Spatial Unemployment Differentials in Colombia

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SPATIAL UNEMPLOYMENT DIFFERENTIALS IN COLOMBIA

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Abstract. This paper studies the geographic distribution of unemployment rates in Colombian urban areas. It introduces measures of spatial correlation and spatial econometric techniques to analyze the dependence in local unemployment rates across municipalities. Results suggest that Colombian municipalities have experienced a polarization process between 1993 and 2005, as municipalities' unemployment rates have followed different evolutions relative to the National average. This process has been accompanied by the creation of unemployment clusters, that is to say, municipalities had very similar unemployment outcomes to those of their neighbors. This analysis uses a spatial Durbin model to explore the influence of various factors in determining differences in regional unemployment rates. According to our findings differences in labor demand, immigration rates, and urbanization are factors behind observed municipal unemployment disparities.

Key words: local labor markets, unemployment differential, polarization, clustering, spatial econometrics, spatial Durbin model.

JEL Classification: R23, C14, C23, C31.

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1. Introduction

There are several reasons why it is important to pursue this research. First, it is relevant for policy intervention due to equity concerns and pure human consequences of higher unemployment, especially in a country where opportunities in the labor market are essential to the well being of individuals because total household's income depends more on labor earnings than it does in developed economies. Second, wide unemployment differentials imply inefficiency in the economy as a whole and might affect both aggregate unemployment and national output. As suggested by Taylor (1996), reducing regional unemployment differentials might lead to higher national output and lower inflationary pressure. Furthermore, reducing regional unemployment might produce large social benefits. For example, it might counteract the downward spiral effect of economic depressed regions(Elhorst, 2003).

Why can the geographic distribution of unemployment be unequal? Economic theory provides a variety of perspectives on the nature and significance of regional unemployment differentials. Regions with favorable economic and demographic attributes might perform better and experience lower unemployment rates than declining regions. Indeed, regions differ in the industrial composition of their employment; in the age, gender, and skill structure of their populations; and in their levels of urbanization and agglomeration of their economic activity. In the short run, regional unemployment disparities reflect disparities in those attributes. In the lung run regional differences will gradually erode through labor mobility and/or firm's relocation. But, why do such differences persist? Three explanations have been offered. First, long run differentials represent an equilibrium where factors such as favorable climatic conditions, or an attractive environment encourage people to stay in regions where unemployment rates are high (Marston, 1985). Second, some persistent regional inequalities might reflect labor market rigidities that restrict mobility (Blanchard et al., 1992). Finally, according to the new economic geography, the polarized structure of unemployment rates may reflect the agglomeration of economic activities. The presence of economies of scale that benefit more booming regions, where workers and production are agglomerated, will exhibit lower unemployment rates relative to sparsely populated, peripheral regions (Epifani and Gancia, 2005, Suedekum, 2004). The self-reinforcing nature of agglomeration economies, which attract more workers and firms, translates into a stable core-periphery unemployment gap. Furthermore, as clusters of activity may extend across borders this can result in clusters of high and low unemployment extending across regions (Puga, 2002).

In the empirical analysis, I aim to assess the contribution of certain factors to the dynamics of the geographical distribution of unemployment rates. In general terms, the municipal unemployment rate is a reduced form function of factors that affect labor supply and labor demand.

These factors can be broadly categorized as labor market dynamics, non-demographic labor market attributes, human capital, demographic characteristics of the local labor force, and municipal attributes. Although it would be reasonable to assess the contribution of each of these factors from the view that unemployment dynamics are only related with factors within the municipality itself, it is also reasonable to assume that unemployment dynamics in a given municipality are related to the behavior of nearby municipalities due to interdependencies brought about by general equilibrium effects. Recently, in an attempt to bring these effects into the analysis, more and more studies have begun to use what is known as spatial econometrics. Some examples include Molho (1995), Aragon et al. (2003), Lopez-Bazo et al. (2002), Overman and Puga (2002), Niebuhr (2003), Patacchini and Zenou (2007) and Cracolici et al. (2007). The term "spatial econometrics" is a concept for explanatory regression models that allow for the fact that what happens in a particular municipality can also affect events in other nearby municipalities.

Let me take a concrete example. Suppose we want to explore the relationship between local human capital and unemployment. We can expect that municipalities with a high proportion of skilled workers experience lower unemployment rates as production shifts towards high-skilled employment, but through human capital externalities nearby municipalities might benefit as well. Here, spatial econometrics enables us to explore whether human capital has any effect on unemployment rate of the same municipalities or whether nearby regions are also affected, and, if they are, the extent of the overall impact.

To avoid an *ad hoc* choice of the specification, this paper uses a spatial Durbin model (SDM). This model is a spatial regression model that includes a spatial lag of the unemployment rate as well as the explanatory variables. The use of the SDM model has several advantages in relation to those models used to analyze regional unemployment differentials in the previous literature. One of these advantages is that it allows us to compute fairly simple diagnostics to test this model against more parsimonious alternatives because it nests most of the spatial models (Elhorst, 2010). A second virtue is that it provides consistent parameter estimates even if the true data generating process is a spatial lag or a spatial error model (LeSage and Pace, 2009). Another strength is that it allows us to explore spatial effects for different explanatory variables whilst not imposing prior restrictions on the magnitude of these effects (Elhorst, 2010). Finally, it allows to estimate summary measures of direct, indirect, and total impacts on unemployment rate arising from changing each explanatory variable in the model following LeSage and Pace (2009).

The spatial econometric exercise is complemented with a decomposition analysis that allow us to quantify how much of the variation in unemployment rates is explained by the variables included in the model and how much is explained by the omitted variables. Moreover, it allows us to assess the relative importance of each regressor with respect to its overall effect on the change in municipal unemployment rates. I also carry out a simulation exercise in which I calculate the new unemployment equilibrium values for each municipality after a change in a single explanatory variable under different scenarios. I calculate four main measures: the number of municipalities affected through the system of interactions, the difference between the observed and simulated unemployment rates, a measure of spatial inequality, and a measure of spatial dependence. A comparison of these measures for different scenarios serves to illustrate how a change in a few municipalities can affect other municipalities through the system of interactions and how it can modify the spatial distribution of unemployment rates.

In what follows, the next section includes a brief literature review of empirical studies devoted to understanding regional differences in unemployment. Section 3 presents the data and describes some underlying trends in Colombian municipal unemployment and potential factors explaining its evolution. Section 4, presents the empirical strategy and the results follow in Section 5. The final section offers concluding remarks.

2. Literature Review

Various theoretical models have explained the existence and persistence of regional disparities in the unemployment rate (Marston, 1985, Blanchard et al., 1992, Decressin and Fatás, 1995, Elhorst, 2003). As stated by Marston (1985) there are two possible explanations. The first one is related to an equilibrium mechanism, while the second is related to a disequilibrium context. According to the first view, each region tends to *its own* equilibrium unemployment rate, which is determined by local demand and supply side factors.[1] In the short run, regional unemployment disparities reflect disparities in these attributes. In the long run regional differences will gradually erode through labor mobility up to a point where only compensating differentials between regions remain (Harris and Todaro, 1970, Marston, 1985). Thus, the spatial distribution of unemployment under this interpretation is characterized by constant utility across areas: high unemployment in one area is compensated by some other positive factors (e.g., local amenities, climatic conditions, quality of life, local housing conditions, etc.). Marston (1985) claims that to the extent that unemployment is of equilibrium nature, any policy oriented to reduce regional disparities is useless "since they cannot reduce unemployment anywhere for long".

[1] Demand side factors can be the industry composition of regional production and the industrial diversity, while supply side factors relate to attributes of the labor force such as the skill composition and the demographic structure of the workforce.

According to the second view, all regions tend to *a competitive* equilibrium unemployment rate (Blanchard et al., 1992). In the short run, regional inequalities reflect the effect of asymmetric shocks (e.g., a shortage of labor demand in some regions). In the long run regional differences will eventually level out and disappear through labor migration and/or firm relocalization. However, labor market rigidities (e.g., wage bargaining, unions, taxation, welfare state arrangements, and labor laws) might restrict mobility and therefore adverse shocks are not fully absorbed before the regional labor market is hit by new shocks. Thus, the persistence of regional unemployment differentials is determined by the whole history of shocks to the economy. Under this theory unemployment differentials can be reduced by encouraging flexible labor markets and by reducing structural rigidities (Blanchard et al., 1992).

The equilibrium-disequilibrium views of regional differences in unemployment rates have recently been challenged by the observed spatial distribution of unemployment rates, in particular by the fact that regions with high (low) unemployment rates are surrounded by other regions with high (low) unemployment rates. Although these patterns are not inconsistent with the equilibrium-disequilibrium views, there is no theoretical causation mechanism that predicts a spatial clustering of unemployment.

Models from the *new economic geography* have attempted to fill this gap. These models posit that the interaction between scale economies and transport costs will create incentives for firms and workers to concentrate in the space. According to Epifani and Gancia (2005), such spatial concentration of economic activity causes core regions, where workers and production are agglomerated, to enjoy lower unemployment than sparsely populated, peripheral regions. Their argument is the following: frictions in the job-matching process lead to equilibrium unemployment, and search costs generate a positive externality of agglomeration on the labor market because agglomeration economies (i.e., productive advantages coming from the spatial concentration of labor and capital) increase firms' profits in the core and induce opening new vacancies, thereby lowering unemployment. The opposite happens in the periphery, where the reduction in firms' profits deteriorates the local labor market conditions. The self-reinforcing nature of agglomeration economies, which attracts more workers and firms to the core regions, translates into a core-periphery unemployment gap. Furthermore, as clusters of activity may extend across several administrative units, this can result in clusters of high and low unemployment extending across regional borders (Puga, 2002). Consistent with this theory, variables affecting the spatial distribution of economic activity also affect regional disparities in unemployment and might lead to the creation of spatial clusters of high and low unemployment.[2]

Several empirical studies have analyzed disparities in regional unemployment rates for different countries (e.g., Molho 1995, Lopez-Bazo et al. 2002, Overman and Puga 2002, Niebuhr 2003, Patacchini and Zenou 2007, Cracolici et al. 2007). In these studies, regional unemployment is related to local area characteristics, personal attributes of local population, local demand variables, and attributes of neighboring regions to take into account the spatial interaction among regions. These empirical studies have brought to light some interesting facts: i. there are important spatial inequalities in unemployment rates within countries (e.g., UK, Spain, Italy, France, Germany, and Turkey) and between countries, ii. within country unemployment differences are more pronounced than between countries inequalities, iii. these differences are highly persistent over time, and iv. adjacent regions tend to have similar unemployment rates than to regions located far away, this is unemployment observed at one point in space is dependent on values observed at other locations.[3]

Persistent regional unemployment inequalities have been explained by spatial differences in labor demand by Molho (1995), Overman and Puga (2002) and Cracolici et al. (2007), for UK, European regions, and Italy respectively. Filiztekin (2009) finds, for Turkey, that not only the differences in labor demand but also regional differences in human capital are the sources of observed disparity across regions. On the other hand, Lopez-Bazo et al. (2002) and Aragon et al. (2003) argue that unequal distribution of amenities is the major cause of spatial inequalities in unemployment rates in Spain and France. Finally, Basile et al. (2009) conclude that the excess of labor supply, migration outflows, and spatial proximity determine the polarization of regional unemployment rates.

