ÁREA 1: ECONOMIA

ECONOMIC COMPLEXITY AND LOCAL EMPLOYMENT MULTIPLIERS

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Abstract

This article integrates indicators from the economic complexity approach with techniques from the literature that measures local employment multipliers. The objective is to assess the heterogeneity of employment multipliers across 558 Brazilian micro-regions, considering the regional complexity level and segmenting the economy into two sectors: complex and non-complex. The results indicate that the complex sector has higher employment multipliers, and these multipliers vary according to the complexity of the regions. Notably, the multipliers of the complex sector are more significant in regions with high economic complexity. Specifically, in these regions, the complex sector can generate between 1.06 and 1.46 jobs within the sector and between 1.71 and 3.25 jobs in the non-complex sector for each additional job created.

Keywords: employment multipliers, economic complexity, regional development.

1 Introduction

The complexity of the productive structure is a relevant predictor of future economic growth (HAUSMANN et al., 2014) and employment (ROMERO et al., 2022; QUEIROZ et al., 2023). Therefore, the shift towards more complex sectors is considered crucial in the literature on economic complexity (HIDALGO et al., 2007). The accumulation of diverse and distinct capabilities provides economies with the opportunity to diversify and gain competitiveness across a wide range of goods, which ultimately impacts overall economic performance. However, the process of economic diversification is strongly path-dependent, and regions face limitations in their ability to diversify. This constraint is reflected in economic polarization resulting from related diversification, exacerbating regional inequalities. This condition creates winners and losers and, among other effects, significantly impacts the job creation process in these economies.

The literature on the Principle of Relatedness (HIDALGO et al., 2018) and its interaction with the economic complexity approach has provided new insights into regional inequalities. Recent studies have found empirical support for the thesis that economic diversification tends to occur in sectors already related to existing structures, contributing to regional growth. There are studies in the literature that find this dynamic for the Netherlands (FRENKEN et al., 2007), Italy (BOSCHMA; IAMMARINO, 2009), Sweden (NEFFKE et al., 2011), the United States (RIGBY, 2015; ESSLETZBICHLER, 2015), Europe (BALLAND et al., 2018) and Brazil (FREITAS et al., 2024; QUEIROZ et al., 2024). However, in the complexity approach, this dynamic results in the emergence of winning and losing regions, where diversification into new, more complex sectors is primarily limited to regions that already possess complex productive capacities (winners). On the other hand, other regions diversify into sectors that are closely aligned with local structures but not necessarily more complex (losers).

Besides that, the literature on complexity and regional inequality is still very limited, focusing mainly on the study of the relationship between indicators of complexity and income inequality. Two notable exceptions are Hartmann and Pinheiro (2022) and Pinheiro et al. (2022). The former assesses the variation in the relationship between complexity and inequality at the regional level compared to the national level. The latter examines the differences in diversification patterns among European regions. In both cases, the authors draw attention to the uneven development resulting from the process of related diversification within regions. Nonetheless, the literature still requires studies that assess the implications of these dynamics and are not restricted to just pointing out the sectors in which diversification could occur more easily.

In this context, this article aims to examine the heterogeneity of local employment multipliers due to differences in regional complexity. This study significantly contributes to understanding the impact of related diversification on job creation. By adapting the conceptual framework established in the literature on local multipliers, this analysis builds on the foundational work of Moretti (2010). In his study, Moretti examines local employment multipliers in tradable and non-tradable sectors in US cities. The innovation of this influential work lies in the proposition of a simplified conceptual and econometric framework for calculating multipliers, utilizing shift-share instruments. Subsequently, numerous analyses have followed this framework to calculate employment multipliers in regions across various countries in Europe, Japan (KAZEKAMI, 2017), China (WANG; CHANDA, 2018) and Brazil (MACEDO; MONASTERIO, 2016; LOYO; MOISÉS; MENDES, 2018; ROCHA; ARAUJO, 2021). Therefore, this paper adapts this framework to calculate multipliers for complex and non-complex sectors.

Based on the complexity indicators developed by Hidalgo and Hausmann (2009), we divided the region's economies into two sectors: complex and non-complex. Using formal labor market data from the micro-regions of Brazil at three different time points (2009, 2014 and 2019), we examined all possible relationships between these sectors, addressing potential endogeneity issues by employing instrumental shift-share variables. In addition to using the conventional shift-share instrument proposed by Moretti and Thulin (2013), we also introduced an instrument that takes into account regional structural changes. Finally, due to the limited explanations available in the literature, we conducted a bootstrap analysis to assess the changes in employment within the same sector.

In general, the multiplier for complex industries is expected to be greater than for non-complex industries. This hypothesis is based on the reasoning that the presence of complex and less ubiquitous activities (manufacturing and modern services) in the local economy tends to create a greater demand for less complex and more ubiquitous activities (trade of food and beverages, services of cleaning, construction materials). Moreover, the analysis takes into account the differentiation of micro-regions according to their complexity levels (Low, Medium-Low, Medium-High and High). It is assumed that complex sector multipliers will be greater in regions that are already complex. These regions tend to have more established institutions, higher labor competition between sectors, and greater labor mobility. These characteristics make the labor supply more responsive to changes in the complex sector. In summary, these hypotheses are supported by the results of econometric tests conducted in the study.

The paper is organized as follows. Section 2 focuses on reviewing the literature on local employment multipliers. Section 3 brings the adaptation of the conceptual framework using the economic complexity approach. Section 4 presents the data used and the econometric specification for measuring employment multipliers adapted from Moretti and Thulin (2013). Section 5 presents the results of the econometric estimates accompanied by the discussion. Finally, Section 6 concludes with final considerations.

2 Literature on Local Employment Multipliers

The methodology employed to measure regional employment multipliers is derived from the seminal article by Moretti (2010). Moretti studies the implications of a permanent increase in jobs in the tradable goods sector, which can result from the arrival of a new firm or a substantial increase in demand from existing firms. According to the assumptions, such a shock affects the general equilibrium of prices. As a result, workers' wages and housing costs increase, unless the supply curves are perfectly elastic. This process leads to an expansion of the city's budget constraint, with more jobs and higher wages, consequently increasing demand in non-tradable sectors such as personal services, restaurants, cleaning services, and more. This represents the multiplier effect for the non-tradable sector (1). On the other hand, the shock also impacts the tradable sector through three distinct effects. First, the rise in local labor costs makes the existing tradable sector less competitive, as prices are not subject to the same local dynamics. Second, there may be increased demand in intermediate tradable sectors, and the extent of this impact depends on the geographic concentration of these industries. Third, agglomeration effects occur as a consequence of the initial employment shock. The combined influence of these factors gives rise to the multiplier effect for the tradable sector (2). Formally, Moretti (2010) proposes the following solution:

$$\Delta N_{ct}^{NT} = \alpha + \beta \Delta N_{ct}^{T} + \gamma d_t + \epsilon_{ct} \tag{1}$$

$$\Delta N_{ct}^{T_1} = \alpha' + \beta' \Delta N_{ct}^{T_2} + \gamma' d_t + \epsilon'_{ct} \tag{2}$$

Where ΔN_{ct}^{NT} and ΔN_{ct}^{NT} are the change over time in the log number of jobs, respectively, in the non-tradable and tradable sectors. Moreover, $\Delta N_{ct}^{T_1}$ is the change in the log number of jobs in a randomly selected part of tradable sector and $\Delta N_{ct}^{T_2}$ represents the change in the log number of jobs in the remaining part of the tradable sector. Finaly, d_t is a dummy variable used to indicate the last period under consideration.

However, the estimation of equations (1) and (2) through OLS can lead to biased estimators due to endogeneity problems and omitted variables. Factors such as increased employment in non-tradable sectors that generate more jobs in tradable sectors, as well as unobservable time-varying shocks to local labor supply, can confound the causal effect of the shock. To address this, Moretti (2010) adopts an instrumental variable approach using a shift-share instrument (BARTIK, 1991). The instrumental variable is constructed as the average nationwide employment growth in manufacturing industries, weighted by the share of these industries in cities during the initial period. By assuming that national changes in employment are exogenous to region-specific dynamics, regression with an instrumental variable can provide unbiased estimators.

In Moretti (2010)'s pioneering study, he provided the initial estimates of multipliers that served as a benchmark for subsequent research. He found that for each additional job created in the tradable sector, 1.6 jobs are generated in the non-tradable sector within the same city. Moreover, Moretti (2010) argues that skilled jobs have a greater multiplier effect due to their concentration of higher wages. Specifically, he found that each additional skilled job generates 2.5 non-tradable jobs. Furthermore, the author suggests that the multiplier for the tradable sector should be relatively smaller, or potentially negative, due to the increase in labor costs associated with it. Formally, Moretti's analysis reveals that an additional job in a specific part of the tradable sector generates 0.26 jobs in the remaining part. This framework and analysis have been replicated and adapted in studies conducted for various countries, expanding the understanding of regional multipliers.

Moretti and Thulin (2013) conducted a similar exercise to assess local employment multipliers in Sweden. They made an adaptation to the instrumental variable used by excluding the reference region in the instrument's measurement to address potential violations of the exogeneity assumption due to the region under analysis being included in the calculation. The findings of Moretti and Thulin (2013) revealed a statistically significant multiplier, although smaller than that observed in the United States. Specifically, the addition of one job in the tradable sector generated between 0.4 and 0.8 jobs in the non-tradable sector. The multiplier was notably higher for skilled jobs and the high-tech industry. In terms of the tradable sector, the multiplier was closer to the range of 0.3 to 0.4, similar to the findings in the United States.

Dijk (2015) furthered the adaptations by attempting to replicate Moretti (2010)'s analysis while also calculating the multipliers using the alternative instrumental variable that excludes the reference city from the calculation. The author argues that estimates obtained with the new instrument are more robust as they align with the plausibility of exogeneity. The results of this exercise yield statistically significant but smaller multipliers. Specifically, the creation of one job in the tradable sector leads to the generation of 0.84 non-tradable jobs in the same city. In the case of skilled jobs, each additional job generates 1.46 jobs in local non-tradable sectors. These multipliers are lower than the 1.6 and 2.5 estimates previously found by Moretti (2010).

Apart from the studies conducted in the United States and Sweden, several other countries have been analyzed using a similar methodology. The literature includes contributions that examine the cases of Italy (BLASIO; MENON, 2011), Spain (GEROLIMETTO; MAGRINI, 2014), United Kingdom (FAGGIO; OVERMAN, 2014), Japan (KAZEKAMI, 2017), China (WANG; CHANDA, 2018), Mexico (HERNANDEZ; ROJAS, 2020) and Brazil (MACEDO; MONASTERIO, 2016; LOYO; MOISÉS; MENDES, 2018; ROCHA; ARAÚJO, 2021).

While not all studies specifically focus on non-tradable and tradable multipliers, they adopt the same measurement methodology to assess the employment multiplier effects in regional economies. For instance, the methodology was employed to calculate employment multipliers in the public sector (FAGGIO; OVERMAN, 2014), the creative industries (GOOS; KONINGS; VANDEWEYER, 2018), and cultural industries (GUTIERREZ-POSADA et al., 2023). Moreover, the same methodology was utilized to gauge the impact of job creation on other variables, including the unemployment rate and the total number of unemployed individuals (ROCHA; ARAÚJO, 2021).

Faggio and Overman (2014) adapted the methodology to examine the impact of public sector employment on local labor markets in the UK. Their study focused on the period between 2003 and 2007. The authors found that additional employment in the public sector led to the generation of 0.5 jobs in the construction and services sectors, while simultaneously reducing 0.4 jobs in the manufacturing sector. However, they did not observe a significant increase in employment within the overall private sector. Notably, employment growth in the public sector did contribute to a 1-to-1 increase in total employment within a given location. This adaptation by Faggio and Overman (2014) served as a reference for subsequent studies investigating similar dynamics.

In Brazil, three studies have examined employment multipliers. Macedo and Monasterio (2016) conducted an analysis similar to Moretti (2010) using data from 21 different economic activities across 123 meso-regions in Brazil. The authors found that for each additional industrial job, 3.78 new jobs were created in the service sector, excluding the metropolitan region of São Paulo. However, when including São Paulo, the multiplier increased to 6.58. Additionally, Macedo and Monasterio (2016) found a multiplier of 6.94 for the influence of high technology industries on local services, which aligns with previous research findings. It's important to note that the authors caution against overgeneralizing these results, as the multipliers are average estimates and may not capture the unique development experiences of each region. Factors such as sector, technology, strategy, and other local characteristics can significantly impact the effect of employment shocks.

Loyo, Moisés and Mendes (2018) conducted a study focusing on employment multipliers in the Brazilian public sector, similar to the work of Faggio and Overman (2014). The study analyzed the period of the first two terms of President Lula, from 2003 to 2010. The findings suggest a change in the multiplier effect between the two terms. During the period of a contractionary fiscal policy (2003-2006), an increase in public sector employment led to a displacement of private sector employment (negative multiplier), with approximately 0.46 private jobs being displaced for every additional public job. In contrast, during the period of an expansionary fiscal policy (2007-2010), the increase in public sector employment was complementary to private sector employment (positive multiplier), resulting in the creation of approximately 0.79 new private jobs for each additional public job.

