SKILLED MIGRATION AND CITIES DYNAMICS: THE CASE OF MINAS GERAIS

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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.

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.

Key-words: migration; regional economics; education; spatial econometrics, Minas Gerais.

Classificação 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[1]. Besides, the analysis carried out in this paper focus on skilled migration from all Brazilian municipalities[2] 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[3]. Minas Gerais is the third richest state in Brazil[4] 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[5].

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-

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[1] Da Mata et al. (2007a) present a survey of theoretical and empirical literature.

[2] Throughout this paper we refer to these units of analysis as either municipalities or cities.

[3] 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.

[4] 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.

[5] 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).

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[6].

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 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[7]. Thus, we employ for our analysis the municipal boundaries.

[6] See Brito et al. (2004) and Augusto & Brito (2006) for details.

[7] 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.

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 majors headquarter to the nearest state capital (to São Paulo)[8].

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:

$$NSM = \frac{SI - SE}{TP}, \tag{1}$$

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,

[8] 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.

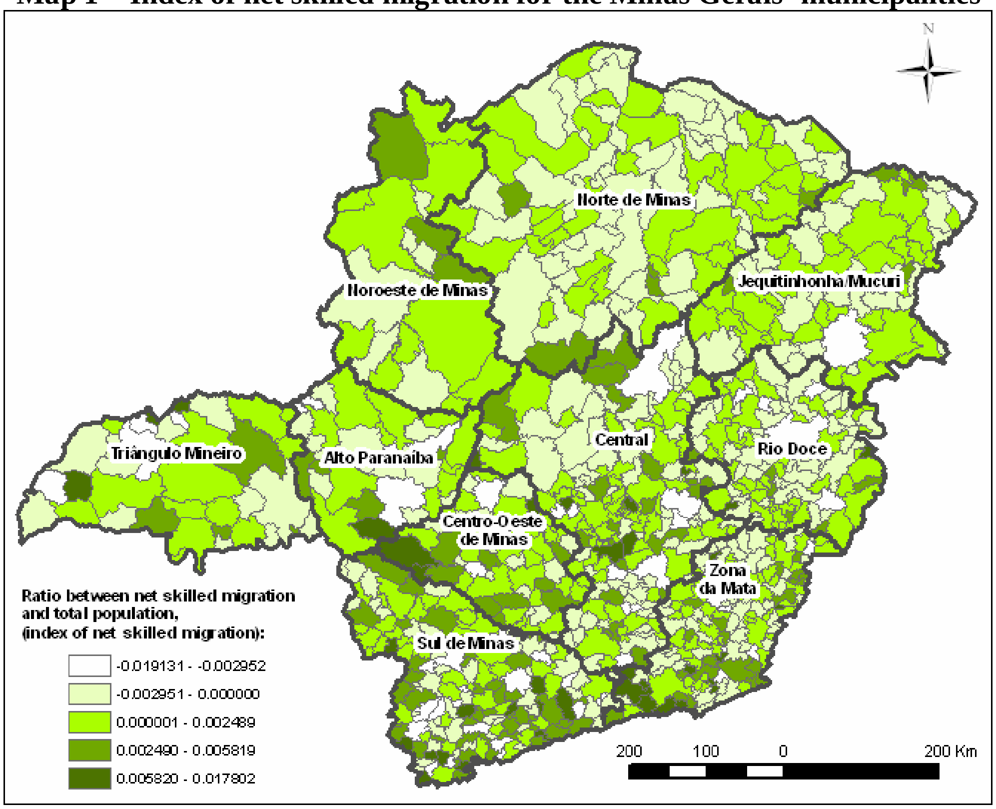
Centro-Oeste de Minas and Sul de Minas) have shown the highest share of municipalities with positive indexes. So, these regions have a higher net inflow of skilled workers weighted by their population. Conversely, two regions present most of their municipality with non-positive indicators. This means 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.

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.

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:

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

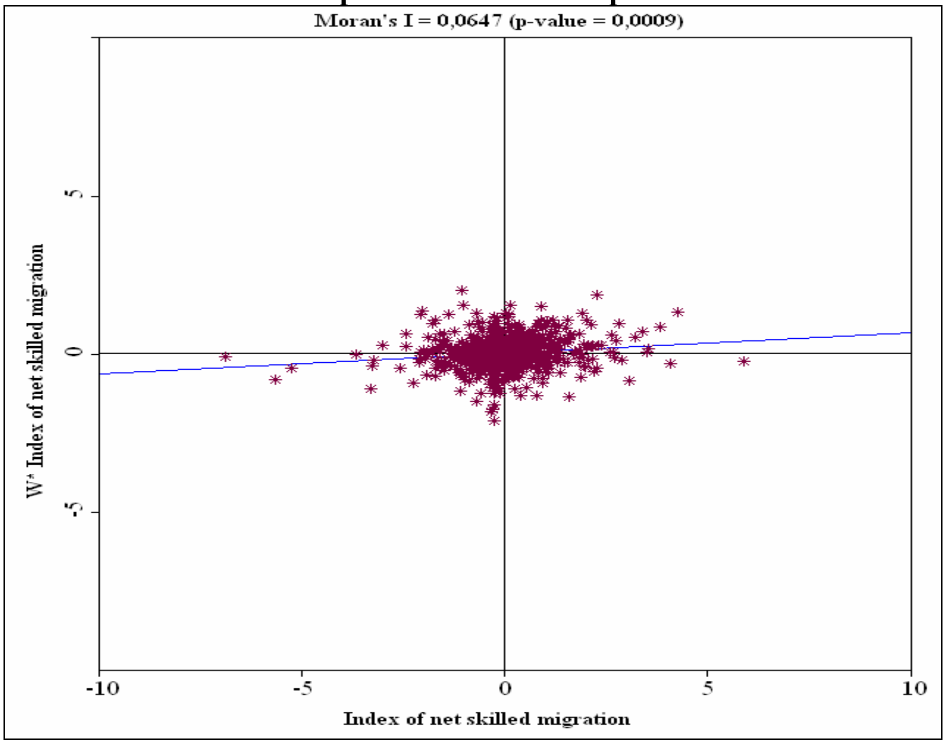
where w_{ij} are elements of the contiguity matrix (W), called Queen[9] matrix. If municipalities i and j share boundaries, then $w_{ij} = 1$, and $w_{ij} = 0$ otherwise. The weight matrix is standardized so as the elements of a row sum up to one. y_i and y_j are the values of the NSM index. These terms are standardized using $\bar{y}$ (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[10] (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[11].

