud. De plus, l’estimation de modèles d’économétrie spatiale révèle l’existence d’une association en U-inversé entre ces deux types d’inégalités. Nos résultats sont discutés en relation avec les questions de rendements d’éducation, d’opportunités d’emploi et de migration.

Introduction

In common with most Latin American countries, Mexico has historically been known for being highly unequal.[1] However, after a surge during the “lost decade” (from the mid-1980s to the mid-1990s), the trend reversed. Between 2000 and 2010, the Gini index declined at an annual pace of 1.16% (Lustig et al. 2013). Some main determinants of this drop are commonly identified, such as increasing incomes among the least qualified workers, the implementation of the North American Free Trade Agreement (NAFTA) and the improved education system (e.g. Esquivel 2011; Lustig et al. 2013). The role of remittances and social transfers such as *Progresa-Oportunidades-Prospera* has also been discussed but remains unclear (Lustig et al. 2013; Campos et al. 2014). The most recent estimates show that income inequality increased in the period 2010–2014 before declining again (Lambert and Park 2019). Yet, Mexico still exhibits a high level of inequality with the fourth highest Gini index among OECD members of 0.458 in 2016 (OECD 2021, Income inequality indicator).

The dynamics of education inequality are also of particular interest. As documented by Legovini et al. (2005) and Gasparini and Lustig (2011), educational upgrading has occurred from the 1980s and has resulted in a decrease in education inequality, with the Gini index for the numbers of years of schooling declining from 0.42 to 0.37. It is interesting to note that the drop in education inequality occurred prior to the decline of income inequality. Nevertheless, improvement in education provision should not minimize other issues such as learning proficiency and high school completion (El Colegio de México 2018).

One of the most distinctive features of inequalities in Mexico is its geographical dimensions. From this perspective, an extensive literature addresses the spatial disparities in terms of mean income, monetary poverty or non-monetary dimensions of socio-economic development (Carrion-I-Silvestre and German-Soto 2007; Barbary 2015; OECD 2015; Bebbington et al. 2016; CONEVAL 2018; Mendoza-Velázquez et al. 2019). Broadly speaking, these studies emphasize that the southern states (Guerrero, Oaxaca, Chiapas, Puebla and, to a lesser extent, states of the Yucatan region) form an enclave of poverty, whereas Mexican-US border states or

[1] As argued by Gasparini (2003, pp. 53–54), the empirical literature “unambiguously suggests that Latin America is the region with the highest levels of inequality in the world, and that this has been true for as long as statistics have been kept”. Focusing more specifically on the Mexican case, Corbacho and Schwartz (2002) explain that income inequality in Mexico is significantly higher than the Latin American average.

the Mexico metropolis exhibit significantly better development outcomes. Studies focusing on municipalities confirm these conclusions and also identify additional pockets of poverty (CONEVAL 2018; Barbary 2015). The existence of such 'territorial poverty traps' (Bebbington et al. 2016) results from spatially differentiated development patterns as documented, for instance, by Rodríguez-Orregia (2005). Ethnicity has also been identified as a crucial issue in the explanation of spatial socio-economic disparities, the least-developed areas being those with the highest prevalence of indigenous groups (e.g. Barbary 2015; CONEVAL 2018).[2]

While this literature provides precious evidence on spatial disparities in socio-economic development, another strand of literature addresses inequalities within states or municipalities. For instance, Lambert and Park (2019) find that income inequality within states has a greater contribution to national inequality than inequality between states. Estimates from the National Council for the Evaluation of Social Development Policy (*Consejo Nacional de Evaluación de la Política de Desarrollo Social*, CONEVAL) show that in 2018 income inequality reaches its highest level in Mexico City (with a Gini index of 0.53) and, to a lesser extent, in the southern states of Oaxaca (0.49), Chiapas and Guerrero (0.48).[3] Studies focusing on intra-municipal income inequality using inequality mapping methods are also of interest and provide different evidence (Székely et al. 2007; Yúnez et al. 2009; Modrego and Berdegué 2015). They show that income inequality within municipalities does not exhibit a clear geographical pattern. However, we can note that inequality appears to be smaller and relatively homogenous in Oaxaca and greater in Sonora, a border region with the U.S. (Yúnez et al. 2009). Put differently, this indicates that municipalities with a high prevalence of indigenous people and low socio-economic outcomes (like in Oaxaca) are not necessarily the most unequal. The empirical literature focusing on education inequality, though less extensive, also provides some interesting facts. Favila-Tello and Navarro-Chávez (2017) provide estimates of education Gini at the state level. Contrary to results on income inequality, this study shows that the highest levels of education inequality are observed in the relatively poor states of Chiapas, Guerrero and Oaxaca. Esposito and Villaseñor (2018) tell the same story by focusing on the municipal level. This could give evidence of a relative disconnection between education and income inequalities.

The empirical literature mostly exhibits a positive association between these two types of inequalities at the country level. However, the relationship is highly complex and may exhibit a U-inverted shape because of increasing returns to education as for Latin America. To our knowledge, no study providing comparative evidence at such a disaggregated level of analysis has been published. This article aims to fill

[2] According to Barbary (2015), the indigenous populations are primarily located in the most remote areas (which impedes their access to productive resources) and have not benefited from migration dynamics to improve their living conditions.

[3] Data available at: http://dgeiawf.semarnat.gob.mx:8080/ibi_apps/WFServlet?IBIF_ex=D1_POBREZA00_27&IBIC_user=dgeia_mce&IBIC_pass=dgeia_mce&NOMBREENTIDAD=*&NOMBREANIO=*.

this gap by providing an extensive investigation of the association between income and education inequalities at the municipal level in Mexico.

More specifically, this article has two purposes. First we construct measures of income and education inequalities that are representative at the municipal level. For income inequality measures, we rely on small area estimation (SAE) and combine data from the 2015 inter-census survey (*Encuesta Intercensal*, EIC) and the 2016 National Survey of Household Income and Expenditure (*Encuesta Nacional de Ingresos y Gastos de Hogares*, ENIGH). We also consider alternative estimates of income inequality provided by the CONEVAL. Second, to examine the association between income and education inequalities for Mexican municipalities, we adopt a three-step approach combining (i) cartographic evidence, (ii) tests for global and local spatial autocorrelation and (iii) multivariate analyses based on spatial econometrics. Our objective is not to provide a causal analysis but instead to develop an exploratory spatial analysis.

Our empirical investigations emphasize the complexity of the relationship between income inequality and education inequalities in Mexico. First, the exploratory spatial analysis provides evidence of a negative association between both types of inequalities, particularly salient among the poor and ethnically diverse municipalities from the southern states such as Oaxaca. Second, results from spatial econometrics analyses reveal the existence a U-inverted association between these two types of inequalities. We discuss our findings in relation to the potential factors that could explain this disconnection: returns to education, employment opportunities and migration.

The article is structured as follows. "Literature Review" section is devoted to the literature review on the relationship between income and education inequalities. The data and the construction of inequality measures are described in "Data and Variables" section. "Results" section presents our results, while "Discussion and conclusion" section discusses our main findings and concludes.

Literature Review

The influence of schooling disparities on income inequality fits in two theoretical corpuses analysing the effect of increased educational attainment on income disparity. Human capital models of earnings (e.g. Mincer 1974) predict a positive association between education and income inequalities as wage differences are the result of an unequal distribution of human capital (schooling and experience). Knight and Sabot (1983) highlighted a more complex association, with two opposing forces at play. As education expands, the share of highly educated workers in the labour force increases, rising, at least initially, wages inequality (composition effect). However, the increased supply of skilled workers lowers premium to higher education, decreasing subsequently income inequality (compression effect).

From an empirical perspective, pioneer studies using cross-country data (Chiswick 1971; Winegarden 1979) emphasize that earnings inequality increases with educational disparities but were subject to much criticism (Ram 1984). More recently, similar results are obtained using macro panel data, giving further support to the human capital theory (De Gregorio and Lee 2002; Rodríguez-Pose and Tselios 2009).

However, the relationship between education, earnings, schooling disparities and income inequality is complex as it depends on highly interrelated mechanisms. Indeed, the effect of average level of schooling on education disparities may be non-linear and exhibit a U-inverted shape in developing countries (Lam 2020) and the effect of an increase in education levels on income inequality depends on the evolution of the skill premium. Using a dataset for 146 countries, Castelló-Climent and Domenech (2014) find that even if education disparities decreased from 1950 to 2010, allowing a reduction of income inequality, this equalizing effect has been offset by increasing returns to education and exogenous forces such as skill-based technological changes and globalization. Besides, the effect of schooling inequality on income inequality is not stable across the different levels of development, some studies finding a large and positive association in emerging and developing economies (Coady and Dizioli 2018) and others only in OECD countries (Földvari and Leeuwen 2011).

