Economic complexity and regional economic development: evidence from Brazil

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Área temática 1: Economia

Abstract
The paper translates the economic complexity methodology to the regional level and assesses the case of Brazil. Overall, it offers four contributions to this literature: First, it introduces the *Activity Space*, a network that links different activities based on the number of shared occupations. Second, it shows estimates of the influence of increments in the complexity index on growth/employment. Third, it proposes a new method to rank promising activities for smart diversification regional strategies. Finally, the study applies the methodology to analyze the case of Belo Horizonte, simulating the potential gains to the city in each development path proposed.

Keywords
Economic complexity; Regional development; Smart specialization strategies; Growth

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1. Introduction

Economic development is intrinsically related to structural change. In its basic meaning, structural change means changing the productive structure of the economy. In the classical literature of economic development, this change means increasing the share of manufacturing in the economy, while reducing the share of agriculture (e.g. Schumpeter, 1934; Prebisch, 1961; Furtado, 1964; Hirschman, 1958; Kaldor, 1966). Structural change, therefore, involves leaning and mastering new economic activities.

As time went by, it became clear that increasing manufacturing production was not enough to guarantee economic development. As technology evolved, some sectors became more science-based than others and markets for manufacturing products changes markedly. While some manufacturing industries became more widespread across the globe, others remained heavily concentrated in a few companies and locations. Consequently, modern approaches to economic development started to highlight that moving into high-tech manufacturing is crucial for sustainable development (e.g. Nelson, 1992; Lundval, 1993; Romero and Britto, 2017).

With the rapid changes in science and technology observed in the past few decades, high-tech manufacturing industries became increasingly more heterogeneous, requiring more specialized knowledge. The pathbreaking work of Hidalgo et al. (2007) explored fine-grained international trade data to build a network that interconnects products according to the probability of competitive co-production. This network, the *Product Space*, indicates the proximity of the productive knowledge required to produce each pair of goods. Moreover, it makes it clear that because of the differences in accumulated knowledge between economies, development is heavily path dependent. As Britto et al. (2019) have shown, the shape of the *Product Space* has gradually changed through time, with clusters of products becoming clearer and more separated. This illustrates the increase in specialized knowledge that led to higher separations between some manufacturing fields.

Hidalgo and Hausmann (2009) went one step further, and using once again disaggregate international trade data, showed that the ubiquity of the competitive production of different goods varies markedly. Furthermore, they also showed that the level of diversification of each economy is associated with its level of income per capita. Combining these two raw measures, the authors created the indexes of complexity of products (*PCI*) and economies (*ECI*). The former indicates the amount of productive knowledge required to produce each good competitively. The latter indicates the amount of productive knowledge available in each economy.

Hausmann et al. (2014) provided evidence that indicates that increasing economic complexity predicts considerably higher growth rates of income per capita in the future, even after controlling for several additional variables. According to their estimates, an increase of one standard deviation in economic complexity is associated with a subsequent acceleration of 1.6 percent per year in the country's long-term growth rate.

Based on this body of work, recent studies have been seeking to use indicators based on the economic complexity methodology to guide the formulation of development policies. Hausmann and Chauvin (2015) used a series of indicators constructed based on economic complexity and on relatedness between products to identify promising sectors for the development of Rwanda. Hausmann *et al.* (2017) used a similar methodology to identify the promising sectors for the development of Panama.

Nonetheless, it is not straightforward to adapt the economic complexity methodology to formulate regional development strategies. At the regional level exports are not as informative as at the national level, since sells to other regions within the same country would not be computed. Furthermore, economic interactions between neighbors are stronger at the regional level, making knowledge spillovers more relevant.

Due to these issues, economic complexity has been applied at the regional level using alternative measures of local knowledge. Balland et al. (2018), for example, use patent data to measure local technological knowledge, using the same methods proposed by Hidalgo et al. (2007) and Hausmann et al. (2014) to guide the formulation of regional smart specialization strategies. Alternatively, Gao et al. (2021) apply the economic complexity methodology using employment data from both China and Brazil, to show that knowledge spillovers are relevant at the regional level, and that improving transport infrastructure helps increasing these spillovers and the productive diversification they foster.

In this paper we provide four important contributions to the literature on economic complexity and regional development using data from Brazilian microregions. First, we propose the construction of a network, the *Activity Space*, that links different activities based on the number of shared occupations. This network allows transposing the *Product Space* to the regional level using employment data. Second, we report econometric tests of the impact of regional economic complexity, calculated using employment data for Brazil, on the growth rates of GDP per capita and of formal employment share. These tests, which are inspired in the ones carried out by Hausmann *et al.* (2014), transpose their results to the regional level. Third, we propose a new method to rank promising activities to be targeted by regional development policies, combining different indicators, as proposed by Hausmann *et al.* (2017), but using weights estimated using a principal component methodology. Fourth, we show that the proposed rule for identifying promising activities for smart diversification strategies performs very well when put to test against regions that presented increases in their economic complexity. Finally, this methodology is illustrated using the example of the Brazilian city of Belo Horizonte. Combining the estimates of the impacts of economic complexity on income and employment, we present some simulations of the potential gains to be obtained following the proposed development path.

2. Regional economic complexity and the *Activity Space*

2.1. Economic Complexity

The seminal paper of Hidalgo and Hausmann (2009) proposed to calculate the product and countries' complexity based on information on the diversification of economies and on the ubiquity of products. The level of diversification of each country is defined as the number of products the country produces with Revealed Comparative Advantage (*RCA*), while the level of ubiquity of each good is defined as the number of countries that produce the good with *RCA*. Formally:

$$RCA_{cp} = \frac{x_{cp}/\sum_p x_{cp}}{\sum_c x_{cp}/\sum_c \sum_p x_{cp}} \quad (1)$$

$$Diversification = k_{c,0} = \sum_p M_{cp} \quad (2)$$

$$Ubiquity = k_{p,0} = \sum_c M_{cp} \quad (3)$$

where x denotes the export quantum, while subscripts c and p denote country and product, respectively. M is a *dummy* variable which equals one if country c exports the good p with *RCA*, and zero otherwise. A *RCA* above one indicates that the country is competitive in the production of the good, while the opposite holds if the index is below one.

Using these measures, Hidalgo and Hausmann (2009) provided evidence that there is a strong positive correlation between income per capita and diversification. In addition, they showed that diversification and ubiquity are negatively correlated, which suggests that countries that are more diversified tend to produce goods that are less ubiquitous.

According to Hidalgo and Hausmann (2009), the competitive production of different types of goods requires different capabilities. Hence, the capabilities present in a country determine the goods it can produce and how difficult it is for the country to start producing goods that require different (or additional) capabilities. As a result, the range of goods a country can produce competitively and the level of complexity of these goods indicates the capabilities a country possesses. The negative correlation between diversification and ubiquity corroborates the idea that countries that possess a high number of capabilities: (i) are more diversified, since they are able to produce a high number of goods competitively; and (ii) produce goods that have lower ubiquity, since the higher number of capabilities enables them to produce more complex goods.