Spatial dependence of the unemployment rates has been explained by three main factors. First, data collection of observations associated with spatial units such as countries, states, regions, census tracts do not accurately reflect the nature of the underlying process generating the sample data. Indeed, workers are mobile and can find employment in neighboring areas, thus, unemployment measured on the basis of where people live could exhibit spatial dependence. For example, Patacchini and Zenou (2007), using UK local data, provide evidence of a significant spatial dependence which is mainly explained by commuting flows

[2] Suedekum (2004) also finds that large core regions will exhibit lower unemployment rates compared to peripheral regions. Moreover, he posits that the core-periphery structure of unemployment resembles the spatial configuration of GDP per capita: low unemployment is centered in the agglomerated area whereas poor regions mostly have high unemployment rates. In other words, regions from the same country, with identical labor market institutions, can evolve very differently, depending on whether they belong to the cluster of central, intermediate or peripheral regions.

[3] See for example, Lopez-Bazo et al., 2002, Overman and Puga, 2002, Niebuhr, 2003, Aragon et al., 2003, Patacchini and Zenou, 2007, Cracolici et al., 2007, Basile et al., 2009. Table A.1 summarizes several aspects from these papers. As a matter of fact, it includes information about regions, time period, data (dependent and independent variables), and the spatial specification selected in the empirical analysis.

between local areas. Molho (1995) suggests that spatial dependence arises through migration across regions. Second, is the spatial concentration of the variables explaining unemployment. For example, regions with favorable economic and demographic conditions may experience lower unemployment rates relative to municipalities with unfavorable conditions. If regions with favorable (or unfavorable) conditions are geographically concentrated this might explain the spatial correlation of unemployment rates (Cracolici et al., 2007). Third, the spatial dependence of unemployment may reflect the agglomeration of economic activities because the linkages between regions tend to tie together labor supply and demand conditions across nearby areas. This is the conclusion that Overman and Puga (2002) draw from analyzing unemployment clusters in Europe.

3. Data Description

This section is divided into two main subsections. The first one describes the data and defines the variables used in the empirical analysis. The second provides an exploratory analysis of the data.

3.1. **Data.** This study uses Colombian Census data from the Integrated Public Use Micro data Series (IPUMS) for 1993 and 2005.[4] The IPUMS database is composed of a 10 percent sample of individual records containing information on persons and households. The unit of analysis is the municipality. I assign individuals to a municipal area on the basis of IPUMS codes, which are geographical divisions that contain no less than 100,000 inhabitants.[5]

Outcome Variable: Unemployment rate is defined as the percentage of unemployed over the working age population. I define an unemployed individual as someone who is not working and currently available for work during the reference week used by the Census.[6]

[4] As mentioned in the previous chapter, the period between 1993 and 2005 corresponds approximately to an entire business cycle. Thus, to a certain extent, the asymmetries in the municipal response to phases in the cycle are minimized and we can fairly assume that both years are comparable in economic terms.

[5] The code aggregates the information from 1052 municipalities into 532 observations. I exclude islands and the municipalities located in the extreme north (i.e., municipalities belonging to Amazonas department) from the analysis. I exclude islands from the analysis because they do not have contiguous geographic neighbors and, therefore, the contiguous spatial matrix contains zero rows. On the other hand, municipalities located in the extreme north are located so far away that the distance spatial weight matrix will contain zero rows.

[6] The International Labor Organization (ILO) set guidelines to declare an unemployed individual as someone who is not working, currently available for work, and *seeking for a job.* The ILO introduced modifications with regard this definition by allowing the partial or full relaxation of the active job search requirement in situations where “the conventional means of seeking work are of limited relevance, where the labor market is largely unorganized or of limited scope, where labor absorption is at the same time inadequate, or where the labor force is largely self-employed”. Since the Colombian labor market fits this description I do not use the active job search requirement in the construction of unemployment rates. Thus, unemployed individuals are those who are not working and are available for work (I exclude then individuals with physical disabilities to work, persons living from rents, and retired workers).

Covariates: In general terms, the unemployment rate is a reduced form function of factors that affect labor supply and labor demand. These factors can be broadly categorized as labor market dynamics, non-demographic labor market variables, human capital attributes, demographic characteristics of the local labor force, and municipal attributes. The variables selected to proxy for these broad categories are the following:[7]

Labor market dynamics: a primary factor determining unemployment differences is employment growth. If a given municipality is creating more employment than the national level, unemployment in that municipality should decrease relatively. However, employment growth at the municipal level may not reduce the unemployment rate. This can occur because a better labor market situation will not only attract jobless workers but also migrants, who may absorb all the new jobs. To control for labor market dynamics, I use a measure of employment growth based on exogenous local labor demand shocks,[8] and the ratio of immigrant to the working age population, which is the percentage of the working age population who change of municipality in the last five years (as in Blanchard et al. 1992, Molho 1995, Bradley and Taylor 1997 and Basile et al. 2009).

Non-demographic labor market variables: the diversity of employment opportunities in a municipality may affect the unemployment rate. The more diverse an economy is, the more readily employment reductions in any given sector can be absorbed into other sectors.[9] The greater the industrial diversity is the more even is the distribution of employees across industries. Here, diversity of employment is measured by one minus a two digit industry Herfindahl index (as in Partridge and Rickman 1997, Mitchell and Bill 2004, 2005). Likewise, employment concentrations in particular sectors may have an additional influence on the unemployment rate. Municipalities specializing in declining industries are expected to exhibit higher unemployment rates than those based around growing activities. Consistent with previous analysis (e.g., Overman and Puga 2002, Niebuhr 2003, Lopez-Bazo et al. 2005, Cracolici et al. 2007 and Basile et al. 2009), I use the employment shares of two main sectors: manufacturing and services.

Human capital variables: to evaluate the effect of human capital on unemployment rates I use the percentage of the working age population who are high school and college graduates (as in

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[7] See Appendix, Table A.2, for a detailed description of the construction of each variable.

[8] This measure is based on the Katz and Murphy (1992) index, that decomposes employment growth into expected share and industry mix components (Stevens and Moore, 1978, Partridge and Rickman, 1995). The reason to use this measure instead a simpler employment growth measure is twofold. First, employment growth predicts perfectly unemployment growth, since I am using an extended definition of unemployment in which the job search condition is relaxed. Second, to avoid collinearity with migration measures and other covariates.

[9] Simon (1988) explains the relationship between industry diversity and unemployment using the following example: consider the case in which individuals are immobile between municipalities, then layoff can be offset only by hiring that occurs in the same municipality. Consider now the case in which each municipality has only one industry. Then, the unemployment that results from layoffs in one industry will never be offset by vacancies at another. By contrast, if each city has many industries, unemployed individuals laid off by some industries may fill vacancies at others.

Overman and Puga 2002, Lopez-Bazo et al. 2005 and Cracolici et al. 2007). In particular, we should expect this share to be inversely related to the unemployment rate through a composition effect, through its positive influence on labor demand, and because skilled individuals are geographically more mobile (Saint-Paul, 1996, Mincer, 1991, Manning, 2004, Martin and Morrison, 2003).

Demographic variables: the structure of the population might have important influences on local labor demand and supply (Elhorst, 2003). I control for this by using the age structure of the population: the percentage of the working age population aged between 15 and 24 and those between 54 and 64 years old. The percentage of females above the age of 15 who are married is included to capture the possibility that married women withdraw from the labor-force. Similarly, women with young children may be more likely to withdraw from the labor force. This is captured by the percentage of women over the age of 15 who are married and have children under the age of 5. These variables were also included in Partridge and Rickman, 1997, Lopez-Bazo et al., 2005 and Cracolici et al. 2007.

Municipal attributes: I control for urbanization using the population density and the percentage of the municipality's population that lives in the urban area (as in Niebuhr, 2003, Cracolici et al., 2007, Mitchell and Bill, 2005). The standard argument for the inclusion of these variables is that coordination failures between employer and job seekers might be mitigated in urban areas because of their greater diversity of employment opportunities. Recent research has expanded on this by arguing that urban labor markets generate human capital externalities that would not exist in less populated areas (Glaeser and Mare, 2001, Rauch, 1993, Moretti, 2004). In turn, congestion effects might can also lead to higher unemployment rates, thus the relationship between urbanization proxies and unemployment rates is a priori unknown.

Spatial Proximity: I measure spatial proximity in terms of contiguity; the neighboring set is therefore defined as the set of municipalities that share a common boundary.[10] I summarize the possible interactions between municipalities using the matrix $W_c = \{w_{ij}\}$, where $w_{ij} = 1$ if municipalities i and j share a common border and 0 otherwise.

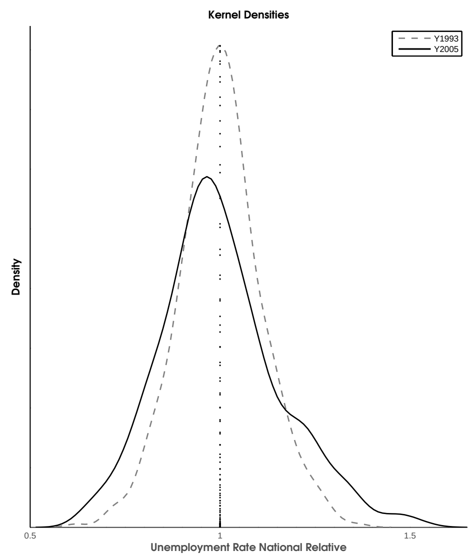
3.2. **Exploratory Evidence.** This section explores the evolution of unemployment rates in Colombian municipalities between 1993 and 2005. It is composed of two subsections. The first one examines whether the unemployment rates have become more or less uneven by comparing municipal rates to the National average. The second subsection analyzes the geographical distribution of unemployment using standard spatial technique, describes the spatial patterns

[10] I use a Delaunay triangulation, which is a mesh of non-overlapping triangles created from municipalities' centroids; municipalities associated with triangle nodes that share edges are neighbors.

of the factors that affect unemployment in a priori grounds and evaluates whether the spatial distribution of unemployment rates varies when these variables are controlled for.

