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Wage inequality across METROPOLITAN municipalities in Mexico, 2010-2020

Desigualdad salarial entre los municipios METROPOLITANOS en méxico: 2010-2020

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ABSTRACT

This work aims to analyze wage inequality from a spatial perspective. We specify a spatial autoregressive model with the average wage per municipality dependent on a spatially lagged variable and other controls like productivity, schooling, and migration. We estimate a quantile regression to determine the spatial effect of wage in a region over quartiles of the wage distribution with data from population censuses in 2010 and 2020. The main findings indicate that territory is critical to explaining wage inequality in 2010 but not 2020. Productivity increased wage inequality in 2020, and internal migration equalizes the wage.

RESUMEN

El objetivo de este trabajo es analizar la desigualdad salarial desde una perspectiva espacial. Especificamos un modelo autorregresivo espacial con el salario promedio por municipio como dependiente de sí mismo rezagado espacialmente y otros controles como productividad, escolaridad, y migración. Estimamos una regresión por cuantiles para determinar el efecto espacial del salario en una región sobre los cuartiles de la distribución del salario con datos de los censos de población 2010 y 2020. Los principales hallazgos indican que el territorio es clave para explicar la desigualdad salarial en 2010 pero no en 2020. La productividad incrementó la desigualdad salarial en 2020, y la migración interna ecualiza el salario.

1. INTRODUCTION

The nature and causes of wage differences is a topic that concerns scientists and politicians. Understanding the origins of wage inequality allows a better comprehension of income inequality because it is the primary source of people's earnings.

The study of wages and their characteristics is a vast topic that we can approach from many perspectives: microeconomics, macroeconomics, economic growth, and public policy, among others. Nevertheless, we can find a few studies dealing with wage differences from a spatial perspective: (Andrés-Rosales et al., 2019; Malkina, 2019; Mazol, 2016; Senftleben-Koenig & Wielandt, 2014; Wang & Xu, 2015). Some studies about wage differences focus on individual characteristics linked to labor productivity as wage inequality sources:(Acemoglu & Autor, 2010; Autor & Dorn, 2009b, 2009a; Card & DiNardo, 2002; Juhn et al., 1993). However, most studies generally leave out the geographic location's role as a defining element of wage inequality. Although workers' characteristics are relevant to explain wage differences, local features, like natural resources, institutions, and historical accidents, also play a determinant role in wage inequality. For example, it is vastly known that the oil industry is a well-paid industry in Mexico, such territories that own this natural resource expect a more significant average wage than other areas which do not own oil. For example, studies considering income leave out states like Campeche and Tabasco, whose income vastly exceeds the rest of the country derived from the oil industry (Esquivel, 1999).

Over the last 30 years, a new structure of economic activity has emerged in Mexico, and high-specialized places have developed in the context of international integration. In some cases, these places have taken advantage of their geographic location, chiefly those close to the northbound, because the principal economic partner is the United States (U.S.). Along with these changes in product composition, a new structure of wages has developed in places with access to high salaries (north) compared to the most backward regions (south), where salaries are relatively low. Under this rationale, wage inequality would increase across territory because some places with high wages arise along with low-wage locations, generating an increasing imbalance (Hanson, 1997; Hanson & Harrison, 1995). Mexico is not an isolated case; Chile also experienced a similar process (Uribe-Echeverría, 1995).

Moreover, beyond geographic location, which is one component to explain wage differences, the neighborhood is an additional factor that matters to the wage distribution since territories are not isolated because they interact with each other and transmit their ups and downs because of the mobility of factors (Isard, 1960). The first element has been widely studied; however, the second has not been studied yet in Mexico.

The present inquiry aims to analyze wage inequality from a spatial perspective and determine the dynamics of the wage differences in a region through a spatial autoregressive model and estimate a spatial quantile regression, combining data from economic and population censuses for the years 2010 and 2020. This work differentiates from the rest because it stresses the territory as an observation unit and combines two data sources. The analysis also focuses on the interaction among municipalities under the rationale that neighborhood matters besides the relative geographic location.

The results from a spatial quantile regression show a negative spatial effect in the lower part of the wage distribution in 2010, which implies that territory contributes to explaining the wage inequality. Nevertheless, the territory no longer explains the wage inequality in 2020, although there is evidence of more spatial dependence among metropolitan municipalities. Furthermore, when wage increases in a municipality, it negatively impacts low-wage municipalities by diminishing average wage, although this impact is weak but statistically significant. These results drive the conclusion that the increase in wages in a territory provokes wage inequality in the region; nonetheless, the stability of this condition is still unknown.

This paper follows the following structure: A first section deals with the outline of wage inequality and the economic transformations in the Mexican economy. In the second section, we develop a theoretical and empirical model of the spatial econometrics structure. Then, we describe data, sources of information, and some statistical information represented through maps and figures; we also conduct spatial autocorrelation tests in this section. In the next section, the spatial quantile regression results arise from data from 2010 and 2020. Finally, the last section is about the conclusions of this inquiry.

2. LITERATURE REVIEW

Economic theory points out that in a free market with perfect factor mobility, the determination of wages is simply a particular case of the general theory of value. Wages are the price of labor; thus, supply and demand laws determine them (Hicks, 1963). Under this approach, because of any number of goods to produce, wage differences result from differences in each economic activity's marginal product where suppliers and demanders occur. However, explaining wage differences is more complex because economic activities do not distribute homogeneously over territory but agglomerate in urban areas. Moreover, the labor market has multiple restrictions like minimum wage law, unions, outsourcing, and lack of information, which noise the interchange between suppliers and demanders.

Although theory points out that wages for the same labor efficiency must be equal in any place (Hicks, 1963), this statement returns the discussion to the starting point, where the wage differences result from the differences in marginal products. One of the first inquiries addressing income inequality comes from Kuznets (1955), analyzing the long-term economic growth path and income distribution changes.

Regional inequality has been one of the leading research topics in economic geography since the 1950s (Mazol, 2016). For example, Williamson (1965) drives one of the first documents on this topic. He disaggregates Kuznets' analysis from a regional perspective. He points out the situation of different wages in an economy separated into regions, arguing that regional interdependence and factor mobility is more intense within a country than between countries, which would, hypothetically, vanish the regional differences.

The underlying idea behind the early documents that address the relationship between economic growth and income inequality is that the first is unbalanced because its distribution upon space is not homogeneous. However, it arises in some territories in the first stage, and thus, inequality rises. Then, factor mobility distributes investment and labor in the country, and backward places increase their income levels to reach the forward ones (Hirschman, 1961).

