REGIONAL AND INDIVIDUAL DETERMINANTS OF LABOR MOBILITY IN BRAZILIAN MANUFACTURING INDUSTRY: A HIERARCHICAL SPATIAL APPROACH FOR THE PERIOD 1999-2002[1]

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This paper aims to investigate individual and regional determinants of industry labor mobility in the state of São Paulo, Brazil. Two individual samples of both unskilled and skilled workers in the formal labor market are analyzed. The methodology adopted here makes use of a hierarchical *logit* model that includes explaining variables at their individual and municipal levels for modeling the probability to migrate besides taking possible spatial heterogeneity and dependence into account. The hierarchical spatial analysis has revealed that the municipal features at the destination place have a greater impact on the skilled workers' decision to migrate.

Keywords: worker mobility; skilled workers; hierarchical spatial regression.

DETERMINANTES REGIONAIS E INDIVIDUAIS DA MOBILIDADE DO TRABALHO NA INDÚSTRIA DE TRANSFORMAÇÃO BRASILEIRA: UMA ABORDAGEM HIERÁRQUICA-ESPACIAL PARA O PERÍODO 1999-2002

Este artigo tem como objetivo principal investigar os determinantes pessoais e regionais da migração de trabalhadores da indústria no estado de São Paulo. São analisadas duas amostras de indivíduos, referentes a trabalhadores não qualificados e qualificados no mercado formal de trabalho. A metodologia aplicada aborda um modelo *logit* hierárquico, que considera as variáveis explicativas nos seus devidos níveis individual e municipal, para modelar a probabilidade de migrar, além de considerar possíveis processos de heterogeneidade e dependência espaciais. A análise hierárquica-espacial revelou que as características municipais no destino têm maior impacto na decisão de migrar dos trabalhadores qualificados.

Palavras-chave: mobilidade de trabalhadores; trabalhadores qualificados; regressão hierárquica-espacial.

DETERMINANTES REGIONALES E INDIVIDUALES DE LA MOVILIDAD LABORAL EN LA INDUSTRIA DE TRANSFORMACIÓN DE BRASIL: UN ENFOQUE JERÁRQUICO-ESPACIAL PARA EL PERÍODO 1999-2002

El objetivo principal de este estudio es investigar los determinantes individuales y regionales de la migración de trabajadores en el Estado de São Paulo. Se analizan dos muestras de individuos,

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una de trabajadores cualificados y otra de no cualificados. La metodología aplicada utiliza un modelo *logit* jerárquico, que tiene en cuenta los respectivos niveles individual y municipal de las variables explicativas, para modelar la probabilidad de migración, además de considerar posibles procesos de heterogeneidad y dependencia espaciales. El análisis jerárquico-espacial revela que las características municipales del destino tiene un mayor impacto en la decisión de migrar en los trabajadores cualificados.

Palabras clave: movilidad de trabajadores; trabajadores cualificados; regresión jerárquica-espacial.

LES DÉTERMINANTS RÉGIONALES ET INDIVIDUELLES DE LA MOBILITÉ DU TRAVAIL: UNE APPROCHE SPATIALE HIÉRARCHIQUE POUR LA PÉRIODE 1999-2002

Cet article vise à étudier les déterminants personnels et régionales de la migration des travailleurs de l'industrie dans l'État de São Paulo. Deux échantillons sont analysés pour les individus, en se référant aux travailleurs qualifiés et non qualifiés dans le marché du travail formel. La méthodologie adoptée ici est basée sur un modèle *logit*, qui considère les variables explicatives de leurs niveaux individuels et municipaux pour modéliser la probabilité de migrer, plus de prendre possible hétérogénéité et la dépendance spatiale en compte. Les résultats de la régression hiérarchique spatiale ont montré que les caractéristiques municipales dans la destination ont un plus grand impact sur la décision des travailleurs qualifiés à migrer.

Mots-clés: la mobilité des travailleurs; les travailleurs qualifiés; régression hiérarchique spatiale.

JEL: J61; O15; O18; R23.

1 INTRODUCTION

Internal migration is a significant phenomenon in Brazil. Some particular characteristics, such as its large geographic size – with persistently large geographical differences in economic performances – and its persistent income inequality over the past decades, have been motivating studies on the wage differentials in order to seek evidence that migration can provide real income gains. Most of these studies on Brazilian internal migration have focused on the migration process at the state level (Sahota, 1968; Silveira Neto, 2005; Mata *et al*., 2007). However, migrants may optimize their migration decisions in the municipality level, for example, considering the destination municipality features as well (Mata et al., 2007).

According to Harris and Todaro (1970), the decision to migrate may be modeled as dependent on several factors: relative wages, which convey the idea that the individual would rather stay in the region with a high unemployment rate, if one's own wage is high enough to offset a reduced probability to find a job elsewhere; the relative employment perspective that reflects the probability of finding a job in the origin region as compared to other regions; real estate prices, which reflect the cost of living in the region of destination, as well as other migration costs, such as those related to physically relocating oneself and other less tangible costs, such as leaving behind an existing network of kinship and friends in the place of origin.

This model was taken as basis for many other studies of migration. However, recent studies put emphasis on other existing determinants as labor migratory flows imply some other features, such as family influence on decision to migrate, uncertainty as to future wage, as well as restricted information. According to Debelle and Vickery (1998), the worker takes all these important issues into account. This is because the decision to migrate is truly an investment decision, since migrants incur in initial costs that reduce their income, and investment returns would only appear in the future. For Pekkala (2003), migrants make a trade-off between the present value of earnings and mobility costs and then decide to migrate viewing net migration gains.

Age and schooling are usually positively correlated with probability to migrate (Stambol, 2003; Stark and Bloom, 1985). Education is an important variable affecting systematic differences of individual responses. Educated people are generally more mobile and adaptable, more innovative and attentive to opportunity changes (Sahota, 1968). As for migrant age, younger people migrate more frequently (Öberg, 1995), provided that they can be better paid in a longer period of time, as compared to people that are close to retiring.

Labor wages are another remarkable factor of migrate decision-making. Migration occurs when the migrant worker would be better paid elsewhere than he/she is paid in the place, country or region of residence, as individuals take resort to migration as a means to improve their living standard or utility function. When it positively affects the migrant's income, then migration contributes to allocative efficiency of labor market, as well as to total productivity of the economy.

As far as the characteristics of the destination regions are concerned, many factors may improve or make their relative immigration attractiveness to decline; and economic factors are considered the most important ones. Among such factors, wage differences between several regions, differentiated possibilities of getting jobs, variable costs of housing and living, availability of industrial employment, among others, are highlighted. Population density may attract migrants or, conversely, convert itself into an expelling factor, that is, it may affect migratory flows both from the origin region or to the destination region (Sahota, 1968).

