Equilibrium. Quarterly Journal of Economics and Economic Policy
Volume 17 Issue 3 September 2022
p-ISSN 1689-765X, e-ISSN 2353-3293
www.economic-policy.pl

ORIGINAL ARTICLE

Citation: Valdez, R. I., & García-Fernández, F. (2022). The distribution of wage inequality across municipalities in Mexico: a spatial quantile regression approach. *Equilibrium. Quarterly Journal of Economics and Economic Policy, 17*(3), 669–697. doi: 10.24136/eq.2022.023

Contact to corresponding author: Rolando I. Valdez, rivaldez@uat.edu.mx

Article history: Received: 18.06.2022; Accepted: 5.09.2022; Published online: 30.09.2022

Rolando I. Valdez
Autonomous University of Tamaulipas, Mexico
orcid.org/0000-0002-1491-305X

Francisco García-Fernández
Autonomous University of Tamaulipas, Mexico
orcid.org/0000-0003-4340-1093

The distribution of wage inequality across municipalities in Mexico: a spatial quantile regression approach

JEL Classification: *R11; R12*

Keywords: *wage inequality; spatial quantile regression; municipalities*

Abstract

Research background: According to classical labor economics, wage differences among regions of a country that has free-factor mobility should eventually vanish. However, the level of wage inequality among Mexican territories is increasing. The nature and causes of this discrepancy are worth identifying.
Purpose of the article: To identify the spatial relationship of wage inequality that existed in the Mexican metropolitan system during the years 2010 and 2015.
Methods: We develop a model of wages that considers the interaction between spatial units within a region. Then, we specify a spatial autoregressive model with the average wage per municipality as a dependent variable. This variable is spatially lagged along with other controls such as productivity, schooling, and migration. We combine data from population and economic censuses. Then, we perform a quantile regression to estimate the spatial effect of wage in a region upon quartiles of the wage distribution.
Findings & value added: Wage inequality increases within a given region when the average wage increases in one of said region's municipalities. This phenomenon occurs because in municipalities that are neighbors of the one that enjoys a wage increase, the average wage tends to decrease. The impact is larger in those municipalities whose average wage is in the lower range of the regional wage distribution. Wage inequality is also increased by internal migration and increased productivity. These latter findings are some of the first for Mexico at this aggregation

level. A novel aspect of our study is its use of territory as an observation unit for which statistics from population and economic censuses are combined to draw inferences about spatial inequality.

Introduction

Because wages are the main source of people's earnings, the nature and causes of wage inequality are of great concern to scientists and politicians alike.

Wages and their characteristics are themselves a broad topic that can be approached from several perspectives. These include microeconomics, macroeconomics, economic growth, public policy, and regional economics. Some studies of wage differences take the classical economic theory of wages as their starting point (Juhn *et al*., 1993; Card & DiNardo, 2002; Autor & Dorn, 2009b, 2009a; Acemoglu & Autor, 2010). As posited sources of wage inequality, these studies focus on individual workers' characteristics that are linked to labor productivity. In contrast, our literature search found few studies that took a spatial perspective in which geographic location was used as an explanatory variable (Andrés-Rosales *et al*., 2019; Malkina, 2019; Mazol, 2016; Senftleben-Koenig & Wielandt, 2014; Wang & Xu, 2015). This gap in the literature could be addressed with benefit because of the key role played by local factors like natural resources, institutions, and historical accidents. Mexico's oil industry provides an example of the importance of those factors *vis a vis* workers' characteristics: that resource-dependent industry — which is one of the best-paid in Mexico — pays high wages to blue-collar workers, who do not need to be highly educated, but who do need to live where the industry's activities are carried out. Thus, the geographical distribution of petroleum reserves causes important spatial inequalities among incomes of workers who have that same educational level.

Mexico's oil industry is also an example of the new geographic structure of economic activity that has emerged in the country during the last 30 years. Places with highly specialized activities have developed in the context of international integration. Some of these places — chiefly those located close to border with the US (Mexico's main economic partner) have taken advantage of their geographic locations. As product compositions have changed in these locations, so has the spatial structure of the nation's wages. This change has been driven by increased access to high salaries in some locations, while salaries remain relatively low in the most backward regions (like southern Mexico). The result has been a regional imbalance in wages.

The effects of geographic location upon wage differences are accompanied by a "neighborhood" effect. Territories are not isolated; instead, they interact with each other, and transmit their ups and downs because of the mobility of factors. The interactions have been widely studied, but not the transmission of economic ups and downs in Mexico.

The present inquiry aims to (1) identify the spatial distribution of wage inequality in the Mexican metropolitan system during the years 2010 and 2015, and (2) determine the dynamics of the wage differences in a region by combining data from economic and population censuses. This work is novel because it deals with the territory as an observation unit, and combines two data sources. Moreover, the analysis used here focuses on the interactions among municipalities, under the hypothesis that the neighborhood effect matters, in addition to the relative geographic location within Mexico (e.g., such as north or south).

The results, which were obtained from a spatial quantile regression, provide evidence that when the average wage increases within a given municipality, the average wage in neighboring low-wage municipalities decreases. This effect is weak, but statistically significant. Thus, these results lead to the conclusion that an increase in wages within a multiple-municipality region causes an increase in the region's level of wage inequality. However, the stability of this condition over time is still unknown.

The structure of this article is as follows. First, the Literature Review discusses previous studies of wage inequality, then describes the transformations that have occurred within the Mexican economy. Next, the Research Methodology section develops a theoretical, auto-regressive spatial model of wage distributions at the municipality level. From that theoretical model, we then develop an empirical model of the spatial econometrics taxonomy. Data and sources of information are described, along with statistical information that is represented through maps and figures. We also conduct spatial autocorrelation tests. Then, we present the spatial quantile regression results for the years 2010 and 2015. The article ends with a Conclusions section.

Literature review

One of the first authors who investigated inequality was Kuznets (1955), who analyzed both the long-term path of economic growth and the accompanying changes in distributions of incomes. Kuznets observed that in the early phases of industrialization, income inequality tends to rise along with total income. Later, this relationship stabilizes, after which income inequality starts to decrease. Although income inequality is chiefly an empirical topic, Acemoglu and Robinson (2002) developed a theory about the political economy underlying Kuznets' curve. Acemoglu and Robinson affirm that at the beginning of the growth path, profits lead the economic development. Therefore, during this stage income tends to concentrate in more-proficient firms (and, of course, in the hands of their owners). However, at some point the resulting inequality becomes untenable. Society then demands better economic conditions, whereupon the government reacts by creating distributive institutions that look out for public interests—not private ones. As a result, the income inequality shrinks.