Based on the information from these indexes, Hidalgo and Hausmann (2009) calculate a Product Complexity Index (*PCI*) and an Economic Complexity Index (*ECI*). The intuition for combining the two indexes is straightforward. On the one hand, a country with high diversification is considered less complex if the products it produces competitively (with *RCA*) present high ubiquity. On the other hand, a product with low ubiquity is considered more complex if it is produced by countries that are very diversified. Consequently, by repeating this process and performing continuous iterations between the two indexes it is possible to extract progressively more refined information about the economic complexity of each product and country. Formally:

$$k_{c,N} = (1/k_{c,0}) \sum_p M_{cp} k_{p,N-1} \quad (4)$$

$$k_{p,N} = (1/k_{p,0}) \sum_c M_{cp} k_{c,N-1} \quad (5)$$

where N denotes the number of iterations.

Substituting (4) into (5) yields:

$$k_{c,N} = \sum_{c'} \widetilde{M}_{cc'} k_{c',N-2} \quad (6)$$

where $\widetilde{M}_{cc'} = \sum_p (M_{cp} M_{c'p})/(k_{c,0}\, k_{p,0})$ and c' denotes other countries besides c.

Equation (6) is satisfied when $k_{c,N} = k_{c,N-2} = 1$, which is the eigenvector associated with the highest eigenvalue of $\widetilde{M}_{cc'}$. However, since this eigenvector is formed of ones, he is uninformative. Hence, the eigenvector associated with the second highest eigenvalue ($\vec{K}$) is used to capture highest part of the system's variance. Thus, *ECI* is calculated as:

$$ECI = (\vec{K} - < \vec{K} >)/sd(\vec{K}) \quad (7)$$

where < > denotes the average, and *sd* denotes the standard deviation.

The same procedure is used to calculate *PCI*, but now substituting (5) into (4) and using the eigenvector associated with the second highest eigenvalue ($\vec{Q}$) of $\widetilde{M}_{pp'}$:

$$PCI = (\vec{Q} - < \vec{Q} >)/sd(\vec{Q}) \quad (8)$$

Using these indexes, Hausmann et al. (2014) provided evidence that indicates that increasing economic complexity predicts considerably higher growth rates and levels of GDP per capita in the future, even after controlling for a series of additional variables. According to their estimates, an increase of one standard deviation in economic complexity is associated with a subsequent acceleration of 1.6 percent per year in the country's long-term growth rate.

Following their seminal results, a series of papers explored other effects of economic complexity. Hartmann et al (2017), for example, found evidence that economic complexity is correlated with lower income inequality. More recently, Mealy and Teytelboym (2020) and Romero and Gramkow (2021) found strong evidence indicating that increasing economic complexity contributes to reduce greenhouse gas emissions and other environmental impacts.

2.2. Product Space

The pathbreaking paper of Hidalgo *et al.* (2007) investigated whether the sectoral composition of each country's competitive exports influences the path, the costs and the speed of it's structural transformations. In this paper, therefore, the authors explore the idea that each country's productive structure influences it's growth and development possibilities, stressing the path-dependence of knowledge and capabilities accumulation.

Hidalgo *et al.* (2007) established how close products are in terms of the capabilities required for their competitive production using the conditional probabilities of exporting each pair of goods with *RCA*. Hence, this method assumes that the probability of producing two products that require similar capabilities for their competitive production is higher than the probability of producing two goods that require different capabilities.

The authors explored the large amount of information in international trade data to calculate the *proximity* between goods as the probability of a country exporting product *p* with *RCA* given that it exports product *j* with *RCA* as well. The level of proximity between two products (*p* and *j*) is given by the authors as:

$$\varphi_{p,j} = min\{P(RCA_j = 1|RCA_p = 1), P(RCA_p = 1|RCA_j = 1)\} \quad (9)$$

Adopting a threshold value for proximity, the authors established the active links between products, creating a network that they called *Product Space*. In this network, therefore, products that use similar capabilities for their competitive production tend to for clusters. Moreover, complex products tend to be located towards the centre of the network, while least complex product tend to locate more towards the fringes of the network.

Using the *Product Space*, Hidalgo *et al.* (2007) showed that, on average, less developed countries produce goods with a limited number of links. This restricts these countries' diversification possibilities, making in more costly for these countries to move towards the production of more complex products, while the opposite holds true for developed countries. Hence, the authors' seminal paper provided three important empirical contributions to the economic development literature. They showed that different countries face different opportunities to diversify their economies and increasing their economic growth, given their distinct productive structures and associated capabilities. Consequently, they highlighted that structural change is highly path dependent. And finally, these results point out that achieving competitiveness in the production of complex goods takes time, since it requires learning new capabilities (Hidalgo *et al.*, 2007: 487).

Seeking to explore the implicit information contained in the *Product Space*, Hausmann et al (2014) developed an indicator that measures the ease of acquiring competitiveness in any given industry as a function of existing capacities in the economy. This indicator would help to identify new diversification possibilities based on the implied costs associated with the acquisition of the new capabilities required for performing new activities competitively.

Assuming that close products use similar productive capacities, Hausmann et al (2014) proposed an index that measures the ease of competitive production of a given good as a function of the competitive production of nearby goods, which serves as a proxy for existing capabilities. This index, called Product Density Index (*PDI*), measures the proximity of a given product to the country's current production structure (products with *RCA*), indicating the difficulty (or cost) of achieving *RCA* in this product. Hence, this measure reflects the amount of new productive knowledge that a region needs to acquire to be able to produce and export a particular product with *RCA*. In other words, the smaller the *PDI*, the more capabilities will have to be acquired and the longer and more difficult/costly will be the process of achieving *RCA* in this product. In this way, products that the country exports without *RCA* but that have a high *PDI* appear as products with high potential to be fostered.

PDI is calculated as the sum of the proximities ($\varphi_{p,j}$) of the products that the country exports with *RCA* in relation to the product p. The index is normalized by the sum of the proximities between all products in the network in relation to the product p. Formally:

$$PDI_{pct} = \frac{\sum_p M_{ict}\,\varphi_{pi}}{\sum_p \varphi_{pi}} \tag{10}$$

Hausmann et al (2014) proposed also a second indicator, called Opportunity Gain Index (*OGI*). This index measures the gains that achieving *RCA* in any given good brings in terms of facilitating the production of more complex goods that were not previously produced/exported competitively in this economy. Formally:

$$OGI_{pct} = \sum_p \frac{(1 - M_{cit})\varphi_{pi} PCI_{it}}{\sum_p \varphi_{pi}} - \left(1 - PDI_{pct}\right) PCI_{\,pt} \tag{11}$$

A high value in the *OGI*, therefore, indicates that the product under investigation is closer to complex products. Hence, this index can be used to devise policies that aim to increase an economy's economic complexity considering several rounds of diversification into progressively more complex goods.