[9] 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.
[10] All computations were carried out using Geoda and ArcGIS9.
[11] See footnote number 7.

Graph 1 – Moran scatterplot



Own elaboration.

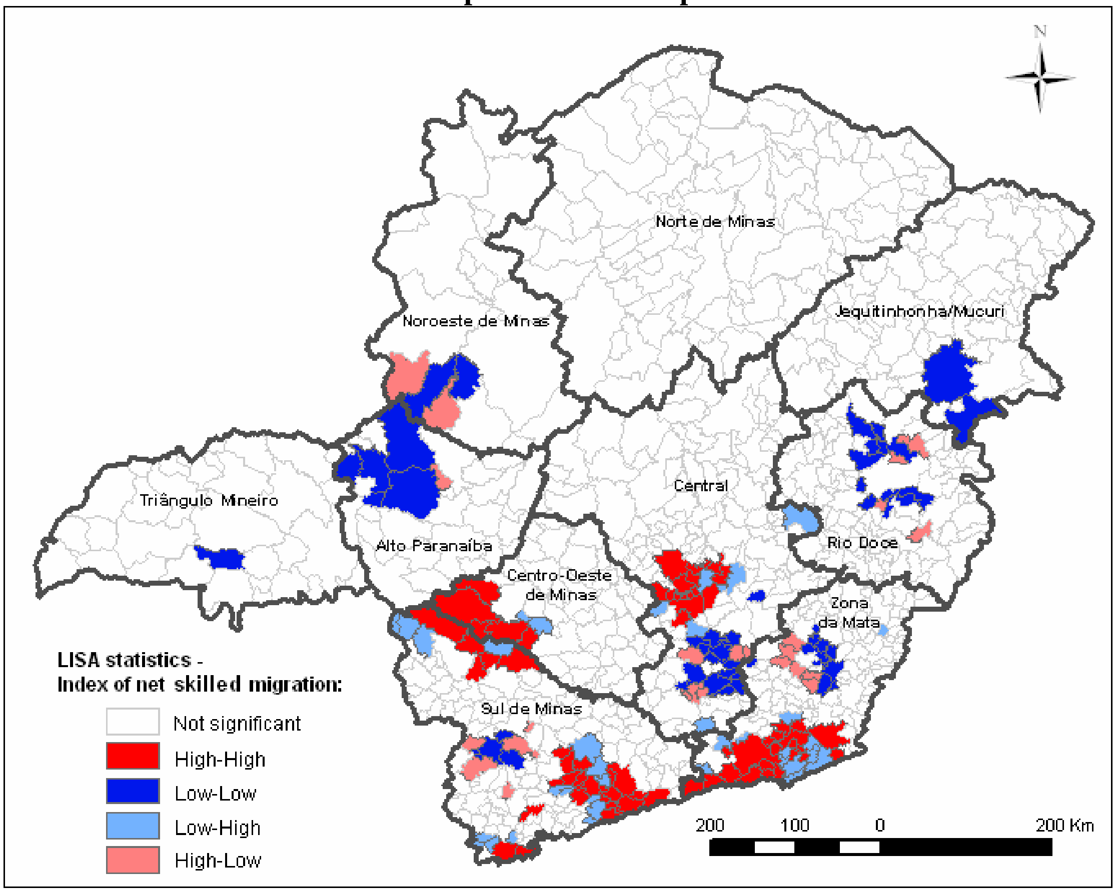
The local version of Moran's *I* statistic is the Local Indicator of Spatial Association (LISA). Anselin (1995) defines a LISA as any statistics satisfying two criteria: first, the LISA for each observation gives an indication of significant spatial clustering of similar values around that observation; 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 macro-regions exhibit low-low (LL) clustering in some places. These macro-regions 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

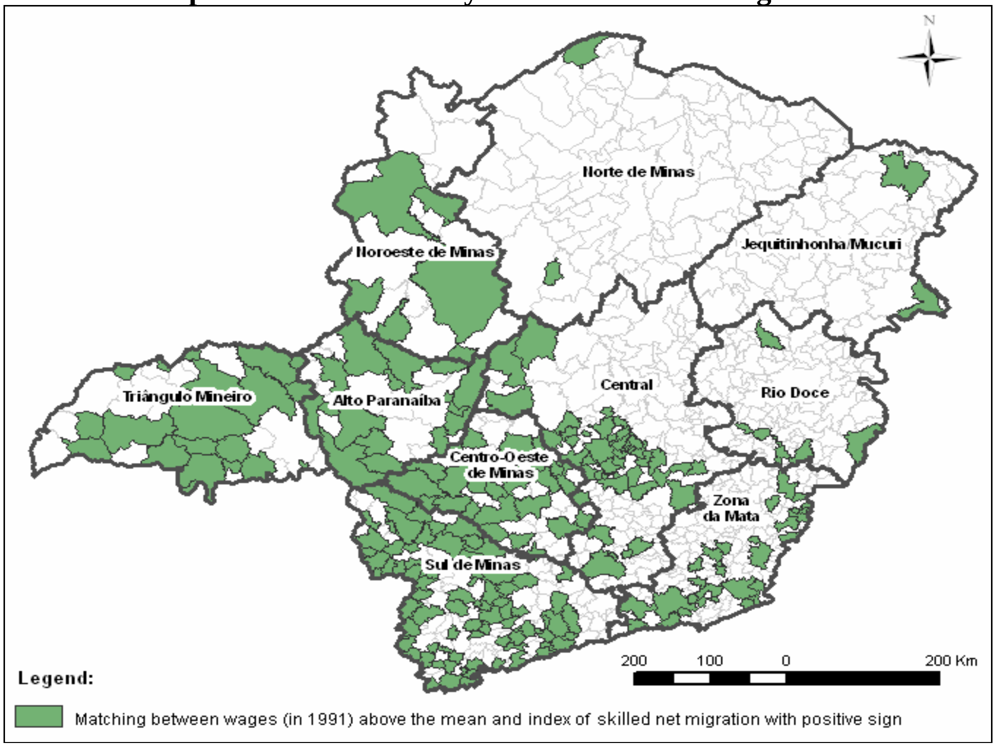


Own elaboration.

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.

Map 3 – Labor market dynamics and skilled migration



Own elaboration.

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).

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[12]), 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.