According to Mazol, (2016, p. 4), "Regional inequality is one of the main research topics in economic geography since the 1950s". Williamson (1965), who disaggregated Kuznets' analysis on a regional scale, pointed out that wage levels may be spatially non-uniform within a given economy. Mazol argued that interdependence, as well as factor mobility, is more intense within a country than between countries. Therefore (hypothetically) the differences between regions must vanish more rapidly.

The underlying idea behind early studies that address the relationship between economic growth and income inequality is that economic growth is spatially inhomogeneous, nor does it begin everywhere at once. Hence, inequality increases at first. Then, as factor mobility distributes investment and labor in the country, the income levels of economically backward places rise to the levels of the places that got an early start.

Economic activities play a key role in determining the degree to which the initial income gap closes. For example, the gap may endure between regions that specialize in agriculture (which has low marginal productivity) and those that specialize in manufacturing (Williamson, 1965). This observation suggests that the way to narrow the income or wage gap is by decreasing differences in productivity.

Support for that suggestion is found in economic theory, which posits that in a free market with perfect factor mobility, the determination of wage levels is simply a special case of the general theory of value. Wages are the price of labor; thus they are determined by supply and demand (Hicks, 1963). In an economy where many types of goods are produced, differences in wages result (in theory) from differences in each economic activity's marginal productivity. However, in practice the explanation for these differences is more complex because economic activities are not distributed homogeneously over geographic space. Instead, they are concentrated in urban areas. Moreover, the labor market has multiple restrictions (e.g., minimum-wage laws, unions, outsourcing, and lack of information) that are not consistent with the general theory of value.

The theory's assertion that wages for the same labor efficiency must be equal regardless of location (Hicks, 1963) returns our discussion to the starting point, which is the idea that differences in wages are the result of differences in marginal productivities.

In this article, we address wage inequality instead of income because wage inequality is a more accurate metric of the labor-factor price (Juhn et *al*., 1993). Increased demand for more skilled labor in one region tends to raise wage inequality. Nevertheless, at the same time, skilled workers are needed in specific activities, while others may not need them; thus, wage inequality may rise even within a region. In this line, changes in employment patterns across occupations and industries have affected the level of wage inequality (Juhn *et al*., 1993; Topel, 1994).

There is an extension of the relationship between trade and wage inequality that comes from the Heckscher-Ohlin theorem, which states that an underdeveloped country, where unskilled labor is abundant, whether this economy shifts towards openness to trade, would export goods with high unskilled labor. At the same time, this comes with an increase in the demand for unskilled workers, rising their wages and narrowing the gap with most skilled workers, thus, reducing the wage inequality (Stolper & Samuelson, 1941). This is the so-called Stolper-Samuelson theorem, corroborated by Wood (1997) when assessing wage inequality and openness for East Asian economies during the 60s and 70s. This author found strong evidence about a narrowing of the wage inequality from openness to trade in economies like Korea, Taiwan, and Singapore, not Hong Kong. However, Latin America's results are the opposite, because a widening in wages is found from the mid-1970s to the early 1980s in Argentina and Chile, whereas from the mid-1980s to the mid-1990s in countries like Colombia, Costa Rica, and Uruguay.

The relationship between trade and economic growth is clear enough. International trade for East Asian countries was the spark for development during the 1960s and 1970s. For Latin American countries, the openness to trade process started in the mid-1980s. In Mexico, for instance, openness to trade was a solution to the debt crisis from the early 1980s and an alternative for seeking to compensate for a decade of null economic growth.

In the early 90s, the development of the New Economic Geography (NEG) triggers a bunch of studies about wage inequality among regions. This theory stresses the idea of a big market that generates pecuniary and non-pecuniary externalities, where, also, a good is manufactured which is transported to another region. Thus, the mobility of the labor factor attracted by the amenities in the agglomerated region increases wage inequality, and it persists until the backward region starts to grow.

The NEG is concerned with the dynamics of forces that concentrate or scatter the economic activity and the openness to trade, transport costs, and others; however, under this framework, geography is not endogenously considered. The NEG ignores some dynamics that are rooted in the territory, and that sometimes occur in a neighborhood within a region.

Regional inequality in Mexico

Mexico's process of opening itself to freer trade began in 1985, when Mexico lowered its trade barriers and signed the General Agreement on Trade and Tariffs (GATT). Then, in 1993, Mexico signed the North America Free Trade Agreement (NAFTA) (Chiquiar, 2008). The goal of this process was to change the economic model to one of export-led growth. Spatially speaking, openness to trade caused important changes in the location of economic activity (Baylis *et al*., 2012)

According to the above-mentioned Stolper-Samuelson theorem, Mexico's increased openness should have decreased the county's wage inequality because industries that produced for the export market would demand more low-skilled labor. Instead, it was the wages of the *most* skilled workers that started to rise (Hanson & Harrison, 1995; Mungaray & Burgos, 2009; Wood, 1997). In addition, relative wages declined with distance from industrial centers — which are located chiefly in border cities — rather than with distance from cities in general (Hanson, 1997). Thus, after NAFTA, regional wage inequality increased rather than decreased (Baylis *et al*., 2012). However, the evidence presented by Aguilera and Castro (2018) suggest that wage inequality between female and male workers did decrease.

One explanation for Mexico's increased wage inequality after openness is that the same few industries and plants that were able to export goods were also the ones that were able to pay higher wages (Hanson & Harrison, 1995). Furthermore, this phenomenon was territorially unbalanced because of the rise of exporting industries in the north of Mexico. Thus, wage differences varied not only by industry, but by region as well (Verhoogen, 2008). These results contradict those of Chiquiar (2008), who found that the effects of trade upon relative prices were consistent with the Stolper-Samuelson theorem. On the other hand, Castro and Félix (2010) found evidence that factors such as productive specialization, diversity of economic-activities diversity, and market access are explanatory elements of the average wage differences among Mexican cities.

An extensive review of the literature on wage inequality in Mexico can be found in Castro and Huesca (2007). Most of the analysis units in that literature are (e.g.) households, workers, sectors, states, or regions. Few authors also include the spatial dimension as an endogenous component, or consider the importance of the geographic location.

One of those authors is Chiquiar (2008), who notes a spatial dimension of wage inequality that was not obvious in other studies: the same skilled workers might expect different wages depending on where they are located. For instance, Pérez-Cervantes (2016) found evidence that workers change the location of their workplace based upon the returns from commuting. He also found that inter-municipal commuters earn 30 percent more than their non-commuting counterparts. Other studies that highlight the spatial perspective in their analyses of wage inequality are Combes and Gobillon (2008); Senftleben-Koenig and Wielandt (2014); Mazol (2016); and Malkina (2019).

For the sake of completeness, we note that a recent study on spatial wage inequality in Mexico during the years 2005 to 2018 found cases where the closing of the wage gap was driven by the precariousness of working conditions, rather than by the catching-up of lower wages (Andrés-Rosales *et al*., 2019).