In the process described before, economic activities play a determinant role in diminishing the income gap between backward and forward regions. Those specialized in agriculture with a low marginal product against regions specialized in manufacturing tend to hold the gap systematically (Delgado, 2006; Williamson, 1965); thus, according to this approach, the path to narrowing the income gap is through narrowing productivity differentials.

This document addresses wage inequality instead of income inequality because the first offers a more accurate dimension of the labor factor price

(Juhn et al., 1993). So that, 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 wage inequality (Juhn et al., 1993; Topel, 1994).

An extension of trade and wage inequality comes from the Heckscher-Ohlin theorem, which states that an underdeveloped economy with abundant unskilled labor shifts towards openness to trade would export goods with a high unskilled labor factor. Simultaneously, this comes with an increase in the demand for unskilled workers, raising their wages and narrowing the gap regarding most skilled workers, thus reducing wage inequality (Stolper & Samuelson, 1941). The last is the so-called Stolper-Samuelson theorem, which Wood (1997) corroborates when assessing wage inequality and openness for East Asian economies during the 60s and 70s. This author found strong evidence about narrowing 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 wages widen from the mid-1970s to the early 1980s in Argentina and Chile. 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 sparked development during the 1960s and 1970s. Latin American countries' openness to trade 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 New Economic Geography (NEG) development triggered many regional wage inequality studies (Krugman, 1980, 1991). This theory stresses the idea of a big market that generates pecuniary and non-pecuniary externalities, where one good is manufactured and transported to another area. Thus, the mobility of the labor factor attracted by the amenities in the agglomerated region increases wage inequality and persists until the backward region grows (Mudiriza & Edwards, 2017).

The NEG is concerned with the dynamics of forces that concentrate or scatter economic activity and the openness to trade, transport costs, and others; however, it does not consider the territory endogenously under its framework. Therefore, the NEG ignores some dynamics rooted in the territory, which sometimes happens in the neighborhood into a region.

The openness to the trade process in Mexico started in 1985 through the reduction in trade barriers and the signing of the General Agreement on Trade and Tariffs (GATT), later, the signing of the North America Free Trade Agreement (NAFTA) in 1993 (Chiquiar, 2008). This process aimed to switch the economic model towards one of export-led growth. Spatially speaking, openness to trade caused relevant changes in the location of economic activity (Baylis et al., 2012)

The expected result after openness to trade in Mexico was the narrowing of wage inequality as a result of the increase of labor demand from those industries linked with the outward market; however, wages of the most skilled workers started to rise, contrary to the Stolper-Samuelson theorem (Hanson & Harrison, 1995; Mungaray & Burgos, 2009; Wood, 1997). Moreover, the evidence points out that the relative wages declined with distance from industrial centers, not between cities (Hanson, 1997), and those centers located chiefly in border cities. Thus, after NAFTA, regional polarization increased rather than diminished (Baylis et al., 2012), although there is evidence that wage inequality declined between female and male workers (Aguilera & Castro, 2018).

One explanation of the wage inequality that rose after the openness to trade is that only an insignificant number of industries and plants could export goods; also, these could pay higher wages (Hanson & Harrison, 1995). This phenomenon is territorially unbalanced because of the export industry's rise in the north of Mexico after openness to trade. Thus, wage differences are not merely by industry but by region (Verhoogen, 2008). These results contradict those of Chiquiar (2008), who found trade effects on relative prices consistent with the Stolper-Samuelson theorem. On the other hand, Castro and Félix (2010) found productive specialization, economic activities diversity, and market access as defining elements of the average wage differences among Mexican cities. An extensive literature review on the wage inequality phenomenon in Mexico is in Castro and Huesca (2007).

Most of the documents cited above exploit analysis units like households, workers, sectors, states, or regions; however, just a few studies consider the spatial dimension as an endogenous component, and neither mentioned before nor the importance of the geographic location.

Chiquiar (2008) points out the spatial dimension of wage inequality, which could not be evident from other studies. This author states that the same skilled workers might expect different wages depending on where they live because industry distribution is uneven across territories. This characteristic requires different labor mixes, so expect a higher mean wage in territories specialized in more skill-intensive industries (Combes et al., 2008).

Combes and Gobillon (2008) directly link the average skills level in a territory with its average wage in their study of French workers and also consider some local characteristics. They found that workers with better labor market characteristics tend to agglomerate in the larger, denser, and more skilled local labor market, yielding more significant wage disparities across territories.

Technological change may underline wage differences across regions due to the changes in the labor market composition and the industry structure. Along with shifts from routine to non-routine tasks of workers, higher compensation for their skills and knowledge arises; This is what Senftleben-Koening and Wielandt (2014) demonstrate in their study of German regions. They find that wage inequality in this country arises from disparities driven by technological changes because more backward regions keep a large share of routine-task jobs. In contrast, forward regions demand more cognitive and non-routine workers.

Mazol (2016) developed a study on wage differences in Belarus' districts related to local characteristics. He finds that the main economic factors contributing the most to decreasing wage differences across regions are industrial development, retail trade, and agricultural development. In contrast, population growth and capital investments raise wages in the wealthiest districts. We can plausibly link industrial development with capital investments as factors that act in the opposite direction, although they are closely related because industrial development requires large amounts of investment. We also highlight population growth as an element of the rising average wage in regions; this is a home market effect, supported by early models from Krugman (1980, 1991), and recently studied by Wang and Xu (2015), who find that wage in China's coastal regions is higher than in inner ones because the firsts are more extensive, in terms of population than the lasts. In contrast with Mazol's results, Malkina (2019) finds that agriculture is critical to narrowing the gap between Russian regions; however, retail trade acts in the opposite direction, increasing wage differences.

A recent study on spatial wage inequality in Mexico finds evidence of narrowing the gap between wages driven by the precariousness of working conditions rather than catching up from lower wages during 2005-2018 (Andrés-Rosales et al., 2019).

3. METHODOLOGY

Wage inequality may increase because of a real salary gain in a specific economic sector, a particular set of plants, or workers. In addition, some wage inequality measures, like the Gini index, Theil index, and variation coefficient, are susceptible to a slight change in both sides of the distribution. For example, a change in the top of wages might carry out a drastic increase in wage inequality.

