Skilled Migration and Cities Dynamics: the Case of Minas Gerais

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Abstract

This article aims to verify why skilled migrants choose to locate in Minas Gerais' cities. A specific indicator of skilled migration is elaborated, coined as "index of net skilled migration". The paper presents, first, the ranking of cities with higher net migration of skilled workers. Next, exploratory spatial data analysis (ESDA) is employed. Spatial econometrics models are carried out to verify the main cities' characteristics that matter to attract skilled migrants. Labor market dynamics, less social and educational inequalities and less crime are important factors behind the skilled migrants' choices to locate in a city in Minas Gerais state.

Keywords: migration; regional economics; education; spatial econometrics, Minas Gerais.

Resumo

O objetivo do artigo é traçar os principais determinantes da migração da mão-de-obra qualificada para as cidades de Minas Gerais. Um indicador específico de migração qualificada é elaborado, denotado por "índice de migração qualificada líquida". O trabalho apresenta, primeiramente, o ranking das cidades mineiras com maior atração de migrantes qualificados. Em seguida, uma análise exploratória de dados espaciais (ESDA) é empreendida. Modelos de econometria espacial são estimados a fim de averiguar as principais características das cidades no que concerne à atração de migrantes qualificados. Dinamismo do mercado de trabalho, menores desigualdade social e educacional e menor nível de violência são condicionantes importantes na escolha de uma cidade em Minas Gerais por parte dos migrantes qualificados.

Palavras-chave: migração; economia regional; educação; econometria espacial, Minas Gerais.

JEL: R23 e J62

1. Introduction

A migrant considers several city characteristics during her decision of where to locate. But, what are the most important city characteristics that the migrant takes into account? What is the role of local and national public policies? The answers of these questions are important to provide the Brazilian cities with a more responsive and competitive environment. According to Sahota (1968), migration analysis will increase our understanding of the mechanism of labor adjustment and thus of an important aspect of the process of economic development. On the other hand, it can serve as a basis for policies concerning employment, antipoverty, and other economic matters.

This paper aims to verify the main determinants of migration for a specific category: the skilled labor force. By skilled labor force, we mean persons with high education attainment (one year of college studies or more). This paper seeks to verify why selected cities of Minas Gerais state have attracted migrants with this profile between 1995 and 2000. What are the main factors that the migrants consider when they migrate to a specific city? Which are the main features: labor market dynamics or local amenities?

But why are skilled migrants important for a particular city?

Skilled migrants bring about positive externalities to a location, since they are likely more productive and entrepreneurs. Da Mata et al. (2007a) point out that education attainment is an important factor to attract skilled migrants to a particular place. Therefore, there is a virtuous cycle: education attracts skilled migrant and skilled migrant increase the average education attainment of the region. And education is one of the major determinants of local-level growth in Brazil (Chomitz et al., 2005).

This paper extends the analysis in Da Mata et al. (2007a), including a larger list of cities characteristics that works as determinants of skilled migration[3]. Besides, the analysis carried out in this paper focus on skilled migration from all Brazilian municipalities[4] to cities in Minas Gerais state between 1995 and 2000. In 2000, Minas Gerais state was divided by 853 municipalities and 10 macro-regions for regional policy implementation and planning[5]. Minas Gerais is the third richest state in Brazil[6] according to Gross Domestic Product (GDP) pictures in 2000. However, if we look at disparities within the state, we verify the existence of extreme economic affluence amidst enormous pockets of poverty[7].

In this context, migration has an important role in economic development of Minas Gerais and of Brazil as a whole. Historically, Brazil has shown huge migratory movements, mainly from Northeast to Southeast region. Most of Brazilian cities and regions were built basically from migrants. In this circumstance, it is useful to investigate specific trends in state-level and local-level, allowing for idiosyncrasies and spatial heterogeneities. Concerning Minas Gerais, Augusto & Brito (2006) indicate a reversion in the migratory behavior from the 90's, where Minas Gerais has shown a positive net migration. While in the periods 1965-1970, 1975-1980, 1986-1991 Minas Gerais showed negative net migration of 516,838, 237,032 and 107,506 people, respectively, it had a positive net migration of 39,125 persons between 1995 and 2000[8].

Notwithstanding the importance of the migration issue, there are relatively few studies concerning the local determinants of migration, i.e., which cities' characteristics are important when a person makes a decision of where to migrate. Most papers about migration in Brazil concentrate on migratory process using state-level data (Sahota, 1968; Ramos & Araújo, 1999; Silveira Neto, 2005; Justo & Silveira Neto, 2006). For example, Justo & Silveira Neto (2006) highlight that spatial controls, social (crime) and natural (climate) local attractiveness, besides income expectation, are important to explain the net rate of inter-regional migration in Brazil. However, in fact, migrants make their choices based on the characteristics of the city destination and not the state of destination. Moreover, the analysis of the migratory process could be improved once population Censuses have data by origin and destiny of the migrants. Indeed, Da Mata et al. (2007a) use municipal data about skilled migration process across Brazilian municipalities.

The rest of the paper is organized as follows. Section 2 describes the dataset that we employ in the paper. The paper presents, in section 3, the ranking of Minas Gerais' cities with higher attraction of skilled migrant. A specific indicator of skilled migration is elaborated, coined as "index of net skilled migration", elaborated from the comparison between skilled immigrants and skilled emigrants (or outmigrants). Then, section 4 uses exploratory spatial data analysis (ESDA) to identify patterns of spatial association or clusters. In section 5, we report the main results concerning the migratory process in Minas Gerais' municipalities. The empirical analysis aims to verify the main cities' characteristics concerning the attraction of skilled migrants. Spatial econometrics models are employed to correct for potential errors in the ordinary least squares (OLS) empirical strategy. Further details are discussed concerning the methodology in section 5. Final section presents the main conclusions, along with some policy implications.

2. Data

Migration data come from the Brazilian Bureau of Statistics (IBGE) Population Census of 2000 (IBGE, 2002). According to the Census, migrant is a person who lived in different cities in two given dates (five years before and in the day of the Census survey). Thus, we analyze migratory process between 1995 and 2000. This variable is considered as "fixed data" migration, whereas in the Census the migrant answers a question such as "in which city did you live five years ago?" It is useful to note that the 2000 Census does not include the question of "last phase" migration, in which the migrant

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[3] Da Mata et al. (2007a) present a survey of theoretical and empirical literature.
[4] Throughout this paper we refer to these units of analysis as either municipalities or cities.
[5] The macro-regional division was defined by the government of Minas Gerais that establishes the 10 following regions: Alto Paranaíba, Central, Centro-Oeste de Minas, Jequitinhonha/Mucuri, Zona da Mata, Noroeste de Minas, Norte de Minas, Rio Doce, Sul de Minas e Triângulo.
[6] Minas Gerais is one of the 27 states (including the Federal District) of Brazil, the second most populous (18 million) and with fourth largest area in Brazil.
[7] Resende (forthcoming) shows that 30% of Minas Gerais population in 2000 is composed of poor people that are inequitably distributed across the state. For example, the Alto-Panaíba, Centro-Oeste de Minas and Sul de Minas regions have about 20% of poor people (similar to the southern region in Brazil). On the other hand, Vale do Jequitinhonha/Mucuri and Norte de Minas regions have about 60% of poor people (similar to the northeast region in Brazil).
[8] See Brito et al. (2004) and Augusto & Brito (2006) for details.

would answer a question such as "in which city did you live previously?". Besides, our migration data does not include international migration. Our main variable is skilled migration. By "skilled migrant", we mean persons with high education attainment (one year of college studies or more) in the period of the Census survey.