Research methods

As the preceding literature review showed, wage inequality may increase because of a real rise in salaries in a specific economic sector, or in a specific set of plants, or within a specific set of workers. A further difficulty in quantifying wage inequality is that some inequality measures, like the Gini index, Theil index, and variation coefficient, are highly sensitive to small changes in both tails of the distribution (Atkinson, 1970; Cowell & Frank, 2011). Hence, modest changes in the highest wages might change the values of such measures drastically.

The model that we develop here for quantifying wage inequality was inspired by the seminal work by Juhn *et al*. (1993) on the returns of skill. We use the following method to express outputs as a Cobb-Douglass function of capital and labor, with the labor factor decomposed into high-skilled and low-skilled fractions. First, we suppose that the country contains i municipalities, each of whose outputs depends upon Capital and Labor, but whose labor force includes many kinds of workers, from low-skilled to high-skilled. To simplify, we group those workers into just two sets: high-skilled and low-skilled. We then use the following Cobb-Douglass function to model the production that results from the i^{th} municipality's combination of labor and capital:

$$Y = AK^{\alpha}(L_h^{\delta} + L_l^{1-\delta-\alpha}) \tag{1}$$

where Y represents output; A the technology that generates a positive effect upon capital K; and the variables L_h *and* L_l represent (respectively) the quantities of high-skilled and low-skilled labor. Parameters α and δ (with $\alpha + \delta < 1$) represent the contributions of (respectively) capital and labor to output. The wage within municipality i for each type of labor is calculated as that type's marginal productivity:

$$\frac{\partial Y}{\partial L_h} = \frac{\delta A K^{\alpha}}{L^{1-\delta}} = w_h \tag{2}$$

$$\frac{\partial Y}{\partial L_l} = \frac{(1-\delta-\alpha)AK^{\alpha}}{L^{\alpha+\delta}} = w_l \tag{3}$$

Thus, the average wage in municipality i is:

$$\frac{w_h + w_l}{2} = \frac{(\partial Y/\partial L_h) + (\partial Y/\partial L_l)}{2} \tag{4}$$

The average calculated in Eq. 4 is the expected value of the wage in municipality i:

$$\frac{w_h + w_l}{2} \equiv E(w) \equiv \overline{w} \tag{5}$$

Although Eq. 5 considers only two kinds of workers, it can be extended to any number. Formally, for n kinds of workers:

$$\overline{w} = \frac{1}{n}\sum_{n=h}^{l} w_n = \frac{1}{n}\sum_{n=h}^{l}\frac{\partial Y}{\partial L_n} \equiv \overline{\Omega} \tag{6}$$

In this way, it is possible to deal more realistically with the fact that within the range between high and low-skilled workers, there are as many marginal productivities as economic activities. Even within the same economic activity, it is possible to find several qualities of labor. Equation 6 means that the average wage in a municipality equals its average marginal productivity of labor. By extension, between-territories differences in wages are explained by differences in marginal productivities of labor.

Thus far, we have not yet considered either territory or spatial dynamics. These factors must be included because the relative locations of municipalities are important not only in themselves, but because of the neighbor interactions, etc. that result. To incorporate territory and spatial dynamics in our model, we note that each municipality's average wage can be expressed via an equation like (6). In addition, the municipalities interact with each other as part of the country's economic dynamics. Municipalities transmit their ups and downs to their neighbors more so than those that are distant (Tobler, 1970). Moreover, spatial wage inequality is an important issue in big countries (Malkina, 2019) like Mexico.

The municipalities within a country interact through many mechanisms, one of which is the workers who travel every day. In many countries, workers move from one place to another for a job, seeking the best pay for their skills and knowledge. High-wage territories are more attractive for workers than low-wages ones, thus generating an imbalance that is made more acute by the fact that the relocation of highly skilled workers leaves low-wage territories with less-productive workers. Low-wage territories could increase their productivity by attracting high-skilled workers, but this would happen only if those workers received a higher wage than they receive at present.

The situation that we have just described leaves two possible outcomes regarding wage differences among neighboring territories. On the one hand, highly skilled workers would be employed in high-wage territories, thereby increasing the wage differences because low-wage territories could employ only low-skilled workers. We might say that this is an imbalance according to NEG's rationale. On the other hand, wage differences among territories would decrease if low-wage territories attracted more skilled workers by paying higher wages. This measure would increase average marginal productivity in low-wage territories, and consequently their average wage.

Based upon this reasoning, the average wage in a territory i is a function of the territory's own average productivity ($\overline{\Omega}_i$) and the average wage of its neighbors ($\overline{w}_j$):

$$\overline{w}_i = \frac{\overline{\Omega}_i}{\overline{w}_j^{\lambda}}; \quad -1 < \lambda < 1 \tag{7}$$

where λ represents the degree of interaction among territories. When there is no interaction among territories, $\lambda=0$¸ and the average wage in territory i depends only upon that territory's own average marginal productivity.

Equation 7 can be log-linearized as follows:

$$\ln \overline{w}_i = \ln \overline{\Omega}_i - \lambda \ln \overline{w}_j \tag{8}$$

Because the goal of our analysis was to identify the spatial relationship of wage inequality, we chose to use quantile regression, which is much better than standard regression for analyzing changes in the dependent variable's distribution (McMillen, 2013). More specifically, quantile regression is preferred for this purpose because a standard regression model provides only a point estimation, at the mean of the wage distribution. Instead, we are more interested in the effect of the same explanatory variables at different points of the wage distribution.

Note that the analysis presented in this article aggregates average wages at the level of individual municipalities. To incorporate that geographical distribution of wages in our analytical framework, we introduce a spatial auto-regressive (AR) model that adds a weighted average of nearby values of the dependent variable to the list of explanatory variables (McMillen, 2013):

$$Y = \rho WY + X\beta + u \tag{9}$$

where Y is the dependent variable (in our case, the average wage of a given municipality); X is a vector of explanatory variables; and W is an $n \times n$ spatial-weight matrix (SWM). We define this matrix in the Results section. The factors ρ and β are constants, as is u. To translate (9) into the quantile-regression parlance, consider that unlike the ordinary least-squares method, quantile regression seeks the arg min of weighted sums of absolute residuals, such that:

$$\hat{\beta}_q = \underset{\beta_q \in \mathbb{R}}{\operatorname{argmin}} \sum_{n=1}^{k} \left| y_n - x_n \beta_q \right| \omega_n \tag{10}$$

Here, β_q is the set of estimated coefficients for each quantile q, and ω_n is the weight of the nth observation (Liao & Wang, 2012). Thus, the econometric specification for spatial quantile regression is as follows:

$$Y = \rho_q WY + X\beta_q + u_q \tag{11}$$

Before stating the empirical model, spatial dependence tests need to be performed to determine the best method for carrying out the analysis. These tests also enable one to determine whether the spatial component needs to be addressed in the models. In the next section, the empirical models are presented along with the data sources.