Consider a country with *i* municipalities where output in each one depends on Capital and Labor, but labor is compounded by many kinds of workers, from low-skilled to high-skilled. To simplify, suppose there are two types of workers, high-skilled and low-skilled. These both sets of workers combine along with capital and technology to produce through the following function:

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

Y represents output, *A* technology that generates positive shock on capital *K,* and *L* represents labor, split into high-skilled *h* and low-skilled *l.* Parameters α and δ represent the share of each factor in output with $\alpha + \delta < 1$. Thus, computing the marginal product of each kind of labor to obtain the wage:

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

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

The average wage in every municipality of the country is determined by the average marginal productivity as follows:

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

The left side of the past equation is the expected value of wage in municipality *i*, such that:

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

The last equation considers just two kinds of workers; however, it can be extended to any number because there are as many qualities as economic activities between high and low-skilled workers. Even in the same economic activity, it is possible to find several attributes of labor. Formally, for *n* kind of workers:

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

The last equation means that the average wage in a municipality equals its average marginal labor productivity; by extension, differences in labor's marginal productivity explain the wage differences among territories.

So far, territory and all the spatial dynamics are out of the analysis; nevertheless, we must consider them because the location matters and its implications, such as neighbors and relative position within a country. In a country, all municipalities solve an equation like sixth; simultaneously, they interact as part of the economic dynamics. Closer municipalities transmit ups and downs to their neighbors more than those distant (Tobler, 1970). Moreover, spatial wage inequality is essential in big countries (Malkina, 2019) like Mexico.

In a country, municipalities interact through many mechanisms; one is the workers who travel daily. In many countries, workers move from one place to another for a job, seeking the best pay for their skills and knowledge. Under this rationale, high-wage territories are more attractive for workers than low-wage ones, generating an imbalance because high-wage territories would employ high-skilled workers leaving the other places with less productive workers. On the other hand, low-wage territories could increase their productivity by attracting high-skilled workers, but this only would happen if workers receive a higher wage than they currently receive.

The last situation leaves two possible outcomes regarding the effect of wages from one territory on its neighbors. On the one hand, high-skilled workers would be employed in high-wage territories, increasing wage differences because low-wage territories could only employ low-skilled workers. We might say that this is an imbalance in an NGE fashion. On the other hand, wage differences would equal territories if low-wage territories attract more skilled workers by paying higher wages, increasing average marginal productivity and average wage.

Thus, the average wage in a territory *i* is explained by its average productivity and the average wage of its neighbors *j*.

$$\bar{w}_i = \frac{\bar{\Omega}_i}{\bar{w}_j^{\rho}} \tag{7}$$

Where represents the degree of interaction across territories. When there is no dependence among territories, ρ=0¸and average wage depends only on average marginal productivity.

Log-linearizing (7):

$$\ln \bar{w}_i = \ln \bar{\Omega}_i - \rho \ln \bar{w}_j \tag{8}$$

Quantile regression is the best approach to analyze and answer the stated question, which is much better suited to analyzing questions involving changes in the dependent variable's distribution (McMillen, 2013). Also, quantile regression offers the opportunity for a complete view of the statistical landscape and the relationships among stochastic variables (Koenker, 2005). Quantile regression owns an advantage against traditional multiple regression analysis because this last focus on the middle part of the distribution of the dependent variable, whereas the former estimates coefficients for any part of it. Mazol (2016) exploits a quantile regression in his study on spatial wage inequality in Belarus.

Moreover, this document uses the average wage per municipality, implying that information aggregates at this geographical level. To accomplish this purpose, we propose a spatial A.R. model; it adds a weighted average of nearby values of the dependent variable to the list of explanatory variables (McMillen, 2013) as follows:

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

Y is the dependent variable, *X* is a set of explanatory variables, and *W* is a *n x n* spatial weight matrix where *n* is the sample size; we define this matrix in the next section. To translate into the quantile regression parlance, consider that this method, instead of ordinary least squares, seeks for the arg min of weighted sums of absolute residuals, such that:

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

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

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

Translating equation (11) into an empirical model and considering that the municipality is the analysis unit, the econometric specification follows a spatial autoregressive structure as follows:

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

For each municipality, is the natural logarithm of the average wage, is the natural logarithm spatially lagged, and is the average marginal product. The last specification needs some control variables to avoid endogeneity issues, but we describe these below.

4. DATA

Considering that the analysis unit is the municipality, we require representative information at this aggregation level. The Population Census has collected data on earnings by job since 2010 and disaggregates it to the municipality level. Thus, we obtained the data from the Population Census 2010 from the Integrated Public Use of Microdata Series (IPUMS) International (Minnesota Population Center, 2020). We also obtained data from the Population Census 2020 driven by the National Institute of Statistics, Informatic and Geography (INEGI). The variable we took as wage corresponds with the person's total income from their labor in the previous month of the survey. The variable is in current prices, and we did not transform it into constant ones because an intertemporal experiment exceeds the scope of this document. Nonetheless, the inflation rate was about 2% on average throughout the entire period (INEGI, 2022).

Along with the earnings data, we also obtained information about workers' characteristics such as age, education, marital and migration status, speaking of indigenous language, and working sector. We also collected data on households' characteristics, such as the availability of public services, to add some controls to the regression.

The economic information, such as production and labor, came from the Economic Census, which also can disaggregate data at the municipality level. We assume that the marginal product, or productivity, is equivalent to the average product, measured as the product by the worker; thus, we define productivity as:

$$\bar{y} = \frac{GVA}{TEP} \tag{13}$$

GVA is the Gross Value Added in current prices as the local GDP's proxy. Authors like Baylis et al. (2012) also use this variable similarly. TEP is the Total Employed Population, which measures labor. Therefore, we retrieved both variables from the economic censuses.

The temporality of these censuses does not match with the Population Census. Economic censuses provide data from 2009 and 2019, one year before the Population Census. Hence, we assume that both information sources (Population census and economic census) contain data from the same year. We can plausibly assume this because the economic structure does not change drastically from one year to another.

An additional drawback comes from the economic census; the primary economic sector is out; this provokes misinformation for small and rural municipalities, such as negative GVA. In other cases, the value reported in this variable is zero for small municipalities, which is problematic for computing ratios or logarithmic transformations. To avoid this drawback, we subset the sample to consider all the municipalities that belong to the Metropolitan System (M.S.) rather than all the country's municipalities. The MS is a compound of 417 municipalities grouped in 74 metropolitan areas.

These municipalities contain 75.1 million people, representing 62.8% of the total population in 2015 (SEDATU et al., 2018).

