Area Development and Policy

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/rard20

Types of occupational relatedness and branching processes across Brazilian regions

Jefferson R. B. Galetti, Milene Simone Tessarin & Paulo César Morceiro

AREA DEVELOPMENT AND POLICY
2024, VOL. 9, NO. 1, 1–23
https://doi.org/10.1080/23792949.2022.2117217

RESEARCH ARTICLE

Types of occupational relatedness and branching processes across Brazilian regions

Jefferson R. B. Galetti [a,b], Milene Simone Tessarin [c,d] and Paulo César Morceiro [b,d]

ABSTRACT

This article draws on a large occupational database of 2514 occupations required for 581 industries in 558 microregions and five macroregions in Brazil and shows that occupational relatedness is associated with regional occupational branching (entry of related and exit of unrelated occupations) in a developing country marked by enormous regional disparities. Three types of occupational relatedness were examined: local synergy-, complementarity- and similarity-relatedness densities. Local synergy- and complementarity-relatedness densities were most closely associated with regional branching, and were more relevant to preventing the decline of specializations than promoting the emergence of new ones. All types of relatedness were more closely associated with preventing the disappearance of occupations from the most backward regions.

ARTICLE HISTORY

Received 27 January 2021; Accepted 21 August 2022

KEYWORDS

occupational relatedness, branching process, related variety, Brazil, developing country

摘要

巴西各地区职业关联类型和分支过程。*Area Development and Policy*. 本文利用巴西558个微观区域和5个宏观区域中581个行业所需的2514个职业的大型职业数据库, 表明在一个区域差异巨大的发展中国家, 职业关联性与区域职业分支 (相关职业的进入和不相关职业的退出) 相关。本文研究了三种类型的职业相关性: 地方协同性密度、互补性密度和相似相关性密度。地方协同和互补相关密度与区域分支关系最为密切, 与促进新专业化出现相比, 地方协同和互补相关密度与防治专业化下降的关联性更大。所有类型的相关性都与防止最落后地区的职业消失密切相关。

关键词

职业关联性, 分支过程, 相关种类, 巴西, 发展中国家

CONTACT Jefferson R. B. Galetti jefferson.galetti@universityofgalway.ie

[a]Whitaker Institute for Innovation and Societal Change, University of Galway, Galway, Ireland

[b]DSI/NRF South African Chair in Industrial Development, College of Business and Economics, University of Johannesburg, Johannesburg, South Africa

[c]Department of Human Geography and Spatial Planning, Faculty of Geosciences, Utrecht University, Utrecht, the Netherlands

[d]Department of Economics, University of Sao Paulo Regional and Urban Economics Lab – NEREUS, Sao Paulo, Brazil

Supplemental data for this article can be accessed at https://doi.org/10.1080/23792949.2022.2117217

RESUMEN

Tipos de proximidad ocupacional y procesos de ramificación en las regiones brasileñas: Types of occupational relatedness and branching processes across Brazilian regions. *Area Development and Policy*. Este artículo utiliza una grande base de datos de 2514 ocupaciones requeridas por 581 industrias en 558 microrregiones y cinco macrorregiones en Brasil; y muestra que la proximidad ocupacional está asociada con el proceso regional de ramificación ocupacional (entrada de ocupaciones relacionadas y salida de ocupaciones no relacionadas), en un país en desarrollo marcado por enormes disparidades regionales. Fueron analizados tres tipos de densidades de proximidad ocupacional: sinergia local, complementariedad y similitud. Las densidades de sinergia local y complementariedad estarían estrechamente asociadas con el proceso de ramificación regional, y serían más importantes para prevenir la salida de especializaciones, en lugar de estimular el surgimiento de estas. Todos los tipos de proximidad estarían relacionados con evitar la destrucción de ocupaciones en las regiones más atrasadas.

PALABRAS CLAVE

proximidad ocupacional, proceso de ramificación, variedad relacionada, Brasil, país en desarrollo

АННОТАЦИЯ

Типы профессиональных связей и процессы ветвления в регионах Бразилии. *Area Development and Policy*. В этой статье используется большая база данных для 2514 профессий, существующих в 581 отрасли в 558 микрорегионах и пяти макрорегионах Бразилии, чтобы показать, что профессиональное родство связано с региональным профессиональным ветвлением (приходом родственных профессий и исчезновением несвязанных профессий) в развивающейся стране, отмеченной огромными региональными различиями. Были исследованы три типа профессионального родства: плотность локальной синергии, взаимодополняемость и сходство. Местные показатели синергии и взаимодополняемости были наиболее тесно связаны с региональным ветвлением и имели большее значение для предотвращения сокращения специализаций, чем для содействия появлению новых. Все виды родства были более тесно связаны с предотвращением исчезновения профессий в наиболее отсталых регионов.

КЛЮЧЕВЫЕ СЛОВА

профессиональное родство, процесс ветвления, родственное разнообразие, Бразилия, развивающаяся страна

1. INTRODUCTION

Several studies have demonstrated the importance of related variety for the development of regional economies, which then influence growth (Frenken et al., 2007), knowledge creation (Kogler et al., 2013), employment growth (Firgo & Mayerhofer, 2018) and local branching (Boschma, 2022; Neffke et al., 2011). Related activities draw on similar capabilities that tend to enhance knowledge spillovers and the probability of learning from each other, providing opportunities for and constraints on knowledge recombination and the emergence and disappearance of activities over time (Boschma et al., 2013). With the payment of increasing attention to human capital and skills (Beckouche, 1991; Beckouche et al., 1988), scholars have focused on occupations as a useful complement for the analyses based on sectors and firms to understand regional development (Barbour & Markusen, 2007; Feser, 2003; Thompson & Thompson, 1985).

In the context of this article, occupational relatedness is derived from sharing similar knowledge that stems from different dimensions and creates different types of relatedness, such as their skill content, degree of complementary of tasks and other factors associated with local agglomeration economies (Farinha et al., 2019; Neffke, 2019; Wixe & Andersson, 2017). Relatedness increases with the similarity between occupations and influences the region's structural change through a branching process, in which new occupations grow out of existing, related ones, and pre-existing, unrelated occupations decline through endogenous dynamics at a local level (Frenken & Boschma, 2007). Thus, branching is a path-dependent process, since future occupational trajectories are built on the current occupational structure. It is linked to related diversification[1] and increases variety to some degree, because new occupations are similar but not the same as the existing ones.

Branching processes depend on the existing knowledge-related variety (Frenken & Boschma, 2007), and benefit from agglomeration economies existing in both diversified cities (Glaeser et al., 1992) and from thick and diversified regional innovation systems (Isaksen & Trippl, 2016), which are characteristics mainly associated with developed countries. However, there is still little understanding of whether and how relatedness affects this process across different regions in developing countries (Whittle & Kogler, 2020). These countries are marked by high rates of labour market informality (Almeida & Carneiro, 2012; Ulyssea, 2018), weak educational and institutional support structures (Hanushek, 2013), and less complex and diversified economic structures (Hartmann et al., 2017; Imbs & Wacziarg, 2003), usually concentrated in a few regions (Henderson, 2002). This enhances disparities within their borders, and hinders knowledge spillovers and recombinations of related occupations (Eder & Trippl, 2019). These characteristics are expected to distribute knowledge variety unevenly across different regions, affecting the relationship between occupational relatedness and the branching process.

With this in mind, the aim of this research was to provide evidence for the process of branching in a developing country by investigating the relationship between occupational relatedness and the emergence and decline of occupational specializations in Brazilian microregions, emphasizing regional disparities and types of relatedness. To achieve this objective, the research proposed to answer three questions.

First, is the occupational relatedness associated with regional branching in a developing country with less knowledge-related variety? Brazil is certainly an interesting case for understanding the dynamics of relatedness in a developing country. It is a continental country in which economic activities and population are unevenly distributed. Regional inequalities can be observed in per capita income, educational levels, access to public services, innovation and research and development (R&D) activities, and labour market conditions. The South and Southeast areas of the country contain most of the population, production and skilled workers, and have the best educational and physical infrastructure. Modern services and manufacturing are also concentrated in the Southern areas, while modern agriculture and natural resource-based activities are localized in the North and Midwest regions.

