NEREUS

Núcleo de Economia Regional e Urbana
da Universidade de São Paulo
The University of São Paulo
Regional and Urban Economics Lab

LOCAL, COMPLEMENTARITY AND SIMILARITY RELATEDNESS IN DIFFERENT REGIONAL AND SECTORAL CONTEXTS

Jefferson Ricardo Bretas Galetti
Milene Simone Tessarin
Paulo César Morceiro

TD Nereus 12-2020
São Paulo
2020

Local, Complementarity and Similarity Relatedness in Different Regional and Sectoral Contexts

Jefferson Ricardo Bretas Galetti[1]; Milene Simone Tessarin[2] e Paulo César Morceiro[2]

Abstract

There is little evidence on the relationship between occupational relatedness and regional specialisation in developing countries with high regional inequality and industrial heterogeneity. We compute local synergy, complementarity and similarity relatedness based on 2 514 occupations to estimate their effects on the occupational structure in 558 Brazilian microregions between 2003 and 2018. We find that the three indexes affect the regional specialisation in distinct magnitudes, and they have different effects in different regional and sectoral contexts. Sectoral complementarities affect structural change and strengthen similarity relatedness. The findings shed light on developing countries' distinct regional contexts rather than 'one-size-fits-all' policies.

Keywords: occupational relatedness, related variety, regional specialisation, developing country.

JEL codes: J21, J24, L23, R12.

1. Introduction

Several scholars have emphasised that occupations can be displayed as a network in an economy in which they are more or less related to each other (Muneepeerakul *et al*., 2013; Shutters *et al*., 2016). The degree of occupational relatedness can influence the future evolution of regional specialisation, since it acts as a mechanism that favours the emergence of occupations that are somehow related to the region's jobs portfolio in a branching process (Boschma and Frenken, 2012; Frenken and Boschma, 2007).

This article aims to deal with three characteristics that arise from these studies. First, these articles focus on the labour market dynamics of developed countries. Second, the authors have used several local resources to measure the degree of relatedness between occupations, such as geographical co-location (Muneepeerakul *et al*., 2013; Shutters *et al*., 2018), labour flow between occupations (Hane-Weijman *et al*., 2020), formal education (Neffke, 2019), and skills (Alabdulkareem *et al*., 2018; Anderson, 2017). However, it is crucial to identify which specific factors most influence the evolution of the occupational

[1] Postdoc at DST/NRF South African Research Chair (SARChI) in Industrial Development, University of Johannesburg. PhD in Economics at Federal University of Rio de Janeiro (UFRJ).

[2] Postdoc at DST/NRF South African Research Chair (SARChI) in Industrial Development, University of Johannesburg. PhD in Economics at University of Sao Paulo (FEA-USP). Researchers at Fipe and Nereus-USP.

structure. Third, the relatedness concept is usually applied as a “universal measure”, regardless of the regional and sectoral contexts (Boschma, 2017).

We focus on the aforementioned characteristics, analysing and comparing the effects of three distinct sources of occupational relatedness on the evolution of jobs in different regional and sectoral contexts in a developing country. First, we test whether the effects of occupational relatedness on structural change in developed countries also explain the dynamics of the labour market in Brazil – a developing country characterised by an enormous level of inequality across regions and industries. Brazil has experienced a period of economic stability since the mid-1990s that resulted in increasing formal employment creation in the 2000s, followed by a turning point in 2014, when the unemployment rate starting increasing, moving from 6.5% to 12% by 2018. In order to improve the understanding of regional dynamics, we need to know whether, besides the movement attached to the economic cycle, the patterns of local specialisation have also influenced the changes in the labour market.

Second, to identify and compare the effects of specific factors on the occupational structure, we follow Farinha *et al*. (2019) and analyse three different sources of relatedness. We compute the geographical co-location of occupations representing the local synergies of the labour market. Although the development of communication and information technologies has increased formal knowledge flow, spatial proximity remains relevant, as it facilitates learning and the transfer of tacit knowledge between workers (Maskell and Malmberg, 1999). However, other forms of proximity facilitate knowledge creation and exchange and interact with geographical proximity to transform the economic structure (Boschma, 2005). The second source of relatedness accounts for complementary tasks performed by different occupations and comes from the frequency that an industry jointly demands those occupations. Modern societies have seen the growth in the stock and complexity of knowledge, further specialisation requirements for individuals, and the increasing level of division of labour and coordination costs of production (Balland and Rigby, 2017; Jones, 2009). Then industries have to collect the socially dispersed knowledge demanding related occupations that complement each other to solve coordination problems and increase the value of production (Neffke, 2019). The third source of relatedness comes from the similarity of skills shared by two occupations. Pairs of occupation are related because their job tasks may require the same set of skills to be performed, and one can substitute for the other to a certain degree. The occupational similarity affects the evolution of a regional specialisation, since people with a similar set of skills tend to agglomerate to reap the benefits of a labour market pool (Farinha *et al*., 2019).

Finally, to better understand under which conditions the occupational relatedness drives structural change at the regional level, we extend the analysis in two ways according to the research agenda outlined in Boschma (2017). First, to add more "geographical wisdom", we test how our three measures of occupational relatedness affect microregions that differ extremely. The Brazilian population is unevenly distributed across the country: although the population average in a microregion is 373 542 inhabitants, according to Ipeadata[2] two of these regions had more than 12 million inhabitants and 11 microregions had more than two million inhabitants in 2018. Second, instead of considering relatedness as a "universal measure", we computed the complementarity relatedness for three sectors (manufacturing, services and natural resources) and tested whether their impacts for the whole country remained the same for different groups of microregions, and how they interacted with occupational similarity. The motivation for distinguishing between sectoral effects on occupational structure derives from the debate about the sources of development. Despite documented cases of premature deindustrialisation among developing countries in general, and in Brazil specifically (Rodrik, 2016; Tregenna and Andreoni, 2020), there is evidence that manufacturing still plays an important role as the engine of growth in developing countries (Szirmai and Verspagen, 2015). Services are labour-intensive and represented 74% and 68% of Brazilian GDP and total occupation in 2017, respectively (Brazilian Institute of Geography and Statistics (IBGE), 2019). Besides their size, some dynamic sectors are classified as services, such as financial and communication and information activities. Finally, Brazil has a comparative advantage in natural resources industries, and most of its global trade integration has occurred under exports of soya beans, oil and iron ore.

This article is linked with the literature on relatedness and the regional path of development. Our contribution is to assess whether the effects of occupational relatedness on the evolution of labour markets hold for a large, complex and unequal developing country. Besides estimating empirical results for the whole country, we also investigate whether the regional specialisation in occupations changes with the size of microregions and sectoral complementary relatedness. Our results may shed light on regional development in other heterogeneous developing countries.

The article is organised as follows. The next section presents the theoretical background of the evolution of occupational structure and its relationship with the relatedness concept. The third section presents the methodology and data used in the estimates. In the fourth section, we specify the econometric model.

[2] Available at http://www.ipeadata.gov.br. Accessed on 07/08/2020.

Section 5 presents the main results, and the section 6 discusses them. The last section concludes and provides some policy implications.

