Estudios económicos. Vol. XLIII (N.S.), N° 87, Julio - Diciembre 2026. 180-220

ECONOMIC COMPLEXITY AND INCOME INEQUALITY IN BRAZILIAN STATES: A NON-LINEAR EMPIRICAL ANALYSIS (2003-2021)[°~]

COMPLEXIDADE ECONÔMICA E DESIGUALDADE DE RENDA NOS ESTADOS BRASILEIROS: UMA ANÁLISE EMPÍRICA NÃO LINEAR (2003-2021)

Leone Gomes-Silva[*]
Guilherme Jonas Costa Da Silva[**]

Recibido: 20 mayo 2025 – *aprobado:* 13 noviembre 2025

Abstract

This paper analyzes the relationship between economic complexity and income distribution in Brazil from 2003 to 2021. The central hypothesis proposes that greater economic complexity reduces income inequality among states, potentially in a non-linear manner that depends on their level of economic development. The results reveal a negative association between economic complexity and income inequality, which indicates that productive diversification and sophistication foster a more equitable distribution of income. More complex regions, particularly those in the South and Southeast, exhibit lower income inequality. At the same time, inequality was positively influenced by the national real minimum wage and negatively by GDP per capita and mean years of schooling. The analysis indicated an absence of a non-linear relationship between complexity and inequality conditional on the states' level of development.

Keywords: economic complexity, income inequality, threshold model, Brazil
JEL Codes: O15, O33, R11, C23

° Gomez-Silva, L. & Costa da Silva, G. J. (2026). Economic Complexity and Income Inequality in Brazilian States: Non-linear Empirical Analysis (2003-2021). *Estudios económicos, 43*(87), pp. 180-220. DOI: 10.52292/j.estudecon.2026.5262

~ Leone Gomes-Silva acknowledges the financial support from FAPEMIG (Foundation for Research Support of the State of Minas Gerais).

* Federal University of Uberlândia; State University of Maringá (UEM), Brazil. ORCID: https://orcid.org/0000-0003-1412-0006. E-mail: leone.gomes@ufu.br

** Federal University of Uberlândia, Brazil. ORCID: https://orcid.org/0000-0002-0947-0821. E-mail: guilhermejonas@yahoo.com.br

ISSN 0425-368X (versión impresa) / ISSN (versión digital) 2525-1295

Resumo

Este artigo analisa a relação entre complexidade econômica e distribuição de renda no Brasil entre 2003 e 2021. A hipótese central é que o aumento da complexidade reduz a desigualdade entre os estados, possivelmente de forma não linear, a depender do nível de desenvolvimento econômico, medido pelo PIB per capita. Os resultados indicam uma correlação negativa entre maior complexidade econômica e menor desigualdade de renda, sugerindo que a diversificação e a sofisticação produtiva contribuem para uma distribuição de renda mais equitativa. Regiões mais complexas, como o Sul e o Sudeste, apresentam menor desigualdade de renda. Além disso, a desigualdade foi positivamente influenciada pelo salário mínimo real nacional e negativamente pelo produto per capita e pela média de anos de estudo. Contudo, não foram encontradas evidências de uma relação não linear entre complexidade e desigualdade condicionada ao nível de desenvolvimento dos estados.

Palavras-chave: complexidade econômica, desigualdade de renda, modelo *threshold,* Brasil
Códigos JEL: O15, O33, R11, C23

Resumen

Este artículo analiza la relación entre la complejidad económica y la distribución del ingreso en Brasil entre 2003 y 2021. La hipótesis central plantea que un mayor nivel de complejidad económica reduce la desigualdad entre los estados, posiblemente de forma no lineal, dependiendo del PIB per cápita. Los resultados muestran una correlación negativa entre mayor complejidad económica y menor desigualdad de ingresos, lo que sugiere que la diversificación y la sofisticación productiva contribuyen a una distribución del ingreso más equitativa. Las regiones más complejas, como el Sur y el Sudeste, presentan menor desigualdad de ingresos. Además, la desigualdad fue influenciada positivamente por el salario mínimo real nacional y negativamente por el PIB per cápita y el promedio de años de escolaridad. Sin embargo, no se encontró evidencia de una relación no lineal entre complejidad y desigualdad condicionada al nivel de desarrollo de los estados.

Palabras clave: complejidad económica, desigualdad de ingresos, modelo umbral, Brasil
Códigos JEL: O15, O33, R11, C23

INTRODUCTION

Existence relies on a complexity that simplistic approaches cannot fully reflect. The world and the universe are intrinsically complex, yet they remain partially understandable, because they mirror the complexity of human actions and social relationships, which shape all surrounding phenomena. Within this perspective, the economy follows this same dynamic, and any excessive simplification of economic processes opposes their fundamental nature.

The academic debate on economic complexity has expanded alongside the rapid growth of technological sophistication and the evolving patterns of interaction among individuals and societies. In this context of profound transformations, the discussion on economic complexity gained relevance, and several theoretical and empirical studies emphasized the importance of understanding this phenomenon to explain development disparities among countries. The seminal work by Hidalgo and Hausmann (2009) represented a turning point. The authors compiled key ideas and underscored the central role of economic complexity in shaping national growth. They used international trade data to develop a bipartite network framework that links country characteristics to the products they export, and they demonstrated that complexity measures correlate with income levels and future growth potential.

This distribution of capabilities also appears at the internal level of a country, where some regions demonstrate a greater capacity to supply a broader range of products. Balland et al. (2019) and Freitas et al. (2023) proposed adaptations of Hidalgo and Hausmann's method for regional analyses and employed data such as wage mass in the Brazilian case. However, regional economic complexity remains a field with substantial gaps.

This article evaluates whether regional economic complexity relates to improvements in income inequality and examines whether this relationship follows a linear or non-linear form. The analysis applies traditional econometric methods for panel data and a Threshold Model to test the presence of non-linearity between economic complexity and income inequality in Brazilian states from 2003 to 2021.

Beyond this introduction, the article includes four sections. The second section reviews the theoretical and empirical literature. The third section characterizes growth, economic complexity, and the structure of income distribution from 2003 to 2021. The fourth section presents the methodology, database, and econometric results. The final section offers the concluding remarks.

I. LITERATURE REVIEW

The debate on economic complexity has intensified in recent years and has moved towards its consolidation as an economic theory. This section presents a theoretical and empirical review that supports the development of this article. The theoretical review outlines the methodological principles of economic complexity and the perspectives derived from these principles to explain development dynamics. The empirical review highlights studies applied to Brazil that incorporate this approach.

I.1. Theoretical Literature Review

The discussion on economic complexity and its relationship with income distribution patterns stems from the broader debate on the importance of structural change, which involves innovations and the transformation of productive processes in regions and countries.

The central role of technological innovation traces back to Schumpeter (1942 [2017]), whose perspective identifies innovation as the driving force of economic development. Aghion and Howitt (1992) expanded the concept of creative destruction and proposed a model in which continuous innovation, driven by firms seeking competitive advantage, enhances productivity but also generates temporary inequalities by displacing outdated technologies. This dynamic highlights the need for public policies that balance incentives for innovation with the protection of declining sectors.

Economic theory, as noted by Ricardo (1817), Prebisch (1962), and Balassa (1978), proposes that exports play a crucial role in growth by transforming the structural characteristics of economies. In this context, Hidalgo et al. (2007) analyzed how the proximity and connectivity of products within the "product space" shape export diversification and national economic growth. Wealthier countries connect to higher value-added products, which facilitates diversification, whereas poorer countries, located in peripheral areas of the product space, face barriers to developing complex sectors. Thus, less developed economies need structural changes to improve their position within this space and approach the levels of developed countries.

Hidalgo and Hausmann (2009) argued that national income rises as the complexity of the productive structure advances, which highlights the need to foster conditions that promote this complexity. The authors introduced the concept of economic complexity by using a bipartite network that links countries to the products they export and, indirectly, to the capabilities required to produce them. The level of complexity of an economy predicts the types of products it can manufacture in the future, which shows that new productions build on already available capabilities.

To assess complexity, the authors used the Revealed Comparative Advantage (RCA) index, which identifies products in which a country holds a specialization:

$$RCA_{cp} = \frac{\left(\frac{X_{cp}}{\sum_c X_{cp}}\right)}{\left(\frac{\sum_p X_{cp}}{\sum_{c,p} X_{cp}}\right)} \quad (1)$$

where:

X_{cp} represents the export value of product p by country c,

$\sum_c X_{cp}$ is the total export value of product p across all countries,

$\sum_p X_{cp}$ is the total export value of all products by country c,

$\sum_{c,p} X_{cp}$ and represents the total export value of all products by all countries.

The method of reflections enables the calculation of complexity indicators. However, Hausmann et al. (2014) highlighted certain limitations, such as the possibility that countries export products they do not produce domestically. Despite these limitations, the approach proposed by Hidalgo and Hausmann offers valuable insights into economic capabilities and their interactions and contributes to understanding global development dynamics.

Thus, the method of reflections relies on two underlying concepts: diversification and ubiquity. In Hidalgo and Hausmann (2009) and Hausmann et al. (2014), diversification () denotes the number of products exported by a country, while ubiquity () refers to the number of countries connected to each product. In simple terms, the ubiquity of a product can be interpreted as the total number of countries that export it with significant export value. Therefore, a high level of ubiquity indicates low sophistication in its production.

$$Diversification = K_{c,0} = \sum_{p} M_{cp} \tag{2}$$

$$Ubiquity = K_{p,0} = \sum_{c} M_{cp} \tag{3}$$

$$K_{c,N} = \frac{1}{K_{c,0}} \sum_{p} M_{cp} K_{p,N-1} \tag{4}$$

$$K_{p,N} = \frac{1}{K_{p,0}} \sum_{c} M_{cp} K_{p,N-1} \tag{5}$$

The definitions of diversification, ubiquity, and their interaction follow from equations (2) and (3). Equations (4) and (5) provide, respectively, the average ubiquity of the products exported by a country and the average diversification of the exporters of each product. The procedure is iterated until the values converge. Substituting equation (5) into (4) yields:

$$K_{c,N} = \overline{M}_{cc'} K_{c',N-2} \tag{6}$$

where

$$\overline{M}_{cc'} = \sum_{p} \frac{M_{cp} M_{c'p}}{K_{c,0} K_{p,0}} \tag{7}$$

From equation (6), the eigenvector associated with the largest eigenvalue is obtained, while the Economic Complexity Index (ICE) derives from the eigenvector associated with the second largest eigenvalue, as shown in equation (8):

$$ECI = \frac{K^{\rightarrow} - <K^{\rightarrow}>}{stdev\ (K^{\rightarrow})} \tag{8}$$

In this expression, < > denotes the average, *stdev* represents the standard deviation, and $K^{\rightarrow}$ corresponds to the eigenvector. The same procedure applies to the Product Complexity Index (PCI), with the only difference being the replacement of country indices (c) with product indices (p).