Rocha and Araújo (2021) conducted a recent study in Brazil, building upon the previous research on job multipliers. They applied a similar econometric strategy to estimate the effects of increased industrial employment on various labor market outcomes. The findings of their study indicate that an additional job in the industrial sector, on average, leads to a reduction of 2.6 unemployed individuals and an increase of 8.4 new jobs in the non-tradable sector. This suggests that industrial employment growth has a positive impact on reducing unemployment and generating employment opportunities in other sectors of the economy. The study also found supporting evidence for the inverse relationship between the growth of industrial employment and the unemployment rate, further highlighting the importance of industrial sector expansion for improving labor market conditions in Brazil.

In recent studies, the methodology has been applied to assess the influence of high-tech and high-skilled jobs, as well as the creative industry. Goos, Konings and Vandeweyer (2018) conducted a study examining labor markets in 227 regions across Europe. Their findings reveal that additional employment in highly skilled occupations can generate up to 5 additional jobs in low-skill-intensive local services within the same region. However, the authors also observe persistent variations in the size of this multiplier across regions. They find that regions with higher levels of immigration, a larger number of less skilled workers, and lower GDP per capita tend to exhibit higher multipliers. This suggests that the characteristics of the region, such as labor market composition and economic development, play a role in shaping the multiplier effect.

A similar analysis was conducted by Lee and Clarke (2019) to examine the multiplier effect of high- tech industry jobs using UK labor market data. The study employed Moretti (2010)'s methodology and included a set of control variables. The findings revealed three main discoveries. Firstly, for every high-tech job created, approximately 0.7 jobs were generated in local services. Secondly, the study found that the growth of high-tech jobs led to a decrease in the average wage of low-skill local workers. However, the authors argued that this wage reduction was primarily driven by new entrants to the labor market, as employment of unskilled workers in the tradable sector remained unaffected.

Finally, Gutierrez-Posada et al. (2023) have recently applied this methodology to evaluate employment multipliers in the cultural and creative industries. The authors made adaptations to the methodology and constructed a 21-year panel dataset for cities in the UK. Their findings indicate that, on average, the addition of one creative job is associated with the creation of at least 1.9 new jobs in the tradable sector of each city. Furthermore, the creative industry accounts for over 16% of the growth in non-tradable employment in the analyzed sample, with more significant impacts observed in locations with larger creative clusters.

Indeed, these two distinct theoretical fields converge towards the central focus of this article. The literature on complexity has primarily centered around investigating the correlation between the Economic Complexity Index (ECI) and income distribution measures, while paying less attention to the exploration of regional inequalities. On the other hand, recent studies on regional employment multipliers, particularly concerning high-tech jobs, have evolved to inquire about the consequences of generating complex employment opportunities. Consequently, the connection between these areas becomes apparent. Thus, the objective here is to provide an answer to the following question: Do complex employment multipliers display heterogeneity based on the level of regional complexity?

3 Conceptual Framework Adapted for Economic Complexity Approach

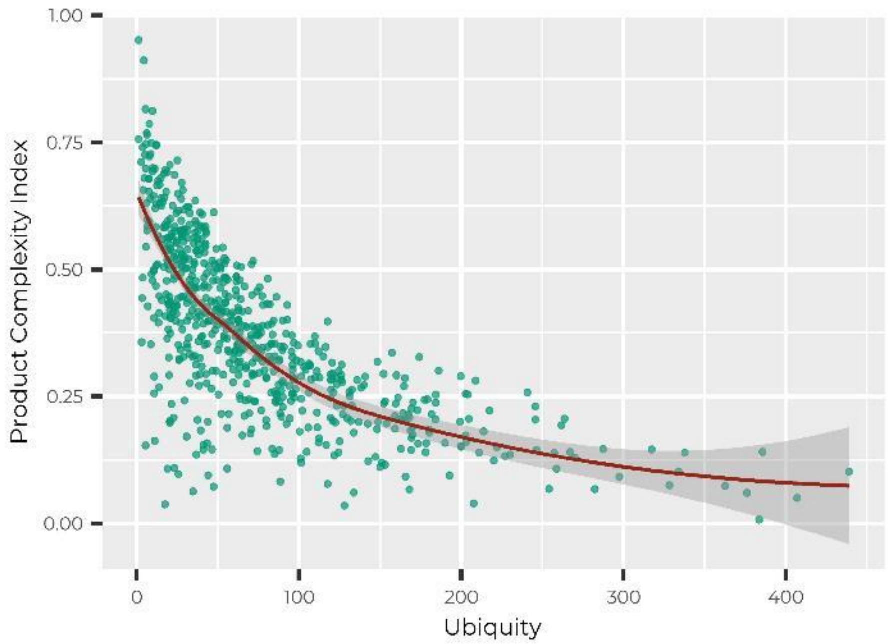
This analysis becomes possible by adapting the conceptual framework developed by Moretti (2010) and Moretti and Thulin (2013). As mentioned earlier, their framework is based on several key assumptions that enable the measurement of local employment multipliers. First, it considers each city as a competitive economy that produces two types of goods and services: tradables and non--tradables. Tradables have prices determined at the national or international level, outside the control of the cities, while non-tradables have locally determined prices.

Moreover, the framework assumes that labor is perfectly mobile across sectors within cities. This assumption ensures that the marginal product and the marginal wage are equalized within cities, leading to efficient allocation of labor resources. Additionally, the utility of workers is influenced by local net wages, the cost of living, and individual preferences for specific locations. The extent of idiosyncratic location preferences affects the geographic mobility of labor, with weaker preferences leading to greater labor mobility and higher elasticity of labor supply. It is also assumed that the housing supply curve is upward sloping, with the slope being influenced by geographical factors and land use regulations. These assumptions collectively form the foundation for estimating local employment multipliers.

The adaptation of these assumptions with the concepts of economic complexity is facilitated by the nature of the main indicators used in this approach. The Economic Complexity Index (ECI) and the Product Complexity Index (PCI) are built from two concepts: diversification and ubiquity. Diversification refers to the quantity of different goods produced competitively in a region, indicating greater complexity. Conversely, ubiquity refers to the widespread production of a good across different regions, indicating lower complexity. On the other hand, goods that are produced by fewer regions competitively are considered more complex. This notion of ubiquity allows us to classify the economy into the production of complex and non-complex goods and services, as well as tradable and non-tradable sectors.

The greater the presence of a sector in local economies (high ubiquity), the more influential local dynamics are in determining its price. Conversely, sectors with a smaller presence in local productive structures (low ubiquity) are less susceptible to local factors in determining their price. As a result, highly ubiquitous activities such as the sale of beverages, food, construction materials, bakery products, cleaning services, and accommodation services are considered less complex. These activities compete with other local actors, and their prices are primarily defined locally. On the other hand, activities with lower ubiquity, such as manufacturing, financial and banking services, and information intelligence services, are more complex and compete at the national or international level. Therefore, their prices are largely determined by factors beyond the local context. The graph below illustrates the comparison between the levels of complexity and ubiquity for a range of productive activities in Brazil.

Figure 1 – Product Complexity Index (PCI) and Ubiquity - Brazilian Economic Activities



Source: own elaboration.

Therefore, our conceptual framework begins by distinguishing between complex and non-complex goods and services. Each micro-region in Brazil can be seen as a competitive economy that allocates its workforce between the production of complex and non-complex sectors. The prices of complex goods and services are determined outside the local dynamics, while non-complex sectors are influenced by local factors. Finally, the hypotheses related to labor force mobility and the upward sloping labor and housing supply curves still apply to the analysis of local employment dynamics within the region.

Our research focuses on examining the impact of shocks on labor demand in both the complex and non-complex sectors of the economy, similar to the approach taken by Moretti (2010) in studying the tradable sector. Specifically, we are interested in understanding the effects of permanent growth in these sectors, whether it be through the attraction of new industries or exogenous increases in labor productivity within existing industries. These shocks not only directly affect employment in the respective sectors but also have indirect effects on the rest of the economy. It is important to note that such shocks may also have implications for the general price equilibrium, as they are likely to result in increased wages for workers and higher housing costs, unless labor and housing supplies are infinitely elastic at the local level.

Moretti (2010) focuses on measuring these two indirect effects. Firstly, there is the multiplier effect on the non-tradable sector, which is a result of the increase in aggregate income within cities. This increase in employment and local wages leads to higher demand in the non-tradable sector. Secondly, there is the multiplier effect on the remaining tradable sector, which is influenced in various ways. Employment in this sector may decrease due to the rising labor costs and decreased competitiveness. Conversely, it may increase if there is a concentration of intermediate tradable goods production locally or due to agglomeration economies. Therefore, our study shares a similar objective, as we seek to examine these dynamics and their implications in the context of complex and non-complex sectors.

We will utilize this adapted conceptual framework to examine the impacts of shocks on both the complex and non-complex sectors of the Brazilian economy. Our analysis will encompass all potential relationships between these sectors and will further differentiate regions based on their level of complexity. Through this investigation, we aim to validate the following hypotheses.

- *Hypothesis 1:* Complex sector employment multipliers are greater.

- *Hypothesis 2:* Multipliers are heterogeneous between regions with different levels of economic complexity.
- *Hypothesis 3:* Job creation by the complex sector is more effective in regions with highly complex production structures.

Hypothesis 1 is based on the premise that the attraction of complex (less common) jobs, such as manufacturing activities, leads to an increased demand for less complex (more common) activities, such as basic services. This relationship is analogous to the one observed between tradables and non-tradables. Conversely, the opposite reasoning lacks the necessary transmission channels to generate significant job creation. Hypothesis 3 follows as a consequence of Hypothesis 2, suggesting that the complex sector has varying impacts on regions based on their existing level of complexity. This is rooted in the understanding that more complex economies are also institutionally more developed regions, characterized by lower wage inequality between sectors and higher competitiveness. As a result, the labor supply in these regions is more sensitive to changes caused by permanent increases in employment within the complex sector. On the other hand, less complex regions, with different characteristics, are not affected in the same manner by the complex sector.

4 Data and Method

4.1 Data

For the analysis in this paper, the primary database will consist of employment data in economic activities across micro-regions in Brazil for the years 2009, 2014, and 2019. These data are sourced from the Annual Social Information Report (RAIS), which is linked to the Brazilian Ministry of Labor and Employment. It is important to note that the RAIS database contains administrative records of all formal establishments in the Brazilian labor market, making it a crucial data source for similar methodological analyses conducted in previous studies on Brazilian regions (MACEDO; MONASTERIO, 2016; LOYO; MOISE ́S; MENDES, 2018; ROCHA; ARAÚJO, 2021).

Similar to Rocha and Araújo (2021), the geographic unit used in this study will be the micro-regions. Economic activities will be classified based on the 6-digit class of the National Classification of Economic Activities (CNAE) provided by the Brazilian Institute of Geography and Statistics (IBGE).

Additionally, although data segmented according to this classification are available from 2006 to 2021, we have chosen the intervals 2009-2014 and 2014-2019. This choice aligns with the literature on multipliers, ranging from classic articles (MORETTI, 2010; MORETTI; THULIN, 2013) to more recent studies (DIJK, 2017; MACEDO; MONASTERIO, 2016; ROCHA; ARAÚJO, 2021), which have also used three time points and two intervals for their analyses.

This classification enables us to create a database that includes 558 Brazilian micro-regions and 670 productive activities, resulting in a total of 373,860 observations per year. Since we are using three time points, the database consists of a total of 1,121,580 observations. However, as explained in the next subsection, our econometric estimation strategy is aggregated at the micro-region level and focuses on the variation in employment between periods. Consequently, the final dataset used for the estimation comprises 1,116 observations.

Finally, this study utilized employment data to measure the complexity indicators according to the method outlined by Hidalgo and Hausmann (2009). Employment data has gained significant traction in subnational analyses due to its timeliness, comprehensive coverage across all territorial dimensions, and detailed specificity (FREITAS et al., 2024; ROMERO et al., 2022). In contrast to foreign trade data, which was the focus of previous studies by Hidalgo et al. (2007) and Hidalgo and Hausmann (2009), employment data emerges as a more fitting choice for regional analysis in Brazil. This is primarily because a substantial number of municipalities in Brazil do not engage in exporting or importing activities, thus lacking pertinent information. Moreover, given the substantial influence of the domestic market on the Brazilian economy, employment data offers a holistic perspective.

4.2 Econometric Specifications

The econometric specification employed to measure the multipliers will be adapted from the approach used by Moretti and Thulin (2013). Their methodology allows for the identification of the indirect effects resulting from a permanent increase in the tradable sector. However, in line with our conceptual framework, we will adapt this approach to examine the indirect effects of exogenous employment shocks in both the complex and non-complex sectors. To accomplish this, we will estimate four equations that capture all possible relationships between these two sectors, which together constitute the economy.