Unemployment Rates. The distribution of unemployment rates in Colombian municipalities has become more uneven. Figure 3.1 plots the kernel estimates of the density for relative unemployment rates, which are defined as the ratio of the municipal unemployment rate to the national average unemployment rate.[11] The dotted line shows the distribution in 1993, while the solid line shows it in 2005. Note that the line (at 1.0) on the horizontal axis indicates the average unemployment rate. The height of the curve at any point gives the density that any particular municipality will experience that relative rate. It is evident that over time more municipalities have experienced unemployment rates below the average, or above 1.2 times that average, and fewer municipalities have unemployment rates close to the National levels.

Figure 3.1. *Municipal Unemployment. 1993 versus 2005.*



Source: Author's calculations from IPUMS data

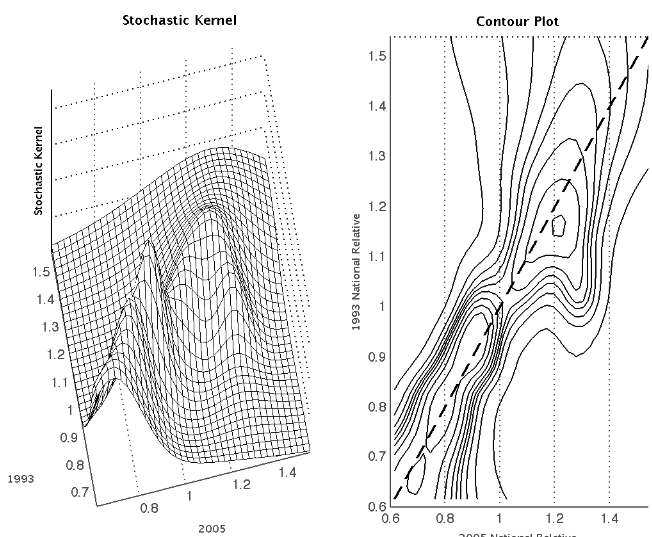
While the differences in the shapes of these two distributions are quite apparent, we cannot argue that they represent a structural process in which municipalities with either high or low unemployment rates have not changed remarkably, while municipalities with intermediate rates have moved towards the extreme distribution. It can also reflect random ups and downs of municipal economic activity. To explore whether it indicates a structural process we need to follow the evolution of each municipality's relative unemployment rate over time. One way to evaluate it is through the estimation of a stochastic kernel (Lucas et al., 1989, Durlauf and Quah, 1999).[12] Indeed, the stochastic kernel provides the likelihood of transiting from one place in the range of values of relative unemployment rates to the others. The left panel of Figure 3.2 plots the transition kernel from the 1993 distribution to the 2005 distribution of the national relative unemployment rates. It provides evidence about the shape of and the

[11] Overman and Puga (2002) use this methodology to evaluate employment clusters across European regions. They argue that using relative unemployment rates helps remove co-movements due to business cycle and trends in the average unemployment rate.

[12] The stochastic kernel is the counterpart of a first-order Markov probability of transition matrix where the number of states tends to infinity. For a formal definition and some properties of stochastic kernels in the study of distribution dynamics, see Durlauf and Quah (1999). The Appendix A5.1. includes the estimation of a probability transition matrix and discusses its results. The transition probability matrix confirms the findings from the stochastic kernel.

mobility within the dynamic distribution. The horizontal axes (for 1993 and 2005) show the relative unemployment rates, with 1.0 representing the National average. The vertical axis measures the density function. In terms of the shape, the key issue is to explore whether or not the stochastic kernel has clear peaks. For example, the presence of a clear single peak provides evidence of convergence, and if it is centered on the value of 1.0 of the 2005 horizontal axis it provides evidence of convergence towards the mean. The presence of more than one peak provides evidence of cluster creation. Moreover, if this were associated with a decline in the middle of the distribution this would suggest polarization.[13] The plot on the right panel shows a two dimensional contour plot of the three dimensional plot. Lines on the contour plot connect points at the same height on the three-dimensional plot (i.e., points with the same density). A 45 degree line is drawn to show where all mass should be concentrated if there was complete persistence in the distribution.

Figure 3.2. *Polarization Evidence from a Stochastic Kernel*



Note: Calculations were carried out using Matlab routine developed by Magrini (2007)

The twin-peak nature of Figure 3.2 confirms that there has been a polarization of unemployment rates. That is, municipalities that had low relative unemployment rates in 1993 tended to maintain or reduce their low relative unemployment rate over the next 12 years. Similarly, municipalities that in 1993 exhibited high relative unemployment rates continued this path

[13] To better understand these figures refer to Figure ?? in the Appendix; it provides three different examples of how these graphs would look like if there is : i. persistence, ii. national mean convergence, and iii. random ups and downs.

until 2005. However, municipalities with intermediate unemployment rates were unlikely to remain there; most experienced their relative rates either increase or decrease.[14]

Spatial Structure of Unemployment and Explanatory Variables. The analysis so far ignores the spatial distribution of unemployment rates. To explore the role of geography in the unemployment distribution I estimate a Moran's I statistic. This test is a summary measure of spatial correlation, which assesses the degree of similarity or dissimilarity of values in spatially close areas.[15] Table 1 shows the estimated Moran's I statistic and its associated significance level for unemployment rates in 1993 and 2005, and the difference between these two years.[16]

Table 1: Spatial Autocorrelation of Local Unemployment Rate and Explanatory Variables

	1993		**2005**		**Difference** 2005-1993	
Variable	**MI**	**p1**	**MI**	**p1**	**MI**	**p1**
Unemployment	0.43	0.00	0.62	0.00	0.35	0.00
Explanatory Variables						
Local Dynamics						
Employment	0.18	0.00	0.15	0.00	0.17	0.00
Migration	0.37	0.00	0.45	0.00	0.19	0.00
Non demographic labor market						
Ind Divers.	0.09	0.00	0.07	0.01	0.06	0.02
Ind Svs	0.16	0.00	0.07	0.00	0.10	0.00
Ind Manu	0.25	0.00	0.10	0.00	0.12	0.00
Human Capital						
College Share	0.25	0.00	0.32	0.00	0.17	0.00
Demographic						
Age 15 24	0.18	0.00	0.42	0.00	0.23	0.00
Age 55 64	0.15	0.00	0.32	0.00	0.08	0.00
Fem Married	0.40	0.00	0.44	0.00	0.11	0.00
Fem Married with children	0.30	0.00	0.53	0.00	0.12	0.00
Municipality Attributes						
Urban	0.26	0.00	0.39	0.00	0.26	0.00
Pop Density	0.19	0.00	0.20	0.00	0.20	0.00

Note: MI represents Moran's I test, which is calculated as $I = \varepsilon' W_c \varepsilon / \varepsilon' \varepsilon$. Where ε represents the residuals from regressing each variable on a constant, and W_c is the spatial weight matrix. P1 is the p-value based on a standardized z-value that follows a normal distribution.

Results show a high positive spatial correlation of raw unemployment rates. Positive autocorrelation implies that municipalities with relative high (low) unemployment rates are located close to other municipalities with relative high (low) unemployment rates. There is also evidence that the geographic distribution of unemployment in Colombia has became more

[14] Additionally, the concentration of unemployment rates, measured by the Theil coefficient, rose from 0.056 in 1993 to 0.123 in 2005. The Theil index is measured as $TC_t = \sum_{i=1}^{N} U_{it} log(U_{it}/WP_{it})$ where U_{it} is the municipal share of unemployment and WP_{it} represents the working population in year t.

[15] The Moran's I-Statistic is defined as : $I = \varepsilon' W_c \varepsilon / \varepsilon' \varepsilon$. Where ε represents the residuals from regressing each variable on a constant (i.e., $y_i = \iota + \varepsilon_i$), and W_c is the spatial weight matrix. Cliff and Ord (1970) show that the asymptotic distribution for Moran's I based on least-squares residuals correspond to a standard normal distribution after adjusting the statistic by subtracting the mean and dividing by the standard deviation of the statistic, i.e., $Z(I) = {}^{I-E(I)}/_{[V(I)]^{1/2}} \sim N(0,1)$. Where $E(I)$ and $V(I)$ represents the mean and variance of I. For a detailed description of the Moran's I test see Anselin, 1988, Anselin and Hudak, 1992, Anselin, 2003a,b, LeSage, 1999.

[16] The null hypothesis states that unemployment rates are randomly distributed across the study area.

clustered over time, since the Moran's I increases over time. This is also confirmed by the fact that the spatial correlation for the difference between unemployment rates for the two years presents positive spatial autocorrelation. Thus, we can argue that while municipalities have followed different unemployment patterns that the National average, they have had very similar unemployment outcomes to those of their neighbors, suggesting the creation of unemployment clusters across the territory.

To explore whether the determinants of unemployment show similar spatial patterns to those of unemployment rates, I estimate the Moran's I test for each variable. Table 1 displays the results for each variable using the contiguity matrix as a proxy for spatial proximity. Results confirm that the determinants of unemployment are positively correlated in the space since the Moran's I is significant different from zero. Given that the Moran's I is similar to a correlation coefficient, we can argue that the variables reflect different intensity of spatial association. In 1993, the Moran's I is high for the migration rate, the share of employment in the manufacturing sector, the college share, the proxies for female participation, and the percent of the municipality's population that lives in the urban area. On the contrary, the Moran's I is low for industrial diversity and the share of employment in the service sector. In 2005, most of the variables exhibit roughly the same spatial correlations patterns: the spatial correlation is high for migration rate, the college share, all demographic variables, and the share of the population living in the urban areas, whereas, all non-demographic labor market attributes exhibit low levels of spatial correlation. The difference between the values of both years also presents positive autocorrelation.

The similarity of unemployment rates across neighbors could simply be driven by neighboring municipalities being similar. To explore this, I re-estimate the Moran's I for unemployment rates conditional on all variables to explore their influence in the spatial association of unemployment rates. If clusters of unemployment are only driven by neighboring attributes, then we should not only observe positive spatial correlation of unemployment determinants but also that after conditioning on the entire set of covariates, the spatial correlation for unemployment rates should diminish considerably, and eventually disappear. Table 2 shows the results from this exercise where the first column depicts the unconditional and the second the conditional Moran's I for unemployment rates for each year and their respective difference. After conditioning for the covariates that might affect unemployment rates the spatial correlation diminishes, especially in 2005. However, it does not disappear, which suggest that unobservable attributes still affect unemployment clustering in Colombian municipalities.

Table 2: Unconditional and Conditional Moran's I test.

	1993		**2005**		**Difference**	
	Uncond.	Cond.	Uncond.	Cond.	Uncond.	Cond.
	(1)	(2)	(1)	(2)	(1)	(2)
Unemployment	**0.43*****	**0.25*****	**0.64*****	**0.26*****	**0.38*****	**0.20*****

***p<0.01,**p<0.05,*p<0.1

Note: Column (1) show the results from the unconditional Moran's I Statistic defined as $I = \varepsilon' W_c \varepsilon / \varepsilon' \varepsilon$; where ε represents the residuals from regressing unemployment rates on a constant and W_c is the spatial weight matrix. Column (2) shows the results from the conditional Moran's I Statistic defined as $I = u' W_c u / u' u$; where u represents the residuals from regressing unemployment rates on a constant and the set of explanatory variables $y_i = \iota + x_i + u_i$ and W_c is the spatial weight matrix. Inference is again based on a standardized z-value that follows a normal distribution.