In the specific Latin American context, the empirical literature has emphasized a disconnection between income and education inequalities that is often referred to the “paradox of progress” (Bourguignon et al. 2005). This paradox stipulates that a more equal distribution of the years of schooling (linked to the expansion of education) may have a short-run disequalizing effect on the distribution of earnings, due to the convexity of the returns to education (i.e. the returns increase proportionally more for higher levels of schooling) (Bourguignon et al. 2005). This suggests that the relationship between education inequality and income inequality may exhibit a U-inverted shape (Gasparini and Lustig 2011). Battistón et al. (2014) provide evidence for this paradox for Latin America during the 1990s and 2000s. Legovini et al. (2005) more specifically observed this phenomenon for Mexico from 1984 to 1994 through a microsimulation model. Yet, other authors emphasize that the trend reversed since the 2000s, the reduction in schooling inequality has an equalizing effect on the earning distribution thanks to a fall of the skill premium (Lustig et al. 2013; Lam et al. 2015).

Although this literature provides interesting evidence at the country level, empirical studies analysing the association between educational and income inequalities at a more disaggregated spatial scale are clearly lacking.

Data and Variables

Analysing the spatial distribution of intra-municipal inequality raises some important methodological issues. Ideally, census data should be privileged to measure inequality at the municipal level insofar as it ensures the representativeness at the municipal scale. This could be done for education inequality since information on educational attainment is available. However, censuses are not adapted for the measurement of income inequality because of the absence of income data collection. Household surveys are better suited as they give accurate information on household income and its components. However, they fail to be representative at a disaggregated level such as municipalities. This is the reason why, in line with the pioneering work of Elbers, Lanjouw and Lanjouw (2003) (ELL), several studies have applied small area estimations (SAE) techniques to measure income inequality among Mexican municipalities (e.g. Székely et al. 2007; Yúnez et al. 2009; CONEVAL 2017). The main objective of small area estimation is to combine census and survey data to simulate representative inequality measures at a spatially disaggregated level. In this article, we provide our own estimates of income inequality in Mexican municipalities based on SAE.

Our primary data source is the 2015 EIC survey implemented by the National Institute of Statistics and Geography (*Instituto Nacional de Estadística y Geografia*, INEGI) with the objective of updating the socio-demographic information between the 2010 census and the one to be carried out in 2020. This survey covers 6.1 million households (more than 22 million individuals) and is representative at the national, state and municipal levels. It provides basic information on households' assets, housing, education, ethnicity, health, etc. However, this survey fails to collect accurate data on household income. This is the reason why we also use the 2016 ENIGH survey from INEGI, which covers more than 70,000 households and provides precise information on household income and its different components.

We adopt the standard approach developed by ELL because of its multiple implementations for poverty mapping, especially by practitioners from the World Bank (e.g. Elbers et al. 2008; World Bank 2010, 2015). This methodology consists of a two-step procedure. The first step of the ELL methodology estimates a welfare model (called the Beta model) based on household survey data (ENIGH data in our case) following Eq. (1):

$$\ln Y_{\mathrm{hm}} = X_{\mathrm{hm}}\beta + \eta_{\mathrm{m}} + \varepsilon_{\mathrm{hm}}, \quad (1)$$

where Y_{hm} is the per capita income of household h in municipality m and X_{hm} are income predictors that must be available and comparable in both the household survey and the census. The error terms η_{m} and $\varepsilon_{\mathrm{hm}}$ represent unexplained variation at municipality and household levels, respectively, and are treated as random effects. This specific structure of the error component explains why model (1) is estimated using Generalized Least Squares (GLS). Two additional elements are important components when estimating the welfare model. First, in addition to household-level variables, ELL recommends including municipal-level variables as covariates to account for heterogeneity between municipalities. Second, in the ELL specification, the household-specific error component $\widehat{\varepsilon_{\mathrm{hm}}}$ is assumed to be heteroscedastic (i.e. to vary between households). The ELL strategy for modelling heteroscedasticity consists of estimating a model explaining the squared predicted household-level residuals by household-level and municipality-level characteristics through a parametric logistic transformation (called the Alpha model).

In the second step of the methodology, the parameter estimates from Eq. (1) are applied to census data (EIC data in our case) in order to predict income for all households and then to estimate welfare indicators (inequality indices in this study). More precisely, a series of k Monte Carlo simulations (usually around one hundred) are implemented. In each simulation, a set of values $\hat{\beta}$, $\widehat{\eta_{\mathrm{m}}}$ and $\widehat{\varepsilon_{\mathrm{hm}}}$ are drawn from their estimated distributions and an estimate of income and inequality indices is produced. After k simulations, we can calculate the average income and inequality indices that can be treated as representative at the municipal level.

The numerous applications of SAE methods provide practical guidelines for constructing the first-stage model. One important issue is that variables are comparable between the survey and the census (both in their definition and in their distribution). Among comparable variables, it is necessary to include a large set of predictors with characteristics for the head of household (age, sex, employment, education) and the household (assets, housing, demographic composition, employment, education, migration, etc.). In addition, ELL recommend the inclusion of municipal-level variables (aggregated means from census data, for instance) in order to reduce the magnitude of the unexplained municipal-level component of the error term η_{m}. Two additional requirements for maximizing the accuracy and robustness of the welfare model emerge from the different SAE applications. First, Tarozzi and Deaton (2009) and Krenzke et al. (2018) suggest taking into account the quadratic functions of quantitative variables. Thus, the squares of all quantitative explanatory variables are included as additional covariates. Second, in order to maximize the explanatory power of the welfare model, many SAE practitioners recommend including interaction terms (e.g. Fuji 2010; Krenzke et al. 2018) and particularly spatial varying interaction terms (e.g. Haslett and Jones 2008; Whitworth 2013). This is the reason why we include several interactions of household-level variables with the urban/rural dummy variable (the choice of the final set of interaction variables depending on their significance). The expression of our welfare model is given by the following equation:

$$\ln Y_{\mathrm{hm}} = \beta_0 + \mathrm{HHC}_{\mathrm{hm}}\beta_1 + \mathrm{HC}_{\mathrm{hm}}\beta_2 + \mathrm{INT}_{\mathrm{hm}}\beta_3 + \mathrm{MC}_{\mathrm{m}}\beta_4 + \eta_{\mathrm{m}} + \varepsilon_{\mathrm{hm}}, \tag{2}$$

where $\mathrm{HHC}_{\mathrm{hm}}$, $\mathrm{HC}_{\mathrm{hm}}$, $\mathrm{INT}_{\mathrm{hm}}$ and MC_{m} are, respectively, household head's characteristics, household's characteristics, interactive terms and municipality's characteristics. The final set of variables included in the income model has been determined by a stepwise procedure and ex-post diagnostics. More precisely, we set the model specification in such a way as to maximize the number of significant variables, to maximize the adjusted R-squared and to minimize the variance in the municipal component of the error term η_{m}. Our SAE estimates also include an heteroscedasticity model (Alpha model) in which residuals predicted from the income model are regressed on all the explanatory variables.

In Table 1, GLS estimates for the logarithm of monthly per capita household income are reported. Following the above-described procedure, more than forty explanatory variables have been included. The estimates perform to a highly competitive extent with an adjusted R-squared close to 0.60 and with the variance of η_{m} being residual (less than 0.015).[4] It is also worth noting that heteroscedasticity is

[4] As explained by Haslett and Jones (2008), in the successful applications of ELL method, the R-squared value of the welfare model tends to be about 0.50 or higher. Our examination of numerous SAE implementations reveals that most of them are based on a welfare model with an adjusted R-squared between 0.5 and 0.7 (e.g. Cuong et al. 2010; World Bank 2015). Moreover, Haslett and Jones (2008) also explain that the variance of the municipal-level component of the error term η_m should be as small as possible. Many SAE applications are based on welfare models with a variance lower than 0.05.