These equations are listed below. The first two, 3 and 4, calculate the multipliers resulting from a shock in the complex sector. In 3, this effect is verified on the non-complex sector of the economy. In 4, a part of the complex sector is randomly selected to check the employment multiplier over the rest of the complex sectors. The logic is the same for the non-complex sector in equations 5 and 6. Respectively, the effect on the complex sector and of a portion of the non-complex sector on the rest of the same sector is calculated.

$$E_{m,t}^{NC} - E_{m,t-5}^{NC} = \beta_0 + \beta_1\left(E_{m,t}^{C} - E_{m,t-5}^{C}\right) + \beta_2 Time + \varepsilon_{m,t} \tag{3}$$

$$E_{m,t}^{C_1} - E_{m,t-5}^{C_1} = \beta_0 + \beta_1\left(E_{m,t}^{C_2} - E_{m,t-5}^{C_2}\right) + \beta_2 Time + \varepsilon_{m,t} \tag{4}$$

$$E_{m,t}^{C} - E_{m,t-5}^{C} = \beta_0 + \beta_1\left(E_{m,t}^{NC} - E_{m,t-5}^{NC}\right) + \beta_2 Time + \varepsilon_{m,t} \tag{5}$$

$$E_{m,t}^{NC_1} - E_{m,t-5}^{NC_1} = \beta_0 + \beta_1\left(E_{m,t}^{NC_2} - E_{m,t-5}^{NC_2}\right) + \beta_2 Time + \varepsilon_{m,t} \tag{6}$$

Therefore, $E_{m,t}^{NC}$ and $E_{m,t}^{C}$ represent the amount of employment, respectively, in the non-complex and complex sectors in micro-region *m* and in period *t*. $E_{m,t}^{C_1}$ reflects employment in a randomly selected portion of the complex sector and $E_{m,t}^{C_2}$ the amount of employment in the rest of the sector. The same is represented for $E_{m,t}^{NC_1}$ and $E_{m,t}^{NC_2}$ for non-complex sector parts. The *Time* variable is a dummy that takes the value 1 referring to the last period (2014-2019). This strategy is adopted to control for possible national shocks in employment in the sector that is the dependent variable. Finally, $\varepsilon_{m,t}$ is the error term. In all equations, the regional employment multiplier is hypothetically represented by β_1.

However, the OLS estimations of these models are likely to be inconsistent. As summarized by Dijk (2015), this is because β_1 is capturing three types of effects. First, it captures the causal effect of job growth in one sector on the other, which is the effect we want to measure. Second, there is likely to be an endogeneity problem, such as when an increase in jobs in the non-complex sector affects the number of jobs in the complex sector (equation 3) or vice versa (equation 5). Third, there may be inconsistencies due to omitted variables, such as changes caused by local public services that influence employment in both sectors.

To address these problems, Moretti and Thulin (2013) propose using an instrumental variable estimation with a shift-share instrument (BARTIK, 1991). The shift-share analysis decomposes employment growth into three distinct effects: growth resulting from the increase in total national employment (national), growth due to the composition of local productive structures (structural), and growth resulting from the performance of these sectors locally compared to the performance of the same sectors in the overall economy (differential). The strategy employed by Moretti and Thulin (2013) is to isolate potentially exogenous changes in job demand by calculating the structural growth component. In this case, the instrumental variable aims to isolate the variation in employment in the tradable sector that is due to national changes, separate from the variation that is due to local changes. For our purposes, we have adapted the calculation of this instrument to suit our analysis:

$$IV_1 = \sum_j E^{\varphi}_{m,j,t-5} \left(\ln\left(E^{\varphi}_{j,t} - E^{\varphi}_{m,j,t}\right) - \ln\left(E^{\varphi}_{j,t-5} - E^{\varphi}_{m,j,t-5}\right)\right) \quad (7)$$

Where φ = $\{C$ (equation 3), C_2 (4), NC (5), NC_2 (6)$\}$.

This instrument, represented by equation (7), includes the national share and the sector-specific shares but excludes regional variation. Unlike Moretti (2010), where the instrument did not exclude the variation of the city itself, this adaptation proposed by Moretti and Thulin (2013) addresses the potential violation of the exogeneity assumption. By excluding the variation of the reference micro--region, the instrument isolates changes in employment in industry *j* of micro-region *m* that arise from national variations in industry *j*. However, the impact of these changes differs across micro-regions due to their unique composition in the base year ($E^{\varphi}_{m,j,t-5}$). According to Moretti and Thulin (2013), the instrument captures exogenous changes in local labor demand, as national changes do not reflect local economic dynamics.

In addition, we will utilize another type of instrument to assess potential changes in the multiplier and enhance the robustness of our results. The instrument proposed in equation (7), as mentioned earlier, is based on the productive structure composition of the micro-regions in the base year, thereby not capturing the effects of structural changes within each local economy over the 5-year interval. To address this limitation, our complementary approach involves using an instrument that isolates changes resulting from national variations and local variations, taking into account the portfolio of economies in the final period ($E^{\varphi}_{m,j,t}$) rather than the initial period. Consequently, changes in the overall economy will continue to manifest differently across micro-regions, but now considering the structural changes observed during the period. This adaptation is inspired by Stilwell (1969)'s proposal, which modifies the shift-share method to calculate the expected net change in employment in a given region based on its final industrial structure. The author's approach is based on the criticism that the conventional method does not capture the diversification that occurred during the studied period. The calculation of this shift-share instrument is shown below:

$$IV_2 = \sum_j E^{\varphi}_{m,j,t} \left(\ln\left(E^{\varphi}_{j,t-5} - E^{\varphi}_{m,j,t-5}\right) - \ln\left(E^{\varphi}_{j,t} - E^{\varphi}_{m,j,t}\right)\right) \quad (8)$$

Still, two important points regarding the estimation strategy should be addressed. Firstly, it is worth noting that most of the studies in this literature do not incorporate control variables in their estimations, although there are exceptions (FAGGIO; OVERMAN, 2014; DIJK, 2017; WANG; CHANDA, 2018; LEE; CLARKE, 2019). In these cases, the variables are typically used to control for city or regional size, the skill level of the workforce or inhabitants, and the unemployment rate. In our analysis, we will replicate the estimations with the inclusion of control variables to assess the robustness of our results. Specifically, we will control for the population size of each micro-region using data from IBGE. Additionally, we will consider the share of employment occupied by individuals with at least an incomplete undergraduate degree as a measure of the region's labor market qualification. The average salary of the micro-region will be used to control for productivity, and the local relatedness average will be employed to account for the proximity of the micro-region to other sectors, which is expected to influence the attraction of new jobs. With the exception of population data obtained from IBGE, the variables will be constructed based on data provided by RAIS. It is important to note that unemployment rate at the micro-region level is not available. The estimations including these control variables will be available in the annexes.

Second, a different estimation strategy is employed for equations (4) and (6). In the literature that examines the effect of a portion of the tradable sector on the rest of the same sector (MORETTI, 2010; MORETTI; THULIN, 2013), there is no specific guidance on how the samples are selected. The authors only mention that a part of the sector is randomly chosen. However, when conducting a single estimation and selecting only one sample, the resulting multiplier is solely determined by that particular sample. As a result, it is not possible to assess the sensitivity of the multiplier to the sample selection process. In other words, the value of the multiplier may significantly differ if a different sample were randomly selected. To address this concern, we will conduct a bootstrap analysis[1]. By randomly selecting multiple samples, we can determine the variability of the resulting multipliers and their trends. This approach allows for a more robust estimate that is not contingent on the estimation based on a single sample.

Finally, it is worth emphasizing that the estimates will be conducted for all micro-regions as well as for sample groups based on their level of complexity. The objective of examining the multipliers for regions according to their complexity is to explore one aspect of regional inequality resulting from diversification into sectors with varying levels of complexity. The classification of the regions' complexity level and the criteria for categorizing complex and non-complex sectors are discussed in a special section of the Annex.

5 Econometric Results

This paper aimed to estimate four main regressions (equations 3 to 6) that capture all possible relationships between complex and non-complex sectors. Additionally, to examine potential heterogeneity across regions, each regression was estimated for different levels of complexity. Following the approach of previous literature (MORETTI; THULIN, 2013; MACEDO; MONASTERIO, 2016), we will provide a summary of the results to facilitate understanding. Tables 1 and 2 present the multipliers for each model specification and level of complexity. Detailed results for each model can be found in the Annex.

Therefore, Table 1 presents the results of employment multipliers in complex sectors over employment in non-complex sectors. Columns (1) and (2) show the OLS estimates without and with controls for observable characteristics that vary over time in the micro-regions. The remaining columns follow the same pattern but include instrumental variable estimation to address potential endogeneity issues. Columns (3) and (4) utilize the instrumental variable proposed by Moretti and Thulin (2013), specified in equation 7. Columns (5) and (6) present the results using the instrumental variable proposed in this study, taking into account the structural changes in local economies over the period, as represented by equation 8.

Table 1 – Complex Employment Multipliers over Non-complex Employment

	Dependent variable:					
	Non-complex employment variation					
	OLS	OLS	IV1	IV1	IV2	IV2
	(1)	(2)	(3)	(4)	(5)	(6)
General Model	1.76*** (0.35)	1.71*** (0.37)	2.25*** (0.33)	2.36*** (0.32)	1.89*** (0.32)	1.87*** (0.33)
Low	-2.26 (2.01)	-1.90 (1.85)	1.95 (4.66)	1.33 (4.61)	-2.71 (2.43)	-2.45 (1.93)
Medium-Low	1.74** (0.78)	0.83 (0.61)	22.17 (20.85)	19.53 (18.96)	2.20*** (0.79)	1.15* (0.60)
Medium-High	1.95*** (0.29)	1.86*** (0.32)	3.25*** (0.32)	3.50*** (0.44)	2.05*** (0.29)	1.98*** (0.34)
High	1.56*** (0.39)	1.51*** (0.37)	2.18*** (0.39)	2.39*** (0.45)	1.71*** (0.36)	1.72*** (0.34)
Controls	No	Yes	No	Yes	No	Yes

Signif.: *p<0.1; **p<0.05; ***p<0.01
Robust standard-errors (clustered at the micro-region) are in parentheses.

As anticipated, the complex sector has a significant impact on the rest of the economy in most cases. On average, the results indicate that one new job in the complex sector leads to the generation of 1.76 to 2.36 additional jobs in the non-complex sector. Furthermore, when controlling for factors such as human capital, proximity, average salary, and the size of the micro-region, the magnitude of the multipliers remains consistent. However, it is important to note that the choice of instrument affects the magnitude of the multiplier. The use of an instrument that considers the variation in the composition of local employment in the final period reduces the multiplier by approximately 0.3. Nevertheless, the overall findings are statistically and economically significant in all cases.

The analysis of the multipliers by complexity groups reveals a more diverse scenario. The results indicate that the most significant effects are observed in regions that are already complex. These regions demonstrate the capability of their complex sectors to have a substantial impact on the rest of the economy when experiencing a permanent increase in employment. However, in less complex regions, the existing local complex sector appears to be insufficient to exert a significant influence on the rest of the economy. Interestingly, among the Medium-Low regions, the results show a notable multiplier effect when considering the effect of structural change in the instrumental variable estimation. This effect is not observed when using the classic instrument. One possible explanation for this finding is that the structural change in these regions has made their economies slightly more complex, enabling a minimum level of complexity that facilitates an increase in employment in the rest of the economy. On the other hand, the Medium-High and High regions consistently demonstrate significant multipliers at 1% in all estimations. For the Medium-High regions, an increase of one job in the complex sector leads to the generation of 3.5 additional jobs in the non-complex sector. Similarly, the High complexity regions experience an increase in employment ranging from 1.51 to 2.39 jobs in the non-complex sector for each additional job in the complex sector.

Table 2, similar to Table 1, presents the estimates of the non-complex employment multipliers over employment in the complex sector. These estimates provide insights into the inverse effect, correcting for endogeneity using instrumental variables. As expected, the results demonstrate smaller magnitudes of multipliers. Job growth in highly ubiquitous and less complex sectors does not have a substantial impact on the more sophisticated sectors of the economy, in comparison to the reverse relationship. On average, one additional job in the non-complex sector results in the generation of 0.37 to 0.45 additional jobs in the complex sector. These findings highlight the asymmetric relationship between the complex and non-complex sectors, with the complex sector exerting a stronger influence on job creation in the non-complex sector compared to the reverse relationship.

