Economic Complexity and Per Capita GDP Growth: A Differences-in-Differences Analysis for Brazilian Municipalities

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ABSTRACT
Studies on economic complexity showed in the last years that regions and countries with more advanced productive structures tend to achieve greater growth. This research aims to assess whether an increase in economic complexity implied in greater GDP per capita growth in Brazilian municipalities, considering the years between 2009 and 2019. We combine impact assessment methods with the economic complexity perspective. We used the Propensity Score Matching (PSM) methodology in conjunction with the differences-in-differences (DID) model. Municipalities that received the treatment were defined as those whose position in the economic complexity ranking increased by more than 0.3, 1.1, 1.5 or 2 standard deviations from the mean of the ranking variations. The results show that an increase economic complexity implied in growth in the per capita GDP of the municipalities in the period, regardless of the cut-off points established.
Keywords: economic complexity; impact evaluation; *Propensity Score Matching*; difference-in-differences.

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1. Introduction

Since the publication of the seminal works that have guided the approach to economic complexity, numerous authors have evaluated the relationship between complexity and other variables that characterize the process of economic development. As pointed out by Hidalgo (2021), several studies have examined the relationship between complexity and income growth (HIDALGO; HAUSMANN, 2009; HAUSMANN et al., 2011; FELIPE et al., 2012), income inequality (HARTMANN et al., 2017), and greenhouse gas emissions (ROMERO; GRAMKOW, 2021). These studies suggest that economic complexity would be an important variable for understanding the development process and a reliable predictor of income growth.

However, studies of the relationship between complexity and income growth have not been able to establish a clear causal relationship between the variables. In the seminal studies on the subject, the methods used do not adequately address potential endogeneity issues, so their results must be interpreted with caution.

This article aims to contribute to the literature on complexity and growth by applying impact evaluation methodologies for investigating this relationship for the first time. Various studies employ the Propensity Score Matching (PSM) methodology in conjunction with the Difference-in-Differences (DID) model for policy evaluation. For instance, Almeida (2014) analyzed the impact of oil royalties on education and healthcare expenditures in the Brazilian municipalities that received them. Jacques (2013) investigated the impact of credit cooperatives on per capita GDP in Brazilian municipalities. Filho and Sousa (2018), on the other hand, evaluated the implementation of Municipal Guards on city safety indicators.

The objective of this article is to assess the impact of increased economic complexity on per capita GDP growth using data from Brazilian municipalities for the period between 2009 and 2019. For this purpose, criteria were developed to identify municipalities that had an increase in complexity with respect to others. Four levels of variation in complexity ranking (0.3 standard deviation (S.D.), 1.1 S.D., 1.5 S.D., and 2 S.D.) were used to classify municipalities into treatment and control groups. Propensity Score Matching (PSM) identified communities with similar observable characteristics in order to capture what would have happened to a city if it had not increased its complexity level-the control group. Then, the Difference-in-Differences (DID) model examined the differences in income growth rates between the two groups.

2. Empirical Analysis

2.1 Complexity indicators

The assessment made in this article is based on the indicators proposed by Hausmann et al. (2007) and Hidalgo and Hausmann (2009). The economic complexity approach developed by these authors posits that income growth in countries is a consequence of structural transformation towards sectors that require a higher amount of knowledge for their production. To measure the level of knowledge required for competitive production of each product and the level of productive knowledge present in each country, these studies propose various indicators based on the concepts of diversification and ubiquity. The authors construct these measures on the basis of the revealed comparative advantage (RCA) indicator developed by Balassa (1965). This indicator expresses the comparison between a sector's participation in the local economy and the local market's participation in the overall economy, thus assessing the ability of regions to engage competitively in a given sector. The index has the following form:

$$RCA_{pc} = \frac{X_{pc}/\sum_p \quad X_{pc}}{\sum_p \quad X_{pc}/\sum_c \quad \sum_p \quad X_{pc}} \tag{1}$$

where X_{pc} represents the quantity of product p exported by country c. Therefore, if the indicator has a value greater than or equal to 1, local production in the sector is competitive in relation to other locations. Conversely, for a value less than 1, the referenced productive activity does not hold significant importance in the analyzed market.

In a complementary way, Hidalgo and Hausmann (2009) emphasize the role of knowledge and productive capabilities in determining the sectors in which economies specialize. The authors argue that productivity levels result from knowledge, especially tacit knowledge, and the internal capabilities that economies possess. Therefore, differences in income between countries are explained by differences in knowledge and capabilities. While it is not possible to directly measure the level of productive knowledge in each economy, it is possible to infer this level based on information contained in the productive structure of economies. To this end, the authors calculate two indicators that underpin the analysis of product and country complexity:

$$D_c = k_{c,0} = \sum_p M_{pc} \tag{2}$$

$$U_p = k_{p,0} = \sum_c M_{pc} \tag{3}$$

where, as defined by Hidalgo and Hausmann (2009), the quantity of goods exported with RCA is defined as the degree of country diversification (D_c), and the quantity of countries exporting a particular commodity with RCA reflects the degree of ubiquity (U_p) of that sector. M_{pc} refers to a binary matrix representing in which sectors, p, countries, c, have RCA. Thus, when there is RCA, the entry takes the value of 1, and otherwise, 0. In these primary indicators, countries with a higher amount of productive knowledge are characterized by high levels of diversification since diversified competitive production requires a greater level of knowledge. Similarly, the lower the degree of ubiquity of products, the higher the requirement for productive knowledge for their competitive production.