[12] 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.

$$\begin{aligned} y &= r Wy + Xb_1 + e \\ e &\sim N(0, s^2 I_n) \end{aligned} \qquad (1)$$

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[13] and b_1 its coefficients vector $(K \times 1)$. W is the row standardized $N \times N$ spatial weight matrix[14]. Thus, Wy is the $N \times 1$ column vector of the endogenous spatial lag variable and r 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: $e = l We + u$ with $|l| < 1$ and $u \sim N(0, s^2 I)$. Thus, we have the spatial AR error model in Equation (2).

$$y = Xb_1 + (I - l W)^{-1} e \qquad (2)$$

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)[15]:

1. Estimate the initial model $y = Xb_1 + e$ by means of OLS.

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[13] We note that the exploratory variables employed in the spatial models are the same that we use in the Ordinary Least Squares (OLS) estimates.

[14] Spatial weight matrix = Queen

[15] See Florax et al. (2003) for further details.

2. Test the hypothesis of no spatial dependence due to an omitted spatial lag or due to spatially autoregressive errors, using LM_r *and* LM_l *, 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 $LM_r^* > LM_l^*$[16] *then estimate* Eq.(1) *using MLLAG*[17]*. If* $LM_r^* < LM_l^*$ *then estimate* Eq.(2) *using MLERROR*[18]*. Otherwise, proceed to step 5.*

5. If ML_r *is significant but* ML_l *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) test is significant and LM(error) is not, 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
Lagrange Multiplier (SARMA)	131.2052	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 l is significant at 1% level and negative. From this model, it is evident that 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 r coefficient is significant at 1% level and negative. This result 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.

[16] "*" means the robust version of LM test.
[17] Maximum likelihood estimators for the spatial autoregressive error model.
[18] Maximum likelihood estimators for the spatial lag model.

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)
l		-0.1055	
		(0.0572)	
r			-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, 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.

THE DYNAMICS OF THE BRAZILIAN INCOME*

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Abstract: This paper aims to measure the degree of income mobility in Brazil in the 1987-2005 period. To achieve that, we consider the axiomatic mobility approach and the dynamic tool suggested by Aebi et al. (1999). The transition probability matrix calculations and the mobility index indicate that Brazil has low intragenerational income mobility, suggesting that Brazilian social structure is relatively rigid.
Keywords: Income mobility; Transition probability matrix; Mobility indices.
JEL Classification: E24; O15; C61.

1. INTRODUCTION

The high and persistent income inequality in Brazil has gained international notoriety. This is due to the fact that income concentration showed high and persistent levels between 1970 and 2000 after gathering strength in the 1960s. This places Brazil at the top of the world's income inequality ranking, giving the country a bad reputation with regard to earnings distribution.[1]

However, some recent changes have turned this trend around, characterizing an inflection point on the path of inequality measures.[2] In this regard, we have the direct and indirect effects of the Real Plan: a) inflation control and the resulting economic stability were key factors in the reduction of income concentration indices, since they created a favorable environment for the implementation of income transfer programs[3] and; b) impacts of trade liberalization and subsequent change in the structure of workforce qualification, with direct effects on earnings distribution.[4]

These characteristics have raised scientific and popular interest in earnings distribution in Brazil, calling for a specific study on this issue. Nevertheless, any strategy aimed at elucidating

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[1] See Neri (2006) and United Nations Development Program (2006).
[2] This change can be seen after 2001, when the indices dropped to the lowest levels ever reported since the mid-1970s. For detailed information, visit the website of the Brazilian Institute for Applied Economic Research: http://www.ipeadata.gov.br.
[3] See Barros et al. (2001) and Neri (2006).
[4] See Figueiredo et al. (2007).

earnings distribution should contemplate two elements: a) the static component, associated with the level of inequality, usually gauged by concentration indices and; b) the dynamic component, related to the notion of "income mobility."[5] The distinction between these two components lays the ground for empirical research. It is common knowledge that most studies seek to investigate income distribution by relying upon the definition of inequality, without showing concern for its counterpart. However, discussions about the origin of income mobility, as well as efforts put in to measure it, have abounded in the economic literature (see, for instance, Fields (2001)).

Mobility can be defined as the evolution of inequality over time since, in practice, individuals and/or families constantly change their economic positions. This movement may be associated with several factors: business cycles, changes in the level of education, promotions, migration, divorces, among others.

As previously pointed out, an increasing number of studies have dealt with income mobility. Roughly speaking, the literature can be categorized into three research groups: a) the first one, known as "axiomatic" approach, is concerned with the formulation of indices and with the description of their properties. In this context, we should cite the studies by Shorrocks (1978), Bartholomew (1982), Geweke et al. (1986) and Fields and Ok (1996); b) the second group seeks to associate the dynamics of income inequality with economic welfare. The studies by Atkinson (1981), Atkinson and Bourguignon (1982), Dordanoni (1992) and Gottschalk and Spolaore (2002) are important references on this issue and; c) the third group consists of empirical investigations, which include a large number of studies and diverse methodologies, but are restricted to a small number of countries.[6]

Note that empirical investigation deserves special attention. The collection of dynamic information requires that a sample of individuals is observed at different periods in time (or at least at two periods). In other words, it is necessary that the data panel identify each person (or family) in a given period. Such requirement, coupled to the lack of data panels with such characteristics, made this field of research become systematically neglected by the Brazilian empirical literature.

Fortunately, some statistical approaches propose solutions to this setback.[7] All that they need is percentage information about individuals in each income class at distinct periods. Most estimation methods produce a Markov transition matrix, which generates a mobility index in the spirit of Shorrocks (1978).

Based on these facts, one may infer that research targeted at investigating income distribution in Brazil should contemplate both dimensions of this phenomenon. In a recent study, Figueiredo and Ziegelmann (2006) partially fulfilled this requirement. In brief, the authors used static tools and detected a statiscally significant change in earnings distribution in Brazil, characterized by an increase in the number of individuals at the more central area of the distribution comparatively to individuals at the lower and upper tails. This movement was

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[5] Income mobility can be better understood by analogy with a hotel, as drawn by Joseph Schumpeter: suppose that a given hotel has more luxurious bedrooms on the upper floors and poor-quality bedrooms on lower floors. Therefore, the higher the floor, the better the quality of the bedrooms. Also suppose that on arriving at the hotel individuals choose to stay on lower floors and that with time they move onto the immediately upper floor. Thus, inequality would be associated with the quality of floors and with their distribution among guests. Mobility is concerned with the degree at which individuals change floors over time.

[6] More specifically to the U.S.A. and Germany. We recommend the studies by Gottschalk (1997), Trede (1998), Morillo (1999) and Aebi et al. (2001).