So far, we have defined the variables of interest, such as the dependent variable and two independent variables; however, we added some controls that explain the wage in a municipality, and they are related to productivity; We do list these control variables in the following table:

TABLE 1
DESCRIPTION OF THE CONTROL VARIABLES

Variable name	Description	Source
avage	Average age	Population census
aveduc	Average years of schooling	Population census
pfemale	Percentage of females	Population census
pnospkind	Percentage of people that do not speak an indigenous language	Population census
pmarr	Percentage of married people	Population census
pelec	Percentage of households with electricity	Population census
pnopipwat	Percentage of households without piped water	Population census
Ppubsewage	Percentage of households with public service sewage	Population census
Pnomigra	Percentage of non-migrants	Population census
pprimsec	Percentage of people working in the primary sector	Population census

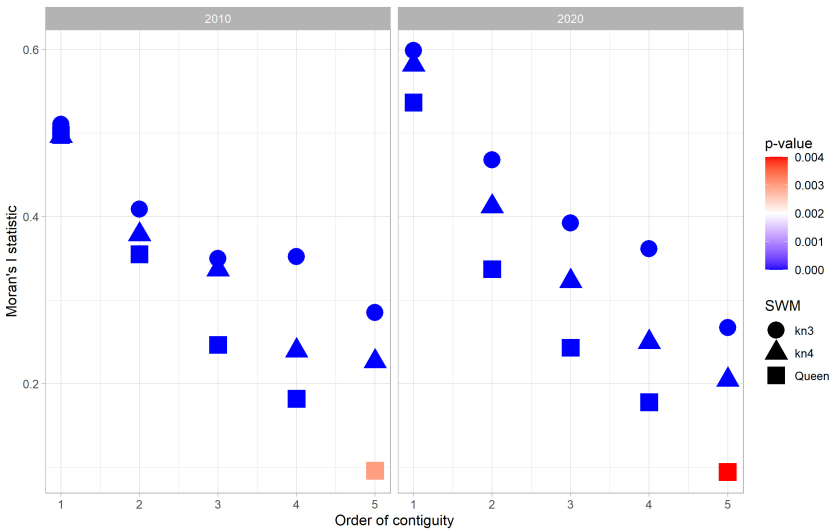
Source: Own elaboration.

5. SPATIAL WEIGHT MATRIX (SWM)

As part of the spatial analysis, we need a spatially lagged variable, which, in our case, corresponds with the average wage spatially lagged. We build this variable as the product of the spatial weight matrix (SWM), which we denote by *W,* multiplied by the average wage. Nevertheless, first, we must choose a proper spatial weight matrix to perform the computations. It is convenient to remind that SWM captures the spatial interaction among territorial units; in other words, it represents the spatial structure of our sample.

Figure 1 shows Moran's I test, which accounts for spatial autocorrelation on the wage variable for 2010 and 2015. We consider three different types of SWM. A queen matrix based on contiguity and two matrices based on three and four nearest neighbors, respectively. Figure 1 shows that the three nearest neighbors matrix accounts for the highest values of the Moran statistic in all contiguity orders in both years. Spatial autocorrelation is lower in 2010 than 2020, and the queen matrix reports the lowest values of the Moran statistic.

FIGURE 1
SPATIAL AUTOCORRELATION OF THE WAGE FOR 2010 AND 2020.



Source: Own elaboration with data from INEGI (2009; 2019; 2020), Minnesota Population Center (2010)

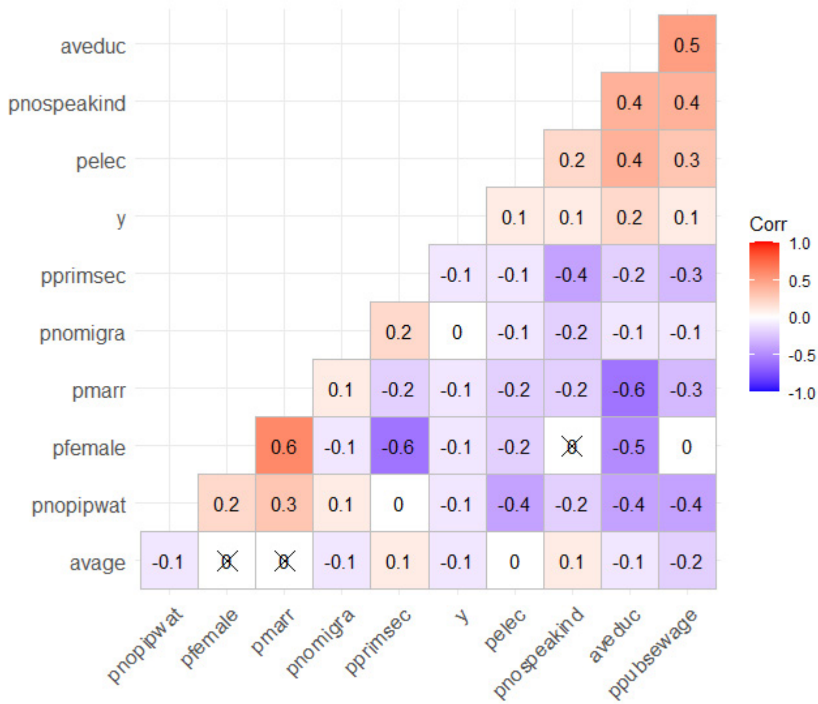
We choose a first contiguity order matrix based on the three nearest neighbors because it maximizes the spatial autocorrelation. Evidence of spatial autocorrelation among spatial units shown in figure 1 means that municipalities' wages move up or down as a group rather than in isolated municipalities. In other words, whether wage increases in a municipality, its neighbors shall do as well.

With all variables and data defined, we pose the estimating equation below:

$$\begin{aligned}\ln(\overline{wage}) = \beta_0 + \rho W \ln(\overline{wage}) + \beta_1\bar{y} + \beta_2 avage + \beta_3 aveduc + \beta_4 pfemale \\ + \beta_5 pnospkind + \beta_6 pmarr + \beta_7 pelec + \beta_8 pnopipwat \\ + \beta_9 ppubsewage + \beta_{10} pnomigra + \beta_{11} pprimsec + u\end{aligned} \tag{14}$$

We show the single correlation among independent variables in figure 2. We computed this statistic because we are concerned about collinearity, which we may discard due to low correlations among variables. For example, only the percentage of people married slightly correlates with the percentage of females and the average years of schooling. Thus, we may proceed with equation 14 as the final econometric specification.