Hidalgo and Hausmann (2009) argued that changes in the productive structure stem from two processes: the combination of existing capabilities and the accumulation of new capabilities combined with the available ones. Thus, economic complexity relates to growth because countries with income below the level expected for their capabilities may produce fewer products while still achieving higher income levels. However, studies such as Freitas et al. (2023) note that this approach may face limitations at the regional level when based exclusively on export data.

Mealy, Teytelboym, and Farmer (2019) reinterpreted the ICE and the PCI and argued that these measures are equivalent to spectral clustering algorithms. These authors proposed the use of data on industrial or occupational employment concentration and demonstrated a strong correlation between the ICE and regional per capita gains in the United Kingdom and the United States. This result indicates that variables such as employment composition provide relevant information for calculating economic complexity and broaden the analysis beyond traditional export data.

Balland et al. (2019) examined the concentration of complex economic activities in large cities and propose complexity metrics based on the density of these activities. Their approach employs the spatial distribution of employment and innovation as an alternative to export data.

In Brazil, Freitas (2019) and Freitas et al. (2023) proposed economic complexity indicators based on formal employment and calculate them through the Revealed Comparative Advantage (RCA) using RAIS data, following the methodology of Hidalgo and Hausmann (2009). The levels of economic complexity directly reflect the productive structure, which shapes resource distribution dynamics.

The emergence of economic complexity measures, such as those in the Atlas of Economic Complexity (Hausmann et al., 2014), reinforces the hypothesis that more complex productive structures relate to a more equitable income distribution. According to Kuznets (1955), income inequality increases during the early stages of industrialization and tends to decrease with economic diversification and the expansion of sectors such as technology, education, and services. This process broadens employment opportunities and access to education and promotes greater equity in income distribution.

Studies such as Felipe et al. (2012) support this relationship and show that countries with high productive capacity and exports of complex products tend to achieve higher levels of development. The authors found that countries exporting complex goods, such as machinery and chemicals, have higher income levels, whereas those specializing in primary goods, such as agriculture and textiles, have lower income.

Hartmann et al. (2017) identified a stable negative relationship between the ICE and the Gini Index, indicating that higher complexity reduces income inequality. Their multivariate regressions confirm that the ICE is a relevant factor in explaining inequality, even after controlling for human capital and institutional characteristics. In the Atlas of Economic Complexity, Hausmann et al. (2014) also showed that economies with higher productive complexity concentrate high-value-added sectors and achieve greater equity, reinforcing the link between productive structure and income inequality.

Lee and Vu (2019) evidenced a negative relationship between economic complexity and income inequality and highlighted that human capital strengthens this effect. The authors demonstrated that investments in secondary and tertiary education play a crucial role, with higher education having the greatest impact on reducing inequality in complex economies. However, they argued that rapid increases in complexity may initially raise inequality due to the demand for skilled workers and adjustments in the labor market. Thus, adequate investments in education and skills development enhance the inequality-reducing effect of economic complexity, especially in countries with high human capital.

Chu and Hoang (2020) examined the influence of economic complexity on income inequality in 88 countries between 2002 and 2017 and highlighted the roles of education, government spending, and trade openness. Unlike other studies, the authors observed that higher economic complexity may worsen inequality in contexts with low education levels and limited economic openness. Efficient implementation of these factors, however, can mitigate inequalities. These findings align with the perspectives of Kuznets (1955) and Lee and Vu (2019) and suggest that the development of a more complex economy requires a long and costly process that may initially intensify inequality before reducing it.

The review presented the role of economic complexity in growth and income inequality and showed that more complex economies tend to reduce disparities. It also emphasized the relevance of incorporating new variables, such as industrial and employment concentration, into regional analyses.

I.2. Empirical Literature Review

The empirical review maps the methods that guide the methodological choice and justify the strategy adopted in the study. To this end, the section examines qualitative and quantitative studies that interpret the relationship between economic complexity and income inequality, with attention to Brazilian regional particularities.

I.2.1. Complexity, Growth, and Development

The debate on complexity has gained relevance as a key element for understanding the dynamics of economic growth. Thus, this section reviews empirical studies that explore the relationship between complexity and regional development, particularly in Brazil.

Carvalho et al. (2022) evaluated the relationship between economic complexity and GDP per capita growth in Brazilian municipalities from 2009 to 2019, using Propensity Score Matching (PSM) and Difference-in-Differences (DID). The authors found that municipalities with greater increases in economic complexity achieved GDP per capita growth between 3.25% and 7.46%, reinforcing the link between productive advancement and growth. However, they did not disaggregate other structural and spatial effects.

Smolski, Ruffoni, and Mascarini (2023) analyzed the influence of complexity and productive proximity (relatedness) on the growth of Brazilian microregions (2002-2020) through spatial econometrics. They reported that higher productive sophistication and the proximity of activities foster GDP per capita growth and encourage the emergence of new industries. The impact is stronger in the North and Center-West regions, whereas it is weaker in the South and Southeast due to their already high levels of complexity. Nevertheless, structural barriers continue to affect the less developed regions of Brazil.

Ribeiro and Almeida (2020) expanded the discussion by investigating income convergence in Brazilian municipalities (2010-2015), integrating economic complexity and technological interdependence into a neoclassical framework. The ICE strengthens human capital, while technological externalities and physical capital are key determinants of growth. Municipalities with lower per capita income grew at a faster pace, which suggests conditional convergence. Localities surrounded by less complex cities absorb knowledge or human capital, which reveals the existence of spillover effects. Policies that promote economic diversification and innovation can support income convergence.

Together, these studies demonstrate the role of economic complexity and productive proximity in regional growth, yet they leave open issues such as the identification of the sectors that actually drive expansion.

In this context, Romero et al. (2024) proposed a classification of promising economic activities, which adds to the discussion. Their study provides relevant contributions to the literature on economic complexity and regional development. Using data from Brazilian municipalities, the authors first carried out econometric tests to relate regional economic complexity to GDP per capita and formal employment per capita. They calculated complexity with employment data following the methodology developed by Hausmann et al. (2014). Moreover, they introduced a new procedure for classifying activities considered promising and preferable in terms of regional development policies, based on a combination of indicators with weights defined through Principal Component Analysis (PCA). The results show that this approach is effective for comparing regions with increasing economic complexity.

Economic complexity is positively correlated with both GDP per capita growth and formal employment per capita, which suggests that more complex municipalities tend to experience more intense economic dynamism. Additionally, the proposed classification method identifies sectors with strong potential to raise economic complexity and growth. For example, in Belo Horizonte, machinery, electronics, vehicles, and chemicals stand out. According to Romero et al. (2024), diversification in promising economic sectors would significantly increase the city's economic complexity and, consequently, both GDP per capita and formal employment. The authors estimated a potential gain of up to 35 percentage points in formal employment in promising activities, which supports the positive impact of complexity-based diversification.

Zagato et al. (2019) deepened the concept of the 'middle-income trap' and presented a cross-country comparison that emphasizes the challenges faced by economies at different stages of development. The study investigates the role of economic diversification in overcoming this trap. The authors assessed the productive structure of 116 countries between 1970 and 2010 and identified difficulties in advancing toward more productive and sophisticated sectors. They also noted that gains in complexity tend to follow an S-shaped trajectory, which implies that intermediate economies encounter specific obstacles when attempting to reach higher complexity levels.

In the case of Brazil, Pereira, Silva, and Larruscaim (2023) analyzed the limited impacts of high-complexity sectors on national growth and argued that the country remains in a condition similar to that of other middle-income economies.

Their results indicate that although Brazil exhibits a diversified export base, most exports still consist of primary goods and low-complexity products. This pattern reveals a tendency toward specialization in goods with limited technological content, which signals a restricted productive structure. The authors further contended that the low complexity of exported goods constitutes a barrier to development, as reflected in a specialization pattern with few high-complexity sectors.

Overall, these studies reinforce the importance of economic complexity as a driver of development and income convergence, especially in settings marked by regional inequalities. The evidence emphasizes the crucial role of a sophisticated and diversified productive structure in promoting growth and reducing inequalities. However, the empirical review also identifies challenges, such as Brazil's external dependence on low-complexity product exports and the 'middle-income trap.'

I.2.2. Economic Complexity and Income Inequality in Brazil

Income inequality remains an obstacle to social progress in emerging economies, including the Brazilian economy. In recent years, academic interest in the relationship between income inequality and economic complexity has increased, which reflects the relevance of a country's productive structure for the distribution of income. Additionally, structural determinants such as wage policies and labor market dynamics, especially the distribution of industrial employment, have also received attention from researchers who investigate this topic. Thus, this section systematizes the main studies on income inequality and economic complexity, categorizes their contributions, and discusses the gaps that persist in the literature.

Initially, studies analyzing structural factors of income inequality in Brazil are revisited because they are fundamental for understanding the determinants of income distribution over time. In this regard, Saboia (2007) evaluated the period 1995–2005 and demonstrated that increases in the real minimum wage contributed to reductions in the Gini Index. However, the author questioned its effectiveness as the sole redistributive policy and suggested income transfer programs as an additional mechanism to improve income distribution.

Likewise, for a more recent period, de Souza (2024) examined the years 2003–2010 and demonstrated that the increase in the real minimum wage, together with social programs, contributed to reducing the Gini Index, although the top 1% continued to concentrate income. Complementing the discussion, Silva (2022) showed that increases in the minimum wage raised average income but did not promote a more equitable distribution of gains because formal employment remained concentrated in lower wage brackets.

Extending the analysis to include poverty, Couto, Brito, and Silva (2021) emphasized the connection between inequality and poverty and highlighted that increases in education levels and economic growth help reduce poverty, whereas informality intensifies it.

In this regard, the discussions presented are relevant both for understanding the determinants of inequality in Brazil and for justifying the selection of control variables in this study, such as the real minimum wage and the industrial employment share. Moreover, by underscoring the limitations of traditional redistributive policies, these studies reinforce the importance of incorporating variables related to the productive structure, such as economic complexity, into the analysis of inequality.

This analytical movement is further reinforced by international studies that examine this relationship across countries before focusing on the Brazilian context at a subnational level. A key contribution in this field is Saia (2022), who adopted a comprehensive approach to investigate the relationship between income inequality and economic complexity in Latin American and Caribbean countries. The research covered 16 nations from 2001 to 2017 and employed a dynamic panel model using the System GMM estimator. The study found a positive correlation between the ICE and income inequality, contradicting the traditional interpretation of the relationship. This result may be explained by educational limitations in the region, which prevent low-income populations from entering sectors with higher economic complexity.