This paper analyses the skilled migration trend at municipality level (Minas Gerais had 853 municipalities in 2000) instead of urban agglomerations/metropolitan areas. The reason for this choice is that the skilled migrant earns a salary that allows living in the municipality that he works and even close to the workplace. This statement is not true when it comes to the less skilled migrants[9]. Thus, we employ for our analysis the municipal boundaries.

Socioeconomic data at municipal level, such as wages, average years of schooling, schooling inequality (ratio persons with more than 12 years of schooling to persons with less than 4 years of schooling), population, health care (medical doctor per 1,000 inhabitants), altitude and income inequality (Gini index) are from the Human Development Atlas ("Atlas do Desenvolvimento Humano no Brasil", IPEA, PNUD e FJP, 2003). The Atlas provides us the data from the Census of 1991 using the 853 municipalities of Minas Gerais in 2000, instead of the existing 722 municipalities in 1991.

The transportation cost (proxy for transportation connectivity) between all Brazilian municipalities and the nearest State capital and between all Brazilian municipalities and São Paulo are from IPEADATA, available at www.ipeadata.gov.br. The transportation cost data are for the year 1995. Transportation cost to the nearest state capital (to São Paulo) is a result of a linear program procedure to calculate the minimum cost between the municipalities ma-

jors headquarter to the nearest state capital (to São Paulo)[10].

Homicide rates of young people come as well from IPEADATA. We made an average of those rates over the period from 1991 to 1995 in order to get rid of outliers values. The housing infrastructure index is made from a principal components analysis employed by Da Mata et al (2007b). It takes into account several dimensions of housing public services and utilities such as sewage, water and garbage collection and it is supposed to capture the quantity and quality of housing infrastructure in Brazilian municipalities. Climatic data (temperature and precipitation) stem from DECRG, World Bank (Chomitz et al, 2005).

3. Cities Ranking

This section aims to answer questions such as: which the regions are showing a brain drain process (more emigration than immigration) and which ones are, inversely, seeing the arrival of migrants with both higher education attainment and productivity?

The last Brazilian census which took place in 2000 provides information about three key variables: SI = Skilled immigration between 1995 and 2000, SE = Skilled emigration between 1995 and 2000 and TP = Total population in 2000. From these variables, we build an index of net

skilled migration (skilled labor force) – NSM – for each of the 853 Minas Gerais' municipalities in 2000. The equation for this indicator is:

$$NSM = \frac{SI - SE}{TP}, \qquad (1)$$

NSM is the ratio between net skilled migration (skilled immigration, SI, minus skilled emigration, SE) and total population (TP) in each municipality. It is important to note that this immigration (emigration) is related to inflow (outflow) of skilled people of all Brazilian regions.

Map 1 shows this indicator for the 853 Minas Gerais' municipalities. The darker is the color in the map, the higher is the value of NSM indicator. Three regions (Noroeste de Minas, Centro-Oeste de Minas and Sul de Minas) have shown the highest share of municipalities with positive indexes. So, these regions have a higher net inflow of skilled workers weighted by their population. Conversely, two regions present most of their municipality with non-positive indicators. This means that there is a brain drain occurring in these regions. Table 1 highlights the distribution of the positive and non-positive indexes of net skilled migration among ten macro-regions of Minas Gerais state.

[9] The 2000 Census does not have information over housing prices and rents. Therefore, the hypotheses of the housing location choice of skilled migrants cannot be evaluated appropriately. Extensions of this paper may deal with this empirical issue.

[10] The transportation cost variables were estimated via the Highway Design and Maintenance Standards Model (HDM-III) of the World Bank. That model predicts the various components of vehicle operating costs (VOC) in a roadway based on the roadway characteristics (pavement type and relief), vehicle characteristics (average capacity), and unit costs in a free-flow traffic environment. The result is the transport cost for two roadway categories (national or state roads). The results of the model were then used with one more variable: the minimum distance between two roadway nodes, i.e., the distance between the major headquarter of the municipality and São Paulo or the nearest state capital major headquarter. This procedure calculates the transportation cost variables, given road and vehicles conditions.

Table 1 – Cities with positive and non-positive indicators by region

Macro region	Municipalities with positive indicators		Municipalities with non-positive indicators		Total	
	number	share	number	Share	number	share
Noroeste de Minas	16	84%	3	16%	19	100%
Centro-Oeste de Minas	38	68%	18	32%	56	100%
Sul de Minas	95	61%	60	39%	155	100%
Triângulo Mineiro	20	57%	15	43%	35	100%
Zona da Mata	81	57%	61	43%	142	100%
Central	87	55%	71	45%	158	100%
Jequitinhonha/Mucuri	35	53%	31	47%	66	100%
Alto Paranaíba	16	52%	15	48%	31	100%
Norte de Minas	42	47%	47	53%	89	100%
Rio Doce	45	44%	57	56%	102	100%
Minas Gerais	**475**	**56%**	**378**	**44%**	**853**	**100%**

Own elaboration.
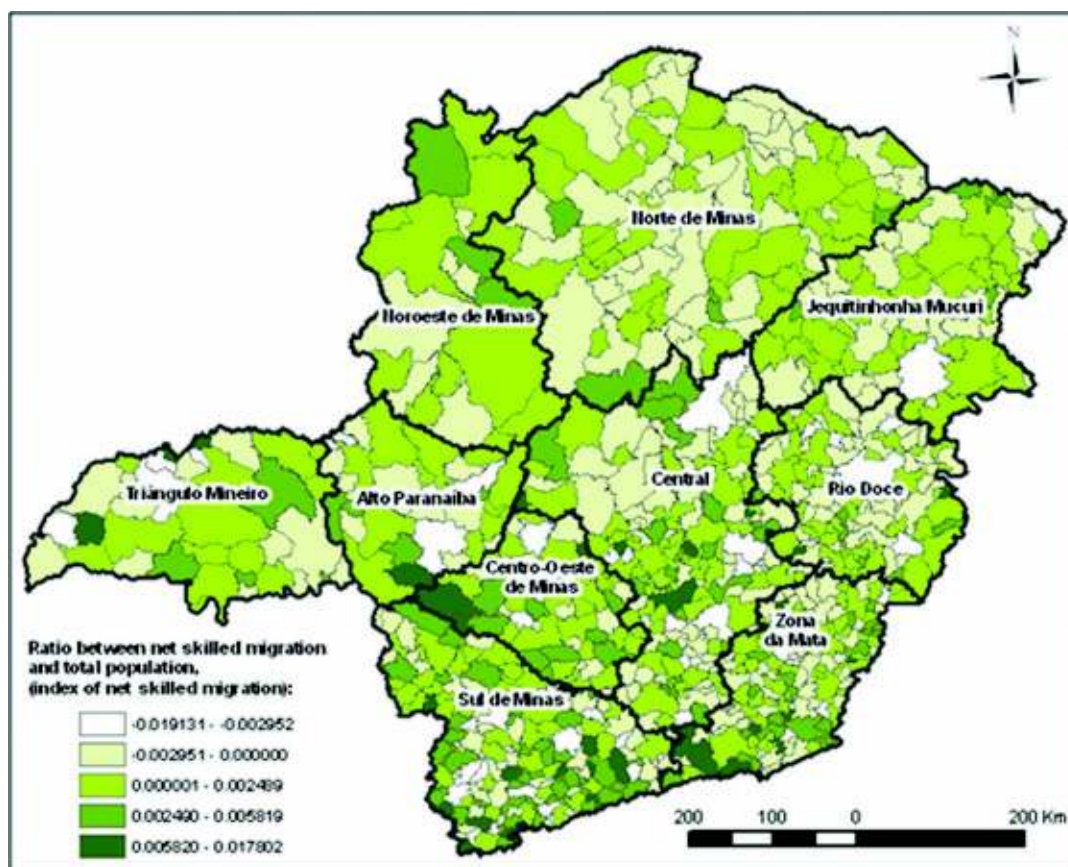
Map 1 – Index of net skilled migration for the Minas Gerais' municipalities
Source: Authors, from data of Demographic Census 2000 – IBGE.