Nonpecuniary variables – the so-called amenities – are also relevant, which may be positive and negative. They encompass several features, such as air and water quality, access to cultural and recreational public resources, low crime level and absence of noise and traffic congestion (Garber-Yonts, 2004). According to Queiroz and Golgher (2008), these features would be a relevant factor for skilled, creative and highly educated people in Brazil. Based on Demographic Census data for 1991 and 2000, Sabbadini and Azzoni (2006) verified that variables, such as income and quality of life, proxied by Human Development Index, were important determinants of highly skilled migrants among Brazilian states.

Several studies were carried out aiming to analyze factors determining an individual's decision to migrate or not from a region, given the relevance of labor mobility mainly that skilled one (Kulu and Bilari, 2004; Dahl, 2004). Migration studies highlight both factors directly related to individuals, their wishes and beliefs, and factors related to the social and geographic environment. Therefore, an analysis of migration determinants should take into account personal factors, as well as those from the social context in which an individual lives.

The present paper studies the migratory flow of skilled workers from industry within the state of São Paulo aiming to determine personal and regional factors influencing intermunicipal migration. From the methodological viewpoint, individual and regional factors influencing labor mobility are treated by using the multilevel *logit* model, which is estimated containing two hierarchical levels – individual and municipal. Our paper throws light on the determinants of the skilled/unskilled migration of workers according to personal and regional characteristics. Additionally, the dependence processes and spatial heterogeneities of the hierarchical model are controlled by spatial hierarchical procedures for dependent and independent variables. This analysis focus on São Paulo as it is a very representative state as it possesses highly educated professionals connected to knowledge-intensive activities (Diniz and Gonçalves, 2001). Furthermore, Baeninger (2004) emphasizes that the main Brazilian migratory flows are engendered in the metropolitan area of São Paulo toward the major regional attraction poles in the state inland. According Mata *et al.* (2007), the city of São Paulo was the most important in terms of net flow of skilled migration in 2000.

We use the Annual Report of Social Information of Ministry of Labor and Employment (Rais-Migra/MTE) panel data from 1999 to 2002. This administrative data is provided by the Labor Ministry of Brazil and it is a rich longitudinal data that follows the same workers in the formal labor market. It is important to highlight that our study focuses on the period after the Brazilian currency liberalization in 1999. This year is considered a milestone in the creation of new formal jobs in comparison to the previous years (Fernandes and Cunha, 2011; Schneider and Rodarte, 2006).

In addition to this introductory section, this paper presents a review of the Brazilian labor market characteristics with emphasis on industry of the state of São Paulo. Section 3 deals with the methodologies used here. The results of the models used are presented in section 4 and final considerations in section 5.

2 BRAZILIAN CONTEXT: LABOR MARKET CHARACTERISTICS IN THE STATE OF SÃO PAULO

The population dynamics of the state of São Paulo has occurred in the metropolitan area of the capital city all through the 20th century (Dedecca, Montali and Baeninger, 2009). This population of the state of São Paulo is concentrated, with approximately 37 million people as of 2000 (Fundação Seade). The São Paulo metropolitan area accounted for 48.3% of this total and the other metropolitan areas and regional poles accounted for 14%.

Queiroz and Golguer (2008), when investigating the distribution of more educated and skilled people in the Brazilian municipalities and states, have concluded that, as for intrastate migration, major migratory flows were channeled from the metropolitan area of São Paulo mainly toward the inland regional attraction poles, namely: Campinas, Sorocaba, São José dos Campos, Ribeirão Preto, Bauru and São José do Rio Preto, which play a crucial role in the relative deconcentration of the state population. This process turns the state of São Paulo into an important area of both intra and interregional migratory flows, which justify the study of the determinants and impacts of such flows as way to better understand the economic and social dynamism of the region.

In addition to being an area of high population density, the metropolitan area of São Paulo is the main nucleus of the economic dynamics of this state. The concentration of value added in this metropolitan area is equally relevant, which accounted for 56% of the total value for the state as a whole. It is also worth mentioning that the value added of the São José dos Campos regional pole exceeds its population. Furthermore, the three major metropolitan areas in the state – São Paulo, Campinas and Santos – account for 66% of value added and 60% of population in this state.

All these figures suggest the interiorization of both population growth – which involves labor migration – and increased economic activities in the state of São Paulo. Medium-sized cities – more distant from the metropolitan area of São Paulo – have also becoming important in this process, though in a quite limited way.

As for formal work in the state, such workers accounted for 66% of the *paulista* (native or pertaining to this state) labor market, when the formalization rate is taken as a portion of occupied people in total population, which contributes to social security.

3 METHODOLOGY

3.1 Multilevel Analysis

Hierarchical models are generally used to study hierarchically organized data, by which observation units of a given level are nested in observation units of a superior level.

Several studies have used the multilevel hierarchical methodology.

In the labor market framework, Queiroz (2001) applied this methodology to investigate the regional wage differentials. Lameira, Gonçalves and Freguglia (2012) used the spatial-hierarchical model to deal with the individual and regional factors influencing the skilled workers' mobility in the formal labor market from 2003 to 2008. Kulu and Billari (2004) analyzed the worker migration in Estonia. They emphasize that several individual determinants of migration such as age, employment status, and ethnic origin interact with environmental conditions in shaping worker behavior. Fontes, Simões and Oliveira (2010) focused on wage disparities among Brazilian urban centers for the demographic census years of 1991 and 2000. The authors showed that, besides human capital, the attributes of the localities where they live and work have important impacts on earnings, being responsible for considerable proportion of total individual wage dispersion in the country.

In the economics of education, Riani (2005) investigates the determinants of educational outcomes at elementary and high school levels based on the spatial-hierarchical methodology. In the analysis of the determinants of housing market prices in Belo Horizonte – state of Minas Gerais – Aguiar, Simões and Golgher (2014) showed that local urban amenities, for example, the second level local variables such as violence and services, explained over 75% of prices' remaining variability.

In the geography of innovation, Srholec (2010) showed that quality of the regional innovation system in the Czech Republic directly influences the likelihood of a firm to innovate and that this effect decreases with the size of the firm. Besides, broader social characteristics of the region are relevant explanatory factors of innovation. In Brazil, Gonçalves, Lemos and De Negri (2011) analyzed Brazilian micro-data of manufacturing firms by the *logit* regression method as well as used hierarchical regression models. The main results reveal that firm-level variables and region-level variables are complementary but the former has more impact on the propensity to innovate than the latter.

According to Radenbush and Byrk (2002) and Hox (2002), these models avoid several problems such as ecologic or atomistic fallacy and a possible dependence between individual observations.