From these two indicators, Hidalgo and Hausmann (2009) then calculate the indices that define the level of complexity of countries - the Economic Complexity Index (ECI) - and products - the Product Complexity Index (PCI). These indices are constructed by iteratively combining diversification and ubiquity indicators. This combination is used so that locations with high (low) diversification but concentrated in the production of highly (less) ubiquitous goods are considered less (more) complex, and so that products that are less (more) ubiquitous but competitively produced by less (more) diversified countries are also considered less (more) complex. This iteration is performed continuously to ensure that the measure of product and country complexity ultimately provides robust information. Formally, this combination is represented as follows:

$$k_{c,N} = \left(\frac{1}{k_{c,0}}\right) \sum_p M_{cp} k_{p,N-1} \tag{4}$$

$$k_{p,N} = \left(\frac{1}{k_{p,0}}\right) \sum_c M_{cp} k_{c,N-1} \tag{5}$$

where N refers to the number of iterations. Replacing (4) in (5), formally, we have:

$$k_{c,N} = \sum_{c'} \varpi_{cc'} k_{c',N-2} \tag{6}$$

And:

$$\varpi_{cc'} = \sum_p (M_{cp} M_{c'p}) / (k_{c,0} k_{p,0}) \tag{7}$$

A equação (6) é satisfeita no momento em que $k_{c,N} = k_{c,N-2} = 1$ - o que representa o autovetor associado ao maior autovalor de $\varpi_{cc'}$. Entretanto, o autovetor de referência deve ser aquele associado ao segundo maior autovalor de $\varpi_{cc'}$, uma vez que o primeiro é composto apenas por valores unitários, não sendo, portanto, informativo. A necessidade de destacar os autovetores associados aos maiores autovalores objetiva encontrar os indicadores que incorporam a maior parte da variância dos dados iniciais. Dessa maneira, o ICE é, formalmente, definido como:

Equation (6) is satisfied if $k_{c,N} = k_{c,N-2} = 1$ - which is the eigenvector associated with the largest eigenvalue of $\varpi_{cc'}$. However, the reference eigenvector should be associated with the second largest eigenvalue of $\varpi_{cc'}$, since the first one consists only of unitary values and is therefore uninformative. The need to focus on the eigenvectors associated with the largest eigenvalues aims to capture indicators that contain the majority of the variance in the initial data. Thus, the Economic Complexity Index (ECI) is formally defined as follows:

$$ICE = \frac{(\vec{K} - <\vec{K}>)}{stdev(\vec{K})} \tag{8}$$

where K is the eigenvector associated with the second largest eigenvalue of $\varpi_{cc'}$, the operator <> denotes the mean, and stdev represents the standard deviation. Following the same reasoning, but substituting (5) into (4), one can find the eigenvector (Q) associated with the second largest eigenvalue of $\varpi_{pp'}$. Thus, the Product Complexity Index (PCI) is formally defined as

$$ICP = \frac{(\vec{Q} - <\vec{Q}>)}{stdev(\vec{Q})} \tag{9}$$

2.2 Constructing the dataset

The main data source used in the research presented in this article was the Annual List of Social Information (RAIS) from the Ministry of Economy's Secretariat of Labor. RAIS is a database of administrative records that provides information on all formal establishments and employment contracts (both salaried and statutory) in Brazil. The submission of information is mandatory and done annually by the establishments themselves. Through RAIS, it is possible to obtain information about formal establishments, employees, and the type of relationship between establishments and employees, known as employment contracts. The data allows for the identification of the municipality where each company is located, enabling the extraction of the number of employment contracts in each municipality, for each year, categorized by economic sector.

The municipal and sectoral economic complexity indicators used in the exercises presented in this study were calculated using sectoral employment data by municipality at the CNAE division level (two-digit). Following the methodology proposed by Hidalgo et al. (2009), the method of reflections was used for the measurement.

Table 1 - Variables used in the PSM and DD regressions

Variable	Definition	Source	PSM	DD
GDP *per capita*	Gross Domestic Product *per capita*.	IBGE	Yes	Yes
ECI	Economic Complexity Index - calculated from equation (8).	RAIS	Yes	Yes
Population	City population.	Datasus	Yes	Yes
Higher Education	The percentage of formal employment with a higher education level relative to the total employed.	RAIS	Yes	Yes

Population density	Population divided by the area of the municipality.	Datasus e IBGE	Yes	Yes
F.E. of Federal Units	Dummy variables for the 27 Brazilian states.	IBGE	Yes	No
F.E. of municipalities	Dummy variables for Brazilian municipalities.	IBGE	No	Yes

In addition, four other variables were used in the configuration of the estimated models. For the matching process - via Propensity Score Matching (PSM) - and the estimation of Difference-in-Differences (DID), we used population, population density, and employment contracts with a completed higher education, as defined by the variable of interest. While the latter variable is also provided by the RAIS, the first two are accessed through the information technology platform of the Brazilian Unified Health System (DATASUS) and the Brazilian Institute of Geography and Statistics (IBGE). Finally, the dependent variable of the research question, GDP per capita, is also provided by the IBGE.

The variables used in the estimations presented in the remaining of the article, along with their respective sources, are summarized in Table 1.