In our analysis, the observation unit is the municipality. Therefore, the econometric specification has the following AR spatial structure:

$$\ln(y) = \beta_0 + \rho W \ln(y) + \beta_1 x_1 + u \tag{12}$$

For each municipality, $\ln(y)$ is the natural logarithm of the average wage in real terms, normalized to constant prices of 2013; $W \ln(y)$ is the spatially lagged natural logarithm; and x_1 is the average marginal productivity. To avoid endogeneity issues, Equation 12 also needs to include control variables, which are described later.

The data used in the present analysis come from two sources. Because the observation unit is the municipality, the analysis requires representative information at this aggregation level. One source of such information is the National Survey of Occupation and Employment (ENOE, in Spanish), which collects data on earnings according to types of employment. However, the ENOE presents data for the nation, and for 32 cities specifically, rather than for individual municipalities. The same limitations apply to data from the National Survey of Households' Income and Spending (ENIGH, in Spanish).

In contrast, municipality-level data on earnings are indeed available from the 2010 Population Census and the 2015 Population Survey. We obtained these data — which are collected every 10 years, for each type of work — from the Integrated Public Use of Microdata Series (IPUMS) international (Minnesota Population Center, 2020). In addition to presenting data on workers' total income from labor during the previous month (which we took as values for the "wage" variable), these sources present data on variables that we used as controls in the empirical equation. These variables include worker characteristics such as age, education, working sector, and marital and migration status. Other control variables are the speaking of an indigenous language, and household information such as availability of utilities and public services.

Economic information used in our analysis (such as for production and labor) came from the Economic Census. This information, too, can be disaggregated at the municipality level. Because we assume that the marginal productivity is equal to worker's productivity, we define productivity as:

$$x_1 = \frac{GVA}{TEP} \tag{13}$$

where GVA is the real[1] Gross Value Added, and TEP is the Total Employed Population.

Periods for data from the Economic Census do not match those of the Population Census and Population Survey. Specifically, the Economic census provides data from 2009 and 2014 — one year earlier than from (respectively) the Population Census and Population Survey. Therefore, we assume that the 2010 Population Census matches with the 2009 Economic Census, and that the 2015 Population Survey matches with the 2014 Economic Census. This assumption is plausible because the economic structure does not change from one year to another.

An additional complication is that the Economic Census does not account for the primary economic sector. This omission distorts the economic picture for small and rural municipalities; for example, by returning negative GVAs. In addition, the GVA is zero for some of the small municipalities, thereby complicating logarithmic transformations and the computation of ratios. To avoid these problems, we consider municipalities that conform to the Metropolitan System (MS) rather than all the country's municipalities. The MS is a composite of 417 municipalities grouped into 74 metropolitan areas. These municipalities contain 75.1 million people, representing 62.8% of the total 2015 population (SEDATU, CONAPO, and INEGI, 2018).

Taking all of the foregoing into consideration, we pose the following estimating equation:

$$\begin{gathered}\ln(y) = \beta_0 + \rho W \ln(y) + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + +\beta_5 x_5 \\ +\beta_6 x_6 + \beta_7 x_7 + \beta_8 x_8 + \beta_9 x_9 + \beta_{10} x_{10} + \beta_{11} x_{11} + \beta_{12} x_{12} + u\end{gathered} \tag{14}$$

The first two independent variables were described above. The remaining variables control for aspects related to the productivity of workers (as in Mincer's equation) and for factors like human capital, development, productive structure, and migration. These variables are described in the table 1.

The single (Pearson's) correlations among independent variables are shown in Figure 1. Two variables are highly correlated: years of schooling, and the percentage of people attending university. The correlation between these variables is high enough (≈0.9) to cause potential collinearity issues that could complicate the drawing of inferences.

[1] In constant 2013 prices.

To avoid such problems, we drop “percentage of people attending university” from the model, thereby obtaining the following econometric specification:

$$\begin{aligned}\ln(y) = \beta_0 + \rho W \ln(y) + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \\ + \beta_6 x_6 + \beta_7 x_7 + \beta_8 x_8 + \beta_9 x_9 + \beta_{10} x_{11} + \beta_{11} x_{12} + u\end{aligned} \tag{15}$$

To use Equation 15 to estimate coefficients for each of the years 2010 and 2015, we split the dataset by year, then used a two-stage quantile regression. The first step was based on quantile regressions with the same quantile as in the second stage. This procedure ensures that the estimate is robust (Kim & Muller, 2004).

Additionally, we performed the calculation shown in Equation 15 with pooled data, and with the restriction that $\rho = 0$. We present the results in table 5 to compare a spatial model with a non-spatial one that uses the same variables.

Results

The first step of the analysis is to test for spatial dependence to justify the use of spatial analysis. To test for spatial dependence, we need a spatial-weight matrix (SWM). Identifying the elements of the SEM is often driven by the choice of observation unit as well as by the data.

To choose an appropriate SWM, we performed the Moran’s-I test on our four key variables: logarithm of the average wage (hereinafter “average wage”), *y*, *k*, and *K*, considering five contiguity orders in a queen-type SWM as well as k-nearest-neighbor SWM.

Table 2 shows information about the data derived from the three types of weight matrices used on Moran’s-I test estimation.

Moran’s-I is used to test global spatial autocorrelation. It depends upon the difference between the test value and the average, and it is defined as follows (Kopczewska, 2021, p. 188):

$$I = \frac{\sum_i \sum_j w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{S^2 \sum_i \sum_j w_{ij}} \tag{16}$$

with

$$S^2 = \frac{1}{n} \sum_i (x_i - \bar{x})^2 \tag{17}$$

where x_i is the observation in territory i, $\bar{x}$ is the average of all territories, n is the number of territories, and w_{ij} is an element of the SWM.

The variables with the highest spatial correlation are wage and stock of capital (Figure 2). Their correlation is statistically significant in 2010 as well as 2015 but is higher in 2015. Figure 2 also reveals that in both years, the Moran's-I values for the wage and the stock of capital decrease with the order of contiguity. Specifically, the Moran's-I value for first-order contiguity of wage is 0.4 in 2010, and >0.5 in 2015. In 2010, productivity (gross value added per worker) shows a statistically significant (but weak) spatial correlation for first- and second-order contiguity, whereas in 2015 the behavior is u-shaped, and significant for fourth- and fifth-order contiguity.

These results show that a single SWM (first-order contiguity) is sufficient to capture the spatial structure of the variables.

We also tested spatial correlation by using a SWM that considered three- and four-k-nearest neighbors. The results (Figure 3) are like those matrices. The Moran's-I statistic is higher for the three nearest neighbors in 2015 than in 2010 (Table 6).

Based upon this evidence, we chose the queen-type spatial-weight matrix with order of contiguity=1, because it maximizes the spatial dependence.