Subsequently, national studies explored the topic further by applying the complexity framework at the state level, revealing regional nuances in income distribution. A key starting point is the work of Morais, Swart, and Jordaan (2021), who investigated the link between economic complexity and income inequality in Brazilian states using panel data from 2002 to 2014. The authors found an inverted U-shaped relationship between economic complexity and inequality, indicating that initial increases in complexity may intensify inequality, whereas beyond a certain threshold, they contribute to its reduction. Moreover, they highlighted that the effects of this relationship are more pronounced in states with higher levels of urbanization and development, underscoring the relevance of territorial dimensions and regional specificities in this debate.

Reinforcing the importance of the regional productive structure in analyzing inequality, Giomo et al. (2023), covering the period 2002-2019, employed econometric techniques such as fixed-effects panel models and Pooled Mean Group estimator (ARDL/PMG). They found an inverse relationship between the ICE and income inequality, suggesting that higher economic complexity is associated with lower inequality. The authors also concluded that the share of the industrial sector has a stronger impact on reducing inequality than economic complexity itself, which further supports the inclusion of this control variable in the present study.

The territorial dimension was examined in greater depth by Rezende et al. (2023), who assessed the interaction between formal employment dynamics and economic complexity in Brazil from 2006 to 2020. They found a persistent concentration of low-complexity, low-wage jobs, which represents a challenge for reducing income inequality. The South and Southeast regions concentrate medium- and high-complexity jobs, thereby perpetuating regional disparities.

Freitas, Souza, and Lima (2024) analyzed Brazilian states between 2012 and 2021, employing fixed-effects panel models, and found a positive correlation between the ICE and income inequality. They attributed this result to differences in occupational and wage structures in more complex regions, which benefit more skilled groups within the population. However, they noted that beyond a certain threshold, economic complexity may contribute to improving income distribution, highlighting a gap in understanding the non-linear behavior of inequality and the structural factors that influence its reduction. The authors also found that trade openness is negatively correlated with inequality, whereas human capital is positively correlated.

Thus, the present study differs both methodologically and empirically from previous research, including Freitas, Souza, and Lima (2024), Giomo et al. (2023), and Morais et al. (2021), by adopting a broader time window (2003-2021) and employing a panel threshold model with endogenous cutoff identification, following Hansen (1999). This approach addresses the limitations of traditional linear specifications.

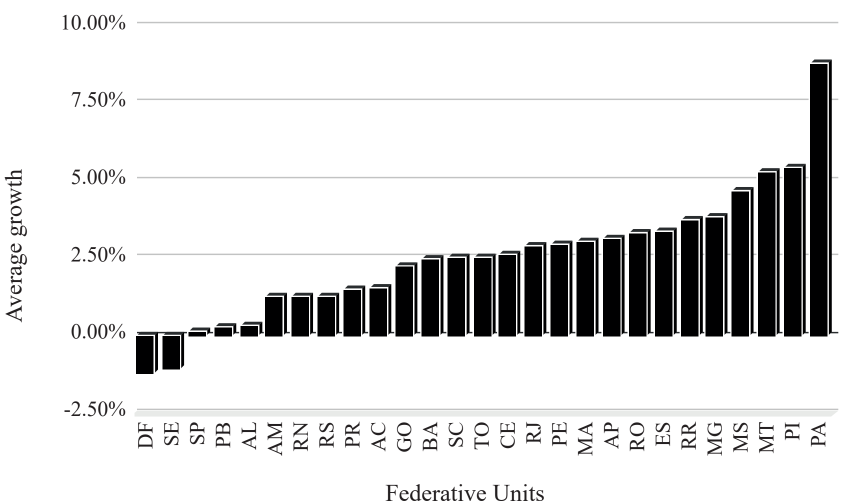
Although the literature suggests that the effects of economic complexity on inequality may vary according to the stage of regional development, existing studies have not formally tested this hypothesis. Another factor relevant for understanding income distribution dynamics is education, either through its connection with poverty (Couto, Brito, & Silva, 2021) or as a structural constraint on increasing complexity (Saia, 2022), which justifies its inclusion as a control variable in this study. Additionally, control variables directly linked to the productive structure and labor income were incorporated, as supported by the literature, including the real minimum wage, the share of industrial employment, and GDP per capita. The latter captures differences in the effect of complexity on inequality according to the stage of development in the threshold model.

II. CHARACTERIZATION OF THE ECONOMY OF THE STATES BETWEEN 2003 AND 2021

Brazilian states have historically exhibited a highly heterogeneous productive structure, shaped by economic cycles that impacted the national territory unevenly. Furtado (1959 [2020]) highlighted the secular cycles of sugar, gold, and coffee, with the latter two concentrated in Minas Gerais and São Paulo. These cycles were driven by export-oriented economic activities predominantly rooted in primary production, giving rise to distinct growth patterns under which regions with large populations coexist with persistent pockets of poverty.

Industrialization is essential for enabling structural change and facilitating the transition from less productive to more productive sectors that operate under increasing returns to scale. These sectors are capable of reducing poverty and fostering development. In Brazil, however, a concentrated and unequal productive structure has been consolidated. Thus, this section examines the Brazilian economy in terms of exports, growth, job, and income generation, which are essential dimensions for understanding the country's economic complexity.

Graph 1. Average Growth Rate of Brazilian States between 2003 and 2021

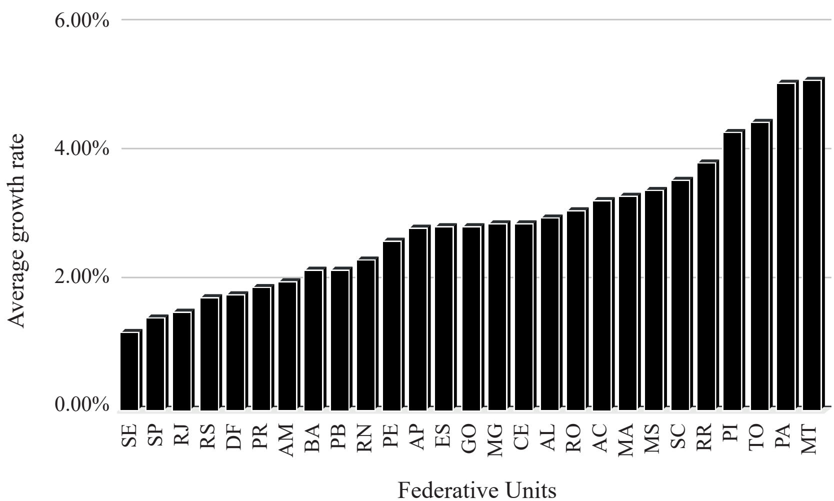


Source: Own elaboration based on IPEADATA data, 2024.

The graph shows that neither any state nor the Federal District (DF) experienced negative performance during the period evaluated (2003-2021). Amapá fluctuated between expansion and contraction and recorded an average growth rate of 2.82%. States such as São Paulo, Rio de Janeiro, and Rio Grande do Sul displayed lower average growth rates than other states, suggesting that a larger economic output is associated with smaller relative increases. These states achieved high positions in the economic complexity ranking (DATAVIVA, 2024), aligning with the findings of Hidalgo and Hausmann (2009), who highlighted that economies that accumulate new capabilities tend to show relatively reduced growth.

Of the seven states in the South and Southeast, four presented average growth rates below 2% (São Paulo, Rio de Janeiro, Rio Grande do Sul, and Paraná). Among the remaining three (Espírito Santo, Minas Gerais, and Santa Catarina), only Santa Catarina exceeded the 3% average, with 3.55%. In the Midwest, only the Federal District displayed a performance below 2%, while Mato Grosso led growth during the period (5.11%). Data from IPEADATA (2024) indicate that although larger economies exhibited smaller growth rates, such as Santa Catarina and Bahia, the latter's average growth rate was significantly higher, explaining the distance between them.

Graph 2. Average Growth Rate of Industries in Brazilian States (2003-2021)



Source: Own elaboration based on IPEADATA data, 2024.

When evaluating the average GDP growth rate associated with industries in Brazilian states, clear regional disparities emerge. Only eleven states recorded sectoral expansion above their overall GDP growth (Graphs 1 and 2). São Paulo, which accounts for the largest share of the national economy, posted a modest average GDP growth rate (1.42%) and an even lower rate for industrial production (0.15%), as shown in Graph 1. Among the six largest economies in 2021 (IPEA-DATA, 2024), only Minas Gerais and Rio de Janeiro registered industrial growth exceeding total GDP growth, which may signal stagnation in the national industry alongside a reallocation of activity toward other sectors.

Table 1. Participation of Brazilian States in Total Exports (2003-2021)

UF	% Exports by State	
SP	25.52%	
MG	13.00%	
RJ	9.79%	
RS	8.48%	
PR	7.79%	
PA	6.77%	
MT	6.02%	96.20%
ES	4.40%	
BA	4.24%	
SC	4.11%	
GO	2.80%	
MS	1.90%	
MA	1.38%	

CE	0.78%	
PE	0.62%	
AM	0.55%	
RO	0.41%	
AL	0.36%	
TO	0.35%	
RN	0.18%	3.80%
PI	0.15%	
AP	0.14%	
PB	0.10%	
DF	0.09%	
SE	0.05%	
RR	0.03%	
AC	0.01%	

Source: Own elaboration based on ComexStat data, 2024.

Of the six largest economies in the country (IPEADATA, 2024), five occupy the top positions in total exports between 2003 and 2021. São Paulo stands out as the leading exporter, accounting for 25.52% of all Brazilian exports—a volume comparable to the combined share of Rio de Janeiro, Rio Grande do Sul, and Paraná (26.06%). Minas Gerais follows as the second-largest exporter, responsible for 13% of the total. Table 1 also shows that 13 of the 27 states concentrated 96.2% of exports, while the remaining 3.8% originated predominantly from states located in the North and Northeast.