FIGURE 2
SINGLE CORRELATION AMONG INDEPENDENT VARIABLES



Source: Own calculations with data from INEGI (2009, 2019, 2020) and Minnesota Population Center (2020).
Note: We describe variable names in table 1.

The last step before stating the empirical model consists in performing the spatial autocorrelation test on the interest variable to justify the spatial approach of this study.

6. RESULTS

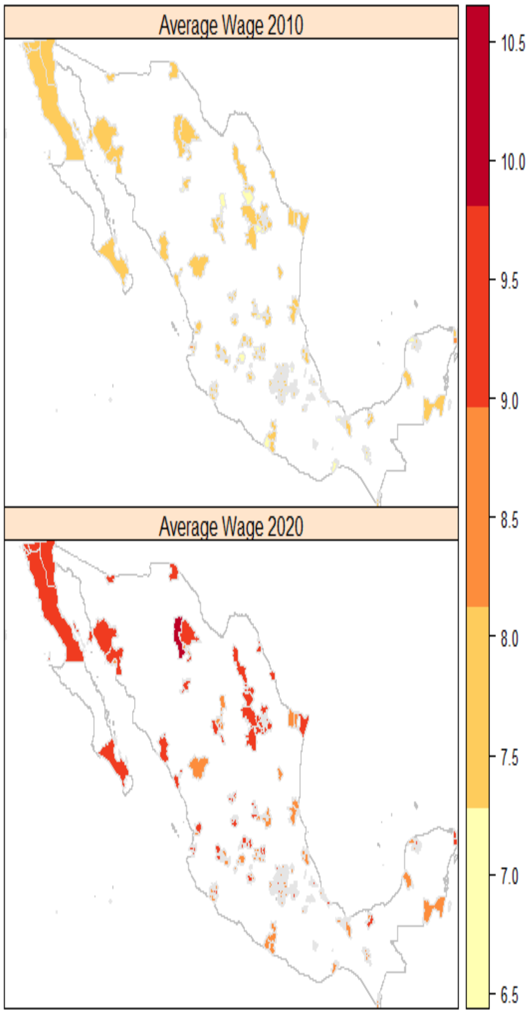
The following map (figure 3) shows the logarithm of the average wage across the municipalities of the metropolitan system in 2010 and 2020. Unfortunately, we cannot compare wages between these years because of the price increments. Although we document evidence about the spatial correlation: the wages change among municipalities as a group; in 2010, the wage was more homogeneous than in 2020. Hence, we expect a more considerable wage inequality in 2020 than in 2010 due to a widening wage distribution.

With this background, we have a clear idea about the distribution of wages, which, overall, high wages are expected in the north, whereas We expect low wages in the south. Now we turn over to estimate the empirical model presented in equation 14. This analysis will allow us to determine the behavior of wages across municipalities at different points of the wage distribution.

The procedure to obtain the results was to split the dataset by year, 2010 and 2020, and get coefficients for these two years separately. The estimation method consists of a two-stage quantile regression developed by Kim and Muller (2004). The results for 2010 of equation 14 are in table 2. It shows five coefficients for each variable; these correspond with every quantile of the average wage distribution across municipalities. Therefore, we classify municipalities that belong to quantile 0.10 and 0.25 as low-wage, those that belong to quantile 0.5 as middle-wage, and 0.75 and 0.90 are high-wage municipalities.

According to the model, the variable of interest is the spatially lagged one, which reports a positive sign in all quantiles. This coefficient is also increasing from quantile 0.10 to 0.90; it is statistically significant from quantile 0.25 to 0.90; this means that an increase of 1% in average wage provokes an increase of 0.27% in the average wage of neighbors belonging to the highest quantile of the wage distribution. On the other hand, an 1% wage increase in municipalities at the quantile 0.25 provokes an increase of 0.16% in neighbors' wages. The evidence on the behavior of the spatial autocorrelation of wage across quantiles suggests that wage inequality tends to increase because the spatial impact of the wage is higher for those municipalities belonging to the highest part of the wage distribution. Thus, an increment of the average wage in a municipality increases wage differences among neighborhoods.

FIGURE 3
SPATIAL DISTRIBUTION OF THE AVERAGE WAGE PER MUNICIPALITY, 2010-2020



Source: Own elaboration with data from INEGI (2009, 2019, 2020), Minnesota Population Center (2020).

Productivity reduced wage inequality in 2010; its impact on the increasing average wage is more prominent for those municipalities belonging to the quantile 0.25 than those at quantile 0.75. Furthermore, this coefficient decreases from municipalities at quantile 0.25 to quantile 0.75, meaning that an increase in the average product positively reduces wage inequality between municipalities.

We cannot omit that the 2008's financial crisis effects underlie the data on these particular estimations. Such a crisis severely impacted high-income municipalities, more accurately, those linked to the U.S. market, due to the demand diminishing from that country (Andrés-Rosales et al., 2019; Castro Lugo & Aguilera Fernández, 2017). Along with productivity spoilage and diminishing average wages due to unemployment.

The average years of schooling show that education returns are higher in low-wage municipalities, with around 8% of every additional year of education returns on wage decreasing along with quantiles. This result implies that education is critical to narrowing the gap between high-wage and low-wage municipalities.

Regarding other control variables, we highlight the effect of the percentage of non-migrants on wages. Our results suggest that migration contributes to narrowing the gap between high-wage and low-wage municipalities because the higher percentage of non-migrants, the lower the expected wage if the municipality belongs to the high part of the wage distribution. However, this variable is statistically insignificant for low-wage municipalities.

Regarding data from 2020, the results are in Table 2. In contrast with table 1, the spatial autoregressive coefficient shows an increment in magnitude, meaning that municipalities' average wage depends more than before on their neighbors. Also, in 2020 the spatially lagged variable is significant at all quantiles of the wage distribution, although at this time, it has no impact on wage inequality as in 2010. The public policy started in 2017 to recover the purchasing power consisted, among others, of a systematic increase of the minimum wage and the vanishing of salary zones, which could explain the last results (Campos-Vázquez & Esquivel, 2020; DOF, 2017). Moreover, based on the previous results, we may affirm that territory is no longer a source of wage inequality.