2.3. Activity Space

At the regional level using export data to measure economic complexity is highly problematic, since transactions between regions within the same country are not computed. Furthermore, economic interactions between neighbors are stronger at the regional level, making knowledge spillovers more relevant. In addition, in regions services play a more prominent role, so that it becomes more relevant to take these activities into account.

To solve these issues, some studies have been using employment or patent data instead of trade data to calculate the indicators of economic complexity. Using employment data has one additional advantage: it makes possible to use information on the number of occupations within companies or regions to measure proximity through occupation similarities.

According to Farjoun (1994), companies diversify through networks of industries that interrelate according to the resources they use. Thus, it is important to observe the similarities between the resources being used (for example, the level of education in different occupations) in order to understand the diversification patterns of companies and regions. From these *Resource-Related Industry Groups*, companies are able to share and transfer similar resources to benefit from and encourage diversification processes (Farjoun, 1994, p. 188).

Following Freitas (2019), from the concept of co-occupation it is possible to estimate the proximity of activities with similar jobs and build the complexity indicators through employment data. First, we define the indicator of effective occupations (*EO*), analogous to the revealed comparative advantage index (*RCA*), as the basis for calculating the complexity indicators using employment data. Formally:

$$EO_{s,o} = \frac{emp_{s,o}/emp_s}{emp_o/emp} \quad (12)$$

where $emp_{s,o}$ is the employment of occupation o in sector s and emp_s is the total employment of sector s in the country. In addition, emp_o is the total employment of the occupation o in the country and emp is the total employment in the country.

Thus, if the *EO* indicator is equal or greater than one, the participation of occupation o in sector s is greater than the participation of occupation o in the country. Hence, the sector in question effectively employs such an occupation. Otherwise, if *EO* is less than one, the conclusion is that the sector does not effectively employs this occupation in the analyzed location.

Using the *EO* indicator it is possible to calculate the proximity between activities and for an *Activity Space*. Proximity is calculated as the probability of an industry employing a certain occupation, given that another industry also employs that occupation. This represents a different way, although similar, of measuring the similarities between industries in terms of occupations. Thus, following Freitas (2019), equation (9) can be adapted to establish the relationship between activities s and i replacing *RCA* by *EO*.

The proximity between activities calculated according to similarities in the resources used by companies has a similar interpretation in relation to the concept of co-occurrence of productive capacities in nearby industries, as proposed by Hidalgo *et al.* (2007). In fact, one of the stylized facts presented by Hidalgo and Hausmann (2009) is the positive correlation between the number of occupations and countries' economic complexity.

Finally, it is important to note that using the *EO* indicator it is also possible to calculate the economic complexity of each region and of each activity following the same methodology described in the previous section.

2.4. Economic Complexity at the regional level

The literature on economic complexity and regional development has been growing rapidly in the last few years. Economic complexity has been applied at the regional level using alternative measures of local knowledge. Balland et al. (2018), for example, use patent data to measure local technological knowledge, using the same methods proposed by Hidalgo et al. (2007) and Hausmann et al. (2014) to guide the formulation of regional smart specialization strategies. Alternatively, Gao et al. (2021) apply the economic complexity methodology using employment data from both China and Brazil, to show that knowledge spillovers are relevant at the regional level, and that improving transport infrastructure helps increasing these spillovers and the productive diversification they foster.

This section shows how existing regional industrial structures can prompt the emergence and expansion of new industries, as well as the possible rebirth or revitalization of old industrial regions. The issue of structural change in regional and urban economics gained prominence through the reassessment of the works of Jane Jacobs and Alfred Marshall. Glaeser *et al.* (1992) deepened the framework of agglomeration economies, which previously focused on the effects of localization and urban size economies, by also investigating the economic importance of urban diversity. This focus on the so-called Jacobs' externalities can be considered the first attempt to assess the effect of the local industrial structure on economic development.

Henderson *et al.* (1995) took another step towards investigating structural change and growth studying whether externalities were more important in sustaining traditional industries than in attracting new industries. They found that new industries, especially the high-tech, entered diversified cities where Jacobs externalities were available, while mature industries benefited more from location externalities generated in more specialized cities. According to Simões and Freitas (2014), Jacobs externalities are more relevant in sectors of high technological intensity, while sectors with low and medium technological intensity are more benefited in medium-sized urban centers, relatively less diversified.

Jacobs' main argument for new industries needing diversified urban economies was that the urban diversity prompts the division of labor in a city. However, the urban growth contribution by the labor division is because diversified urban economies give rise to opportunities for innovation, and not so much is less because of technical efficiency. This fits very well into the Schumpeterian concept of innovation as successful new combinations of productive forces, i.e., old ideas.

An important implication of this is that knowledge is treated as an articulated set of qualitatively different ideas. On the other hand, cognitive theory emphasizes a trade-off between diversity and similarity: although there is greater ease of communication between actors who share overlapping competencies, only actors who do not share overlapping competencies and knowledge can really offer something new to be learned (Nooteboom, 2000).

Hence, the fact that social learning may require an optimal level of cognitive distance may explain why, after several empirical studies, the evidence on the effects of Jacobs externalities is still inconclusive (De Groot *et al.*, 2009). Regional knowledge spillovers only happen between certain industries, since a more effective communication is often hampered by the cognitive distance between these. Recently, several authors (Almeida & Kogut, 1999; Boschma & Frenken, 2009; 2011; Gilsing et al., 2007; Menzel, 2008) have suggested that industries are more likely to learn from each other when they are technologically related. Thus, a broad set of technologically related industries in a region should be more beneficial for growth than a diversified set of industries in a broad range of technological areas, given that it is the combination of distance and cognitive proximity that brings together the positive sides of diversity and similarity across industries.

Frenken *et al*. (2007) argue that regions with a greater degree of variety in related industries present more learning opportunities and, consequently, a higher dissemination of local knowledge. Using data for the Dutch economy, the authors show that regions with a higher degree of "related variety" often present higher employment growth. The same result was also found for other countries (Essletzbichler, 2005; Bishop & Gripaios, 2009).

Boschma and Iammarino (2009) argue that related variety can also flow from one region to another through commercial links between industries. Using regional trade data, the authors show that inter-regional knowledge flows are, in fact, associated with regional employment growth, when these come from industries related to industries in the region.

In these studies, the industrial base of a region is treated as a stable property. This makes sense in the short term because the industrial composition of a regional economy changes slowly over time. However, it is likely that the relationship between regional industries not only drives the incremental growth of existing industries through agglomeration economies but may be responsible for more radical changes in the regional productive structure. In fact, industrial kinship can be an important factor in attracting new industries to the region and in the disappearance of unrelated industries. This is a fundamental aspect because it sheds light on how the Schumpeterian process of creative destruction develops regionally over the long term. Similarly, understanding how new regional growth paths emerge has been repeatedly raised by economic geographers as one of the most intriguing and challenging questions of the field (Scott, 1988; Storper & Walker, 1989; Martin & Sunley, 2006). After all, the industrial history of regions is expected to affect how regional structures create new activities over time, and how they transform and restructure of their economies.