Second, do these different regional contexts affect the dynamics between occupational relatedness and branching? In developing countries with an uneven distribution of activities, it is particularly relevant to know whether different local economies can transform themselves by relying on their existing capabilities. A better understanding of the role of relatedness in potential future branching paths is crucial for developing place-based policies, which consider factors related to local capabilities, economic structure and workers' skills as a guide for policy interventions.

Third, are different types of occupational relatedness equally associated with branching across distinct regional contexts? Data from a detailed database with information on 2514 occupations and 558 Brazilian microregions was used to compute three types of relatedness between occupations (after Farinha et al., 2019) and assess their relationship with the branching process: local synergy relatedness based on the geographical co-location of occupations; complementarity relatedness, measured by the frequency at which an industry jointly demands pairs of occupations; and similarity relatedness, which accounts for the required skills shared by occupations.

Our contribution to the literature is threefold. First, a developing country is analysed in order to fill a gap deriving from the fact that the occupational relatedness literature is focused mainly on developed countries (Farinha et al., 2019; Hane-Weijman et al., 2021; Shutters et al., 2016). Second, the research focused on heterogeneity across regions to understand whether local characteristics are expected to influence the branching process differently (Boschma, 2017; Xiao et al., 2018). Third, evidence is provided disentangling three types of occupational relatedness (Farinha et al., 2019; Wixe & Andersson, 2017) and their association with occupational recombination in the Brazilian labour market. In contrast with our approach, previous studies of relatedness in Brazil investigated the performance of firms (Jara-Figueroa et al., 2018), industries (Galetti et al., 2021), goods (Alonso & Martín, 2019) and university–industries collaboration (Garcia et al., 2018). To the best of our knowledge, this is the first work addressing the relationship between relatedness and occupational branching in the Brazilian labour market.

The article proceeds with a theoretical discussion of the association between distinct types of occupational relatedness and path-dependent regional branching. It also includes an overview of the regional disparities in the Brazilian economy, and elaborates on how the role of relatedness can differ according to local characteristics. Next, a description of the data and the methods used is provided. The fourth section introduces an econometric model, while the fifth section presents the results. In the following section, we discuss the results and their association with regional issues. The seventh section presents the robustness tests. Finally, the last section concludes and provides some policy implications.

2. THEORETICAL BACKGROUND

2.1. Occupational relatedness and regional branching

The process of recombining different knowledge in order to create new activities, which in turn will substitute for pre-existing ones, has a long tradition in economics (Schumpeter, 1942; Weitzman, 1998). Recently more attention has been paid to the role of human capital in processes of learning, recombination of knowledge and structural transformation of regional economies (Acs et al., 2012; Beckouche, 1991). In addition, since the spatial division of labour changes and activities are relocated, occupations employed by the same industry may vary across regions. This approach has redirected the focus to the capabilities and skills of the labour force as a complement to studies based on firms and industries (Feser, 2003; Thompson & Thompson, 1985).

Knowledge recombination in workplaces may occur more effectively when occupations are related (Farinha et al., 2019; Hane-Weijman et al., 2021; Wixe & Andersson, 2017). Workers in occupations with related knowledge sets facilitate spillovers through continuous on-the-job and social interactions (Nooteboom, 2000), enhancing the processes of learning, recombining, creating and diffusing new types of knowledge in and through processes of doing and interacting, thereby improving skills and competencies through routines, as well as by integrating tacit and technical knowledge (Muneepeerakul et al., 2013; Shutters et al., 2016). As a result, the transformation of regional economies over time is conditioned by the existing related variety of occupational specializations in a path-dependent branching process in which new occupations emerge out of those already present in local economies. At the same time, relatedness also influences the disappearance of unrelated occupations (Frenken & Boschma, 2007).

Relatedness encompasses the role of distance in successful knowledge spillovers across occupations. The geographical proximity of actors emphasizes an essential role of local synergy in providing more opportunities for unplanned and face-to-face interactions that will enhance knowledge spillovers and learning (Bathelt et al., 2004; Maskell & Malmberg, 1999; Storper & Venables, 2004). For these reasons, actors located in the same place benefit from location-specific externalities to recombine knowledge and transform the economic structure (Muneepeerakul et al., 2013; Shutters et al., 2016).

However, other types of proximity also allow the formation of relatedness between occupations based on other distances than the geographical one (Boschma, 2005; Torre & Rallet, 2005). Scholars have assessed mechanisms of occupational relatedness using workers' skills similarity and the complementary demand for workers. In the case of skill similarity, pairs of occupations are related because they draw upon similar types and levels of skill used to perform a multitude of tasks (Farinha et al., 2019). These occupations are employed jointly to enhance learning within specific tasks based on skills that may overlap and substitute to some degree for one another. In addition, occupations are related if they perform interdependent tasks and complement each other in a way that what a worker knows is enhanced by what his or her co-workers also know (Neffke, 2019).

In sum, local synergy, similarity and complementary relatedness are expected to influence the future paths of regional branching. In the light of these considerations, two hypotheses were formulated in relation to the Brazilian case:

Hypothesis 1: *The probability of regions developing new occupations (entry) related to their current specialization is higher than the likelihood of developing unrelated occupations.*

Hypothesis 2: *The probability of regions extinguishing pre-existing occupations (exit) unrelated to their current specialization is higher than the likelihood of extinguishing related occupations.*

2.2. Stylized facts about Brazilian regional disparities

Processes of branching are expected to occur mainly in regions with a large variety of knowledge available for recombination (Frenken & Boschma, 2007; Isaksen & Trippl, 2016), but little is known about how relatedness influences this process in developing countries (Boschma, 2017; Whittle & Kogler, 2020).

Distinct levels of knowledge variety and innovation capacity in Brazil offer an ideal context to provide evidence on those aspects. Brazil is a continental country with 210 million inhabitants, and has one of the highest income inequality levels in the world. Disparities across regions are also high, since the average personal income in the Southern parts of the country was 1.8 times higher than in the Northern areas in 2013 (Barufi et al., 2016). The Southeast and South regions account for 56.5% of the population, 71.3% of the GDP and 75.8% of manufacturing production (Barufi et al., 2016; De Araújo et al., 2019). Despite some recent deconcentration in income per capita, industrial output and manufacturing employment clear polarization remained observable between the rich South–Southeast and the poor North–Northeast (Campolina Diniz & Vieira, 2016; Resende et al., 2016).

The regional dualism in Brazil persists in the long run (Reis, 2014), since the distribution of personal, cognitive and analytical skills is concentrated in industrial areas with larger markets (Ehrl & Monasterio, 2019). A total of 67% of all formal workers are concentrated in the Southern regions, despite the higher growth rate of formal workers in the Northern and Midwest areas between 2003 and 2014. In terms of employment by economic activities, the

Southeast region accounts for half of all industrial employment, while the North region accounts for just 3.7% (de Macedo & Porto, 2021). The North and Midwest have advantages in resource-based industries, although long distances and the poor quality of roads adversely affect their competitiveness. The concentration patterns in the Southeast provide agglomeration economies that favour the emergence and development of manufacturing activities (Azzoni & Haddad, 2018) with higher levels of economic complexity (Herrera et al., 2021).

These persistent regional disparities produce different levels of knowledge-related variety that may affect the association between occupational relatedness and regional branching usually found in developed countries. A few studies focused on Brazil indicate that relatedness matters for development in the whole country. Jara-Figueroa et al. (2018) found that the performance of pioneer firms improves when they hire workers with experience in related industries and work experience in the same location, but did not find evidence that it matters that workers have past experience in related occupations. Alonso and Martín (2019) found product relatedness density is associated with the emergence of new products, but the relatedness calculated from the country's imports was not statistically significant, probably because of the low level of Brazilian firms' participation in global value chains. Taking on board the regional dimension, Galetti et al. (2021) found that skill relatedness is associated both with the entry and growth of industries in most advanced microregions and tends more effectively to prevent exit from smaller regions.