Table 1 Income model for small area estimation (GLS estimates)

Variables	Coefficient	Robust z-statistics	*p* value
Constant	8.0757***	184.34	0.000
Household head characteristics			
Male	− 0.0093	− 1.54	0.124
Age	− 0.0043***	− 6.05	0.000
Age squared	0.00005***	8.92	0.000
Indigenous (self-description)	− 0.0142***	− 3.24	0.001
Literate	0.0610***	8.39	0.000
Secondary education or higher	0.0188***	2.68	0.007
In a couple	0.0164**	2.56	0.010
Household characteristics			
Urban	0.1265***	10.00	0.000
Migration (= 1 for households whose head lived in another municipality in 2010)	0.0509***	4.98	0.000
Household size	− 0.3053***	− 63.38	0.000
Household size squared	0.0189***	45.34	0.000
Proportion of male	− 0.4073***	− 13.58	0.000
Proportion of male squared	0.5153***	17.15	0.000
Proportion of children (11 y.o. or less)	− 0.0606*	− 1.91	0.056
Proportion of children squared	− 0.2857***	− 5.28	0.000
Proportion of hh members (15 y.o or more) with at least secondary education	0.1791***	8.41	0.000
Proportion of hh members with at least secondary education squared	0.0259	1.30	0.193
Employment rate (for 12–65 y.o. members)	0.3805***	14.43	0.000
Employment rate squared	0.0692***	2.84	0.005
Number of rooms per capita	0.0244***	4.94	0.000
Number of rooms per capita squared	0.0055***	9.74	0.000

Table 1 (continued)

Variables	Coefficient	Robust z-statistics	*p* value
HH with access to piped water into dwelling	0.0529***	10.22	0.000
HH with access to piped sewer system	0.0336***	5.78	0.000
HH equipped with a car	0.1498***	21.07	0.000
HH equipped with a mobile phone	0.1228***	15.50	0.000
HH equipped with a computer	0.1823***	32.28	0.000
HH with access to the internet	0.1579***	12.34	0.000
HH equipped with a washing machine	0.0668***	14.60	0.000
HH equipped with a refrigerator	0.0519***	8.31	0.000
HH equipped with a flat screen tv	0.0695***	17.07	0.000
HH with access to pay tv	0.1355***	33.60	0.000
Interaction terms			
Urban * household size	− 0.0150***	− 6.97	0.000
Urban * internet	− 0.0329**	− 2.44	0.015
Urban * mobile phone	− 0.0348***	− 3.31	0.001
Urban * car	0.0777***	9.15	0.000
Municipal controls			
Municipal employment rate	0.9586***	10.80	0.000
Municipal secondary education rate	0.2569***	3.94	0.000
Municipal migration rate	0.3522***	4.98	0.000
Municipal car equipment rate	0.2543***	7.19	0.000
Municipal computer equipment rate	0.2026***	2.61	0.009
N	69,078		

Table 1 (continued)

Variables	Coefficient	Robust z-statistics	p value
Adjusted R^2 (Beta model)	0.583		
Adjusted R^2 (Alpha model)	0.015		
Sigma eta squared	0.013		
Variance of epsilon	0.270		

Level of statistical significance: 1%***, 5%** and 10%*

Source Authors' calculations based on ENIGH data found to be negligible ($R^2 < 0.02$ in the Alpha model). The parameter estimates from this model are then applied to EIC data through 100 Monte Carlo simulations. From these simulations, the mean per capita household income and the main measures of income inequality are calculated. We mainly use the Gini index[5] but we have also calculated the generalized entropy indices to test the robustness of our results in relation to alternative inequality measures.[6] Interestingly, CONEVAL has also proposed estimates of the municipal Gini index based on the 2015 EIC survey (CONEVAL 2017). Compared to its previous estimates for 2000 and 2010 that were based on the ELL approach, CONEVAL uses an updated SAE methodology, the empirical best predictor methodology assuming heteroscedasticity (EBPH). The latter is based on a linear random effects model to control for non-observable heterogeneity between municipalities and assumes that every household in every municipality has its own variance. It seems relevant to assess how these estimates match with our own estimates and to what extent their association to education inequality is similar or not.

Our measure of education inequality is the Gini index applied to the number of years of schooling available in the EIC survey. We calculate the education Gini for individuals aged over 15 and use a formula that allows for 0-values.

Lastly, we calculate an index of ethno-linguistic diversity based on information on the indigenous language spoken, as available from the EIC data (104 indigenous languages or dialects are identified). We use the popular index of ethnic fractionalization that is derived from the Herfindahl concentration index and known as the Ethno-Linguistic Fractionalization (ELF) index or the Generalized Variance (GV) index. This index, in its normalized form (Normalized Generalized Variance, NGV), can be expressed as follows (Budescu and Budescu 2012):

$$\mathrm{NGV} = \frac{C}{(C-1)}\left(1 - \sum_{i=1}^{C} P_i^2\right), \tag{3}$$

where P_i is the proportion of people who belong to the ethnic group i and C is the number of groups. NGV measures "the probability that two randomly selected individuals from a particular population belong to different subgroups (…). A high value (probability) reflects a higher degree of diversity" (Budescu and Budescu 2012, p. 217).

5 Our calculation of the Gini index is based on the following formula:

$$G = 1 + \frac{1}{n} - \frac{2}{\bar{y}\,n^2}\sum\nolimits_{i=1}^{n}(n+1-i)y_i$$

6 The class of entropy indices is defined with the following formula:

$$GE(\alpha) = \frac{1}{\alpha^2 - \alpha}\left(\frac{1}{n}\sum\nolimits_{i=1}^{n}\left(\frac{y_i}{\bar{y}}\right)^{\alpha} - 1\right)$$

The parameter represents the weight given to distances between incomes in different parts of the income distribution. For lower (higher) values of, GE() is more sensitive to income changes in the lower (upper) tail of the distribution. Using the most common values for (0, 1 and 2), three main indices can be derived: the mean log deviation GE(0), the Theil index GE(1) and half the squared coefficient of variation GE(2).

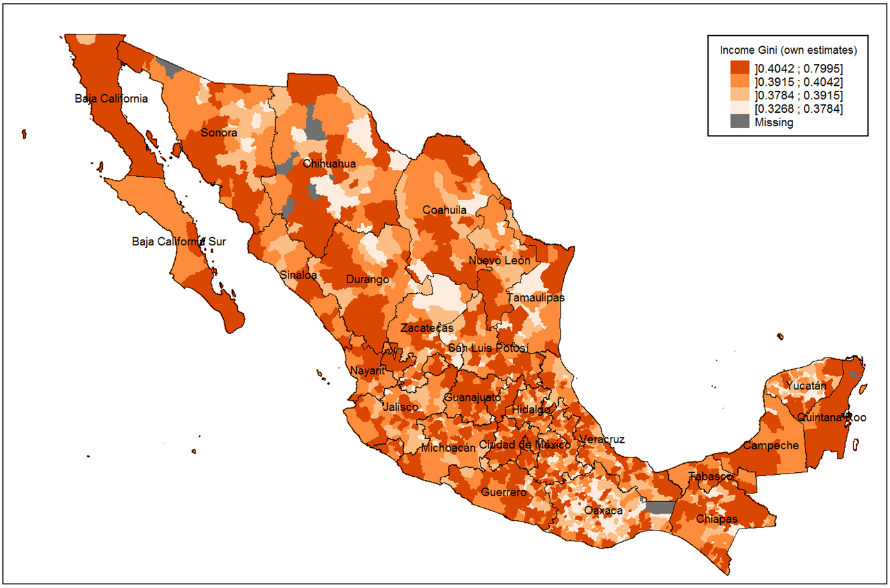

Fig. 1 Income Gini index (own estimates), 2015. *Source* Authors' calculations

Results

Cartographic Evidence

This cartographic evidence is based on Choropleth maps for our main variables of interest (Figs. 1 and 2 and 5, 6, 7, 8, and 9 in the Appendix). On each map, the four classes correspond to the quartiles of the considered variable across municipalities. In addition, the matrix of Spearman correlation coefficients for all of the variables considered in the empirical investigations is reported in Table 2.