Table 2 highlights the top ten municipalities of Minas Gerais state concerning the index of net skilled migration. Nova Lima is the place with the highest index value, following by Belmiro Braga and Gonçalves. These ten municipalities are concentrated in four macro-regions: Central, Zona da Mata, Sul de Minas and Triângulo Mineiro.

Table 2 – Top 10 cities (all)

Ranking – Minas Gerais	Municipality	Macro region	Indicator of net skilled migration
1	Nova Lima	Central	0.017802
2	Belmiro Braga	Zona da Mata	0.013061
3	Gonçalves	Sul de Minas	0.012481
4	Brumadinho	Central	0.011769
5	Senador Cortes	Zona da Mata	0.010914
6	Cedro do Abaeté	Central	0.010870
7	Pedro Teixeira	Zona da Mata	0.010570
8	Maripá de Minas	Zona da Mata	0.009990
9	União de Minas	Triângulo Mineiro	0.009617
10	Santa Rita de Ibitipoca	Zona da Mata	0.009068

Source: Own elaboration.

Table 3 presents a similar ranking, but now for the group of municipalities with population higher than 50,000 inhabitants. Nova Lima is the city in Minas Gerias with highest net skilled migration indicator. Poços de Caldas, Sete Lagoas, Leopoldina and São Sebastião do Paraíso are the following cities. It is interesting to ascertain that Belo Horizonte, the state capital, presents a brain drain process (i.e., a negative index) while some of its neighboring cities, such as Nova Lima, Sete Lagoas and Contagem, show the opposite process.

Table 3 – Top 10 cities (with population above 50,000 inhabitants in 2000)

Ranking – Minas Gerais	Municipality	Macro region	Indicator of net skilled migration
1	Nova Lima	Central	0.017802
2	Poços de Caldas	Sul de Minas	0.004994
3	Sete Lagoas	Central	0.003949
4	Leopoldina	Zona da Mata	0.003750
5	São Sebastião do Paraíso	Sul de Minas	0.003489
6	Uberlândia	Triângulo Mineiro	0.002958
7	Araxá	Alto Paranaíba	0.002778
8	Contagem	Central	0.002749
9	Januária	Norte de Minas	0.002144
10	Três Pontas	Sul de Minas	0.002023

Own elaboration.

Appendix I illustrates the NSM ranking for all Minas Gerais' cities with population above 50,000 inhabitants in 2000. In the next section, we employ an exploratory spatial data analysis (ESDA) to investigate the distribution pattern displayed in Map 1.

> *In this section we use exploratory spatial data analysis (ESDA) to identify spatial patterns regarding the indicator of net skilled migration (NSM). ESDA is a set of techniques aimed at describing and visualizing spatial distributions and at detecting patterns of spatial association or clusters (Anselin, 1998a,b). Essentially, these methods...*

4. Exploratory Spatial Data Analysis (ESDA)

In this section we use exploratory spatial data analysis (ESDA) to identify spatial patterns regarding the indicator of net skilled migration (*NSM*). ESDA is a set of techniques aimed at describing and visualizing spatial distributions and at detecting patterns of spatial association or clusters (Anselin, 1998a,b). Essentially, these methods measure global and local spatial autocorrelation.

Global spatial autocorrelation is based on Moran's *I* statistic (Cliff & Ord, 1981). For the NSM index between 1995 and 2000, this statistic is written in the following matrix form:

$$I = \frac{1}{\sum_{i \neq j} w_{ij}} \sum_{i \neq j} w_{ij} \left(\frac{y_i - \bar{y}}{s_y} \right) \left(\frac{y_j - \bar{y}}{s_y} \right), \quad (1)$$

whereare elements of the contiguity matrix (W), called Queen[11] matrix. If municipalities i and j share boundaries, then $w_y = 0$, and otherwise. The weight matrix is standardized so as the elements of a row sum up to one. y_1 and y_1 are the values of the NSM index. These terms are standardized using y (mean) and s_y (standard deviation). If $I \approx 0$, then there is no evidence of spatial autocorrelation. If Moran's I statistic is larger than zero, there is a positive autocorrelation, i.e., municipalities with high (low) NSM indexes tend to be next to neighboring municipalities with high (low) NSM indexes. On the other hand, if Moran's I statistic is smaller than zero, there is a negative autocorrelation, i.e., municipalities with high (low) NSM indexes tend to be close to neighboring municipalities with low (high) NSM indicators. The statistical significance of Moran's I is based on the permutation approach[12] (Anselin, 1995).

Graph 1 shows Moran's I statistic and Moran scatterplot for the NSM indicator between 1995 and 2000. The Moran scatterplot displays the spatial lag "$W^* NSM$ index" against the "NSM index", both standardized. "$W^* NSM$ index" is a measure of skilled migration in neighboring cities. The four different quadrants of the scatterplot correspond to four types of local spatial association between a municipality and its neighbors: (a) in the first quadrant we have (HH) a municipality with a high "$W^* NSM$ index" value surrounded by municipalities with high NSM index values; (b) in quadrant II, (HL) a municipality with a high value surrounded by municipalities with low values; (c) in quadrant III we see (LL) a municipality with a low value surrounded by municipalities with low values; and (d) in quadrant IV, (LH) a municipality with a low value surrounded by municipalities with high values.

Quadrants HH and LL refer to positive spatial autocorrelation, which indicate spatial clustering of similar values, whereas quadrants LH and HL represent negative spatial autocorrelation, indicating spatial clustering of dissimilar values.

The indicator is positively spatially autocorrelated since the Moran's I statistic is significant with a p-value equal to 0.0009. This result suggests that the null hypothesis of no spatial autocorrelation is rejected and that the distribution of the NSM index is by nature clustered over the period 1995-2000. In other words, municipality tend to be located close to each other in a certain pattern – municipalities with relatively high (low) NSM indexes are near other cities with relatively high (low) NSM indexes – rather than randomly. Moreover, these results are robust in respect to the choice of the spatial weight matrix[13].