Table 2 – Non-complex Employment Multipliers over Complex Employment

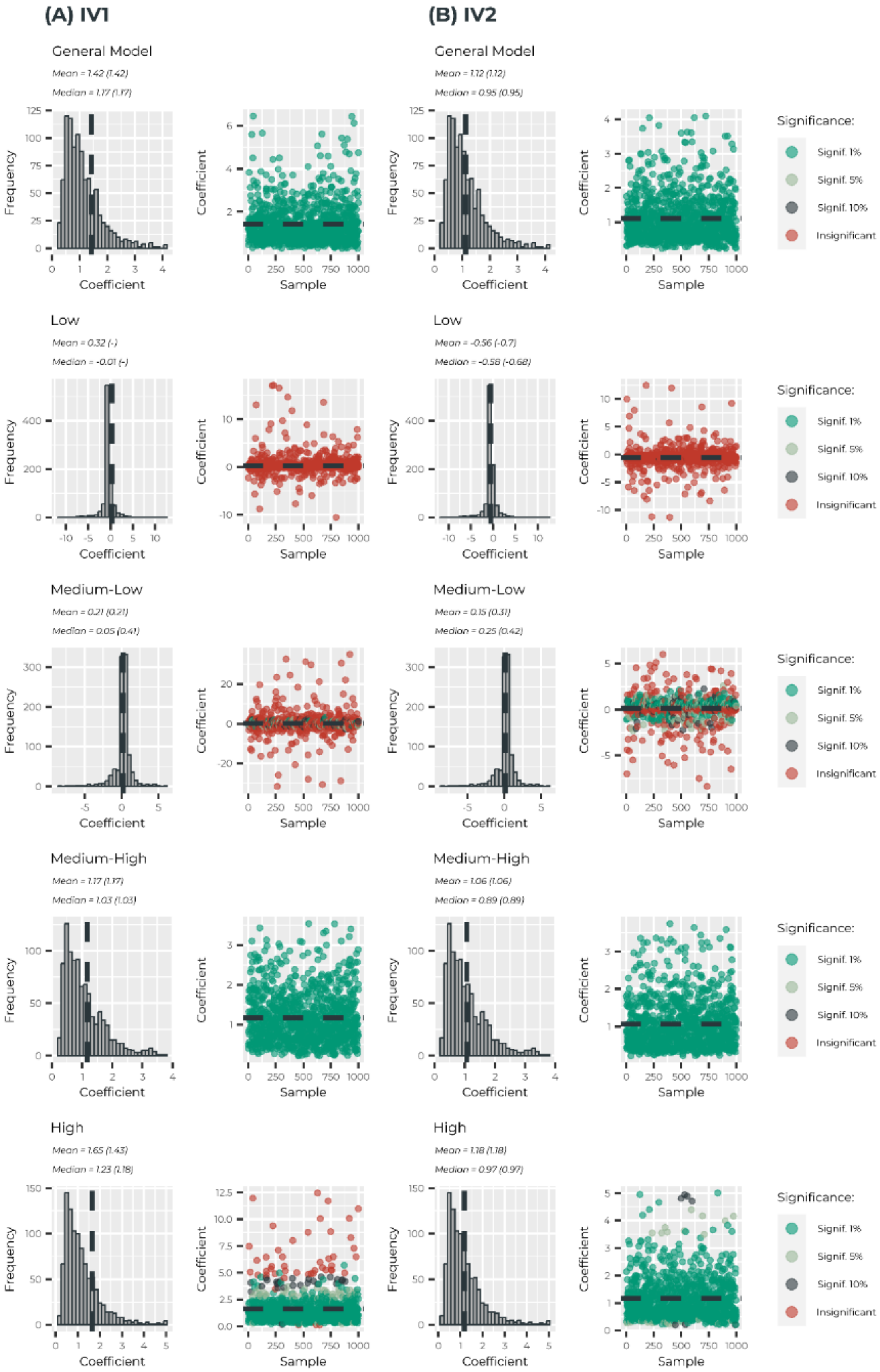
	Dependent variable: Complex employment					
	OLS	OLS	IV1	IV1	IV2	IV2
	(1)	(2)	(3)	(4)	(5)	(6)
General Model	0.39*** (0.05)	0.38*** (0.04)	0.45*** (0.06)	0.43*** (0.05)	0.39*** (0.05)	0.37*** (0.05)
Low	-0.01* (0.00)	-0.01* (0.00)	-0.01** (0.00)	0.00 (0.01)	-0.01** (0.00)	-0.01*** (0.00)
Medium-Low	0.04*** (0.01)	0.02* (0.01)	0.05** (0.02)	0.05 (0.03)	0.04*** (0.01)	0.02** (0.01)
Medium-High	0.22*** (0.04)	0.18*** (0.03)	0.28*** (0.04)	0.28*** (0.04)	0.24*** (0.03)	0.19*** (0.04)
High	0.40*** (0.06)	0.38*** (0.06)	0.47*** (0.07)	0.43*** (0.06)	0.41*** (0.07)	0.36*** (0.06)
Controls	No	Yes	No	Yes	No	Yes

Signif.: *p<0.1; **p<0.05; ***p<0.01

Robust standard-errors (clustered at the micro-region) are in parentheses.

Among the complexity groups, the regions with higher complexity levels continue to exhibit the highest multipliers. It is evident that the absence of a robust complex sector in low and medium-low complexity economies limits the potential impact of permanent increases in the non-complex sector. In these economies, the multipliers are close to zero or even negative, suggesting a crowding-out effect in the complex sector. Conversely, highly complex micro-regions show significant impacts, with the multipliers approaching the overall effect. In these regions, an increase of one job in the non-complex sector generates between 0.36 and 0.47 new jobs in the complex sector. These findings highlight the importance of a strong and developed complex sector in driving employment generation.

Figure 2 – Complex-Complex Multiplier



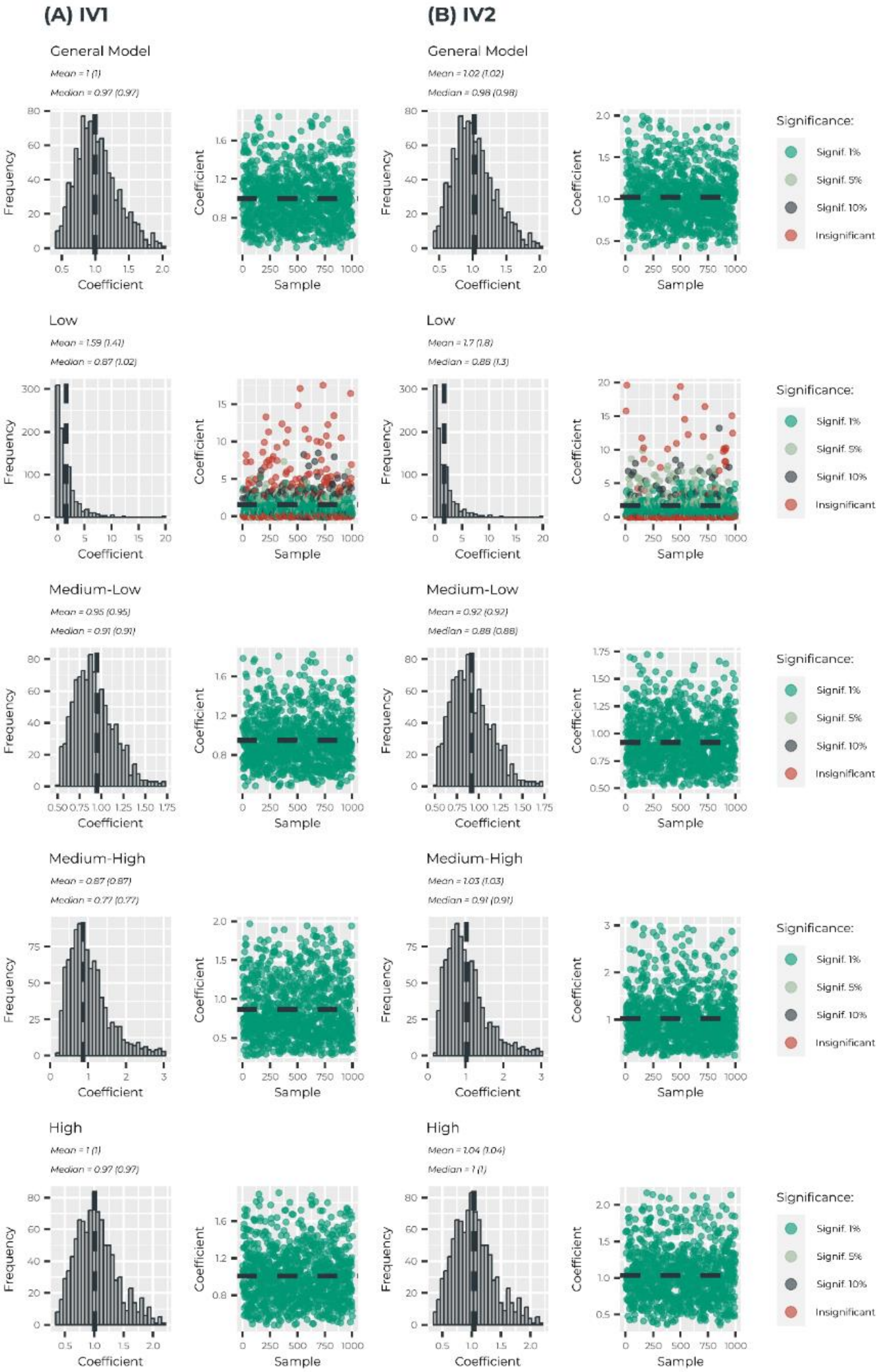
Source: own elaboration.

Finally, Figures 2 and 3 provide a summary of the remaining estimates, focusing on the influence of a portion of economic activity within the complex and non-complex sectors, respectively, on the rest of the activities in the same sector. Since the literature does not specify the method of selecting the sample for this analysis, we employed a bootstrap approach, randomly selecting parts of the reference sector 1,000 times. For clarity, the bootstrap estimations presented in the figures only include the instrumental variable specification without control variables. As observed in the results presented in Tables 1 and 2, the inclusion of control variables does not significantly alter the magnitude and significance of the multipliers.

Therefore, Figure 2 displays the results for the estimates of equation 4, with two columns representing different instruments. Column (A) shows the estimates using the conventional shift-share instrument, while column (B) presents the estimates with the adapted shift-share instrument. Each row corresponds to a type of region or the general model, and for each column, two graphs are provided. The first graph is a histogram plot depicting the distribution of estimated multipliers across the replicates, and the second graph shows the multiplier values for each sample from 1 to 1,000, indicating whether they are statistically significant. Additionally, the mean and median values of the resulting multipliers are provided for each estimate (A and B). The values in parentheses represent descriptive statistics for the significant multipliers up to 10% significance level. Figure 6 follows the same format but presents the results for equation 6.

Figure 2 illustrates that the average multiplier for the rest of the complex sector, resulting from an increase of 1 job in a portion of the complex sector, ranges from 1.12 to 1.42. However, the level of complexity in the micro-regions affects the magnitude of this multiplier. In less complex regions, the multiplier is less robust, with only a few estimates being statistically significant, particularly in low complexity micro-regions. For Medium-Low, the significant multiplier estimates are 0.21 (A) and 0.31 (B). As the level of complexity increases, the magnitude of the multiplier also increases. High complexity regions exhibit stronger performance compared to the general case. With the conventional shift-share instrument, an increase of 1 job in a portion of the complex sector generates, on average, 1.65 jobs in the rest of the sector. These findings align with the earlier results, indicating the limited efficiency of the complex sector in less complex regions.

Figure 3 – Non-Complex-Non-Complex Multiplier



Source: own elaboration

However, the evaluation of non-complex multipliers reveals a slightly different scenario. Figure 3 reveals that, on average, the multiplier for the rest of the non-complex sector resulting from an increase of 1 job in a portion of the non-complex sector is 1-to-1. In other words, the increase of one job in the non-complex sector generates one job in the rest of the sector. Interestingly, Low micro--regions stand out in this case. The significant multipliers for the non-complex sector in these regions are 1.41 (A) and 1.8 (B). This indicates that the impact of job creation in the non-complex sector is more pronounced in low complexity micro-regions. Additionally, when considering the structural change of these regions, there is an observed increase of 0.4 in the average multipliers for the non-complex sector. On the other hand, the other micro-regions exhibit multipliers similar to the general average in both types of estimates.

Table 3 – Multipliers Summary Table

	Multiplier:	
	Complex Employment Multiplier over Non-complex Employment	
	IV1 (1)	IV2 (2)
General Model	2.25***	1.89***
Low	1.95	-2.71
Medium-Low	22.17	2.20***
Medium-High	3.25***	2.05***
High	2.18***	1.71***
	Non-complex Employment Multiplier over Complex Employment	
	IV1 (1)	IV2 (2)
General Model	0.45***	0.39***
Low	-0.01**	-0.01**
Medium-Low	0.05**	0.04***
Medium-High	0.28***	0.24***
High	0.47***	0.41***
	Complex Employment Multiplier over Complex Employment[b]	
	IV1 (1)	IV2 (2)
General Model	1.42	1.12
Low	-	-0.7
Medium-Low	0.21	0.31
Medium-High	1.17	1.06
High	1.43	1.18
	Non-complex Employment Multiplier over Non-complex Employment[b]	
	IV1 (1)	IV2 (2)
General Model	1.00	1.02
Low	1.41	1.80
Medium-Low	0.95	0.92
Medium-High	0.87	1.03
High	1.00	1.04

[b] As the estimates were via bootstrap, we report the mean value of the multipliers that were significant up to 10%. Signif.: *p<0.1; **p<0.05; ***p<0.01

The results of the econometric tests are summarized in Table 3. As the multipliers do not vary considerably with the inclusion of control variables, we report the two main specifications: IV_1 (1) refers to the regression only with the conventional shift-share instrument, and IV_2 (2) with the adapted shift-share instrument. In Table 3, we observe that the complex sector demonstrates the highest multipliers, signifying its substantial impact on local employment. However, the extent of this influence varies significantly among micro-regions, depending on their level of complexity. In regions characterized by lower complexity, the complex sector exhibits limited effects, not only on itself but also on the non-complex sector. In contrast, complex regions experience a pronounced influence from the complex sector on the labor market, presenting the most potent multipliers.