2. Theoretical background

2.1. Occupational relatedness and structural change

In modern economies, the complexity of economic activities has increased sharply over time, compelling workers to narrow down their specialisation in specific knowledge areas, at the same time that regions have to distribute their knowledge across different individual workers (Balland and Rigby, 2017; Hidalgo and Hausmann, 2009; Jones, 2009). On the one hand, this division of labour promotes productivity growth, but on the other hand, it increases the coordination costs of production once the workers need to perform jointly to produce goods and services (Neffke, 2019; Shutters *et al*., 2016).

In this context, workers are the principal repository of knowledge. They create, recombine and learn new knowledge by doing and interacting among themselves, thereby improving skills, know-how, competencies and experiences through routines and by integrating tacit and technical knowledge to perform tasks (Muneepeerakul *et al*., 2013; Shutters *et al*., 2016, 2018). Workers optimise the cognitive distance among themselves to improve the flows of information (Nooteboom, 2000, 2001) and channel new knowledge to firms (Wixe and Andersson, 2017).

As we cannot observe all the workers' skills and characteristics directly, we use occupations as a proxy to build an economic structure linking different workers' knowledge. In this sense, occupations represent workers in a relational dimension in which their value depends on the context in which they are employed (Neffke, 2019; Shutters *et al*., 2018). According to relatedness literature, regions recombine related workers' knowledge, taking into account the local context, to create competitive advantages and transform themselves (Frenken and Boschma, 2007). Since firms incur costs to coordinate different occupations, links among those occupations represent specific solutions to the coordination problems.

Previous empirical evidence for developed countries suggests that the degree of relatedness between occupations facilitates some future paths of development and precludes others. The current specialisation and interdependencies between and among occupations determine the region's possible development paths (Farinha *et al*., 2019; Muneepeerakul *et al*., 2013; Shutters *et al*., 2016, 2018).

Shutters *et al*. (2016) show how interactions both among creative and between creative and non-creative occupations influence regional specialisation in those job classes. A region's current specialisation is highly related to the creative occupation in which the region specialises. While a region increases its creative specialisation, the non-creative occupations also increase, indicating an important, interdependent role between occupations. Farinha *et al*. (2019) confirm that cities specialise in new jobs related to existing ones in the city and extinct jobs unrelated to their portfolio, although the degree of relatedness seems to prevent the exit of jobs more than promoting entry.

2.2. Different sources of occupational relatedness, regional and sectoral contexts

What are the sources that can link related occupations? Farinha *et al*. (2019) separate the effects of the current specialisation on the development path into three related variety indexes: local synergy, complementarity and similarity between occupations. Following these authors, we also focus on these three sources of occupational relatedness.

Local synergy

The first source of relatedness is derived from the most common source used in previous studies, the geographical co-location of jobs, which computes the frequency in which pairs of occupations are found together in the same region (Muneepeerakul *et al*., 2013; Shutters *et al*., 2018). This source emphasises the role played by spatial proximity in knowledge transfer and the learning process through social interactions. Explicit and tacit knowledge are complementary, and the more the amount of explicit knowledge becomes available worldwide, the higher is the value of tacit knowledge for regional competitiveness. The spatial proximity facilitates tacit knowledge exchange, since it does not travel for long distances and is difficult for other regions to imitate (Gertler, 2003; Maskell and Malmberg, 1999). On the one hand, local synergy draws attention to the regional context, but on the other hand, it does not allow a disentanglement of the effects of several local capabilities on the occupational structure, such as access to infrastructure and natural resources, and the quality of the institutional environment.

Complementarity

The industry's demand for workers allows us to compute the complementarity between occupations. If an industry often jointly demands pairs of occupations, it means that those combinations reduce coordination costs and increase the value of goods and services produced. Neffke (2019) found evidence that complementary co-workers increase the value of a worker, measured by his/her wage. For this reason, we can argue that, if complementarity positively affects the value of a worker, it possibly increases the productivity and the value of a firm's output when it employs complementary occupations. Therefore, the frequent co-use of occupations indicates that they are complementary, and industries benefit from employing them jointly to maximise their profits.

Similarity

The third source of relatedness comes from the skills and characteristics that occupations commonly share and use to perform a job. For instance, car mechanics share similar skills with motorcycle mechanics and, conditional on the local structure, a region can diversify into both occupations simultaneously, or employ one occupation as a substitute for another in the same job. Therefore, occupations with a high degree of similarity are substitutable to some degree, and this characteristic has shown adverse effects on their wages (Neffke, 2019). In contrast, similarity allows a better transition between occupations in the case of economic shocks and enhances the trend of people with similar skills agglomerates to benefit from the labour market pool (Alabdulkareem *et al*., 2018; Farinha *et al*., 2019; Neffke and Henning, 2013).

Besides considering the differentiated sources of occupational relatedness, we also explored whether the effects of those indexes change with the microregions' size in developing countries. The occupational network density increases with city size, and larger cities create a larger amount of information and present a higher probability of specialising in more complex occupations and becoming more integrated, interdependent and economically efficient (Shutters *et al*., 2018). These characteristics derived from the fact that, as a city grows, the agglomeration economies allow more social interactions and knowledge spreading, better learning opportunities, and more efficient job matching (Glaeser and Resseger, 2010; Neffke, 2019). On the other hand, peripheral and less-populated regions benefit to a lesser extent from knowledge spillovers. Firms in these regions have to compensate for the lack of access to knowledge and have to create alternative strategies, such as building strong internal expertise through workforce training (Eder and Trippl, 2019; Grillitsch and Nilsson, 2015; Isaksen, 2015; Rodríguez-Pose and Wilkie, 2019). In addition, in low-density regions, specialisation in industries in which firms share common knowledge seems to have higher effects on regional growth (Caragliu *et al*., 2016).

Furthermore, the degree of occupational relatedness can significantly differ, depending on the nature of the industry that jointly demands complementary occupations. Different ways of coordinating the production process also may affect the relationship between relatedness and the regional specialisation.

Evidence from the US and Mexico indicates that labour linkages are more important for explaining the agglomeration patterns in services, while the manufacturing patterns are driven by input-output linkages (Diodato *et al*., 2018).

In sum, we investigate the extent to which the future development path of occupational structure in Brazilian microregions is related to the current structure. We hypothesise that the probability of a region specialising in a new occupation class is higher if that class is closely related to other occupations present in the regional economy. In contrast, an existing occupation class has a higher likelihood of exiting the local economy if it is unrelated to other existing occupations. Therefore, the region's occupational specialisation and structural change are not random events, but hinge on the degree of different sources of relatedness between occupations.

In order to test whether different geographical and sectoral contexts can affect the explanatory power of occupational relatedness, we focus on the comparison of three sources of relatedness and analyse whether their effects are different for microregions with different population levels. Moreover, we compute complementarity relatedness for three groups of industries, namely manufacturing, services and natural resources, to investigate how different sectoral relatedness affects distinct microregions. Because of the diversity of local resources and more opportunities for knowledge flow, we expect stronger effects of relatedness in the most populated microregions.

Besides the relevance of a deep understanding of the dynamics of developing countries (Chauvin *et al*., 2017), analysing the structural change in microregions with large differences can shed light on the circumstances of relatedness matters. The next section presents the methodology and data used to compute all these indexes.