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Moran's I = 0,0647 (p-value = 0,0009)
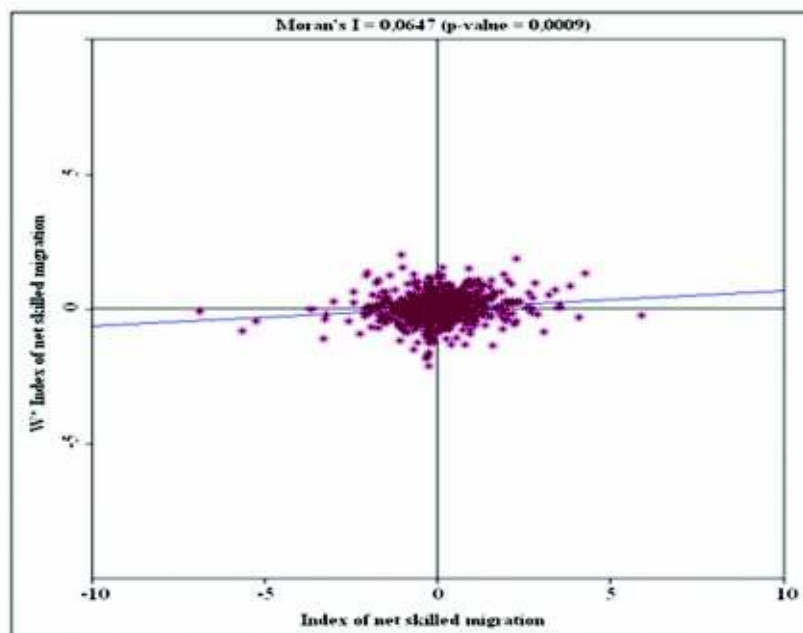
Graph 1 – Moran scatterplot
Own elaboration.

[11] We employ this matrix in the rest of our analysis. In addition, all following results are also robust to the use of a k-nearest neighbors spatial weight matrices, for $k = 5, 10$ and 20.
[12] All computations were carried out using Geoda and ArcGIS9.
[13] See footnote number 7.

The local version of Moran's *I* statistic is the Local Indicator of Spatial Association (LISA). Anselin (1995) defines a LISA as any statistics satisfying two criteria: first, the LISA for each observation gives an indication of significant spatial clustering of similar values around that observation; second, the sum of the LISA for all observations is proportional to a global indicator of spatial association. Thus, in Map 2 we have one LISA statistic for each municipality. The variable used in the LISA approach is our NSM indicator. A positive value for LISA indicates spatial clustering of similar values (either high or low) whereas a negative value points out spatial clustering of dissimilar values between a municipality and its neighbors. In addition, the statistic significance of LISA is based on the aforementioned permutation approach..

Map 2 identifies high-high (HH) clustering in four macroregions of Minas Gerais state: Central, Centro-Oeste, Sul de Minas e Zona da Mata. For example, the high-high clustering in Central macroregion comprises 16 municipalities: Nova Lima, Sabará, Santa Luzia, Vespasiano, Ribeirão das Neves, Contagem, Ibirité, Brumadinho, Bonfim, Esmeralda, Betim, Sarzedo, Mario Campos, São Joaquim de Bicas, Igarapé and Mateus Leme. We can see that Belo Horizonte, the state capital, is next to this cluster and presents a low-high LISA indicator. It means that Belo Horizonte has a relatively low NSM index and is localized close to other municipalities with relatively high indexes of NQM. This fact corroborates the brain drain process occurring in Belo Horizonte suggested in section 3.

On the other hand, eight macroregions exhibit low-low (LL) clustering in some places. These macroregions are: Central, Jequitinhonha/Mucuri, Rio Doce, Zona da Mata, Sul de Minas, Alto Paranaíba, Noroeste de Minas and Triângulo Mineiro. For example, the low-low cluster in Central macro-region has 15 municipalities: Jaceaba, Congonhas, Conselheiro Lafaiete, Ouro Branco, Queluzita, Santana dos Montes, São Brás do Suaçuí, Coronel Xavier Chaves, Lagoa Dourada, Capela Nova, Caranaíba, Carandaí, Ressaquinha, Senhora dos Remédios and Lamim. Furthermore, we can observe across Minas Gerais state the low-high (LH) and high-low (HL) clustering.
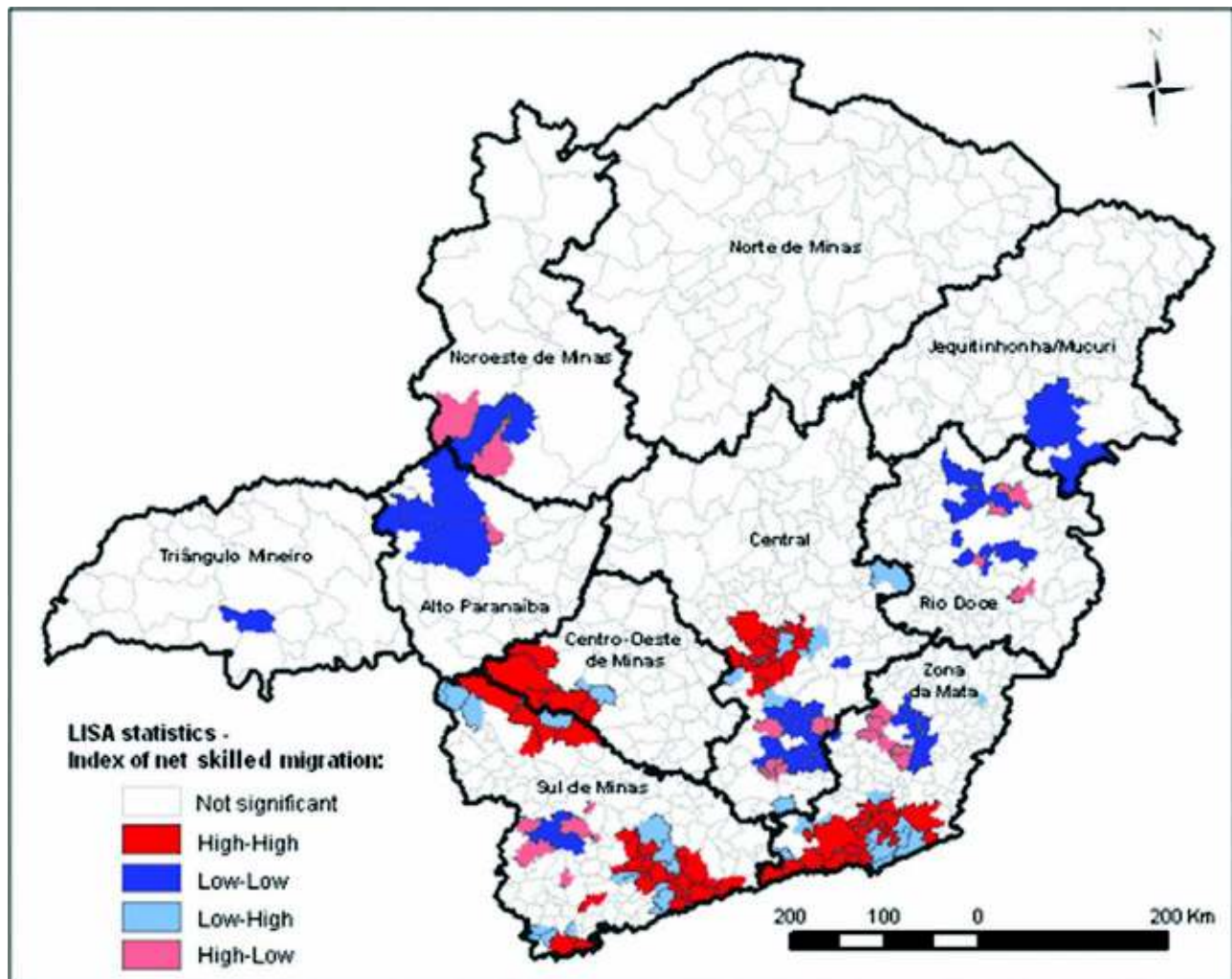
Map 2 – Cluster Map
Own elaboration.