Bathelt & Boggs (2003) and Glaeser (2005) show that new local industries are often related to activities already established in the region. In addition, recently, there is more systematic evidence showing that territories are more likely to expand and diversify towards sectors that are closely related to their existing activities (Hausmann & Klinger, 2007; Hidalgo *et al.*, 2007). Focusing on changes in export portfolios over time, Hausmann & Klinger (2007) showed that countries expanded their export mix, moving towards products that were related to their current export agenda, which implies that a country's position in the product space affects their opportunities for diversification. As a result, rich countries specialized in the more densely connected parts of the product space presented more opportunities to sustain economic growth than poorer countries.

Boschma & Frenken (2009) call the process by which new activities arise from technologically related industries by "regional ramifications". The reason this process of regional branching takes place is that new industries can connect to existing ones through various knowledge transfer mechanisms. These mechanisms are: (i) diversification of firms; (ii) entrepreneurship in the form of spinoffs; (iii) mobility of workers; (iv) social networks. The branching process is essentially a regional phenomenon, as these mechanisms operate primarily – but not exclusively – at the regional level, that is, within subnational regions rather than across regions.

In their diversification strategies, firms tend to develop their previously existing competencies. The reason for this is that, as Nelson & Winter (1982) argue, intra-firm diversification is not simple, as companies seeking new markets and new technologies face fundamental uncertainties. However, companies try to limit these uncertainties and avoid large switching costs by carrying out local search processes in the technological sense, that is, aimed at technologies and markets similar to those in which the companies became known. Likewise, Penrose (1959) conceives firm growth as a progressive process of related diversification, in which firms diversify towards products that are technologically related to their current products. This opinion is supported by the fact that mergers and acquisitions present higher levels of performance when connecting companies with related technological knowledge bases (Piscitello, 2004; Cassiman *et al.*, 2005). Since new divisions of companies are often established within existing facilities, the internal diversification of companies is often not only local, in cognitive terms, but also in geographic terms.

In sum, there are good reasons why firm-level-related diversification (through internal and external growth) is geographically biased, although systematic empirical evidence for such a hypothesis seems to be scarcely discussed.

Regional diversification through entrepreneurship generally occurs when new companies in an emerging industry are created by entrepreneurs who have previously gained knowledge and experience in a related industry in the same region. There is considerable evidence that these companies benefit economically from the experiences acquired by entrepreneurs in related industries, reflecting in their greater chances of survival (Klepper, 2007). Longitudinal studies also confirm that these experienced entrepreneurs play a crucial role in the regional diversification process. Boschma & Wenting (2007) show that, in the early stages of development of the UK automobile industry, companies had a higher survival rate when those responsible had already worked in related industries, such as bicycle and bus assemblers or in the area of mechanical engineering, and when their regions stood out for the strong presence of these related industries. Kia's case also reflects this very well. Founded in 1944 in South Korea as a bicycle manufacturer, it later went on to produce military vehicles and equipment.

Regional diversification through labor mobility has not yet been so explored. Worker mobility is often considered as a key mechanism of knowledge diffusion (Almeida & Kogut 1999; Heuermann 2009), but until recently little attention had been paid to *spillovers* between firms in related industries with respect to labor mobility. Boschma *et al*. (2009) provide empirical evidence that the economic effects of workflows cannot be properly assessed without paying attention to how the knowledge flows are related to existing knowledge bases in companies. They point out that the entry of employees with skills related to the plant's knowledge base was positively associated with productivity increases, while the hiring new employees with skills already available at the plant was negatively associated with the productivity measure. However, the study of the role of labor mobility in the constitutive phases of an industry deserves further development. If, in fact, labor mobility induces industrial ramification, this phenomenon is likely a regional phenomenon, as most workers who change job remain in the same region (Boschma *et al*., 2009; Timmersmans & Boschma, 2013).

Social media can be another source of regional diversification. They are considered an important channel for the dissemination of knowledge and learning among companies (Powell *et al*., 1996, Sorenson *et al*., 2006; Ter Wal, 2009). However, the importance of networks for innovations, and thus for the development of new economic activities, may depend on the degree of technological kinship between network partners. It is likely that there is an optimal level of cognitive proximity between network partners in order to stimulate new ideas, and at the same time allow effective communication (Boschma & Frenken, 2009). Studies on networks of alliances between companies show that new knowledge is developed when actors bring different, but related, competences (Gilsing *et al*., 2007). Breschi & Lissoni (2003) state that social networks tend to be highly localized and that they can contribute to the process of regional diversification.

The implications of the above should not be underestimated. First, the industrial relationship at the regional level should affect how Schumpeter's creative destruction process will shape the economic landscape, i.e, the kinship between industries influences both incoming and existing industries that are going to leave a region. Second, the rise and fall of industries are conditioned to regional industrial structures established in the past, and this is supported by the notion of regional trajectory dependence (Rigby & Essletzbichler, 1997). Third, the trajectory dependency process implies that there is some degree of coherence in the region's industrial profile. However, this coherence is constantly redefined through the process of creative destruction. The entry of new industries in a region, although technologically related to existing local industries, is likely to inject new variety into the region, which reduces technological coherence. In contrast, exit from existing industries increases the industrial coherence of regions, because unrelated industries are more likely to be selected, leading to a decrease in variety.

3. Empirical Investigation

3.1. Database

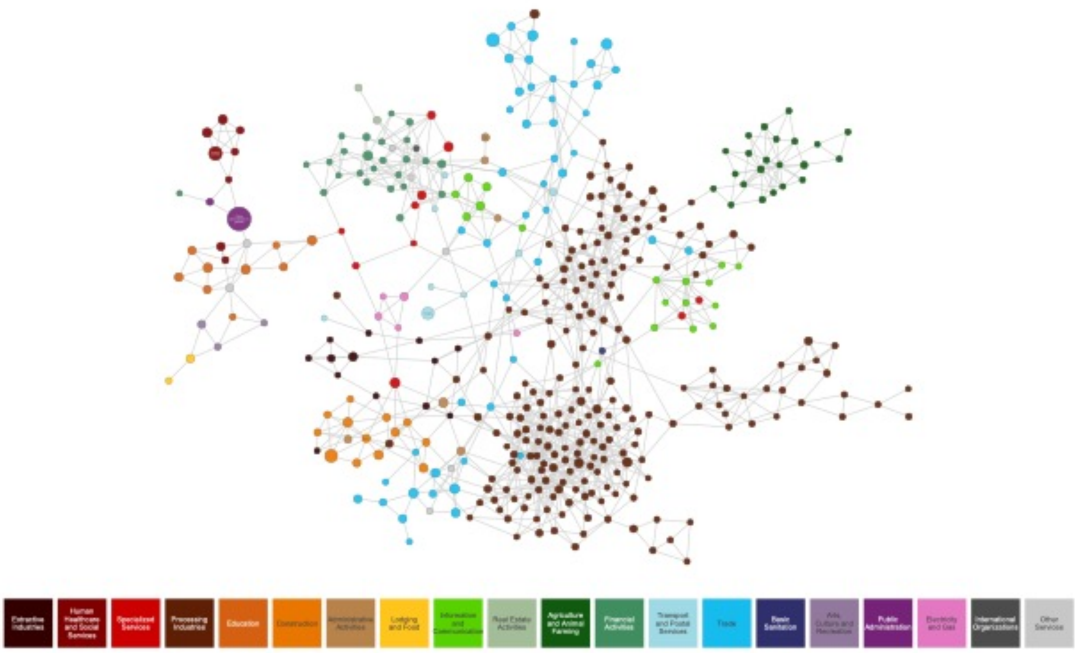
The empirical investigation presented in this paper is based on employment data for the municipalities and microregions of Brazil in the period between 2006 and 2018. The employment data used in the construction of the *Activities Space* and the economic complexity indicators of local activities come from RAIS (Annual Report of Social Information) of the Brazilian Ministry of Employment, which provides the number of employees by sector of economic activity classified according to the CNAE (version 2.0) classification and by occupation within each activity at both analytical levels of this work. GDP per capita comes from the Brazilian Institute of Geography and Statistics (IBGE).