6 Concluding Remarks

Covering gaps in the literature on complexity and regional inequalities, this article adapts the methodology of local employment multipliers (MORETTI, 2010; MORETTI; THULIN, 2013) to assess the regional multipliers of complex and non-complex sectors. The concern of the most recent literature to evaluate high-tech job multipliers (LEE; CLARKE, 2019) was one of the justifications for understanding this conceptual framework under the complexity approach. In addition, the relationship between these sectors and their magnitude were taken into account to verify how good or how bad it is to have, respectively, a productive structure towards more complex or less complex sectors. This intention resides in the scarcity of literature in evaluating possible implications of the uneven regional development to which the regions are submitted in light of complexity (PINHEIRO et al., 2022).

The econometric results offer important evidence regarding employment multipliers in the context of complexity. First, the hypothesis is confirmed that the multiplier of the complex sector is the largest. Second, the heterogeneity of multipliers is notable when considering micro-regions with different levels of complexity. Third, it appears that in less complex regions, the complex sector does not have a significant effect on itself and on the non-complex sector. The most positive effects in these regions are reserved for the influence that the non-complex sector has on itself. Fourth, the same cannot be said for regions that are already complex, as they are where the complex sector exerts the most prominent influence on the labor market, concentrating the largest multipliers for this sector. In short, the econometric results demonstrate that the bad news for less complex regions is a complex sector incapable of generating jobs, while the good news for complex regions is a complex sector capable of generating between 1.06 and 1.46 jobs in the same sector and between 1.71 and 3.25 in the non-complex sector of the economy.

These findings quantify one of the implications of the uneven development faced by Brazil's regions in terms of complexity. It shows that the development path followed by less complex regions limits their diversification opportunities to less complex sectors only. As a result, these regions are unable to develop a complex sector that can have positive spillover effects on the rest of the economy. This lack of diversification leads to almost non-existent multipliers for the complex sector in these regions. On the other hand, regions that are already complex benefit from related diversification, as their productive structure concentrates similar capabilities for the production of other complex activities. This dynamic results in a complex sector that can exert a significant influence on the overall economy. Hence, the multipliers of the complex sector in these regions are substantial.

While this work provides valuable contributions to the literature, it is important to acknowledge its limitations. The classification of sectors as complex or non-complex is a subjective decision and may influence the magnitude of the multipliers. Choosing a more inclusive classification would likely decrease the multipliers' magnitude and favor Medium-Low complexity regions, as evidenced by robustness tests in the annex. Moreover, the level of aggregation of economic activities can also impact the multipliers, with higher levels potentially yielding different magnitudes. Additionally, it is crucial to note that the estimates represent average impacts and do not account for variations in local conditions within each region group. Local factors and the specific characteristics of individual activities within the complex or non-complex sectors can also influence the multiplier effect. Therefore, the multipliers are still sensitive to local and sector-specific factors.

Bibliography

BALLAND, P.-A. et al. Smart specialization policy in the European Union: relatedness, knowledge complexity and regional diversification. *Regional Studies*, p. 1–17, 2018.

BARTIK, T. J. Who Benefits from State and Local Economic Development Policies? Kalamazoo: W.E. Upjohn Institute for Employment Research, 1991.

BLASIO, G. de; MENON, C. Local Effects of Manufacturing Employment Growth in Italy. *Giornale degli Economisti*, v. 70, n. 3, p. 101–112, 2011.

BOSCHMA, R.; IAMMARINO, S. Related Variety, Trade Linkages, and Regional Growth in Italy. *Economic Geography*, v. 85, n. 3, p. 289–311, 2009.

DIJK, J. J. V. Local multipliers, mobility, and agglomeration economies. Discussion Paper No. 771, University of Oxford, 2015.

DIJK, J. J. V. Local employment multipliers in U.S. cities. *Journal of Economic Geography*, v. 17, n. 2, p. 465–487, 2017.

EFRON, B.; TIBSHIRANI, R. An Introduction to the Bootstrap. New York: Chapman & Hall, 1993.

ESSLETZBICHLER, J. Relatedness, Industrial Branching and Technological Cohesion in US Metropolitan Areas. *Regional Studies*, v. 49, n. 5, p. 752–766, 2015.

FAGGIO, G.; OVERMAN, H. The effect of public sector employment on local labour markets. *Journal of Urban Economics*, v. 79, n. C, p. 91–107, 2014.

FREITAS, ELTON; BRITTO, Gustavo; AMARAL, Pedro. Related industries, economic complexity, and regional diversification: An application for Brazilian microregions. *Papers in Regional Science*, v. 103, 2024.

FRENKEN, K.; OORT, F. V.; VERBURG, T. Related Variety, Unrelated Variety and Regional Economic Growth. *Regional Studies*, v. 41, n. 5, p. 685–697, 2007.

GEROLIMETTO, M.; MAGRINI, S. Spatial analysis of employment multilpliers in Spanish labor markets. RIEDS - Rivista Italiana di Economia, Demografia e Statistica - The Italian Journal of Economic, Demographic and Statistical Studies, v. 68, n. 3-4, p. 87–94, 2014.

GOOS, M.; KONINGS, J.; VANDEWEYER, M. Local high-tech job multipliers in Europe. *Industrial and Corporate Change*, v. 27, n. 4, p. 639–655, 2018.

GUTIERREZ-POSADA, D. et al. Creative Clusters and Creative Multipliers: Evidence from UK Cities. *Economic Geography*, v. 99, n. 1, p. 1–24, 2023.

HARTMANN, D.; PINHEIRO, F. Economic complexity and inequality at the national and regional level. arXiv.org, n. 2206.00818, 2022.

HAUSMANN, R. et al. The Atlas of Economic Complexity: Mapping Paths to Prosperity. 1. ed. Cambridge: The MIT Press, 2014. v. 1.

HERNANDEZ, N.; ROJAS, I. Employment local multipliers in Mexico. Sobre México. *Revista de Economía*, v. 1, p. 5–37, 2020.

HIDALGO, C. et al. The Principle of Relatedness: Proceedings of the Ninth International Conference on Complex Systems. p. 451–457, 2018.

HIDALGO, C.; HAUSMANN, R. The Building Blocks of Economic Complexity. Proceedings of the National Academy of Sciences of the United States of America, v. 106, p. 10570–5, 2009.

HIDALGO, C. et al. The Product Space Conditions the Development of Nations. *Science*, v. 317, p. 482–487, 2007.

KAZEKAMI, S. Local Multipliers, Mobility, and Agglomeration Economies. Industrial Relations: A *Journal of Economy and Society*, v. 56, n. 3, p. 489–513, 2017.

LEE, N.; CLARKE, S. Do low-skilled workers gain from high-tech employment growth? High-technology multipliers, employment and wages in Britain. *Research Policy*, v. 48, n. 9, 2019.

LOYO, A. O. L.; MOISES, A. R. F.; MENDES, V. Impacto de mudanças no emprego no setor público sobre o mercado de trabalho local: evidências para as mesorregiões brasileiras de 2003 a 2010. *Estudos Econômicos*, v. 48, p. 77–106, 2018.

MACEDO, G.; MONASTERIO, L. Local multiplier of industrial employment: Brazilian mesoregions (2000-2010). *Brazilian Journal of Political Economy*, v. 36, n. 4, p. 827–839, 2016.

MORETTI, E. Local Multipliers. *American Economic Review*, v. 100, n. 2, p. 373–377, 2010.

MORETTI, E.; THULIN, P. Local multipliers and human capital in the United States and Sweden. *Industrial and Corporate Change*, v. 22, n. 1, p. 339–362, 2013.

NEFFKE, F.; HENNING, M.; BOSCHMA, R. How Do Regions Diversify over Time? Industry Relatedness and the Development of New Growth Paths in Regions. *Economic Geography*, v. 87, n. 3, p. 237–265, 2011.

PINHEIRO, F. et al. The Dark Side of the Geography of Innovation. Relatedness, Complexity, and

Regional Inequality in Europe. Papers in Evolutionary Economic Geography (PEEG), n. 2202, 2022.

QUEIROZ, A. R.; ROMERO, J. P.; FREITAS, E. E. Economic complexity and employment in Brazilian states. *CEPAL Review*, p. 177–196, 2023.

QUEIROZ, A.R., ROMERO, J.P.; FREITAS, E.E. Relatedness and regional economic complexity: Good news for some, bad news for others. *EconomiA*, Vol. ahead-of-print No. ahead-of-print, 2024.

RIGBY, D. L. Technological Relatedness and Knowledge Space: Entry and Exit of US Cities from Patent Classes. *Regional Studies*, v. 49, n. 11, p. 1922–1937, 2015.

ROCHA, R. M.; ARAÚJO, B. C. Local multiplier effect of the tradable sector on the Brazilian labor market. *Letters in Spatial and Resource Science*s, v. 14, n. 3, p. 269–286, 2021.

ROMERO, J. et al. Economic complexity and regional development: evidence from Brazilian municipalities. Proceedings of the EAEPE Conference, p. 1–25, 2022.

STILWELL, F. J. B. Regional Growth and Structural Adaptation. *Urban Studies*, v. 6, n. 2, p. 162–178, 1969.

WANG, T.; CHANDA, A. Manufacturing growth and local employment multipliers in China. *Journal of Comparative Economics*, v. 46, n. 2, p. 515–543, 2018.

Annex

Complexity Classifications

As in Queiroz et al. (2024), the micro-regions were divided according to their complexity level. The classification adopted takes into account the value of the ECI and separates the regions into 4 distinct groups:

(1) *Low complexity:* micro-regions with an ECI up to 0.25.

(2) *Medium-low complexity:* micro-regions with an ECI between 0.25 and 0.50.

(3) *Medium-high complexity:* micro-regions with an ECI between 0.50 and 0.75.

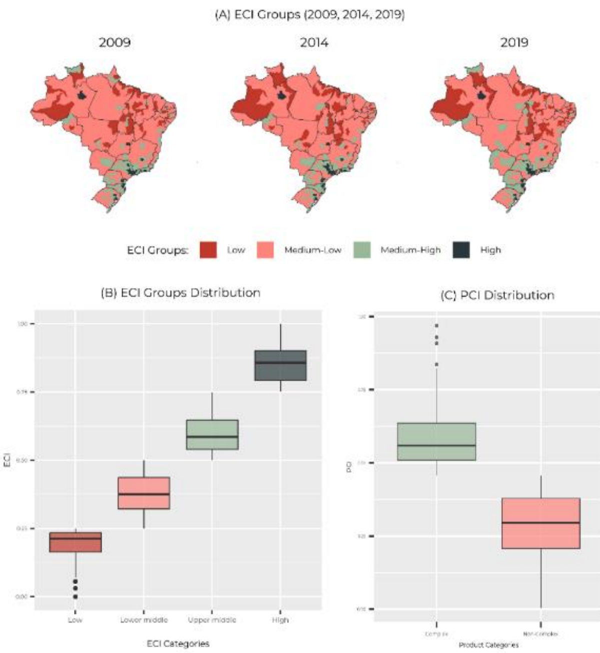
(4) *High complexity:* micro-regions with an ECI above 0.75.

The existing literature has yet to establish a consensus on a method for classifying regions according to their complexity levels. While previous studies, such as Freitas (2024), often categorize regions based on the distribution of the ECI, this approach leads to the aggregation of regions with vastly different complexity levels. To overcome this, we have evaluated regions based on their individual index values. This approach allows for a more nuanced understanding of complexity levels, even if it results in groups with varying sizes. However, it's important to acknowledge that this strategy relies on setting arbitrary thresholds for differentiating the ECI values.

The classification of complex and non-complex sectors in this study differs from the classification of tradables and non-tradables. Instead, we use an indicator that reflects the complexity of each sector, specifically based on the Product Complexity Index (PCI). As there are no studies that directly relate the complexity approach to the calculation of multipliers, we have established criteria to differentiate economic activities based on their PCI values. We adopted two strategies to ensure robustness. The first strategy is more aggressive, classifying activities in the last tertile of the PCI as “complex” and those in the first and second tertiles as “non-complex”. Additionally, we conducted robustness tests considering the PCI value itself, rather than its distribution. The second strategy categorizes activities as complex when they have a positive PCI and as non-complex when they have a negative PCI, before normalizing the indicator between 0 and 1. This classification includes many more sectors as complex compared to the previous categorization. The results can be found in the Annex.

Figure 4 provides a descriptive analysis of the classifications used for regions and productive activities according to complexity. Figure 4A presents the micro-regions according to the ECI groups for the years considered in the analysis. It is observed that the level of complexity of the regions remains constant in the years 2009, 2014, and 2019, showing few perceptible changes. The high and medium-high complexity groups are mainly concentrated in the South and Southeast regions, around large urban centers, while the low and medium-low complexity groups are located in more inland regions and also in the North, Northeast, and Midwest regions. Figure 4B, in turn, presents the distribution of observations by ECI groups. It is observed that the complexity value is relatively close between each group, except for a few extreme values in the Low complexity group. Finally, Figure 4C refers to the distribution of the complexity of activities according to the PCI groups. The complex sector has a more asymmetric distribution than the non-complex sector, with some outliers having a PCI close to 1.