3. Methodology, data and relatedness density indexes

The main variables of interest are the relatedness density measures based on occupations and the regional economy. These are the local synergy, the complementarity and the similarity relatedness densities. To calculate them, we used information from two databases. The Annual Social Security Information Report (*Relação Anual de Informações Sociais* – RAIS), published by the Ministry of Economy in Brazil, is the main database providing information about the number of workers employed in 2 514 occupations required for 581 industries in 558 microregions. This database provides information about 50 million workers covered by social security, representing 65% of the Brazilian workforce (Ulyssea, 2018).

The second database is the adaptation of the Occupational Information Network (O*NET) to Brazil's current occupation classification (CBO). Maciente (2013) uses information from worker characteristics, worker requirements, experience requirements and occupational requirements to link the 263 attributes (skills) of occupations in the US to the Brazilian structure of jobs.

To estimate the degree of relatedness in all the dimensions employed in this article, we follow the method presented by Hidalgo *et al*. (2007). The strategy consists of counting how often two occupations are found together in the same microregion, employed by the same industry, and require the same skill to perform their tasks. Those calculations result in three relatedness-density indexes: geographical, industry, and skill relatedness. Those indexes are transformed further to obtain the local synergy, complementarity and similarity indexes, our main variables of interest.

To calculate the geographical relatedness, we have to identify in which occupations Brazilian microregions are specialised, using the location quotient ($LQ_{r,j}$).

$$LQ_{r,j,t} = \frac{x_{r,j,t}/\sum_j x_{r,j,t}}{\sum_r x_{r,j,t}/\sum_r \sum_j x_{r,j,t}}, \qquad (1)$$

where $x_{r,j,t}$ represents the number of occupation j's employees in microregion r at time t. Therefore, a microregion r that presents $LQ_{r,j,t} > 1$ is specialised in occupation j at time t, since the share of that occupation in the microregion is higher than the country's share. The degree of relatedness (φ) between two occupations comes from the lowest value of the conditional probability of a microregion specialising in an occupation class j, given that it is already specialised in occupation class o at time t.

$$\varphi_{j,o,t} = \min\{P(LQ_{j,t}|LQ_{o,t}), P(LQ_{o,t}|LQ_{j,t})\}, \qquad (2)$$

where the term $P(LQ_{j,t}|LQ_{o,t})$ represents the probability of a microregion r specialising in occupation j, given that it is specialised in occupation o.

We calculate the industry and skill-relatedness indexes by employing the revealed comparative advantage (RCA) index based on Balassa (1965), which is widely used in relatedness literature. To compute the industry-relatedness index, we select the most relevant occupations (those with $RCA > 1$) that industries employ in their operational processes. Equation (2) provides the joint probability that an industry s demanding both occupation classes j and o provides the degree of relatedness (φ) between those different classes. Likewise, the skill-relatedness degree (φ) between two occupations classes, j and o, is computed regarding the skills more relevant to perform tasks that they share (those skills with $RCA > 1$).

To link the three relatedness indexes with the regional economy, we compute the relatedness density index measuring the distance between an occupation class j and the existing occupational structure in a microregion r.

$$Relatedness\ density_{r,j,t} = \frac{\sum_{o \in r, j \neq o} \varphi_{j,o,t}}{\sum_{o \neq j} \varphi_{j,o,t}} \times 100, \qquad (3)$$

The relatedness density index ranges from 0% to 100%. If the value is 0%, the microregion r is not specialised in any occupation o that is related to occupation j at time t. Conversely, if the value is 100%, the microregion r is specialised in all occupation classes related to the occupation j. If a microregion r is currently specialised in most of the occupations related to an absent occupation j, the relatedness density of microregion r will be high, and so will be the probability of regional specialisation in occupation j in the future.

We need one more step to find all the indexes that we employ in the empirical tests. Following Farinha *et al*. (2019) and Neffke (2019), we have to regress a relatedness variable on the two remaining variables to find an index net of the other variables' effects. The geographical-, industry- and skill-relatedness measures are correlated, and all of them influence the regional specialisation. To disentangle the role of each variable in the evolution of jobs, we exclude the overlapping effects of those relatedness indexes through regression analysis. For example, to obtain the local synergy relatedness from geographical relatedness, we have to regress the latter variable on industry and skill relatedness using a three-way fixed-effects model for occupation (θ_j), microregion (δ_r) and time (τ_t). Thus, we save the residuals of the regression, $\varepsilon_{j,r,t}$, as the local synergy density measure.

$$Geographical\ relatedness\ density_{j,r,t} = \beta_1 \cdot Industry\ relatedness\ density_{j,r,t} + \beta_2 \cdot Skill\ relatedness\ density_{j,r,t} + \theta_j + \delta_r + \tau_t + \varepsilon_{j,r,t}, \quad (4)$$

And

$$Local\ synergy\ relatedness\ density_{j,r,t} = \varepsilon_{j,r,t}. \ (5)$$

Unlike Farinha *et al*. (2019), we also disentangled the effects of complementarity and similarity relatedness. Repeating the same calculation, we obtained the complementarity-relatedness density from a regression of industry relatedness on skill- and geographical-relatedness density, and the similarity-relatedness density from a regression of skill- on industry- and geographical-relatedness densities.

Therefore, local synergy density represents the distance between an occupation j and the current occupational specialisation of a microregion r in terms of sharing the same location and excluding the effects of the industry and skills relatedness. The same occurs for complementarity and similarity densities.

4. Econometric analyses

To formally test whether the three occupational-relatedness densities drive the evolution of the labour market in Brazil, we estimated some econometric equations. Equation (6) estimates whether a microregion r enters (exits) an occupational specialisation at time $t + 1$ in occupations that are related (less related) to its regional structure at time t.

$$SChange_{r,j,t+1} = \beta_1 \cdot Relatedness\ density_{r,j,t} + \beta_i \cdot Z_i + \theta_j + \delta_r + \tau_t + \varepsilon_{j,r,t}. \ (6)$$

In equation (6), the variables are defined as follows:

$SChange_{r,j,t+1} = [Entry_{r,j,t+1}, Exit_{r,j,t+1}]$

$Entry_{r,j,t+1} = 1$, if $LQ_{r,j,t+1} \geq 1$ and $LQ_{r,j,t} < 1$

$Exit_{r,j,t+1} = 1$, if $LQ_{r,j,t+1} < 1$ and $LQ_{r,j,t} \geq 1$

The term $Relatedness\ density_{r,j,t}$ represents the three indexes that we calculate, namely local synergy, complementarity and similarity-relatedness densities. The term Z_i represents control variables that can influence changes in the occupational specialisation. Three variables at the occupational level are included as a control. Using the method of reflections developed by Hidalgo and Hausmann (2009), we calculated the occupation complexity index. Complex occupations are those present simultaneously in a few and more diversified regions. We also added the total number of employees and the average wage of workers – both by occupation classes. At the regional level, we included the total number of employees as a proxy for the size of the local economy and the average wage of workers by microregions.