2.3 Empirical strategy

The ideal way to evaluate the impact of improving the productive structure on local income levels would be to conduct an experiment in which the increase in complexity is an exogenous process. This implies that municipalities' decisions of municipalities to move forward in the production and marketing of more complex products are independent of the characteristics and conditions of the locality. However, the decisions and/or choices of municipalities (i.e. their firms and agents) towards more complex production structures are multidimensional in nature and therefore suffer from endogeneity problems. In this sense, a quasi-experimental methodology seems appropriate when it is not possible to control the assignment of treated groups.

The objective of this article is to analyze what would have happened to the per capita GDP of the municipalities that experienced an increase in complexity if this increase had not taken place. To evaluate the evolution of GDP in these municipalities, it is also necessary to consider the pre-treatment characteristics of the municipalities in order to identify the difference in GDP per capita levels between municipalities with and without an increase in economic complexity.

The difficulty with impact evaluation lies in the fact that it is not possible to observe the same cities in two distinct states within the same time frame: the treated state as it becomes more complex, and the untreated state as it becomes less complex. In an attempt to solve this problem, it is possible to use counterfactuals from the treated group, considering those municipalities with similar characteristics that did not improve in the complexity ranking during the analyzed time period. However, a simple comparison between these two groups of municipalities would yield biased results, since there are other variables that differentiate them and influence both the treated condition and the outcome variable (GDP per capita). Therefore, in order to define the relevant treatment group, it is necessary to match municipalities with similar characteristics. The technique of propensity score matching (PSM), introduced by Rosenbaum and Robin (1983), is widely used to define a statistical comparison group, in this case for municipalities that have increased their level of complexity. This technique uses observable variables to match municipalities, finding within the control group those that are most similar in terms of observable characteristics. The identified control group was then used to estimate a difference-in-differences (DID) model that allowed for a comparison of per capita GDP growth between treated and control municipalities.

2.3.1 Treatment and control groups

The selection of the treatment and control groups is crucial for the design of the study. Since the Economic Complexity Index is a relative variable that varies from year to year in terms of the level of product complexity, it was decided not to analyze the absolute value of the variable, but rather the changes that municipalities experienced in the complexity ranking. In addition, robustness tests were conducted using different thresholds for increases and decreases in the ranking to validate the results.

In order to define the threshold for an increase in the complexity ranking, the scores were based on standard deviations (SD) from the mean in terms of variation in the complexity ranking. The initial estimation was conducted considering communities that experienced a 0.3 SD increase in complexity ranking compared to those that did not experience such an increase. The robustness estimates include communities that had variations of 1.1, 1.5, and 2 SDs. These SD values were chosen based on the results of the propensity score matching (PSM) analysis. First, all SD values between 0 and 2 were matched. Models were then selected where statistically similar treatment and control groups were found with respect to observable characteristics.

2.3.2 PSM and DID models

To identify the true differences in means between the treated and control groups, it is necessary to use a strategy that corrects for selection bias. In this article, the difference-in-differences (DID) method was used. Denoting Y(D) as the potential outcome for the municipality, where Y(1) represents the outcome under the treatment and Y(0) represents the outcome for the same community in the counterfactual condition of not receiving the intervention, the equation $E[Y(1) - Y(0)]$ would represent the average treatment effect (ATE). However, as noted above, it is not possible to observe the same municipality in both the treatment and control conditions simultaneously. Therefore, the difference in means $E[Y(1) \mid D = 1] - E[Y(0)|D = 0]$ is not an appropriate estimator of the ATE.

When summing and subtracting the counterfactual in the equation of observed differences in means, it is possible to determine the bias. After performing the operations and rearranging the terms, we have the treatment effect on the treated plus a selection bias, which refers to the average impact of the treatment, as observed in the equation below:

$$E[Y(1) - Y(0)|D=1] + E[Y(0)|D=1] - E[Y(0)|D(0)] \quad (10)$$

The matching technique addresses the problem of selection bias by replacing randomization with conditioning on covariates. Selection bias is eliminated only if treatment is purely random among communities with the same propensity score. Conditioning on the propensity score can reduce selection bias and improve the estimation of the treatment effect using observable data. By conditioning on X to account for the observable effects that determine self-selection, we obtain the average treatment effect on the treated (ATT), which is the first term in equation (10). The approach proposed by Rosenbaum and Rubin (1983) addresses the dimensionality problem by using the propensity score $p(xi)$, which gives the probability of receiving the treatment for community i based on its characteristics Xi, and allows for the comparison of treated and control groups with similar propensity scores.

Propensity Score Matching (PSM) is a method that uses a probit model where the dependent variable is related to economic complexity - where the value "1" indicates that the municipality has moved up in the economic complexity ranking, and "0" otherwise. The selection of explanatory variables aims to understand the possible characteristics that influence the probability of a municipality increasing or decreasing its level of complexity. By including this information, the goal is to control for potential differences between the treated and control groups by identifying the specifics of each municipality and correcting for them in a way that isolates the potential impact of an increase in complexity for the treated group.

The construction of the control group is based on the Nearest Neighbor Matching (NNM) technique, which combines the results of all control group units that have propensity scores statistically similar to the propensity score of the treated unit (CAMERON; TRIVEDI, 2005). In addition, a nearest neighbor with replacement approach was used.