However, these studies focused on products, firms and industries rather than on occupational relatedness and did not ask whether regional disparities affect occupational branching processes. As the South and Southeast have more knowledge-related variety available for recombination, while the North, Northeast and Midwest suffer from a lack of variety and weak agglomeration externalities that may result in a reduced knowledge base and few recombination opportunities (Eder & Trippl, 2019), two further hypotheses were adopted:

Hypothesis 3: *The probability of developing new, specialized occupations (entry) related to current regional specialization is higher in the South–Southeast regions than in the North–Northeast–Midwest areas of the country.*

Hypothesis 4: *The probability of extinguishing occupational specializations (exit) related to current regional specialization is lower in the South–Southeast areas compared with the North–Northeast–Midwest regions.*

3. METHODOLOGY, DATA AND RELATEDNESS DENSITY INDEXES

The main variables of interest are the three types of occupational relatedness: local synergy-, complementarity- and similarity-relatedness densities. To calculate them, two databases were used. The first was the Annual Social Security Information Report (*Relação Anual de Informações Sociais* – RAIS), published by the Ministry of Economy in Brazil, which provides information about the number of workers employed in the 2514 occupations required for 581 industries in 558 microregions of the country. This database provides information about 50 million workers covered by social security, representing 65% of the Brazilian workforce (Ulyssea, 2018). The second database was Maciente's (2013) adaptation of the Occupational Information Network (O*NET) to Brazil's current occupation classification (CBO) by using information about worker characteristics, worker requirements, experience requirements and occupational requirements to link the 263 attributes (skills) of occupations in the United States to the Brazilian structure of jobs.

To estimate the three types of occupational relatedness, this research followed Hidalgo et al. (2007), counting how often two occupations are found together in the same microregion (geographical relatedness), employed by the same industry (industry relatedness), and require the same skill set to perform their tasks (skill relatedness) to compute each relatedness index. These indexes were transformed further to obtain the local synergy, complementarity and similarity indexes, the main variables of interest.

To calculate the geographical relatedness, occupational specializations in Brazilian microregions were identified using the location quotient ($LQ_{r,j}$):

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

where $x_{r,j,t}$ represents the number of occupation j's employees in microregion r at time t. Therefore, a microregion r with $LQ_{r,j,t}>1$ is specialized in occupation j at time t, since the share of that occupation in the microregion is higher than in the country. Employing the location quotient ensures that the focus is on changes in the relative positions of the relevant regional occupational specializations (Boschma et al., 2013; Kuznets, 1973). The degree of relatedness (φ) between two occupations was derived from the lowest value of the conditional probability of a microregion specializing in an occupation class j, given that it is already specialized in occupation class o at time t.

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

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

The industry- and skill-relatedness indexes were calculated by employing the revealed comparative advantage (RCA) index. To compute the industry-relatedness index, the most relevant occupations (those with RCA > 1) that industries employ in their operational processes were selected. Equation (2) defines the degree of relatedness through the joint probability of an industry s demanding both occupation classes j and o. Likewise, the degree of skill-relatedness between two occupations classes, j and o, was computed regarding the skills more relevant to performing tasks that they share (those skills with RCA > 1).

To link the three relatedness indexes with the regional economy, the relatedness density index (Hidalgo et al., 2007) was calculated by measuring the distance between occupation j and the existing occupational structure in a microregion r:

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

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

One more step is needed to find all the indexes employed in the empirical tests. Following Farinha et al. (2019) and Neffke (2019), a relatedness variable was regressed on the two remaining variables to find a net index of the other variables' effects. The geographical-, industry- and skill-relatedness measures were correlated, and all of them influenced regional branching. To disentangle the role of each variable, the overlapping effects of those relatedness indexes were excluded through regression analysis. For example, to obtain the local synergy relatedness from geographical relatedness, the latter variable was regressed on industry and skill relatedness using a three-way fixed-effects model for occupation (θ_j), microregion (δ_r)

and time (τ_t). The residuals of the regression, $\varepsilon_{j,r,t}$, were used as the measure of local synergy relatedness density:

$$\begin{aligned} &\textit{Geographical relatedness density}_{j,r,t} \\ &\quad = \beta_1 \cdot \textit{Industry relatedness density}_{j,r,t} + \beta_2 \cdot \textit{Skill relatedness density}_{j,r,t} \\ &\quad + \theta_j + \delta_r + \tau_t + \varepsilon_{j,r,t} \end{aligned} \tag{4}$$

$$\textit{Local synergy relatedness density}_{j,r,t} = \varepsilon_{j,r,t} \tag{5}$$

The effects of complementarity and similarity relatedness were also disentangled. Repeating the same calculation, the complementarity-relatedness density was derived from a regression of industry relatedness on skill- and geographical-relatedness densities, 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 specialization of a microregion r in terms of sharing the same location and excluding the effects of industry and skills relatedness. Complementarity density measures the degree to which two occupations are demanded jointly by the same industry, and the presence of those occupations in the regional economy r, regardless of the role of location and their skill content. Finally, similarity density represents the degree of relatedness between an occupation j and the structure of the regional labour market, considering the presence of other occupations that use the same skills to perform their jobs, net of the influence of local capabilities and the demand by different industries.

4. ECONOMETRIC MODEL

To test whether the three occupational-relatedness densities were associated with the branching in the regional labour markets in Brazil several econometric equations were estimated. Equation (6) estimates whether a microregion r develops (loses) an occupational specialization at time $t+1$ in occupations that are related (unrelated) to its regional structure at time t.

$$\textit{Reg\_branch}_{r,j,t+1} = \beta_1 \cdot \textit{Relatedness density}_{r,j,t} + \beta_i \cdot Z_j + \theta_j + \delta_r + \tau_t + \varepsilon_{j,r,t} \tag{6}$$

where $\textit{Reg\_branch}_{r,j,t+1}$ is the dependent variable and denotes the process of branching in which occupational specialization j emerges ($\textit{Entry}_{r,j,t+1}$) and declines ($\textit{Exit}_{r,j,t+1}$) in microregion r at time $t+1$. These variables are defined as follows:

$$\textit{Reg\_branch}_{r,j,t+1} = \left[\textit{Entry}_{r,j,t+1}, \textit{Exit}_{r,j,t+1}\right]$$

$$\textit{Entry}_{r,j,t+1} = 1, \text{ if } LQ_{r,j,t+1} \geq 1 \text{ and } LQ_{r,j,t} < 1$$

$$\textit{Exit}_{r,j,t+1} = 1, \text{ if } LQ_{r,j,t+1} < 1 \text{ and } LQ_{r,j,t} \geq 1$$

The term $\textit{Relatedness density}_{r,j,t}$ represents the three indexes that were calculated, namely local synergy-, complementarity- and similarity-relatedness densities in microregion r for occupation j at time t. The term Z_j represents control variables that can influence changes in occupational specializations. Three variables at the occupational level are included as a control. Using the method of reflections developed by Hidalgo and Hausmann (2009), the occupational complexity index was calculated. Complex occupations are those present simultaneously in a few and more diversified regions. We also added the total employment and average wage of workers by occupation classes. At the regional level, population density (inhabitants per

Table 1. Variables.

Dependent variables	
Entry	When a microregion develops a new occupational specialization at time $t+1$ (entry = 1; and 0 otherwise)
Exit	When a microregion loses a pre-existing occupational specialization at time $t+1$ (exit = 1; and 0 otherwise)
Independent variables	
Local synergy density	Percentual value of occupational specializations in microregion r that are related in terms of local capabilities to occupation j at time t
Complementarity density	Percentual value of occupational specializations in microregion r that are related in terms of complementarity to occupation j at time t
Similarity density	Percentual value of occupational specializations in microregion r that are related in terms of skill similarity to occupation j at time t
Occupational complexity	Index indicating the degree of occupational complexity. Complex occupations are those that tend to be present in very few microregions and to be found in more diversified ones
Occ. total employment	Total number of workers in occupation j
Occ. wage	Average minimum wage in occupation j
Pop. density (log)	Inhabitants/km^2 in microregion r
GDP pc (log)	Real gross domestic product (GDP) per capita in microregion r
College education (%)	Number of college-educated workers divided by the total number of workers in microregion r
Manufac. employment (%)	Share of workers employed in the manufacturing sector in microregion r

square kilometre) was added to assess the role of agglomeration externalities in the emergence and decline of occupational specializations, as well as regional GDP per capita in order to investigate the role of the size of the regional economy. The share of manufacturing workers in the total of workers for each microregion was also included to control for the local industrial specialization. Finally, to verify the influence of human capital proxied by the educational level, the share of workers with a college degree was included. All variables are reported in Table 1. Descriptive statistics are reported in Tables A1 and A2 in the supplemental data online.