An important inference from the spatial correlation among spatial units (Figure 3) is that a given municipality's wages and other variables are not independent from those of its neighbors. Instead, when the wage increases in a given municipality, it rises in neighboring municipalities as well. The same is true of productivity.

Figure 4 shows the average wage across the municipalities of the metropolitan system. There is a generalized increase in the wage from 2010 to 2015; i.e., the map is noticeably darker in 2015 than in 2010. However, the increases are more likely in the north and the center of the country than in the south. This result corroborates the evidence of spatial correlation that was shown earlier: wage increases among groups of municipalities, rather than in isolated ones.

Recall that this investigation of spatial dependence was done to determine whether a spatial analysis is justified. Having shown that this is so, we now estimate the empirical model. The ensuing analysis (using Equation 15) will allow us to determine the role of wages across municipalities.

Results for 2010 are shown in table 1. There are five coefficients for each variable. Each coefficient corresponds with every quantile of the average wage distribution across municipalities. For simplicity and reporting purposes, we classify municipalities that belong to quantiles 0.10 and 0.25

as low-wage; those that belong to quantile 0.5 as middle-wage; and the rest as high-wage.

The variable of interest is the spatially lagged one: *Wln(y)*. As expected, its coefficient is negative for all quantiles in both years. In addition, this coefficient decreases from quantile 0.10 to 0.90. It is statistically significant only for quantiles 0.10 and 0.25. This result means that an increase of 1% in a given municipality's average wage provokes a decrease of 0.02% in the average wage of neighbors that belong to the lowest quantile of the wage distribution, and a decrease of 0.01% in the average wage of neighbors that belong to quantile 0.25. Therefore, an increase in the average wage of a municipality increases wage inequality within the municipality's neighborhood. These results corroborate the existence (in 2010) of a spatial-effect component in the lowest part of the wage distribution across Mexican metropolitan municipalities.

Productivity did not affect wage inequality in 2010. Although productivity differences are positively correlated with wage, there are no productivity differences between the upper and lower quantiles.

Results for two of the control variables (the percentages of females and migrant people in a municipality) are noteworthy. A higher female percentage reduces the average wage; the decrease is larger on the wage distribution's lower tail. In contrast, a higher percentage of migrants increases the average wage, with a greater impact on the distribution's higher tail. Thus, migration increases wage inequality.

The last row of Table 3 shows the impact of the percentage of people working in the primary sector. As the study of the coefficients across quantiles suggests that a higher percentage of workers in this sector decreases the average wage in every part of the wage distribution.

Results for 2015 (Table 4) differ in important ways from those for 2010. In particular, *Wln(y)* is statistically insignificant, meaning that for 2015 there is no spatial effect on wages in a neighborhood. On the other hand, productivity becomes relevant because its coefficient increases as we move towards upper quantiles, and is statistically significant except for quantile 0.10. Thus, productivity is relevant to explaining wage inequality.

In 2015, the coefficient of education (x_3) was larger for middle-wage municipalities. The variation of this coefficient across quantiles has an inverted U-shape. This result implies that there is no evidence that wage inequality derives from education, and thus further implies that education is irrelevant to reducing wage inequality. Coefficients for migration in 2015 show the same behavior as in 2010: a higher percentage of migrant persons increases the average wage on the upper side of the wage distribution more so than on the lower side. Hence, migration does increase wage inequality.

Discussion

Our results suggest lines for further research, and also present interesting contrasts with previous studies of wage inequality in Mexico.

First, we will discuss the spatial effect of wages at the neighborhood level. We found that when the average wage increases in a given municipality, the nearby low-wage municipalities suffer an even greater decrease in their average wages. Thus, wage inequality increases within a neighborhood when the average wage increases in one of the neighborhood's municipalities. We conjecture that this wage effect was not statistically significant for quantiles from 0.5 and above in 2010 because the labor factor had low mobility. For example, it is plausible that workers are not inclined to commute if they are currently well-paid. Even those who are not well-paid, but live in a high-wage municipality, might stay put in hopes of finding better conditions there at a later time if they have no other options.

Some authors have found that NAFTA increased territorial wage differences (Aguilera & Castro, 2018; Andrés-Rosales *et al*., 2019; Baylis *et al*., 2012). The present study supports those findings by explaining the underlying dynamic of the post-NAFTA structure. Northern municipalities became attractive places for foreign investment by exploiting their comparative advantage of location, and thus could increase their average wage. As a result, the average wage became even lower in backward municipalities.

We also found that wage inequality is increased by increases in productivity. The explanation for this correlation is found in technological advances and the capability of firms to export. Technological advances increase both productivity and profits, thereby allowing higher wages for workers. Similarly, industries that sell to lucrative foreign markets can offer higher pay. One study that supports these explanations is Esquivel and Rodríguez-López (2003), who found that although NAFTA increased the demand for unskilled labor in Mexico, it also increased the demand for skilled, technologically proficient labor. Therefore, (and contrary to the predictions of the Stolper-Samuelson theorem) wage inequality persisted to isolate the real wage from technological change and trade between unskilled and skilled workers, where technological change affected the first, deteriorating the gains from the openness to trade. In the same line, Verhoogen (2008) finds that the more productive plants produce higher quality goods than the less productive plants, therefore, the more-productive plants pay higher wages to maintain high quality. As a result, wage inequality increases.

Our finding that internal migration increases wage inequality is neither corroborated nor contradicted by the literature because most of the literature on the effects of migration uses a between-country approach rather than a within-country one. Still, our finding is in line with NEG theory, which predicts that initially, factor mobility increases wage inequality among regions, after which the low-wage regions will catch up with the high-wage ones.

Conclusions

In this inquiry, we analyze the role of space in wage inequality through a spatial econometric strategy. We estimate a spatial quantile regression with average wage per municipality as a dependent variable, combining data from population census, and economic census for 417 municipalities that make up the Mexican metropolitan system.

One of our main findings is that when the average wage increases in a municipality, it drops significantly in low-wage municipalities that belong to the same neighborhood. This phenomenon causes an increase in wage inequality among municipalities. The underlying spatial dynamics are related to labor-factor mobility. Because workers are attracted to high-wage municipalities, low-paying municipalities are left with even lower levels of the average wage. Labor-factor mobility (or rather, the low level of it) also explains why this phenomenon is not statistically significant for high-wage municipalities: low-wage workers who live in them count on improving their conditions, someday, by remaining there.

Future studies of the effects of wages might compute interquartile ranks to assess effects upon inequality. In such assessments, the main challenge is to compute standard errors. Other areas for future study of wages include effects on welfare and economic growth, and whether the phenomenon that we report here persists in the long run.

Our second main finding is that productivity increases wage inequality by raising wages on the upper side of the distribution. This effect was stronger in 2015 than in 2010. Future studies might consider the impact of economic growth on wages.