The CNAE classification is disaggregated into 672 activity classes from all sectors (services, manufacturing and agriculture). Moreover, employment is divided into 596 occupations within each activity. The database covers the 5570 Brazilian municipalities, which are grouped into 558 microregions.

3.2. Brazilian Activity Space

Using the employment information from the RAIS database it is possible to calculate the *Activity Space* for Brazil following the methodology presented in section 2.3, as presented in Figure 1. The network shows that manufacturing activities (in brown) and modern services (e.g. in dark green) are more connected and localized more towards the center of the network, highlight their importance for diversification and development.

Figure 1: *Activity Space* for Brazil



Source: Auhtors own elaboration based on employment data from RAIS.

3.3. Econometric Specification

To analyze the impact of the economic complexity index (*ECI*) on future economic growth at the regional level, we estimate a set of regressions in which the dependent variable is either the annualized growth rate of GDP per capita, or the growth rate of the share of formal work on total population.

The estimated equation for GDP per capita follows the specification used by Hausmann et al (2014):

$$\Delta y_{i,t} = \alpha + f_i + f_t + \beta_1 ECI_{i,t} + \beta_2 ECI_{i,t-1} * log\,(y)_{i,t} + \beta_3 log\,(y)_{i,t-1} + \varepsilon \qquad (13)$$

where y is the GDP per capita, f are fixed effects for individuals i (municipalities/microregion) and periods t (annual dummies), α is the constant, ε is the residuals. Among the explanatory variables are the initial GDP per capita (log) and a multiplicative variable between *ECI* and initial GDP. The former seeks to capture the effect of the classic hypothesis of convergence or technological catch-up. The multiplicative term seeks to capture the non-linearity of the effect of *ECI* on the growth rate. Hypothetically, this effect is negative because the potential gains from increasing *ECI* also reduce with the increase in GDP per capita and *ECI* over time.

The impact of *ECI* on the evolution of formal employment was evaluated by estimating the following equation, analogous to equation (13):

$$\Delta l_{i,t} = \alpha + f_i + f_t + \beta_1 ECI_{i,t} + \beta_2 ECI_{i,t-1} * log\,(l)_{i,t} + \beta_3 log\,(l)_{i,t-1} + \varepsilon \qquad (14)$$

where l is the ratio of formal jobs in the economy in relation to the population. The interpretation of the variables is the same as in equation (13).

Finally, two level models were also estimated including among the explanatory variables the formal employment ratio (log) and the GDP per capita (log) as in equations (15) and (16), respectively, with the objective to eliminate collinearity, since *ECI* was estimated from employment data, which has a high correlation with GDP.

$$log\,(y)_{i,t} = \alpha + f_i + f_t + \beta_1 ECI_{i,t} + \beta_2 log\,(l)_{i,t} + \varepsilon \qquad (15)$$

$$log\,(l)_{i,t} = \alpha + f_i + f_t + \beta_1 ECI_{i,t} + \beta_2 log\,(y)_{i,t} + \varepsilon \qquad (16)$$

Traditional panel data methods were used to estimate equations (13) to (16). Across all models and specifications, time and municipal/microregion fixed effects were introduced. Tests confirmed the option for fixed effects.

3.4. Regression Results

The estimation results are presented in Table 1. Both parameters and models are highly significant. More than that, the models corroborate all assumed hypotheses, including identical parameters for the ECI (0.04) at the micro-region level to those of the seminal study by Hausmann et al. (2014) at the country level and using export data. This result is important as it validates the use of employment data in the assessment of production complexity.

Table 1: ECI and GDP and employment growth

	Microregions				Municipalities			
	Growth rate (GDP per capita)	Log (GDP per capita)	Growth rate (employment)	Log (emp)	Growth rate (GDP per capita)	Log (GDP per capita)	Growth rate (employment)	Log (emp)
ECI	0.0459***	0.0673***	0.5573***	0.0370***	0.0727***	0.0591***	1.5515***	0.0223***
Log (GDP per capita)				0.3717***				0.3197***
Log (GDP per capita) t-1	-0.3753***				-0.4207***			
ECI x GDPpc					-0.0044**			
Log (emp/total emp)						0.1205***		
Log (emp/total emp) t-1		0.4252***	-0.6048***				-0.7974***	
ECI x Log (emp/total emp)			-0.0790***				-0.3510***	
Constant	4.2191***	8.0730***	4.1629***	2.6314***	3.7865***	8.1664***	3.7883***	1.6550***
N	6138	6696	6138	6696	61213	66789	61215	66789
R2	0.253	0.8961	0.3945	0.5009	0.2532	0.8275	0.5669	0.17
F	157.12	4100.00	278.99	472.79	1500.00	23000.00	5600.00	964.36

Notes: * p<0.05; ** p<0.01; *** p<0.001. 1 Year dummies were used in all equations to control for time fixed effects and were generally significant. 2 The model included municipal fixed effects.

Source: Authors own elaboration using data from IBGE and RAIS.

It is important to highlight the high explanatory power of the level models. The temporal to transversal variance of both GDP per capita and the formal employment ratio are largely explained by the variance in the ICE. Specifications with only the ECI among the explanatory resulted in an R^2 of 0.75. The inclusion of the variable employment (log) and GDP per capita (log) in the estimates brings the parameters to a very close and consistent level in all models.

The ratio of formal employment in the population, in turn, is more elastic to the change in the ECI than the GDP per capita itself. An interesting note is that the effect of the ECI on employment growth is less significant than that on the growth of the ratio of formal employment to population. This indicates a fundamental role of ECI in formalizing the population in the labor market. In other words, it is possible to interpret that the increase in the complexity of the municipality is associated with the increase in the quality of jobs generated in the location.