Interesting stylized facts arise from this explanatory analysis. First, Colombian municipalities have experienced a polarization in their unemployment rates between 1993 and 2005. Second, the unemployment outcomes of individual municipalities have closely followed those of their neighbors, creating clusters of low and high unemployment. Third, the potential determinants of unemployment rates also present a strong spatial correlation. Fourth, the *neighbors* effect remains strong, even after controlling for similarities in municipal attributes. This suggests that there might still omitted variables that affect unemployment spatial patterns in Colombian municipalities.

4. Empirical Strategy

This section explains the empirical parametric strategy that will be used to assess the main determinants of the evolution of municipal unemployment rates. The analysis is based on a spatial Durbin model, which provides the basis for an unemployment regression model that is sufficiently general to allow for different types of spatial interdependencies. LeSage and Pace (2009) posit that if unobserved or unknown, but relevant variables following a first-order spatial autoregressive process are omitted from the model, and these variables are correlated with independent variables that are included in the model, a spatial Durbin model will produce unbiased coefficient estimates.[17] In the Appendix, I follow LeSage and Pace (2009) to show how a seemingly non-spatial linear regression can lead to a spatial Durbin model that includes spatial lags of both the dependent and independent variables. In this section, however, I focus on the spatial Durbin specification, discuss some issues related to the interpretation of the results, and present the empirical strategy to select the best specification.

The spatial Durbin model that describes the relationship between the growth in unemployment rates and the independent variables is given by

[17] They also show that the spatial Durbin model will produce unbiased coefficient estimates, even in the case that the true data generating process would be a spatial error model (SEM) or a spatial autorregresive model.

$$\Delta y_i = \alpha_0 \iota + \rho W_c \Delta y_i + \eta_1 \Delta X_i + \eta_2 W_c \Delta X_i + \Delta \mu_i \tag{4.1}$$

With the associated data generating process

$$\Delta y_i = (I_n - \rho W_c)^{-1} (\alpha_0 \iota + \Delta X_i \eta_1 + W_c \Delta X_i \eta_2 + \Delta \mu_i) \tag{4.2}$$

Where Δy_i is the difference in unemployment rates between 1993 and 2005, i.e., $\Delta y_i = y_{i,t} - y_{i,t-1}$. This difference is modeled as a function of the spatial lag of the dependent variable, $W_c \Delta y_i$, which captures spatial effects working through the dependent variable; ρ is the scalar parameter that reflects spatial dependence, which is expected to be positive in our model, indicating that unemployment rates are positively related to a linear combination of neighboring unemployment rates, as it was shown in the data description. The model also includes the explanatory variables in differences, $\triangle X_i$, and a spatial lag of the explanatory variable, $W_c \Delta X_i$. Finally, $\Delta \mu_i$ is the error term that is assumed to be $\Delta \mu_i \sim N(0, \sigma^2 I_n)$. Coefficient estimates on the spatial lag of the explanatory variables capture two types of spatial relationships: spatial effects working through the unemployment rate and spatial effects working through the explanatory variables.

When the model includes a spatially lagged dependent variable, as in this case, the least squares estimates of the parameters will be biased and inconsistent. According to Anselin (2010), there are two main approaches to estimate spatial econometric models: i. maximum likelihood (ML), and ii. and instrumental variables in the context of generalized method of moments (GMM). The maximum likelihood provides consistent estimates under the assumption that the error term is normally distributed. The GMM approach, on the other hand, gives consistent estimates without assuming that error term has any particular distribution, except that they are independent and identically distributed. However, Pace et al. (2010) found that the performance of GMM techniques is affected when estimating a spatial Durbin Model in the presence of spatially autocorrelated regressors. Consequently, I choose the maximum likelihood procedure over the GMM approach.[18]

The spatial Durbin model (SDM) has several advantages to other models used to explain the unemployment rates. The most important advantage is that it allows us to consistently estimate the effect of the explanatory variables when endogeneity is induced by the omission of a (spatially autorregresive) variable. In this case omitted variables can be for example the

[18] Estimation of these models is carried out using Matlab routines developed by LeSage (1998).

propensity for inter-municipal trade, agglomeration economies, and transportation improvements; this is explained in the Appendix. A second strong point is that this model let us quantify the magnitude of spillover effects arising from both the dependent and the independent variables. Another strength is that it provides a general framework to test this model against alternative specifications. The following lines explain these two last aspects in more detail.

Model Interpretation. While linear regression parameters have a straightforward interpretation as the partial derivatives of the dependent variable with respect to the explanatory variables, in the SDM specification, given by equation 4.1, interpretation of the parameters becomes more complex. The complexity arises from the simultaneous feedback nature from the spatial lag terms. In other words, the parameters measure the effect arising from a change in explanatory variables in municipality i on unemployment rates in other municipalities $j \neq i$. Indeed, the partial derivatives take the form of a $n \times n$ matrix:

$$\frac{\partial \triangle y}{\partial \triangle x_k} = (I_n - \rho W_c)^{-1}(I_n \eta_{1k} + W_c \eta_{2k}) = S_k(W_c) \tag{4.3}$$

LeSage and Pace (2009) propose scalar summary measures for the $n \times n$ matrix of direct, indirect, and total spatial effects arising from changes in the explanatory variable x on the dependent variable vector representing municipal unemployment rate. The *average direct effect* is the average of the diagonal elements of the matrix $S_k(W_c)$ (i.e, $\left(\sum_{i=1}^{n} \partial y_i / \partial x_{ik}\right)/n$). This measure summarizes the impact of changes in the ith municipality of variable k using an average across municipalities. For example, if a municipality raises its human capital, the average direct effect accounts for the localized effect and feedback effects, where municipality i affects municipality j and municipality j also affects observation i.[19] The *average indirect effect* is the average of the row-sums of the matrix elements, which corresponds to cross-partial derivatives. This summary impact measure reflects the impacts falling on municipalities other than the own-municipality. It is important to stress that indirect impacts will often exceed the direct impacts because the scalar summary measures cumulative impacts over all regions in the model. Finally, *the average total effect* is the sum of the direct and indirect impacts.[20]

Spatial Durbin model versus other specifications. It is important to highlight that the spatial Durbin model subsumes the spatial error model (SEM), the spatial autorregressive model

[19] The magnitude of this type of feedback depends on : i. the location of the municipalities in geographic space, ii. the degree of connectivity among municipalities governed by the spatial weight matrix (W_c), iii. the parameter ρ that measures the strength of spatial dependence of unemployment rates, and iv. the parameters η_{1k} and η_{2k} (Fischer, 2009, LeSage and Pace, 2009)

[20] LeSage and Pace (2009) provide an approach to calculate measures of dispersion that can be used to draw inferences regarding the statistical significance of direct and indirect effects. These are based on simulating parameters from the normally distributed parameters ρ, η_1, η_2, and σ_ϵ^2, using the estimated means and the variance-covariance matrix.

(SAR), the least-squares spatially lagged X regression model (labeled SLX by LeSage and Pace 2009), and the OLS, which are the most widely used specifications to analyze local unemployment rates. The SEM assumes that correlation across municipalities is mostly a nuisance spatial dependence problem caused by the municipal transmission of random shocks. In other words, it arises when the observed and unobserved variables are not correlated $\gamma = 0$ and when the restriction $\eta_2 = -\rho\eta_1$ holds; this restriction is labeled a "common factor restriction" by Anselin (1988). The SAR includes a spatial lag of unemployment rates from neighboring municipalities, but excludes the influence of the spatial lagged explanatory variables, this model arises by assuming $\eta_2 = 0$. The SLX assumes spatial independence between unemployment rates, but includes characteristics from neighboring municipalities in the form of spatially lagged explanatory variables, it arises by imposing $\rho = 0$. Finally, imposing the restrictions $\rho = 0$ and $\eta_2 = 0$ yields the standard least-squares regression model.

The selection of the correct specification is very important since each specification produces rather different interpretations. I follow the test procedure proposed by Elhorst (2010) to find out which is the most likely candidate to explain the data. First, I estimate equation (4.1) without spatial lags by OLS and test whether the SAR or the SEM are more appropriate to describe the data using the classic Lagrange Multiplier test proposed by Anselin (1988).[21] If the OLS is rejected in favor of any of the spatial specifications the spatial Durbin model should be estimated. Subsequently, a likelihood-ratio test can be used to test if the SDM can be simplified to the SEM (e.g., Ho: $\eta_2 = -\rho\eta_1$) or to the SAR (Ho: $\eta_2 = 0$).[22] If both hypotheses are rejected, then the spatial Durbin best describes the data. If the OLS is not rejected in favor of any spatial specification the OLS should be re-estimated including spatially lagged independent variables to test whether they are significantly different from zero using a standard F test. If the estimates are not different from zero, we can conclude that OLS model best describes the data and that there is no empirical evidence in favor of any type of spatial interaction effect.

5. Results

This section reports and discusses the empirical findings. It is divided into three main subsections. Initially, I compare the results from ordinary least squares to those of the spatial Durbin Model, I discuss which is the best specification and then discuss the results. I also propose a decomposition exercise to learn the relative importance of different factors. It aims to assess how much of the change in unemployment rates is explained by each explanatory

[21] This test is based on the residuals of the OLS and follows a chi-squared distribution with one degree of freedom.
[22] Both tests follow a chi-squared distribution with K degrees of freedom, where K is the difference in degrees of freedom from each model.

variable and their spatial lags, and how much is induced by the spatial correlation of the residual component. While the regression analysis help us to understand which among the independent variables are related to the change in unemployment rates, and to explore the forms of these relationships, the decomposition analysis help us to understand the relative influence of each factor explaining the outcome variable. Finally, I carry out a simulation exercise in which I calculate the new unemployment equilibrium values for each municipality after a change in a single explanatory variable under different scenarios.

Table 3: Parameter Estimates from OLS and SDM.