Since microregions and occupations have time-constant unobserved effects, the econometric specification is a three-way fixed-effects model[3] to deal with the problem of omitted variables. We estimated the equations using ordinary least square (OLS) regression and included dummy variables to control for time (τ_t), region (δ_r) and occupation (θ_j). Another econometric issue present is the fact that errors are correlated within groups of observations, such as microregions and occupations. For this reason, the regression results are adjusted using heteroskedasticity-robust standard errors clustered at the microregion and occupation level (Cameron *et al*., 2011; Wooldridge, 2003). Our panel consists of data for 2 514 occupation classes and 558 microregions over a period ranging from 2003 to 2018. We divided the period into four non-overlapping samples: 2003 to 2006, 2007 to 2010, 2011 to 2014, and 2015 to 2018, thus avoiding large variations that may have occurred in a specific year. As all the independent variables are lagged by one period, our panel has 4 053 870 observations.[4] To facilitate comparisons across estimates, we normalised all the non-binary variables by subtracting the mean and dividing by standard variation.

5. Results

5.1. Baseline model

The descriptive statistics and correlation of the variables are displayed in Table A1 and A2 in the Appendix. In the period of observation, there were 3 546 017 combinations in which a microregion could specialise in a new occupation and 159 415 events in which a microregion entered a new

[3] As an additional test, we estimated the regressions, including microregion-time and occupation-time fixed effects.
[4] The initial database consisted of 4 208 436 observations (2 514 × 558 × 3). However, some observations were not possible to compute for all the indexes, and for this reason those observations were excluded.

specialisation. As a result, we estimated the probability of a new regional specialisation to be 4.5%. The probability of exit specialisation was 25.9%, since there were 507 853 opportunities to exit and 131 468 exit events.

Table 1 – Entry and exit models

	Dependent variable					
	Entry at time t+1			Exit at time t+1		
	(1)	(2)	(3)	(4)	(5)	(6)
Local Synergy	0.035***	0.030***	0.031***	-0.062***	-0.053***	-0.053***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Complementarity	0.028***	0.025***	0.025***	-0.051***	-0.046***	-0.046***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Similarity	0.011***	0.009***	0.009***	-0.022***	-0.017***	-0.017***
	(0.0004)	(0.0005)	(0.0005)	(0.001)	(0.001)	(0.001)
Occupation Complexity			0.011***			-0.014
			(0.001)			(0.013)
Occupation Total Employment			-0.001			-0.016
			(0.002)			(0.012)
Occupation Wage			-0.004***			-0.015
			(0.001)			(0.020)
Region Total Employment			-0.006**			0.001
			(0.003)			(0.004)
Region Wage			-0.002			0.014**
			(0.002)			(0.006)
Observations	3,546,017	3,546,017	3,546,017	507,853	507,853	507,853
R^2	0.066	0.059	0.059	0.130	0.102	0.103
Adjusted R^2	0.063	0.058	0.058	0.114	0.097	0.097
Residual Std. Error	0.201	0.201	0.201	0.412	0.416	0.416

Note: Entry (Exit) takes a value equal to 1 if a microregion enters (exits) an occupational specialisation in the regional economic structure at time t+1, and 0 otherwise. All the non-binary variables are normalised by subtracting the mean and dividing by the standard deviation. Heteroskedasticity-robust standard errors (clustered at microregion and occupation level) are shown in parentheses. Columns (1) and (4) include microregion-time and occupation-time fixed effects. The other estimates include time, microregion, and occupational fixed-effects. Coefficients are statistically significant at * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Columns (1) to (3) in Table 1 present the results of the econometric analyses of the new occupational specialisation (entry), while columns (4) to (6) show the results for the extinct specialisations (exit) in the microregions. All three dimensions of occupational relatedness confirm our hypothesis that regional specialisation depends on the degree of relatedness between pairs of occupations: the higher the relatedness density, the higher the probability of specialisation in new occupations, and the smaller the likelihood of losing existing specialisation.

The stronger effect comes from the local synergy density, which emphasises the importance of spatial proximity for knowledge spillovers and the learning process of workers. An increase of one standard deviation in this variable increases the probability of a new microregion's occupational specialisation in a range from 3.0% to 3.5%. The local synergy effect is even bigger for preventing the exit of regional occupations, since an increase of one standard deviation decreases the probability of losing specialisation by between 5.3% and 6.2%. The occupational relatedness derived from the industries' complementary demand is associated with a higher probability of new specialisation (2.5% to 2.8%) and a decrease in the likelihood of exit (4.6% and 5.1%) when the variable is increased by one standard deviation. The similarity of occupations presents the weaker association with the microregion's structural change, since an increase of one standard deviation increases the probability of entry by 1.0% and decreases the probability of exit by 1.7% to 2.2%.

5.2. Regional and sectoral extensions

We extend the analysis to investigate whether the results found in the previous section remain the same for microregions with distinct population level and relatedness density computed from different economic sectors. Although several studies have confirmed the effects of related variety on the regional development path, there is little evidence showing under what conditions these effects matter (Boschma, 2017).

The first modification is to divide the microregions into two distinct groups, one with peripheral microregions encompassing the bottom 20% of less-populated microregions, and a second sample with the top 20% of most populated microregions, both in the period from 2003 to 2006. Each group has 112 microregions, and the former has an average population of 57 094 inhabitants, while the second group has an average population of 1 043 611 inhabitants. We aim to explore whether the effects of occupational relatedness increase with the population size of microregions (Kok and ter Weel, 2014; Shutters *et al.*, 2018), and whether the peripheral microregions also have the future structural change constrained by their current occupational structure. The second modification consists of including three more relatedness density indexes according to equations (1) to (3). We compute three additional indexes considering only the industries classified as Manufacturing, Services (excluding Public Administration), and Natural Resources (Agriculture and Mining and quarrying). We are interested in whether the effects of sectoral complementarity-relatedness density vary among differently populated microregions. Moreover, we include interaction terms between similarity and sectoral complementarity densities to account for the effects of occupations that have both characteristics simultaneously.

Tables 2 and 3 present the results of empirical analyses of the extended models regarding the peripheral and the most populated microregions, respectively. All the main variables of interest present the expected signs and are significant for the two groups of microregions. The local synergy density remains the most important variable influencing the structural change in both peripheral and large microregions.