TABLE 2
RESULTS FROM SPATIAL QUANTILE REGRESSION WITH DATA FROM 2010

	Quantile				
Variable	0.10	0.25	0.50	0.75	0.90
Wln(wage)	0.0882	0.1686**	0.2201***	0.2187***	0.2743***
	(0.1220)	(0.0685)	(0.0702)	(0.0630)	(0.0832)
avgva	0.1359	0.1983***	0.1788***	0.1516***	0.1823
	(0.0849)	(0.0571)	(0.0528)	(0.0569)	(0.1380)
avage	-0.0468***	-0.0367***	-0.0245***	-0.0246***	-0.0310***
	(0.0093)	(0.0062)	(0.0057)	(0.0086)	(0.0088)
aveduc	0.0810***	0.0762***	0.0507***	0.0610***	0.0367
	(0.0228)	(0.0234)	(0.0186)	(0.0168)	(0.0232)
pfemale	-0.0429***	-0.0309***	-0.0128*	-0.0134	-0.0239*
	(0.0099)	(0.0070)	(0.0075)	(0.0097)	(0.0121)
pnospeakind	0.0016	0.0018	0.0011	0.0004	0.0010
	(0.0011)	(0.0014)	(0.0012)	(0.0010)	(0.0013)
pmarr	-0.0235***	-0.0211***	-0.0122***	-0.0125***	-0.0149***
	(0.0056)	(0.0036)	(0.0036)	(0.0040)	(0.0040)
pelec	0.0081	0.0048	0.0038	0.0026	0.0085
	(0.0100)	(0.0101)	(0.0072)	(0.0052)	(0.0097)
pnopipwat	-0.0002	0.0004	0.0009	0.0005	0.0011
	(0.0012)	(0.0013)	(0.0007)	(0.0006)	(0.0013)
ppubsewage	0.0001	-0.0001	-0.0001	0.0002	0.0003
	(0.0006)	(0.0006)	(0.0005)	(0.0005)	(0.0008)
Pnomigra	-0.0052	-0.0076**	-0.0141***	-0.0176***	-0.0213***
	(0.0033)	(0.0038)	(0.0032)	(0.0036)	(0.0069)
pprimsec	-0.0157***	-0.0168***	-0.0176***	-0.0116***	-0.0102***
	(0.0035)	(0.0030)	(0.0023)	(0.0041)	(0.0031)
(Intercept)	11.1796***	10.0657***	8.8009***	9.3289***	9.8022***
	(1.9793)	(1.1275)	(1.2061)	(1.0546)	(1.5507)
n	417	417	417	417	417

Significance codes: p<0.01 ***, p<0.05 **, p<0.10 *. Note: Standard errors in parenthesis

Own elaboration with data from INEGI (2009, 2019, 2020), Minnesota Population Center (2020).

On the other hand, productivity becomes more relevant with this data because we find coefficients that increase as we move towards upper quantiles. These are statistically significant for quantiles 0.75 and 0.90. Thus, productivity is relevant to explain wage inequality in 2020. This effect is consistent with other studies like Castro Lugo and Aguilera Fernández (2017); Baylis et al. (2012); Andrés-Rosales et al. (2019); Esquivel and Rodriguez-Lopez (2003).

In 2020, education return was higher for middle-wage municipalities; the behavior of this coefficient across quantiles is like a U-inverted shape. This result implies that education is irrelevant to narrowing wage inequality because there is no evidence of wage inequality derived from education.

Migration has a different effect in 2020 regarding 2010. reports the same behavior as in 2010; a higher percentage of no migrant population diminishes the average wage in municipalities belonging to the upper side of the wage distribution, except for quantile 0.90, higher than on the lower side of wage distribution; hence, migration helps on narrowing the gap in wage differences.

First, we highlight the differences in the results after this exercise. The main one corresponds to the role that plays the wage at a territorial level. Whereas in 2010, wage inequality increased when a municipality increased its average wage because it provoked a higher diminishing average wage in low-wage municipalities, in 2020, the spatial dependence of this variable is higher but no longer helps to explain the wage inequality. Other authors have found similar results through different methodologies; for instance, Aguilera and Castro (2018); Andrés-Rosales et. ál. (2019; Baylis et al., 2012); Baylis et. ál. (2012).

Studies from Esquivel and Rodríguez-López (2003) and Verhoogen (2008) support our findings about the wage inequality provoked by an increment in productivity. The explanation of this phenomenon comes from technical change and the capability of firms to export. Technological change implies changes in productivity and gains from it, allowing higher wages for the workers. On the other hand, industries linked to the external sector that can export goods also can pay more to their workers; thus, openness to trade implies an increase in wage inequality.

TABLE 3
RESULTS FROM SPATIAL QUANTILE REGRESSION WITH DATA FROM 2020

	Quantile				
	0.10	0.25	0.50	0.75	0.90
Wln(wage)	0.3808***	0.3918***	0.3614***	0.3964***	0.3470***
	(0.1002)	(0.0712)	(0.0672)	(0.0678)	(0.0966)
avgva	0.0694	0.0512	0.0870	0.1377*	0.2225**
	(0.0473)	(0.0527)	(0.0541)	(0.0718)	(0.1026)
avage	-0.0286**	-0.0121	-0.0048	-0.0120	0.0094
	(0.0115)	(0.0079)	(0.0081)	(0.0106)	(0.0183)
aveduc	0.0941***	0.1040***	0.1119***	0.0977***	0.0810***
	(0.0216)	(0.0132)	(0.0132)	(0.0173)	(0.0244)
pfemale	0.0037	-0.0024	-0.0024	0.0026	0.0006
	(0.0050)	(0.0031)	(0.0033)	(0.0041)	(0.0049)
pnospeakind	0.0020	0.0016	0.0007	-0.0011	-0.0004
	(0.0020)	(0.0014)	(0.0015)	(0.0013)	(0.0016)
pmarr	0.0015	0.0009	0.0034**	0.0032**	0.0006
	(0.0026)	(0.0014)	(0.0014)	(0.0016)	(0.0034)
pelec	-0.0213	-0.0001	-0.0112	-0.0034	0.0087
	(0.0199)	(0.0141)	(0.0174)	(0.0267)	(0.0530)
pnopipwat	0.0027	0.0005	-0.0018	-0.0035*	-0.0069**
	(0.0018)	(0.0016)	(0.0013)	(0.0020)	(0.0029)
ppubsewage	-0.0006	-0.0004	0.0001	0.0005	0.0011*
	(0.0006)	(0.0004)	(0.0004)	(0.0004)	(0.0006)
pnomigra	-0.0043	-0.0064*	-0.0112**	-0.0149***	-0.0107
	(0.0044)	(0.0037)	(0.0052)	(0.0054)	(0.0077)
pprimsec	-0.0056**	-0.0069***	-0.0046***	-0.0039	-0.0040
	(0.0026)	(0.0016)	(0.0013)	(0.0024)	(0.0031)
(Intercept)	7.6901	5.3073***	6.7649***	6.4797**	4.8006
	(2.1341)	(1.6292)	(1.9340)	(2.8960)	(5.0384)
n	416	416	416	416	416

Significance codes: p<0.01 ***, p<0.05 **, p<0.10 *. Note: Standard errors in parenthesis

Own elaboration with data from INEGI (2009, 2019, 2020), Minnesota Population Center (2020).