	OLS 1	**SDM 1**	
	β_k	η_{1k}	η_{2k}
Local dynamics			
Employment	-0.06	-0.02	-0.12
	[0.02]***	[0.02]*	[0.04]***
Migration	-0.14	-0.08	-0.20
	[0.05]***	[0.04]**	[0.08]***
Non demographic labor market			
Ind Diversity	0.04	0.03	-0.01
	[0.02]**	[0.02]**	[0.02]
Ind Svs	0.01	-0.01	0.02
	[0.02]	[0.03]	[0.03]
Ind Manu	-0.04	-0.06	0.07
	[0.04]	[0.03]*	[0.06]
Human capital			
College Share	-0.32	-0.30	0.16
	[0.08]***	[0.07]***	[0.16]
Demography			
Age 15 24	-0.18	-0.14	0.01
	[0.05]***	[0.05]***	[0.00]
Age 55 64	0.15	0.02	0.07
	[0.11]	[0.08]	[0.23]
Fem married	-0.23	-0.16	0.03
	[0.07]***	[0.06]***	[0.14]
Fem married with children	0.32	0.12	0.22
	[0.07]***	[0.07]*	[0.08]***
Municipality attributes			
Urbanization	0.05	0.01	0.05
	[0.02]***	[0.01]	[0.03]
Pop density	-0.03	-0.06	0.29
	[0.10]	[0.09]	[0.19]
Unemployment			
Neighbors' unemployment (ρ)		0.30	
		[0.06]***	
Constant	0.03	-0.01	
	[0.01]***	[0.03]	
No. Observations	497	497	
R^2	0.21	0.35	
Model Specification Tests			
LM SEM	55.99		
LM SEM p-value	0.00		
LM SAR	70.87		
LM SAR p-value	0.00		
SDM Log Likelihood			972.63
SAR Log Likelihood			954.75
SEM Log Likelihood			948.09

*** p<0.01, ** p<0.05, * p<0.1

Note: The dependent variable is the change in unemployment rates between 1993 and 2005; the independent variables are in first differences. Standard errors are in brackets. The weight matrix used for SDM takes the form of a binary first-order contiguity matrix, W_c, in which only direct interaction between geographically neighboring regions is allowed for, two regions are defined as neighbors when they show a common boundary.

Table 3 compares ordinary least squares results with those of the spatial Durbin model. The first column presents the results from an ordinary least square regression assuming that disturbances are independent and identically distributed. The second and third columns present the results from the SDM where spatial lags of both dependent and independent variables are included. The dependent variable is the difference in the unemployment rate of municipality i between 1993 and 2005. To be consistent with the exploratory evidence, described in Section 3, I use the same set of explanatory variables in first differences.[23]

Before interpreting the results, let me discuss the selection of the best specification. As mentioned in the empirical strategy section, I follow the decision rule suggested by Elhorst (2010). Initially, I use the Lagrange Multiplier (LM) test to explore whether the SEM or the SAR models are more appropriate than OLS models to describe the data. Results of both LM SEM and LM SAR tests, for both OLS specifications, reject the null hypothesis of no spatial correlation in the model's residuals. These results indicate that OLS residuals, without controlling for the spatial lag of the unemployment rate (in the SEM model) or controlling for it (in the SAR model), are spatially correlated.[24] Ordinary least squares estimates might, therefore, lead to inconsistent and/or inefficient parameter estimates.[25]

Now, it is important to evaluate whether the spatial Durbin model is the best spatial specification. Recall that the SDM nest most models used in the spatial econometrics literature: the spatial autocorrelation model (SAR) and the spatial error model (SEM). We can carry out a likelihood-ratio tests (LRT) to select the best specification. The LRT for SAR versus SDM equals to 35.76, which is chi-squared distributed with 12 degrees of freedom, and the associated p-value is 0.001. The LRT for SEM versus SDM is equal to 49.08, which is chi-squared distributed with one degree of freedom, and also an associated p-value which is very low. In both cases the best specification is the spatial Durbin model. In other words, both observed and unobserved explanatory variables exhibit spatial dependence. Moreover, both observed and unobserved variables are correlated by common spatial correlated shocks. This implies that spatial effects are substantive phenomena rather than random shocks diffusing through the space.

On that account, the preferred specification is SDM. As emphasized in the previous section, correct interpretation of the parameter estimates require that we consider the direct, indirect

[23] Other specifications were also estimated. For example, to avoid multicollinearity, changes in unemployment rates were divided into two components: local dynamics and initial conditions. In other words, changes in unemployment rates were regressed on employment growth, and net migration change (to control for local dynamics or disequilibrium factors), and initial sectoral composition, initial skill composition, initial age and sex structure, urbanization and population density at the beginning of the period. Also Bayesian models for spatial Durbin models with heteroskedasticity where estimated. Results, available upon request, are remarkably robust.

[24] Since OLS is rejected in favor of both spatial specifications, we can also argue that the least squares spatial lagged X regression (SLX) can be ruled out from the analysis.

[25] OLS estimates will be inconsistent and inefficient if there are omitted variables correlated with independent variables. Moreover, even in the absence of correlation between omitted variables and independent variables OLS estimates remain unbiased, but are no longer efficient. In the presence of spatial error dependence, standard error estimates will be biased downward, producing Type I errors Anselin (1988). The loss of information implicit in this spatial error dependence must be accounted for in estimation in order to produce unbiased standard error estimates.

and total effects associated with changes in the regressors. Table 4 presents the corresponding scalar summary of impact estimates, along with inferential statistics.

If we consider the ***average direct impacts***, it is important to notice that they are close to the SDM model coefficient estimates reported in Table 3. Differences between these two measures are feedback effects that arise from induced effects in the neighbors of the neighbors of municipality i, and in turn in the neighbors of those neighbors, and so on throughout the whole system, including some feedback effects to the municipality itself. In this case the feedback effects depend on: i. the neighbor's unemployment parameter ($\rho = 0.30$), ii. the parameters estimates of each explanatory variable and its spatial lag (i.e., η_1 and η_2), and the degree of connectivity between municipalities, which is determined by the contiguity matrix. Given that the direct impact estimates and the model estimates of the non-spatial lagged variables are in most cases similar, we can conclude that feedback effects are inexistent.

Table 4: Direct, Indirect and Total Impact Estimates.

Variables	Direct impact	Indirect impact	Total impact
Employment growth	-0.02	-0.17	-0.19
	[0.01]**	[0.05]***	[0.06]***
Migration	-0.09	-0.31	-0.40
	[0.04]***	[0.10]***	[0.11]***
Ind Diversity	0.02	-0.01	0.02
	[0.02]	[0.04]	[0.05]
Ind Svs	-0.01	0.03	0.03
	[0.02]	[0.05]	[0.05]
Ind Manu	-0.06	0.07	0.02
	[0.03]**	[0.09]	[0.10]
College Share	-0.30	0.09	-0.21
	[0.08]***	[0.21]	[0.23]
Age 15 25	-0.14	-0.05	-0.18
	[0.05]**	[0.14]	[0.14]
Age 55 64	0.03	0.09	0.12
	[0.10]	[0.29]	[0.32]
Fem married	-0.16	-0.01	-0.16
	[0.06]***	[0.18]	[0.20]
Fem married wc	0.13	0.36	0.49
	[0.07]**	[0.07]***	[0.09]***
Urbanization	0.02	0.08	0.09
	[0.01]**	[0.04]***	[0.04]***
Population density	-0.04	0.07	0.03
	[0.03]	[0.10]	[0.07]

*** p<0.01, ** p<0.05, * p<0.1

Note: Results are based on specification SDM from Table 3. Standard errors, in brackets, are based on 10.000 sampled raw parameter estimates of the SDM. The weight matrix takes the form of a binary first order contiguity matrix.

Direct impact estimates show interesting features that are consistent with the empirical literature analyzing unemployment rates in different countries and regions.[26] First, there is evidence that employment growth, migration flows, and the share of employment in the manufacturing sector are negative related with unemployment growth rates at the municipal level. Second, the evolution of working age population with high skills is negative related to the unemployment growth rate, large, and significant, as would be expected. Third, the variables proxying for demographic structure are also correlated with unemployment growth, especially those for female labor participation. Fourth, urbanization variables seem to be positively related with unemployment growth rates. Finally, the parameters for industry diversity, the share of individuals in the agricultural sector, the share of elder individuals, and the population density are not related to unemployment rates after conditioning on the other variables.

[26] See for example Molho (1995), Lopez-Bazo et al. (2002, 2005), Morrison (2005), Overman and Puga (2002), Niebuhr (2003), Cracolici et al. (2007), Patacchini and Zenou (2007).

The ***average indirect impacts***, second column of Table 4, represent the effect of each variable on unemployment in municipalities other than the own municipality: general equilibrium effects. The presence or absence of these effects, combined with the results for the average direct impacts, might allow us to better understand the spatial evolution of unemployment rates. Before discussing the results it is important to clarify two aspects. First, there are some evident discrepancies between the average indirect impact and the model coefficients on the spatially lagged explanatory variables presented in Table 3. These discrepancies arise, as for the direct effects, from the spatial multiplier.[27] In general terms, the indirect effect is larger (in absolute terms) than the spatial lag coefficient from the SDM model. Second, it is also evident that indirect effects are considerably larger than the mean direct impact. To understand this we need to recall that the scalar summary of the indirect effects measures the *cumulative average* impact over space that would result from a change in municipal unemployment rates induced by changes in the explanatory variables. They do not represent marginal impacts. For example, the marginal impact from a one percent change in a single municipality's employment on each of the other municipalities' unemployment rates might be small, but cumulatively the impact measures -0.19 percent. Of course, the impact on municipalities located close to municipality i will be greater than the impact on more remotely related municipalities.

Turning to the results, it is evident that for some variables the local effect dominates: the employment share in manufacturing, the skill composition of the labor force, and some demographic factors. This is because a change in any of these variables has a negative effect on municipal unemployment rates but their effects are confined to the local labor market. On the other hand, employment growth, immigration rates, the percentage of females above the age of 15 who are married and have children under the age of five, and urbanization have both important localized effects (measured by direct effects) and spatial spillover effects (measured by indirect effects). The presence of both direct and indirect effects implies that a municipality-specific change in any of these variables does not only affect the respective local labor market, but instead spillover to neighboring municipalities. The induced changes of unemployment in neighboring municipalities again spillover to adjacent municipalities, including the municipality where the change took place. According to Molho (1995), this process of spatial adjustments continues until a new equilibrium of regional unemployment is reached.

Total impact estimates, reported in the last column of Table 3, measure the sum of the direct and indirect impacts from the previous two columns. From these estimates we see

[27] LeSage and Pace (2009) emphasize that it is a mistake to interpret the η_{2k} coefficients in Table 3 as representing spatial spillover magnitudes since both point estimates and inference might vary. This is a point that has been largely neglected in the empirical literature analyzing unemployment rates where the parameters of spatial lagged variables are interpreted as spatial spillover effects.

somehow surprising that taking into account both direct and indirect impacts leads to a total impact that is not significantly different from zero the share of manufacturing, the college share, the share of working age population aged between 15 and 25 years old, and the percentage of females that are married.[28] On the other hand, the average total impact for employment growth, migration, the proxy for female labor participation, and urbanization remain significant and their effects are in line with those discussed before.