[7] Most studies include the calculation of relative entropy except for Lee et al. (1977). See Adelman et al. (1994), Golan et al. (1996) and Aebi et al. (1999).

compatible with a higher level of economic welfare. Nonetheless, despite the importance of these results, the study does not measure mobility.

In an attempt to fill this gap, the present paper aims to measure income mobility in Brazil between 1987 and 2005. To do so, we use the axiomatic approach to income mobility and construct a Markov transition matrix by utilizing the dynamic tools developed by Aebi et al. (1999). Thereafter, we calculate the mobility indices described in Prais (1955) and Shorrocks (1978).

The rest of the paper is structured as follows. Section 2 presents the assumptions related to Markov properties. Section 3 lays out the inference methods. In Section 4 the empirical results are shown, whereas Section 5 presents the final remarks.

2. INCOME DISTRIBUTION: A DYNAMIC ANALYSIS

The main objective of a study on economic mobility is to measure welfare distribution over time. In this regard, four methodological aspects should be taken into account. Firstly, the data on economic units should be identified and monitored over time. Secondly, one should be able to apply the analysis to a wide variety of economic units. Usually, individuals or families are sampled. Thirdly, several welfare dimensions can be investigated, but the income dimension is the one most commonly used. Finally, studies focus on the comparison of the initial year with the final year.

These characteristics favor the use of Markov transition matrices as a tool for measuring economic mobility. However, their use implies a fundamental hypothesis: the evolution of income distribution over time will be governed by a first-order Markov process. Thus, earnings distribution will follow a stochastic process represented by a transition matrix which, under certain circumstances, will converge to an equilibrium regardless of the initial distribution. In this section, we present the major assumptions related to this model. To do that, we depart from hypothetical matrix A. This matrix represents income transition probabilities between two time periods (**I** and **II**):

$$A = \begin{pmatrix} 0.64 & 0.29 & 0.04 & 0.03 & 0.00 \\ 0.14 & 0.56 & 0.26 & 0.03 & 0.01 \\ 0.02 & 0.22 & 0.54 & 0.21 & 0.01 \\ 0.01 & 0.04 & 0.27 & 0.54 & 0.14 \\ 0.00 & 0.01 & 0.05 & 0.27 & 0.67 \end{pmatrix}.$$

The transition matrix serves as a basis for Markov chain models. The elements of A represent the probability of individuals belong to class i in year **I** and migrate to class j in year **II**, i.e., transition probability p_{ij}. Therefore, by looking at the first row of the matrix, we can say that the individual who was in the first income *quintile* at year **I** has the following transition probabilities towards year J: 0.64 of staying at the same level; 0.29 of moving into the second class; 0.04 of moving up to the third class; 0.03 of ending up in the fourth class and; zero probability of reaching the top of the income distribution. A similar analysis can be carried out for the remaining rows of the matrix.

After establishing the framework for the Markov model, the following assumptions should be considered:

(S1) Population Homogeneity: the transition probability is the same for all individuals in the investigated income classes.

(S2) First-Order Markov Process: the current position of individuals at time m depends only on their immediately preceding past position at time $m-1$.

(S3) Time Homogeneity: the transition probabilities, p_{ij}, remain unchanged over time.

Therefore, the evolution of income can be described by $n(t_m) = n(t_{m-1})P$, where $n(t_m)$ represents the vector of marginal probabilities for each income class m periods after the beginning of the process. As previously mentioned, under these circumstances, the process will converge to a steady state, in such a way that the distribution of the equilibrium, n^*, will not rely on the initial distribution $n(t_0)$.

The association between the Markov process and income distribution over time was developed by Champernowne (1953). From then on, this strategy has been widely referenced in the specialized literature.[8] Note that this approach is not the only alternative for investigating the dynamics of earnings distribution. Some non-Markov models can be found in the literature, such as that developed by Lydall (1974).[9]

In the following we describe the estimation method used to estimate transition matrices. This method and the difficulties surrounding its implementation will be dealt with in the subsequent section.

3. INFERENCE METHODS

The discussion in Section 2 exposes the basic theoretical features of Markov processes applied to the income evolution over time. It also provides the main argument in favor of using transition matrices as a tool for measuring economic mobility. Nevertheless, the latter topic deserves special attention, since the nature of the data does not always allow for the implementation of this strategy.

For instance, the analysis of the dynamics of Brazilian income stumbles upon some considerable setback: the Brazilian National Household Survey (PNAD), major source of data, does not provide information on each individual (or family) on a yearly basis. In other words, an individual in class i in the vector of the initial year (1987) would probably not belong to the sample in of the final year (2005). Even if it were in the final sample, we could not identify it. It is only possible to have percentage information on the number of observations within each income class in the several sampled years. This characteristic hinders the implementation of

[8] With regard to personal income distribution, the following studies are of note: Shorrocks (1976), Gottschalk (1997) and Aebi et al. (2001). The study by Quah (1996) uses the Markov approach to investigate the process of income convergence across countries.

[9] In brief, the author suggests that the distinction between permanent and transitory income may invalidate some considerations about the model.

models based on conventional Markov transition matrices and it might have discouraged research into the dynamics of Brazilian income.

Fortunately, some alternative methods are available in the literature. The studies by Lee et al. (1977), Adelman et al. (1994) and Golan, Judge and Miller (1996) are relevant in this case. Recently, the tool proposed by Aebi et al. (1999) has been combined with the previous approaches, presenting at least one advantage: the ability to collect dynamic information from only two vectors over time. To do that, one should take for granted that the income transition probabilities between the two periods can be optimally estimated based on iterative criteria, so as to minimize the distance between the estimated and the "true" income transition process.

The optimization criterion is based on the calculation of relative entropy,[10] found at the fundamental hypothesis of statistical mechanics, as follows: the selected income transition process should represent the most likely alternative amongst all possible options.[11] The subsequent subsection will take a further look at the arguments presented herein and will give special attention to the construction of the Markov transition matrix. Subsection 3.2 will deal with the mobility indices described by Prais (1955) and Shorrocks (1978).