The hypothesis of the study is that an increase in economic complexity in municipalities leads to higher growth in per capita GDP in those places. The DID model can be specified in a generic form as follows:

$$Y_{it} = \alpha + \delta D_i + \rho T_t + \gamma D_i * T_t + \beta_1 X_{it} + \beta_2 \omega + \mu_t + \tau_i + \epsilon_{it} \quad (11)$$

where Y is the per capita GDP of the municipalities. The vector X represents the observed characteristics (covariates or control variables) of municipality i. The subscript *t* denotes the time period. The variable T takes the value 1 in the period following the increase or decrease in economic complexity, and 0 otherwise. D is the binary variable indicating whether municipality *i* was actually treated, taking the value 1 if treated (had an increase in the ranking of economic complexity) and 0 if not treated. The term D*T represents the interaction between D and T, and γ is the treatment effect-the improvement in economic complexity achieved by DID. The term ω represents the weights from PSM. This is an alternative method of obtaining the ATT by using the propensity score as an explanatory variable in the DID regression, further reducing the influence of variables that may affect the outcome variable. Finally, μ_t, τ_i and ϵ_{it} represent the fixed effects of time, municipality and the regression residuals, respectively. It should be noted that the variables used in PSM were the same when considering variations in complexity ranking of 0.3, 1.1 SD, and 2 SD to maintain comparability across models.

In order to use this method, there are several assumptions that need to be verified. The first assumption, common support, ensures that each treatment group has at least one control group to serve as a counterfactual (SCORZAFAVE et al., 2015). The second assumption requires that the pre-treatment temporal trend of the outcome variable is the same for both groups, which is the starting point for analyzing the evolution of economic complexity in municipalities. The idea is that a similar time trend indicates that both groups responded similarly to each factor affecting the outcome variable before the start of the analysis period. Therefore, we conducted a test to verify whether there was the same temporal trend for both groups (FILHO; PINTO, 2017).

Another assumption is that the composition of the treatment and control groups does not change significantly between the pre- and post-analysis periods. In the case of this article, this assumption is true because the units of analysis are municipalities and data were obtained for the entire analysis period (FILHO; PINTO, 2017).

Finally, the last condition required by the DID method is that the treatment and control groups are not specifically affected by changes that occur after the treatment. To reduce the likelihood of this happening, we use several relevant variables in the PSM, with the aim of making the treatment and control groups as similar as possible in terms of observable variables (FILHO; PINTO, 2017). In this sense, given the hypothesis of selection on observables, propensity score matching removes selection bias. In addition, the DID method controls for bias due to unobserved variables that are fixed over time. The two methods address different problems, but not simultaneously. Therefore, the combination of DID and PSM addresses selection bias in both observable and unobservable time-invariant variables.

In summary, the following steps were carried out in this study:

a) Definition of treatment and control groups: Municipalities were divided into treatment and control groups based on their increase in the economic complexity ranking. Different levels of increase, measured in standard deviations (0.3, 1.1, 1.5 and 2 SD), were considered to form the treatment groups;

b) Estimation of treatment decision - propensity score: The propensity score was estimated for each community using a probit model, taking into account the observed characteristics of the communities. This score determined the control group that would be as similar as possible to the treatment group before the point of analysis of complexity;

c) Estimation of the weighted DID using the propensity score: The Difference-in-Differences (DID) method was used to estimate the average treatment effect weighted by the propensity score. DID compares the differences in mean GDP per capita between the treatment and control groups before and after treatment, thus controlling for selection bias;

The analysis period covered the change in the economic complexity ranking of municipalities from 2009 to 2019. These steps were taken to analyze the impact of increasing economic complexity on per capita GDP in municipalities.

3. Results

3.1 Descriptive analysis

Table 2 shows the means of the variables used for matching and for identifying the municipalities that make up the control group. It also shows the hypothesis test for a difference between means before and after matching. It can be seen that the two groups had different observable characteristics before matching. Only in terms of the population did the means test indicate that the two groups were similar at the 95% significance level. However, after matching, the test for difference in means indicated that the null hypothesis of zero difference in means between groups could not be rejected. This confirms that the treatment and control groups are similar with 95% confidence given the variables used.

Table 2 - Means test between treated and control groups on PSM variables before and after pairing

		Before matching			After matching (0,3 S.D.)		
	Grupo	Mean	t. estat.	P-valor	Mean	t. estat.	Value-p
Log(Population)	Treatment	9.04	0.60	0.54	9.13	0.55	0.58
	Control	9.05			9.11		
Log(GDP *per capita*)	Treatment	2.12	5.27	0.00	1.814	-0.09	0.92
	Control	2.20			1.816		
ECI	Treatment	-0.52	12.02	0.00	-0.34	-0.59	0.11
	Control	-0.357			-0.29		
Higher Education	Treatment	0.183	-12.24	0.00	0.119	1.12	0.26
	Control	0.154			0.116		
Population density	Treatment	32.95	3.09	0.00	35.969	1.28	0.22
	Control	35.71			32.524		

Table 3 shows the descriptive statistics of these variations for the different standard deviation values of the complexity ranking considered in this article. On average, it can be observed that a variation in the ranking of 0.3 standard deviations represents an increase of 690 positions for the treatment group and a decrease of 352 positions for the control group. For 1.1 standard deviations, there is an average increase of 1198 positions for the treated municipalities and a decrease of 219 positions for the control group. At 1.5 standard deviations, there is an average increase of 1455 positions for the first group and a decrease of 124 positions for the second group. Finally, for 2 standard deviations, there is an average increase of 1796 positions for the treatment group and an increase of 80 positions for the control group.