Let us first examine the spatial distribution of intra-municipal income inequality. In Fig. 1, we report our own SAE estimates of the Gini index for the year 2015, while the SAE estimates proposed by the CONEVAL for the same year are presented in Fig. 5. Although the levels of inequality obtained from these two measures are potentially not strictly comparable because of the different implementations of SAE, the observation of these two maps calls for two comments. First, there is relative coherence between our estimates and CONEVAL's ones with regard to the spatial distribution of income inequality across Mexican municipalities (Spearman correlation coefficient equal to 0.48 and significant at 5% level). Second, as already emphasized by Yúnez et al. (2009), we cannot observe any clear geographical pattern in the distribution of income inequality. There are spatially dispersed 'pockets' of high income inequality without clear geographical rationale. Nevertheless, it should be noted that there is an obvious concentration of low levels of within-municipality income inequality in Oaxaca state and, to a lesser extent, in Yucatán state. The same diagnosis is emphasized with entropy indices, though it is less pronounced with the

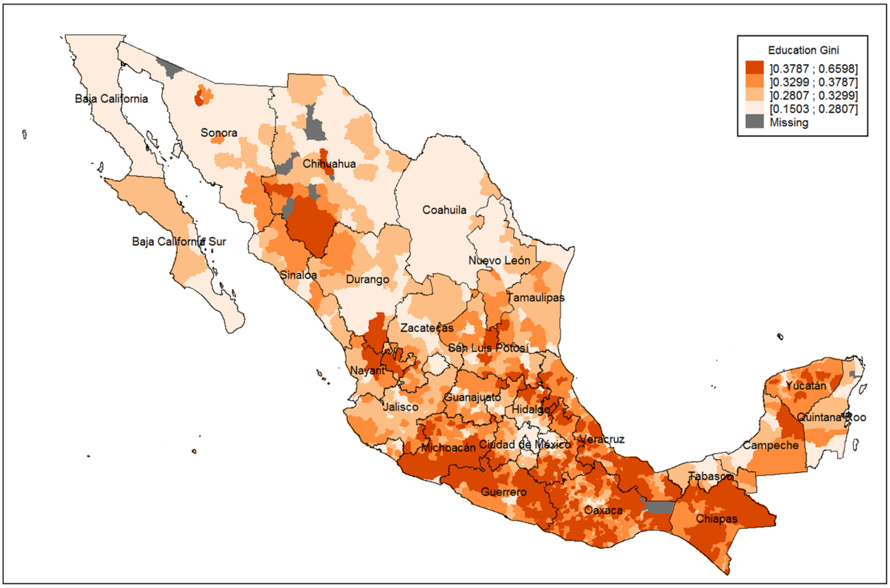

Fig. 2 Education Gini index, 2015. *Source* Authors' calculations

GE(2) index (results not reported, available upon request). With CONEVAL's measure, we also observe a concentration of low levels of income inequality in municipalities of the US-border northern states. This is less evident with our own estimates.

To go further in the comparison between these two estimates, Figs. 6 and 7 in the Appendix map the two Gini index based on population-weighted quartiles. Interesting differences are highlighted. With our own estimates, only a limited number of municipalities belong to the top population-weighted quartile. This means that the highest levels of income inequality are primarily observed in highly urbanized municipalities (e.g. Mexico City, Guadalajara or Monterrey). Conversely, low levels of income inequality are primarily observed in small municipalities (e.g. municipalities from Oaxaca State). The CONEVAL's measure classifies much more municipalities in the top population-weighted quartile indicating that the highest levels of income inequality are not necessarily concentrated in the biggest cities. This difference suggests that the choice of the SAE methodology is not neutral in the measurement of intra-municipal income inequality.

It seems interesting to compare the spatial distribution of income inequality with economic development and ethnic diversity, two features of spatial socio-economic disparities in Mexico. As shown in Table 2, our income inequality measures are strongly and positively correlated with the municipal average income level, while moderately and negatively correlated with ethnic fractionalization. The comparison of Fig. 1 with Fig. 8 (municipal average income) and Fig. 9 (ethno-linguistic fractionalization index) in the Appendix gives additional evidence. The situation of municipalities belonging to the Oaxaca state is particularly illustrative as we observe a combination of low (relative) degrees of income

Table 2 Spearman bivariate correlations

	Income Gini	Income Gini (CONEVAL)	GE(0)	GE(1)	GE(2)	Education Gini	Per capita household income	Years schooling	NGV
Income Gini	1								
Income Gini (CONEVAL)	0.4791*	1							
GE(0)	0.9986*	0.4790*	1						
GE(1)	0.9786*	0.4606*	0.9754*	1					
GE(2)	0.8854*	0.4094*	0.8769*	0.9539*	1				
Education Gini	− 0.3383*	0.0789*	− 0.3556*	− 0.2925*	− 0.1996*	1			
Per capita household income	0.5586*	0.1066*	0.5875*	0.4947*	0.3676*	− 0.7563*	1		
Years schooling	0.5296*	0.1207*	0.5441*	0.4654*	0.3479*	− 0.8622*	0.8720*	1	
NGV	− 0.1825*	0.0346	− 0.1909*	− 0.1659*	− 0.1345*	0.3379*	− 0.4485*	− 0.2980*	1

Level of statistical significance: 5%*

Source Author's calculations

inequality, poor economic outcomes and very high levels of ethnic diversity. The same is true in Yucatán state, though to a lesser extent. However, it is worth noting that the degrees of correlation are less pronounced with CONEVAL's measure of income inequality. We observe a small positive correlation with average income (+ 0.11, significant at 5% level) and a zero correlation with ethno-linguistic fractionalization.

The spatial distribution of education inequality tells a very different story. As shown in Fig. 2, there is a much more striking geographical pattern for the education Gini index than for the income Gini index. There is a concentration of high levels of education inequality among the poor and ethnically fragmented municipalities of the southern states of Chiapas, Oaxaca and Guerrero but also in the states of Michoacán, Veracruz and Puebla. We also observe additional clusters of high education inequality in the southern part of Chihuahua and in the border region between the states of Durango, Nayarit and Jalisco. On the contrary, the lowest levels of education inequality are observed among the most developed municipalities of the US-border northern states (Baja California, Sonora, Chihuahua, Coahuila and Nuevo Leon) and those located all around the federal district of Mexico. Put differently, this means that there is a strong negative association between education inequality and socio-economic development and a positive association between education inequality and ethnic diversity, as confirmed by Spearman correlation coefficients (Table 2).

This descriptive spatial analysis tends to suggest a negative correlation between income and education inequality, which is confirmed by Table 2. The Spearman coefficients between our measures of income inequality (Gini and entropy indices) and the education Gini are significant (at 5% level) and negative (Table 2). When CONEVAL's measure of income inequality is considered, we observe a very small positive correlation (+ 0.08, significant at 5% level) with the education Gini, thus indicating slight differences in the nature of the association related to the measure of income inequality taken into account. Table 5 in the Appendix which cross tabulates quartiles of income Gini (own estimates) and education Gini supports this result. Only 10.29% (13.75%) of municipalities within the bottom-25% (top-25%) of the distribution of the income Gini (own estimates) belong to the bottom-25% (top-25%) of the distribution of education Gini. Thus, low levels of income and education inequalities are rarely observed simultaneously in a municipality (around 6% of the total sample). The same logic applies with CONEVAL estimates (Table 6) even if the percentages are higher.

In a nutshell, this mapping analysis tends to highlight a negative association between the spatial distribution of income and education inequalities across Mexican municipalities. More precisely, the higher the level of economic development and/or the lower the degree of ethnic diversity, the more unequal the within-municipality income distribution. The evidence is a little less striking with CONEVAL's Gini estimates but does not contradict these findings. Conversely, education inequality tends to be greater (lower) among municipalities that are the least (most) developed and the most (least) ethnically diverse. To further investigate the negative association between income and education inequalities, it seems relevant to identify the potential existence of spatial spillovers.

Table 3 Moran's I statistics for the variables of interest

Variables	Moran's I	z	*p* value
Income Gini	0.071***	78.695	0.000
Income Gini (CONEVAL)	0.019***	21.520	0.000
GE(0)	0.048***	54.718	0.000
GE(1)	0.014***	18.693	0.000
GE(2)	0.000	0.681	0.248
Education Gini	0.105***	114.982	0.000
Per capita household income	0.129***	141.148	0.000
Years of schooling	0.095***	104.713	0.000
NGV	0.116***	126.852	0.000

Level of statistical significance: 1%***, 5%** and 10%*

Source Authors' calculations

Spatial Autocorrelation Analysis

To test for the presence of global spatial autocorrelation for our variables of interest, we calculate the Moran's I statistic[7] using a row-standardized inverse-distance spatial weights matrix (Table 3). We find significant and positive spatial autocorrelation for all variables, with the exception of the GE(2) income inequality measure. With regard to inequalities, this means that municipalities with a high (low) degree of income or education inequality tend to cluster in space. However, to go further, it seems relevant to examine spatial autocorrelation at the local level.