Support for the first two hypotheses carried an expectation of a positive and statistically significant coefficient for future occupational specialization entry (Hypothesis 1), and a negative and statistically significant coefficient for occupational specialization exit at time $t+1$ (Hypothesis 2) for all three types of $Relatedness\ density_{r,j,t}$. Regarding the model with regional extensions, higher coefficients of $Relatedness\ density_{r,j,t}$ were expected for occupational specialization entry in the South–Southeast regions compared with the North–Northeast–Midwest areas (Hypothesis 3) and smaller coefficients for occupational exit (Hypothesis 4).

Since microregions and occupations have time-constant unobserved effects, a three-way fixed-effects econometric model specification was adopted to deal with the problem of omitted variables. The equations were estimated using ordinary least squares (OLS)

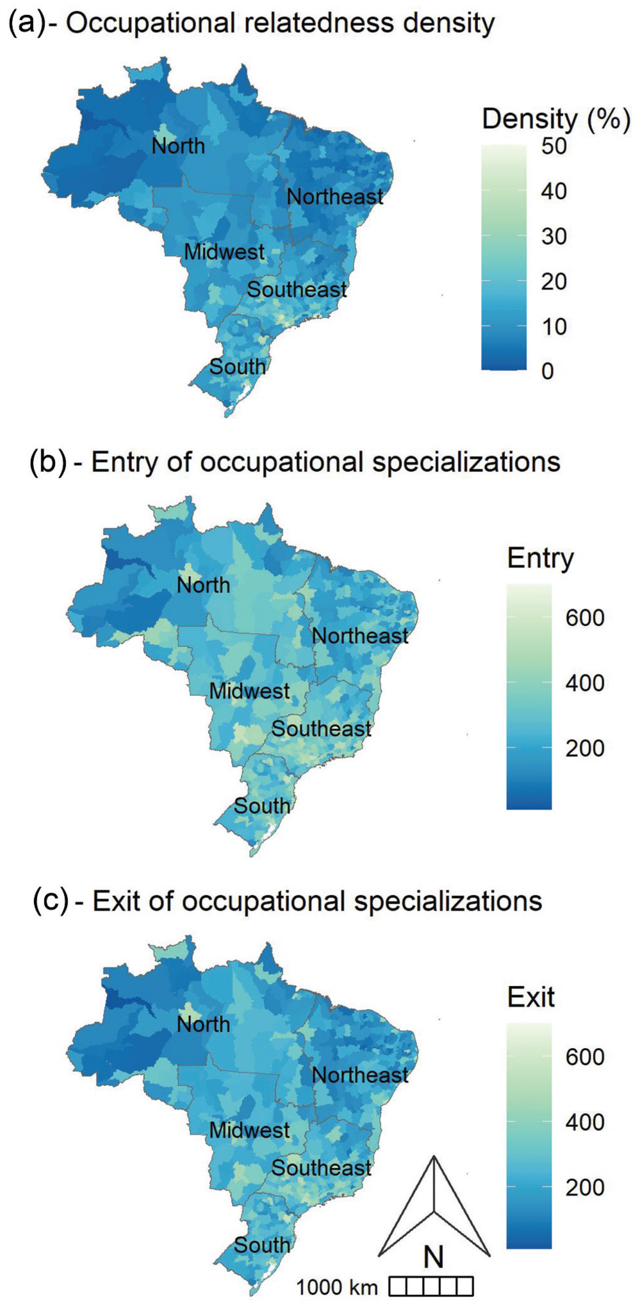

Figure 1. Spatial distribution in Brazil: (a) occupational relatedness density, (b) entry of new specializations, and (c) exit of pre-existing specializations.

Source: Authors' estimations.

regression and included dummy variables to control for time (τ_t), region (δ_r) and occupation (θ_j). Since the errors are correlated within groups of observations, the regression results were adjusted using heteroskedasticity-robust standard errors clustered at the microregion and occupation level (Wooldridge, 2003). The panel consisted of data for 2514 occupation classes and 558 microregions over a period ranging from 2003 to 2018. The period was divided into four non-overlapping samples: 2003–06, 2007–10, 2011–14 and 2015–18, thus smoothing large variations that may have occurred in a specific year. As all the independent variables were lagged by one period, the panel had 4,053,870 observations. All the non-binary variables (except for population density and GDP per capita) were normalized by subtracting the mean and dividing by the standard variation to facilitate comparisons across estimates.

5. RESULTS

5.1. Regional branching in Brazilian microregions

As the geographical unit of analysis, Brazilian microregions were used.[2] The Brazilian Institute of Geography and Statistics (IBGE) groups municipalities according to economic and social similarities. This classification considers characteristics and levels of economic production and their relevance for municipalities within microregions, as well as the spatial interaction patterns that account for the influence of municipalities in the coordination of social and economic relations (IBGE, 1990).

Figure 1 plots the spatial distribution of occupational relatedness[3] (Figure 1, A), occupation entry (Figure 1, B) and occupation exit (Figure 1, C) across microregions between 2003 and 2014. Microregions in the South and Southeast present higher relatedness densities than microregions in other areas, except for the Manaus Free Trade Zone in Amazonas state (North), which receives subsidies to develop an industrial hub. Entry into new occupations is spread across all regions, while the exit is concentrated more in Southern areas.

5.2. Results of the econometric analysis – baseline model

Table 2 reports the results of the econometric analyses for the emergence of new occupational specializations (entry) in models 1–4 and for the decline of specializations (exit) in the Brazilian microregions in models 5–8. Local synergy- and complementarity-relatedness density, either alone or jointly, are positively associated with the emergence of specializations. The coefficient of similarity relatedness was unexpectedly negatively associated with entry in model 3, but it becomes positive and significant in the complete model 4. Indeed, in the complete model, all the relatedness density coefficients increased compared with the models in which they entered alone. These results confirm Hypothesis 1, which stated that a regional economy develops new specializations closely related to its current labour market structure for all the types of relatedness.

The local synergy density showed the strongest association with occupational specialization. Its coefficients were larger than complementarity and at least three times bigger than the similarity coefficients. An increase of 1 SD (standard deviation) in local synergy density increased the probability of a new occupational specialization emerging by a range from 1.8 to 3.1 percentage points. Complementarity relatedness was associated with a higher probability of a new specialization entering the regional economy, ranging from 0.8 to 2.5 percentage points when the value of the variable increased by 1 SD. The similarity-relatedness density was more weakly associated with occupation entry, since an increase of 1 SD increased that probability by 0.9 percentage points.

The relationship between relatedness and occupation exit was even larger: the coefficients were almost twice as high, on average, as the values for entry. An increase of 1 SD in local synergy saw a decrease in the probability of a region losing a specialization by between 3.2 and 5.3 percentage points. The occupational relatedness derived from the industries'