In addition, GDP per capita and total employment lagged in a period have a negative relationship with the growth rates of GDP per capita and employment ratio, respectively, confirming the convergence hypothesis.

Finally, it is important to note that the effect of the ECI reduces as the output and formal employment grow in the municipality/microregion, confirming the hypothesis that the windows of opportunity are larger the smaller the level of product/employment/CI E.

4. Complexity based diversification strategies

4.1. Economic Diversification Score

Taking the economic complexity literature as reference, several studies have sought to use the indicators discussed in the previous section to devise diversification policies. Hausmann and Chauvin (2015), for example, used a series of indicators constructed based on economic complexity and on relatedness between products to identify promising sectors for the development of Rwanda. Hausmann *et al.* (2017) and Romero and Freitas (2018) used a similar methodology to identify the promising sectors for the development of Panama and Brazil, respectively.

These studies gathered a series of variables related to three relevant dimensions related to each product not exported with *RCA*: (i) *Markets*; (ii) *Capabilities*; and (iii) *Gains* (in terms of economic complexity). The variables were then normalized and put together in a weighted sum to generate a score of promising industries to be fostered through development policies. The main problem with this methodology is that the weights attributed to each variable are completely arbitrary. Hence, in this paper, we seek to solve this problem and improve the economic complexity smart diversification score by using a Principal Component Analysis (PCA) method.

Brazilian foreign trade data were gathered from SECEX and UN COMTRADE classified by product according to the Mercosur Common Nomenclature (NCM) classification. A correspondence table provided by IBGE was used to associate NCM products to economic activities classified by CNAE (version 2.0). Four-year averages of the variables were calculated to smooth short-term fluctuations and reduce eventual measurement errors. Year 2006 was dropped from the analysis.

The procedure carried out to estimate the weights of the variables followed a series of steps. First, sub-samples of municipalities/microregions were defined based on the characteristics of their productive structures in terms or High/Low Density and Complexity. Second, the weights attributed to each variable within each dimension (*Capabilities*, *Markets* and *Gains*) were defined by applying the PCA method. Third, after defining these weights, two scores were generated, one with homogeneous weights, and the other with the weights calculated via PCA. Fourth, these scores were used to try to analyze the proportion of sectors that gained *RCA* in municipalities/microregions that showed an increase in their *ECI* during the period evaluated predicted by each score, in order to validate their quality.

In this paper, for each dimension a PCA was performed. It was decided to keep the "n" components generated that cumulatively explained at least 80% of the variance of each one of the dimensions. Principal Component Analysis (PCA) has the main objective of explaining the structure of variance and covariance of a random vector, composed of p-random variables, through the construction of linear combinations of the original variables. It allows the researcher to reorient the data so that the first few dimensions explain as much information as possible. The individual main components are linear combinations of random variables X1, X2, Xn. Geometrically, these linear combinations represent the selection of a new coordinate system obtained by rotating the original system with X1, X2, Xn as the coordinate axes. Hence, PCAs are used to discover and interpret dependencies that exist between variables and to examine relationships that may exist between individuals.

To assess the improvements proposed in this research for the identification of promising activities, we built three versions of the *EDS*, considering: (i) all variables with equal weight; (ii) all variables with weights defined by the PCA method; (iii) eliminating some of the variables and considering the weights defined by the PCA method.

Table 2 shows the variables considered to calculate the Economic Diversification Score (*EDS*) and the results of the weights in the three versions indicated above. The PCA was carried out considering the sample of 593 municipalities belonging to the High Density (average *PDI*>median *PDI*) and High Complexity (*ECI*>0) quadrant and which presented growth in the *ECI* in the three periods analyzed in this research. To calculate the weights, the variables referring to the most recent period available in the database were used, from 2015 to 2018.

Table 2: Variables considered in the Economic Diversification Scores (*EDSs*) and their weights

Dimensions	Weights	Indicators	Models tested		
			All variables with equal weights	All variables with weights via PCA	Selected variables with weights via ACP
Capabilities	0.33	Employment	0.333	0.359	0.359
		Revealed Comparative Advantage (*RCA*)	0.333	0.583	0.583
		Employment growth rate	0.333	0.058	0.058
Markets	0.33	Imports (municipality/microregion)	0.111	0.104	0.088
		Revealed Comparative Disadvantage (*RCD*) (municipality/microregion)	0.111	0.04	0.157
		Import growth (municipality/microregion)	0.111	0.042	0.173
		Imports (state)	0.111	0.12	-
		Revealed Comparative Disadvantage (*RCD*) (state)	0.111	0.093	-
		Import growth (state)	0.111	0.216	0.583
		Imports (country)	0.111	0.132	-
		Revealed Comparative Disadvantage (*RCD*) (country)	0.111	0.102	-
		Import growth (country)	0.111	0.15	-
Gains	0.33	Product Density Index (*PDI*)	0.25	0.216	0.216
		Product Complexity Index (*PCI*)	0.25	0.293	0.293
		Opportunity Gain Index (*OGI*)	0.25	0.271	0.271
		Number of connections in the network	0.25	0.22	0.22

Source: Authors own elaboration.

To assess the predictive capacity of the *EDSs* proposed here in identifying promising activities, we performed a simple validation test. First, we created rankings for the sectors identified as promising by each of the three versions of the *EDS* in period 1. Then, we selected the industries in which the municipalities that have increased their *ECI* did not have *RCA* in period 1 (2007 to 2010) and achieved *RCA* in period 3 (2015 to 2018). Finally, from the number of activities found in the previous step, we verified how many of them were well ranked in each of the rankings built by the three versions of the *EDS*. The limit was defined by the number of sectors that transitioned from *RCA*<1 to *RCA*>1. For example, if a municipality X had 14 sectors that reached *RCA*>1 in period 3, we evaluated the first 14 sectors indicated in each of the rankings built to identify how many of the activities that achieved *RCA* were identified as promising by each rule. Similarly, if a municipality Y had 30 sectors that reached *RCA*>1 in period 3, we verified the first 30 activities indicated in each of the rankings. From these comparisons we calculated the average rate of success of each score as the ratio of the number of activities found in the final step of the process in relation to the total number of new activities with *RCA* (for each municipality or microregion).

Table 3 shows the mean percentages of correct predictions for each of the scores. Column 1 shows the percentages of the 3 different rules if applied to all municipalities. All 3 rules have a similar rate of correct predictions, around 30%, which indicates that about 1 in every 3 activities that actually obtained *RCA* in period 3 were targeted as promising by the rules. Column 2 presents the percentages only for the sectors that gained *RCA* in period 3 and that had *PCI*>0, that is, above average. As can be seen, in this case the results improve considerably: rule 3 presents a correctly predicts 41.4% of the activities, 3.4 percentage points better than rule 1, and 2 percentage points better than rule 2. The same pattern is observed in columns 3 and 4. The difference is that now the rates are evaluated considering only the municipalities with High Density and High Complexity, with was the subsample used to calculate weights using PCA.