Figure 4 – Complexity Classification - Sectors[1] and Micro-regions[2]

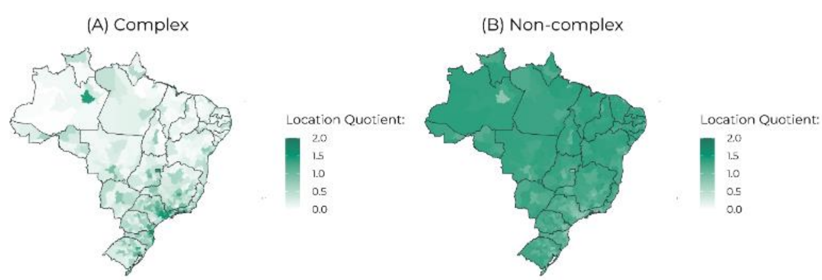


Source: own elaboration.

[1] Complex sectors are those falling within the third tertile of PCI values, while non-complex sectors are in the first and second tertiles. [2]The micro-regions were categorized based on ECI values as follows: Low ($0,00 \leq ECI \leq 0,25$), Medium-Low ($0,25 < ECI \leq 0,50$), Medium-High ($0,50 < ECI \leq 0,75$), High ($0,75 < ECI \leq 1,00$).

Building on the analysis conducted by Rocha and Araújo (2021), we calculated the location quotient for both the complex sector (Figure 5A) and the non-complex sector (Figure 5B) to evaluate their distribution and specialization within the region. The data reveals that employment in the complex sector is more concentrated, especially in the Southeast and South regions. In contrast, employment in the non-complex sector shows a more even distribution across the entire territory, with a significant presence in all regions of the country. This distribution pattern supports the notion that non-complex activities are influenced more by local dynamics and driven by local consumption. After discussing the sector classification, we will now present the results of the econometric tests.

Figure 5 - Location Quotient of Complex and Non-Complex Sectors



Source: own elaboration.

Econometric Tests

Table 4 – Complex Employment Multiplier over Non-complex Employment – Brazil

	Dependent variable: Non-complex employment variation					
	OLS	OLS	IV_1	IV_1	IV_2	IV_2
	(1)	(2)	(3)	(4)	(5)	(6)
Complex emp. variation	1.757***	1.711***	2.246***	2.360***	1.878***	1.866***
	(0.351)	(0.371)	(0.326)	(0.318)	(0.323)	(0.334)
Skilled emp. share		189,349		97,949		167,492
		(137.268)		(93.460)		(109.712)
Average salary		−16.257		4,288		−11.344
		(11.647)		(25.084)		(10.863)
Relatedness		954.090***		98,842		749.570*
		(352.331)		(1,010.238)		(404.533)
Population		−0.001		−0.005*		−0.002
		(0.006)		(0.003)		(0.002)
Constant	6,635.350***	−1,862.114	5,155.273***	2.346,926	6,269.919***	−855.585
	(1,082.038)	(1,457.763)	(818.358)	(3,602.602)	(831.705)	(1,287.591)
Observations	1.116	1.116	1.116	1.116	1.116	1.116
R^2	0,705	0,717	0,703	0,705	0,705	0,716
Adjusted R^2	0,705	0,716	0,702	0,703	0,705	0,715
Residual Std. Error	16.806,120	16.498,140				
F Statistic	1,332.936***	468.713***	2,333.715***	2,455.329***	2,860.256***	3,063.636***

Note: *p<0.1; **p<0.05; ***p<0.01.

Table 5 – Complex Employment Multiplier over Non-complex Employment – Low complexity regions

	Dependent variable: Non-complex employment variation					
	OLS	OLS	IV_1	IV_1	IV_2	IV_2
	(1)	(2)	(3)	(4)	(5)	(6)
Complex emp. variation	−2.260	−1.904	1,948	1,333	−2.712	−2.450
	(2.014)	(1.852)	(4.661)	(4.613)	(2.426)	(1.932)
Skilled emp. share		−10.482		−13.708		−9.938
		(13.905)		(12.546)		(11.307)
Average salary		−21.962**		−24.147***		−21.593***
		(9.010)		(7.733)		(7.669)
Relatedness		646.410***		740.381***		630.549***
		(241.171)		(252.101)		(222.223)
Population		0.010***		0.009***		0.010***
		(0.002)		(0.002)		(0.002)
Constant	1,755.006***	313,579	1,616.346***	174,052	1,769.886***	337,129
	(353.117)	(454.079)	(430.854)	(373.606)	(365.433)	(324.723)
Observations	84	84	84	84	84	84
R^2	0,131	0,421	0,080	0,391	0,130	0,420
Adjusted R^2	0,109	0,376	0,057	0,343	0,109	0,375
Residual Std. Error	1.677,151	1.403,568				
F Statistic	6.080***	9.336***	10.077***	51.858***	12.499***	56.520***

Note: *p<0.1; **p<0.05; ***p<0.01.

Table 6 – Complex Employment Multiplier over Non-complex Employment – Medium-Low complexity regions

	Dependent variable: Non-complex employment variation					
	OLS	OLS	IV_1	IV_1	IV_2	IV_2
	(1)	(2)	(3)	(4)	(5)	(6)
Complex emp. variation	1.736**	0,826	22,172	19,534	2.202***	1.146*
	(0.780)	(0.613)	(20.851)	(18.963)	(0.794)	(0.602)
Skilled emp. share		29,340		−68.261		27,674
		(29.461)		(84.695)		(21.780)
Average salary		−8.927***		−15.880		−9.046**
		(3.312)		(13.896)		(3.586)
Relatedness		535.126***		194,948		529.319***
		(110.584)		(474.058)		(117.959)
Population		0.009***		−0.006		0.009***
		(0.002)		(0.020)		(0.002)
Constant	3,854.759***	−781.069	−1,868.199	2.668,596	3,724.303***	−722.186
	(298.359)	(785.104)	(5,800.894)	(3,274.697)	(286.111)	(639.169)
Observations	678	678	678	678	678	678
R^2	0,249	0,392	0,084	0,064	0,247	0,391
Adjusted R^2	0,247	0,387	0,081	0,056	0,244	0,386
Residual Std. Error	4.095,395	3.695,021				
F Statistic	112.050***	72.250***	25.246***	52.477***	244.952***	440.894***

Note: *p<0.1; **p<0.05; ***p<0.01

Table 7 – Complex Employment Multiplier over Non-complex Employment – Medium-High complexity regions

	Dependent variable: Non-complex employment variation					
	OLS	OLS	IV_1	IV_1	IV_2	IV_2
	(1)	(2)	(3)	(4)	(5)	(6)
Complex emp. variation	1.952***	1.860***	3.249***	3.504***	2.049***	1.984***
	(0.293)	(0.320)	(0.316)	(0.439)	(0.291)	(0.339)
Skilled emp. share		46,610		−156.636		31,177
		(195.341)		(200.930)		(188.676)
Average salary		−11.811***		−3.768		−11.200***
		(4.524)		(4.974)		(4.149)
Relatedness		580.041***		359.693*		563.309***
		(203.150)		(197.803)		(178.600)
Population		0,002		−0.009		0,002
		(0.004)		(0.007)		(0.004)
Constant	9,662.240***	4.004,793	5,628.124***	6,168.414*	9,362.184***	4.169,087
	(936.456)	(3,719.961)	(1,005.297)	(3,589.663)	(902.486)	(3,580.855)
Observations	286	286	286	286	286	286
R^2	0,653	0,668	0,612	0,607	0,652	0,667
Adjusted R^2	0,650	0,661	0,610	0,599	0,650	0,660
Residual Std. Error	9.217,099	9.082,166				
F Statistic	266.085***	93.428***	452.372***	457.337***	546.452***	573.602***

Note: *p<0.1; **p<0.05; ***p<0.01

Table 8 – Complex Employment Multiplier over Non-complex Employment – High complexity regions

	Dependent variable: Non-complex employment variation					
	OLS	OLS	IV_1	IV_1	IV_2	IV_2
	(1)	(2)	(3)	(4)	(5)	(6)
Complex emp. variation	1.564***	1.514***	2.178***	2.393***	1.713***	1.717***
	(0.391)	(0.374)	(0.394)	(0.447)	(0.365)	(0.342)
Skilled emp. share		3.191,032		−152.729		2.415,835
		(2,482.336)		(2,685.871)		(2,201.685)
Average salary		−58.344		48,504		−33.573
		(55.506)		(107.614)		(40.620)
Relatedness		1.462,201		−2,496.765		544,379
		(2,015.385)		(4,649.433)		(1,904.817)
Population		0,001		−0.008		−0.001
		(0.009)		(0.007)		(0.003)
Constant	31,845.440**	−4,265.097	11.092,800	40.474,100	26,828.230***	6.106,969
	(13,686.980)	(30,416.180)	(12,143.970)	(53,352.000)	(9,957.823)	(31,554.320)
Observations	68	68	68	68	68	68
R^2	0,743	0,755	0,724	0,717	0,741	0,752
Adjusted R^2	0,735	0,731	0,716	0,689	0,733	0,728
Residual Std. Error	61.867,360	62.336,340				
F Statistic	93.816***	31.307***	155.795***	148.934***	199.652***	200.799***

Note: *p<0.1; **p<0.05; ***p<0.01

Table 9 – Non-complex Employment Multiplier over Complex Employment - Brazil

	Dependent variable: Complex employment variation					
	OLS	OLS	IV_1	IV_1	IV_2	IV_2
	(1)	(2)	(3)	(4)	(5)	(6)
Non-complex emp. variation	0.390***	0.379***	0.446***	0.428***	0.395***	0.375***
	(0.050)	(0.040)	(0.057)	(0.047)	(0.054)	(0.046)
Skilled emp. share		−22.396		−43.374		−20.723
		(55.198)		(44.677)		(42.455)
Average salary		−4.943		−1.510		−5.216
		(10.222)		(8.558)		(8.716)
Relatedness		100,566		−55.863		113,039
		(404.133)		(339.486)		(348.056)
Population		0,003		0.002*		0.003**
		(0.002)		(0.001)		(0.001)
Constant	−1,630.818***	−1,569.569	−2,302.735***	−937.847	−1,693.986***	−1,619.941
	(443.129)	(1,198.809)	(526.413)	(1,080.785)	(485.105)	(1,151.255)
Observations	1.116	1.116	1.116	1.116	1.116	1.116
R^2	0,692	0,704	0,692	0,703	0,692	0,704
Adjusted R^2	0,691	0,703	0,691	0,701	0,691	0,703
Residual Std. Error	7.914,573	7.767,226				
F Statistic	1,249.502***	440.224***	2,502.499***	2,689.932***	2,451.324***	2,579.722***

Note: *p<0.1; **p<0.05; ***p<0.01

Table 10 – Non-complex Employment Multiplier over Complex Employment – Low complexity regions

	Dependent variable: Complex employment variation					
	OLS	OLS	IV_1	IV_1	IV_2	IV_2
	(1)	(2)	(3)	(4)	(5)	(6)
Non-complex emp. variation	−0.008*	−0.010*	−0.010**	0,001	−0.009**	−0.011***
	(0.004)	(0.006)	(0.005)	(0.010)	(0.004)	(0.004)
Skilled emp. share		0,879		1,007		0,861
		(0.926)		(0.778)		(0.712)
Average salary		0,453		0,694		0,420
		(0.346)		(0.494)		(0.347)
Relatedness		−22.334		−29.590		−21.320
		(16.626)		(24.364)		(19.428)
Population		0,0002		0,0001		0,0002
		(0.0002)		(0.0002)		(0.0002)
Constant	46.523*	45,315	49.623**	42,921	47.449**	45,650
	(24.678)	(34.691)	(23.105)	(41.260)	(23.405)	(43.501)
Observations	84	84	84	84	84	84
R_2	0,026	0,090	0,026	0,071	0,026	0,090
Adjusted R_2	0,002	0,019	0,002	−0.002	0,002	0,019
Residual Std. Error	100,244	99,376				
F Statistic	1,095	1,275	1,546	6,097	2,324	8,015

Note: *p<0.1; **p<0.05; ***p<0.01.