Table 2. Entry and exit of occupational specialization models: Brazil

	Entry of occupations at time $t+1$				Exit of occupations at time $t+1$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Local synergy	0.018***			0.031***	−0.032***			−0.053***
	(0.001)			(0.001)	(0.001)			(0.001)
Complementarity		0.008***		0.025***		−0.019***		−0.046***
		(0.001)		(0.001)		(0.001)		(0.002)
Similarity			−0.002***	0.009***			0.006***	−0.017***
			(0.001)	(0.0005)			(0.002)	(0.001)
Occ. complexity	0.010***	−0.003***	−0.001	0.011***	−0.011	0.018	0.012	−0.014
	(0.001)	(0.001)	(0.001)	(0.001)	(0.013)	(0.011)	(0.011)	(0.013)
Occ. total employment	−0.001	0.001	0.0004	−0.001	−0.015	−0.017	−0.016	−0.016
	(0.002)	(0.002)	(0.002)	(0.002)	(0.012)	(0.012)	(0.012)	(0.012)
Occ. wage	−0.004***	−0.002***	−0.002***	−0.004***	−0.016	−0.017	−0.017	−0.014
	(0.001)	(0.001)	(0.001)	(0.001)	(0.020)	(0.020)	(0.020)	(0.020)
Pop. density (log)	−0.020***	−0.013***	−0.010**	−0.037***	0.017	0.009	−0.007	0.073**
	(0.005)	(0.005)	(0.005)	(0.008)	(0.031)	(0.028)	(0.028)	(0.035)
GDP pc (log)	0.0005	0.003	0.004*	−0.006	0.003	0.001	−0.005	0.022
	(0.003)	(0.003)	(0.002)	(0.004)	(0.013)	(0.012)	(0.013)	(0.013)
Education (region)	0.001*	0.001	0.001**	−0.0004	0.005	0.001	0.001	0.009*
	(0.001)	(0.0005)	(0.0005)	(0.001)	(0.004)	(0.004)	(0.004)	(0.005)
Manufac. employment (%)	0.002***	0.002***	0.002***	0.002*	−0.010*	−0.011**	−0.010**	−0.011*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.005)	(0.005)	(0.005)	(0.006)
Observations	3,546,017	3,546,017	3,546,017	3,546,017	507,853	507,853	507,853	507,853
R^2	0.051	0.048	0.046	0.059	0.093	0.090	0.088	0.103

Note: Heteroskedasticity-robust standard errors (clustered at the microregion and occupation level) are shown in parentheses. All the estimates include region, occupation and time fixed effects. Coefficients are statistically significant at *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table 3. Stylized characteristics of five Brazilian macroregions (average of constituent microregions), 2003–14.

	Midwest	North	Northeast	South	Southeast
Entry – total (2007–14)	15,650	15,899	44,016	29,021	54,829
Exit – total (2007–14)	13,014	12,703	33,859	24,053	47,839
Geographical relatedness	12.13	8.74	7.91	15.31	16.51
Industry relatedness	13.29	9.66	8.68	16.07	17.23
Skills relatedness	12.34	8.90	8.07	15.28	16.27
Population density (inhabitants/km^2)	22.3	18.8	106.0	62.0	179.5
GDP per capita (R$1000)	27.4	14.0	10.4	26.3	27.0
Employees	64,896	33,659	38,553	74,591	129,391
Minimum wage	2.40	2.27	1.80	2.41	2.44
Education (% college degree)	10.5	10.6	13.4	11.5	11.4
Manufacturing employees (%)	12.9	11.0	12.2	25.6	17.9

Note: GDP, gross domestic product.
Source: RAIS, IPEADATA; authors' elaboration.

complementary demand was associated with a decrease in the likelihood of exiting from 1.9 to 4.6 percentage points when the value of the variable increased by 1 SD. An increase of 1 SD in similarity-relatedness density was connected with an expected negative and significant association with the likelihood of exit for only the complete model 8 when all other dimensions of relatedness were included. These results also support Hypothesis 2, which states that the higher the relatedness density, the lower the probability of losing an existing occupational specialization for the three measures of relatedness.

Regarding control variables in the full model 4, both the complexity of occupations and the share of manufacturing employment were positively associated with the probability of a new occupational specialization. In contrast, population density and the average occupational wage were negatively associated with the entry of specializations. In the full exit model 8, the higher the population density and the share of workers with a college degree, the higher the probability of a decline in occupations. Finally, a higher share of manufacturing workers reduced the probability of an exit of occupations.

5.3. Model extension – regional analysis

The analysis was extended to investigate whether differentiated regional contexts influence the association between relatedness and branching. To test the role of relatedness across different regions, 558 microregions were allocated to five macroregions (Midwest (baseline), North, Northeast, South and Southeast) and dummy variables were included for each of them.

Table 3 reports some descriptive statistics averaged by microregions within the macroregions, including geographical, industry and skill relatedness, population density and GDP per capita. Microregions in the Southeast presented the most pronounced change and accounted for 34.4% of all new occupational specializations and 36.4% of all exits between 2007 and 2018. They were followed by microregions in the Northeast (27.6% and 25.8%, respectively) and South (18.2% and 18.3%), while microregions in the North and Midwest accounted for around 10% of all entries and exits of occupations in the Brazilian labour market.

Table 4. Entry and exit of occupational specialization models: regional analysis.

	Entry of occupations at time $t + 1$				Exit of occupations at time $t + 1$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Local synergy (LSRD)	0.016***			0.031***	−0.032***			−0.059***
	(0.002)			(0.002)	(0.003)			(0.003)
Complementarity (CRD)		0.009***		0.027***		−0.024***		−0.059***
		(0.001)		(0.001)		(0.005)		(0.004)
Similarity (SRD)			−0.001	0.010***			0.010*	−0.016***
			(0.002)	(0.001)			(0.006)	(0.003)
Occ. complexity	0.010***	−0.003***	−0.001	0.011***	−0.013	0.018	0.012	−0.015
	(0.001)	(0.001)	(0.001)	(0.001)	(0.013)	(0.011)	(0.011)	(0.013)
Occ. total employment	−0.001	0.001	0.0004	−0.001	−0.015	−0.017	−0.016	−0.016
	(0.002)	(0.002)	(0.002)	(0.002)	(0.012)	(0.012)	(0.012)	(0.012)
Occ. wage	−0.004***	−0.002***	−0.002***	−0.004***	−0.016	−0.017	−0.017	−0.013
	(0.001)	(0.001)	(0.001)	(0.001)	(0.020)	(0.020)	(0.020)	(0.020)
Pop. density (log)	−0.020***	−0.013***	−0.010**	−0.036***	0.020	0.009	−0.010	0.074**
	(0.005)	(0.005)	(0.004)	(0.008)	(0.032)	(0.028)	(0.027)	(0.035)
GDP pc (log)	0.0005	0.003	0.004*	−0.006	0.004	0.001	−0.005	0.023*
	(0.003)	(0.003)	(0.003)	(0.004)	(0.013)	(0.012)	(0.013)	(0.014)
Education (region)	0.001*	0.001	0.001**	−0.0005	0.006	0.001	0.001	0.010**
	(0.001)	(0.0005)	(0.0005)	(0.001)	(0.004)	(0.004)	(0.004)	(0.005)
Manufac. employment (%)	0.002***	0.002***	0.002***	0.002**	−0.010*	−0.011**	−0.010**	−0.011*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.005)	(0.005)	(0.005)	(0.006)

(Continued)

Table 4. (Continued).

	Entry of occupations at time $t + 1$				Exit of occupations at time $t + 1$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LSRD × *North*	0.003			−0.00002	−0.008**			−0.004
	(0.002)			(0.002)	(0.004)			(0.005)
LSRD × *Northeast*	0.001			0.001	−0.004			−0.005
	(0.002)			(0.002)	(0.004)			(0.004)
LSRD × *South*	0.002			0.0001	−0.001			0.006*
	(0.002)			(0.002)	(0.003)			(0.003)
LSRD × *Southeast*	0.001			−0.0004	0.003			0.008***
	(0.002)			(0.002)	(0.003)			(0.003)
CRD × *North*		−0.001		−0.003		0.007		0.005
		(0.002)		(0.002)		(0.008)		(0.008)
CRD × *Northeast*		−0.001		−0.001		0.004		−0.001
		(0.001)		(0.001)		(0.006)		(0.006)
CRD × *South*		−0.001		−0.003**		0.006		0.017***
		(0.001)		(0.001)		(0.005)		(0.005)
CRD × *Southeast*		−0.0003		−0.001		0.006		0.016***
		(0.001)		(0.001)		(0.005)		(0.005)
SRD × *North*			−0.003	−0.006***			0.006	0.010*
			(0.002)	(0.001)			(0.008)	(0.006)
SRD × *Northeast*			0.002	−0.001			−0.007	−0.002
			(0.002)	(0.001)			(0.007)	(0.004)

(Continued)

Table 4. (Continued).