Table 2 – Entry and exit models – Peripheral Microregions

	Dependent variable							
	Entry at time t+1				Exit at time t+1			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Local Synergy	0.034***	0.030***	0.028***	0.032***	-0.088***	-0.053***	-0.053***	-0.056***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.006)	(0.005)	(0.006)	(0.005)
Complementarity	0.028***	0.026***	0.025***	0.029***	-0.080***	-0.061***	-0.061***	-0.066***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.007)	(0.006)	(0.007)	(0.006)
Similarity	0.011***	0.008***	0.006***	0.009***	-0.027***	-0.011*	-0.014**	-0.015**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.005)	(0.006)	(0.006)	(0.007)
Manufacturing Relatedness		-0.003*				-0.013		
		(0.002)				(0.015)		
Services Relatedness			-0.001				-0.014	
			(0.002)				(0.016)	
Nat. Resources Relatedness				-0.002				-0.016
				(0.002)				(0.010)
Occupation Complexity		0.013***	0.009***	0.017***		-0.082**	-0.084***	-0.082**
		(0.002)	(0.001)	(0.002)		(0.032)	(0.030)	(0.033)
Occupation Total Employment		-0.0001	-0.001	0.001		-0.030*	-0.030*	-0.031*
		(0.003)	(0.003)	(0.003)		(0.016)	(0.016)	(0.016)
Occupation Wage		-0.008***	-0.004***	-0.009***		-0.020	-0.021	-0.017
		(0.002)	(0.001)	(0.002)		(0.049)	(0.045)	(0.051)
Region Total Employment		-0.427**	-0.377**	-0.506**		0.525	0.528	0.426
		(0.165)	(0.154)	(0.195)		(0.544)	(0.556)	(0.580)
Similarity x Manufacturing Relatedness		-0.0003				-0.006		
		(0.001)				(0.008)		
Similarity x Services Relatedness			-0.001				-0.015**	
			(0.001)				(0.007)	
Similarity x Nat. Resources Relatedness				0.001				-0.007
				(0.001)				(0.008)
Observations	756 718	665 792	742 068	523 517	56 962	55 376	56 940	52 947
R^2	0.082	0.068	0.070	0.067	0.241	0.155	0.157	0.153
Adjusted R^2	0.073	0.065	0.067	0.063	0.154	0.121	0.123	0.121
Residual Std. Error	0.158	0.165	0.160	0.179	0.413	0.419	0.420	0.418

Note: Entry (Exit) takes a value equal to 1 if a microregion enters (exits) an occupational specialisation in the regional economic structure at time t+1, and 0 otherwise. Peripheral microregions encompass the bottom 20% of less-populated microregions. All the non-binary variables are normalised by subtracting the mean and dividing by the standard deviation. Heteroscedasticity-robust standard errors (clustered at microregion and occupation level) are shown in parentheses. Columns (1) and (5) include microregion-time and occupation-time fixed effects. The other estimates include time, microregion, and occupational fixed-effects. Coefficients are statistically significant at * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

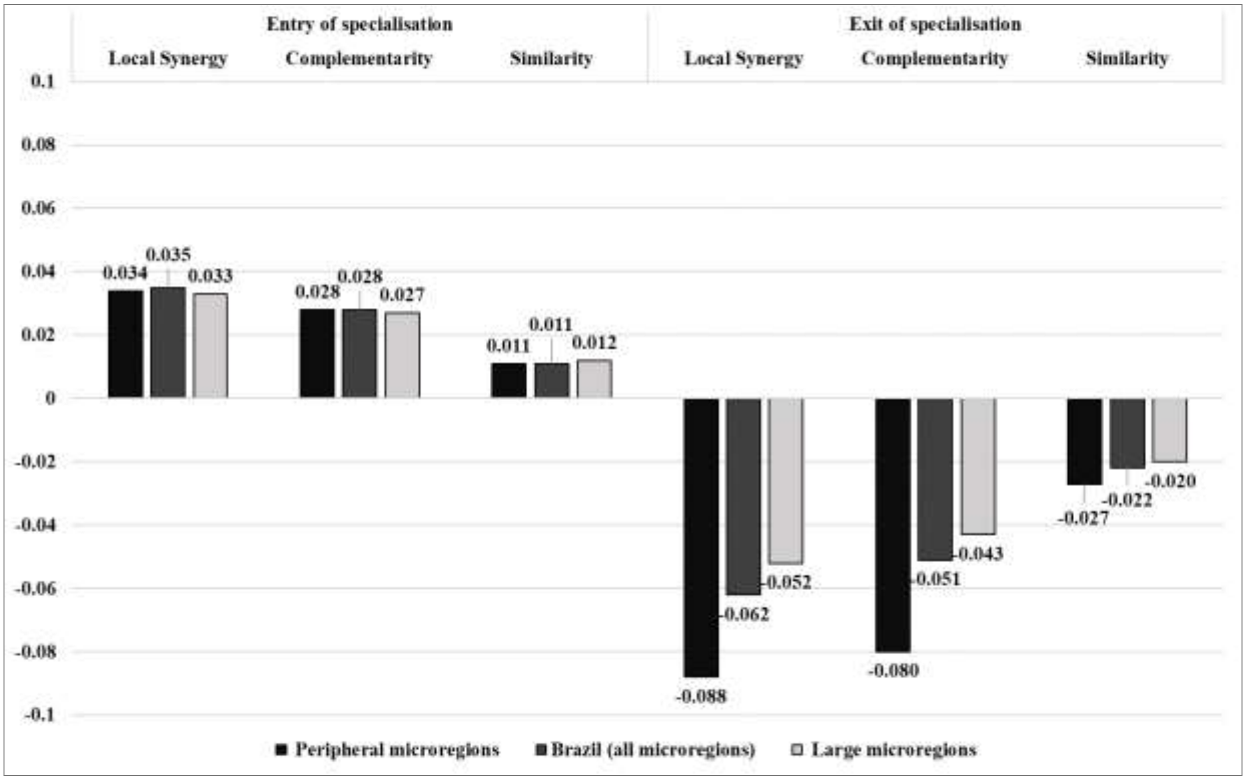
Table 3 – Entry and exit models – Large Microregions

	Dependent variable							
	Entry at time t+1				Exit at time t+1			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Local Synergy	0.033***	0.032***	0.032***	0.033***	-0.052***	-0.050***	-0.048***	-0.051***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
Complementarity	0.027***	0.026***	0.027***	0.027***	-0.043***	-0.039***	-0.036***	-0.040***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Similarity	0.012***	0.008***	0.008***	0.009***	-0.020***	-0.011***	-0.007**	-0.012***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)	(0.003)
Manufacturing Relatedness		0.002*				-0.010***		
		(0.001)				(0.004)		
Services Relatedness			-0.002				-0.016***	
			(0.002)				(0.004)	
Nat. Resources Relatedness				-0.001				-0.015***
				(0.001)				(0.003)
Occupation Complexity		0.001	0.002	0.002		0.049***	0.045***	0.041***
		(0.003)	(0.002)	(0.003)		(0.011)	(0.011)	(0.012)
Occupation Total Emp.		0.003	0.002	0.003		-0.014	-0.013	-0.014
		(0.003)	(0.003)	(0.003)		(0.010)	(0.010)	(0.010)
Occupation Wage		-0.002	-0.003	-0.002		-0.032**	-0.023	-0.035**
		(0.002)	(0.002)	(0.003)		(0.014)	(0.014)	(0.016)
Region Total Emp.		-0.004	-0.004*	-0.002		-0.001	0.001	-0.004
		(0.003)	(0.003)	(0.002)		(0.004)	(0.003)	(0.004)
Similarity x Manufacturing Relatedness		0.001***				-0.003***		
		(0.0003)				(0.001)		
Similarity x Services Relatedness			0.001***				-0.003**	
			(0.0003)				(0.001)	
Similarity x Nat. Resources Relatedness				0.001***				-0.003**
				(0.0004)				(0.001)
Observations	647 286	565 959	632 858	445 397	166 394	155 209	166 150	131 067
R^2	0.071	0.058	0.058	0.057	0.144	0.105	0.105	0.106
Adjusted R^2	0.060	0.054	0.054	0.053	0.103	0.091	0.091	0.091
Residual Std. Error	0.248	0.251	0.251	0.253	0.406	0.406	0.408	0.400