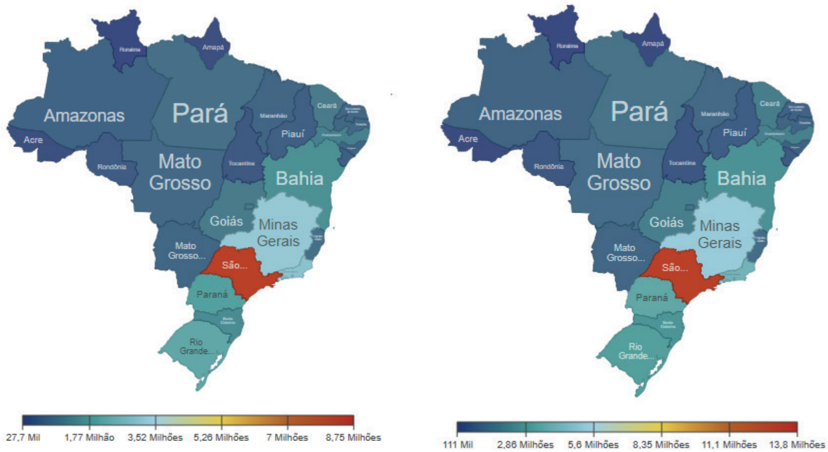
These figures reinforce the persistent regional disparities previously noted. States in the southern part of Brazil tend to display more favorable economic conditions than those in the northern regions, a pattern reflected in the Regional Economic Complexity Index (ICE-R), presented in Appendix A. São Paulo consistently ranked first in economic complexity, although its index declined over the period. In contrast, southern states such as Rio Grande do Sul, Santa Catarina, and Paraná improved their positions. Amazonas represents an exception among northern states, supported by the industrial base established in the Manaus Free Trade Zone (ZFM), as noted by Marchioro, Gubert, and Gubert (2014). On the other hand, Rio de Janeiro experienced a decline in its ranking, attributed to economic and political crises, as highlighted by Ribeiro and Passos (2024), which enabled southern states to advance.

Among the states with the lowest complexity, Pará recorded a particularly unfavorable trajectory, falling from 18th place in 2003 to last in 2015, although it showed modest recovery through 2021, according to the *Pará Industry Bulletin* (FAPESPA, 2023). Rondônia, by contrast, made substantial progress, rising from 22nd to 13th place. In the Northeast, Pernambuco, despite losing positions, remained the most complex state, whereas Bahia and Ceará encountered difficulties in improving their performance. The Central-West region presented mixed outcomes: the Federal District remained relatively stable, and Mato Grosso do Sul advanced over part of the period but declined in 2021. Overall, the results suggest that the ICE-R aligns with economic disparities, reflecting greater diversification of the production structure in the South and Southeast compared to the North, Northeast, and Central-West, which continue to face more pronounced development constraints.

Understanding income distribution requires analyzing not only the quantity of jobs created but also their qualitative composition. The predominance of low-wage employment, together with structural inequality, widens the gap between groups of workers and distorts the perception of distributive advances—a composition effect highlighted by Carvalhaes et al. (2014). The labor market plays a central role in shaping inequality, and in Brazil, formal employment expanded during the first two decades of the 21st century, supported by economic growth and domestic policies such as the real increase in the minimum wage. Saboia et al. (2021, p. 4) emphasized that greater formalization enhanced social protection for the population, especially for lower-income groups, thereby contributing to a reduction in inequality.

In 2003, Brazil had approximately 29.5 million formal jobs, with São Paulo accounting for 29.6% of the total. Rio de Janeiro, Minas Gerais, and Rio Grande do Sul also registered a substantial volume of formal employment. By 2021, the number of formal jobs increased to 48.7 million, representing growth of 64.3% since 2003. São Paulo remained the leading state, with 28.4% of total formal employment, followed by Minas Gerais and Rio de Janeiro. Roraima, although the state with the lowest number of formal jobs, recorded an increase of approximately 300% compared with 2003, yet its share remained only 0.23% of the total.

Figure 1. Distribution of Total Employment Across the Brazilian Federative Units in 2003 and 2021

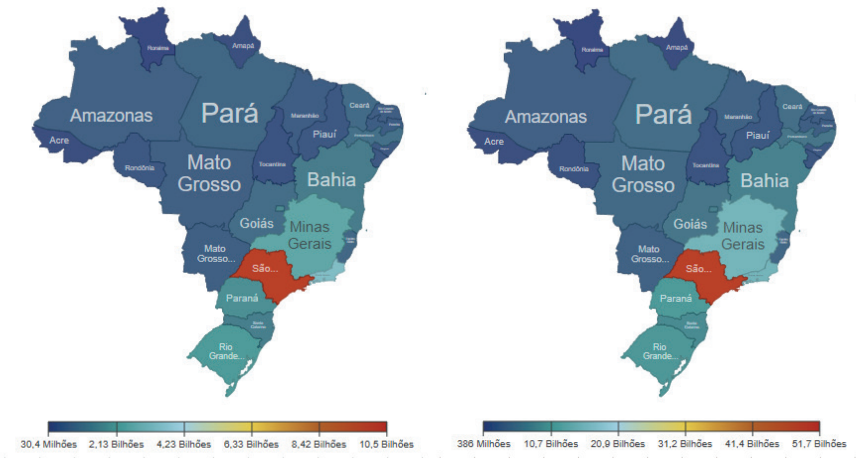


Source: Data Viva, 2024.

Industry in Brazil plays an important social role and offers higher wages, as it requires greater specialization and sophistication (IEDI, 2022). Data from the Annual Social Information Report (RAIS, 2024) provide evidence of the share of industrial employment in each state's total formal labor market. In 2003, Santa Catarina ranked first, with 34.7% of its jobs in manufacturing, followed by São Paulo, with 23.1%.

The Federal District and Amapá recorded the lowest shares, at 3.7% and 4.7%, respectively. Although Amapá showed a modest temporary increase in 2012, the Federal District continued to present the lowest proportion, a position later surpassed by Amapá and Roraima in 2021. Santa Catarina remained the leader with 30.9%, while São Paulo's share declined to 18.5%. The Southern region continued to hold the highest shares overall. In contrast, Alagoas, which had 26.5% in 2003, experienced a marked decline to 13.6% in 2021, despite increasing its total number of jobs by 66.67% (RAIS, 2024).

Figure 2. Total Payroll by State in 2003 and 2021



Source: Data Viva, 2024.

The wage bill in Brazil, as shown in Figure 2, reflects the distribution of employment across states, with São Paulo leading in 2003 with USD 10.5 billion. In 2021, São Paulo remained in first place with USD 51.7 billion, followed by Rio de Janeiro and Minas Gerais, both with USD 14.9 billion. Amapá and Roraima contributed the smallest shares to the total wage bill. According to Data Viva (2024), the distribution of the manufacturing wage bill follows the same pattern, with São Paulo leading in both years. Santa Catarina, which recorded a lower wage bill than several states in 2003, demonstrated rapid advancement, not only in industrial employment but also in the earnings generated by this activity.

Although both the wage bill and employment expanded over the period, the structure of industrial employment and the distribution of income derived from industrial production did not undergo substantial changes, except in the case of Santa Catarina, which experienced accelerated growth. The increase in the wage bill is associated with minimum wage appreciation policies which, even without consistently expanding the share of industrial employment, may have contributed to mitigating income inequality, as noted by several authors. Saboia et al. (2021, p. 27) emphasized that the sustained rise in the minimum wage until 2017 prevented a deterioration in income distribution, although this trend was later reversed by the economic crisis and labor market informalization.

The analysis of income inequality in 2003, 2012, and 2021, presented in Table 2, reveals a downward trend in the Gini Index, indicating a reduction in income disparities. Santa Catarina stood out, rising from eighth position in 2003 to become the state with the lowest index in 2021 (0.397). Between 2003 and 2021, Brazil experienced substantial growth in formal employment and total wage income, supported by minimum wage appreciation policies. Despite the decline in the share of industrial employment, Santa Catarina maintained its leadership, with stronger advances in both employment and wage income compared to other states.

Table 2. Gini Index of Brazilian States in 2003, 2012, and 2021

Federative Units	2003	2012	2021
Acre	0.579	0.508	0.479
Alagoas	0.607	0.427	0.472
Amapá	0.558	0.525	0.481
Amazonas	0.600	0.484	0.459
Bahia	0.591	0.547	0.500
Ceará	0.568	0.524	0.526
Federal District	0.630	0.571	0.551
Espírito Santo	0.554	0.457	0.453
Goiás	0.528	0.457	0.428
Maranhão	0.577	0.485	0.484
Mato Grosso	0.548	0.481	0.448
Mato Grosso do Sul	0.539	0.464	0.459
Minas Gerais	0.546	0.467	0.433
Pará	0.519	0.512	0.492
Paraíba	0.568	0.506	0.558
Paraná	0.602	0.533	0.527
Pernambuco	0.544	0.464	0.444
Piauí	0.589	0.531	0.540
Rio de Janeiro	0.559	0.474	0.514

Federative Units	2003	2012	2021
Acre	0.579	0.508	0.479
Alagoas	0.607	0.427	0.472
Amapá	0.558	0.525	0.481
Rio Grande do Norte	0.563	0.480	0.542
Rio Grande do Sul	0.525	0.517	0.524
Rondônia	0.538	0.482	0.445
Roraima	0.506	0.451	0.405
Santa Catarina	0.542	0.420	0.397
São Paulo	0.578	0.550	0.540
Sergipe	0.479	0.486	0.506
Tocantins	0.565	0.485	0.491

Source: Own elaboration based on PNAD data from IBGE, 2024.

The analysis indicates that Santa Catarina improved its position in the economic complexity ranking and achieved one of the most significant reductions in the Gini Index, suggesting a link between economic complexity and inequality reduction. However, the national structure of income distribution remained largely unchanged, concentrated in the South and Southeast. Moreover, the real minimum wage played a crucial role in increasing the wage bill, which may have contributed to the reduction of the Gini Index in Brazilian states.

To establish the preliminary relationship of interest, we analyzed the spatial distribution and descriptive association between the ICE-R and the Gini Index from 2003 to 2021. Although the raw linear association between the variables was weak (see Section III.3 for further details), the descriptive ranking (Appendix A) reveals a clear pattern: states consistently located at the top of the economic complexity ranking—primarily in the South and Southeast—tend to present lower average levels of income inequality (Gini Index) than federative units with lower complexity. This regional disparity, suggesting a relationship between productive sophistication and equity, reinforces the relevance of conducting a more rigorous analysis that accounts for unobserved heterogeneity among states, a subject examined in the following section.

III. METHODOLOGY AND RESULTS

To test the hypothesis and achieve the objectives, this section briefly presents the methodology, the database, and the main results. The aim is to contribute to the discussion on the relationship between economic complexity and income inequality at the regional level and to address a gap in the literature, namely the verification of a potential non-linear relationship between the ICE and income inequality, measured by the Gini Index.

III.1. Panel Data Methodology

The cross-sectional model evaluates different individuals (Brazilian states) at a single point in time, allowing a "snapshot" of their characteristics and enabling the comparison of variables that affect them at a specific moment. Although straightforward, it does not consider causal relationships between variables and is more susceptible to seasonal distortions. By contrast, the time series regression model incorporates time but analyzes a single object of interest, which limits its suitability for assessing several units simultaneously.