	Entry of occupations at time $t + 1$				Exit of occupations at time $t + 1$			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
SRD × South			−0.001	−0.002			−0.001	0.003
			(0.002)	(0.001)			(0.006)	(0.003)
SRD × Southeast			−0.002	−0.001			−0.004	−0.003
			(0.002)	(0.001)			(0.006)	(0.003)
Observations	3,546,017	3,546,017	3,546,017	3,546,017	507,853	507,853	507,853	507,853
R^2	0.051	0.048	0.046	0.059	0.093	0.090	0.088	0.103

Note: Heteroskedasticity-robust standard errors (clustered at the microregion and occupation level) are shown in parentheses. All the estimates include region, occupation and time fixed effects. Coefficients are statistically significant at *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table 4 presents the econometric results of the extended models, including interaction terms between relatedness and macroregions. The complete model 4 shows that the probability of entry of a new specialization associated with complementarity relatedness is lower for microregions in the South than in other parts of the country. Microregions in the North displayed a lower probability of specializing in a new occupation involving skills similar to a current specialization.

The main regional differences were found in the relationship between relatedness and the decline in specializations. In model 5, where local synergy density entered the equation alone, the role of that type of relatedness in protecting a microregion from exit was a little higher for the North. However, in full model 8, that relationship became statistically insignificant. In this model, the North region was more likely to lose an occupational specialization if it shared similar skills. However, the estimates for microregions in the South and Southeast showed that the higher the local synergy and complementarity densities, the higher the probability of an occupational specialization leaving the economy compared with other regions. While an increase of 1 SD in local synergy and complementarity densities decreased the probability of exit by the same value (5.9 percentage points) for microregions in the Midwest, North, and Northeast, for microregions in the South, these probabilities were 5.3 and 4.2 percentage points, respectively. In the Southeast, they were 5.0 and 4.3 percentage points.

These results do not support Hypotheses 3 and 4: regional branching in the most knowledge-varied microregions in the South and Southeast did not show a stronger association with types of occupational relatedness than in the North, Northeast and Midwest areas, with a lower variety of knowledge available for recombinations. Microregions in the South and North depend less on, respectively, complementarity and similarity densities to introduce a new specialization into their economies. In contrast, microregions in the North, Northeast and Midwest regions rely more on local synergy and complementarity densities to protect themselves from losing occupational specializations.

6. DISCUSSION

The empirical analysis reveals consistent findings for the whole country and its diverse regions: the three types of relatedness matter for both the emergence and decline of occupational specializations over time. However, the relevance of each of them differs.

Local synergy density was the most relevant type of relatedness for regional branching. Agglomeration economies stemming from local interactions among workers emphasize the relevance of spatial proximity to facilitate learning through face-to-face interactions (Storper & Venables, 2004), more effective access to 'local buzz' (Bathelt et al., 2004), and tacit knowledge exchange (Maskell & Malmberg, 1999). Complementarity density was the second most important type of relatedness. The demand for complementary workers by local industries gathers socially sparse knowledge specializations among individuals, reinforces occupational relatedness, and influences regional branching processes in Brazil. The similarity density revealed a weaker relationship with regional branching, suggesting that, although the results were as expected, the partial degree of substitution between skill-related occupations may slow local knowledge recombination. Previous evidence shows that the degree of substitution derived from skill similarity had adverse effects on workers' wages (Neffke, 2019), while it does not seem to improve the probability of a firm's survival and increase its relative chance of being acquired, although similarity also decreases the risk of exit from the market (Borggren et al., 2016). However, the benefits of similarity relatedness for potential knowledge spillovers seem to be still higher than its costs due to opportunities for recombination derived from the tendency of people with similar skills to agglomerate to benefit from the labour market pool.

In addition, the three types of occupational relatedness are more effective in preventing the disappearance of current specializations than promoting new occupations in Brazilian microregions. One explanation for this outcome may be social clauses and the persistence of labour regulations that have followed trade liberalization in Brazil and other developing countries since the 1980s (Coslovsky, 2014). These protective regulations end up increasing the costs of dismissing workers (Almeida & Carneiro, 2012), and therefore may influence the exit of occupational specializations.

The findings above are in line with previous studies focused on developed countries. However, some results for the regional analysis were not as expected. In general, and contrary to our hypotheses, high levels of occupational relatedness were associated more strongly with preventing exit from backward regions and did not reveal any advantage for promoting the entrance of specializations in the advanced ones.

Although similarity-relatedness density in the North was less associated with local branching as hypothesized, microregions in the advanced South rely less than other regions on complementarity relatedness to diversify their economies. One possible explanation is that these microregions are more able to specialize in new occupations based on unrelated knowledge. However, the same result was not observed for microregions in the Southeast, another advanced area of Brazil. Thus, except for the two cases above, the emergence of specializations does not seem to follow different patterns across distinct regions.

Economies in the South and Southeast are also less protected from exit associated with local synergy and complementarity densities than lagging microregions in the North, Northeast and Midwest. In some ways, this result for occupational relatedness is similar to that of Galetti et al. (2021) for industrial relatedness. They also found a stronger influence of relatedness on preventing exit from smaller microregions than from diversified and larger ones. In less-developed regions, firms have to rely more on internal resources to compensate for the lack of diversity and skilled workers (Eder & Trippl, 2019). Thus, on-the-job experience reinforces occupational relatedness in these thin labour markets. As a result of fewer opportunities to find complementary occupations in local labour markets, cutting the workforce can be costly. These local characteristics allow specializations in relatively few and related occupations that are essential to the regional economy. Therefore, occupational exit could disarticulate the economic structure of the Midwest and Northern areas more than it would in more diversified regions.

The likelihood of a specialization losing local relevance increases with population density, GDP per capita and level of regional education. In contrast, the probability of developing a new occupational specialization decreases in microregions with higher population density. These results suggest the presence of a deconcentration process towards Northern and Midwest regions already noted by several scholars (Resende et al., 2016). Finally, higher levels of manufacturing workforce support local productive change, as it promotes new occupational specializations and diversifies labour markets in the places where it occurs. Current processes of premature deindustrialization (Morceiro, 2018) could be a concern for regional economies, as they make the emergence and retention of local occupations difficult, and prevent local transformations towards more diversified structures.

7. ROBUSTNESS TEST

Additional robustness tests were conducted to verify two aspects of the research. First, the econometric specifications were changed to ameliorate potential endogeneity issues derived from omitted variables bias. Equation (6) was estimated with region–time and occupation–time fixed effects (see Table A3 in the supplemental data online) capturing temporal shocks common to all occupations in a region and common to all regions for a given occupation. Region–occupation fixed effects were also employed to control for time-invariant, unobserved characteristics related to a specific occupation in a specific region and time fixed effects (see Table A4 online). These models presented only one difference compared with the baseline model. The coefficient for similarity density was not statistically significant for the decline in occupational specializations in the model with region–occupation and time fixed effects.

In the second set of tests, microregions were separated into three groups of regions – Midwest, North–Northeast and South–Southeast (see Table A5 in the supplemental data online). The results confirm that the higher local synergy and complementarity relatedness, the lower the probability of occupational exit from microregions in the North–Northeast and Midwest compared with the more advanced microregions in the Southern areas. Less-advanced microregions had a slightly lower probability of entry associated with similarity relatedness in comparison with the other regions.

These additional tests confirm the previous results and suggest that all types of occupational relatedness matter for path-dependent regional branching, although the intensity of that association differs across types of relatedness and regions with different levels of development.

8. CONCLUSIONS

As little is known about the relationship between relatedness and regional branching in developing countries (Whittle & Kogler, 2020), this research examined the association between types of occupational relatedness and the emergence of and decline in occupational specializations in 558 Brazilian microregions.

The results revealed that occupational relatedness is associated with regional branching in a developing country marked by regional disparities. It was also found that the relationship between relatedness and regional branching depended on both the types of occupational relatedness and regional characteristics. Local synergy- and complementarity-relatedness densities revealed the strongest association with regional branching, yet were more relevant to preventing the decline of specializations than promoting the emergence of new ones. In addition, all types of relatedness revealed a greater association with preventing the disappearance of occupations from the most backward regions.