3.1. Income Dynamics Using Cross-Section Information

The aim of this subsection is to introduce the fitting method proposed by Aebi et al. (1999). Before doing that, the following initial assumptions are necessary: a) the incomes of N different individuals over time follow a sequence of discrete probability distributions $\{q_t\}$, with $t \in \{1, 2, ...\}$; b) the time evolution of this income distributions occurs through a Markov chain, with initial distribution q_0 and; c) each density q_t can be discretized into k partitions (income classes). Then, the sequence of k-vectors $\{(q_{1t}, q_{2t}, ..., q_{kt})'\}$ will have the following properties: $q_{it} \geq 0$ and $\sum_{i=1}^{k} q_{it} = 1$, with $t \in \{1, 2, ...\}$.

We assume that the classes income joint distribution between two periods t and s, s>t, can be represented by a two-dimensional function $F = (F_{ij})_{i,\, j=1,...,k}$. Here F_{ij} denotes the probability of an individual who belongs to class i at initial time (t) is in class j at final time (s).

In this context, F is a bivariate joint density of an unobserved stochastic process that represents the "history" of income distribution. That being said, we may assume that the income dynamics between two periods can be indirectly measured by the product between the probability transition matrix $P = (p_{it})_{i,\, j=1,...,k}$ and arbitrary initial distribution of individuals income class at time t, given by $J = (J_1, ..., J_k)'$. Thus, distribution F is defined as follows:

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[10] Usually, the entropy method is used when the data have some kind of limitation (incomplete observations, small sample size or misspecification of the data generating process). However, despite its importance, it has been underinvestigated in the econometric literature. Nevertheless, here we cite some examples: a) White (1982) develops a maximum likelihood estimator for the case of misspecification of the model; b) Kitamura and Stutzer (1997) propose a GMM-like estimator, but with relative robustness for small samples and; c) Golan et al. (1996) synthesize the use of entropies in several econometric fields (linear, nonlinear and dynamic models,).

[11] In this context, the measurement of the dynamics of income distribution will be equivalent to fitting cell probabilities for contingency tables, where only marginal distributions are observed. This physical mechanics problem has been widely investigated by statistical studies. For further details, see Aebi (1997).

$$F = diag(J)P, \qquad [3.1]$$

where operator $diag(\cdot)$ turns the $k \times 1$ vector into a $k \times k$ diagonal matrix. Usually, definition (3.1) is not compatible with distributions q_t and q_s, requiring an adjustment. Thus F-adjusted (F^{adj}) must satisfy the following ***initial and terminal restrictions***

$$q_t = F^{adj} i \text{ and } q_s = \left(F^{adj}\right)' i, \qquad [3.2]$$

where i represents a $k \times 1$ vector with all elements equal to one.

The fitting method consists in: a) computing the probabilities of observing each particular income transition process and; b) selecting the process whose probability of generating the particular observed configuration of classes distribution has the lowest speed of convergence to zero as the sample size increases. In other words, supposedly, there are infinite densities F, each of them associated with a probability of occurrence[12] and; an optimization criterion is used to select the "most probable" income transition. The probabilities are calculated using the maximum likelihood method. The selection of the most probable F should consider that the probability of observing a particular process converges to zero as the number of individuals tends to infinity $N \to \infty$. Thus, we have the large deviation principle, i.e., the selected F^{adj} should have the slowest convergence rate to zero in terms of probability, within the set of all two-dimensional distribution z .

Let us now have a look at the fitting method in more detail. As previously reported, the first step consists in determining the probability of observing a particular income transition configuration. Under the hypothesis that the incomes of N individuals are independent, this probability will be

$$\prod_{i,j=1}^{k} \left(J_i p_{ij}\right)^{\Gamma_{ij}},$$

Where $\Gamma_{i,j}$ denotes how many persons starting in income class i in period t arrive in income class j in period s. We know that the income transition of N individuals between densities q_t and q_s can occur through several paths. These several possibilities are summarized by the following arrangement:

$$\binom{N}{\Gamma_{11}}\binom{N-\Gamma_{11}}{\Gamma_{21}}\binom{N-\Gamma_{11}-\Gamma_{21}}{\Gamma_{31}}\cdots\binom{N-\sum_{j=1}^{k}\Gamma_{1j}}{\Gamma_{21}}$$

[12] This assumption is confirmed by Csiszár (1975), who observed that the set of two-dimensional distribution that satisfy (3.2), dubbed z , contains infinite elements.

$$\begin{pmatrix} N - \sum_{i}^{k-1}\sum_{j=1}^{k-1}\Gamma_{ij} - \sum_{j=1}^{k-1}\Gamma_{kj} \\ \Gamma_{kk} \end{pmatrix} = \frac{N!}{\prod_{ij=1}^{k}\Gamma_{ij}!}.$$

Thus, the probability of following a particular path Γ will be calculated using the following formula:

$$P_N(\Gamma \mid diag(J)P) = \frac{N!}{\prod_{ij=1}^{k}\Gamma_{ij}!}\prod_{i,j=1}^{k}\left(J_i p_{ij}\right)^{\Gamma_{ij}} = N!\frac{\prod_{i,j=1}^{k}\left(J_i p_{ij}\right)^{\Gamma_{ij}}}{\Gamma_{ij}!}. \quad [3.3]$$

After calculating the probabilities, we must now select the income transition that is closest to the “true” process. To do that, we use a fundamental hypothesis of statistical mechanics:[13] the selected two-dimensional density will represent the “most probable” income transition process amongst all densities belonging to z . Considering this principle is equivalent to minimizing the convergence of (3.3) to zero. i.e., minimizing[14]

$$\lim_{N\to\infty}\frac{1}{N}\log P_N(\Gamma \mid diag(J)P) = -H(y \mid diag(J)P), \quad [3.4]$$

where $y = (y_{i,j})$ denotes matrix $\Gamma / N = (\Gamma_{ij} / N)$. Function $H(y \mid diag(J)P)$ stands for the relative entropy for the two-dimensional distribution y with respect to $diag(J)P$, and is defined by

$$H(y \mid diag(J)P) = \sum_{i,j}^{k} y_{ij}\log\left(\frac{y_{i,j}}{JP}\right). \quad [3.5]$$

Ellis (1986) demonstrates that $H(y \mid diag(J)P)$ is a non-negative and strictly convex function. Note that (3.5) has an infimum equal to zero if $y = diag(J)P$. Thus, relative entropy measures the distance between the estimated $diag(J)P$ and unobserved y processes. Therefore, the optimization process consists of the minimization of (3.5), being subject to continuity restrictions (3.2). The Lagrangian for this problem will be

$$L = \sum_{i,j}^{k} y_{ij}\log\left(\frac{y_{i,j}}{JP}\right) - \sum_{i,j}^{k} l_{i,t}\left(\sum_{i,j}^{k} y_{ij} - q_{i,t}\right) - \sum_{i,j}^{k} l_{i,s}\left(\sum_{i,j}^{k} y_{ij} - q_{i,s}\right). \quad [3.6]$$

[13] For further details, see Chapter 1 in Ellis (1986).
[14] For further details, see Chapter 1 in Golan et al. (1996).