Our third main finding is the effect of migration on wage inequality. Our result is one of the first from a spatial perspective using municipalities as an observation unit. A higher percentage of migrants in a municipality increases the average wage in high-wage municipalities, thus increasing wage inequality among municipalities. This finding receives theoretical support from NEG, but firm conclusions cannot be drawn without further studies that consider additional theoretical elements.

One of the main limitations of this inquiry is the lack of data that would be needed for making comparisons over time. It is not possible to contrast the results from one year to another because every estimation follows a certain data-generating process, although they include the same observations and variables. A panel data analysis might provide results that are more definitive than were possible in this study.

An additional limitation of this document consists in the analysis is carried out for a subset of municipalities. Although these municipalities are highly representative of the country, their selection of them implies a spatial disruption of the territory, where most of the metropolitan areas are disconnected from each other. This drawback implies that the analysis here presented is consistent with a "within metropolitan areas" rather than "between metropolitan areas".

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Annex

Table 1. Description of variables used in the econometric specification

Variable	Name	Description	Source
y	*Wage*	The average wage in a municipality	Population census
x_1	*gva*	Average gross value added per municipality	Economic Census
x_2	*age*	Average age in a municipality	Population census
x_3	*yrschool*	Average years of schooling in a municipality	Population census
x_4	*pfemale*	Percentage of females in a municipality	Population census
x_5	*pnospeakind*	Percentage of people not speaking an indigenous language in a municipality	Population census
x_6	*pmarr*	Percentage of people married in a municipality	Population census
x_7	*pelec*	Percentage of households with electricity in a municipality	Population census
x_8	*pnopipwat*	Percentage of households without piped water in a municipality	Population census
x_9	*ppubsewage*	Percentage of households with public sewage service in a municipality	Population census
x_{10}	*pattenduniv*	Percentage of people attending university in a municipality	Population census
x_{11}	*pmigrant*	Percentage of migrant people in a municipality	Population census
x_{12}	*pprimsec*	Percentage of people working in the primary sector in a municipality	Population census

Table 2. Summary of SWM

Type	Municipalities	Average neighbors	Percentage of nonzero	Nonzero links
Queen	417	3.8	0.92	1608
3 nearest neighbors	417	3	0.71	1251
4 nearest neighbors	417	4	0.95	1668

Table 3. Estimating results of equation (15) using spatial quantile regression with data from 2010

	Quantile				
Variable	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**
(Intercept)	11.3784***	11.6145***	11.3279***	9.7928***	7.6146***
	(2.3363)	(1.5487)	(1.4870)	(0.8948)	(1.2525)
Wln(y)	-0.0202***	-0.0113**	-0.0060	0.0006	-0.0002
	(0.0052)	(0.0046)	(0.0052)	(0.0097)	(0.0072)

Table 3. Continued

Variable	Quantile 0.10	0.25	0.50	0.75	0.90
x_1	0.1781	0.2709***	0.3132***	0.2558**	0.2167
	(0.1188)	(0.0827)	(0.0841)	(0.1008)	(0.1475)
x_2	-0.0242	-0.0233***	-0.0128	0.0023	0.0116
	(0.0150)	(0.0089)	(0.0104)	(0.0101)	(0.0189)
x_3	0.1414***	0.1641***	0.1525***	0.1697***	0.1388***
	(0.0236)	(0.0214)	(0.0182)	(0.0173)	(0.0247)
x_4	-0.0575***	-0.0493***	-0.0485***	-0.0467***	-0.0234
	(0.0118)	(0.0118)	(0.0083)	(0.0119)	(0.0149)
x_5	0.0027*	0.0030*	0.0006	-0.0001	0.0010
	(0.0014)	(0.0018)	(0.0013)	(0.0013)	(0.0014)
x_6	-0.0252***	-0.0176***	-0.0111**	-0.0079*	-0.0104*
	(0.0070)	(0.0057)	(0.0049)	(0.0045)	(0.0061)
x_7	0.0047	-0.0090	-0.0113	-0.0052	0.0052
	(0.0193)	(0.0120)	(0.0113)	(0.0067)	(0.0083)
x_8	0.0010	0.0015	0.0008	0.0014	0.0009
	(0.0013)	(0.0010)	(0.0009)	(0.0014)	(0.0015)
x_9	-0.0002	-0.0005	0.0005	0.0007	0.0011
	(0.0008)	(0.0007)	(0.0005)	(0.0006)	(0.0008)
x_{11}	0.0090	0.0136**	0.0164***	0.0194***	0.0218***
	(0.0056)	(0.0062)	(0.0047)	(0.0048)	(0.0060)
x_{12}	-0.0158***	-0.0186***	-0.0208***	-0.0122***	-0.0153***
	(0.0037)	(0.0028)	(0.0038)	(0.0039)	(0.0048)
n	417	417	417	417	417

Notes: Values in parentheses are standard errors; Significance codes: *** p<0.01; ** p<0.05; * p<0.10; Estimations performed in R by the first author

Table 4. Estimating results of equation (15) using spatial quantile regression with data from 2015

	Quantile				
Variable	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**
(Intercept)	9.7198***	9.5882***	9.2774***	10.4772***	10.5071***
	(1.4909)	(1.2185)	(1.2018)	(1.7129)	(1.8791)
Wln(y)	-0.0098	-0.0073	-0.0004	-0.0028	-0.0014
	(0.0063)	(0.0050)	(0.0045)	(0.0057)	(0.0066)
x_1	0.1212	0.2038**	0.3629***	0.5412***	0.7127***
	(0.0888)	(0.0835)	(0.0831)	(0.1370)	(0.1746)
x_2	-0.0090	-0.0309**	-0.0166**	-0.0116	-0.0095
	(0.0156)	(0.0123)	(0.0071)	(0.0102)	(0.0164)
x_3	0.1137***	0.1284***	0.1412***	0.1324***	0.1103***
	(0.0247)	(0.0161)	(0.0143)	(0.0151)	(0.0219)
x_4	-0.0017	-0.0058	-0.0069**	-0.0032	-0.0029
	(0.0053)	(0.0036)	(0.0027)	(0.0037)	(0.0073)
x_5	0.0020	0.0024	0.0010	0.0004	-0.0009
	(0.0026)	(0.0015)	(0.0011)	(0.0015)	(0.0020)
x_6	-0.0044	-0.0090*	-0.0078***	-0.0129***	-0.0189***
	(0.0058)	(0.0048)	(0.0024)	(0.0036)	(0.0062)
x_7	-0.0171	-0.0046	-0.0081	-0.0179	-0.0119
	(0.0140)	(0.0127)	(0.0113)	(0.0163)	(0.0164)
x_8	0.0015	0.0016	-0.0009	-0.0030*	-0.0020
	(0.0017)	(0.0017)	(0.0012)	(0.0017)	(0.0028)
x_9	-0.0019***	-0.0010*	-0.0002	-0.0002	0.0007
	(0.0006)	(0.0005)	(0.0004)	(0.0005)	(0.0007)
x_{11}	0.0087*	0.0086*	0.0130***	0.0150***	0.0153*
	(0.0045)	(0.0050)	(0.0032)	(0.0055)	(0.0078)
x_{12}	-0.0067***	-0.0080***	-0.0051**	-0.0027	-0.0032
	(0.0019)	(0.0015)	(0.0021)	(0.0018)	(0.0026)
n	417	417	417	417	417

Notes: Values in parentheses are standard errors; Significance codes: *** $p<0.01$; ** $p<0.05$; * $p<0.10$
Estimations performed in R by the first author.