To do so, the Moran's local index of spatial autocorrelation (LISA) developed by Anselin (1995) provides a decomposition of the Moran's global statistic into the degree of spatial association associated with each spatial unit. This allows detecting local clusters and local outliers. More precisely, a high positive value of local Moran's statistic for a given spatial unit (i.e. municipality) implies similarity with the neighbouring values. This refers to spatial clusters, including high–high clusters or hot spots and low–low clusters or cold spots. Conversely, a high negative value for a given spatial unit implies dissimilarity from the neighbouring values. This refers to spatial outliers, including high–low and low–high combinations. Figures 3 and 4, respectively, present the results of this local spatial autocorrelation analysis, respectively, for the income Gini (own estimates) and the education Gini. The corresponding results for CONEVAL estimates of the income Gini are reported in Fig. 10 in the Appendix.

Results for our own estimates of the income Gini (Fig. 3) indicate that only few spatial outliers are identified, thus confirming the predominance of positive spatial autocorrelation. Interestingly, cold spots (low–low configurations) are highlighted in Oaxaca and Yucatan states. This supports the idea of a concentration of municipalities with

[7] The Moran's I statistic is a correlation coefficient measuring the overall spatial autocorrelation of a dataset.

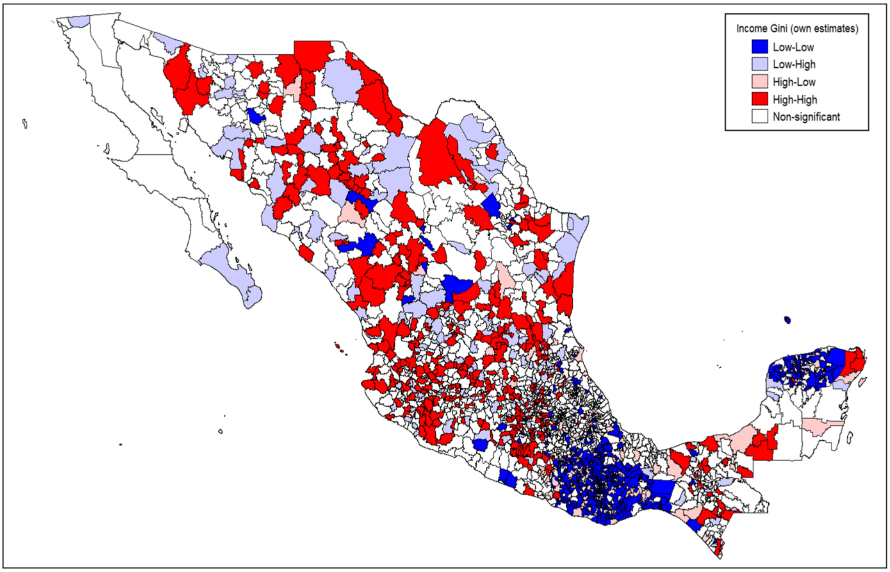

Fig. 3 Local spatial autocorrelation analysis (LISA) for the income Gini (own estimates), 2015. *Source* Authors' calculations

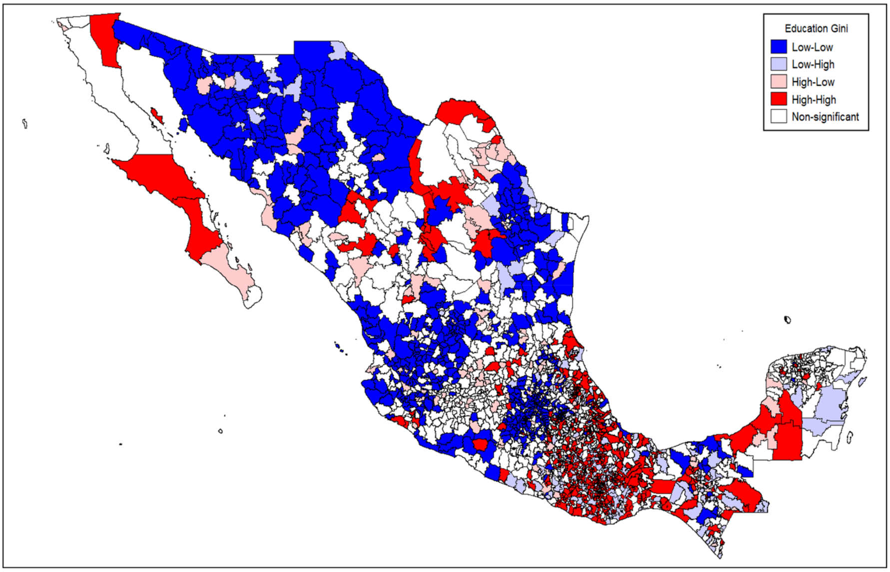

Fig. 4 Local spatial autocorrelation analysis (LISA) for the education Gini, 2015. *Source* Authors' calculations

low levels of income inequality in these two states. In addition, we observe small hot spots (high–high configurations) around the federal district and throughout the Northern part of the country without a clear geographical pattern. Broadly speaking, our findings for CONEVAL estimates (Fig. 10) are fully in line with those based on our own estimates of income Gini. It is worth noting, however, that the cold spots highlighted in Oaxaca are slightly less pronounced.

The hot and cold spot analysis for the education Gini provides very different results (Fig. 4). First, we observe hot spots dispersed throughout the Southern states (Oaxaca, etc.). Moreover, contrary to what we observe for the income Gini, we highlight cold spot areas around the federal district and in the Northern part of Mexico, particularly in the US-border states of Sonora, Chihuahua and Coahuila.

All in all, this analysis highlights the existence of local spatial autocorrelation and tends to confirm the disconnection between income and education inequalities. Tables 7 and 8 in the Appendix that reports cross-tabulation for hot and cold spots between income and education Gini indices give additional support to this result. Based on our own estimates of the income Gini (Table 7), no municipality exhibits a low–low configuration simultaneously for the income Gini and the education Gini. In the same vein, only one municipality has a high–high combination for the two measures of inequality. The small prevalence of low–low and high–high configurations is largely confirmed when CONEVAL estimates are considered (Table 8).

Multivariate Analysis

To further explore the association of education inequality with income inequality, we perform an econometric analysis. Our objective is not to establish a causal relationship but rather to explore, in a multivariate framework, the nature of the association between both variables. More precisely, to reveal the possible non-linear nature of this association, we adopt a very simple quadratic specification, as expressed in Eq. (4):

$$GINI\_INC_i = \beta_0 + \beta_1 GINI\_EDU_i + \beta_2 GINI\_EDU_i^2 + \beta_3 X_i + \varepsilon_i, \tag{4}$$

where $GINI\_INC_i$ is the income Gini of municipality i, $GINI\_EDU_i$ the education Gini and X_i the vector of control variables. Two control variables are included in this regression framework: the municipal average per capita household income that accounts for the level of economic development and the ethno-linguistic fractionalization index (NGV) that accounts for ethnic diversity. As emphasized by our previous empirical investigations, one important issue that we need to address is the presence of spatial spillovers. To do so, we adopt a spatial econometric model that includes a spatially lagged dependent variable in the right-hand side and a spatial autoregressive process in the error term. This model is known as a SARAR model and, based on Eq. (5), can be expressed as follows:

$$\begin{matrix} GINI\_INC_i = \beta_0 + \beta_1 GINI\_EDU_i + \beta_2 GINI\_EDU_i^2 + \beta_3 X_i + \lambda W GINI\_INC_i + \varepsilon_i \\ \text{with } \varepsilon_i = \rho W \varepsilon_i + u_i \end{matrix}, \tag{5}$$

Table 4 Econometric estimates (SARAR models) of the relationship between income inequality (own estimates) and education inequality

	(1)	(2)	(3)	(4)
Constant	0.3515***	0.3042***	0.2422***	0.2700***
	(51.70)	(25.22)	(21.47)	(27.57)
Income	0.0094***	0.0106***	0.0067***	0.0194***
	(3.88)	(11.12)	(5.70)	(22.66)
Income squared				-0.0007***
				(-13.34)
Years of schooling			0.0091***	
			(8.23)	
NGV	0.0094***	0.0091***	0.0071***	0.0126***
	(3.88)	(3.76)	(2.94)	(5.34)
Education Gini	0.0330***	0.2808***	0.3234***	0.3262***
	(3.00)	(5.73)	(6.76)	(7.09)
Education Gini squared		-0.3288***	-0.2806***	-0.3417***
		(-5.24)	(-4.41)	(-5.58)
N	2,457	2,457	2,457	2,457
Turning point (education Gini)		0.4270	0.5762	0.4773
Spatial autoreg. coef. (λ)	0.0000***	0.0000***	-0.0000	0.0000***
Spatial error coefficient (ρ)	0.0018***	0.0018***	0.0018***	0.0018***

Level of statistical significance: 1%***, 5%** and 10%*

Source Authors' calculations

where W is the spatial-weighting matrix. The parameters λ and ρ account for spatial autocorrelation. We use a raw-standardized inverse-distance weighting matrix and estimate the model through generalized spatial two-stage least squares. In this estimation procedure, we allow the errors to be heteroskedastically distributed over the observations.