Panel data regression integrates both approaches and comprises three dimensions: multiple objects of interest (Brazilian states), time, and variables that affect the object of interest over time. Baltagi (2001) identified three main procedures: pooled data regression, which independently analyzes observations; fixed-effects regression, which controls for unobserved differences by isolating the effect of explanatory variables; and random-effects regression, which treats unobserved differences as random variables, capturing non-systematic effects across units.

In addition to traditional panel data estimations, this article applies a panel threshold model proposed and refined by Hansen (1999, 2000) and Caner and Hansen (2004). Hansen (1999) introduced the regression methodology for non-dynamic panels with fixed effects and a threshold, questioning whether regression functions are uniform across all observations. The threshold panel approach divides the sample into two distinct categories based on a threshold variable (q_{it}), which classifies the observations according to their value. This regression structure can be expressed as follows:

$$y_{\mathrm{it}}=\mu_i+\beta_1' x_{\mathrm{it}} I(q_{\mathrm{it}} \leq \gamma)+\beta_2' x_{\mathrm{it}} I(q_{\mathrm{it}}>\gamma)+e_{\mathrm{it}} \tag{9}$$

where $I(\cdot)$ is an indicator function that differentiates observations according to (q_{it}) and (x_{it}), which represent the threshold and explanatory variables, respectively.

The estimation procedure removes fixed effects by subtracting the means over time, resulting in the transformed equation:

$$y_{it}^{*}=\beta' x_{it}^{*}(\gamma)+e_{it}^{*} \tag{10}$$

The threshold coefficient is determined through the Ordinary Least Squares (OLS) method, which minimizes the sum of squared concentrated errors S1(γ), and it is validated through bootstrap techniques, as proposed by Hansen (1999). The threshold model allows the examination of relationships between variables from a non-linear perspective, identifying critical points and regime changes (Hansen, 2000). This paper employs these techniques to test the hypothesis, aiming to provide innovative results for the ongoing debate.

III.2. Variables and Database

This study conducts a panel data analysis of Brazilian states from 2003 to 2021, using annual data from IPEADATA of the Institute for Applied Economic Research (IPEA), DATAVIVA from the Center for Development and Regional Planning at the Federal University of Minas Gerais (Cedeplar/UFMG), the Brazilian Institute of Geography and Statistics (IBGE), Global Data Lab, and the Annual Social Information Report (RAIS) from the Ministry of Labor and Employment.

The economic variables analyzed include the Gini Index, the ICE-R, the National Real Minimum Wage, the Share of Industrial Employment in Total Employment, GDP per capita, and Mean Years of Schooling. The ICE-R follows the methodology of Hidalgo and Hausmann (2009), adapted by Freitas (2019) and Freitas et al. (2023), based on RAIS wage data, which allows for more accurate regional analyses.

The share of industrial employment was calculated by the author using raw RAIS data. The Gini Index was obtained from the National Household Sample Survey (PNAD) and Continuous PNAD (IBGE), while GDP per capita and the real minimum wage were extracted from IPEADATA. The average years of schooling in Brazilian states throughout the study period were measured using data from the Global Data Lab. For the minimum wage, the annual arithmetic mean was applied due to wage adjustments in certain years. The next section presents the results of the econometric estimates.

The control variables included in the model were selected based on empirical evidence presented in the specialized literature on income inequality in Brazil. The national real minimum wage was incorporated due to its central role in redistributive policies, as highlighted by Saboia (2007), de Souza (2024), and Silva (2022), who noted both its positive effects on average income and its limitations in promoting greater equity in distribution.

The share of industrial employment was incorporated based on the argument that the productive structure influences income inequality, either through the concentration of low-complexity jobs (Rezende et al., 2023) or through the sector's capacity to provide higher wages and encourage productive sophistication (Giomo et al., 2023; Freitas, Souza, and Lima, 2024). From this perspective, more highly qualified individuals would tend to benefit in a context of increasing productive sophistication. Consequently, several authors, including Morais, Swart, and Jordaan (2021), Giomo et al. (2023), and Freitas, Souza, and Lima (2024), sought to incorporate educational effects in their analyses. Following this approach, the present study adopts Mean Years of Schooling (Educ) as a proxy to capture the impact of higher professional qualifications on income inequality.

Although GDP per capita is frequently used as an explanatory variable for inequality, as in Morais, Swart, and Jordaan (2021), who analyzed the relationship between complexity and inequality in Brazilian states, it assumes a different role in this study. Here, it is employed as a threshold variable in the non-linear model, following the methodology proposed by Hansen (1999, 2000).

The choice of GDP per capita as a threshold variable is grounded in its widely recognized capacity to reflect the development level of the states, a hypothesis also considered by Ribeiro and Almeida (2020) and Zagato et al. (2019), who emphasized the importance of structural parameters for understanding the dynamics of regional inequality. This methodological design aims to capture the heterogeneity of Brazilian states in terms of economic and productive development, enabling an assessment of whether the relationship between economic complexity and income inequality is conditioned by this level of development.

III.3. Results and Discussion

The economic complexity of Brazilian states reveals clear patterns of structural inequality and productive specialization over time. States such as São Paulo, Rio de Janeiro, Rio Grande do Sul, and Santa Catarina consistently occupy the highest positions in the ranking, reflecting diversified and sophisticated economies characterized by advanced industrial sectors, high value-added services, and greater innovation capacity. In contrast, states in the North and Northeast regions, including Acre, Amapá, Tocantins, and Piauí, exhibit significantly lower values in the ICE-R, indicating a greater reliance on primary activities and limited productive diversification. From 2003 to 2021, some relative changes were observed, such as the ascent of Santa Catarina and Paraná and fluctuations in certain states of the Southeast; however, the overall hierarchy continues to demonstrate the concentration of economic complexity in the South and Southeast. This pattern underscores the relevance of public policies aimed at promoting productive diversification and reducing regional inequalities.

The Pearson correlation calculated for the entire period (2003–2021) between the Gini Index and the ICE indicates a statistically negligible linear association (). At first glance, this result could suggest the absence of a relationship between the variables. However, it reinforces the need and methodological soundness of employing a panel data model with fixed effects. Both economic complexity and income inequality are structural dimensions shaped by unobserved state-specific characteristics, including institutional arrangements, cultural factors, and historical infrastructure, which are not captured in the raw correlation. The fixed-effects model, by controlling for this idiosyncratic heterogeneity, allows for the identification of the true temporal impact of economic complexity on inequality.

To examine the impact of the ICE on the Gini Index, a model was formulated that, in addition to the variables previously described, incorporates the following independent variables: average national real minimum wage (Salmr), the share of industrial employment in total employment for each state and the Federal District (Indempg), Mean Years of Schooling (Educ), and GDP per capita for each state, including the Federal District (Pibpc). Initially, static panel models with fixed and random effects were estimated according to the following equations:

$$Gini_{\mathrm{it}}=\alpha_i+\beta_1 ice_{\mathrm{it}}+\beta_2 salmr_t+\beta_3 Indempg_{\mathrm{it}}+\beta_4 Pibpc_{\mathrm{it}}+\beta_5 Educ_{\mathrm{it}}+\mu_{\mathrm{it}} \quad (11)$$

$$Gini_{\mathrm{it}}=\alpha+\beta_1 ice_{\mathrm{it}}+\beta_2 salmr_t+\beta_3 Indempg_{\mathrm{it}}+\beta_4 Pibpc_{\mathrm{it}}+\beta_5 Educ_{\mathrm{it}}+c_i+\nu_{\mathrm{it}} \quad (12)$$

where α_i represents the fixed effects specific to each Federative Unit (UFi); μ_{it} is the error term of the fixed-effects model; c_i denotes the random effects of each UFi; ν_{it} is the error term of the random-effects model; and α is the constant common to all states.

Table 3. Estimated Parameters with Panel Data Using Fixed Effects and Random Effects

Dependent Variable: Gini Index			
	Fixed Effects*	Random Effects	Robust Fixed Effects
Economic Complexity Index (ice)	-0.035* (0.008)	-0.001 (0.006)	-0.035* (0.014)
Real National Minimum Wage (salmr)	0.029 (0.039)	0.069*** (0.041)	0.029 (0.018)
Industrial Employment Share (indempg)	0.389* (0.108)	0.101 (0.082)	0.389 (0.275)
GDP per capita (Pibpc)	0.059** (0.027)	0.073* (0.028)	0.059*** (0.029)
Mean Years Schooling (Educ)	-0.028* (0.002)	-0.028* (0.002)	-0.028* (0.003)
Constant	0.648* (0.028)	0.688* (0.024)	0.648* (0.061)
Observations	513	513	513
R^2 Within States	0.4666	0.4437	0.4666
R^2 Between States	0.0781	0.0276	0.0781
F-statistic	84.16	333.64	27.14

Note 1: Statistical significance at the 1%, 5%, and 10% levels is indicated by the symbols *, **, and ***, respectively.
Note 2: The Hausman Test with prob>chi² 0.0000 indicates preference for the fixed-effects model.
Source: Own elaboration with results obtained through Stata software.

In the fixed-effects model, all estimated parameters were statistically significant at the evaluated levels, with the exception of the real minimum wage. The ICE, significant at 1%, showed a negative coefficient (-0.035), indicating that increases in the economic complexity of Brazilian states are associated with reductions in income inequality. Considering the mean Gini Index in 2021 (0.484), an increase of one unit in the ICE results in an average reduction in inequality of 7.2%. This outcome underscores the relevance of policies oriented toward productive diversification and the enhancement of economic complexity.

The coefficients estimated for the average real minimum wage (Salmr), GDP per capita (Pibpc), and share of industrial employment (Indempg) presented positive signs, which indicates that increases in these variables are associated with higher levels of inequality. Specifically, the fixed-effects estimation without lag reveals that increases in GDP per capita, significant at 5%, and in the share of industrial employment, significant at 1%, may correspond with a concentration of income. This finding suggests that productivity gains and benefits derived from industrial expansion did not translate into a more equitable distribution of profits and wages.

Conversely, the real minimum wage, despite being part of an extensive state policy, was not statistically significant in explaining variations in income inequality. Mean Years of Schooling (Educ), significant at 1%, exhibited a negative association with the Gini Index, indicating that higher professional qualification, captured by increased average years of schooling, contributes to the reduction of income inequality.

In the random-effects model, the ICE and the share of industrial employment (Indempg) lost statistical significance, although they preserved the coefficient signs observed in the fixed-effects estimation. In contrast, the national real minimum wage (Salmr), unlike in the fixed-effects model, was statistically significant at the 10% level. The remaining variables were statistically significant at the 1% level, with particular attention to Mean Years of Schooling (Educ), which presented a negative coefficient of magnitude comparable to that obtained in the fixed-effects estimation.