The results for employment suggest that job generation has significant effects on local unemployment. But this effect is not confined to the local labor market. Unemployment in neighboring municipalities is affected as well. This result can be explained by inter-municipal interactions working through interregional trade. For example, employment growth in a given municipality generates employment growth in neighboring municipalities, which translates into lower unemployment in both the local labor market and its neighbors.[29]

Municipalities with a net increase in labor force through migration had, conditional to the other factors, lower unemployment growth. Moreover, its effect is not confined to local areas since it exhibits significant indirect effects. Literature analyzing the effect of migration on local labor markets provides numerous explanations for negative localized effects; here I describe three suggested by Pischke and Velling (1997). First, natives and migrants could be complements in production. Second, migrants might enter into labor market sectors that have very low native participation levels. If there is low job competition across these sectors, there would be low labor market pressure from increased immigration. Finally, there might be consumption externalities in the sense that immigrants might also demand goods and services produced locally, which will reduce the unemployment rates locally. A negative indirect effect implies that mobility across regions is an important factor to reduce asymmetries in labor outcomes and, therefore, nearby municipalities tend to share shocks in the long term as suggested by Blanchard et al. (1992), Molho (1995).[30]

[28] To understand these results it is important to recall that these effects represent the average total impact on a given observation from a change in all municipalities. For example, changing the share of individuals with higher education in all municipalities has little or no total impact on the unemployment rate of a typical municipality. The intuition here arises from the notion that is relative advantages in these variables that matter most to reduce unemployment in a given municipality.

[29] This result is in line with those findings from Molho (1995) and Niebuhr (2003) who include in their regressions the spatial lag of unemployment rates among the set of explanatory variables. Their results indicate that the effect of this variable is negative and significantly different from zero.

[30] Only two reviewed papers, from Table A.1, include migration related variables: Lopez-Bazo et al. (2002), Basile et al. (2009). Lopez-Bazo et al. (2002) use a net migration variable (in-migration minus out-migration to the total population) among the set of explanatory variables of regional unemployment rates in Spain for 1985 and 1997. Their results show a negative effect of net migration on unemployment rates only for 1997. Basile et al. (2009) include both the migration rate and a spatial lag of it among other control variables to explain the evolution of regional unemployment rates in Italy between 1995 and 2007. The effect of the non-spatial lagged variable is negative, while, the effect of the spatially lagged is positive. They argue that the equilibrating mechanism of migration is dominated by a selective process, where most qualified workers move across the space (e.g. brain drain effect).

On the other hand, the local effects of female participation, represented by the share of females that are married and have children, are standard, suggesting that local unemployment rates increase with concentrations of this group of individuals. Indirect effects are also positive, and might arise from the fact that this variable exhibits strong spatial correlation. In the same vein, the change of unemployment tends to be higher in highly urbanized municipalities, as indicated by the positive direct and indirect impact of the share of population living in the urban area. One reason for this result is the presence of crowding externalities that lead to search frictions and lower matching efficiency in urbanized municipalities, moreover, these effects spread across the borders because job seekers also look for job in neighboring municipalities. Another explanation might be an above average increase in the labor supply in these municipalities. If highly urbanized municipalities attract migrants from the rural areas, the corresponding increase in labor supply might result in a increase in unemployment rates.

In sum, the findings of this section allows us to understand which among the independent variables are related to the change in unemployment rates, and to explore the forms of these relationships. Differences across municipalities in labor demand, immigration, sectoral specialization, educational attainment and urbanization are factors behind observed municipal unemployment disparities. These results are consistent with those of Overman and Puga (2002) and Cracolici et al. (2007) for European regions and Italy respectively. The empirical results also make it clear that some characteristics of neighboring municipalities play an important role in determining unemployment rates. For example, municipalities neighboring municipalities with high employment growth were more prone to have better labor outcomes. Immigration seems to play a self-equilibrating role in reducing municipal disparities as predicted by Burridge and Gordon (1981), Blanchard et al. (1992), Molho (1995). On the contrary, municipalities neighboring municipalities with a high share of women married with children under the age of five, and highly urbanized are more likely to have higher unemployment rates.

Decomposition. Using the results described before we can assess the relative importance of each regressor with respect to its overall effect on the change in municipal unemployment rates. Here, I propose a simple decomposition exercise to achieve this goal. To start, note that equation (4.1) can be expressed as:

$$\Delta y_i = (I_n - \hat{\rho} W_c)^{-1}[\hat{\alpha}_0 \iota + \hat{\eta}_1 \Delta X_i + \hat{\eta}_2 W_c \Delta X_i + \Delta \hat{\mu}_i] \tag{5.1}$$

Where $\hat{\alpha_0}, \hat{\rho}, \hat{\eta_1}, \hat{\eta_2}$ are the maximum likelihood estimates of equation (4.1), shown in Table 3, and $\Delta\hat{\mu_i}$ is the error in predicting the value of Δy_i, given the value of ΔX_i. Equation 5.1

can be rewritten as:

$$\Delta y_i = \tilde{\alpha_0} + \left(\Delta y_i - \Delta y_i^1\right) + \Delta\mu_i^* \tag{5.2}$$

Where the first term of the right hand side is the constant term taking into account the feedback effects of the neighbor's unemployment (i.e., $\tilde{\alpha_0} = (I_n - \hat{\rho}W_c)^{-1}[\hat{\alpha}_0\iota]$); the second term is the difference between the observed unemployment growth, Δy_i, and unemployment growth if we assume that none of the explanatory variables changed between 1993 and 2005, $\Delta y_i^1 = (I_n - \hat{\rho}W_c)^{-1}[\hat{\alpha}_0\iota + \Delta\hat{\mu}_i]$, thus, this term equals to $\Delta y_i - \Delta y_i^1 = (I_n - \hat{\rho}W_c)^{-1}[\hat{\eta}_1\Delta X_i + \hat{\eta_2}W_c\Delta X_i]$; the last term is $\Delta\mu_i^* = (I_n - \hat{\rho}W_c)^{-1}\Delta\hat{\mu}_i$.[31]

By rearranging terms, dividing both sides by $\Delta\tilde{y_i} = \Delta y_i - \tilde{\alpha_0}$, and summing over i , we have

$$1 = \frac{1}{N}\sum_{i=1}^{N}\left[\frac{\Delta y_i - \Delta y_i^1}{\Delta\tilde{y_i}}\right] + \frac{1}{N}\sum_{i=1}^{N}\left[\frac{\Delta\mu_i^*}{\Delta\tilde{y_i}}\right] \tag{5.3}$$

The first part of the right hand side is the part that is explained by the change of the explanatory variables, and the second part represents the change induce by the spatial correlation of the residual component, recall that $\Delta\mu_i^* = (I_n - \hat{\rho}W_\tau)^{-1}\Delta\hat{\mu}_i$. Note also that having $\Delta\mu_i^*$ rather than $\Delta\hat{\mu}_i$ in equation 5.3 allows for the second fraction to be non-zero.[32]

Using the information from Table 3 we can evaluate how much of the change in unemployment rates is explained by the explanatory variables and how much is induced by the spatial correlation of the residual component. According to the results of this exercise, in Table 5, 88.4 percent of the change in unemployment rates is explained by both the explanatory variables and their spatial lags. The unexplained part corresponds to 11.6 percent of the variation in unemployment rates. In addition, we can evaluate the relative importance of each variable and its spatial lag by decomposing the first term of equation 5.3. To do so, we only need to set the coefficient for each explanatory variable k of interest to zero, estimate the unemployment difference under that scenario (i.e., reestimate Δy_i^1), and recalculate the first term of equation 5.3.

Table 5 presents the results: the first column shows the percentage of the change unemployment rates that is explained by local effects of each dependent variable (i.e., Δy_i^1 is evaluated at $\eta_{1k} = 0$), the second column shows the percentage explained by their spatial lags (i.e., Δy_i^1 is evaluated at $\eta_{2k} = 0$), and the third how much is explained by each variable (i.e., Δy_i^1 is evaluated at $\Delta X_k = 0$). It is evident from the results that 22.3 percent of the change

[31] Note that $\Delta\hat{\mu}_i$ should be uncorrelated across space (parallel to what is assumed about the error component $\Delta\mu_i$), while $\Delta\mu_i^*$ should indeed be correlated across space.

[32] I Thank Giordano Mion for this idea.

in the unemployment rate is explained by the explanatory variables, while 66.1 percent is explained by their spatial lag. The results also indicate that the overall situation is best characterized as several variables each contributing some, rather than there being a single dominant explanatory variable. However, among these variables it is clear that employment growth, migration, and urbanization explain 67.7 percent of the variation in unemployment. The largest contribution to unemployment is made by employment growth, which accounts for 32.1 percent, the next largest by migration, which accounts for 23.2 percent, and the smallest by urbanization, whose weight is 12.3 percent. Notice however that most of these percentages is explained by the spatial lags of these variables.

Table 5: Decomposition

Variables	η_{1k} (%)	η_{2k} (%)	X_k (%)	$\Delta\mu_i^*$ (%)
Total	**22.3**	**66.1**	**88.4**	**11.6**
Employment growth	3.8	28.4	32.1	
Migration	8.9	14.3	23.2	
Ind Diversity	-6.6	2.3	-4.3	
Ind Svs	-1.8	7.2	5.4	
Ind Manu	5.0	-3.6	1.4	
College Share	-4.7	6.1	1.4	
Age 15 25	9.1	-0.1	8.9	
Age 55 64	1.3	1.3	2.5	
Fem married	10.2	-0.5	9.7	
Fem married wc	-4.1	-2.4	-6.4	
Urbanization	2.4	9.9	12.3	
Population density	-1.1	3.1	2.0	

Note: The first column presents the results of $\Omega_k = 1/N \sum_{i=1}^{N} \left[\Delta y_i - \Delta y_i^1 / \Delta \tilde{y_i}\right]$ when Δy_i^1 is evaluated at $\eta_{1k} = 0$, the second column displays the results of Ω_k when Δy_i^1 is evaluated at $\eta_{2k} = 0$, the third column presents the results of Ω_k when Δy_i^1 is evaluated at $X_k = 0$, the last colum shows the results from $1/N \sum_{i=1}^{N} \left[\Delta \mu_i^* / \Delta \tilde{y_i}\right]$

Simulation. We can also use the estimated results to calculate the unemployment equilibrium values for each municipality after a change in a single explanatory variable, i.e., the expected values given the model. I conduct a simple simulation in which each variable is assumed to increase 1 percent in some municipalities, while all the other variables are held constant. Here, I present the results only for employment growth, migration rates, college share, and urbanization. In doing so, I calculate four relevant measures: i. the number of observations that are affected through the system of interactions, ii. the difference in the expected unemployment rate under this scenario versus the expected value given the model and the observed data, iii. an inequality effect measured by the percentage change in the Theil index, and iv. an agglomeration effect calculated as the percentage change in the Morans' I test for unemployment rates. The following table compares these measures for seven different scenarios that differ in the number of treated municipalities: Scenario 1 assumes that the analyzed variable increases 10 percent in all municipalities, Scenario 2 assumes that the change takes place only in the capital of each Department, Scenarios 3 to 6 compare the results when municipalities are grouped in quartiles according to the initial unemployment rate,[33] finally Scenario 7 modifies those municipalities that exhibited higher unemployment rates in 1993 and their 3 closest neighbors.