In our paper, the dependent variable is a binary variable. For this case, *a logit* regression was used, which is a collection of N groups (second level units) for the two-level hierarchical model, with a random sample of n_j units at level 1 (individuals) in each group j (j=1…N). This kind of function is still convenient as its predicted value is changed into a logarithmic chance of success, *log-odds*, *as* can be seen in (1).

$$\eta_{ij} = \log\left(\frac{\pi_{ij}}{1-\pi_{ij}}\right), \tag{1}$$

in which η_{ij} is the logarithmic chance of success for the individual *i*, and π_{ij} is the success probability of this individual.

In hierarchical analysis, it is firstly convenient to take into account the model containing explaining variables at the second level, and the intercept having a random effect. Therefore, the intercept value is taken as the expected average value for the dependent variable, which varies between units of level 2 (Gelman and Hill, 2007). Then, it follows that,

$$\eta_{ij} = \beta_{0j} + \varepsilon_{ij}, \tag{2}$$

where $i = 1\ldots N$ are units at level 1, individuals, in this case; $j = 1 \ldots J$ are units at level 2, municipalities; β_{0j} is the average result for the j_{-th} unit; e_{ij} is the random effect on level 1;

The following model to be estimated is intended to calculate the variability associated to level 1. Therefore, the independent variables corresponding to this level, for example, related to the individual, are added. In this study, this null model form is defined in (3) for the first level equation:

$$\eta_{ij} = \beta_{0j} + \beta_{1j}X_{1ij} + \ldots + \beta_{6j}X_{6ij} + \varepsilon_{ij}, \tag{3}$$

in which the underwritten *i* and *j* are indices for individuals and municipalities, respectively. Additionally, β_{0j} = intercept; β_{kj} = parameters to be estimated for the model; ε_{ij} = random error term; X_{kij} = explaining variables (X_{1ij} = Age dummies; X_{2ij} = sex dummy; X_{3ij} = 1 for high technology sector and 0 otherwise; X_{4ij} = Set of dummies for business firm size: small (0-99 employees), medium (100-499 employees) and big (>499 employees); X_{5ij} = sectoral average wage; X_{6ij} = Experience, for example, the number of months of worker at the same job.

Level 2 in this model shows a simple form presented by a null model:

$\beta_{0j} = \gamma_{00} + u_{0j}$, with $u_{0j} \sim N(0, \tau_{00})$, and γ_{00} = ratio logarithm of average chance between *paulistas* municipalities; τ_{00} = variance of the ratio logarithm of average chance between *paulistas* municipalities.

After estimating this model, the explaining variables of the second level are gradually included, as this is a random intercept model. From this point on, the variance in this model becomes conditional. The statistical inclusion and significance of these explaining variables mean that the worker's propensity to migrate varies with the municipality in question, due to the features of each municipal context. Such contextual characteristics can be represented as described in (4):

$$\beta_{0j} = \gamma_{00} + \gamma_{01} Z_{1j} + \ldots + \gamma_{09} Z_{9j} + u_{0j} \,, \tag{4}$$

where Z_{sj} = municipal explaining variables (described in chart 1); *s* are the contextual characteristics of each municipality *j*. Z_{1j} = average schooling years for the population over 25 years of age; Z_{2j} = proportion of innovative firms; Z_{3j} = Gini coefficient of the distribution of the monthly income of persons; Z_{4j} = annual average of job admissions; Z_{5j} = number of inhabitants per square kilometer; Z_{6j} = sum of wages for total municipal population divided by the number of inhabitants; Z_{7j} = carbon dioxide emissions; Z_{8j} = total number of automotive vehicles divided by total population; Z_{9j} = total occurrence number of crimes divided by total population.

An index of proportional reduction in variance or "explained variance" is used so as to include contextual variables in order to explain the intercept variability. Then, it follows that:

$$\text{Percentage of Explained Variance} = \frac{\tau_{00(non-conditional)} - \tau_{00(conditional)}}{\hat{\tau}_{00(non-conditional)}}. \tag{5}$$

The value of this index, if multiplied by 100, results in the percentage of the intercept variance in the null model, which is being explained through the inclusion of variables at the second level.[5]

3.2. Exploratory spatial analysis and spatial econometrics

The conventional approach of the multilevel model already includes spatial heterogeneity in coefficients. However, in order to verify if there is spatial dependence at the global and local levels, the Moran I and Local Indicators of Spatial Association (Lisa) are estimated (Anselin, 1988; Anselin, 1999 *apud* Baeninger, 2004; LeSAGE and Pace, 2008).

5. The software used in the econometric estimations was Hierarchical Linear and Nonlinear Modeling (HLM).

Besides, spatial econometric techniques are used to detect whether the spatial effect is valid and, in case it is valid, some asymptotical tests will be used to examine whether the spatial dependence assumes the form of an omitted spatially lagged dependent variable or spatial error autocorrelation, such as the Lagrange Multiplier test (LM-LAG) and its robust version (LM-Robust-LAG).

3.3 Hierarchical spatial analysis of determinants of labor migration

The starting point for introducing the spatial feature in the development of this hierarchical model was the work of Morenoff (2003). This author starts from the structural equation of the spatial lag model, which assumes that the spatial effects act through a dependent variable. However, the model represented in this fashion conveys an endogenous variable, W_Y, which can only be estimated by using the maximum-likelihood method, instrumental variables or method of moments. Then Morenoff has included spatial lags of independent variables in his hierarchical model, for example, variable W_X, an alternative he could find to introduce spatial effect in his hierarchical analysis.

Accordingly, the methodology used in the present analysis is based on Morenoff's (2003) solution and its adaptation for studying educational performance accomplished by Riani (2005). According to Riani, estimating this model consists in three steps. Firstly, the second level of the non-conditional hierarchical model is to be obtained, for example, when variables of level 2 are not included in the analysis, but only those of level 1. Such error terms are termed u_{0j} and ε_{ij} from the null model equation. Secondly, spatial econometric tests are carried out in these residues. By performing these tests, it is possible to determine whether the spatial effect is achieved as a spatial lag or spatial error.

In the third place, the hierarchical spatial model is estimated with two different specifications. The first consists in adding the spatial error term to the second level of the hierarchical model. The spatial dependence of both observed and non-observed variables is then corrected. The second specification consists in including the spatially lagged dependent variable in contextual variables, for example, all regional variables with significant Moran's I. It is worth mentioning that using this strategy does not control the spatial effects of non-observed variables, but only those observed ones. Nevertheless, this strategy is useful as it allows observing which covariable is more spatially correlated to independent variables.

3.4 Description of database and variables

The data used in this paper come from the Rais-Migra and Ipeadata. The Rais-Migra database, from the MTE is derived from administrative records of the Rais. Its goal is the longitudinal follow-up of professional trajectories of workers according to the geographical, sectorial and occupational characteristics, allowing for the achievement of mobility studies of individuals in the labor market (MTE, 2003). Rais is an administrative record and its coverage may be considered as a formal labor market census in Brazil. However, its the coverage does not include the share of informal workers in the labor market.