Table 4 reports different estimations for our own measures of the income Gini while Table 9 in the Appendix do the same for CONEVAL estimates. It is worth noting that the two income inequality measures exhibit different spatial dependence patterns. For our own Gini estimates, the spatial autoregressive coefficient is positive and significant (with the exception of regression 3), indicating the existence of spatial spillovers (i.e. income inequality in a given municipality increases with income inequality in neighbouring municipalities). Surprisingly, the reverse is true for CONEVAL estimates with a negative and significant coefficient highlighted. This partly contradicts the results from the spatial exploratory analysis that provided evidence of positive spatial dependence for both measures. However, the autoregressive coefficients are close to zero, which qualifies the importance of such different spatial associations.

Let us now discuss the influence of education inequality on income inequality. In Table 4, regression 1 tests the linear relationship between both types of inequality and emphasizes a positive and significant (at 1% level) association

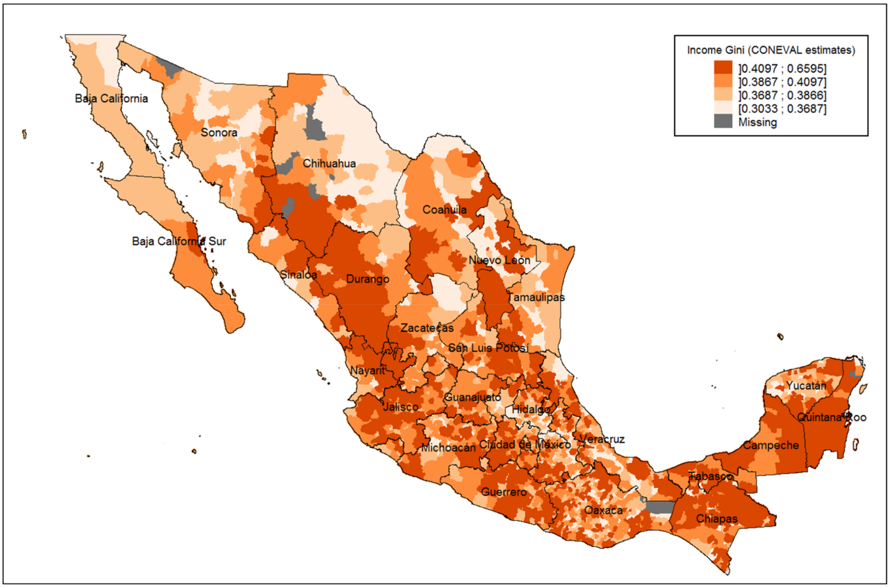

Fig. 5 Income Gini index (CONEVAL estimates), 2015. *Source* Authors' calculations based on CONEVAL data

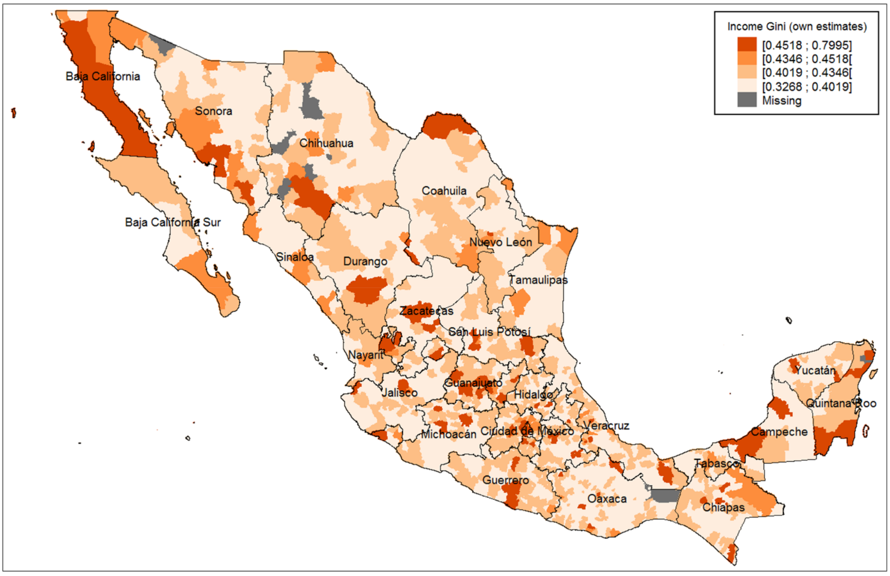

Fig. 6 Income Gini index (own estimates), population-weighted quartiles, 2015. *Source* Authors' calculations

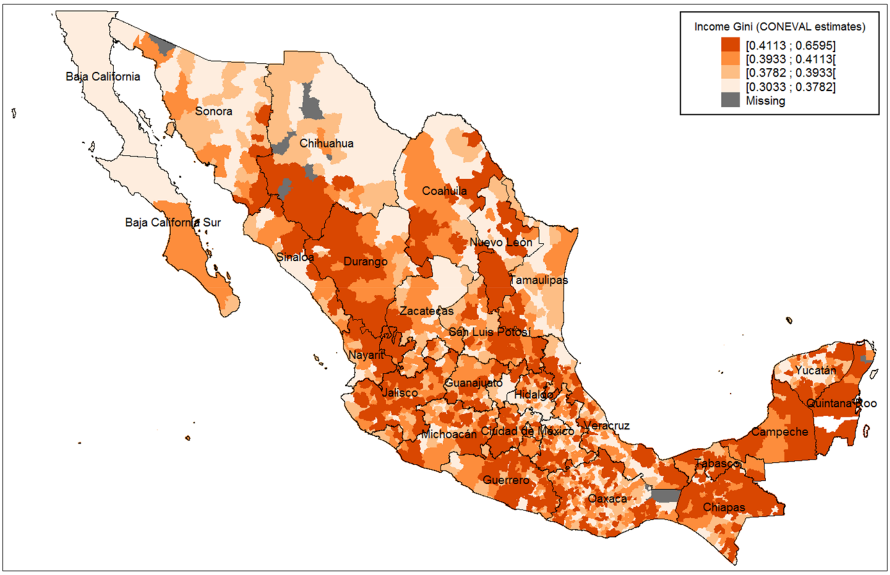

Fig. 7 Income Gini index (CONEVAL estimates), population-weighted quartiles, 2015. *Source*: Authors' calculations

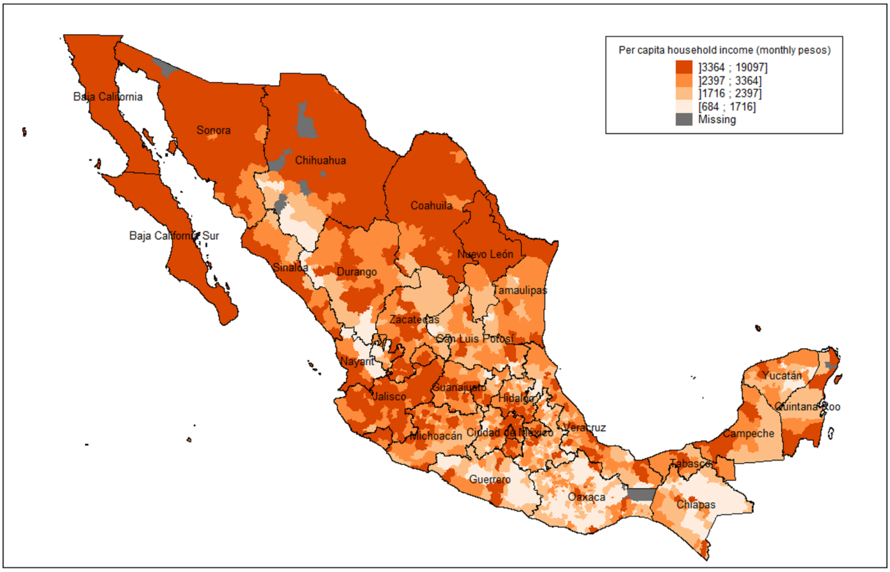

Fig. 8 Mean per capital household income (monthly pesos), 2015. *Source* Authors' calculations

that could support part of the existing empirical literature. However, regression 2 testing the quadratic relationship shows that the association is probably more complex. Indeed, these results emphasize the existence of a U-inverted