The Hausman test, with close to zero, indicated preference for the fixed-effects model, which also demonstrated robustness. In the robust fixed-effects estimation, Salmr and Indempg were not statistically significant, even though Indempg had been significant at the 1% level in the non-robust specification. Conversely, Pibpc, which was significant at 5% in the non-robust model, was only significant at the 10% level in the robust fixed-effects estimation. ICE and Educ remained consistently significant at the 1% level across both robust and non-robust models.

Importantly, the magnitude of the estimated coefficients remained unchanged, with only standard errors adjusted, which allowed for a more accurate assessment of statistical significance in the robust model.

These results support the conclusion that increases in economic complexity, as well as in educational attainment, contribute to reducing income inequality in Brazilian states. This finding aligns with Hartmann et al. (2017), who indicated that economies with higher productive complexity tend to exhibit lower income inequality, as productive diversification expands employment opportunities. Lee and Vu (2019) also supported this relationship, arguing that more complex economies are associated with improved institutional quality and higher levels of unionization, thereby reducing inequality.

The magnitude and sign of the estimated coefficients in the fixed-effects model (Table 3) enable direct comparison with recent literature, particularly studies focusing on the Brazilian Federative Units. The negative and significant coefficient for the ICE (-0.035) corroborates the inequality-reducing effect reported by Giomo et al. (2023) and supports the view that a more complex productive structure contributes to a more equitable income distribution. Although Morais et al. (2021) investigated the relationship between complexity and inequality through a non-parametric analysis, the linear coefficient estimated in this study reinforces their conclusion that economic sophistication negatively affects inequality.

However, the negative coefficient for the ICE diverges from the results reported by Freitas et al. (2024), who, in a similar analysis over a shorter period, found a positive correlation between complexity and inequality. Introducing economic complexity as a central variable is essential, as it provides a more nuanced measure of the productive structure and suggests that economic sophistication, by itself, tends to reduce inequality, serving as a structural counterbalance to the potential disparities generated by aggregate growth alone.

Regarding the control variables, the positive coefficient estimated for the Share of Industrial Employment (0.389) contrasts with the findings of Giomo et al. (2023), who observed a mitigating effect on inequality through a similar indicator.

The absence of a statistically significant relationship between inequality and the real minimum wage, as well as between inequality and the share of industrial employment, does not confirm the findings of Saboia (2007) and de Souza (2024), who identified a positive association between real wage gains and reductions in inequality. Nonetheless, the results are consistent with Silva (2022), who demonstrated that, despite increases in average earnings, rises in the minimum wage in the formal sector did not contribute to a more equitable distribution of income.

GDP per capita, although important as a proxy for productivity, exhibited a positive relationship with income inequality, even though its statistical significance declined from 5% to 10% in the robust fixed-effects model. This result may be interpreted in light of Kuznets (1955), who argued that initial stages of economic growth tend to increase income concentration before enabling a more equitable redistribution. It is worth noting that the reference to Kuznets (1955) is interpretative and serves to illustrate how the positive relationship between GDP per capita and inequality may reflect early phases of economic development. This study does not aim to formally test the Kuznets Curve hypothesis, which would require the inclusion of a quadratic specification for GDP per capita. The focus of the empirical analysis lies in examining a potential non-linear effect of economic complexity on inequality, conditional on the level of development, a hypothesis addressed in the threshold models estimated below.

The redistributive framework of Brazilian states remains insufficient to reconcile average economic growth with reductions in inequality, reinforcing the need for social policies and productive diversification to mitigate these effects. Accordingly, and with the objective of advancing the empirical discussion, models with temporal lags are also estimated, represented by the following equations:

$$Gini_{\text{it}}=\alpha_i+\varphi Gini_{i(t\text{-}1)}+\beta_1 ice_{i(t\text{-}1)}+\beta_2 salmr_{t\text{-}1}+\beta_3 Indempg_{i(t\text{-}1)}+\beta_4 Pibpc_{i(t\text{-}1)}+\beta_5 Educ_{i(t\text{-}1)}+\mu_{\text{it}} \quad (13)$$

$$Gini_{\text{it}}=\alpha+\varphi Gini_{i(t\text{-}1)}+\beta_1 ice_{i(t\text{-}1)}+\beta_2 salmr_{(t\text{-}1)}+\beta_3 Indempg_{i(t\text{-}1)}+\beta_4 Pibpc_{i(t\text{-}1)}+\beta_5 Educ_{i(t\text{-}1)}+c_i+v_{\text{it}} \quad (14)$$

Here, $(t\text{-}1)$ refers to the variable lagged by one time period, and $Gini_{i(t\text{-}1)}$ is the lagged Gini Index, associated with a parameter that captures the impact of the past value of income inequality on its current level.

In the lagged estimations, it was observed that, in the fixed-effects model, the estimated coefficients were significant at the 1% level, while lagged GDP per capita $\left(Pibpc_{i(t\text{-}1)}\right)$ displayed a negative sign and was significant at 5%, indicating a reducing effect on the current Gini Index. The lagged share of industrial employment $\left(Indempg_{i(t\text{-}1)}\right)$ was not statistically significant. The lagged ICE $\left(ice_{i(t\text{-}1)}\right)$ presented a negative sign (-0.023), reinforcing that an increase in economic complexity is associated with a reduction in income inequality. Conversely, the lagged average real minimum wage $(salmr_{t\text{-}1})$ exhibited a positive sign (0.155), suggesting that past increases in this variable contribute to raising the Gini Index.

Table 4. Estimated Parameters of Panel Data Models with Lags using Fixed Effects and Random Effects

Dependent Variable: Gini Index			
	Fixed Effects*	Random Effects	Robust Fixed Effects
Lagged Gini Index ($Gini_{(i,t-1)}$)	0.387* (0.043)	0.708* (0.032)	0.387* (0.055)
Lagged Economic Complexity Index ($ice_{(i,t-1)}$)	-0.023* (0.008)	0.007* (0.002)	-0.023* (0.009)
Lagged Real National Minimum Wage ($salmr_{(t-1)}$)	0.155* (0.038)	0.164* (0.039)	0.155* (0.024)
Lagged Industrial Employment Share ($indempg_{(i,t-1)}$)	0.166 (0.106)	-0.101* (0.031)	0.166 (0.166)
Lagged GDP per capita ($pibpc_{(i,t-1)}$)	-0.052** (0.026)	-0.057** (0.027)	-0.052** (0.021)
Lagged Mean Years Schooling ($Educ_{(i,t-1)}$)	-0.015* (0.002)	-0.005* (0.002)	-0.015* (0.003)
Constant	0.388* (0.039)	0.193* (0.026)	0.388* (0.064)
Observations	486	486	486
R^2 Within States	0.5348	0.4836	0.5348
R^2 Between States	0.0337	0.9695	0.0337
F-statistic	86.81	863.56	93.15

Note 1: Statistical significances at the 1%, 5%, and 10% levels are indicated by *, **, and ***, respectively.
Note 2: The Hausman Test with prob>chi² 0.0000 indicates a preference for the fixed-effects model.
Source: Own elaboration based on results obtained with Stata software.

In the random-effects model, some divergences emerged: the lagged ICE $\left(ice_{i(t\text{-}1)}\right)$ showed a positive sign with statistical significance, while the lagged share of industrial employment $\left(Indempg_{i(t\text{-}1)}\right)$ presented a negative sign and was significant at the 1% level. The Hausman test demonstrated a preference for the fixed-effects model, suggesting greater robustness.

Table 4 highlights that, in the robust fixed-effects model, lagged GDP per capita $\left(Pibpc_{i(t\text{-}1)}\right)$ maintained statistical significance at the 5% level. Comparing the robust fixed-effects models with and without lags, it is observed that GDP per capita was the only variable with a difference in signs, although its statistical significance was preserved, weakly in the robust fixed-effects model without lags, where it was significant at 10%. As suggested by Freitas, Souza, and Lima (2024), the relationship between economic complexity and inequality may not be linear, with a level of complexity beyond which income tends to be distributed more equitably. Following the literature that associates economic complexity with development (Hidalgo and Hausmann, 2009), a Threshold Panel model is proposed, according to Hansen (1999, 2000), to capture changes in parameter effects. The estimated model is as follows:

$$Gini_{\mathrm{it}}=\beta_0+\beta_1 Gini_{i(t\text{-}1)}+\beta_2 salmr_t+\beta_3 indempg_{\mathrm{it}}+\beta_4 Educ_{\mathrm{it}}+\beta_5 ice_{\mathrm{it}} I(Pibpc_{\mathrm{it}} \leq \gamma)+\alpha_t+\epsilon_{\mathrm{it}} \quad (15)$$

$I(\cdot)$ is an indicator function that takes the value of one if the expression inside the parentheses is true and zero otherwise; γ is the estimated threshold value; α_t represents time fixed effects; and ϵ_{it} denotes the model's error term.

In the initial estimation of the linear model with time effects, the ICE showed a negative effect on income inequality, whereas the share of industrial employment (Indempg) was not statistically significant according to the HAC t-value. Although the Durbin-Watson test indicated controlled autocorrelation, heteroskedasticity was confirmed and automatically addressed by the Gretl software through robust standard errors and HAC t-values, which increases the reliability of the estimated coefficients.

In the threshold model, ICE was estimated as dependent on the regime defined by GDP per capita (Pibpc) threshold, while $Gini_{i(t\text{-}1)}$, Salmr, Indempg, and Educ were treated as exogenous variables.

When evaluating the ICE as dependent on the regime, as shown in Table 5, the results prior to the bootstrap assessment suggested that ICE would exert a negative impact on income inequality associated with changes in GDP per capita (Pibpc), although with slightly different magnitudes above and below the threshold. A direct analysis of the results indicates that when Pibpc is below the threshold of 0.059, ICE reduces the Gini Index by -0.022, whereas when Pibpc exceeds the threshold, the impact of ICE on income inequality is stronger, causing a reduction of -0.027 in the Gini Index for each unit increase in ICE.

Thus, the coefficients associated with ICE indicate a negative impact on the Gini Index, with magnitudes that vary according to the estimated threshold (0.059). However, the bootstrap test rejected the existence of an effective threshold based on Pibpc, suggesting that the introduction of the threshold does not significantly improve the model.