Table 3: Validation tests of the EDSs

	Correct predictions			
	Test 1	Test 2	Test 3	Test 4
	All municipalities	All municipalities with *PCI*>0	All municipalities in the same group as Belo Horizonte	All municipalities in the same group as Belo Horizonte with *PCI*>0
Ranking 1	31.60%	38.00%	30.60%	35.70%
Ranking 2	30.50%	39.40%	30.00%	37.00%
Ranking 3	30.20%	41.40%	29.10%	37.00%
Number of observations	4440	1033	635	362

Source: Authors own elaboration.

The results found suggest the importance of the refinements carried out in the research, indicating that the use of weights calculated via PCA with sub-samples of municipalities/microregions similar to the region under investigation increased the proportion of sectors predicted as promising by the scores and that effectively achieved RCA in municipalities/microregions were an increase in economic complexity was observed.

4.2. Alternative strategies

To improve even further the smart diversification strategies stablishing following the *ODS* proposed in the previous section, activities were classified according to a series of strategies, following a classification proposed by the Brazilian National Export Plan (2015-2018), namely: (i) *Maintenance*, (ii) *Consolidation*, (iii) *Recovery*, and (iv) *Betting*. The scores were used to rank the most promising sectors within each of these strategies. The purpose of this ranking, therefore, is to bridge the gap between the proposed methodology for the selection of promising sectors and different smart diversification strategies, based on some extra information about characteristics of local competitiveness and of sectoral market dynamics.

Table 4: Smart diversification strategies – subgroups

Subgroups	Definition	Parameters
Maintenance	Sectors that are well positioned in the market and have a comfortable situation in relation to their main competitors	*RCA* >= 1,5 and municipal and national employment growth > 0
Consolidation	Sectors that are not yet consolidated but are growing at a pace close to or above that of their competitors.	0,5 =< *RCA* < 1,5 and Municipal and national employment growth > 0
Recovery	Sectors that have not yet consolidated or products that were once consolidated but have been reducing their market share.	*RCA* >= 0,5 and employment growth < 0 and national > 0
Bets	Sectors whose participation is very low, but whose exports are growing in the market.	0 < *RCA* < 0,5 and municipal and national employment growth > 0

Note: Based on the National Export Plan 2015-2018. Activities that did not fit into subgroups were discarded.

Source: Authors own elaboration.

The four strategies presented in Table 4 offer a comprehensive view of the products and activities with global, national and municipal competitiveness according to the smart diversification score proposed in the previous section. Through the typology presented in Table 4 it becomes possible to outline short, medium, and long-term development strategies.

In this sense, short-term strategies should focus on strengthening activities classified in the *Recovery* and *Maintenance* categories, since it encompasses sectors that were once competitive in the municipality, but are now declining, and sectors that are currently competitive in the region. The *Consolidation* strategy, in its turn, should be associated with medium-term development strategies, since it focuses on sectors that the municipality already has a certain level of competitiveness, but does not yet have *RCA*. Finally, the *Betting* strategy would be associated with long-term strategies, as it considers sectors in which the region's competitiveness is still low.

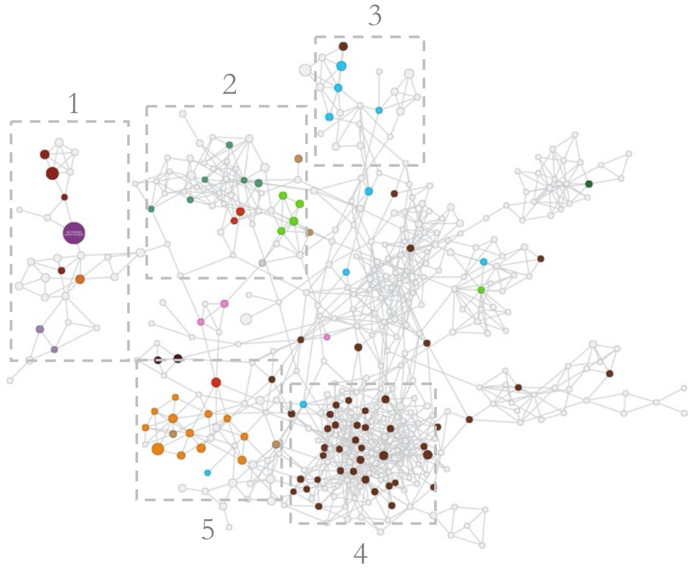
5. The case of Belo Horizonte

To illustrate how the Economic Diversification Score (*EDS*) can be used to help devising regional development policies, the *EDS* calculated using some selected variables and weights estimated using PCA was applied to the case of the city of Belo Horizonte. The city, located in the state of Minas Gerais, in the center of Brazil, is among the top 10 cities of the country both in terms of GDP per capita and economic complexity. Moreover, its microregion covers a large industrial area were one of the main factories of the car manufacturer Fiat is located.

5.1. Identifying promising activities for Belo Horizonte

Figure 2 shows the *Activity Space* of the microregion of Belo Horizonte in 2018. The dots colored mark the activities in which the region is competitive, i.e. with *RCA*>1. In this figure it is possible to identify four clusters: (1) public services; (2) modern services; (3) trade; (4) manufacturing; (5) construction. Although we aim to identity promising activities for the municipality of Belo Horizonte, it is important to consider the activities of its microregion in order to take into account the sectors that are competitive in nearby municipalities.

Figure 2: *Activity Space* of the microregion of Belo Horizonte in 2018



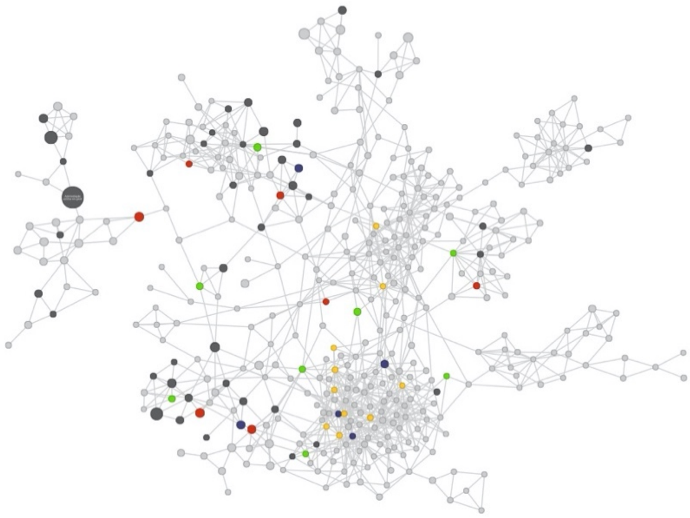
Source: Authors own elaboration.

Using the *EDS* presented in section 4.1 it was possible to identify the top 10 most promising activities within each the diversification strategy presented in section 4.2. Figure 3 shows the position of these 40 promising activities in the *Activity Space*. The figure shows that the Bets (in yellow) are in general associated with industrial activities, which tend to present higher complexity, while the remaining activities identified are more spread around the network.