Finally, we investigate the relationship between labor market dynamics and skilled migration. The aim of this analysis is to shed light on why high skilled people migrate. The main hypothesis is that skilled migrants are looking for higher salaries. So, we match municipalities that experienced both wages above the state mean in 1991 and a net inflow of skilled migrants between 1995 and 2000. Map 3 shows that 224 (26%) municipalities are in this situation. This suggests that the relationship could be true: municipalities with dynamic labor markets are capable of attracting high skilled migrants. These municipalities are clustered in six macro-regions: Central, Zona da Mata, Sul de Minas, Centro-Oeste de Minas, Alto Paranaíba e Triângulo Mineiro. Within those six macro-regions there are 212 municipalities with high wages and positive NSM index, which represent 25% of all municipalities in Minas Gerais state.

Nevertheless, the literature suggests that there is actually a "menu" of amenities that the migrant choose when migrates. The empirical analysis that we undertake in the next section follows Da Mata et al. (2007a) and it aims at testing the relationship verified here and other options in the migrants' set of choices.

5. Determinants of skilled migration

This part points out the main determinants of skilled migration for the case of Minas Gerais' cities. We use a slightly different version of our net skilled migration (NSM) indicator as the depend variable in this empirical analysis. Specifically, the variable we employ is the difference between skilled immigration and skilled emigration. Total municipal population is used as exploratory/control variable in all models, instead of using it as a weight in the dependent variable.

Several factors are assessed in different econometric specifications: labor market, amenities, social capital, education, health, infrastructure, among others. Table 4 presents the results of several specifications. First, all models were estimated through Ordinary Least Square (OLS). Latter we relax some of the classical regression hypothesis and we use some spatial regression techniques (see section 5.1).
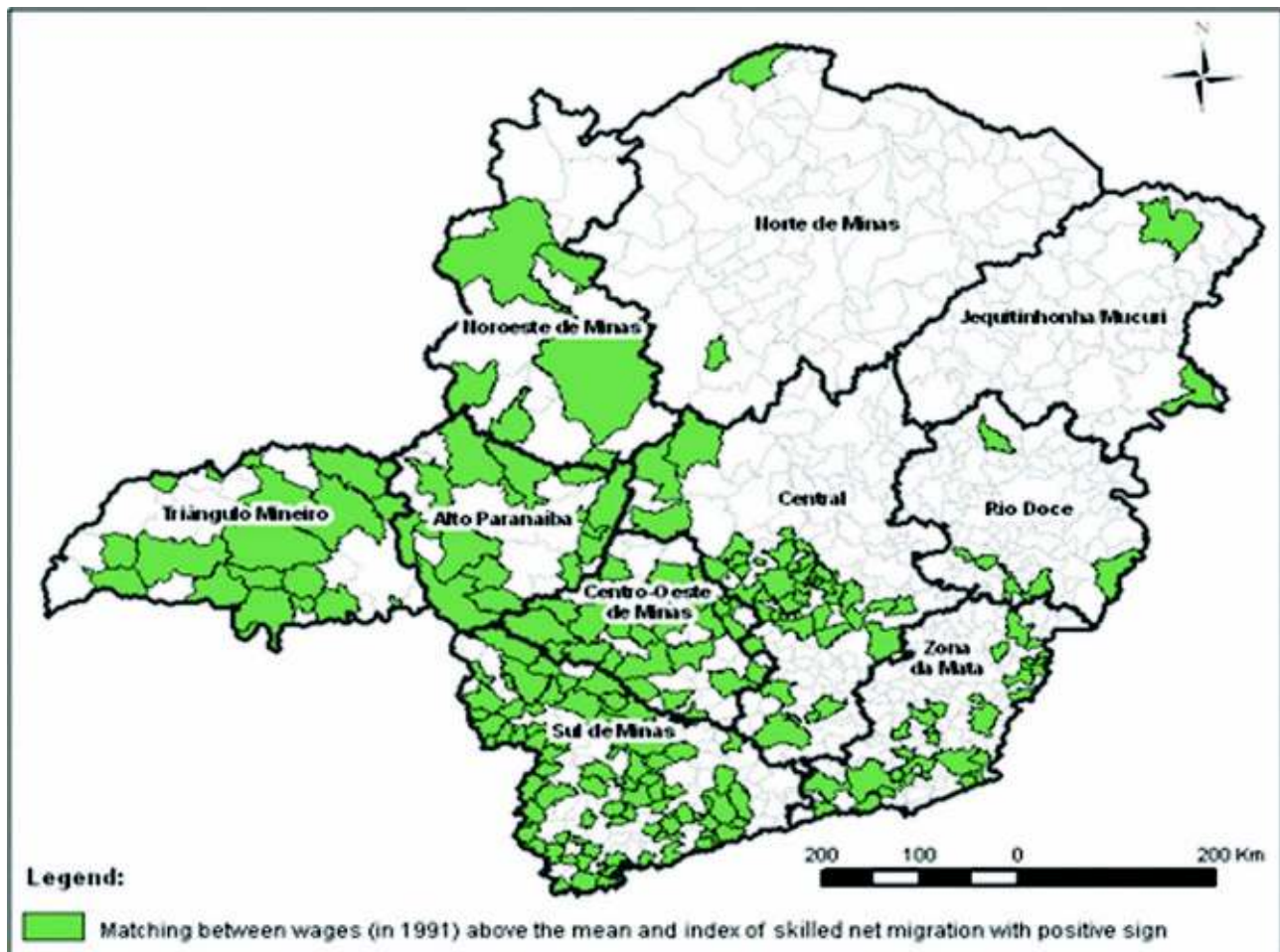
Map 3 – Labor market dynamics and skilled migration
Own elaboration.

Labor market dynamics is statistically significant in almost every specification. The higher the wage in the early 1990's, the greater was the migration to that locality during 1995-2000. One interesting patter is that upon the inclusion of more control variables the wage in 1991 becomes more significant and its impact over skilled migration enhances. This suggests that labor market is relevant explanation once you consider other factors that might explain the migration process. The results support other finds of the literature (see Da Mata et al, 2007a, for more details).

Skilled migrants tend to go to places where more skilled people live. The positive and significant value of (municipal average) years of schooling in all regression says that there is in fact a virtuous cycle between education attainment and skilled migration, as said before. The spillovers associated to human capital are part of the explanation; places that put more value on a better qualification also attract more skilled migrants.

Total population had a negative sign in some regressions, which indicates a tendency to skilled migrants to move to small size cities. On the other hand, in some specifications, the population coefficient was positive, indicating that the urban agglomerations still attracts skilled migrants. The last regression (11), after controlling for several city characteristics, population size was important so as to attract migrants. In sum, for the case of the cities in Minas Gerais, agglomeration economies (factors that attract people and firms to cities) have a bigger impact then disagglomeration economies (factors that repulse people and firms).