Table 5. Estimated Parameters using Panel Data with Threshold Effects (Threshold Regime)

	Coefficient	Adjusted Standard Error (HAC_SE)	R^2 Between States	Durbin-Watson	Homoscedasticity Test (Prob)
Linear Model with Time Effects					
Economic Complexity Index (ice)	-0.023*	(0.008)	0.7899	2.0084	0.000
Lagged Gini Index ($Gini_{i(t\text{-}1)}$)	0.469*	(0.061)			
Real National Minimum Wage (salmr)	4.847*	(0.679)			
Industrial Employment Share (indempg)	0.147	(0.154)			
Mean Years Schooling (Educ)	0.005	(0.015)			
Constant	0.380*	(0.094)			
Threshold Model with 1 Threshold(s)					
Lagged Gini Index ($Gini_{i(t\text{-}1)}$)	0.467*	(0.061)	0.7918	1.9944	0.000
Real National Minimum Wage (salmr)	4.775*	(0.693)			
Industrial Employment Share (indempg)	0.17	(0.151)			
Mean Years Schooling (Educ)	0.004	(0.015)			
1st Regime: ICE × I (PIBpc ≤ 0.059)	-0.022*	(0.008)			
2nd Regime: ICE × I (PIBpc > 0,059)	-0.027*	(0.009)			
Constant	0.384*	(0.094)			

Note 1: Statistical significances at the 1%, 5%, and 10% levels are indicated by *, **, and ***, respectively.
Note 2: The Bootstrap value (p-value) for validation of the Threshold regime was 0.565.
Source: Own elaboration using results obtained using the Gretl software.

Although the threshold effect was not statistically significant, the adoption of the panel threshold model was adequately justified. The selection of this methodology is based both on the recurrent hypothesis, widely addressed in the literature, that the relationship between economic complexity and inequality may present non-linear characteristics, as well as on its empirical relevance, since it enables a formal test of this assumption. Indeed, the absence of evidence of non-linearity during the analyzed period constitutes a relevant contribution to the literature, as it suggests that, between 2003 and 2021 in the Brazilian economy, the relationship between economic complexity and inequality tended to follow a predominantly linear pattern.

The econometric exercises conducted in this study indicate that the coefficients of the ICE remain statistically significant in explaining reductions in income inequality. The literature also identifies education as a robust factor in accounting for reductions in income inequality, which was confirmed by the estimates obtained for the period 2003-2021.

In this context, the diffusion of benefits related to complexity gains may depend on other structural dimensions, such as human capital qualification, which, when combined, could generate relevant effects on the income distribution structure. As discussed, the results confirm the educational effects reported by Morais, Swart, and Jordaan (2021), Giomo et al. (2023), and Freitas, Souza, and Lima (2024) in reducing income inequality. However, further clarification is required regarding whether, and to what extent, advances in educational levels strengthen the influence of complexity on income inequality. Consequently, it is plausible to consider that the impact of complexity on inequality may depend on other threshold variables, such as educational indicators, which opens avenues for future research.

The main contribution of this study lies in formally testing the hypothesis of non-linearity between economic complexity and inequality, demonstrating that, for the analyzed period, empirical evidence does not support regime changes and that the relationship remained practically linear. This result reinforces the argument that productivity gains derived from greater productive complexity, as reflected in GDP per capita as a proxy for development, are not sufficient to modify the trajectory of income distribution, revealing a structural limitation in the dissemination of benefits associated with economic complexity.

FINAL REMARKS

This article empirically examined the relationship between regional economic complexity and income distribution in Brazilian states from 2003 to 2021. The analysis considered the hypothesis that increases in complexity contribute to reductions in income inequality, potentially in a non-linear manner. The econometric procedures confirmed the association between greater productive complexity and lower income inequality. The threshold model did not identify inflection points associated with GDP per capita during the analyzed period, therefore indicating an absence of evidence supporting non-linearity. Consequently, the hypothesis was only partially validated. Nevertheless, the study achieved its primary objective, and its main contribution lies in applying a threshold panel data model to explore the relationship between economic complexity and income inequality from an innovative non-linear perspective.

The data showed that the most diversified and complex Brazilian states are located primarily in the South and Southeast regions, reflecting persistent historical regional disparities. The results underscore economic complexity as a relevant dimension in reducing income inequality and reinforce the importance of policies that promote productive diversification and economic sophistication. Moreover, the positive effect of the lagged average real minimum wage identified in the robust fixed-effects model suggest an association with income concentration, possibly reflecting disparities in the distribution of profits and wages. Despite the differing result for GDP per capita in the model without lags, the robust lagged model indicates that productivity gains may reduce inequality. Similarly, the average years of schooling, which aimed to capture the contribution of human capital qualification, show that higher educational levels are associated with reductions in income disparities.

In summary, the article contributed to the debate by testing the hypothesis of non-linearity in the relationship between economic complexity and income inequality and by indicating opportunities for future research in the Brazilian context. Further studies could incorporate additional metrics for defining thresholds, such as indicators of educational and professional qualification, which are more directly related to occupational mobility and economic sophistication.

APPENDIX A. Ranking of Economic Complexity of the Federative Units

Ranking position	2003		2006		2009		2012		2015		2018		2021	
	UF	ICE-R	UF	ICE-R	UF	ICE-R	UF	ICE-R	UF	ICE-R	UF	ICE-R	UF	ICE-R
1º	SP	2.907	SP	2.793	SP	2.718	SP	2.581	SP	2.485	SP	2.43	SP	2.511
2º	RJ	1.969	RJ	1.935	RJ	2.032	RJ	1.554	SC	1.648	SC	1.732	SC	1.608
3º	RS	1.248	AM	1.276	SC	1.308	RS	1.277	RJ	1.598	RS	1.595	RS	1.514
4º	AM	1.127	RS	1.265	RS	1.183	SC	1.273	RS	1.391	PR	1.506	RJ	1.39
5º	SC	0.986	SC	1.025	PR	1.141	PR	1.267	PR	1.377	RJ	1.435	PR	1.338
6º	PR	0.931	PR	0.99	AM	0.981	AM	1.143	AM	1.031	AM	0.722	AM	1.053
7º	DF	0.802	MG	0.33	PE	0.353	DF	0.961	DF	0.521	DF	0.695	DF	0.632
8º	PE	0.357	PE	0.256	ES	0.287	ES	0.399	ES	0.45	ES	0.349	ES	0.47
9º	MG	0.259	CE	0.186	DF	0.214	PE	0.278	MG	0.376	MG	0.293	MG	0.381
10º	CE	-0.002	DF	0.166	MG	0.097	CE	0.223	PE	0.257	PE	0.188	PE	0.123
11º	ES	-0.007	ES	0.11	CE	0.019	MG	0.064	CE	-0.071	CE	-0.045	CE	0.119
12º	BA	-0.102	BA	0.092	SE	-0.126	PB	-0.092	GO	-0.165	MS	-0.113	GO	-0.203
13º	SE	-0.301	SE	-0.139	RN	-0.19	BA	-0.156	BA	-0.252	GO	-0.157	RO	-0.297
14º	PB	-0.367	RN	-0.189	BA	-0.225	RN	-0.292	SE	-0.421	BA	-0.39	BA	-0.383
15º	GO	-0.472	GO	-0.291	MS	-0.259	MS	-0.312	MS	-0.441	RO	-0.456	MS	-0.438
16º	AL	-0.52	PB	-0.327	AL	-0.365	GO	-0.367	RN	-0.492	MT	-0.514	SE	-0.558
17º	RN	-0.558	AL	-0.541	PB	-0.404	SE	-0.584	PB	-0.563	RN	-0.562	PB	-0.585
18º	PA	-0.578	MT	-0.612	GO	-0.426	AL	-0.661	MT	-0.582	SE	-0.587	RN	-0.594
19º	MT	-0.592	MS	-0.69	MT	-0.613	MT	-0.671	RO	-0.617	AL	-0.589	AL	-0.613
20º	RR	-0.645	PA	-0.718	MA	-0.691	MA	-0.804	RR	-0.665	PB	-0.659	MT	-0.687
21º	MS	-0.761	RO	-0.72	PI	-0.805	PI	-0.832	AP	-0.859	RR	-0.697	PA	-0.776
22º	RO	-0.777	RR	-0.767	TO	-0.817	RO	-0.865	MA	-0.892	AC	-0.959	MA	-0.789
23º	PI	-0.814	MA	-0.966	RO	-0.851	RR	-0.919	AL	-0.91	MA	-0.977	PI	-0.792
24º	MA	-0.931	PI	-1.053	PA	-0.902	PA	-0.986	PI	-0.956	PI	-1.007	RR	-0.842
25º	AC	-1.032	AP	-1.112	AC	-1.118	TO	-1.009	TO	-1.053	TO	-1.014	AP	-1.102
26º	AP	-1.046	TO	-1.115	RR	-1.173	AP	-1.213	AC	-1.085	PA	-1.071	TO	-1.145
27º	TO	-1.078	AC	-1.184	AP	-1.367	AC	-1.255	PA	-1.109	AP	-1.149	AC	-1.335

Source: Author’s elaboration based on DATAVIVA data.

REFERENCES

Aghion, P., & Howitt, P. (1992). A Model of Growth Through Creative Destruction. *Econometrica*, *60*(2), 323-351. https://doi.org/10.3386/w3223

Balassa, B. (1978). Exports and economic growth: further evidence. *Journal of Development Economics*, *5*(2), 181-189. https://doi.org/10.1016/0304-3878(78)90006-8

Balland, P. A.; Jara-Figueroa, C.; Petrali, S.; Steijn, M.; Rigby, D., & Hidalgo, C. A. (2019). Complex economic activities concentrate in large cities. Nature Human Behaviour, *4*(3), 248-254. https://doi.org/10.1038/s41562-019-0803-3

Caner, M. & Hansen, B. E. (2004). Instrumental variable estimation of a threshold model. *Econometric Theory*, *20*(5), 813-843. https://doi.org/10.1017/S0266466604205011

Carvalhaes, F. A. de O.; Barbosa, R. J.; Souza, P. H. G. F. de, & Ribeiro, C. A. C. (2014). Os impactos da geração de empregos sobre as desigualdades de renda: Uma análise da década de 2000. *Revista Brasileira de Ciências Sociais, São Paulo*, *29*(85), 79-89.

de Carvalho, D. E.; Stein A. de Q.; Queiroz, A. R.; Romero, J. (2022). *Complexidade econômica e crescimento do PIB per capita: uma análise de diferenças-em-diferenças para os municípios brasileiros*. [Anais]. 50° Encontro Nacional de Economia. ANPEC. Fortaleza, Brasil. <Disponível: https://en.anpec.org.br/>. Acesso em: 22 out. 2024.