Our evidence points to internal migration as a factor that increases wage inequality within a region. However, most inquiries about this topic focus on international migration through a cross-country rather than a within-country approach. Whether migration increases wage inequality aligns with NEG theory, which predicts that factor mobility increases wage inequality across regions; this imbalance persists until the low-wage regions catch up with the high-wage ones.

7. CONCLUSIONS

This inquiry analyzes the space's role in wage inequality through a spatial econometric strategy. We estimate a spatial quantile regression with average wage per municipality as a dependent variable, and this same variable spatially lagged with data from population census from 2010 and 2020.

The main findings show evidence that when wages increased in a municipality in 2010, the average wage diminished in low-wage municipalities more than in high-wage ones belonging to the same neighborhood, which caused an increase in wage inequality across municipalities. However, in 2020, this behavior changed; although the average wage is more spatially dependent, its increase does not generate wage inequality; thus, the territory is no longer a source of wage inequality. Future inquiries might assess the impact of the most recent policy on minimum wage, which seeks to recover the purchasing power of people. However, our evidence is insufficient to affirm that spatial wage inequality has vanished due to the mentioned policy. Also, further studies might measure whether this phenomenon persists in the long run and the effects on welfare, or economic growth, to mention a few. Technically, future works implementing the same methodology should emphasize computing direct and indirect effects and interquartile estimations.

Productivity also increases wage inequality because an increment of this variable provokes an increase in wages on the upper side of the distribution, chiefly in 2020. This inequality is driven by technical change, although we cannot discard the hypothesis of efficiency salaries which refers to firms that pay salaries above average to keep high productivity levels.

We highlight the impact of migration on wage inequality, and we recognize our result as one of the first from a spatial perspective using municipalities as an observation unit. Municipalities with higher percentages of non-migrants show a lower average wage, more likely in high-wage municipalities.

BIBLIOGRAPHY

ACEMOGLU, D., & AUTOR, D. (2010). *Skills, Tasks and Technologies: Implications for Employment and Earnings* (No. 16082; NBER Working Paper Series). http://www.nber.org/papers/w16082

AGUILERA, A., & CASTRO, D. (2018). "NAFTA and Wage Inequality in Mexico: An Analysis for Border Cities, 1992-2016." *Frontera Norte*, *30*(60), 85–110. https://doi.org/http://dx.doi.org/10.17428/rfn.v30i60.1363

ANDRÉS-ROSALES, R., CZARNECKI, L., & MENDOZA-GONZÁLEZ, M. Á. (2019). "A spatial analysis of precariousness and the gender wage gap in Mexico, 2005–2018." *Journal of Chinese Sociology*, *6*(1), 1–21. https://doi.org/10.1186/s40711-019-0104-2

AUTOR, D. H., & DORN, D. (2009a). *Inequality and Specialization: The Growth of Low-Skill Service Jobs in the United States* (No. 4290; Discussion Paper Series).

AUTOR, D. H., & DORN, D. (2009b). *The growth of low skill service jobs and the polarization of the U.S. labor market* (No. 15150; NBER Working Paper Series). http://www.nber.org/papers/w15150

BAYLIS, K., GARDUÑO-RIVERA, R., & PIRAS, G. (2012). "The distributional effects of NAFTA in Mexico: Evidence from a panel of municipalities." *Regional Science and Urban Economics*, *42*(1–2), 286–302. https://doi.org/10.1016/j.regsciurbeco.2011.09.006

CAMPOS-VÁZQUEZ, R. M., & ESQUIVEL, G. (2020). "The effect of doubling minimum wage and decreasing taxes on inflation in Mexico." *Economics Letters*, *189*, 1–4. https://doi.org/https://doi.org/10.1016/j.econlet.2020.109051

CARD, D., & DINARDO, J. E. (2002). "Skill-Biased Technological Change and Rising Wage Inequality: Some Problems and Puzzles." *Journal of Labor Economics*, *20*(4), 733–783. https://doi.org/https://doi.org/10.1086/342055

CASTRO, D., & FÉLIX, G. (2010). "Apertura comercial, relocalización espacial y salario regional en México." *Estudios Fronterizos, Nueva Época*, *11*(21), 43–79. http://www.scielo.org.mx/scielo.php?script=sci_arttext&pid=S0187-69612010000100002&lng=es&nrm=iso

CASTRO LUGO, D., & AGUILERA FERNÁNDEZ, A. (2017). "Apertura comercial y desigualdad salarial en México: un análisis regional para los años 1992 y 2014." *Semestre Económico*, *20*(45), 109–131.

CASTRO LUGO, D., & HUESCA REYNOSO, L. (2007). "Wage inequality in México: a review." *Papeles de Población*, *13*(54), 225–264. https://rppoblacion.uaemex.mx/article/view/8613

CHIQUIAR, D. (2008). "Globalization, regional wage differentials and the Stolper-Samuelson Theorem: Evidence from Mexico." *Journal of International Economics*, *74*(1), 70–93. https://doi.org/10.1016/j.jinteco.2007.05.009

COMBES, P. P., DURANTON, G., & GOBILLON, L. (2008). "Spatial wage disparities: Sorting matters!" *Journal of Urban Economics*, *63*(2), 723–742. https://doi.org/10.1016/j.jue.2007.04.004

DELGADO, M. (2006). "Economía, territorio y desigualdades regionales." *Revista de Estudios Regionales*, *75*, 93–128.