We build two measures of inequality: the first related to education and the other to income. More unequal cities receive less skilled migrants. These variables complement the story of the overall importance of education and labor market dynamics. Skilled labor force tend to migrate towards cities with higher wages, income and average education attainment, but they always take into account how income and education are distributed within the population. This suggests that migrant choose cities with less social instability.

Transportation costs (to São Paulo and to the nearest State capital) do not appear as a significant variable in the last regressions (8)-(11). Theses variables were used so as to capture how important "congestion effects" are. Congestion may be seen as a component of disagglomeration economies, i.e., those factor which repulse people from certain places. Violence and pollution are other types of disagglomeration economies. Since there is a close relation between city size and congestion, total population coefficient might be capturing part of the congestion effect and then the transportation cost coefficients become not significant.

Several measures of climate amenities were used. Mean temperatures (June and December), altitude and total annual precipitation do not appear to matter to skilled migrants. One explanation could be that we are using amenity variables within the same state and because of that we are not seeing enough variation in those variables.

Homicides among youngsters is a important factor concerning the decision of the skilled migrants. The coefficient for homicides is negative and statistically significant. This indicator of violence supports the results found in another two variables: income and education inequality. They all can be seen as proxies for social (in)stability and they give the same prescription: skilled migrants rather move to cities with less instability.

We add two variables related to health sector performance, the ratio medical doctors per a thousand inhabitants and infant mortality rate, but they did not appear as statistically significant. These results may be due to a failure of those variables to hold the real efficiency and quality of the municipal housing sector. Additionally, the index used as proxy for local housing infrastructure quality was not significant in the regressions. Housing in Brazil is a quite complex question that always involves a plethora of aspects such as urban regulation. The index of housing infrastructure does not entail those regulations and thus does not provide a comprehensive view of the problem. The constant term was significant just in the first specification. Finally, the last equation includes regional dummies (for each of the 9 macro-regions[14]), but the results remain the same.

The next section presents some robustness tests. Hitherto the analysis could have omitted one important variable: the migration flow of neighboring municipalities. Intuitively, a migratory process in one place is affected by migration to others municipalities. There is so a spatial autocorrelation: the magnitude of one variable in a certain location depends on the value of the same variable in nearby locations. This is the case when there is a competition among municipalities to have the "best" migrants. Thus we estimate two additional models: (a) spatial lag model and (b) spatial AR error model. In the presence of spatial autocorrelation, the OLS coefficients are not either efficient or consistent anymore. We present details of those models in the next subsection.

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[14] We exclude one (Alto Paranaíba dummy) of the dummy variables from the regression to avoid perfect multicollinearity.

Table 4 – Results of Ordinary Least Square (OLS) estimation

Dependent Variable: Net migration of skilled workers between 1995-2000	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Method	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Wage in 1991	0.1801	0.2229	0.2997	0.5018*	0.5690*	0.5564*	0.6041*	0.6022*	0.6398**	0.6242*	0.8288**
	(0.2137)	(0.2186)	(0.2200)	(0.2337)	(0.2425)	(0.2489)	(0.2500)	(0.2404)	(0.2430)	(0.2540)	(0.2900)
Years of schooling in 1991	19.4616*	25.9693*	41.0002**	27.1863*	29.4225*	29.5100*	35.5851*	38.4496**	39.3219**	37.4997*	40.8156*
	(8.8908)	(10.6879)	(12.2315)	(13.3827)	(13.4797)	(13.4929)	(13.8998)	(13.3693)	(13.5854)	(16.0528)	(17.6237)
Population in 1991	-0.0017**	-0.0016**	-0.0017**	-0.0017**	-0.0017**	-0.0017**	-0.0017**	0.0007*	0.0007*	0.0007*	0.0007*
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Schooling Inequality in 1991		-129.2904	-198.9292	-102.7014	-129.4374	-127.8487	-220.8313	-730.793**	-792.241**	-784.387**	-855.993**
		(165.7445)	(167.5596)	(171.4005)	(173.7484)	(173.9883)	(181.4250)	(184.8342)	(191.7023)	(195.3104)	(204.2804)
Gini index in 1991		-205.3946	-231.3566	-275.413*	-267.701*	-263.088*	-271.887*	-281.255*	-308.276*	-307.722*	-325.148**
		(119.2510)	(119.3342)	(120.2572)	(120.7049)	(122.4855)	(122.4270)	(117.7212)	(119.7487)	(119.8451)	(122.9582)
Transport cost to São Paulo			0.0587*	0.1093**	0.1424**	0.1435**	0.1093*	0.0823	0.0780	0.0825	0.0487
			(0.0234)	(0.0309)	(0.0470)	(0.0473)	(0.0510)	(0.0491)	(0.0502)	(0.0544)	(0.0721)
Transport cost to the nearest capital				-0.1216*	-0.1322**	-0.1343**	-0.1262*	-0.0844	-0.0842	-0.0876	-0.0517
				(0.0486)	(0.0509)	(0.0517)	(0.0518)	(0.0501)	(0.0507)	(0.0531)	(0.0757)
Mean temperature in June					-1.3876	-1.9154	-2.5420	-3.8975	-2.7092	-2.6539	6.9815
					(13.5648)	(13.7719)	(13.7586)	(13.2302)	(13.2905)	(13.3006)	(15.3421)
Mean temperature in December					-5.8184	-4.2670	-7.9263	-7.2190	-7.6385	-7.4121	-12.8841
					(14.3804)	(15.9423)	(16.0535)	(15.4360)	(15.4511)	(15.4962)	(16.3799)
Altitude						0.0079	0.0111	-0.0066	-0.0041	-0.0018	0.0147
						(0.0352)	(0.0352)	(0.0339)	(0.0340)	(0.0356)	(0.0428)
Annual precipitation							-0.0990	-0.0614	-0.0540	-0.0523	0.0016
							(0.0555)	(0.0536)	(0.0540)	(0.0546)	(0.0686)
Homicides of young (mean 91-95)								-30.4339**	-30.1482**	-30.1491**	-29.9128**
								(3.6463)	(3.6790)	(3.6811)	(3.7605)
Doctors per 1,000 inhabitants in 1991									14.5242	14.5779	13.6171
									(14.2784)	(14.2888)	(14.3756)
Infant mortality rate in 1991									0.4865	0.4804	0.4667
									(0.6190)	(0.6200)	(0.6264)
Index of housing infra-structure in 1991									1.8179	0.5610	
									(8.5193)	(9.0072)	
Constant	-45.666*	44.8030	-40.3591	12.7469	126.9481	95.1037	325.0416	296.5633	265.1010	259.3330	54.5425
	(17.8796)	(65.2824)	(73.4426)	(76.2227)	(133.4719)	(194.1407)	(232.8821)	(223.9465)	(226.9914)	(228.7236)	(272.8348)
Macro-regional dummies	No	No	No	No	No	No	No	No	No	No	Yes
Obs	853	853	853	853	853	853	853	853	853	853	853
R-squared	0.37	0.38	0.38	0.39	0.39	0.39	0.39	0.44	0.44	0.44	0.44
AIC	11052.84	11053.07	11048.78	11044.47	11045.72	11047.67	11046.46	10980.5	10982.88	10984.83	10998.12
BIC	11071.84	11081.56	11082.02	11082.46	11093.21	11099.91	11103.44	11042.23	11054.11	11060.81	11116.84

Note: Standard errors in parentheses; * significant at 5%; ** significant at 1%; AIC = Akaike Information Criterion, BIC = Schwarz's Bayesian information criteria.