The first panel of Table 6 presents the results for employment growth. It is evident that if all municipalities experienced a higher 10 percent increase in the employment growth, the expected unemployment rate is 1.9 percentage points lower, the distribution across the space is 7 percent more unequal, and the spatial correlation of unemployment rates does not change. When we assume that only the main cities of each department, 31 observations, experience a change in the employment growth, 476 municipalities are finally affected through the system of interactions between municipalities, the new equilibrium unemployment is 0.12 percentage points lower, inequality remains at the same level, and unemployment becomes slightly more agglomerated in the space.

Particular interesting results are those from Scenarios 3 to 6 in which we assume that the employment change takes place on a subset of municipalities, which are defined on the basis of the lower, median, and upper quartiles of the initial cross-country distribution of unemployment rates. Note that the new equilibrium unemployment rate is the same in all scenarios (0.48 percentage points lower), but important differences in both inequality and agglomeration measures arise. In fact, if the municipalities that did better (i.e., had lower unemployment rates) in 1993 face an additional increase in the employment growth of 10 percent, the distribution of unemployment rates becomes more unequal and more agglomerated. On the contrary, if the 10 percent increase in employment growth takes place in those municipalities that did worse (i.e., had higher unemployment rates), the distribution of unemployment rates throughout the country becomes more equal and less agglomerated.

Another interesting result is that from Scenario 7, which suggest that the reduction in aggregate unemployment rates can be almost the double than those in Scenario 6 if we modify the employment variable not only in the municipalities with high initial concentrations of unemployment but also in their three closest neighbors. Such a reduction is accompanied by a decrease in municipal inequalities and spatial agglomeration.

[33] Scenario 3 assumes that the change takes place in the 25 percent of municipalities that exhibited lower unemployment rates in 1993, Scenario 4 modifies those between the 25th and the 50th percentile, Scenario 5 those between the 50th and 75th percentile, while Scenario 6 assumes that it takes place in the 25 percent of municipalities that exhibited higher unemployment rates in 1993.

Table 6: Simulation, Selected Variables.

Variable	Scenario	Obs Treated (1)	Obs Affected (2)	Unemp. Change (3)	Pol. Effect (4)	Aggl. Effect (5)
Employment	1. All municipalities	497	497	-1.92	7.38	0
	2. State capital	31	476	-0.12	0	0.17
	3. Lower 25 percent	124	460	-0.47	10.66	12.84
	4. 25th-50th percentile	125	485	-0.49	4.1	6.8
	5. 50th-75th percentile	124	497	-0.48	0.82	1.68
	6. Higher 25 percent	124	488	-0.48	-8.2	-21.15
	7. Higher 25 percent + 3 neighbors	220	493	-0.84	-9.02	-20.51
Migration	1. All municipalities	497	497	-3.97	16.39	0
	2. State capital	31	483	-0.25	1.64	0.17
	3. Lower 25 percent	124	468	-0.98	24.59	24.65
	4. 25th-50th percentile	125	491	-1.01	9.84	13.77
	5. 50th-75th percentile	124	497	-0.99	1.64	5.09
	6. Higher 25 percent	124	489	-0.99	-17.21	-42.23
	7. Higher 25 percent + 3 neighbors	220	496	-1.74	-17.21	-39.63
College Share	1. All municipalities	497	497	-2.11	8.2	0
	2. State capital	31	467	-0.13	4.92	-4.05
	3. Lower 25 percent	124	452	-0.53	22.95	1.04
	4. 25th-50th percentile	125	481	-0.52	8.2	-3.24
	5. 50th-75th percentile	124	497	-0.52	-0.82	1.19
	6. Higher 25 percent	124	476	-0.52	-15.57	-14.38
	7. Higher 25 percent + 3 neighbors	220	491	-0.93	-11.48	-21.61
Urbanization	1. All municipalities	497	497	0.92	-3.28	0
	2. Province capital	31	464	0.06	-0.82	0.03
	3. Lower 25 percent	124	450	0.23	-4.92	-5.87
	4. 25th-50th percentile	125	481	0.24	-2.46	-2.89
	5. 50th-75th percentile	124	497	0.23	-0.82	-0.61
	6. Higher 25 percent	124	475	0.23	4.1	9.46
	7. Higher 25 percent + 3 neighbors	220	489	0.41	4.1	9.78

Note: Column (1) present the number of municipalities that exhibit a 10 percent increase in the variable analyzed, Column (2) presents the number of municipalities that exhibit a change in their unemployment rates, Column (3) presents the change in unemployment rate, that is $\frac{1}{N}\sum_{i=1}^{N}[\Delta y(x_k)_i - \Delta y_i]$ where $\Delta y(x_k)_i$ is the simulated unemployment rate and Δy_i is the observed unemployment rate, Column (4) shows the polarization effect, which is the percentage change between the simulated Theil index and that from the observed data (i.e., Theil: 0.12), Column (5) present the agglomeration effect, which is the percentage change between simulated spatial correlation test and that from the observed data (i.e., 0.35)

Results for migration and college share are in line with those from employment growth, while the results of urbanization work in the opposite direction. In fact, an increase in the urbanization rate of one percentage point in the entire sample increases unemployment rate by 0.92 percentage points, the distribution of unemployment rates becomes more equal, while the spatial correlation does not change.

In sum, this simulation exercise shows some interesting features concerning both the aggregate and spatial distribution of unemployment rates when some of the explanatory variables change. First, is that localized interventions affect other municipalities through the system of interactions across municipalities; this means general equilibrium effects spread over the space. Second, it shows that localized interventions can lead to different spatial outcomes depending on the targeted area. Changes in some areas can have differential effects on the spatial distribution of unemployment rates (making them more equal or unequal across space) and in the creation of clusters of municipalities of high and low unemployment rates. In this particular case, increasing employment, migration, and the share of individuals with some college or more in those municipalities that were bad performers in 1993 led to a reduction in aggregate unemployment rates accompanied by a reduction in both the spatial inequality and the spatial agglomeration.

6. Conclusion

This article increases our understanding of the differences in unemployment rates across Colombian municipalities. Using municipal data at the urban level for 1993 and 2005, this paper shows that Colombian municipalities are characterized by diverging unemployment rates, a type of polarization process, in which municipalities are moving away from the national average. This process has been accompanied by a clustering effect of the unemployment rate since municipalities with high (low) unemployment rates seem to be surrounded of municipalities with high (low) unemployment rates. Moreover, variables that might affect the evolution of unemployment rates exhibit the same spatial patterns. This suggests that the spatial evolution of unemployment rates is the result of different types of municipalities, in terms of economic and socio demographic attributes, are clustered in the space. A simple exploratory analysis confirms that these variables do exert some effect on the spatial evolution of unemployment rates, but even when controlling for similarities in municipal attributes the *neighbors* effect remains strong.

To explore the effect of diverse variables on the evolution of unemployment rate I use spatial econometric techniques. The approach adopted here uses a unified method for dealing with uncertainty regarding model specification, specifically, the appropriate spatial regression model to be employed. The preferred specification was a spatial Durbin model which allows for two types of spatial interdependencies in the evolution of unemployment rates: spatial effects working through the change in municipal unemployment rates, and the spatial effects working through a set of conditioning variables. The use of this model has two main advantages in relation with those models used to evaluate unemployment differentials in the previous literature. First, as Elhorst (2010) and Fingleton and Gallo (2010) highlight, it is the only spatial technique that produces consistent coefficient estimates when endogeneity is induced by the omission of a (spatially autoregressive) variable. Second, it allows us to correctly quantify the magnitude of general equilibrium effects among municipalities.

The results from this exercise suggest that differences across municipalities in labor demand, immigration, sector specialization, educational attainment, and urbanization are factors behind observed municipal unemployment disparities. The findings also confirm the fact that spatial effects are relevant factors when interpreting municipal disparities in unemployment rates in Colombia. In particular, they show that changes in employment growth, immigration, and urbanization affect not only the local labor market but also their effects spread to neighboring municipalities. According to the decomposition exercise, these variables explained 67.7 percent of the variation of unemployment. Moreover, the spatial effects of these variables account for 52.6 percent of the total variation.

Finally, I carried out a simulation exercise to illustrate how a change in few municipalities can affect other municipalities through the system of interactions and how it can modify the spatial distribution of unemployment rates. This simple exercise shows that spatial considerations must be taken into account when using targeted policy to help lift areas out of unemployment. For example, targeting job creation where unemployment concentrations are high helps not only to reduce aggregate unemployment but also municipal unemployment inequalities. On the other hand, targeting job creation where unemployment is low leads to larger spatial inequalities while having the same effect on aggregate unemployment.

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Appendix

Table A.1: Literature Review.

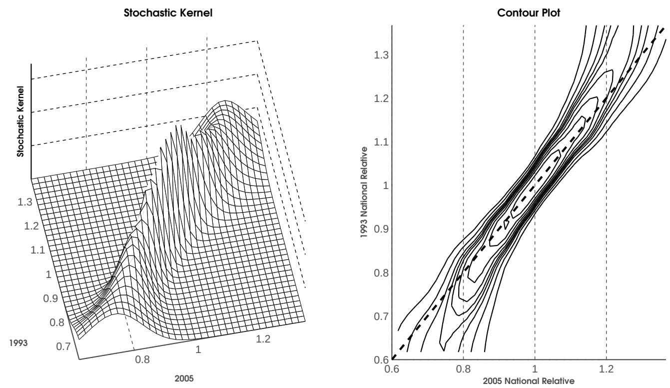
Study	Country, years, units	Dependent Variable	Independent Variables	Spatial Model
Molho (1995)	UK 1991; 280 local labor market areas	$ln(U_{it}/(1-U_{it}))$	Accessibility, employment growth, neighbors' employment growth, housing market, and neighbors' unemployment.	SLX
Lopez-Bazo et al. (2002)	Spain 1985-1997; 50 provinces	$U_{i,t}-U_{nat,t}$	Employment growth, net migration, industry mix ($ln(man_{it})$, $ln(agr_{it})$), human capital, young, male-female participation, unit labor costs, and neighbors' unemployment.	SAR
Overman and Puga (2002)	Europe 1986,1996; 147 regions	$U_{it}-U_{i,t-1}$	Industry mix ($ln(man_{it})$, $ln(agr_{it})$), human capital, young, female participation, initial unemployment, and neighbors' unemployment.	SAR
Niebuhr (2003)	Europe 1986,1998; 359 regions	$U_{it}-U_{i,t-1}$	Employment growth, neighbors' employment growth, Industry mix ($ln(man_{it})$, $ln(svs_{it})$), population density, and neighbors' unemployment.	SAR
Aragon et al. (2003)	Midi-Pyrénées 1993-1991; 174 districts	U_{it}	Industry mix ($ln(man_{it})$, $ln(svs_{it})$), demographic structure, housing market, population density, and neighbors unemployment.	SEM
Cracolici et al. (2007)	Italy 2003; 103 provinces	$log(U_{it})$	Industry mix ($ln(man_{it})$, $ln(agr_{it})$), neighbors' industry mix, demographic structure, housing market, and neighbors' unemployment.	SLX
Patacchini and Zenou (2007)	UK 1985-2003; 288 regions	U_{it}	Commuting flows, temporal and spatial lag of unemployment rates.	Panel SAR
Basile et al. (2009)	Italy 1991,1996,2001;	U_{it}	Industry mix, human capital, agglomeration externalities, labor productivity, agglomeration, supply and demand mismatch, temporal and spatial lag of unemployment rates.	SDM Panel

Note: U_{it} refers to unemployment rate. SLX is the spatial lagged independent variables, SAR spatial autoregressive model, SEM spatial error model, SDM spatial Durbin model.