Note: Entry (Exit) takes a value equal to 1 if a microregion enters (exits) an occupational specialisation in the regional economic structure at time t+1, and 0 otherwise. Large microregions encompass the top 20% of less-populated microregions. All the non-binary variables are normalised by subtracting the mean and dividing by the standard deviation. Heteroscedasticity-robust standard errors (clustered at microregion and occupation level) are shown in parentheses. Columns (1) and (5) include microregion-time and occupation-time fixed effects. The other estimates include time, microregion, and occupational fixed-effects. Coefficients are statistically significant at * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Although the entry of a new specialisation depends on the relatedness densities, large microregions do not present any advantage compared to peripheral microregions. Conversely, in peripheral microregions, the effect of preventing the exit of specialisations increases when compared to the results found for the whole country, and even more when compared to the most populated microregions. Figure 1 plots the estimated coefficients for the whole country (baseline), peripheral and large microregions, and shows that the most pronounced differences are in the exit of specialisations.

Figure 1 – Estimated coefficients for entry of new and exit of old specialisations in different regional contexts



Source: Author's estimations

The inclusion of sectoral complementarity relatedness does not change the results for our original relatedness indexes, both in peripheral and large microregions, although its effects differ between two regional groups. In peripheral microregions (Table 2), an increase in the manufacturing complementary index reduces the probability of the emergence of a new occupational specialisation, and the services complementarity index increases the effects of the similarity density in preventing the exit of specialisations. In the largest microregions in Table 3, the manufacturing relatedness is positively associated with the emergence of new specialisations, and all three sectoral relatedness indexes increase the effects of the similarity density. Moreover, an increase in all three sectoral relatedness indexes reduces the likelihood of the regional extinction of a specialisation. A similar effect on the exit of occupations is observed when those variables interact with similarity density.

In sum, we can state five findings of our modifications in the baseline model. First, large and peripheral microregions do not present different estimates in relatedness densities for the entry of occupational specialisations. Second, different occupational relatedness measures are more important to prevent the extinction of old specialisations in peripheral regions than to create new ones. Third, manufacturing relatedness increases the probability of a new occupational specialisation in the most populated microregions but reduces it in the peripheral microregions. Fourth, higher sectoral relatedness indexes decrease the probability of occupational exit in large microregions. Finally, interaction terms between sectoral complementarities and similarity density present the expected signs for the largest microregions, and only the interaction with services relatedness reinforces the impact of similarity density in preventing occupational exit in peripheral microregions.

6. Discussion

The empirical analysis reveals consistent findings for the whole country and for different regional and sectoral contexts. First, the occupational relatedness, regardless of the source, influences both the emergence of new and the extinction of old occupational specialisation over time. Similar to the findings of Farinha *et al*. (2019) for the US labour market, the effects of relatedness seem to be stronger to prevent the exit of a microregion's occupations in Brazil. The effects of local synergy density on structural change emphasise the relevance of different capabilities localised in the same area to facilitate the knowledge flow between workers. Complementary density can be seen as a mechanism to gather the knowledge dispersed among different workers, manage the coordination costs, and increase the value of production. Thus, the pattern of demand for complementary occupations also influences the evolution of occupational structure in microregions. In turn, similarity density presents the weaker effects on the structural change, maybe because of its degree of substitution between pairs of occupations.

Although we have found some critical differences between microregions with different population levels, the scale effects of large microregions did not present any significant difference in the entry of new occupational specialisation compared to small areas. This result seems to confirm that the consistent effects of occupational relatedness found in several studies (Farinha *et al*., 2019; Muneepeerakul *et al*., 2013; Shutters *et al*., 2018) fit well into the Brazilian context, regardless of the region's size.

However, in terms of agglomeration economies, smaller microregions tend to benefit more from specialisation externalities, while diversity is more relevant for large microregions (Caragliu *et al*., 2016). In peripheral microregions, firms have to hire workers from a smaller labour market and rely more on internal resources to compensate for the lack of diversity (Eder, 2019). Moreover, other types of local proximity may be relevant, such as social proximity based on friendship and kinship (Boschma, 2005). The smaller the size of a microregion, the more relevant is the role played by firms in managing the coordination costs of production and linking complementary occupations. Thus, relatively few firms are able to coordinate a significant part of the local labour market, and cutting the workforce can be costly since there are not many workers who can substitute each other. These local characteristics allow specialisation in relatively few occupations that are essential to the regional economy. The extinction of an occupational specialisation therefore is more difficult in and costly for small microregions – one such exit can disarticulate the economic structure – than it is in larger and diversified microregions.

The results for different sectoral contexts also are linked to the differences in the regional context. Lack of economic diversity can explain the unexpected result of manufacturing relatedness in the peripheral microregions: an increase in that index reduces the probability of a new occupation entering those areas. In smaller microregions with a current occupational structure related to the manufacturing labour demand pattern, the likelihood of developing a new specialisation in the future is lower. In contrast, more complex activities such as manufacturing tend to agglomerate in more populated areas to benefit from a large labour market with more specialised workers. In these microregions, manufacturing seems to play its role as an engine of structural change due to its positive influence on new regional specialisation. This does not mean that manufacturing is not essential to peripherical microregions, but its effects on occupational structure seem to require some capabilities that are more easily found in large microregions with a certain degree of complexity and diversity.

Although not significant alone, the interaction between service relatedness and similarity density improves the importance of the latter in preventing the extinction of occupational specialisation in peripheral microregions. In other words, workers sharing the same skills are more valuable to the maintenance of small local economies when the services sector is coordinating the complementary demand for workers.

Large microregions have a higher probability of finding both complementary and substitute occupations, since workers benefit from agglomerating in those regions. Regardless of the sector, a great labour market pool facilitates firms to hire workers with adequate skills to adapt to changes in production or economic transitions, reducing the likelihood of extinguishing occupation classes. Thus, all three sectoral-relatedness indexes present a negative relationship with the probability of occupations leaving large microregions. Moreover, distinct ways of solving the knowledge dispersion across workers (through sectoral-complementary demand) augment the value of similarity density in microregions, with a high probability of finding a larger pool of substitute workers.

7. Conclusion

We investigated the effects of three different relatedness indexes on the evolution of occupational structure in 558 Brazilian microregions. Our findings support the relatedness literature in which the related variety influences the emergence and extinction of occupational specialisations at the regional level. We considered the individual worker as the main repository of knowledge and looked at the spatial proximity (local synergy) as an enabling factor for a better flow of knowledge among workers. Furthermore, we studied the other two sources of relatedness between occupations, namely the complementarity relatedness stemming from pairs of occupations that are jointly demanded by the same industry, and the similarity relatedness originating from the same skill being shared by two different occupations.

The stronger explanatory effects on occupational structure come from the local synergy density, emphasising the role played by local capabilities. The second most important factor influencing structural change is the complementarity density. This source emphasises the relevance of industries in gathering diverse types of knowledge dispersed among individual workers and their capacity to coordinate those workers to produce valuable output. Finally, a weaker effect comes from the similarity density. All of these seem to be more significant in preventing the extinction of old specialisations rather than the emergence of new ones.