Table 3 - Descriptive Statistics of Ranking Variations by Each Standard Deviation

D.P.	Group	Minimum	Maximum	Mean	Standard Deviations.
0.3	Control	-2738	191	-351.7	469
0.3	Treatment	193	4916	690	496
1.1	Control	-3265	710	-219.3	589
1.1	Treatment	717	4916	1197.6	499
1.5	Control	-3265	955	-124	651
1.5	Treatment	981	4916	1454.6	508
2	Control	-1283	1307	80.7	578
2	Treatment	1309	4916	1795.8	521

We should note that the higher the standard deviation value considered as a threshold, the greater the average gain in complexity ranking positions, as this sets limits further to the right of the distribution of variations in complexity ranking. In other words, with higher values of the standard deviation, we select as treated only those municipalities that had a significant increase in complexity ranking.

We should note that the higher the standard deviation value considered as a cutoff point, the greater the average gain in complexity ranking positions, as this sets limits further to the right of the distribution of variations in complexity ranking. In other words, with higher values of the standard deviation, we select as treated only those municipalities that had a significant increase in complexity ranking.

For the effectiveness of PSM, as highlighted by Scorzafave et al. (2015), it is necessary to confirm the common support hypothesis to ensure that treatment observations have comparison units, the control group, in the vicinity of the propensity score distribution. Figure 2 shows the common support region for the entire sample (regardless of the location of the municipalities) used in this study, assuming a variation in complexity ranking of 0.3 standard deviations from 2006 to 2019. It is possible to identify an overlap of the two distribution curves (for the control and treatment groups), indicating that municipalities that experienced a complexity increase are compatible with untreated units in terms of observable characteristics, thereby facilitating the matching process.

Figure 1 - Common Support of Propensity Score (Kernel Density) for Treatment and Control groups by Complexity Increase - Total (0.3 SD Cut-off)