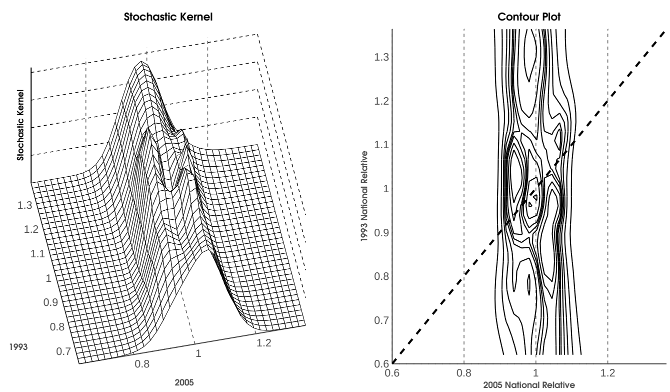
Table A.2: Data Description.

Variable	**Description**
Unemployment rate	The ratio of the non-employed to the working age population. Excludes individuals with physical disabilities to work, persons living from rents, and retired workers.
Employment growth	The employment growth for municipality m in year t equals $EmpG_{mt} = [(\sum g_{Nat,t,i}E_{m,t-1,i})/E_{m,t-1}] - g_{nat,t}$, where $g_{Nat,t,i}$ is the national growth rate in industry i, $E_{m,t-1,i}$ is municipality m's employment in industry i, $E_{m,t}$ is municipality m's total employment in year $t-1$, and $g_{nat,t}$ id the average of national employment growth in year t. The summation is over all two digit sector industries.
Migration Rate	Percentage of the working age population that change of municipality in the last five years.
Industry Diversity	Industry diversity is measured as 1 minus a two digit Herfindahl index, which is $H_c = \sum_{i=1}^{N} S_{im}^2$, where $S_{im}^2 = L_{im}/\sum_{i=1}^{N} L_{im}$ and L_{im} is the employment in industry i in municipality m
Industry Svs	Share of labor in services in total employment.
Industry Manu	Share of labor in manufacturing in total employment.
Human capital	Percentage of the working age population that finished high school and/or college.
Age 15 24 (55-64)	Share of population aged 15-24 (55-64) years in the population in the working age group.
Urbanization	Share of population of the municipality living in the urban area.
Population Density	Ratio population over surface in square kms.

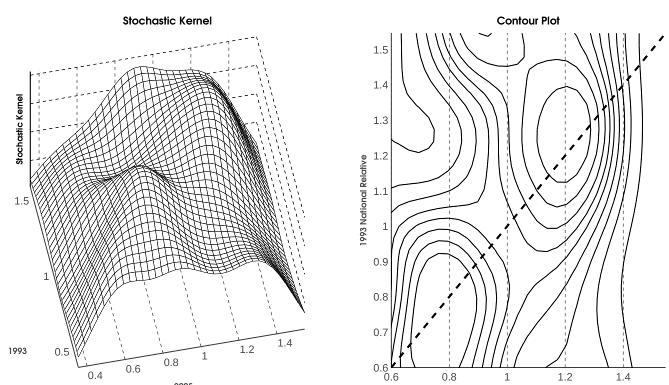
Figure A.1. *Stochastic Kernel Comparison*



(a) *No Change*



(b) *Mean Convergence*



(c) *Random Ups and Downs*

A5.1. Transition Matrix. Table A.3 shows the transition probability matrix linking the 1993 and 2005 distributions of National relative unemployment rates. The first row shows the behavior of municipalities starting with relative low unemployment rates. By 2005, 89 percent of the municipalities that started with a relative low unemployment rate remained below 0.75 times the national average. The last row depicts the municipalities that started with high relative unemployment rates; in this case, all of them remained at that level. Thus, municipalities with high or low unemployment rates did not experience important changes. On the contrary, municipalities with intermediate levels (second, third, and fourth rows) experienced greater mobility, particularly to the extreme of the distribution. These figures suggest that Colombian municipalities have become polarized in terms of their unemployment rates.

Table A.3: Transition Matrix.

	2005 ranges of relative unemployment rates				
1993	0.0-0.75	0.75-0.85	0.85-1.00	1.00-1.25	1.25- +
0.0-0.75	87.50	12.50	0.00	0.00	0.00
0.75-0.85	9.29	66.43	15.00	8.57	0.71
0.85-1.00	0.00	47.62	20.95	30.48	0.95
1.00-1.25	0.40	14.11	15.73	62.10	7.66
1.25- +	0.00	0.00	0.00	0.00	100.00

Source: Author's calculations based on IPUMS data

A5.2. Motivation for the Spatial Durbin Model. In this section, I follow LeSage and Fischer (2009), LeSage and Pace (2009) to motivate the use of the spatial Durbin model. I consider a scenario where we assume that there are important explanatory variables missing, the omitted variables are spatially autocorrelated and, in addition, they are correlated with the explanatory variables in the model. Here, I show that these assumptions lead to a spatial Durbin model that, according to LeSage and Pace (2009), helps to mitigate the omitted variable bias in spatial regression. The point of departure is a model that expresses the municipal unemployment rate as a linear function of the observed variables, municipal and time effects, and a disturbance term:

$$y_{it} = X_{it}\beta + \alpha_i + \alpha_t + \varepsilon_{it} \tag{6.1}$$

Where i represents municipalities and $t = \{1993, 2005\}$, y_{it} is the unemployment rate for each municipality i at time t , X_{it} is a matrix of explanatory variables, α_i represents municipal fixed effects, α_t represents the time effects, and ε_{it} represents the disturbance term. We can use first-order differences to remove the municipal and time fixed effects and any potential bias arising from it,

$$\Delta y_i \quad = \quad \alpha_0\iota + \Delta X_i\beta + \Delta\varepsilon_i \tag{6.2}$$

Where $\triangle y_i = y_{i,t} - y_{i,t-1}$, $\triangle X_i = X_{i,t} - X_{i,t-1}$, $\triangle\varepsilon_i = \varepsilon_{i,t} - \varepsilon_{i,t-1}$, and α_0 is the constant term. Expression 6.2 represents a linear model with independent and identically distributed disturbances. However, as it was shown in Section (3) disturbances are far from being independent and identically distributed even after conditioning on observables. This suggests that there might be omitted time-variant variables that are themselves spatially correlated (e.g., propensity for interregional trade, agglomeration economies, transportation improvements). We can assume that the error term in equation 6.2 comprises these omitted variables, so that $\Delta\varepsilon_i = \Delta Z_i$, where ΔZ_i is spatially correlated so that,

$$\Delta Z_i \quad = \quad \rho W_c \Delta Z_i + \Delta \upsilon_i \tag{6.3}$$

Where ρ is a scalar parameter reflecting the strength of spatial dependence in the process governing the time-variant omitted variables, $\Delta\upsilon_i$ is a vector of disturbances that are assumed to be distributed $N(0, \sigma^2 I_n)$, W_c is a $n \times n$ spatial weight matrix, where $w_{ij} = 0$ if $i = j$, row-standardized, and assume that $(I_n - \rho W_c)^{-1}$ exists. Therefore, each element of $W_c \triangle Z$ represents a linear combination of elements of the unobserved municipal attributes associated with neighboring municipalities.

If ΔX_i and ΔZ_i are uncorrelated the least-squares estimates for β_k in expression 6.2 are unbiased even if both the observed and unobserved (unmeasured) variables exhibit spatial dependence. It is very unlikely, however, that these variables are uncorrelated. There might be, for example, time-variant demand or supply shocks that commonly affect these variables. Thus, we are subject to omitted variable bias if equation 6.2 is estimated by OLS. The solution to this problem according to LeSage and Pace (2009) is to eliminate the effect of omitted variable by estimating a spatial Durbin model. This derives from the assumption that if there is correlation between ΔX_i and ΔZ_i, there will be correlation between ΔX_i and $(I_n - \rho W_c)\Delta Z_i$, and we can assume that this correlation can be expressed as a simple linear dependence like

$$(I_n - \rho W_c)\Delta Z_i \quad = \quad \Delta X_i \gamma + \Delta u_i \tag{6.4}$$

$$\Delta \upsilon_i \quad = \quad \Delta X_i \gamma + \Delta u_i \tag{6.5}$$

Where Δu_i is assumed to be distributed $\Delta u_i \sim N(0, \sigma^2 I_n)$. It follows that,

$$
\begin{aligned}
(6.6) \qquad \Delta y_i &= \alpha_0 \iota + \Delta X_i \beta + (I_n - \rho W_c)^{-1} \Delta v_i \\
(6.7) \qquad \Delta y_i &= \alpha_0 \iota + \Delta X_i \beta + (I_n - \rho W_c)^{-1} (\Delta X_i \gamma + \Delta u_i) \\
(6.8) \qquad (I_n - \rho W_c) \Delta y_i &= (I_n - \rho W_c)(\alpha_0 \iota + \Delta X_i \beta) + (\Delta X_i \gamma + \Delta u_i) \\
(6.9) \qquad \Delta y_i &= \alpha_0 \iota + \rho W_c \Delta y_i + \Delta X_i (\beta + \gamma) + W_c \Delta X(-\rho \beta) + \Delta u_i \\
(6.10) \qquad \Delta y_i &= \alpha_0 \iota + \rho W_c \Delta y_i + \Delta X_i \eta_1 + W_c \Delta X \eta_2 + \Delta u_i
\end{aligned}
$$

Where $\eta_1 = (\beta + \gamma)$ and $\eta_2 = (-\rho \beta_k)$. This expression represents what has been labeled a spatial Durbin model (SDM). According to LeSage and Pace (2009), it indicates that although ΔZ_i is omitted, provided W_c is known, unbiased estimates can be obtained by estimating this equation.

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