In (3.6), $l_{i,t}$ and $l_{i,s}$ are 2k Lagrangian multipliers associated with restriction (3.2). According to Corollary 3.3 proposed by Csiszár (1975), the problem will have a solution if at least one of the income transition processes satisfies restriction (3.2). The strict convexity of the relative entropy warrants the existence of a unique solution.

The optimal solution is obtained from the differentiation of (3.6) in relation to $y_{i,j}$. By equaling the first-order condition to zero, we obtain:

$$F^{adj} = \Phi_t F \Phi_s, \qquad [3.7]$$

where $\Phi_t = diag(f_{1,t},...,f_{k,t})$ and $\Phi_s = diag(f_{1,s},...,f_{k,s})$ correspond to the exponentials of Lagrangian multipliers associated with the initial and terminal conditions. In quantum mechanics, these elements are known as Schrödinger multipliers.[15] Note that, if all multipliers are equal to one, there will be no fitting, indicating that F satisfies (3.2).

Schrödinger multipliers can be obtained from the differentiation of (3.6) in relation to $l_{i,t}$ resulting in the Schrödinger system:[16]

$$f_{it} J_i \sum_{j=1}^{k} p_{ij} f_{is} = q_{it}$$

$$\left(\sum_{i=1}^{k} f_{it} J_i p_{ij} \right) f_{is} = q_{js},$$

Yielding to

$$P^{adj} = \tilde{\Phi}_s^{-1} P \Phi_s,$$

where $\tilde{\Phi}_s = diag(\tilde{f}_{1,s},...,\tilde{f}_{k,s}) = diag\left(\sum_{j=1}^{k} p_{1j} f_{js},...,\sum_{j=1}^{k} p_{kj} f_{js} \right)$, with $P = (p_{ij})$. Note that the fitting of matrix P will only depend on the multipliers related to the terminal condition. Expression (3.8) contains the dynamic information on income for the study period and its analysis is based on that of traditional Markov matrices.

3.2. Mobility Indices

According to Shorrocks (1978), the mobility index corresponds to a real function $M(\cdot)$, defined from the set of transition matrices P. From now on some axioms are imposed.

(N) Normalization: $0 \le M(P) \le 1$, $\forall P \in \mathrm{P}$.

[15] See Aebi and Nagasawa (1992) and Aebi (1996).

[16] This system is solved using an iterative computational criterion called Iterative Proportional Fitting Procedure (IPFP).

(M) Monotonicity: $P \succ P' \leftrightarrow M(P) > M(P')$.

(I) Immobility: $M(I) = 0$.

(PM) Perfect Mobility: $M(P) = 1$, if $P = ux'$, where $u = (1,...,1)'$ and $x'u = 1$.

The first axiom restricts the variation of the index to the interval [0*;* 1]. The second axiom associates the characteristics of the transition matrix? the mobility index. That is, if a matrix P has a larger mobility than a matrix P', it will be socially preferable ($\succ$) and its index will be necessarily higher. In other words, since the probability of movement across income classes is represented by the elements outside the main diagonal of the transition matrix, then if $p_{ij} \geq p'_{ij}$, $\forall i \neq j$ and $p_{ij} > p'_{ij}$ for any $i \neq j$, the mobility indices for the matrices will be: $M(P) > M(P')$.

The latter two axioms represent two extreme situations. In the first case, we have a static society represented by an identity matrix. So, there is no mobility across income classes. The opposite situation occurs in perfect mobility, represented by a matrix P, necessarily with identical rows.

Some indices are presented based on these axioms, with a special focus on the measure proposed by Prais (1955):

$$M_P = \frac{r - tr(P)}{r - 1},$$

where $tr(\cdot)$ represents the matrix trace and r stands for its rank.

However, Shorrocks (1978) raises the following question: how can we make comparisons between matrices with different periods? That is, in order for comparisons across mobility indices to be coherent, the index must be dissociated from the effect of time (T). Thus, it is possible to carry out the analysis without worrying about the size of the interval between the two time periods (Δ_t). To do that, the author introduces a new axiom:

(TI) Time Invariance: $M(P;T) = M(P^{\Delta_t}; \Delta_t T), \; \Delta_t > 0$.

The index does not depend on a particular observation over time, since it is compensated for by the size of the interval used for the construction of the transition matrix. Two indices are compatible with the new axiom:

$$M_D = 1 - \left|\det(P)\right|^{a/T}, \; a > 0, \qquad [3.10]$$

where $\det(P)$ corresponds to the determinant of the transition matrix P. The second measure is represented by:

$$M_L = 1 - |q_2|, \qquad [3.11]$$

where q_2 is the second eigenvalue of matrix P.

Theorem 1 proposed by Geweke et al. (1986) warrants that indices (3.10) and (3.9) will be compatible with axiom structures **N**, **M**, **I**, **PM** and **TI**. To achieve that, the eigenvalues of P must all be real and non-negative.

Another important characteristic of the matrix can be measured by:

$$h = -\frac{\log 2}{\log|q_2|},$$

i.e., by the speed of convergence of the calculated matrix to the Markov chain with an equilibrium distribution. Alternatively, h can be interpreted as a half life of the transition process. Intuitively, a rigid structure (low mobility) is associated with a slow convergence process, but the opposite occurs in case of perfect mobility.

In summary, these indices allow measuring income mobility using transition matrices. Note that the alternatives shown herein are valid for discrete processes. Geweke et al. (1986) extend these results to continuous-time Markov processes. This alternative is not within the scope of this study, though.

4. RESULTS

4.1. Data and Implementation of the Optimization Process

This subsection aims to discuss the nature and manipulation of data and to describe the major strategies related to the optimization process implemented in the study. "Family income,"[17] based on the Brazilian National Household Survey (PNAD) conducted by the Brazilian Institute of Geography and Statistics (IBGE), was used as variable, using the month of September of the respective years as reference. The first step consisted of currency conversion and deflation.[18] To obtain that, we used the procedure suggested by Corseuil and Foguel (2002).