To identify promising macro-sectors, it is also possible to group the 10 most promising activities within each diversification strategy both for Belo Horizonte and its microregion into more aggregated CNAE sectors, at 2 digits.

Among the promising activities, the macro-sectors *Machines*, *Electronics* and *Vehicles* encompasses 8 activities. Among these activities, 6 are from the *Bets* strategy. Next comes the *Chemical-Pharmaceutical* (3 activities) sector, and *Metallurgy* (2 activities). Moreover, several specialized services associated with production are identified as promising, such as *Infrastructure*, *IT* and *Machine Maintenance* (6 activities). The results are very similar both for the municipality and the microregion.

Figure 3: Promising activities for the municipality of Belo Horizonte



Notes: Red=*Recovery*; Yellow=*Bets*; Green=*Consolidation*; Blue=*Maintenance*; Dark-Grey=VCR>1.

Source: Authors own elaboration.

The message that emerges from this analysis of promising sectors classified into macro-sectors, therefore, is that the *Machinery*, *Chemicals* and *Metal-Mechanical* sectors are the ones that concentrate the greatest number of promising activities. In addition, the importance of developing the sector of *Modern Services* linked to production is also highlighted.

5.2. Projecting the diversification gains of Belo Horizonte

After identifying the promising activities for Belo Horizonte, it is also possible to calculate how much would the city's economic complexity increase if it achieved *RCA* in some of the targeted activities. Then, using the estimates of the impact of *ECI* on the growth rates of GDP per capita and employment presented in section 3 it is possible to estimate by how much would these variables increase in response to the increase in the city's *ECI*.

Table 5 presents the potential gains (average marginal effects) of different diversification strategies. Only the *Consolidation* and *Bets* strategies were considered, as well as the combination of both. The *Maintenance* strategy is presented to show the inverse relationship, measuring the negative effects of losing *RCA* in these activities.

The estimated effects of *RCA* loss in *Maintenance* activities indicates that losing competitiveness in these 7 sectors could lead to a 3.41% decrease in the municipal *ECI*, which would result in a reduction of 0.7 percentage points in the municipality's growth rate and 15 percentage points in the growth rate of the formal employment ratio.

At the other end of the analysis, the acquisition of *RCA* in the 10 products of the *Bets* strategy would bring a 7.9% gain in *ECI* and an increase in the municipal GDP per capita growth rate of around 1.6 percentage points. This effect is even greater in the formal labor market, increasing the formal employment growth rate by almost 35 percentage points.

The results presented in this section demonstrate the importance of devising short-term and long-term development strategies. More than that, the results show that the opportunity cost for the municipality of Belo Horizonte is considerably higher than that of the microregion in all the strategies presented, which should be carefully looked at by local public managers.

Table 5: Projected gains in GDP per capita and employment by acquiring *RCA* in the indicated promising activities: municipality and microregion of Belo Horizonte

	Municipality				Microregion			
	*Maintenance**	*Consolidation*	*Bets*	Promising sectors	*Maintenance**	*Consolidation*	*Bets*	Promising sectors
Total products in the category	7	5	10	15	10	4	10	14
Projected ECI	2.741	2.901	3.062	3.113	2.836	2.990	3.078	3.176
ECI gain (%)	-3.41%	2.23%	7.90%	9.70%	-1.59%	3.75%	6.81%	10.22%
Rate of change of GDP per capita (%)	-0.70%	0.46%	1.63%	2.00%	-0.21%	0.50%	0.90%	1.35%
Rate of change of employment (%)	-15.03%	9.84%	34.78%	42.71%	-2.55%	6.03%	10.94%	16.41%
Counterfactual level of employment (gain)**	-0.22%	0.14%	0.50%	0.61%	-0.17%	0.40%	0.73%	1.09%
Counterfactual GDP per capita (gain)***	-0.57%	0.37%	1.32%	1.63%	-0.31%	0.73%	1.32%	1.98%

Notes: The *ECI* for Belo Horizonte in 2019 was 2.84 and for the microregion 2.88. * The Mantenance strategy shows the loss if the municipality loses RCV in the sectors. ** Average marginal effect of *ECI* on GDP growth estimated at 0.073 and on employment growth at 0.557. 1 Counterfactual GDP per capita was calculated from the average marginal effect of *ECI* on GDP per capita estimated at 0.06 for the municipality and 0.07 for the region. 2 Counterfactual formal employment level was calculated from the average marginal effect of *ECI* on GDP per capita estimated at 0.02 for the municipality and 0.04 for the region.
Source: Authors own elaboration based on data from RAIS and IBGE.

Finally, it is important to note that the increase in complexity has effects not only on growth, but also on exports, as pointed out by Romero and Britto (2017), on inequality, as pointed out by Hartmann *et al.* (2017) and on greenhouse gas emission, as shown by Romero and Gramkow (2021). The combination of this evidence, therefore, supports the need for smart diversification strategies to overcome the bottlenecks faced by peripheral regions, reinforcing the importance of structural change for economic development. The challenge is to create the right incentives for economic diversification to take place in the desired direction.

6. Concluding remarks

The literature on economic complexity and regional development has been growing rapidly in the last few years. Economic complexity has been applied at the regional level using alternative measures of local knowledge. Balland et al. (2018), for example, use patent data to measure local technological knowledge, using the same methods proposed by Hidalgo et al. (2007) and Hausmann et al. (2014) to guide the formulation of regional smart specialization strategies. Alternatively, Gao et al. (2021) apply the economic complexity methodology using employment data from both China and Brazil, to show that knowledge spillovers are relevant at the regional level, and that improving transport infrastructure helps increasing these spillovers and the productive diversification they foster.

This paper sought to contribute to the literature on economic complexity and regional development using data from Brazilian microregions in four ways. First, it proposed the construction of a network, the *Activity Space*, that links different activities based on the number of shared occupations. This network allows transposing the *Product Space* to the regional level using employment data.

Second, it reported econometric tests of the impact of regional economic complexity, calculated using employment data for Brazil, on the growth rates of GDP per capita and of formal employment share. These tests, which are inspired in the ones carried out by Hausmann *et al.* (2014), transpose their results to the regional level.

Third, it proposed a new method to rank promising activities to be targeted by regional development policies, combining different indicators, as proposed by Hausmann *et al.* (2017), but using weights estimated using a principal component methodology.

Fourth, it showed that the proposed rule for identifying promising activities for smart diversification strategies performs very well when put to test against regions that presented increases in their economic complexity.

Finally, this methodology is illustrated using the example of the Brazilian city of Belo Horizonte. Combining the estimates of the impacts of economic complexity on income and employment, the paper presents simulations of the potential gains to be obtained following the proposed development path.

The evidence presented in this paper, therefore, provides important contributions for the formulation of regional development policies. More specifically, it provides an interesting framework for identifying promising activities to be candidates to be targeted by policymakers to promote regional economic development.

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