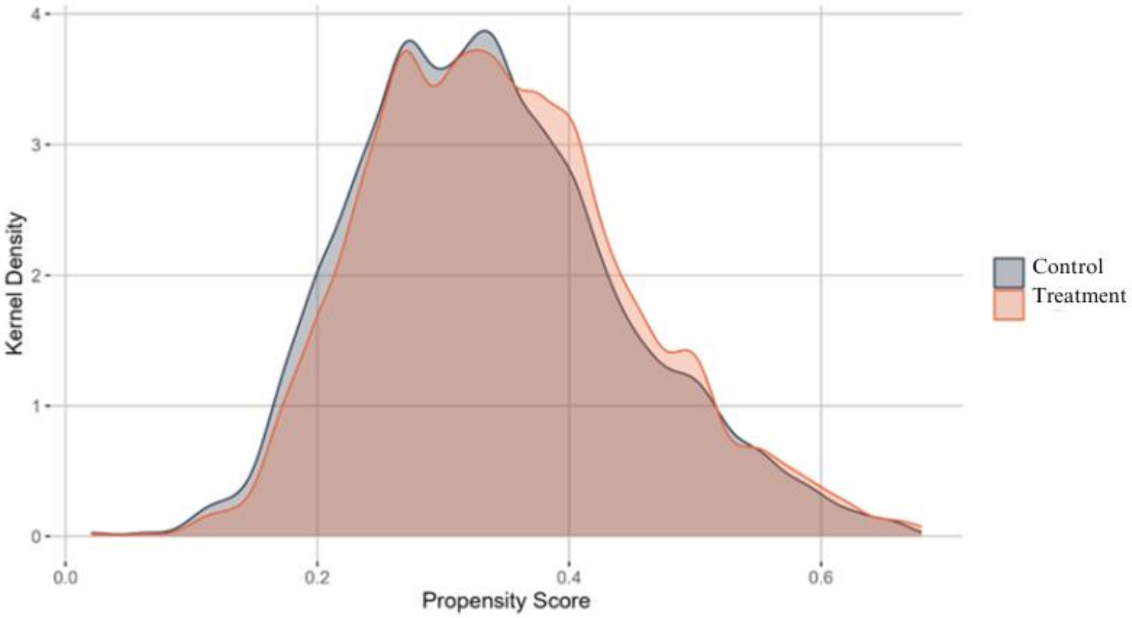


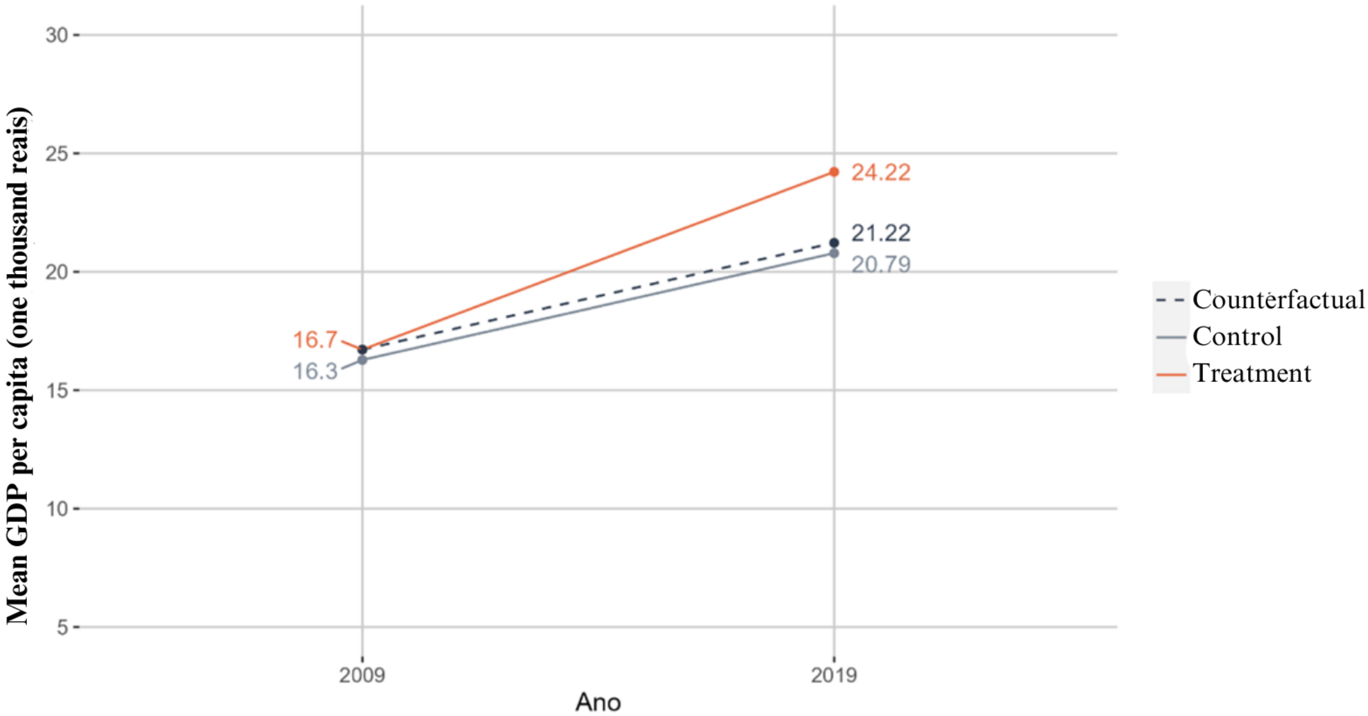
Figure 2 - Mean GDP per capita for treatment and control groups after matching and treatment group counterfactual (0.3 SD cut-off)

Figure 2 shows the mean of the outcome variable (GDP per capita) for the treatment and control groups, considering a cutoff of 0.3 standard deviations in the variation of the complexity ranking from 2006 to 2019. It can be observed that both groups experience similar growth between 2006 and 2008. Only in 2008 and 2009 does the growth rate of the treatment group appear to be slightly lower than that of the control group, causing the average of the two groups to converge.

This analysis is important because it helps to confirm the second hypothesis highlighted by Scorzafave et al. (2015), which postulates that the temporal trend of the outcome variable should be the same for both groups before the treatment. The fluctuations observed between 2008 and 2009 in the treatment group are much smaller than the fluctuations that occurred after the treatment - after 2009. Thus, we believe that the overall time trend appears to be similar for both groups before the treatment, confirming the second hypothesis.

Figure 3 shows the graph of per capita GDP growth if the municipalities in the treatment group had not experienced an increase in complexity ranking (counterfactual). This means that if the municipalities in the treatment group had not moved up in the complexity ranking, they would have followed the same trend in per capita GDP growth as the municipalities in the control group and would have had an average per capita income that was 300 reais lower. It is worth noting that this figure does not take into account other variables that may influence the income differences between the two groups and that are included in the estimates.

Figure 3 - Projection of average per capita GDP outcomes for the treatment and control groups after matching and the treatment group counterfactual (0.3 SD cut-off).



3.2 Model's results

Table 4 presents the results of the difference-in-differences estimation model for the treatment effect of an increase in complexity ranking (0.3 standard deviations) on Brazilian municipalities for the years 2006 and 2019. This model was considered the main model due to its larger sample size and its parsimony in the selection of the control group, including cities that had smaller increases in complexity ranking.

Thus, even for both estimations - the one with fewer parameters (I) and the one with more parameters (II) - the results indicate that having the treatment of improvement in the complexity ranking led to a significant increase in per capita GDP of the municipalities between 2009 and 2019. The difference in the coefficient value between the two models for the variable of interest in the study - treatment * time - may be due to the influence of other variables that affect per capita GDP and were included in the estimation with more parameters (II). Therefore, in estimation (II), the coefficient value of interest decreased, and thus, the treatment effect as well.

The results indicate that municipalities that experienced an increase in complexity ranking had an average annual increase in GDP per capita of 3.25% compared to municipalities that experienced a decrease in complexity ranking over the same period. The use of matching ensures that the treated and control groups are similar, given the observable characteristics in the PSM. Thus, we are comparing municipalities that are similar in terms of the observable variables we are considering, and thus the outcome variable (GDP per capita) would not be affected by differences between the groups in these important characteristics. In addition, by using DID estimation, we are able to control for unobservable variables that are constant over time, such as certain institutional characteristics of the municipalities. It should be noted that time and municipality fixed effects were included to capture differences between years as well as persistent differences between municipalities over time.

Table 4 - Estimates of the increase in complexity ranking among Brazilian municipalities after matching to 0.3 standard deviations between 2006 and 2019.

	(I)	(II)
	0.3 S.D.	
Treatment * Time	0.040***	0.032***
	(0.0054)	(0.0038)
Teatment	0.171**	0.637***
	(0.0837)	(0.0324)
Time	0.696***	1.214***
	(0.0039)	(0.0060)
PSM weights	0.073	-0.359***
	(0.6087)	(0.0283)
ECI		0.056***
		(0.0043)
Population		-0.482***
		(0.0265)
Higher Education		-0.041***
		(0.0125)
Population density		-0.000***
		(0.0001)
Constant	1.897***	6.450***
	(0.0536)	(0.2705)
F.E. of time	Yes	Yes
F.E. of municipalities	Yes	Yes
Observations	39606	39606
Adjusted R^2	0.87	0.95

Note: Dependent variable: log of GDP per capita. Standard error in parentheses. Significance of the coefficients: *** ($p < 0{,}01$), ** ($p < 0{,}05$), * ($p<0{,}1$).