Two considerations are necessary: a) the concept of family income and; b) family size adjustment. Family income was regarded as the sum of all earnings received by the individuals living in the same household. After that, the sample was adjusted for family size. The adjustment was based on the following rule: $R_{adj} = R_d / n^e$, where R_{adj} is the adjusted income; R_d is the household income; n is the number of individuals in the household, and e is the elasticity of family size. Parameter e is related to the existence of economies of scale.[19] An intermediate value was considered for elasticity ($e = 0.5$), following the recommendation by Atkinson et al. (1995).[20] Only the positive incomes were included, and the outliers (adjusted incomes greater than 50,000 Reais) were left out.

The analysis of income transition is carried out using two time periods. In this study, they correspond to 1987 and 2005. The necessary information for the estimation is summarized in the

[17] Several studies use this variable as object of analysis, among them we have: Jenkins (1995), Burkhauser et al. (1999) and Aebi et al. (2001).
[18] All of the values are denominated in Reais as of January 2005.
[19] Consider two extreme cases: a) $e = 1$ there are no economies of scale and; b) $e = 0$ there are economies of scale, i.e., an infinite number of individuals can live equally well in a given household.
[20] Note that other values have been tested for e. However, no significant changes occurred in the results.

vectors of the percentage of individuals per income class. There, partitions represent income *deciles* ($k = 10$), in which 1987 stands for the initial year.

The estimation of transition process F requires *a priori* specifications for J and P. After that, the optimization process initiates, with the use of the Iterative Proportional Fitting Procedure (IPFP) (see, for instance, Deming and Stephan (1940)), producing matrices F^{adj} and P^{adj}.

Let us assume $J = q_{1987}$, i.e., an arbitrary distribution equal to the relative frequency of individuals per income class at the initial year. The construction of matrix P was based on the following assumption: an individual can only move into an immediately higher or lower class once a year.[21] For example, a person who belongs to the second decile in 1987 will only move to the first or third decile in 1988. Matrices with this property are known as 3-band.[22] Therefore, the initial specification for the two-dimensional density will be: $F_1 = diag(q_{1987})P^{18}_{3-band}$.

4.2. The Dynamics of Income Distribution in Brazil

Table 4.1 shows the percentage of individuals per income decile for years 1987 and 2005. First, we can see that the "transition" between the two periods was favorable to the intermediate income class (3 through 8). This movement was followed by an increase on the average income (around 2.10%) and by the reduction in income inequality (Gini's coefficient). Figueiredo and Ziegelmann (2006) use static tools and confirm the statistical significance of this change and its compatibility with a better level of economic welfare. However, despite the importance of these results, what can we assure about income dynamics in this period?

The starting point for answering this question is established in Table 4.2, which represents the Markov transition matrix for 18 years of mobility in Brazil.

Table 4.1: Percentage of Individuals per Income *Decil*e

Income Deciles	**Years**	
	1987	**2005**
[1]	10.00	5.75
[2]	10.00	7.91
[3]	10.00	10.48
[4]	10.00	13.39
[5]	10.00	12.14
[6]	10.00	11.82
[7]	10.00	10.55
[8]	10.00	10.05
[9]	10.00	8.91
[10]	10.00	9.01
Average income	840.09	857.67
Gini's coefficient	0.577	0.542

Source: Research data.

Observe that the individual who was in the first *decil*e in 1987 has the following transition probabilities: 0.280 of staying at the same level; 0.307 of migrating to the second *decile*; 0.210

[21] An alternative can be found in Tauchen (1986).

[22] A matrix will be $(2y+1)$ **-band** if its elements $a_{ij} = 0$, when $|i - j| > y$.

of moving to the third decile; 0.121 of ending up in the fourth decile and; decreasing probabilities all lower than 0.05 after the fifth decile. Therefore, belonging to the poorest 10% at the initial year is a determining factor for not reaching the top of the distribution at the final year.

Table 4.2: Markov Transition Matrix – 1987-2005.

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
[1]	0.280	0.307	0.210	0.121	0.048	0.021	0.009	0.003	0.001	0.000
[2]	0.183	0.228	0.216	0.172	0.093	0.056	0.031	0.016	0.005	0.000
[3]	0.068	0.118	**0.190**	**0.214**	**0.151**	**0.113**	0.076	0.048	0.019	0.003
[4]	0.026	0.062	**0.141**	**0.201**	**0.171**	**0.149**	**0.114**	0.084	0.042	0.010
[5]	0.010	0.034	**0.102**	**0.175**	**0.173**	**0.165**	**0.140**	**0.114**	0.067	0.020
[6]	0.004	0.020	0.075	**0.152**	**0.165**	**0.173**	**0.152**	**0.135**	0.089	0.035
[7]	0.002	0.013	0.056	**0.129**	**0.155**	**0.169**	**0.160**	**0.150**	0.111	0.055
[8]	0.001	0.007	0.038	**0.102**	**0.134**	**0.159**	**0.159**	**0.163**	0.140	0.097
[9]	0.000	0.002	0.018	0.060	0.093	**0.124**	**0.139**	**0.165**	0.187	0.212
[10]	0.000	0.000	0.003	0.015	0.030	0.052	0.076	0.125	0.230	0.469

Source: Research data.

The behavior of the tenth decile is similar to that of the first one, but in an opposite fashion, that is, those who belonged to this class in 1987 have a small probability of migrating to lower classes. Except for the poorest 20% and the richest 20% ((1-2) and (9-10)), transition probabilities are always higher than 0.10 at the "middle" of the distribution (figures in boldface), indicating a favorable movement to intermediate income classes.

Some information related to the transition matrix is provided in Table 4.3. The first piece of information, represented by the relative entropy value, refers to the distance between the estimated and "true" processes. The value of 0.137 suggests goodness-of-fit, given that the infimum for this measure is zero (see formula (3.5)). The speed of convergence to the Markov chain with equilibrium distribution is relatively high. This is perceived by the observation of the "half life" value for the process ($h = 1.495$). According to Shorrocks (1978), a structure with perfect mobility has full convergence in only one period ($h \to 0$). Slower speeds of convergence are associated with large "half life" values ($h \to \infty$). Another important characteristic can be captured from the square of the second eigenvalue of matrix ($q_2^2 = 0.396$). For Theil (1972), this index represents "mobility imperfection".

Table 4.3: Information Related to the Transition Matrix

Information	**Values**
Relative Entropy	0.137
Half Life (h)	1.495
Index M_P	0.396
q_2^2	0.864
Index M_D	0.933*
Index M_L	0.371

Source: Research data. *$a = 1$.