As this is a multilevel study, the data analyzed here comprised both the sample of individuals (level 1) and information on territorial analytical units, for example, municipalities in the state of São Paulo. The second level included 645 municipalities in this state.

The sample of individuals comprised data on 848,333 workers – males and females – aged from 25 to 68. In order to specifically analyze mobility determinants of skilled workers, two subsamples – skilled workers with more than 11 years of schooling and unskilled workers with less than 11 years of schooling – were provided. The skilled worker sample comprised 324,596 individuals.

The analyzed dependent variable is binary and it assumed value 1 in case the individual has migrated in any year of the period 1999-2002, and 0 if not. If the same worker migrates twice or more these movements are considered as a new migration. However, this paper does not analyze return migration. In case the individual has migrated, the regional variables refer to the destination municipalities and, if not, they refer to the municipalities of origin – in both cases data refer to the year 2000.[6] The variables for personal and regional features are described in box 1.

BOX 1
Description of variables

Variables	Description/source
Level 1	
Experience	Number of months of worker at the same job. Rais-Migra
Sex dummy	Assumes value 1, if the individual is a female and 0 if male. Rais-Migra
Age dummies	3 dummies: people from 25 to 30 years of age; those aged 30-45 and; more those than 45. Rais-Migra

(Continues)

6. It is important to highlight that we are analyzing the migration process from 1999 to 2002. As mentioned in the text, our control variables that explain the migration flows are from 2000 and intend to capture structural characteristics of the regions. However, migration decisions may be made over a wide time span. Therefore, we may capture only part of the migration process. Further work could address this sort of analysis.

(Continued)

Variables	Description/source
Sectoral average wage	Sectoral average wage, based on the average wage in the worker's destination industry as proxy for mobility wage expectation before the worker mobility. Rais-Migra
Firm size dummies	Dummy for business firm size: small (0-99 employees), medium (100-499 employees) and big (>499 employees). Rais-Migra
Dummy for high technology sector	1 for high technology sector, for example, that sector showing a high and high-medium relation of between R&D expenditures and value added in the Brazilian industrial structure. The first category encompasses electrical material and machinery, electronics and other transport materials; the second category includes informatics, machines and equipment, automotive instruments and vehicles. We have used the taxonomy elaborated by Furtado and Carvalho (2005).
Level 2	
Gini coefficient	Gini coefficient of the distribution of the monthly income of persons in 2000 Census/IBGE.
Average schooling	Average schooling years for the population over 25 years of age in 2000 – United Nations Development Programme/Ipeadata.
Income *per capita*	Sum of wages for total municipal population divided by the number of inhabitants in 2000 – Census/IBGE/Ipeadata.
Net admissions to job	Annual average of job admissions (admissions versus layoffs) in 1996, 1997 and 1998 from Ministry of Labor (Caged).
Population density	Number of inhabitants per square kilometer in 2000 – Census/Ipeadata.
Proportion of innovative firms	Proportion of firms in the municipal industrial sector, as measured by the value added of innovative and export-engaged firms in relation to total value added of the municipality in 2000, according to Lemos *et al*. (2005).
Carbon dioxide emissions	CO_2 emissions – 10^6 t/year in 2000. Statistical yearbook of energetics of the state of São Paulo.
Automobiles/inhabitants	Total number of automotive vehicles divided by total population in 2000. National Record System Of Automotive Vehicles – 2001.
Crimes/inhabitants	Total occurrence number of crimes divided by total population in 2000. A State Foundation System For Socioeconomic Data Analysis – 2000

Authors' elaboration.

4 RESULTS

The random-effect analysis of model 1 of unskilled workers in the formal labor market (table 1) allows us to conclude that the null hypothesis of considering the intercept as having a random effect was rejected. The contextual variance (u_{0j}) was significantly different from zero, being thus acceptable that the municipalities showed distinct values of probability to migrate. As can be seen, the variance component of model 1 was equal to 0.490 and significant at 1%. Therefore, the probability to migrate for all municipalities differed according to the characteristics of each of their own.

TABLE 1
Results of multilevel regressions for the unskilled workers' probability to migrate by municipalities in the state of São Paulo (1999-2002)

Fixed effect[1]	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7		Model 8	
	Coeff.	*p*-value	Coeff.	*p*-value	Coeff.	*p*-value	Coeff.	*p*-value	Coeff.	*p*-value	Coeff.	*p*-value	Coeff.	*p*-value	Coeff.	*p*-value
Intercept	-0.009	0.821	-0.011	0.788	1.860	0.000	1.592	0.000	1.586	0.000	1.354	0.000	1.324	0.000	1.360	0.000
Population density	-	-	0.054	0.050	0.060	0.027	0.096	0.001	0.095	0.001	0.076	0.008	0.091	0.003	0.087	0.910
Gini coefficient	-	-	-	-	-3.552	0.000	-2.491	0.000	-2.473	0.000	-2.524	0.000	-2.484	0.000	-2.433	0.001
Schooling of adult population	-	-	-	-	-	-	-0.041	0.000	-0.042	0.000	-0.081	0.000	-0.079	0.000	-0.076	0.000
Proportion of innovative firms	-	-	-	-	-	-	-	-	0.063	0.687	0.002	0.991	-0.008	0.962	0.010	0.951
Income *per capita*	-	-	-	-	-	-	-	-	-	-	0.002	0.004	0.002	0.004	0.002	0.002
Net admissions	-	-	-	-	-	-	-	-	-	-	-	-	0.042	0.141	-0.008	0.954
Emissions of CO_2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-0.098	0.411
Automobiles/inhabitant	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-0.178	0,092
Crimes/inhabitant	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-2.547	0.262
Experience	-0.032	0.000	-0.032	0.000	-0.032	0.000	-0.032	0.000	-0.032	0.000	-0.032	0.000	-0.032	0.000	-0.032	0.000
Sex dummy	-0.536	0.000	-0.537	0.000	-0.536	0.000	-0.536	0.000	-0.536	0.000	-0.537	0.000	-0.537	0.000	-0.537	0.000
Sectoral average wage	0.073	0.000	0.073	0.000	0.073	0.000	0.074	0.000	0.074	0.000	0.073	0.000	0.073	0.000	0.073	0.000
Dummy of medium-sized firm	-0.372	0.000	-0.371	0.000	-0.372	0.000	-0.372	0.000	-0.372	0.000	-0.372	0.000	-0.372	0.000	-0.372	0,000
Dummy of large firm	0.009	0.482	0.009	0.474	0.009	0.483	0.008	0.506	0.008	0.505	0.008	0.496	0.008	0.495	0.008	0,495
Age dummy (< 30 years)	-0.134	0.000	-0.135	0.000	-0.134	0.000	-0.134	0.000	-0.134	0.000	-0.135	0.000	-0.135	0.000	-0.135	0.000
Age dummy (from 30 to 45)	0.155	0.000	0.155	0.000	0.155	0.000	0.155	0.000	0.155	0.000	0.155	0.000	0.155	0.000	0.155	0.000
Dummy of high technology sector	-0.204	0.000	-0.204	0.000	-0.205	0.000	-0.205	0.000	-0.205	0.000	-0.204	0.000	-0.204	0.000	-0.204	0.000
Random effect[2]	σ^2	*p*-value	σ^2	*p*-value	σ^2	*p*-value	σ^2	*p*-value	σ^2	*p*-value	σ^2	*p*-value	σ^2	*p*-value	σ^2	*p*-value
Coefficient	0.490	0.000	0.487	0.000	0.461	0.000	0.436	0.000	0.437	0.000	0.432	0.000	0.431	0.000	0.417	0.000
Explained variance (%)	-	-	0.612	-	5.918	-	11.02	-	10.82	-	11.84	-	12.04	-	14.90	-
Number of observations																
Level 1	-	-	848,333	-	848,333	-	848,333	-	848,333	-	848,333	-	848,333	-	848,333	-
Level 2	-	-	645	-	645	-	645	-	645	-	645	-	645	-	645	-
Number of migrants – values 1 of dependent variable	-	-	149,099	-	149,099	-	149,099	-	149,099	-	149,099	-	149,099	-	149,099	-