As far as policy implications are concerned, this article provides a rationale for regional policies that look at a region's current specializations. First, although the nature of activities, industries, and skills differs across regions, as in developed countries, the local degree of relatedness affects the creation and extinction of occupations. Particularly for countries with high levels of regional inequality, policies oriented to attracting more related occupations can be the first step towards sustained development. Therefore, a deep knowledge of local competitive advantages and capabilities can be more efficient than focusing on very ambitious industries that are distant from the knowledge and technology present in that economy. Second, although regional branching in less-developed regions is associated with occupational relatedness, a lack of knowledge variety may cause economic lock-in, thus preventing the entrance of new occupations. In this case, policy should focus on avoiding this trap by providing incentives to increase the introduction of new products and technologies already employed in more advanced regions, establishing non-local pipelines and networks (Bathelt et al., 2004), and improving amenities, educational and physical infrastructure in order to attract more skilled workers. Third, in order to create alternative development paths, regions also need to learn how to recombine unrelated knowledge (Grillitsch et al., 2018) that is socially dispersed in both local and external sources (Hassink et al., 2019). Therefore, policies oriented to developing new knowledge and establishing long-distance links between local firms and non-local firms and universities (Garcia et al., 2018) can help regions combine more 'distant' areas of knowledge.

As for limitations, the database does not cover the whole Brazilian labour market. In developing countries, informality is a relevant problem that prevents development and increases regional inequality. Due to the lack of information about informality, one can only speculate about the link between relatedness and informal occupations. Informal activities have more difficulty connecting with and exploiting non-local resources, involve more micro-enterprises and entail more entrepreneurs who hire informal workers and require jacks-of-all-trades to perform a higher number of tasks requiring similar skills. These features may increase the relevance of local characteristics and strengthen the role of relatedness in the entry and exit of occupational specializations. However, further studies are required to examine in detail this relationship.

NOTES

1. Grillitsch et al. (2018) define path branching as a diversification into new, related industries and path diversification as a diversification into a new industry based on unrelated knowledge combinations.
2. The excessive urban concentration in large Brazilian cities increases the costs of living, including time lost with long commuting from peripheral to central municipalities where central business districts are located (Henderson, 2002). These costs may affect the evolution of regional occupational specializations since workers can commute from one microregion to another. Although the data did not permit directly dealing with this influence, classifying municipalities into microregions alleviates this problem to some degree because peripheral municipalities where many workers live are grouped around the central municipality, which is the principal regional workplace.
3. Figure 1 depicts geographical relatedness, computed from Equations (1–3), before excluding the overlapping effects of skill- and industry-relatedness indexes.

DISCLOSURE STATEMENT

No potential conflict of interest was reported by the authors.

FUNDING

This study was funded by the National Research Foundation of South Africa and DSI/NRF South African Research Chair in Industrial Development [grant number 98627]; and by the Global Excellence and Stature (GES) 4.0 fellowship from the University of Johannesburg.

ORCID

Jefferson R. B. Galetti http://orcid.org/0000-0001-5582-1875
Milene Simone Tessarin http://orcid.org/0000-0003-2922-8335
Paulo César Morceiro http://orcid.org/0000-0002-9548-0996

REFERENCES

Acs, Z. J., Audretsch, D. B., Braunerhjelm, P., & Carlsson, B. (2012). Growth and entrepreneurship. *Small Business Economics*, *39*(2), 289–300. https://doi.org/10.1007/s11187-010-9307-2

Almeida, R., & Carneiro, P. (2012). Enforcement of labor regulation and informality. *American Economic Journal Applied Economics*, *4*(3), 64–89. https://doi.org/10.1257/app.4.3.64

Alonso, J. A., & Martín, V. (2019). Product relatedness and economic diversification at the regional level in two emerging economies: Mexico and Brazil. *Regional Studies*, *53*(12), 1710–1722. https://doi.org/10.1080/00343404.2019.1605441

Araújo, I. F. D., Gonçalves, E., & Almeida, E. (2019). Effects of dynamic and spatial externalities on local growth: Evidence from Brazil. *Papers in Regional Science*, *98*(2), 1239–1259. https://doi.org/10.1111/pirs.12402

Azzoni, C. R., & Haddad, E. A. (2018). Regional disparities. In E. Amann, C. R. Azzoni, & W. Baer (Eds.), *The Oxford handbook of the Brazilian economy*. Oxford University Press. https://doi.org/10.1093/oxfordhb/9780190499983.001.0001

Barbour, E., & Markusen, A. (2007). Regional occupational and industrial structure: Does one imply the other? *International Regional Science Review*, *30*(1), 72–90. https://doi.org/10.1177/0160017606296727

Barufi, A. M. B., Haddad, E. A., & Nijkamp, P. (2016). Industrial scope of agglomeration economies in Brazil. *The Annals of Regional Science*, *56*(3), 707–755. https://doi.org/10.1007/s00168-016-0768-3

Bathelt, H., Malmberg, A., & Maskell, P. (2004). Clusters and knowledge: Local buzz, global pipelines and the process of knowledge creation. *Progress in Human Geography*, *28*(1), 31–56. https://doi.org/10.1191/0309132504ph469oa

Beckouche, P. (1991). French high-tech and space: A double cleavage. In G. Benko & M. Dunford (Eds.), *Industrial change and regional development* (pp. 205–225). Belhaven Press.

Beckouche, P., Savy, M., & Veltz, P. (1988). Nouvelle économie, nouveaux territoires. *CERTES, Suppléménf à La Lettre de La DATAR*, 3.

Borggren, J., Eriksson, R. H., & Lindgren, U. (2016). Knowledge flows in high-impact firms: How does relatedness influence survival, acquisition and exit? *Journal of Economic Geography*, *16*(3), 637–665. https://doi.org/10.1093/jeg/lbv014

Boschma, R. (2005). Proximity and innovation: A critical assessment. *Regional Studies*, *39*(1), 61–74. https://doi.org/10.1080/0034340052000320887

Boschma, R. (2017). Relatedness as driver of regional diversification: A research agenda. *Regional Studies*, *51*(3), 351–364. https://doi.org/10.1080/00343404.2016.1254767

Boschma, R. (2022). Global value chains from an evolutionary economic geography perspective: A research agenda. *Area Development and Policy*, *7*(2), 123–146. https://doi.org/10.1080/23792949.2022.2040371

Boschma, R., Minondo, A., & Navarro, M. (2013). The emergence of new industries at the regional level in Spain: A proximity approach based on product relatedness. *Economic Geography*, *89*(1), 29–51. https://doi.org/10.1111/j.1944-8287.2012.01170.x

Campolina Diniz, C., & Vieira, D. J. (2016). Brazil: Accelerated metropolization and urban crisis. *Area Development and Policy*, *1*(2), 155–177. https://doi.org/10.1080/23792949.2016.1202085

Coslovsky, S. V. (2014). Flying under the radar? The state and the enforcement of labour laws in Brazil. *Oxford Development Studies*, *42*(2), 190–216. https://doi.org/10.1080/13600818.2013.875135

de Macedo, F. C., & Porto, L. R. (2021). *Evolução regional do mercado de trabalho no Brasil (2000–2018): Apontamentos para a Política Nacional de Desenvolvimento Regional (PNDR)*. Instituto de Pesquisa Econômica Aplicada, 90.