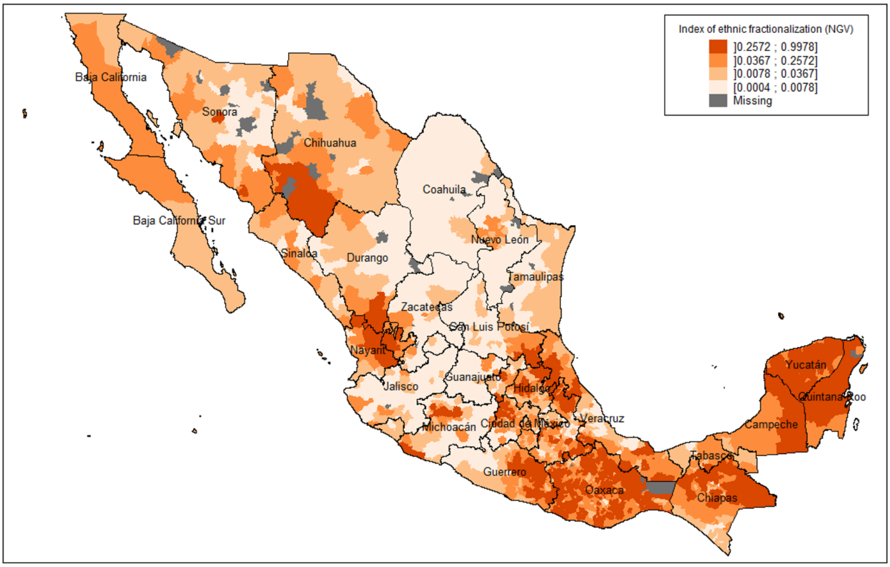

Fig. 9 Index of ethno-linguistic fractionalization (NGV), 2015. *Source* Author's calculations

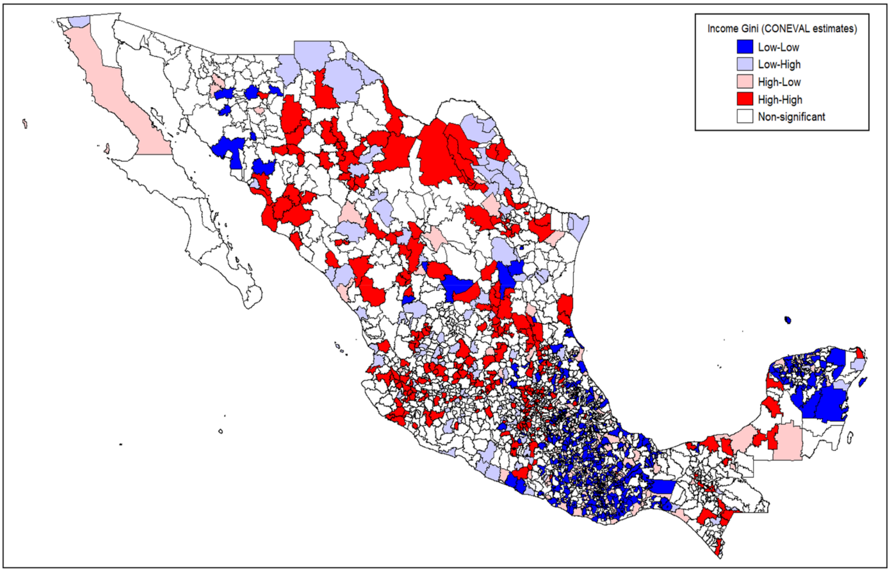

Fig. 10 Local spatial autocorrelation analysis (LISA) for the income Gini (CONEVAL estimates), 2015. *Source* Authors' calculations based on CONEVAL data

association between income inequality and education inequality that is significant at the 1% level. The turning point of the relationship is reached for an education Gini equal to 0.427, a value close to the 89th percentile of the distribution

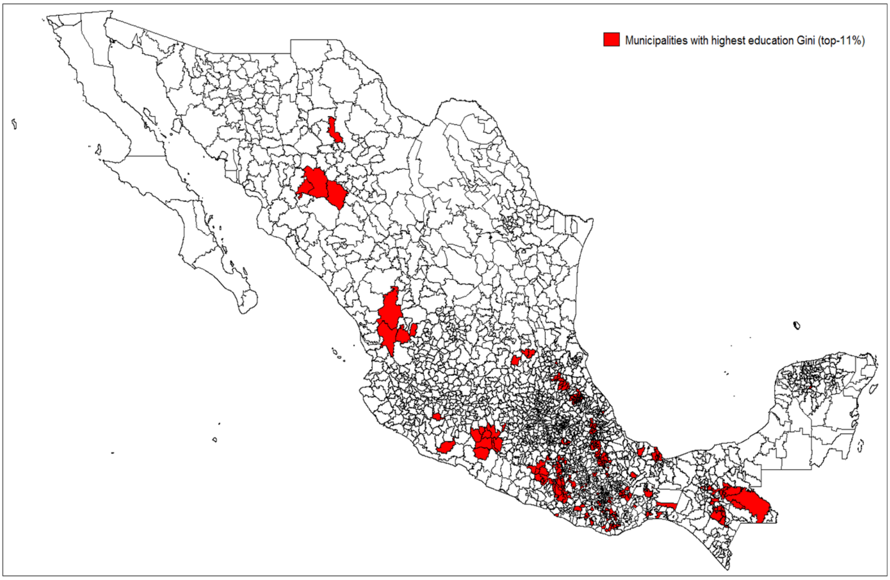

Fig. 11 Municipalities with the highest levels of education inequality (top-11%). *Source* Authors' calculations

of the education Gini. Put differently, this means that, among the municipalities with the highest levels of education disparities, the association tends to become negative. Figure 11 reported in the Appendix highlights the Mexican municipalities that are concerned with this decreasing association. Interestingly, most of them (approximately 75%) are from the poor and ethnically diverse states of Oaxaca (45%), Chiapas, Guerrero and Puebla. With CONEVAL's Gini (Table 9), the U-inverted association is confirmed (regression 2), even though the turning point is reached at a higher level of education Gini (0.487 corresponding to the 96th percentile).

To test for the sensitivity of our results, we estimate alternative specifications of model (5). First, we carry out estimations including the average number of years of schooling as an additional control variable (regressions 3 in Table 4 and 9). Second, we estimate the model by including the squared income as an additional control variable, as in a Kuznets curve framework (regressions 4 in both Tables). These additional estimations confirm the U-inverted relationship between education and income inequalities. However, the turning points are reached at higher levels of education inequality. Note that in the case of CONEVAL estimates, when years of schooling are included (regression 3 in Table 9), the turning point is reached for an education Gini equal to 0.918, which is largely above the maximum value observed in our sample. To sum up, these econometric investigations highlight the non-linear nature of the association between income and education inequalities, even if the turning point is very unstable, depending on model's specification.

Discussion and Conclusion

This article aimed to examine the geographical distribution of education and income inequalities among Mexican municipalities in 2015. To do so, we constructed measures of income inequality (using SAE methodology) and education inequality that are representative at the municipal level based on ENIGH and EIC surveys. We also use alternative estimates of income inequality provided by CONEVAL. The combination of cartographic evidence, tests for spatial autocorrelation together with a multivariate analysis based on spatial econometrics tools provide interesting results. First, our exploratory spatial analysis shows that there is a negative association between income and education inequalities at the municipal level. This is particularly true among the poorest and the most ethnically diverse municipalities where a combination of high levels of education inequality and low levels of income inequality is primarily observed. Rural municipalities from Oaxaca state are illustrative of that. Among the richest municipalities, there is a greater convergence of education levels but relatively high levels of income inequality. Municipalities from the area of Mexico metropolis are typical of this configuration. Second, our econometric investigations confirm the complexity of the relationship between income inequality and education inequality with a U-inverted association highlighted. This means that income inequality has an increasing association with education inequality in the lower parts of the distribution of education inequality until reaching a turning point. Although the turning point is reached at relatively high levels of education inequality and varies greatly according to the model's specification, we show that municipalities concerned with the decreasing association are primarily located in the poor and ethnically fragmented southern states.