Authors' elaboration.
Source: Based on the model results.
[1] Coefficients of explaining variables.
[2] Variance, due to inclusion of parameters in the random intercept β_0, which vary in more than one level. This indicates an intraclass variation due to the existing correlation for the probability to migrate between individuals who have migrated to the same municipality of destination.

The probability to migrate decreased if migrants were females, which revealed male prevalence in migration flows. The age-group dummies were significant, suggesting the role of age as a determinant factor of migration. The dummy lower than 30 years of age presented a negative sign, while that for 30-45 years showed a positive sign. This indicates that middle-age individuals have showed higher propensity to migrate, while younger individuals lower propensity to migrate as compared to those individuals aged 45 years or more.

The fact of older workers showing lower propensity to migrate as compared to those of middle ages is in accordance with the hypothesis that propensity to migrate decreases with age as happened in Spain (Bover and Arellano, 2002) and USA (Sjaastad, 1962). The negative sign of the 25-30 age dummy was not the same as that thoroughly pointed to in the literature, which usually shows people under 30 years of age presenting higher mobility than older ones (Mitchell, 2008; Stambol, 2003; Pissarides and Wadsworth 1989). As for the present paper, such fact may be related to that this age group comprised many people looking for their first job. Additionally, the database used in this paper was restrained to people aged 25 years and over due to the need to study those with age enough to complete higher education.

The experience obtained in this work was inversely related to the probability to migrate. The opportunity cost to migrate was possibly higher than that of those with no or lower work experience, due to the job stability already got by the former. This result was also found by Dahl (2004) for Denmark who asserted that the tacit experience accumulated during years of work and incorporated by these individuals would probably be less regionally transferable.

The dummy indicating people employed in the high-technology sector showed a negative sign. As these workers were less mobile than others suggest that tacit knowledge incorporated by these individuals was relatively less mobile, as far as firms localized in different municipalities were concerned. Size of the firm localized in the worker's destination municipality was also a relevant factor for understanding the mobility propensity. Probability of moving to another municipality was positively affected if the firm in the destination municipality was a big one, as compared to the dummy referenced "small-sized firm". Naturally, this result reflected the capacity of attraction big business exerts on workers *vis-à-vis* small firms. However, the same result did not hold for medium-sized business, the sign of which was negative.

Labor productivity differences were generally reflected in the worker's income. For this reason, the wage variable was one of the most important variables among those influencing migration. The result found confirmed the economic theory, which argues that individuals will migrate if they are able to earn more money in their destination place of work (Sjaastad, 1962).

The inclusion of explaining variables in level 2 was carried out in a successive way so as to test the sensitivity of stability results of those variables included in the models. It can be observed that the variance explained in the intercept increased from 0.6% to approximately 15%, when municipal features were included.

Variables of level 1, in turn, presented high stability in its coefficients independently of the model used, which suggested robustness of individual abilities when explaining variables of propensity to migrate.

The conditional model 2 includes the municipal population density that explained less than 1% of the intercept variance, for example, not even 1% of the variation in the average propensity to migrate was explained by differences in the level of population density observed between the *paulistas* cities. Probability to migrate increased if the destination municipality was more populated. According to Pellegrini and Fotheringham (1999), a positive sign is expected, because this variable is somehow related to city size and hence to the number of job opportunities available, and availability of high-leveled urban amenities as well. Furthermore, individuals are expected to have more information about opportunities in big metropolitan cities than in small cities. This result is usually found in the literature (Etzo, 2007, Beals, Levy and Moses, 1967).

The negative effect of income inequality in the municipality of destination had higher impact on the decision to migrate as the model now explains 6% of the intercept variation. Average schooling of the population presented a negative sign. It is possible that people with more years of schooling were migrating to municipalities showing lower average schooling. This result was also found by Beals, Levy and Moses (1967) when analyzing interregional migration in Ghana.

The proportion of innovative firms in the municipalities did not have effect on unskilled workers due to absence of significance. Cities with higher income *per capita* have proved to be more attractive for migrant workers, as can be certified by the positive coefficient of the income *per capita* variable. Sahota (1968) – when analyzing state migration in Brazil – found that migration elasticity in relation to regional income *per capita* was positive; and younger people were more sensitive to this variable.

As for labor market dynamism in the destination city ("net admissions"), this variable presented a negative sign when amenity variables were included, which was not significant however. Once variables indicating quality of life were included, the model was then able to explain 15% of the intercept variance. The three variables (pollution degree, traffic congestion and violence degree) showed the expected negative sign, but traffic congestion alone was statistically significant (10%).

Table 2 shows the results for skilled individuals. It can be perceived that the hypothesis that the intercept was considered as having a random effect on such workers is also acceptable. When model 2 (conditional) is compared to model 1 (non-conditional), 2.8% of the intercept variance is explained by including population density. A higher decrease can be perceived, when – in addition to this variable – the Gini coefficient and adult population average schooling are included (model 4). In this latter case, three contextual measures jointly explain 11% of the intercept variance. As can be seen in model 7, the explained variable percentage is approximately 18%, when all contextual variables are included. Therefore, municipal features exerted higher impact on skilled workers' probability to migrate than on unskilled workers. According to Mata *et al.* (2007), skilled migrants look for places with higher labor market dynamism that may be represented by wages and greater number of urban amenities.