Table 5. Pooled OLS and a spatial autoregressive regression of equation 15 pooling both datasets 2010 and 2015

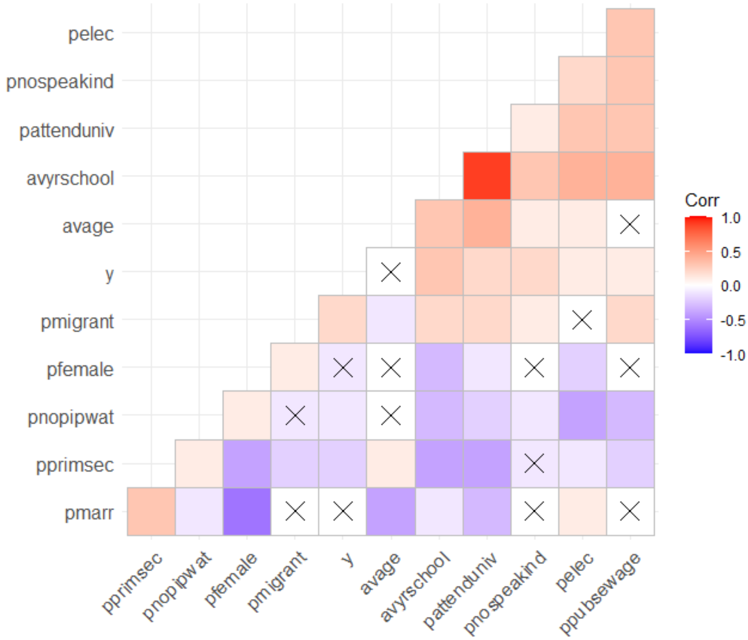
	lwage	**lwage**
Wlnwage		0.017***
		(0.004)
y	0.025	0.017
	(0.045)	(0.044)
k	-0.015*	-0.016*
	(0.007)	(0.006)
lkstock	0.038***	0.038***
	(0.004)	(0.004)
avage	-0.008	-0.008
	(0.005)	(0.005)
avyrschool	0.180***	0.178***
	(0.007)	(0.007)
pfemale	-0.032***	-0.031***
	(0.001)	(0.001)
pnospeakind	-0.002*	-0.002**
	(0.001)	(0.001)
pmarr	-0.009***	-0.009***
	(0.002)	(0.002)
pelec	-0.003	-0.003
	(0.006)	(0.006)
pnopipwat	0.001	0.001
	(0.001)	(0.001)
ppubsewage	0.000	0.000
	(0.000)	(0.000)
pmigrant	0.011***	0.011***
	(0.002)	(0.002)
pprimsec	-0.006***	-0.006***
	(0.001)	(0.001)
(Intercept)	9.099***	8.925***
	(0.657)	(0.646)
n	834	834
R-squared	0.876	
AIC		-527.832

Table 6. Moran's-I statistics and p-values

		k		**Stock of K**		**Wage**		**y**	
year	order of contiguity	Moran's-I	p-value	Moran's-I	p-value	Moran's-I	p-value	Moran's-I	p-value
2010	1	-0.001	0.900	0.296	0.000	0.434	0.000	0.133	0.001
2010	2	-0.013	NA	0.163	0.000	0.305	0.000	0.063	0.071
2010	3	0.002	NA	0.173	0.000	0.190	0.000	0.042	0.207
2010	4	-0.011	NA	0.105	0.002	0.142	0.000	0.044	0.165
2010	5	-0.010	NA	0.088	0.008	0.078	0.016	0.020	0.467
2015	1	0.108	0.005	0.339	0.000	0.529	0.000	0.159	0.000
2015	2	0.002	0.889	0.196	0.000	0.316	0.000	0.114	0.001
2015	3	0.046	0.160	0.180	0.000	0.217	0.000	0.077	0.024
2015	4	0.075	0.018	0.130	0.000	0.161	0.000	0.104	0.002
2015	5	0.083	0.007	0.103	0.002	0.100	0.002	0.048	0.123

Source: prepared by the authors using data from INEGI (2009; 2014), Minnesota Population Center (2020).

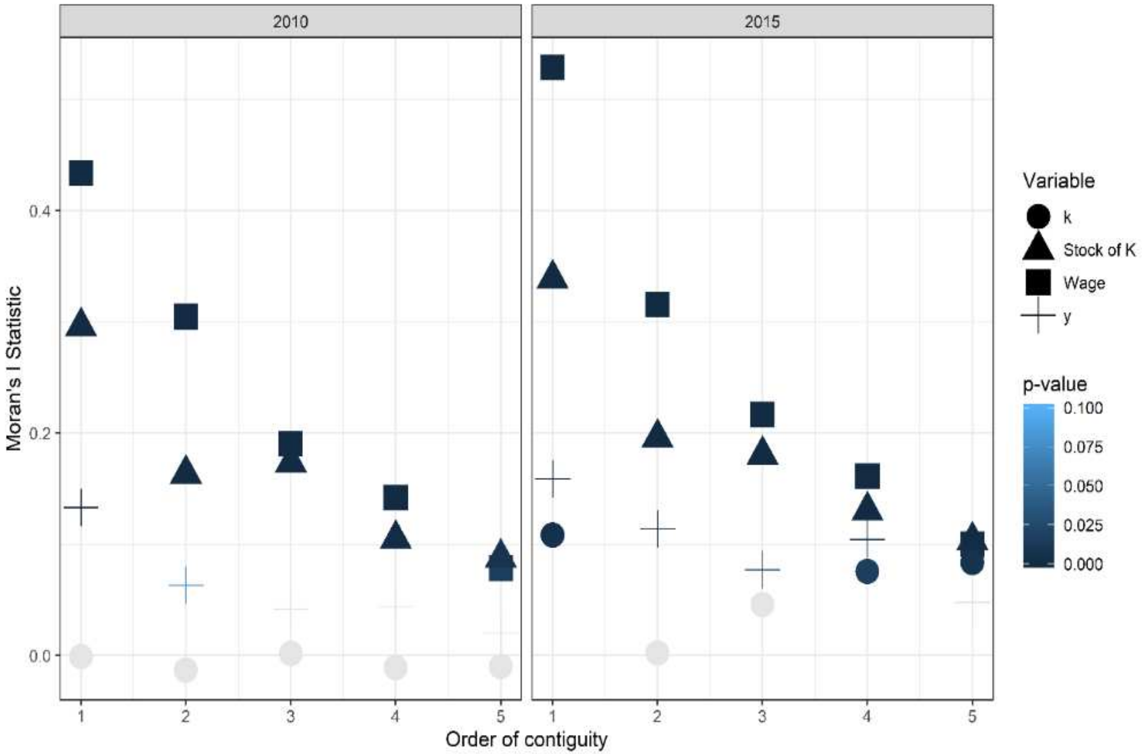
Figure 1. Single (Pearson's) correlation among independent variables



Notes: Color intensity indicates the degree of correlation. Crosses indicate statistically insignificant correlations. Two of the variables are highly correlated (red square): years of schooling, and the percentage of people attending university.