The coefficient of the treatment variable alone, considering the entire period, suggests that the two groups are, on average, different in terms of GDP per capita. The statistically significant coefficient can be explained by the period analyzed, since it takes into account the years before and after the treatment. As can be seen in Table 2, the means of GDP per capita are statistically equal before the treatment. However, after the treatment, the mean between the two groups changes, as evidenced by the coefficient of the variable of interest.

In addition, the coefficient of the time variable was also significant and positive in both models, indicating a trend of increasing GDP per capita from 2009 to 2019 compared to the entire period (2006 to 2019), independent of the treatment effect. The inclusion of this variable removes the influence of this trend.

It is also observed that the variable ECI is significant and positive, indicating that higher levels of complexity in municipalities are associated with higher growth in GDP per capita, as previously observed in the literature for different years and regions (HIDALGO; HAUSMANN, 2009; FELIPE et al., 2012; ROMERO; SILVEIRA, 2018).

3.3 Robustness Tests

The common support and parallel trends assumptions are validated by assuming variations in complexity ranking of 1.1 SD, 1.5 SD, and 2 SD. The graphs examining the assumptions for the pre-treatment outcome variable can be found in Tables A1, A2, and A3 in the Appendix.
Table 5 presents the estimates of complexity ranking increases of 1.1, 1.5, and 2 SD for Brazilian municipalities after matching, between 2006 and 2019. The results show that the selection of municipalities in the treatment group based on the standard deviations of complexity ranking increases and decreases did not significantly affect the results. In all regressions, municipalities that experienced an increase in complexity ranking had higher GDP per capita than similar municipalities with respect to observable characteristics that did not experience an increase in ranking.

Table 5 - Estimates of the increase in complexity ranking among Brazilian municipalities after matching to 1.1, 1.5 and 2 standard deviations between 2006 and 2019.

	(I)	(II)	(III)	(IV)	(V)	(VI)
	1.1 S.D.		1.5 S.D.		2 S.D.	
Treatment * Time	0.068***	0.052***	0.065**	0.047***	0.084***	0.072***
	(0.0090)	(0.0062)	(0.0120)	(0.0087)	(0.0176)	(0.0125)
Treatment	0.350***	0.643***	-0.109	0.582***	0.241***	-0.491***
	(0.0867)	(0.1103)	(0.0816)	(0.0879)	(0.0934)	(0.1633)
Time	0.695***	1.238***	0.707***	1.245***	0.716***	1.275***
	(0.0059)	(0.0100)	(0.0078)	(0.0134)	(0.0102)	(0.0200)
PSM weights	-1.124***	-1.510***	0.094	-0.138	0.804***	0.371***
	(0.1126)	(0.0694)	(0.1599)	(0.0900)	(0.0994)	(0.1343)
ECI		0.064***		0.069***		0.066***
		(0.0064)		(0.0081)		(0.0121)
Population		-0.522***		-0.529***		-0.580***
		(0.0507)		(0.0637)		(0.1079)
Higher Education		-0.056***		-0.037*		-0.0046
		(0.0176)		(0.0209)		(0.0369)
Population density		-0.000***		-0.0017		-0.006***
		(0.0005)		(0.0012)		(0.00194)
Constant	3.860***	8.694***	2.086***	6.150***	0.885***	6.402***
	(0.1657)	(0.5004)	(0.1688)	(0.5226)	(0.1584)	(1.0928)
F. E. of time	Yes	Yes	Yes	Yes	Yes	Yes
F. E. of municipalities	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15554	15554	9380	9380	4788	4788
Adjusted R^2	0.84	0.94	0.83	0.93	0.82	0.92

Note: Dependent variable: log of GDP per capita. Standard error in parentheses. Significance of the coefficients: *** ($p < 0,01$), ** ($p < 0,05$), * ($p<0,1$).

For the estimates assuming a 1.1 SD increase in complexity ranking, the difference in annual per capita GDP is 5.33%. At 1.5 SD, municipalities in the treatment group experienced an average increase in per capita GDP of 4.81% compared to the control group. In the case of a 2 SD increase in complexity ranking, municipalities that experienced an increase in complexity experienced an average annual increase in per capita GDP of 7.46%.

Finally, it is important to emphasize that the more restrictive the criteria for considering municipalities that had fluctuations in the complexity ranking, the greater the increase in per capita GDP. In other words, the more we restrict the selection of treated and control municipalities (before matching) to those that experienced more significant decreases or increases in the ranking, the greater the differences in per capita GDP between the two groups. This result was expected, because by imposing this restriction, we are considering only municipalities that have undergone a profound structural change in terms of the complexity of their productive structures. As a result, the income gap between the two groups is exacerbated.

4. Final considerations

The concept of economic complexity has been growing and evolving, with several studies showing that regions or countries with higher levels of complexity in their production structures tend to achieve higher economic growth. These studies use a variety of models and data for estimation, including the inclusion of different types of controls, fixed effects, and robustness analyses. However, caution should be exercised in making causal claims between complexity and economic growth due to endogeneity issues in these models.

This article uses the propensity score matching (PSM) methodology in conjunction with the difference-in-differences (DID) model to assess the impact of increased economic complexity on the growth of per capita GDP in Brazilian municipalities from 2009 to 2019.