TABLE 2
Results of multilevel regressions for the skilled workers' probability to migrate in municipalities of the state of São Paulo (1999-2002)

Independent variables	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7		Model 8	
	Coeff.	*p*-value	Coeff.	*p*-value	Coeff.	*p*-value	Coeff.	*p*-value	Coeff.	*p*-value	Coeff.	*p*-value	Coeff.	*p*-value	Coeff.	*p*-value
Intercept	-0.742	0.000	-0.749	0.000	-0.611	0.096	-0.905	0.012	-0.981	0.007	-1.173	0.002	-1.243	0.001	-0.632	0.088
Population density	-	-	0.087	0.001	0.087	0.001	0.124	0.000	0.112	0.000	0.097	0.000	0.121	0.000	0.119	0.000
Gini coefficient	-	-	-	-	-0.261	0.703	0.934	0.184	1.113	0.112	1.052	0.132	1.149	0.097	1.010	0.159
Schooling of adult population	-	-	-	-	-	-	-0.044	0.000	-0.053	0.000	-0.086	0.000	-0.083	0.000	-0.091	0.000
Proportion of innovative firms	-	-	-	-	-	-	-	-	0.437	0.004	0.385	0.011	0.368	0.013	0.469	0.003
Income *per capita*	-	-	-	-	-	-	-	-	-	-	0.002	0.015	0.002	0.014	0.002	0.006
Net admissions	-	-	-	-	-	-	-	-	-	-	-	-	0.070	0.007	-	-
Emissions of CO_2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-0.092	0.050
Automobiles/inhab.	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-0.160	0.216
Crimes/inhab.	-	-	-	-	-	-	-	-	-	-	-	-	-	-	3.115	0.193
Experience	-0.015	0.000	-0.015	0.000	-0.015	0.000	-0.015	0.000	-0.015	0.000	-0.015	0.000	-0.015	0.000	-0.014	0.000
Sex dummy	-0.431	0.000	-0.431	0.000	-0.431	0.000	-0.431	0.000	-0.431	0.000	-0.431	0.000	-0.431	0.000	-0.438	0.000
Sectoral average wage	0.224	0.000	0.223	0.000	0.223	0.000	0.224	0.000	0.224	0.000	0.223	0.000	0.224	0.000	0.075	0.000
Dummy of medium-sized firm	0.355	0.000	0.355	0.000	0.355	0.000	0.355	0.000	0.355	0.000	0.356	0.000	0.355	0.000	0.140	0.000
Dummy of large firm	0.482	0.000	0.482	0.000	0.482	0.000	0.481	0.000	0.481	0.505	0.482	0.000	0.482	0.000	-0.332	0.000
Age dummy (< 30 years)	-0.150	0.002	-0.150	0.002	-0.150	0.002	-0.150	0.002	-0.150	0.002	-0.151	0.001	-0.151	0.001	-0.284	0.000
Age dummy (> 45 years)	0.152	0.001	0.152	0.001	0.152	0.001	0.152	0.001	0.152	0.001	0.151	0.001	0.151	0.001	-0.275	0.000
Dummy of high technology sector	-0.287	0.000	-0.287	0.000	-0.287	0.000	-0.286	0.000	-0.287	0.000	-0.287	0.000	-0.288	0.000	-0.190	0.000
	σ^2	*p*-value	σ^2	*p*-value	σ^2	*p*-value	σ^2	*p*-value	σ^2	*p*-value	σ^2	*p*-value	σ^2	*p*-value	σ^2	*p*-value
Coefficient	0.422	0.000	0.410	0.000	0.411	0.000	0.375	0.000	0.368	0.000	0.363	0.000	0.355	0.000	0.347	0.000
Explained variance (%)	-	-	2.84	-	2.61	-	11.14	-	12.80	-	13.98	-	15.88	-	17.77	-
Number of observations																
Level 1	324,596	-	324,596	-	324,596	-	324,596	-	324,596	-	324,596	-	324,596	-	324,596	-
Level 2	643	-	643	-	643	-	643	-	643	-	643	-	643	-	643	-
Number of migrants – values 1 of dependent variable	56,833	-	56,833	-	56,833	-	56,833	-	56,833	-	56,833	-	56,833	-	56,833	-

Authors' elaboration.
Source: Based on the model results.

As for variables of level 1, the signs of variable coefficients were usually equal to those found for unskilled workers, except for the dummy for the medium-sized firms, whose sign turned out to be positive. It should be also noticed that sectoral wage had a significantly higher impact on skilled workers.

As for municipal features, the signs of variables were mostly equivalent. It is remarkable that the Gini coefficient was not significant now. This suggests that skilled workers are not concerned with regional inequality when they migrate.

Schooling of adult population also presented a negative sign. According to Sahota (1968), the sign of this variable can be justified by the fact that more educated migrant individuals must compete with individuals with more schooling years in the destination region. Then, *ceteris paribus*, a high level of average education in the destination region may be an unencouraging factor for the entry of more skilled workers.

The proportion of innovative firms in the destination municipality becomes significant, which positively affects the probability to migrate in a municipality. This means that the composition of firms with higher technological content attracts migration of skilled workers, since these innovative businesses in average are employers of more qualified labor.

As for variables measuring quality of life, only those referring to carbon dioxide emissions were significant. Therefore, worst air quality had a negative effect on the probability to migrate. The verified statistical non-significance of vehicles and crimes per person may be related to the results of the spatial exploratory analysis that has revealed agglomerations of cities with higher proportion of innovative businesses as, for example, Campinas and São Paulo, which attract skilled migrants.

Nevertheless, these big cities – which show several kinds of agglomeration diseconomies – are still attracting migrants, mainly those qualified ones who seem to consider as relevant other municipal features.

As shown in table 2, approximately 18% of intermunicipal variability of skilled workers' propensity to migrate can be attributed to territorial variables (the municipality itself). This means that – despite the fact that municipal characteristics are more relevant for skilled workers than for unskilled workers – individual variables show a higher weight in propensity to migrate *vis-à-vis* municipal variables. However, regional factors are nonneglegible when explaining labor mobility.

4.1 Controlling spatial effects

The Moran's I statistic was estimated aiming to detect spatial autocorrelation in the study variables. As can be seen in table 3, there was a positive and significant autocorrelation in all variables, except for the variables of net admissions and automobiles per inhabitants. For this reason, these two variables were excluded from the spatial analysis. For the remaining variables, the positive Moran's I test means that there was similarity between the variable value and its spatial location, which indicated data concentration.

TABLE 3
Moran's I statistic for the variables representing the characteristics of 645 municipalities in São Paulo in 2000

Variable	Moran's I	Prob.
Gini coefficient	0.365	0.000
Average schooling of population aged 25and over	0.109	0.024
Proportion of innovative firms	0.345	0.000
Income *per capita*	0.327	0.000
Population density	0.723	0.000
Net admissions	0.025	0.461
Crimes/inhabitant	0.320	0.000
Emissions of CO_2	0.035	0.079
Automobiles/inhabitants	0.011	0.796

Author's elaboration.
Source: Results of spatial exploratory data analysis.