Finally, we have the values for the mobility indices. We calculate measures (3.9), (3.10) and (3.11). The magnitude of these results is evident compared to international values. Table 4.4 shows some indices for industrialized and developing countries. Note that Brazil has one of the lowest mobility indices, being only superior to the Colombian mobility index.

Table 4.4: International Income Mobility

Countries	Index M_L
Chile	0.655
China	0.652
Peru	0.539
USA	0.478
Germany	0.473
Malaysia	0.373
Colombia	0.229

Source: Gottschalk (1997), Birchenall (2001) and Fields (2001).

This result indicates that Brazilian social structure still presents relative rigidity. In other words, the income class in which an individual is inserted will determine his/her future social position. Or equivalently, there is a large intragenerational dependence that shows how strongly the income of an individual at time t can influence his/her income at $t + 1$. For example, an economic agent belonging to the poorest 10% has a very low probability of moving up socially and reaching the upper income class.

Such behavior is coherent with the results related to intergenerational dependence, i.e., the role of parent's income in the determination of their child's income. This finding is corroborated by Ferreira and Veloso (2006), who use the PNAD data for 1996 and found low intergenerational mobility in Brazil. That is, parent's income tends to be transferred to their descendents in a greater magnitude than it is observed in industrialized countries.

However, the study by Figueiredo et al. (2007) demonstrates that, even at lower levels than those of industrialized countries, the increase in the Brazilian intergenerational mobility in the last few years is an undeniable fact. In brief, the authors measure this mobility based on the effect of parent's educational level on their child's educational level. Their results show a remarkable reduction in this influence between 1987 and 2003. In summary, educational mobility rose from 0.493 in 1987 to 0.550 in 2003, indicating that parent's level of education has an increasingly lower influence on their child's educational status.

Nevertheless, before stating a final judgement, we should highlight the following: the period selected for the construction of the transition matrix (1987 to 2005) is characterized by intense changes in domestic and external relations in Brazil. These changes can be summarized by inflation control and subsequent economic stability, favoring the implementation of income transfer programs, and by trade liberalization and the consequent change in workforce qualification and wages. The effects of these changes on static elements of income distribution have already been discussed by Neri (2006) and Figueiredo et al. (2007). It should be underscored that the use of such a heterogeneous period may bias the results for mobility.

In order to circumvent this problem, we estimate a transition matrix by considering only the period after the Real Plan (1995 to 2005). In this case, the two-dimensional density that triggers the optimization process will be: $F_2 = diag(q_{1995})P_{3-band}^{10}$. The results of this experiment are shown in Tables A.1 and A.2 in the Appendix. We find some changes in transition probabilities, a lower speed of convergence for the Markov chain with an equilibrium distribution and a greater mobility imperfection. Nevertheless, mobility indices, albeit lower than those shown in Table 4.3, did not change substantially, which indicates that the selected period has a negligible effect on the construction of the matrix.

Therefore, our conclusion is that Brazil has relatively rigid income mobility, both in the intergenerational and intragenerational spheres. Despite that, roughly speaking, the movement of economic agents occurs towards the intermediate income classes. This behavior is coherent with the static results described by Figueiredo and Ziegelmann (2006), Neri (2006) and Figueiredo et al. (2007). One of the key arguments of these studies is that this movement suggests some improvement in the distribution pattern and indicates that changes, although slow, are still underway, towards a higher level of social welfare. However, although mobility is part of this context, this conclusion cannot be carried over to dynamic results, given that the axiomatic approach used herein does not establish an explicit link with the theory of economic welfare.

5. FINAL REMARKS

The present study aims to measure income mobility in Brazil between 1987 and 2005. For achieving that, we use the axiomatic approach to mobility and estimate the Markov transition matrix and calculate the respective mobility indices. Due to database limitations, more specifically to the lack of information on each individual (or family) on a yearly basis, we choose to implement an inference method based on the calculation of relative entropy. The estimation process comprised two periods (1987-2005 and 1995-2005), as a way to filter out possible biases related to the changes observed in the first half of the 1990s (roughly speaking, the trade liberalization process and the implementation of the Real Plan).

Results suggest that Brazil has low intragenerational income mobility, indicating that its social framework is relatively rigid. In other words, the income class in which an individual is inserted will determine his/her future social position. This finding concerns both the estimation for the whole period (1987-2005) and the inference for the period after the Real Plan (1995-2005), indicating that the selected period has a negligible effect on the construction of the matrix.

As for the movement on income distribution, there is an increase at intermediate income classes in detriment of tail weights. This result is in line with static evidence, which shows this movement and also its influence on the rise of social welfare in recent times. However, even though income mobility is part of this phenomenon, the evidence found in this study is not enough to provide a formal link between income dynamics and the theory of welfare. In this regard, notwithstanding the importance of measuring mobility in Brazil, a question is left unanswered: is the mobility index measured by an axiomatic approach consistent with a higher level of economic welfare?

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APPENDIX

Table A.1: Markov Transition Matrix – 1995-2005.

	[1]	**[2]**	**[3]**	**[4]**	**[5]**	**[6]**	**[7]**	**[8]**	**[9]**	**[10]**
[1]	0.357	0.293	0.195	0.088	0.038	0.018	0.008	0.002	0.001	0.000
[2]	0.247	0.232	0.214	0.133	0.078	0.049	0.029	0.014	0.004	0.000
[3]	0.100	0.129	0.203	0.180	0.138	0.108	0.076	0.045	0.019	0.002
[4]	0.039	0.070	0.155	0.174	0.162	0.147	0.118	0.082	0.045	0.008
[5]	0.016	0.039	0.113	0.153	0.166	0.165	0.147	0.112	0.072	0.017
[6]	0.007	0.024	0.084	0.134	0.159	0.173	0.160	0.133	0.096	0.030
[7]	0.003	0.014	0.063	0.113	0.150	0.170	0.170	0.148	0.120	0.049
[8]	0.001	0.008	0.043	0.090	0.130	0.160	0.169	0.161	0.152	0.086
[9]	0.000	0.003	0.020	0.053	0.091	0.126	0.149	0.165	0.205	0.188
[10]	0.000	0.000	0.003	0.014	0.031	0.055	0.083	0.127	0.257	0.430

Source: Research data.

Table A.2: Information Related to the Transition Matrix

Information	**Values**
Relative Entropy	0.117
Half Life (h)	1.685
Index M_P	0.860
q_2^2	0.439
Index M_D	0.930*
Index M_L	0.337

Source: Research data. $*a = 1$.