Table 11 – Non-complex Employment Multiplier over Complex Employment – Medium-Low complexity regions

	Dependent variable: Complex employment variation					
	OLS	OLS	IV_1	IV_1	IV_2	IV_2
	(1)	(2)	(3)	(4)	(5)	(6)
Non-complex emp. variation	0.036***	0.020*	0.052**	0,046	0.042***	0.025**
	(0.010)	(0.011)	(0.025)	(0.031)	(0.011)	(0.011)
Skilled emp. share		4,560		3,659		4,377
		(4.003)		(3.693)		(3.797)
Average salary		0,540		0,771		0,587
		(0.545)		(0.590)		(0.572)
Relatedness		7,441		−7.285		4,447
		(16.630)		(20.488)		(18.427)
Population		0.001**		0,0004		0,001
		(0.0003)		(0.001)		(0.0004)
Constant	124.870***	−166.171**	56,149	−141.186**	98.799**	−161.092**
	(40.343)	(74.941)	(108.173)	(69.917)	(45.693)	(69.605)
Observations	678	678	678	678	678	678
R_2	0,085	0,150	0,083	0,133	0,084	0,149
Adjusted R_2	0,082	0,142	0,080	0,125	0,082	0,141
Residual Std. Error	587,623	568,035				
F Statistic	31.198***	19.688***	49.188***	120.827***	77.498***	124.621***

Note: *p<0.1; **p<0.05; ***p<0.01

Table 12 – Non-complex Employment Multiplier over Complex Employment – Medium-High complexity regions

	Dependent variable: Complex employment variation					
	OLS	OLS	IV1	IV1	IV2	IV2
	(1)	(2)	(3)	(4)	(5)	(6)
Non-complex emp. variation	0.223***	0.185***	0.285***	0.277***	0.241***	0.189***
	(0.038)	(0.033)	(0.036)	(0.041)	(0.033)	(0.039)
Skilled emp. share		72,399		47,026		71,237
		(61.732)		(56.360)		(47.905)
Average salary		−1.019		0,900		−0.931
		(1.499)		(1.391)		(1.462)
Relatedness		−19.585		−95.689*		−23.071
		(52.492)		(53.969)		(54.235)
Population		0.004**		0,003		0.004***
		(0.002)		(0.002)		(0.001)
Constant	−395.127	−1,604.384*	−1,366.347***	−1,747.367*	−687.182	−1,610.934**
	(491.399)	(974.305)	(480.487)	(1.037.250)	(452.373)	(789.383)
Observations	286	286	286	286	286	286
R^2	0,505	0,587	0,500	0,564	0,504	0,586
Adjusted R^2	0,502	0,578	0,497	0,554	0,501	0,578
Residual Std. Error	3.114,047	2.866,343				
F Statistic	144.359***	65.967***	275.378***	400.046***	313.411***	397.771***

Note: *p<0.1; **p<0.05; ***p<0.01.

Table 13 – Non-complex Employment Multiplier over Complex Employment – High complexity regions

	Dependent variable: Complex employment variation					
	OLS	OLS	IV1	IV1	IV2	IV2
	(1)	(2)	(3)	(4)	(5)	(6)
Non-complex emp. variation	0.397***	0.367***	0.470***	0.429***	0.406***	0.363***
	(0.061)	(0.062)	(0.066)	(0.057)	(0.068)	(0.064)
Skilled emp. share		519,451		−32.061		551,618
		(973.918)		(935.670)		(892.323)
Average salary		−32.608		−17.674		−33.480
		(42.528)		(34.549)		(33.583)
Relatedness		1.464,970		954,748		1.494,728
		(1,973.919)		(1,547.434)		(1,497.905)
Population		0,004		0,003		0.004*
		(0.003)		(0.002)		(0.003)
Constant	180,175	−21,054.210	−6,057.145	−16,044.010	−579.861	−21,346.430
	(3,809.242)	(19,788.340)	(3,942.946)	(18,464.360)	(4,398.631)	(17,987.960)
Observations	68	68	68	68	68	68
R^2	0,710	0,736	0,706	0,732	0,710	0,736
Adjusted R^2	0,702	0,710	0,697	0,705	0,701	0,710
Residual Std. Error	31.160,470	30.695,850				
F Statistic	79.732***	28.385***	157.040***	172.192***	159.020***	168.067***

Note: *p<0.1; **p<0.05; ***p<0.01.

Table 14 – Complex Employment Multiplier over Non-complex Employment - Brazil Other classification by PCI

	Dependent variable: Non-complex employment variation					
	OLS	OLS	IV_1	IV_1	IV_2	IV_2
	(1)	(2)	(3)	(4)	(5)	(6)
Complex emp. variation	0.999***	1.028***	1.066***	1.176***	0.997***	1.064***
	(0.105)	(0.097)	(0.066)	(0.039)	(0.075)	(0.063)
Skilled emp. share		96,728		61,921		88,142
		(73.833)		(61.693)		(65.796)
Average salary		−8.213		−1.327		−6.515
		(6.676)		(11.352)		(7.638)
Relatedness		559.590**		268,539		487.799*
		(232.639)		(433.044)		(269.444)
Population		−0.005*		−0.006*		−0.005*
		(0.003)		(0.003)		(0.003)
Constant	4,312.912***	365,142	3,955.080***	1.818,492	4,322.209***	723,624
	(550.285)	(996.362)	(318.825)	(1,598.182)	(367.036)	(984.612)
Observations	1.116	1.116	1.116	1.116	1.116	1.116
R^2	0,803	0,841	0,803	0,838	0,803	0,841
Adjusted R^2	0,803	0,840	0,803	0,837	0,803	0,840
Residual Std. Error	10.647,080	9.597,411				
F Statistic	2,272.685***	975.795***	3,935.483***	5,287.281***	4,377.301***	6,049.851***

Note: *p<0.1; **p<0.05; ***p<0.01.

Table 15 – Complex Employment Multiplier over Non-complex Employment – Low complexity regions - Other classification by PCI

	Dependent variable: Non-complex employment variation					
	OLS	OLS	IV_1	IV_1	IV_2	IV_2
	(1)	(2)	(3)	(4)	(5)	(6)
Complex emp. variation	0,144	−0.593	−1.986	−1.679	0,527	−0.505
	(1.313)	(1.072)	(11.254)	(8.810)	(1.503)	(0.782)
Skilled emp. share		−11.781		−10.719		−11.867
		(14.355)		(12.750)		(11.775)
Average salary		−22.816**		−22.166***		−22.869***
		(8.863)		(7.452)		(8.138)
Relatedness		679.773***		660.766***		681.321***
		(240.649)		(211.839)		(255.261)
Population		0.010***		0.010***		0.010***
		(0.002)		(0.003)		(0.002)
Constant	1,641.155***	261,404	1,775.822**	296,669	1,616.955***	258,533
	(338.490)	(430.491)	(879.293)	(383.085)	(342.091)	(306.152)
Observations	84	84	84	84	84	84
R^2	0,114	0,408	0,097	0,404	0,113	0,408
Adjusted R^2	0,092	0,362	0,075	0,357	0,091	0,362
Residual Std. Error	1,676.910 (df = 81)	1.405,747				
F Statistic	5.202***	8.845***	10.228***	52.543***	10.479***	52.999***

Note: *p<0.1; **p<0.05; ***p<0.01.

Table 16 – Complex Employment Multiplier over Non-complex Employment – Medium-Low complexity regions - Other classification by PCI

	Dependent variable: Non-complex employment variation					
	OLS	OLS	IV_1	IV_1	IV_2	IV_2
	(1)	(2)	(3)	(4)	(5)	(6)
Complex emp. variation	1.799***	1.407***	3.341***	3.072***	2.001***	1.633***
	(0.363)	(0.368)	(0.464)	(0.540)	(0.376)	(0.397)
Skilled emp. share		30,566		24,826		29,787
		(25.513)		(24.332)		(20.702)
Average salary		−9.159***		−9.789***		−9.245***
		(2.942)		(3.603)		(3.326)
Relatedness		416.782***		312.004**		402.560***
		(99.839)		(123.299)		(104.846)
Population		0.005***		0.001		0.004**
		(0.002)		(0.002)		(0.002)
Constant	2,577.400***	−200.015	1,451.190***	434,527	2,429.568***	−113.885
	(260.111)	(691.658)	(344.099)	(581.341)	(228.005)	(535.392)
Observations	678	678	678	678	678	678
R^2	0,390	0,446	0,357	0,391	0,389	0,445
Adjusted R^2	0,389	0,441	0,355	0,386	0,388	0,440
Residual Std. Error	3.365,879	3.217,535				
F Statistic	216.220***	90.152***	327.642***	456.230***	465.665***	563.294***

Note: *p<0.1; **p<0.05; ***p<0.01.

Table 17 – Complex Employment Multiplier over Non-complex Employment – Medium-High complexity regions - Other classification by PCI

	Dependent variable: Non-complex employment variation					
	OLS	OLS	IV_1	IV_1	IV_2	IV_2
	(1)	(2)	(3)	(4)	(5)	(6)
Complex emp. variation	1.015***	1.103***	1.489***	1.662***	1.039***	1.157***
	(0.111)	(0.173)	(0.200)	(0.253)	(0.105)	(0.188)
Skilled emp. share		42,180		−52.903		32,934
		(164.167)		(157.954)		(157.862)
Average salary		−7.788**		−3.002		−7.322**
		(3.946)		(3.353)		(3.121)
Relatedness		457.385***		322.990**		444.316***
		(172.661)		(146.297)		(142.521)
Population		−0.004		−0.010**		−0.004
		(0.004)		(0.004)		(0.003)
Constant	6,802.463***	2.766,596	3,969.230***	3.437,298	6,659.012***	2.831,819
	(699.598)	(2,967.211)	(1,079.046)	(2,666.405)	(651.711)	(2,799.737)
Observations	286	286	286	286	286	286
R^2	0,652	0,674	0,629	0,648	0,652	0,674
Adjusted R^2	0,650	0,667	0,626	0,640	0,650	0,667
Residual Std. Error	7.752,148	7.560,655				
F Statistic	265.440***	96.105***	497.866***	531.921***	535.233***	586.689***

Note: *p<0.1; **p<0.05; ***p<0.01.

Table 18 – Complex Employment Multiplier over Non-complex Employment – High complexity regions - Other classification by PCI

	Dependent variable: Non-complex employment variation					
	OLS	OLS	IV1	IV1	IV2	IV2
	(1)	(2)	(3)	(4)	(5)	(6)
Complex emp. variation	0.934***	0.977***	1.023***	1.190***	0.938***	1.027***
	(0.115)	(0.083)	(0.069)	(0.078)	(0.085)	(0.052)
Skilled emp. share		779,453		−504.135		481,939
		(1,406.949)		(1,405.941)		(1,289.456)
Average salary		−16.313		20,947		−7.677
		(33.743)		(49.254)		(32.473)
Relatedness		262,793		−1,079.397		−48.304
		(1,407.900)		(2,022.342)		(1,334.442)
Population		−0.005		−0.008		−0.005
		(0.003)		(0.005)		(0.004)
Constant	11,866.190*	15.630,890	6,963.532*	31.478,650	11,683.100***	19.304,140
	(6,359.463)	(20,850.930)	(4,210.323)	(25,900.780)	(4,207.490)	(20,549.060)
Observations	68	68	68	68	68	68
R^2	0,841	0,877	0,840	0,868	0,841	0,876
Adjusted R^2	0,836	0,864	0,835	0,855	0,836	0,864
Residual Std. Error	37.435,370	34.080,850				
F Statistic	172.342***	72.217***	304.936***	377.436***	337.955***	445.285***

Note: *p<0.1; **p<0.05; ***p<0.01.

Table 19 – Non-complex Employment Multiplier over Complex Employment - Brazil Other classification by PCI

	Dependent variable: Complex employment variation					
	OLS	OLS	IV1	IV1	IV2	IV2
	(1)	(2)	(3)	(4)	(5)	(6)
Non-complex emp. variation	0.788***	0.780***	0.904***	0.839***	0.812***	0.769***
	(0.101)	(0.068)	(0.051)	(0.024)	(0.046)	(0.044)
Skilled emp. share		−28.844		−48.895		−25.336
		(58.571)		(53.541)		(53.252)
Average salary		−2.809		0,508		−3.389
		(9.599)		(8.454)		(8.609)
Relatedness		−46.901		−199.739		−20.161
		(373.295)		(313.985)		(324.514)
Population		0.006***		0.006**		0.006**
		(0.002)		(0.003)		(0.003)
Constant	−2,262.525***	−2,228.733*	−3,380.496***	−1,653.450	−2,496.451***	−2,329.382*
	(801.776)	(1,242.802)	(339.895)	(1,139.275)	(283.250)	(1,208.741)
Observations	1.116	1.116	1.116	1.116	1.116	1.116
R^2	0,793	0,839	0,793	0,838	0,793	0,839
Adjusted R^2	0,793	0,838	0,792	0,837	0,793	0,838
Residual Std. Error	9.455,032	8.359,529				
F Statistic	2,135.419***	963.065***	4,040.601***	5,491.577***	4,332.588***	5,607.049***

Note: *p<0.1; **p<0.05; ***p<0.01.