DOF. (2017). *Resolución del H. Consejo de Representantes de la Comisión Nacional de los Salarios Mínimos que revisa los salarios mínimos generales y profesionales vigentes desde el 1o. de enero de 2017 y establece los que habrán de regir a partir del 1o. de diciembre*. https://www.dof.gob.mx/nota_detalle.php?codigo=5505642&fecha=24/11/2017#gsc.tab=0

ESQUIVEL, G. (1999). "Convergencia regional en México, 1940-1995." *Trimestre Economico*, *66*(4), 725–761. http://www.jstor.org/stable/20857005.

ESQUIVEL, G., & RODRÍGUEZ-LÓPEZ, J. A. (2003). "Technology, trade, and wage inequality in Mexico before and after NAFTA." *Journal of Development Economics*, *72*(2), 543–565. https://doi.org/10.1016/S0304-3878(03)00119-6

HANSON, G. H. (1997). "Increasing returns, trade and the regional structure of wages." *Economic Journal*, *107*(440), 113–133. https://doi.org/10.1111/1468-0297.00145

HANSON, G. H., & HARRISON, A. (1995). "Trade, Technology, and Wage Inequality." In *NBER Working Paper Series* (No. 5110; NBER Working Paper Series, Vol. 91, Issue 5110). https://doi.org/10.1017/CBO9781107415324.004

HICKS, J. R. (1963). *The theory of wages* (2nd ed.). Palgrave Macmillan. https://doi.org/10.1007/978-1-349-00189-7

HIRSCHMAN, A. O. (1961). *La estrategia del desarrollo económico* (Primera). Fondo de Cultura Económica.

INEGI. (2009). *Censos Económicos*.

INEGI. (2019). *Censos Económicos*.

INEGI. (2020). *Censo de Población y Vivienda*. Instituto Nacional de Estadística Geografía e Informática. https://www.inegi.org.mx/programas/ccpv/2020/#Resultados_generales

ISARD, W. (1960). *Methods of regional analysis: An introduction to regional science*. The MIT Press.

JUHN, C., MURPHY, K. M., & PIERCE, B. (1993). "Wage inequality and the rise in returns to skill." *Journal of Political Economy*, *101*(3), 410–442. https://doi.org/10.1086/261881

KIM, T.-H., & MULLER, C. (2004). "Two-stage quantile regression when the first stage is based on quantile regression." *The Econometrics Journal*, *7*(1), 218–231. https://doi.org/https://doi.org/10.1111/j.1368-423X.2004.00128.x

KOENKER, R. (2005). *Quantile Regression* (A. Chesher & M. Jackson, Eds.). Cambridge University Press.

KRUGMAN, P. (1980). "Scale Economies, Product Differentiation, and the Pattern of Trade." *The American Economic Review*, *70*(5), 950–959. http://www.jstor.org/stable/1805774 .

KRUGMAN, P. (1991). "Increasing Returns and Economic Geography." *Journal of Political Economy*, *99*(3), 483–499. http://www.jstor.org/stable/2937739 .

KUZNETS, S. (1955). "Economic Growth and Income Inequality." *The American Economic Review*, *45*(1), 1–28. https://doi.org/10.2307/2220605

LIAO, W. C., & WANG, X. (2012). "Hedonic house prices and spatial quantile regression." *Journal of Housing Economics*, *21*(1), 16–27. https://doi.org/10.1016/j.jhe.2011.11.001

MALKINA, M. (2019). "Spatial wage inequality and its sectoral determinants: the case of modern Russia." *Oeconomia Copernicana*, *10*(1), 69–87. https://doi.org/10.24136/oc.2019.004

MAZOL, A. (2016). *Spatial Wage Inequality in Belarus* (No. 35; Issue June).

MCMILLEN, D. P. (2013). "Quantile Regression for Spatial Data." In *Media*. Springer. https://doi.org/10.1007/978-3-642-21720-3

MINNESOTA POPULATION CENTER. (2020). *Integrated Public Use Microdata Series, International: Version 7.3 [dataset]*. Minnesota Population Center. https://doi.org/https://doi.org/10.18128/D020.V7.3

MUDIRIZA, G., & EDWARDS, L. (2017). "Can the New Economic Geography explain regional wage disparities in South Africa?" *Proceedings of Biennial Conference of the Economic Society of South Africa*, *January*, 1–37.

MUNGARAY, A., & BURGOS, B. (2009). "Apertura externa, inequidad salarial y calificación laboral en México, 1984-2002." *Problemas Del Desarrollo. Revista Latinoamericana de Economía*, *39*(152), 122–145. https://doi.org/10.22201/iiec.20078951e.2008.152.7705

SEDATU, CONAPO, & INEGI. (2018). *Delimitación de las zonas metropolitanas de México 2015* (1st ed.).

SENFTLEBEN-KOENIG, C., & WIELANDT, H. (2014). *Spatial Wage Inequality and Technological Change* (No. 649; Discussion Papers, Issue SFB649DP2014-038). https://ideas.repec.org/p/hum/wpaper/sfb649dp2014-038.html

STOLPER, W. F., & SAMUELSON, P. A. (1941). "Protection and Real Wages." *The Review of Economic Studies*, *9*(1), 58–73. https://doi.org/10.2307/2967638.

TOBLER, W. R. (1970). "A Computer Movie Simulating Urban Growth in the Detroit Region." *Economic Geography*, *46*, 234–240. https://doi.org/10.1126/science.11.277.620.

TOPEL, R. H. (1994). "Regional labor markets and the determinants of wage inequality." *American Economic Review*, *84*(2), 17–22. https://doi.org/10.2307/2117794.

URIBE-ECHEVERRÍA, F. (1995). "Reestructuración económica y desigualdades interregionales. El caso de Chile." *Revista de Estudios Regionales*, *43*, 297–337.

VERHOOGEN, E. A. (2008). "Trade, quality upgrading, and wage inequality in the mexican manufacturing sector." *Quarterly Journal of Economics*, *123*(2), 489–530. https://doi.org/10.1162/qjec.2008.123.2.489.

WANG, J., & XU, J. (2015). "Home market effect, spatial wages disparity: an empirical reinvestigation of China." *Annals of Regional Science*, *55*(2–3), 313–333. https://doi.org/10.1007/s00168-015-0700-2.

WILLIAMSON, J. G. (1965). "Regional inequality and the process of national development: A description of the patterns." *Economic Development and Cultural Change*, *XIII*(4), 1–84. https://www.jstor.org/stable/1152097

WOOD, A. (1997). "Openness and wage inequality in developing countries: The Latin American challenge to East Asian conventional wisdom." *World Bank Economic Review*, *11*(1), 33–57. https://doi.org/10.1093/wber/11.1.33.