As an existing autocorrelation was indicated, it became necessary to detect what spatial process really occurred by analyzing the regional level residues. The diagnostic tests for spatial autocorrelation carried out in the OLS regressions revealed an existing spatial lag process in both samples (tables 4 and 5).

TABLE 4
Regression estimates for the hierarchic model without covariables at level 2 for the probability to migrate of unskilled individuals

Variables	OLS model – OLS's residues		2SLS model – OLS's residues	
	Coefficient	Prob.	Coefficient	Prob.
Constant	1.365	0.000	1.261	0.001
Spatially *Lagged Dep. Variable* (Wy)	-	-	0.137	0.082
Population density	0.084	0.023	0.083	0.022
Gini coefficient	-2.843	0.000	-2.546	0.001
Average schooling of population	-0.083	0.000	-0.078	0.000

(Continues)

(Continued)

Variables	OLS model – OLS's residues		2SLS model – OLS's residues	
	Coefficient	Prob.	Coefficient	Prob.
Proportion of innovative firms	0.021	0.909	-0.023	0.903
Income *per capita*	0.003	0.001	0.002	0.009
Net admissions	-0.008	0.923	-0.001	0.990
Emissions of CO_2	-0.098	0.500	-0.092	0.525
Autos/inhabs	-0.118	0.043	-0.121	0.037
Crimes/ inhabs	0.232	0.926	0.619	0.805
R^2	0.082	-	-	-
R^2 adjusted	0.069	-	-	-
Tests of spatial dependence	Value	Prob.	Value	Prob.
LM test for spatial error	5.242	0.022	0.355	0.551
Robust LM test for spatial error	0.469	0.501	-	-
LM test for spatial lag	6.091	0.014	-	-
Robust LM test for spatial lag	1.319	0.038	-	-

Source: Residue regression results.
Author's elaboration.
Note: LM = lagrange multiplier.

As for the unskilled workers' sample, the Lagrange robust multiplier test was not significant for autocorrelation in a spatial error form, except for spatial lag, which indicates that spatial dependence was presented in this way. The two robust tests in the skilled people sample were significant.

In the lag model estimate, the coefficient of the Wy term, for example, the spatial autoregressive parameter (ρ), was significant in both cases. The spatial lag of the Wy term coefficient was equal to 0.137 and significant at 10%, as the unskilled worker sample was first taken into account. The spatial lag coefficient of the dependent variable means that the average probability to migrate of individuals in a given municipality is related to changes in the observed variables included in the model and those non-observed variables in neighboring municipalities.

Some variables showed a decreased effect in the lag model, such as population density and net admissions. As for the sample of individuals with more than 11 years of schooling (table 5), it is worth noting that, once positive, the Gini coefficient became negative. Finally, it can be noted that, in both cases, the diagnostic test pointed to a remaining spatial error after introducing the spatial lag term. And this is because the Lagrange multiplier (LM_λ) for the spatial error keeps it significance, even when the spatial lag term (Wy) is included.

TABLE 5
Regression estimates for the hierarchic model without covariables at level 2 for the probability to migrate of skilled individuals

Variables	OLS model – OLS's residues		2SLS model – OLS's residues	
	Coefficient	Prob.	Coefficient	Prob.
Constant	-0.492	0.240	0.828	0.104
Spatially lagged dep. variable (Wy)	-	-	1.209	0.000
Population density	0.131	0.001	0.102	0.017
Gini coefficient	0.723	0.373	-1.147	0.216
Average schooling of population	-0.074	0.000	-0.026	0.269
Proportion of innovative firms	0.406	0.048	-0.204	0.406
Income *per capita*	0.001	0.141	-9.109	0.920
Net Admissions	0.116	0.195	0.022	0.819
Emissions of CO_2	0.088	0.580	-0.160	0.357
Auto/inhabitant	-0.071	0.267	-0.109	0.103
Crime/inhabitant	5.381	0.049	2.972	0.307
R^2	0,111	-	-	-
R^2 adjusted	0.101	-	-	-
Spatial dependence tests	Value	Prob.	Value	Prob.
LM test for spatial error	6.091	0.014	28.119	0.000
Robust LM test for spatial error	5.400	0.020	-	-
LM test for spatial lag	8.443	0.004	-	-
Robust LM test for spatial lag	7.752	0.005	-	-

Source: Prepared by the authors from the results of residue regressions.
Authors' elaboration.
Note: LM = lagrange multiplier.

4.2 Hierarchical-spatial analysis of the probability to migrate determinants

An existing spatial error process turned the hierarchical model coefficients into unreliable estimates as they might be biased and/or inefficient. Aiming at correcting this problem, an attempt was made to include the spatial effect into the hierarchical model in the spatially lagged error term or spatially lagged dependent variable fashions. When using the first fashion estimation, the existing spatial autocorrelation was controlled both for observed and non-observed variables. On the other hand, only the observed factors were controlled, when the spatial lag of independent variables alone were considered. However, this method showed which independent variable was more spatially correlated to the probability to migrate.

The hierarchical-spatial model results for unskilled and skilled workers can be found in tables 6 and 7. With a view to make comparisons easier, results of the better specified model – model 8 of the two samples – can also be seen in these tables. To the extent that, for this analysis, the interest variables are contextual, results for variables of level 1 were not shown; they are not different from the previous ones however.

It can be seen from table 6 that the error spatial autocorrelation was significant for unskilled workers, which suggested that there was a non-observed spatial component in the data. The variance component decreased and the model then explained 21.6%[7] of the intercept variance; and model 8 (with no spatial component) explained 14.8% (see table 1). As for signs and significance of the variables, there were no changes when the error spatial term was added. The Gini coefficient turned out to be significant however.

When the features of neighboring municipalities were added, it is worth noting that the income inequality level and population density affected migration positively, while these variables did not affect migrants' decision in their own destination municipality. This suggests that – for some economic variables – unskilled workers took into account a larger territorial extension than that of the municipality they were bound to. Other variables – such as the proportion of innovative firms in the destination municipality or in its vicinity – held their negative influence on their decision to migrate. This model showed a slightly higher variance component than that of error spatial term (0.393 > 0.384), indicating that the spatial pattern seen in the error term was given by unmodeled effects, which were not randomly distributed in space.

As for skilled individuals (table 7), including spatial effects has caused the impact of some contextual variables to decline. The Gini coefficient, income *per capita* and crimes per inhabitant have become significant with the inclusion of the error spatial term. Differently from the result for unskilled workers, the features of neighboring municipalities were in the majority significant for the skilled individual sample. Probability to migrate was higher if the municipality was surrounded by municipalities having a high proportion of innovative firms in their economies, a low criminality level, as well as showing a higher income *per capita*. The hierarchical-spatial of error accounted for 15.4% of the intercept variance, while the lag model did the same for 24.4%.