Table 20 – Non-complex Employment Multiplier over Complex Employment - Low complexity regions - Other classification by PCI

	Dependent variable: Complex employment variation					
	OLS	OLS	IV_1	IV_1	IV_2	IV_2
	(1)	(2)	(3)	(4)	(5)	(6)
Non-complex emp. variation	0,001	−0.004	0,001	0,015	0,001	−0.005
	(0.006)	(0.006)	(0.012)	(0.017)	(0.006)	(0.005)
Skilled emp. share		0,930		1,166		0,914
		(1.052)		(0.944)		(0.851)
Average salary		0,511		0.952*		0,479
		(0.421)		(0.507)		(0.396)
Relatedness		−14.881		−28.024		−13.944
		(17.828)		(24.700)		(20.179)
Population		0,0002		0,00002		0,0002
		(0.0002)		(0.0002)		(0.0002)
Constant	62.112**	33,387	61.552**	28,775	62.199**	33,716
	(25.636)	(38.033)	(28.414)	(41.702)	(24.791)	(43.706)
Observations	84	84	84	84	84	84
R^2	0,021	0,098	0,021	0,059	0,021	0,097
Adjusted R^2	−0.003	0,027	−0.003	−0.014	−0.003	0,027
Residual Std. Error	114,188	112,444				
F Statistic	0,872	1,388	1,743	8,734	1,743	8,458

Note: *p<0.1; **p<0.05; ***p<0.01.

Table 21 – Non-complex Employment Multiplier over Complex Employment – Medium-Low complexity regions - Other classification by PCI

	Dependent variable: Complex employment variation					
	OLS	OLS	IV_1	IV_1	IV_2	IV_2
	(1)	(2)	(3)	(4)	(5)	(6)
Non-complex emp. variation	0.128***	0.090***	0.205***	0.204***	0.139***	0.097***
	(0.021)	(0.018)	(0.041)	(0.050)	(0.027)	(0.021)
Skilled emp. share		0,260		−3.763		0,012
		(6.012)		(5.998)		(5.301)
Average salary		1,155		2.135**		1,216
		(0.741)		(0.990)		(0.741)
Relatedness		17,459		−39.949		13,915
		(22.577)		(35.605)		(23.775)
Population		0.002***		0,001		0.002***
		(0.0004)		(0.001)		(0.0005)
Constant	232.376***	−314.945***	−66.165	−231.276*	190.150*	−309.779***
	(74.975)	(104.668)	(160.458)	(127.266)	(97.309)	(97.237)
Observations	678	678	678	678	678	678
R^2	0,270	0,404	0,263	0,346	0,270	0,403
Adjusted R^2	0,268	0,398	0,261	0,340	0,268	0,398
Residual Std. Error	897,734	813,757				
F Statistic	124.858***	75.736***	185.997***	387.741***	280.595***	467.634***

Note: *p<0.1; **p<0.05; ***p<0.01.

Table 22 – Non-complex Employment Multiplier over Complex Employment – Medium-High complexity regions - Other classification by PCI

	Dependent variable: Complex employment variation					
	OLS	OLS	IV1	IV1	IV2	IV2
	(1)	(2)	(3)	(4)	(5)	(6)
Non-complex emp. variation	0.418***	0.345***	0.543***	0.525***	0.471***	0.359***
	(0.079)	(0.051)	(0.064)	(0.069)	(0.074)	(0.064)
Skilled emp. share		90,816		49,442		87,772
		(93.348)		(86.414)		(73.578)
Average salary		−2.615		0,487		−2.386
		(2.465)		(2.039)		(2.307)
Relatedness		−8.969		−139.039*		−18.538
		(94.449)		(79.502)		(87.174)
Population		0.009***		0.007***		0.009***
		(0.002)		(0.001)		(0.001)
Constant	599,071	−1,698.526	−1,007.929	−1,958.160	−79.365	−1,717.626
	(842.091)	(1,472.606)	(694.498)	(1,507.178)	(842.630)	(1,129.445)
Observations	286	286	286	286	286	286
R^2	0,524	0,660	0,517	0,633	0,522	0,660
Adjusted R^2	0,520	0,653	0,513	0,625	0,519	0,653
Residual Std. Error	4.972,767	4.230,193				
F Statistic	155.662***	90.382***	291.069***	515.041***	349.383***	549.036***

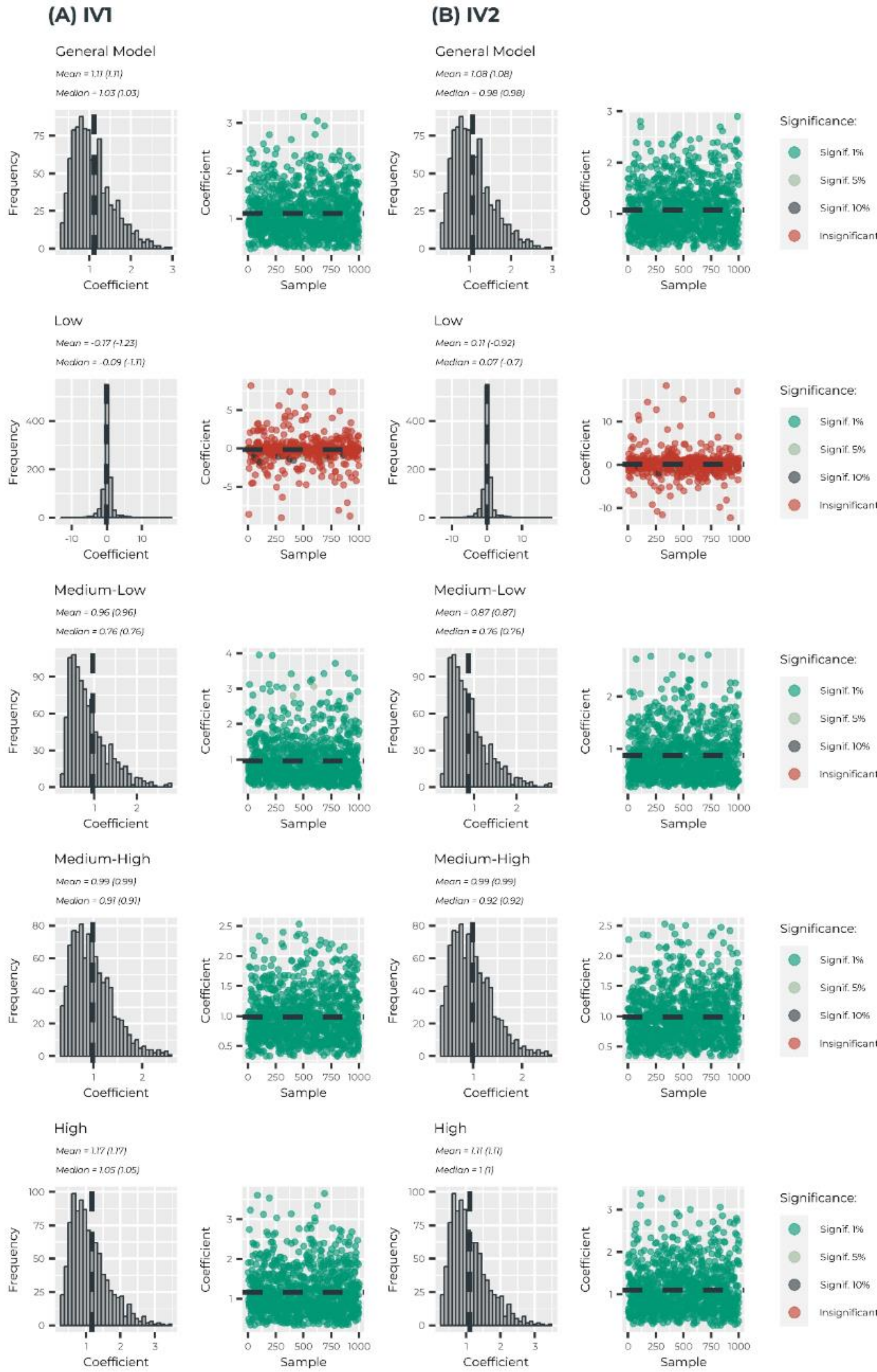
Note: *p<0.1; **p<0.05; ***p<0.01.

Table 23 – Non-complex Employment Multiplier over Complex Employment – High complexity regions - Other classification by PCI

	Dependent variable: Complex employment variation					
	OLS	OLS	IV1	IV1	IV2	IV2
	(1)	(2)	(3)	(4)	(5)	(6)
Non-complex emp. variation	0.816***	0.790***	0.958***	0.843***	0.845***	0.778***
	(0.122)	(0.090)	(0.044)	(0.027)	(0.038)	(0.052)
Skilled emp. share		763,086		409,629		844,896
		(1,021.613)		(1,051.104)		(1,057.935)
Average salary		−27.138		−17.211		−29.436
		(40.048)		(35.010)		(34.755)
Relatedness		1.234,200		893,755		1.312,998
		(1,818.144)		(1,471.889)		(1,454.675)
Population		0.007**		0.007*		0.007*
		(0.004)		(0.004)		(0.004)
Constant	3.425,726	−29,372.390	−5,567.473**	−26,341.440	1.572,597	−30,073.930
	(6,393.797)	(20,538.380)	(2,768.934)	(19,683.990)	(3,706.937)	(19,590.250)
Observations	68	68	68	68	68	68
R^2	0,825	0,874	0,821	0,873	0,825	0,874
Adjusted R^2	0,820	0,862	0,815	0,861	0,820	0,862
Residual Std. Error	34.986,000	30.638,590				
F Statistic	153.567***	70.705***	280.847***	403.972***	311.900***	415.117***

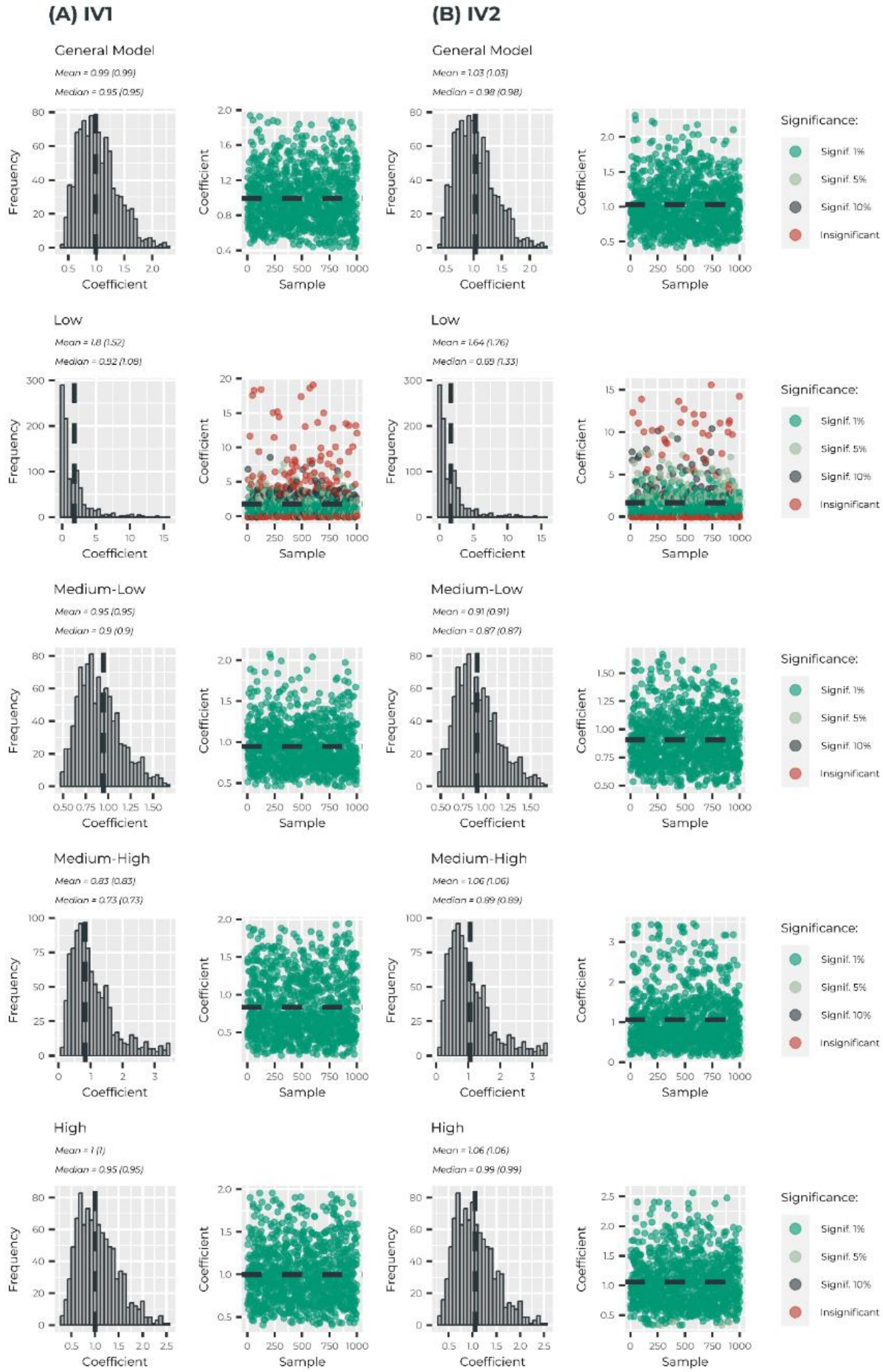
Note: *p<0.1; **p<0.05; ***p<0.01.

Figure 6 - Complex-Complex Multiplier - Other classification by PCI



Source: own elaboration.

Figure 7 – Non-Complex-Non-Complex Multiplier - Other classification by PCI



Source: own elaboration.