We extended the analysis to encompass different regional and sectoral contexts. The most populated microregions did not show any advantage in introducing a new occupational specialisation compared to peripheral areas. This result confirms that consistent effects of related variety on the evolution of occupational structure hold for a developing-country context. The regional context differs in preventing the extinction of jobs once the effects are stronger for the peripheral microregions when compared to the whole country and especially to large microregions. Specialisation in a few industries seems to play a role in explaining this result, since it is more costly for peripheral microregions to extinguish occupations that are at the core of the local economy. In addition, a few firms coordinating the production process are more able to influence the maintenance of occupation classes in small regions. Moreover, social proximity based on friendship and kinship may be relevant.

In terms of sectoral contexts, the effects of manufacturing, services, and natural resources relatedness are significant in preventing the exit of occupations from the most populated microregions. Moreover, they increase the effects of similarity density in these microregions. The complementarity role played by manufacturing presented a mixed result: in large microregions, relatedness density increases the likelihood of the emergence of a new occupational specialisation, while the opposite occurs in smaller microregions. This result may indicate that larger microregions already possess the basic requirements for manufacturing development, which less-populated microregions do not yet have. The indexes based on services and natural resources relatedness do not influence occupational specialisation in smaller microregions, except for the interaction term between services relatedness and similarity density, which reduces the likelihood of exit.

Our results contribute to the relatedness literature by expanding the empirical tests to investigate whether the findings in developed countries hold for a complex and highly unequal developing country such as Brazil. It also contributes by expanding the analysis and verifying whether the results remain the same for different regional and sectoral contexts, and under which conditions relatedness matters for the structural change (Boschma, 2017).

This article also has policy implications, as it provides a rationale for the development of regional policies that should look at occupations related to the region's current specialisation, instead of promoting 'one-size-fits-all' policies and activities that are far from meeting local capabilities. Our findings highlight that policies should fit into regional and sectoral contexts, especially in a developing country marked by huge internal disparities. The diversity of resources located in large microregions may require policies oriented to new specialisations linked to related industries that are more complex, while poorly diversified microregions certainly require policies that prevent firms from becoming locked in in stagnant industries. Future research could focus on how related variety can contribute to the development of poor regions and how to prevent them from being left behind by highly diversified regions.

References

Alabdulkareem, A., Frank, M.R., Sun, L., AlShebli, B., Hidalgo, C., Rahwan, I. (2018) Unpacking the polarization of workplace skills. **Science Advances**, 4(7): eaao6030.

Anderson, K.A. (2017) Skill networks and measures of complex human capital. **Proceedings of the National Academy of Sciences**, 114(48): 12720–12724.

Balassa, B. (1965) Trade liberalisation and 'revealed' comparative advantage. **The Manchester School**, 33(2): 99–123.

Balland, P.-A., Rigby, D. (2017) The geography of complex knowledge. **Economic Geography**, 93(1): 1–23.

Boschma, R. (2005) Proximity and innovation: a critical assessment. **Regional Studies**, 39(1): 61–74.

Boschma, R. (2017) Relatedness as driver of regional diversification: a research agenda. **Regional Studies**, 51(3): 351–364.

Boschma, R., Frenken, K. (2012) Technological relatedness and regional branching. In H. Bathelt, M. P. Feldman and D. F. Kogler (eds) **Beyond Territory:** Dynamic Geographies of Innovation and Knowledge Creation. London: Routledge doi:10.4324/9780203814871-11.

Cameron, A.C., Gelbach, J.B., Miller, D.L. (2011) Robust inference with multiway clustering. **Journal of Business & Economic Statistics**, 29(2): 238–249.

Caragliu, A., de Dominicis, L., de Groot, H.L.F. (2016) Both Marshall and Jacobs were right! **Economic Geography**, 92(1): 87–111.

Chauvin, J.P., Glaeser, E., Ma, Y., Tobio, K. (2017) What is different about urbanization in rich and poor countries? Cities in Brazil, China, India and the United States. **Journal of Urban Economics**, 98: 17–49.

Diodato, D., Neffke, F., O'Clery, N. (2018) Why do industries coagglomerate? How Marshallian externalities differ by industry and have evolved over time. **Journal of Urban Economics**, 106: 1–26.

Eder, J. (2019) Innovation in the periphery: a critical survey and research agenda. **International Regional Science Review**, 42(2): 119–146.

Eder, J., Trippl, M. (2019) Innovation in the periphery: compensation and exploitation strategies. **Growth and Change**, 50(4): 1511–1531.

Farinha, T., Balland, P.-A., Morrison, A., Boschma, R. (2019) What drives the geography of jobs in the US? Unpacking relatedness. **Industry and Innovation**, 26(9): 988–1022.

Frenken, K., Boschma, R.A. (2007) A theoretical framework for evolutionary economic geography: industrial dynamics and urban growth as a branching process. **Journal of Economic Geography**, 7(5): 635–649.

Gertler, M.S. (2003) Tacit knowledge and the economic geography of context, or The undefinable tacitness of being (there). **Journal of Economic Geography**, 3(1): 75–99.

Glaeser, E.L., Resseger, M.G. (2010) The complementarity between cities and skills. **Journal of Regional Science**, 50(1): 221–244.

Grillitsch, M., Nilsson, M. (2015) Innovation in peripheral regions: do collaborations compensate for a lack of local knowledge spillovers? **The Annals of Regional Science**, 54(1): 299–321.

Hane-Weijman, E., Eriksson, R.H., Rigby, D. (2020) How do occupational relatedness and complexity condition employment dynamics in periods of growth and recession? **Papers in Evolutionary Economic Geography** (PEEG), No. 2011, Department of Human Geography and Spatial Planning, Economic Geography Group, Utrecht University.

Hidalgo, C.A., Hausmann, R. (2009) The building blocks of economic complexity. **Proceedings of the National Academy of Sciences**, 106(26): 10570–10575.

Hidalgo, C.A., Klinger, B., Barabási, A.-L., Hausmann, R. (2007) The product space conditions the development of nations. **Science**, 317(5837): 482–487.

IBGE - Instituto Brasileiro de Geografia e Estatística (2019) **Sistema de contas nacionais**: Brasil 2017. Rio de Janeiro: IBGE.

Ipeadata. Accessed: 7th August 2020 <http://www.ipeadata.gov.br/Default.aspx. >.

Isaksen, A. (2015) Industrial development in thin regions: trapped in path extension? **Journal of Economic Geography**, 15(3): 585–600.

Jones, B.F. (2009) The burden of knowledge and the "death of the renaissance man": is innovation getting harder? **The Review of Economic Studies**, 76(1): 283–317.

Kok, S., ter Weel, B. (2014) Cities, tasks, and skills. **Journal of Regional Science**, 54(5): 856–892.

Maciente, A.N. (2013) **The determinants of agglomeration in Brazil**: input-output, labor and knowledge externalities. Dissertation Graduate College of the University of Illinois at Urbana-Champaign, Illinois.