5.1. Spatial Correction

This subsection describes the methodology that tests and deals with the spatial dependence in the econometric model that relates net skilled migration (our dependent variable) and the explanatory variables. We use the classical strategy outlined in Florax et al. (2003) to effectively distinguish between the alternative specifications of the econometric models in the presence of spatial dependence.

According to Anselin (1988), spatial econometrics suggests two alternatives models: spatial lag model and spatial AR error model. In the former model, the specification contains a spatially lagged dependent variable. Under the assumption of a normal distribution for the error terms, Equation (1) can be estimated using maximum likelihood procedures.

$$y = \rho Wy + X\beta + \varepsilon$$
$$\varepsilon \sim N(0, \sigma^2 I_n \qquad (1)$$

Where y is $N \times 1$ column vector with observations for net skilled migration for each municipality. X is the $N \times K$ matrix that represents the exploratory variables[15] and β_1 its coefficients vector. W is the row standardized $N \times N$ spatial weight matrix[16]. Thus, W_y is the $N \times 1$ column vector of the endogenous spatial lag variable and ρ is the spatial lag coefficient that measures the externality of net skilled migration across municipalities. Ignoring this sort of spatial dependence will yield biased estimates.

In the spatial AR error model, we follow the standard assumption that the error term in OLS specification follows a first order spatial autoregressive process: with and . Thus, we have the spatial AR error model in Equation (2).

$$y = X\beta_1 + (I - \lambda W)^{-1} \varepsilon \qquad (2)$$

As is well-known, use of OLS in the presence of non-spherical errors would yield unbiased estimates for the estimated parameters but a biased estimate of the parameters' variance. Thus, inferences based on the OLS estimates would be misleading.

The distinction between a spatial lag and a spatial error specification is often difficult in practice. This paper follows the approach proposed by Florax et al. (2003) to choose the best econometric specification for the empirical migration model discussed here. The strategy consists of the estimation of the standard OLS model to check for spatial dependence applying the (robust) Lagrange multiplier (LM) tests. Next we replicate the methodology proposed in Florax et al. (2003, p. 562)[17]:

1. Estimate the initial model $y = X\beta_1$ by means of OLS.
2. Test the hypothesis of no spatial dependence due to an omitted spatial lag or due to spatially autoregressive errors, using LM_ρ and LM_λ, respectively.
3. If both tests are not significant, the initial estimates from step 1 are used as the final specification. Otherwise proceed to step 4.
4. If both tests are significant, estimate the specification pointed to by the more significant of the two robust tests. For example if $LM_\rho* > LM_\lambda*$[18] then estimate Eq.(1) *using MLLAG[19]. If then estimate* Eq.(2) *using MLERROR[20]. Otherwise, proceed to step 5.*
5. If ML_ρ is significant but ML_λ is not, estimate Eq.(1) *using MLLAG. Otherwise, proceed to step 6.*
6. Estimate Eq.(2) *using MLERROR.*

Given the methodology suggested above, we run the last specification of the empirical migration model in section 5, that is, the specification 11 in Table 4 using OLS method. Table 5 shows the diagnostic results for spatial dependence from the specification 11 (Table 4). Following steps 1-6 described above, we chose the spatial lag model since LM(lag) statistic is higher than and LM(error), which indicates that the spatial lag model specification is appropriate.

Table 5 – Diagnostics for Spatial Dependence

Test	Value	P-value
Lagrange Multiplier (lag)	59.6786	0.0000
Robust LM (lag)	129.5248	0.0000
Lagrange Multiplier (error)	1.6803	0.1949
Robust LM (error)	71.5265	0.0000

Note: Spatial weight matrix = Queen.

Next we report the estimation results for the spatial models. The columns (2) and (3) of Table 6 point out the spatial error model and spatial lag model, respectively. Column (1) shows again the OLS model for comparison purpose. In model (2), the term is only significant at 7% level and negative. From this model, a positive random shock introduced into a specific municipality will not only affect the skilled migration in that location but will also influence the skilled migration performance of other municipalities in Minas Gerais. Concerning the spatial lag model (3), the coefficient is significant at 1% level and negative. This result means that the higher the net skilled migration to

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[15] We note that the exploratory variables employed in the spatial models are the same that we use in the Ordinary Least Squares (OLS) estimates.
[16] Spatial weight matrix = Queen
[17] See Florax et al. (2003) for further details.
[18] "*" means the robust version of LM test.
[19] Maximum likelihood estimators for the spatial autoregressive error model.
[20] Maximum likelihood estimators for the spatial lag model.

a specific municipality, the lower is the attraction of skilled migrants to neighboring municipalities. This pattern of migration highlights the competition among neighboring municipalities for skilled migrants.

Moreover, it is important to note that the sign and the significance of the estimated coefficients for all three methods are similar. However, we mention that according to the diagnostic tests reported in Table 5, the appropriate model is the spatial lag (3). Skilled migrants choose to go to cities in Minas Gerais state with higher salaries and education level, less education and social inequalities, and less crime. These are main factors behind the skilled migrants' choices to locate in a Minas Gerais' municipality.

Table 6 – Results of Spatial Models

Dependent Variable: Net migration of skilled workers	(1)	(2)	(3)
Method	OLS	ML-Error model	ML-Lag model
Wage in 1991	0.8288**	0.8465**	0.9298**
	(0.2900)	(0.2747)	(0.2695)
Years of schooling in 1991	40.8156*	40.9933*	35.8674*
	(17.6237)	(16.9675)	(16.4019)
Population in 1991	0.0007*	0.0007*	0.0008**
	(0.0003)	(0.0003)	(0.0003)
Schooling Inequality in 1991	-855.9925**	-897.5574**	-881.9608**
	(204.2804)	(199.0074)	(190.1224)
Gini index in 1991	-325.1478**	-323.1800**	-287.6879**
	(122.9582)	(119.2195)	(114.3678)
Transport cost to São Paulo	0.0487	0.0409	0.0422
	(0.0721)	(0.0674)	(0.0670)
Transport cost to the nearest capital	-0.0517	-0.0388	-0.0353
	(0.0757)	(0.0705)	(0.0703)
Mean temperature in June	6.9815	7.9073	1.4660
	(15.3421)	(13.9601)	(14.2892)
Mean temperature in December	-12.8841	-13.12127	-6.2561
	(16.3799)	(15.0289)	(15.2484)
Altitude	0.0147	0.0175	0.0289
	(0.0428)	(0.0409)	(0.0398)
Annual precipitation	0.0016	0.0045	0.0059
	(0.0686)	(-0.0628)	(0.0638)
Homicides of young (mean 91-95)	-29.9128**	-29.3883**	-30.6613**
	(3.7605)	(3.6928)	(3.4959)
Doctors per 1,000 inhabitants in 1991	13.6171	14.6555	16.4751
	(14.3756)	(14.0926)	(13.3608)
Infant mortality rate in 1991	0.4667	0.4208	0.1751
	(0.6264)	(0.6083)	(0.5827)
Index of housing infra-structure in 1991	0.5610	0.3281	-0.2398
	(9.0072)	(8.5965)	(8.3713)
Constant	54.5425	31.9055	-22.3034
	(272.8348)	(254.4160)	(253.5766)
		-0.1055	
		(0.0572)	
			-0.4210**
			(0.0473)
Macro-regional dummies	Yes	Yes	Yes
Obs	853	853	853
R-squared	0.44	0.44	0.50

Note: Standard errors in parentheses; * significant at 5%; ** significant at 1%. Spatial weight matrix = Queen.