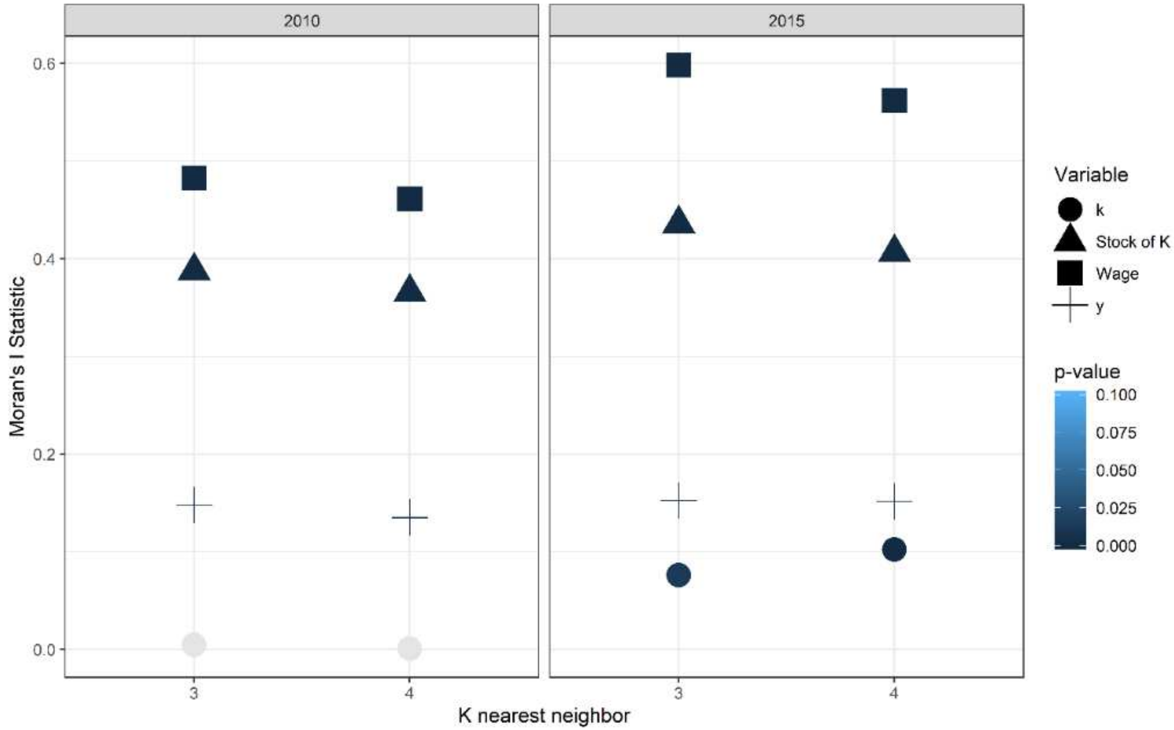
Source: calculated by the authors using data from INEGI (2009; 2014) and Minnesota Population Center (2020).

Figure 2. Correlogram of wage (Wage), gross value added per worker (y), capital per worker (k), and stock of capital (Stock of K) with a queen matrix, for 2010 and 2015



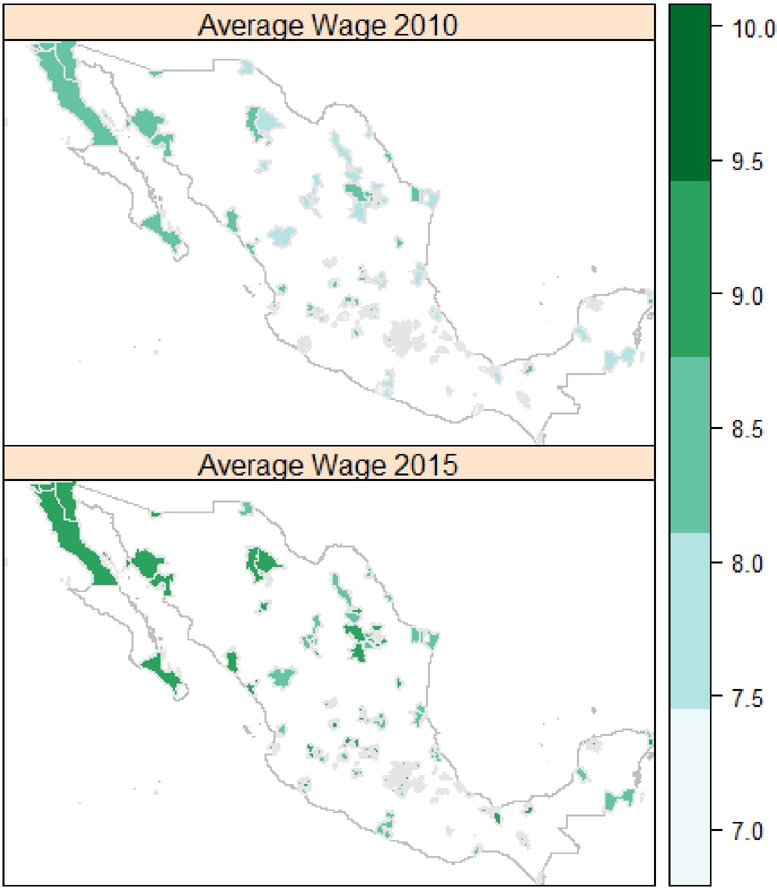
Source: prepared by the authors using data from INEGI (2009, 2014)), Minnesota Population Center (2020).

Figure 3. Spatial correlation of wage (Wage), gross value added per worker (y), capital per worker (k), and stock of capital (Stock of K) with k-nearest neighbor matrix, for 2010 and 2015



Source: prepared by the authors using data from INEGI (2009; 2014), Minnesota Population Center (2020).

Figure 4. Spatial distribution of the average wage per municipality in 2010 and 2015



Source: prepared by the authors using data from Minnesota Population Center (2020).