The results indicate that the treatment of improved complexity ranking led to an increase in per capita GDP of municipalities between 2009 and 2019. The results indicate that the treatment of improved complexity ranking led to an increase in per capita GDP of municipalities between 2009 and 2019. Average changes in municipal GDP per capita of 3.25%, 5.33%, 4.81%, and 7.46% were observed for 0.3, 1.1, 1.5, and 2 standard deviations, respectively.

Thus, our results provide support for the existing literature, which suggests that there is a positive relationship between complexity and the per capita income of regions. However, because there are variables that may simultaneously influence both the increase in complexity and the increase in income, analysis using impact evaluation methods provides more robust evidence of the relationship between these variables.

Finally, it is important to emphasize that we cannot claim to have completely eliminated endogeneity. However, the methodology used in this article certainly contributes to reducing this bias by comparing similar groups in terms of the average of the variables considered. In addition, the DID approach eliminates unobservable variables that are fixed over time and may affect the final estimates.

In future research, additional robustness analyses could be conducted to validate the results. This could include using different time periods, such as the 1970s and 1980s, when Brazil experienced significant improvements in its industrial production structure. Another alternative is to consider different ways of classifying the control group using PSM. In addition, the inclusion of instrumental variables along with the DID estimates would provide further confidence in the robustness of the results.

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APPENDIX

Figure A1 – 1.1 S.D cut-off

A. Common Support B. Mean differences

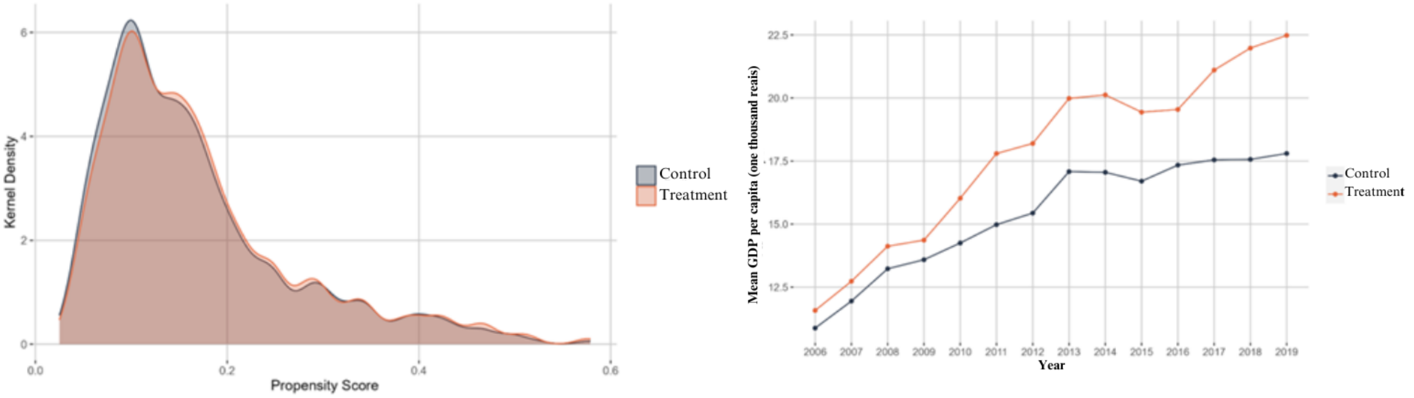

Figure A2 – 1.5 S.D cut-off

A. Common Support B. Mean differences

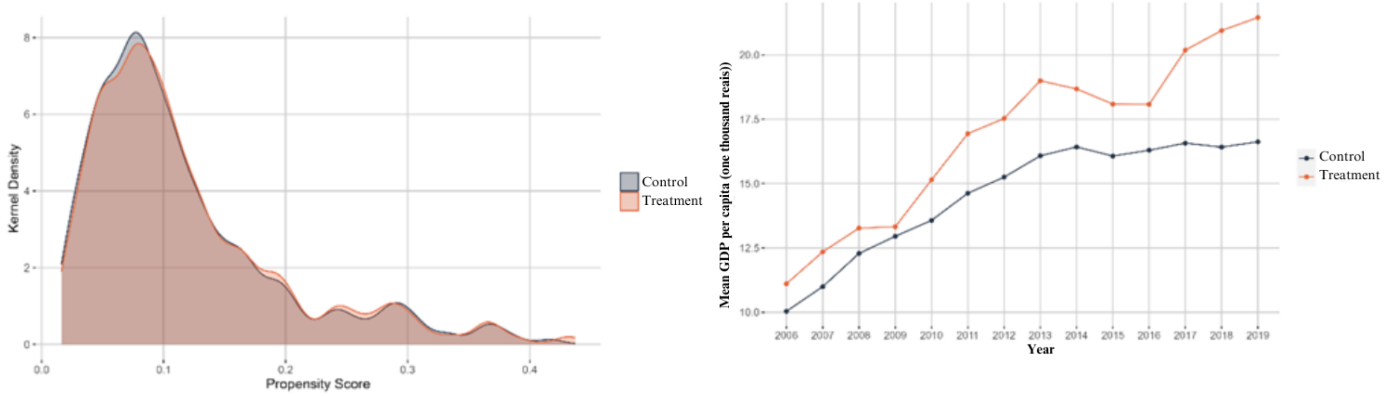

Figure A3 – 2 S.D cut-off

A. Common Support B. Mean differences