Chu, L.. K. & Hoang, D. P. (2020). How does economic complexity influence income inequality? New evidence from international data. *Economic Analysis and Policy, 68*, 44–57. https://doi.org/10.1016/j.eap.2020.08.004

Couto, A. C. L.; Brito, E. C., & da Silva, C. (2021). Crescimento pró-pobre: uma análise da heterogeneidade nos estados brasileiros (2012-2019). *Acta Scientiarum. Human and Social Sciences, 43*. https://doi.org/10.4025/actascihumansoc.v43i1.56101

DATAViva. Base de dados do Centro de Desenvolvimento e Planejamento Regional (Cedeplar), UFMG. Disponível em: <https://legacy.dataviva.info/pt/>. Acesso em: 13 jan. 2026.

Fundação Amazônia de Amparo a Estudos e Pesquisas - FAPESPA. (2023). *Boletim da Indústria Paraense*. Disponível em: <https://www.fapespa.pa.gov.br/boletins/>. Acesso em: 21 nov. 2024.

Felipe, J.; Kumar, U.; Abdon, A., & Bacate, M. (2012). Product complexity and economic development. *Structural Change and Economic Dynamics, 23*(1), 36-68. https://doi.org/10.1016/j.strueco.2011.08.003

Freitas, E. E. (2019). *Indústrias relacionadas, complexidade econômica e diversificação regional: uma aplicação para microrregiões brasileiras*. [Tese Doutorado em economía, Universidade Federal de Minas Gerais]. https://repositorio.ufmg.br/handle/1843/37951

Freitas, E. E.; Romero, J. P.; Britto, G; Stein, A., & Torres, R. (2023). Dataviva: espaço de atividades e indicadores regionais de complexidade econômica. (Cedeplar - UFMG, Textos para Discussão No. 657). https://www.cedeplar.ufmg.br/pesquisas/td/TD%20657.pdf

Freitas, E. E.; Souza, M. E. V., & Lima, N. V. de A. (2024). *Complexidade econômica e desigualdade de renda: uma análise das unidades federativas brasileiras*. 22° Encontro Nacional de Economia, Enaber, São Paulo. https://diamantina.cedeplar.ufmg.br/portal/download/diamantina-2024/D20_195.pdf

Furtado, C. (2020) *Formação econômica do Brasil*. São Paulo: Companhia das Letras.

Gala, P. (2017). Complexidade econômica: uma nova perspectiva para entender a antiga questão da riqueza das nações. (1a ed.). Rio de Janeiro: Contraponto.

Giomo, D.; Avellar, A. P. M.; Cardozo, S. A., & Vieira, F. V. (2023). Impacto da complexidade econômica na desigualdade de renda nas unidades da federação brasileira: uma análise econométrica. [Anais]. 51° Encontro Nacional de Economia. ANPEC, Rio de Janeiro. Disponível em: <https://en.anpec.org.br/>. Acesso em: 29 set. 2024.

GLOBAL DATA LAB. Subnational Human Development Index (SHDI): version 8.4. Nijmegen: Radboud University, 2025. Database: Mean Years of Schooling, Brazil, Subnational regions, 2003-2021. https://globaldatalab.org/shdi/. Acesso em 20 set. 2025.

Hansen, B. E. (1999). Threshold effects in non-dynamic panels: Estimation, testing, and inference. *Journal of Econometrics, 93*(2). 345–368. https://doi.org/10.1016/S0304-4076(99)00025-1

Hansen, B. E. Sample splitting and threshold estimation. Econometrica, v. 68, n. 3, p. 575–603, 2000. https://doi.org/10.1111/1468-0262.0024.

Hausmann, R.; Hidalgo, C. A.; Bustos, S.; Coscia, M.; Simoes, A.; yildirim, M. A. The Atlas of Economic Complexity: mapping paths to prosperity. Cambridge, MA: The MIT Press, 2014. https://doi.org/10.7551/mitpress/9647.001.0001.

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

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

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

Instituto Brasileiro de Geografia e Estatística - IBGE. (2024). *Pesquisa Nacional por Amostra de Domicílios: microdados*. https://www.ibge.gov.br/estatisticas/sociais/populacao/9127-pesquisa-nacional-por-amostra-de-domicilios.html?=&t=microdados

Instituto de Estudos para o Desenvolvimento Industrial (IEDI). Indústria e estratégia de desenvolvimento socioeconômico do Brasil. 24 jun. 2022. https://www.iedi.org.br/artigos/. Acesso em: 24 nov. 2024.

IPEADATA. PIB Estadual per capita - preços de mercado (preços de 2010). Seção Regional: Contas Regionais. Brasília, DF: Ipea, 2024. http://www.ipeadata.gov.br/. Acesso em 20 jan. 2024.

IPEADATA. Salário mínimo real (GAC12_SALMINRE12). Seção Macroeconômico: Salário e renda. Brasília, DF: Ipea, 2026. http://www.ipeadata.gov.br/. Acesso em 20 jan. 2024.

Kuznets, S. (1955). Economic Growth and Income Inequality. *The American Economic Review, 45*(1), 1-28. https://www.jstor.org/stable/i304619

Lee, KangKook, & Vu, Trung. (2019). *Economic complexity, human capital, and income inequality: A cross-country analysis*. (MPRA Paper No. 94960). https://mpra.ub.uni-muenchen.de/94960/1/MPRA_paper_94960.pdf

Marchioro, L.W.; Gubert, D., & Gubert, V. A. (2014). Teoria dos Polos de Crescimento e Desenvolvimento de Perroux e a implantação na Zona Franca de Manaus na região Norte do Brasil. *Revista de Estudos Sociais, 16*(31), 186-202. https://periodicoscientificos.ufmt.br/ojs/index.php/res/article/view/2091

Mealy, P.; Teytelboym, A., & Farmer, J. D. (2019). Interpreting economic complexity. *Science Advances, 5*(1). https://www.science.org/doi/10.1126/sciadv.aau1705

Morais, M. B.; Swart, J., & Jordaan, J. A. (2021). Economic Complexity and Inequality: Does Regional Productive Structure Affect Income Inequality in Brazilian States? *Sustainability, 13*(2), 1006. https://doi.org/10.3390/su13021006

Pereira, A. J.; da Silva, G. J., & Larruscaim, I. de M. (2023). Padrão de exportação e desenvolvimento econômico, ou, o que se exporta importa: uma análise da complexidade econômica da estrutura produtiva brasileira. [Anais]. 51°

Encontro Nacional de Economia, ANPEC, Rio de Janeiro. Disponível em: <https://en.anpec.org.br/>. Acesso em: 22 set. 2024.

Prebisch, R. (1962). El desarrollo económico de la América Latina y algunos de sus principales problemas. *Boletín Económico de América Latina, 3*(1), 1-23.

Relação Anual de Informações Sociais - RAIS. (2024). Microdados: base RAIS Vínculos. [PDET - Programa de Disseminação de Estatísticas do Trabalho]. Brasília, DF: Ministério do Trabalho e Emprego. https://bi.mte.gov.br/bgcaged/login.php.

Rezende, E. H.; dos Santos, F. G.; Silva, C. S.; Stein, A. de Q., & Romero, J. P. (2023). Complexidade econômica e emprego formal no Brasil: evidências de regressão produtiva entre 2006 e 2020. *Mercado de Trabalho, 29*(76), 61-78. http://dx.doi.org/10.38116/bmt76/nt2

Ribeiro, A. das C., & Passos, W. (2014). Competitividade, produtividade e emprego industrial fluminense: uma análise do período 2001-2021. *Espaço e Economia, 13*(27). https://doi.org/10.4000/12ge4

Ribeiro, M. P., & de Almeida, E. S. (2020). Convergência de Renda, Interdependência Tecnológica e Complexidade Econômica: Evidências Empíricas do Brasil. [Anais]. 48° Encontro Nacional de Economia, ANPEC, Rio de Janeiro. Disponível em: <https://en.anpec.org.br/>. Acesso em: 22 out. 2024.

Ricardo, D. (1817). Princípios de economia política e tributação. São Paulo: LeBooks.

Romero, J. P.; Freitas, E.; Silveira, F.; Britto, G.; Cimini, F., & Jayme Jr, F. G. (2024). Complexity-based diversification strategies: a new method for ranking promising activities for regional diversification. *Spatial Economic Analysis*, *20*(4), 640-663. https://doi.org/10.1080/17421772.2024.2384744

Saboia, J.; Neto, J. H.; Simões, A., & Dick, P. C. (2021). Mercado de trabalho, salário-mínimo e distribuição de renda no Brasil no passado recente. *Revista de Economia Contemporânea, Rio de Janeiro, 25*(22), 1-30. https://doi.org/10.1590/198055272521

Saboia, J. (2007). Efeitos do salário mínimo sobre a distribuição de renda no Brasil no período 1995/2005: resultados de simulações. *Revista Econômica, 9*(2), 132. https://doi.org/10.22409/economica.9i2.p132

Saia, P. P. (2022). Desigualdade de Renda e Complexidade Econômica: a América Latina e o Caribe no Século XXI. [Mestrado em Ciências Econômicas, Universidade Estadual de Campinas, Instituto de Economia]. https://repositorio.unicamp.br/Resultado/Listar?guid=1770734830975

Schumpeter, J. A. (2017). Capitalismo, socialismo e democracia. São Paulo: Editora UNESP Digital.

Silva, L. G. (2022). Comportamento Setorial do Emprego e da Remuneração da Economia Brasileira, no Período 2005 a 2013. [Monografia Graduação em Ciências EconômicasUniversidade Estadual do Sudoeste da Bahia].

Smolski, F. M. da S.; Ruffoni, J., & Mascarini, S. (2023). *Impactos da complexidade econômica e relatedness sobre o crescimento econômico das microrregiões brasileiras*. [Anails]. 51° Encontro nacional de Economía ANPEC: Rio de Janeiro. Disponível em: <https://en.anpec.org.br/>. Acesso em: 13 set. 2024.

de Souza, C. A. (2024). Crescimento e distribuição de renda no Brasil entre 2003 e 2010. [Monografia Bacharelado em Ciências Econômicas, Instituto de Economia, Universidade Estadual de Campinas]. Disponível em: <https://repositorio.unicamp.br/>. Acesso em: 03 out. 2024.

Summa, R. (2014). Uma nota sobre a relação entre salário mínimo e inflação no Brasil a partir de um modelo de inflação de custo e conflito distributivo. (Instituto de Economia, UFRJ, Texto para Discussão, No. 012). https://www.ie.ufrj.br/images/IE/TDS/2014/TD_IE_012_2014_SUMMA.pdf

Zagato, L., Gala, P., Pinheiro, F.L., & Hartmann, D. (2019). A armadilha da renda média e os obstáculos à transformação estrutural: a curva S da complexidade econômica. (São Paulo School of Economics, Working Paper No. 508). Disponível em: <https://bibliotecadigital.fgv.br/>. Acesso em: 19 out. 2024