Based on such results, we could conclude that level 2 variables had direct and indirect effects on the probability to migrate. The direct effect would be that impact on probability to migrate caused by changes in contextual variables in the

7. The figure 0.490 is the variance component of the hierarchical model with no contextual variables (table 1) and the figure 0.384, the variance component of the hierarchical model including the spatial error (table 6).

municipality of destination. On the other hand, the indirect effect would be that provoked by changes in contextual variables in the municipalities neighboring the destination place.

TABLE 6
Results of hierarchical models without and with spatial effects for the unskilled labor sample

Independent variables	Hierarchical model (model 8)		Spatial error model		Spatially lagged independent variable model	
Fixed effect[1]	Coefficient	Prob.	Coefficient	Prob.	Coefficient	Prob.
Intercept	1.360	0.000	1.374	0.000	1.507	0.001
Gini coefficient	0.087	0.910	0.084	0.005	0.039	0.328
Average schooling of population	-2.433	0.001	-2.173	0.002	-2.367	0.003
Proportion of innovative firms	-0.076	0.000	-0.070	0.000	-0.072	0.000
Income *per capita*	0.010	0.951	0.055	0.725	0.040	0.807
Net admissions	0.002	0.002	0.002	0.008	0.002	0.030
Population density	-0.008	0.954	-0.004	0.952	0.009	0.893
Crimes/inhabitants	-0.098	0.411	-0.098	0.406	-0.075	0.539
Emissions of CO_2	-0.178	0.092	-0.183	0.086	-0.155	0.093
Automobiles/inhabitants	-2.547	0.262	-2.147	0.344	-1.187	0.624
W OLS's residues	-	-	0.160	0.001	-	-
W population density	-	-	-	-	0.103	0.055
W Gini coefficient	-	-	-	-	0.066	0.931
W average schooling of population	-	-	-	-	-0.063	0.001
W proportion of innovative firms	-	-	-	-	0,001	0.979
W income *per capita*	-	-	-	-	0.003	0.001
W net admissions	-	-	-	-	-0.095	0.669
W emissions of CO_2	-	-	-	-	0.030	0.832
W automobiles/inhabitants	-	-	-	-	0.144	0.719
W crimes/inhabitants	-	-	-	-	-3.204	0.171
Random effect[2]						
Variance component	0.490	0.000	0.384	0.000	0.393	0.000

Authors' elaboration.
Source: Results of spatial models.
[1] Coefficients of explaining variables.
[2] Variance, due to inclusion of parameters in the random intercept β_0, which vary in more than one level. This indicates an intraclass variation due to the existing correlation for the probability to migrate between individuals who have migrated to the same municipality of destination.
Note: W = spatial lag.

TABLE 7
Results of hierarchical models with spatial effects for skilled workers

Independent variables	Hierarchical model (model 8)		Spatial error model		Spatially lagged independent variable model	
Fixed effect[1]	Coefficient	Prob.	Coefficient	Prob.	Coefficient	Prob.
Intercept	-0.632	0.088	-1.202	0.001	-2.014	0.000
Gini coefficient	1.010	0.159	0.102	0.014	0.892	0.253
Average schooling of population	-0.091	0.000	-0.083	0.174	-0.046	0.010
Proportion of innovative firms	0.469	0.003	0.332	0.026	0.028	0.010
Income *per capita*	0.002	0.006	0.010	0.019	0.043	0.055
Net admissions	-	-	0.095	0.119	0.026	0.053
Population density	0.119	0.000	0.119	0.028	0.069	0.065
Crimes/inhabitants	-0.092	0.050	2.062	0.026	-0.239	0.061
Emissions of CO_2	-0.160	0.216	-0.050	0.375	-0.190	0.370
Automobiles/inhabitants	3.115	0.193	-0.154	0.235	0.134	0.530
W OLS's residues	-	-	0.143	0.001	-	-
W population density	-	-	-	-	0.031	0.084
W Gini coefficient	-	-	-	-	1.608	0.094
W average schooling of population	-	-	-	-	-0.780	0.060
W proportion of innovative firms	-	-	-	-	1.265	0.000
W income *per capita*	-	-	-	-	0.001	0.005
W net admissions	-	-	-	-	0.002	0.713
W emissions of CO_2	-	-	-	-	0.190	0.006
W automobiles/inhabitants	-	-	-	-	0.134	0.461
W crimes/inhabitants	-	-	-	-	-3.239	0.360
Random effect[2]						
Variance component	0.422	0.000	0.357	0.000	0.319	0.000

Authors' elaboration.
Source: Elaborated by the authors from results of spatial models.
[1] Coefficients of explaining variables.
[2] Variance, due to inclusion of parameters in the random intercept β_0, which vary in more than one level. This indicates an intraclass variation due to the existing correlation for the probability to migrate between individuals who have migrated to the same municipality of destination.
Note: W = spatial lag.

5 CONCLUSION

Migration studies have highlighted the role of both factors with direct relation to individuals and factors related to social and geographic environment. Therefore, a thorough analysis of migration determinants should take into account personal factors, as well as those of the context in which an individual lives. This paper aimed to determine the characteristics of the individual labor mobility in the industry of the state of São Paulo, the role of contextual factors in defining migratory flows and the pattern of migration and – more specifically – whether skilled workers migrate for the same reasons of other workers generally do in the formal labor market.

The hierarchical model analysis showed that individual determinants of migration were all statistically significant both for the unskilled and skilled workers.

The worker's experience restrained mobility between regions and, for this reason, the tacit knowledge incorporated by this individual was less liable to move. Conversely, wage at destination had a positive impact on migration. Women were less inclined to migrate, as well as those people over 45 years of age and those less than 30, in relation those other individuals aged 30-45. When contextual variables were included, the explained variance model of unskilled workers' reached 15%, while that for skilled workers reached 18%.

Spatial dependence was added to the hierarchical model in the form of spatial error and spatial lag of contextual variables. The results of this hierarchical-spatial analysis revealed that the individual's decision to migrate, especially that for skilled workers, was influenced in several ways by different scale factors, such as those related to individual personally, one's occupation, municipalities of destination, as well as to general features of the destination municipality neighborhood.

When multilevel modeling was applied, it was intended to capture the effect of contextual variables linked to the probability to migrate, since individual factors would be controlled. Our results indicated that qualified migrants from São Paulo industry were attracted to cities whose economies were capable to generate employment, in which a significant portion of their output was determined by innovative and export business firms.

The results show that regional factors are nonneglegible when explaining labor mobility, mainly for skilled workers. Based on the example of the role played by the high proportion of innovative firms in the destination municipality for skilled workers' migration, we conclude that there are potential beneficial effects to integrate public policies for education, labor market and innovation. The aforementioned policies should be planned not only at a local level but also at a regional level to the extent that regional factors and spatial autocorrelation are present when we deal with the drivers of labor mobility.

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