Part of the explanation of the complexity of the association between income and education inequalities is very probably linked to the relationship between education and labour income. Our results echo the "paradox of progress" previously explained. In the richest Mexican municipalities combining low levels of education inequality and high levels of income inequality such as the Mexico metropolitan area or some municipalities within the US-border regions, it may be argued that the educational upgrading has reduced education inequality but contributed to the increase in income inequality. Conversely, municipalities with high levels of education inequality (such as municipalities from Oaxaca, Chiapas or Guerrero) have probably benefited less from the educational upgrading. For these municipalities, we suggest that the low degree of income inequality could be explained by the pattern of the local labour markets. The lack of employment opportunities (particularly off-farm opportunities) may explain low returns to higher education and could then explain that disparities in education attainments do not result in strong disparities in occupational status and income. This might indicate the existence of labour market frictions (i.e. mismatching between labour supply and demand). Besides, the agrarian structure of these local economies results in predominance of farm incomes that are traditionally less unequally distributed than off-farm incomes. In a nutshell, we argue that investigating the geographical disparities in terms of education's returns, employment opportunities and labour income seems to be a relevant area for research in order to better understand the disconnection between income and education inequalities, particularly among municipalities from the poor and ethnically fragmented southern states.

Migration also potentially matters as it may affect the income distribution in the origin area through remittances. In Mexico, most remittances are concentrated in central and southern states (Mexico City, Guanajuato, state of Mexico, Jalisco, Michoacan, Puebla and Oaxaca). For example, in 2016, income from remittances accounted for 9.3% of the GDP of the state of Oaxaca (El Colegio de México 2018). The (limited) existing literature on this issue shows that the effect of remittances on income inequality is region-specific and also depends on the origin of remittances. Focusing on rural Mexico, Taylor et al. (2008) show that international remittances (mainly from the US) are income equalizing in the region with the highest migration prevalence (i.e. West-Central region) and income disequalizing in the region with the lowest prevalence (South-South-East). However, using more recent data, Arslan and Taylor (2012) show that US-remittances become progressively less disequalizing in this latter region, thus giving support to the migration diffusion hypothesis. With regard to internal remittances, both studies conclude on an income equalizing effect. Arslan and Taylor (2012) also highlight a significant effect of migration on non-remittances income that in return influences the distribution of income. This means that there are multiple channels through which migration may affect (positively or negatively) income inequality. More evidence on these complex and potentially antagonist effects is thus required. Besides, migration and remittances may also impact the distribution of education. McKenzie and Rapoport (2007) point out that migration lowers education inequality in rural Mexico by reducing schooling at the top of the education distribution. Examining how migration and remittances simultaneously affect the distribution of education and income inequalities at the local level is as well a relevant area for research.

Appendix

See Tables 5, 6, 7, 8 and 9; Figs. 5, 6, 7, 8, 9, 10 and 11.

Table 5 Crosstab analysis between quartiles of income Gini (own estimates) and education Gini, 2015

Quartiles of income Gini (own estimates)	Quartiles of education Gini Q1	Q2	Q3	Q4	Total
Q1 (N)	63	131	170	248	612
Row %	10.29	21.41	27.78	40.52	100.00
Cell %	2.58	5.36	6.95	10.14	25.02
Q2 (N)	138	136	175	162	611
Row %	22.59	22.26	28.64	26.51	100.00
Cell %	5.64	5.56	7.15	6.62	24.98
Q3 (N)	165	193	137	117	612
Row %	26.96	31.54	22.39	19.12	100.00
Cell %	6.75	7.89	5.60	4.78	25.02
Q4 (N)	246	151	130	84	611
Row %	40.26	24.71	21.28	13.75	100.00
Cell %	10.06	6.17	5.31	3.43	24.98
Total	612	612	612	611	2446
%	25.02	24.98	25.02	24.98	100.00

Source Authors' calculations

Table 6 Crosstab analysis between quartiles of income Gini (CONEVAL estimates) and education Gini, 2015

Quartiles of income Gini (CONEVAL)	Quartiles of education Gini Q1	Q2	Q3	Q4	Total
Q1 (N)	179	128	167	138	612
Row %	29.25	20.92	27.29	22.55	100.00
Cell %	7.32	5.23	6.83	5.64	25.02
Q2 (N)	163	145	139	164	611
Row %	26.68	23.73	22.75	26.84	100.00
Cell %	6.66	5.93	5.68	6.70	24.98
Q3 (N)	161	165	149	137	612
Row %	26.31	26.96	24.35	22.39	100.00
Cell %	6.58	6.75	6.09	5.60	25.02
Q4 (N)	109	173	157	172	611
Row %	17.84	28.31	5.70	28.15	100.00
Cell %	4.46	7.07	6.42	7.03	24.98
Total	612	611	612	611	2443
%	25.02	24.98	25.02	24.98	100.00

Source Authors' calculations

Table 7 Crosstab analysis for local spatial autocorrelation between income Gini (own estimates) and education Gini, 2015

Income Gini (own estimates)	Education Gini					
	Low–low	Low–high	High–low	High–high	Non-significant	Total
Low–Low (N)	0	112	0	298	143	553
Row %	0.00	20.25	0.00	53.89	25.86	100.00
Cell %	0.00	4.56	0.00	12.13	5.82	22.51
Low–High (N)	71	0	40	2	75	188
Row %	37.77	0.00	21.28	1.06	39.89	100.00
Cell %	2.89	0.00	1.63	0.08	3.05	7.65
High–Low (N)	0	71	0	59	40	170
Row %	0.00	41.76	0.00	34.71	23.53	100.00
Cell %	0.00	2.89	0.00	2.40	1.63	6.92
High–High (N)	216	0	33	1	144	394
Row %	54.82	0.00	8.38	0.25	36.55	100.00
Cell %	8.79	0.00	1.34	0.04	5.86	16.04
Non-significant (N)	292	118	51	188	503	1,152
Row %	25.35	10.24	4.43	16.32	43.66	100.00
Cell %	11.88	4.80	2.08	7.65	20.47	46.89
Total	579	301	124	548	905	2457
%	23.57	12.25	5.05	22.30	36.83	100.00

Source Author's calculations

Table 8 Crosstab analysis for local spatial autocorrelation between income Gini (CONEVAL estimates) and education Gini, 2015

Income Gini	Education Gini					
(CONEVAL)	Low–low	Low–high	High–low	High–high	Non-significant	Total
Low–Low (N)	26	100	4	172	133	435
Row %	5.98	22.99	0.92	39.54	30.57	100.00
Cell %	1.06	4.07	0.16	7.00	5.41	17.70
Low–High (N)	74	0	6	1	54	135
Row %	54.81	0.00	4.44	0.74	40.00	100.00
Cell %	3.01	0.00	0.24	0.04	2.20	5.49
High–Low (N)	3	54	2	96	72	227
Row %	1.32	23.79	0.88	42.29	31.72	100.00
Cell %	0.12	2.20	0.08	3.91	2.93	9.24
High–High (N)	97	0	47	3	129	276
Row %	35.14	0.00	17.03	1.09	46.74	100.00
Cell %	3.95	0.00	1.91	0.12	5.25	11.23
Non-significant (N)	379	147	65	276	517	1,384
Row %	27.38	10.62	4.70	19.94	37.36	100.00
Cell %	15.43	5.98	2.65	11.23	21.04	56.33
Total	579	301	124	548	905	2457
%	23.57	12.25	5.05	22.30	36.83	100.00

Source Author's calculations

Table 9 Econometric estimates (SARAR models) of the relationship between income inequality (CONEVAL estimates) and education inequality

	(1)	(2)	(3)	(4)
Constant	0.3635***	0.3061***	0.1336***	0.2736***
	(41.53)	(13.48)	(5.43)	(11.78)
Income	0.0025***	0.0034***	− 0.0075***	0.0119***
	(3.34)	(4.10)	(− 8.27)	(7.70)
Income squared				− 0.0007***
				(− 6.53)
Years of schooling			0.0250***	
			(15.04)	
NGV	0.0301***	0.0293***	0.0258***	0.0323***
	(6.24)	(6.03)	(5.62)	(6.70)
Education Gini	0.0876***	0.3963***	0.5251***	0.4406***
	(5.03)	(3.52)	(4.93)	(3.90)
Education Gini squared		− 0.4062***	− 0.2860**	− 0.4243***
		(− 2.71)	(− 2.01)	(− 2.83)
N	2,457	2,457	2,457	2,457
Turning point (education Gini)		0.4878	0.9180	0.5191
Spatial autoreg. coef. (λ)	− 0.0000***	− 0.0000***	− 0.0000***	− 0.0000***
Spatial error coefficient (ρ)	0.0036***	0.0035***	0.0040***	0.0037***

Level of statistical significance: 1%***, 5%** and 10%*

Source: Authors' calculations

Data availability The data that support the findings of this study are available on request from the corresponding author.

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