5. Conclusions

This paper aims to understand why selected cities of Minas Gerais state have attracted skilled migrants between 1995 and 2000. This paper extends the analysis of Da Mata et al. (2007a), including a larger list of cities characteristics that works as determinants of skilled migration. Additionally, we use exploratory spatial data analysis (ESDA) techniques to identify spatial patterns regarding the skilled migration process among the cities of Minas Gerais.

In this paper we elaborate a specific indicator of skilled migration, coined as "index of net skilled migration". The paper made a ranking of Minas Gerais' cities in respect to our indicator of net skilled migration (NSM). Nova Lima, Belmiro Braga and Gonçalves were the top three cities in terms of the highest index value. For the group of municipalities with population above 50,000 inhabitants, Nova Lima, Poços de Caldas and Sete Lagoas were the top three. Next, exploratory spatial data analysis (ESDA) was used. This exploratory analysis shows that municipalities tend to be close to each other in a certain pattern rather than randomly. The following sections sought to verify the main factors that the skilled migrants evaluate when they move to a city of Minas Gerais state.

Our results suggest that cities must include in their development strategies measures to retain and attract skilled workers, since they bring about positive externalities to a location and are likely more productive and entrepreneurs. This paper dealt with the cities characteristics that act as magnets for skilled migrants. The empirical results show that skilled migrants search for places with dynamic labor markets, where they encounter higher wage. Less income inequality and less crime are also important factors that help to explain why skilled workers choose one location in detriment of another one. Once more, the results show evidences that space matters. Specifically, it means that the higher the net skilled migration to a specific municipality, the lower is the attraction of skilled migrants to neighboring municipalities. This pattern of migration highlights the competition among neighboring municipalities for skilled migrants.

Several city characteristics were not statistically significant such as transport costs, climate amenities,

> *Extensions of this paper would include better explanatory variables such as an index of health sector quality, the industry composition of the municipality (which sector the migrant will work in?), a better measurement of real/local wages (using a local price index to deflate nominal wages) and ...*

variables related to health care and the index of housing infrastructure. Contrary to the findings of Da Mata et al. (2007a) for all Brazilian municipalities, the results for the Minas Gerais case show that mean temperatures (June and December), altitude, and total annual precipitation do not appear to matter to skilled migrants. The paper provides some evidences that the migrant rather choose cities in Minas Gerais due to labor market and social aspects than to climate amenities. Therefore, there is a chief role for adequate public policy practices to improve cities competitiveness.

Extensions of this paper would include better explanatory variables such as an index of health sector quality, the industry composition of the municipality (which sector the migrant will work in?), a better measurement of real/local wages (using a local price index to deflate nominal wages) and an index of housing regulation and housing prices/rents.

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APPENDIX 1:

Table 7 – Index of net skilled migration for municipalities with population above 50,000 inhabitants in 2000

Ranking – Minas Gerais	Municipality	Macro region	Index of net skilled migration	Total Population in 2000
1	Nova Lima	Central	0.017802	64,387
2	Poços de Caldas	Sul de Minas	0.004994	135,627
3	Sete Lagoas	Central	0.003949	184,871
4	Leopoldina	Zona da Mata	0.003750	50,097
5	São Sebastião do Paraíso	Sul de Minas	0.003489	58,335
6	Uberlândia	Triângulo Mineiro	0.002958	501,214
7	Araxá	Alto Paranaíba	0.002778	78,997
8	Contagem	Central	0.002749	538,017
9	Januária	Norte de Minas	0.002144	63,605
10	Três Pontas	Sul de Minas	0.002023	51,024
11	Divinópolis	Centro-Oeste de Minas	0.002017	183,962
12	São João del Rei	Central	0.001967	78,616
13	Manhuaçu	Zona da Mata	0.001816	67,123
14	Betim	Central	0.001705	306,675
15	Vespasiano	Central	0.001700	76,422
16	Ubá	Zona da Mata	0.001434	85,065
17	Pedro Leopoldo	Central	0.001418	53,957
18	Sabará	Central	0.001417	115,352
19	Ribeirão das Neves	Central	0.001205	246,846
20	Pará de Minas	Central	0.001152	73,007
21	Ibirité	Central	0.001080	133,044
22	Juiz de Fora	Zona da Mata	0.001045	456,796
23	Passos	Sul de Minas	0.001038	97,211
24	Formiga	Centro-Oeste de Minas	0.000931	62,907
25	Santa Luzia	Central	0.000896	184,903
26	Varginha	Sul de Minas	0.000661	108,998
27	Caratinga	Rio Doce	0.000604	77,789
28	Ipatinga	Rio Doce	0.000559	212,496
29	Araguari	Triângulo Mineiro	0.000311	101,974
30	Unaí	Noroeste de Minas	0.000229	70,033
31	Patos de Minas	Alto Paranaíba	0.000113	123,881
32	Pirapora	Norte de Minas	0.000111	50,300
33	Muriaé	Zona da Mata	0.000061	92,101
34	Montes Claros	Norte de Minas	-0.000027	306,947
35	Curvelo	Central	-0.000251	67,512
36	Paracatu	Noroeste de Minas	-0.000294	75,216
37	Patrocínio	Alto Paranaíba	-0.000382	73,130
38	Janaúba	Norte de Minas	-0.000776	61,651
39	Pouso Alegre	Sul de Minas	-0.000926	106,776
40	Coronel Fabriciano	Rio Doce	-0.001183	97,451
41	Itaúna	Centro-Oeste de Minas	-0.001310	76,862
42	Conselheiro Lafaiete	Central	-0.001315	102,836
43	João Monlevade	Central	-0.001581	66,690
44	São Francisco	Norte de Minas	-0.001861	51,497
45	Belo Horizonte	Central	-0.001978	2,238,526
46	Timóteo	Rio Doce	-0.002174	71,478
47	Lavras	Sul de Minas	-0.002293	78,772
48	Cataguases	Zona da Mata	-0.002366	63,980
49	Barbacena	Central	-0.002560	114,126
50	Uberaba	Triângulo Mineiro	-0.002849	252,051
51	Ponte Nova	Zona da Mata	-0.003029	55,303
52	Teófilo Otoni	Jequitinhonha/Mucuri	-0.003114	129,424
53	Itabira	Central	-0.003337	98,322
54	Governador Valadares	Rio Doce	-0.003738	247,131
55	Três Corações	Sul de Minas	-0.004762	65,291
56	Itajubá	Sul de Minas	-0.004824	84,135
57	Ituiutaba	Triângulo Mineiro	-0.005399	89,091
58	Ouro Preto	Central	-0.008546	66,277
59	Viçosa	Zona da Mata	-0.014427	64,854
60	Alfenas	Sul de Minas	-0.019131	66,957

Own elaboration.