Maskell, P., Malmberg, A. (1999) Localised learning and industrial competitiveness. **Cambridge Journal of Economics**, 23(2): 167–185.

Muneepeerakul, R., Lobo, J., Shutters, S.T., Goméz-Liévano, A., Qubbaj, M.R. (2013) Urban economies and occupation space: can they get "there" from "here"? **PLOS ONE**, 8(9): e73676.

Neffke, F. (2019) The value of complementary co-workers. **Science Advances**, 5(12): 1-11.

Neffke, F., Henning, M. (2013) Skill relatedness and firm diversification. **Strategic Management Journal**, 34(3): 297–316.

Nooteboom, B. (2000) Learning by interaction: absorptive capacity, cognitive distance and governance. **Journal of Management and Governance**, 4(1): 69–92.

Nooteboom, B. (2001) **Learning and Innovation in Organizations and Economies**. Oxford: Oxford University Press.

Rodríguez-Pose, A., Wilkie, C. (2019) Innovating in less developed regions: what drives patenting in the lagging regions of Europe and North America. **Growth and Change**, 50(1): 4–37.

Rodrik, D. (2016) Premature deindustrialization. **Journal of Economic Growth**, 21(1): 1–33.

Shutters, S.T., Lobo, J., Muneepeerakul, R., Strumsky, D., Mellander, C., Brachert, M., Farinha, T., Bettencourt, L.M.A. (2018) Urban occupational structures as information networks: the effect on network density of increasing number of occupations. **PLOS ONE**, 13(5).

Shutters, S.T., Muneepeerakul, R., Lobo, J. (2016) Constrained pathways to a creative urban economy. **Urban Studies**, 53(16): 3439–3454.

Szirmai, A., Verspagen, B. (2015) Manufacturing and economic growth in developing countries, 1950–2005. **Structural Change and Economic Dynamics**, 34: 46–59.

Tregenna, F., Andreoni, A. (2020) Deindustrialisation reconsidered: structural shifts and sectoral heterogeneity. **IIPP Working Paper Series** (WP 2020-06), Institute for Innovation and Public Purpose, University College London.

Ulyssea, G. (2018) Firms, informality, and development: theory and evidence from Brazil. **American Economic Review**, 108(8): 2015–2047.

Wixe, S., Andersson, M. (2017) Which types of relatedness matter in regional growth? Industry, occupation and education. **Regional Studies**, 51(4): 523–536.

Wooldridge, J.M. (2003) Cluster-sample methods in applied econometrics. **American Economic Review**, 93(2): 133–138.

Appendix

Table A1 – Descriptive statistics

Statistic	N	Mean	St. Dev.	Min	Pctl (25)	Pctl (75)	Max
All microregions							
Entry	3 546 017	0.04	0.2	0	0	0	1
Exit	507 853	0.3	0.4	0	0	1	1
Local Synergy	4 053 870	0.0	3.1	-41.3	-1.6	1.4	83.5
Complementarity	4 053 870	0.0	2.6	-42.3	-1.4	1.3	45.2
Similarity	4 053 870	0.0	2.0	-22.7	-1.1	1.1	26.0
Occup. Complexity	4 053 870	43.4	15.2	0.0	33.1	52.7	100.0
Occup. Total Emp.	4 053 870	16 129	87 282	1	334	6 428	2 266 479
Occupation Wage	4 053 870	5.2	5.8	0.3	2.0	6.0	72.2
Region Total Emp.	4 053 870	72 565	289 950	240	8 651	46 733	6 022 172
Region Wage	4 053 870	2.2	0.7	1.0	1.7	2.5	8.0
Manufacturing Relat.	3 592 962	15.1	8.1	0.0	8.9	19.7	84.3
Services Relat.	3 980 772	13.1	7.5	0.0	7.6	17.2	80.1
Nat. Resources Relat.	2 872 026	17.0	8.3	0.0	10.6	22.2	77.8
Population	4 053 870	326 795	849 857	2 250	95 163	280 288	13 387 106
Peripheral microregions							
Entry	756 718	0.03	0.2	0	0	0	1
Exit	56 962	0.3	0.4	0	0	1	1
Local Synergy	813 680	0.0	2.0	-16.5	-1.2	1.2	26.2
Complementarity	813 680	0.0	1.7	-13.3	-1.0	0.9	26.0
Similarity	813 680	0.0	1.3	-11.2	-0.9	0.9	7.5
Region Total Emp.	813 680	6 536	4 841	240	3 175	8 762	29 464
Region Wage	813 680	2.0	0.5	1.0	1.7	2.2	5.0
Manufacturing Relat.	721 168	9.1	4.6	0.0	5.6	12.1	44.2
Services Relat.	799 008	7.3	3.8	0.0	4.4	9.9	44.3
Nat. Resources Relat.	576 464	11.0	5.4	0.0	6.9	14.6	56.3
Population	813 680	57 094	17 721	2 251	44 344	70 910	82 778

Large microregions							
Entry	647 286	0.1	0.3	0	0	0	1
Exit	166 394	0.2	0.4	0	0	0	1
Local Synergy	813 680	0.0	4.9	-41.3	-2.1	2.4	80.0
Complementarity	813 680	0.0	4.1	-42.3	-2.1	1.9	45.2
Similarity	813 680	0.0	3.1	-22.7	-1.6	1.5	26.0
Region Total Emp.	813 680	277 362	603 982	11 338	66 097	248 169	6 022 172
Region Wage	813 680	2.7	0.9	1.3	2.0	3.2	7.4
Manufacturing Relat.	721 168	23.4	9.3	0.0	16.9	29.0	84.3
Services Relat.	799 008	21.2	8.8	2.0	15.1	26.5	80.1
Nat. Resources Relat.	576 464	24.7	8.9	0.0	18.3	30.6	77.8
Population	813 680	1 043 611	1 712 159	339 308	407 459	941 946	13 387 106

Source: Author’s estimations

Table A2 – Correlation

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]
[1] Entry	1												
[2] Exit		1											
[3] Occup. Complexity	-0.11	0.09	1										
[4] Region Total Emp.	0.04	-0.04	0.00	1									
[5] Occup. Total Emp.	0.03	-0.07	-0.17	0.00	1								
[6] Region Wage	0.06	-0.03	-0.01	0.40	0.00	1							
[7] Occupation Wage	-0.03	0.04	0.25	0.00	-0.06	0.01	1						
[8] Local Synergy	0.04	-0.06	-0.05	0.00	0.00	0.01	0.00	1					
[9] Similarity	-0.01	0.02	0.00	0.00	0.00	0.00	0.00	-0.01	1				
[10] Complementarity	0.04	-0.07	0.02	0.00	0.00	0.01	0.00	-0.41	-0.43	1			
[11] Manufacturing Relat.	0.09	-0.10	-0.04	0.44	0.00	0.60	-0.04	0.01	0.00	0.18	1		
[12] Services Relat.	0.11	-0.10	-0.05	0.46	0.02	0.61	-0.03	0.00	0.06	0.20	0.90	1	
[13] Nat. Resources Relat.	0.07	-0.09	0.00	0.37	-0.01	0.58	-0.07	-0.01	0.03	0.12	0.87	0.86	1

Source: Author's estimations