Eder, J., & Trippl, M. (2019). Innovation in the periphery: Compensation and exploitation strategies. *Growth and Change*, *50*(4), 1511–1531. https://doi.org/10.1111/grow.12328

Ehrl, P., & Monasterio, L. (2019). Skill concentration and persistence in Brazil. *Regional Studies*, *53*(11), 1544–1554. https://doi.org/10.1080/00343404.2019.1585798

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. https://doi.org/10.1080/13662716.2019.1591940

Feser, E. J. (2003). What regions do rather than make: A proposed set of knowledge-based occupation clusters. *Urban Studies*, *40*(10), 1937–1958. https://doi.org/10.1080/0042098032000116059

Firgo, M., & Mayerhofer, P. (2018). (Un)related variety and employment growth at the sub-regional level. *Papers in Regional Science*, *97*(3), 519–547. https://doi.org/10.1111/pirs.12276

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. https://doi.org/10.1093/jeg/lbm018

Frenken, K., Oort, F. V., & Verburg, T. (2007). Related variety, unrelated variety and regional economic growth. *Regional Studies*, *41*(5), 685–697. https://doi.org/10.1080/00343400601120296

Galetti, J. R. B., Tessarin, M. S., & Morceiro, P. C. (2021). Skill relatedness, structural change and heterogeneous regions: Evidence from a developing country. *Papers in Regional Science*, *100*(6), 1355–1376. https://doi.org/10.1111/pirs.12629

Garcia, R., Araujo, V., Mascarini, S., Santos, E. G. D., & Costa, A. (2018). Is cognitive proximity a driver of geographical distance of university–industry collaboration? *Area Development and Policy*, *3*(3), 349–367. https://doi.org/10.1080/23792949.2018.1484669

Glaeser, E. L., Kallal, H. D., Scheinkman, J. A., & Shleifer, A. (1992). Growth in cities. *Journal of Political Economy*, *100*(6), 1126–1152. https://doi.org/10.1086/261856

Grillitsch, M., Asheim, B., & Trippl, M. (2018). Unrelated knowledge combinations: The unexplored potential for regional industrial path development. *Cambridge Journal of Regions, Economy and Society*, *11* (2), 257–274. https://doi.org/10.1093/cjres/rsy012

Hane-Weijman, E., Eriksson, R. H., & Rigby, D. (2021). How do occupational relatedness and complexity condition employment dynamics in periods of growth and recession? *Regional Studies*, *56*(7), 1176–1189. https://doi.org/10.1080/00343404.2021.1984420

Hanushek, E. A. (2013). Economic growth in developing countries: The role of human capital. *Economics of Education Review*, *37*, 204–212. https://doi.org/10.1016/j.econedurev.2013.04.005

Hartmann, D., Guevara, M. R., Jara-Figueroa, C., Aristarán, M., & Hidalgo, C. A. (2017). Linking economic complexity, institutions, and income inequality. *World Development*, *93*, 75–93. https://doi.org/10.1016/j.worlddev.2016.12.020

Hassink, R., Isaksen, A., & Trippl, M. (2019). Towards a comprehensive understanding of new regional industrial path development. *Regional Studies*, *53*(11), 1636–1645. https://doi.org/10.1080/00343404.2019.1566704

Henderson, V. (2002). Urbanization in developing countries. *The World Bank Research Observer*, *17*(1), 89–112. https://doi.org/10.1093/wbro/17.1.89

Herrera, W. D. M., Strauch, J. C. M., & Bruno, M. A. P. (2021). Economic complexity of Brazilian states in the period 1997–2017. *Area Development and Policy*, *6*(1), 63–81. https://doi.org/10.1080/23792949.2020.1761846

Hidalgo, C. A., & Hausmann, R. (2009). The building blocks of economic complexity. *Proceedings of the National Academy of Sciences*, *106*(26), 10570–10575. https://doi.org/10.1073/pnas.0900943106

Hidalgo, C. A., Klinger, B., Barabási, A. -L., & Hausmann, R. (2007). The product space conditions the development of nations. *Science*, *317*(5837), 482–487. https://doi.org/10.1126/science.1144581

IBGE. (1990). Divisão regional do Brasil em mesorregiões e microrregiões geográficas, 1.

Imbs, J., & Wacziarg, R. (2003). Stages of diversification. *American Economic Review*, *93*(1), 63–86. https://doi.org/10.1257/000282803321455160

Isaksen, A., Trippl, M. (2016). Path development in different regional innovation systems: A conceptual analysis. In M. D. Parrilli, R. D. Fitjar, & A. Rodríguez-Pose (Eds.), *Innovation drivers and regional innovation strategies* (pp. 82–100). Routledge.

Jara-Figueroa, C., Jun, B., Glaeser, E. L., & Hidalgo, C. A. (2018). The role of industry-specific, occupation-specific, and location-specific knowledge in the growth and survival of new firms. *Proceedings of the National Academy of Sciences*, *115*(50), 12646–12653. https://doi.org/10.1073/pnas.1800475115

Kogler, D. F., Rigby, D. L., & Tucker, I. (2013). Mapping knowledge space and technological relatedness in US cities. *European Planning Studies*, *21*(9), 1374–1391. https://doi.org/10.1080/09654313.2012.755832

Kuznets, S. (1973). Modern economic growth: Findings and reflections. *The American Economic Review*, *63*(3), 247–258. http://www.jstor.org/stable/1914358

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

Maskell, P., & Malmberg, A. (1999). Localised learning and industrial competitiveness. *Cambridge Journal of Economics*, *23*(2), 167–185. https://doi.org/10.1093/cje/23.2.167

Morceiro, P. C. (2018). Evolution and sectoral competitiveness of the Brazilian manufacturing industry. In E. Amann, C. R. Azzoni, & W. Baer (Eds.), *The Oxford handbook of the Brazilian economy* (pp. 243–265). Oxford University Press. https://doi.org/10.1093/oxfordhb/9780190499983.001.0001

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. https://doi.org/10.1371/journal.pone.0073676

Neffke, F. (2019). The value of complementary co-workers. *Science Advances*, *5*(12), eaax3370. https://doi.org/10.1126/sciadv.aax3370

Neffke, F., Henning, M., & Boschma, R. (2011). How do regions diversify over time? Industry relatedness and the development of new growth paths in regions. *Economic Geography*, *87*(3), 237–265. https://doi.org/10.1111/j.1944-8287.2011.01121.x

Nooteboom, B. (2000). Learning by interaction: Absorptive capacity, cognitive distance and governance. *Journal of Management and Governance*, *4*(1), 69–92. https://doi.org/10.1023/A:1009941416749

Reis, E. (2014). Spatial income inequality in Brazil, 1872–2000. *EconomiA*, *15*(2), 119–140. https://doi.org/10.1016/j.econ.2014.06.006

Resende, G. M., de Carvalho, A. X. Y., Sakowski, P. A. M., & Cravo, T. A. (2016). Evaluating multiple spatial dimensions of economic growth in Brazil using spatial panel data models. *The Annals of Regional Science*, *56*(1), 1–31. https://doi.org/10.1007/s00168-015-0706-9

Schumpeter, J. A. (1942). *Capitalism*. Socialism and Democracy.

Shutters, S. T., Muneepeerakul, R., & Lobo, J. (2016). Constrained pathways to a creative urban economy. *Urban Studies*, *53*(16), 3439–3454. https://doi.org/10.1177/0042098015616892

Storper, M., & Venables, A. J. (2004). Buzz: Face-to-face contact and the urban economy. *Journal of Economic Geography*, *4*(4), 351–370. https://doi.org/10.1093/jnlecg/lbh027

Thompson, W. R., & Thompson, P. R. (1985). From industries to occupations: Rethinking local economic development. *Economic Development Commentary*, *9*(3), 12–18.

Torre, A., & Rallet, A. (2005). Proximity and localization. *Regional Studies*, *39*(1), 47–59. https://doi.org/10.1080/0034340052000320842

Ulyssea, G. (2018). Firms, informality, and development: Theory and evidence from Brazil. *American Economic Review*, *108*(8), 2015–2047. https://doi.org/10.1257/aer.20141745

Weitzman, M. L. (1998). Recombinant growth. *The Quarterly Journal of Economics*, *113*(2), 331–360. https://doi.org/10.1162/003355398555595

Whittle, A., & Kogler, D. F. (2020). Related to what? Reviewing the literature on technological relatedness: Where we are now and where can we go? *Papers in Regional Science*, *99*(1), 97–113. https://doi.org/10.1111/pirs.12481

Wixe, S., & Andersson, M. (2017). Which types of relatedness matter in regional growth? Industry, occupation and education. *Regional Studies*, *51*(4), 523–536. https://doi.org/10.1080/00343404.2015.1112369

Wooldridge, J. M. (2003). Cluster-sample methods in applied econometrics. *American Economic Review*, *93*(2), 133–138. https://doi.org/10.1257/000282803321946930

Xiao, J., Boschma, R., & Andersson, M. (2018). Industrial diversification in Europe: The differentiated role of relatedness. *Economic Geography*, *94*(5), 514–549. https://doi.org/10.1080/00130095.2018.1444989