MANUFACTURING AND ECONOMIC COMPLEXITY: A DISAGGREGATED EMPIRICAL ANALYSIS

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Abstract

This paper aims to analyze empirically how manufacturing, disaggregated into subsectors by R&D intensity, influence the level of economic complexity (ECI). For this, two methods are used: i) the parametric, by means of long panel data models and ii) the non-parametric: a) Data Envelopment Analysis (DEA) and b) Malmquist Decomposition to calculate the total factor productivity (TFP) and its components. The econometric results suggests that the allocation of workers in the manufacture of high R&D has a positive impact on the ECI level of all sample of countries analyzed, whereas in the sectors of lower R&D have a greater impact in emerging countries, but lower effects (or negative) on advanced countries. In general, the non- parametric results present a relationship between efficiency in manufacturing subsectors and economic complexity as an inverted U shape. However, an upward trajectory for high R&D sectors has shown the relevance of this segment to the economic complexity of emerging countries.

JEL Classification: O10, O32, O33

Key Words: Manufacturing; Economic Complexity; Data Envelopment Analysis (DEA); Panel Data

MANUFATURA E COMPLEXIDADE ECONÔMICA: UMA ANÁLISE EMPÍRICA DESAGREGADA

Resumo

O objetivo deste trabalho é analisar empiricamente como a indústria manufatureira, desagregada em subsetores por intensidade de P&D, influencia o nível de complexidade econômica (ECI). Para cumprir esse objetivo foram utilizados dois métodos: i) o paramétrico, por meio de análise de dados em painel longos, e ii) dois métodos não paramétrico: a) Análise Envoltória de Dados (DEA) b) o método de Decomposição de Malmquist para cálculo da produtividade total dos fatores (PTF) e seus componentes. De uma maneira geral, o método paramétrico revelou que a alocação de trabalhadores na manufatura de alto P&D impacta positivamente o nível de ECI de todos os países analisados, já os setores de baixo P&D apresentam um impacto positivo em países emergentes, mas mais fraca (ou negativa) na amostra de países avançados. A relação entre a eficiência nos subsetores da indústria manufatureira e a complexidade econômica exibe um comportamento similar ao U invertido. Entretanto, a trajetória tipicamente ascendente para os setores de alto P&D evidenciou a maior importância desse segmento para a complexidade econômica dos países emergentes.

Classificação JEL: O10, O32, O33

Palavras-chave: Manufatura; Complexidade Econômica; Análise Envoltória de Dados; Dados em Painel

Área 6 - Crescimento, Desenvolvimento Econômico e Instituições

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1. INTRODUCTION

The importance of manufacturing for economic growth is evident from the classical development economics, such as Rosenstein-Rodan, Nurkse, Prebisch, Hirschman, Leibenstein, Hirschman, Myrdal, among others[5]. According to Ros (2013) the classical literature of development economics generated a view of the development as a process in which increasing returns to scale - mainly in industry - and elastic labor supplies play key roles.

More recently, Rodrik (2013a) presents a model in which the economy is divided between the natural resources sector, the services sector, and the manufacturing sector. Among the three sectors, the manufacturing would be the only one that would have characteristics consistent with the so-called unconditional convergence. As the sector produces tradable goods, these can be quickly integrated into the global production network, which would facilitate the transfer and absorption of technology. Therefore, the quickest way to carry out the catching up process would be through the implementation of policies aimed at building modern manufacturing industries, which employ an increasing share of the economy´s workforce (RODRIK, 2013a).

Rodrik (2013b) presents that unlike economies (as a whole), manufacturing industries exhibit strong unconditional convergence in labor productivity. Rodrik (2013b) ´s results are highly robust to changes in the sample and specification. The coefficient of unconditional convergence is estimated in almost 3% *per* year in the author´s baseline specification, covering 118 countries. Notwithstanding, despite this strong convergence within manufacturing verified by Rodrik (2013b), aggregate convergence fails due to the small share of manufacturing employment and value added in low-income countries as well as the slow pace of industrialization.

Beside´s Rodrik (2013b) ´s results the literature also points to a positive relationship among *per capita* income and economic complexity (HAUSMAN *et al*., 2011). Moreover, the latter is interconnected to manufacturing industries. Gabriel and Missio (2018) highlight that manufacturing has a relevant influence on the level of economic complexity, given the possibility of the sector to incorporate new technologies and increase the use of companies' capacity through learning by doing. Therefore, this sector has greater capacity in emerging economies to boost economic growth.

Therefore, a fundamental question arises concerning which sectors within manufacturing would better fuel economic growth as well as economic complexity in heterogenous countries. Despite the presented results, Gabriel and Missio (2018) did not deepen in an intra-industrial analysis, that is, given the finding that the manufacturing industry positively influences the income convergence process through economic complexity, there is an empirical gap as far as it is necessary to verify which sectors within manufacturing are more efficient in order to increase the level of economic complexity, in order to reduce the *per capita* income gap between developing and developed economies.

In this context, the present research has the objective of analyzing how the manufacturing industry, disaggregated into subsectors - according to the level of R&D (high R&D, medium high R&D, medium low R&D and low R&D) -, influences the level of economic complexity and, consequently, the country's income. In order to achieve this goal, two methods were used: i) the parametric, using long panel data models, and ii) the non-parametric, using the Data Envelopment Analysis (DEA) and the Malmquist decomposition method. From the non-parametric methodology, efficiency boundaries were determined for disaggregated sectors according to R&D level, relating them to the economic complexity in a heterogenous sample of countries.

Thus, the novelties of this work lies in three main points: a) for a heterogenous sample of countries in the period between 1963 and 2012 empirically appraise if and how the allocation of employment in the different manufactured sub-sectors influence economic complexity; b) measures efficiency by Data Envelopment Analysis (DEA) for the four levels of R&D defined, relating the results to the level of economic complexity of the sample; and, c) expand the analysis for the specific Brazilian case, comparing

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[5] In this work the term industry refers to the divisions 10-45 of the International Standard Industrial Classification (ISIC) and when referring to the manufacturing industries are being considered the divisions 15-37 of the International Standard Industrial Classification (ISIC). In section 3 these definitions are further discussed based on our data sample and R&D intensity.

its manufacturing subsectors in terms of technical efficiency change and technological change as well as total factor productivity (TFP), according to a non-parametric method (Malmquist decomposition)[6].

This article is divided into six sections, in addition to this brief introduction. In the second section, we address the discussion about economic growth and its relationship with manufacturing as well as economic complexity. In the third section, the database is presented (section 3), the methodology used in the research for the parametric approach to panel data (subsection 3.1.), the non-parametric approach from the Data Envelopment Analysis (DEA, subsection 3.2) and nonparametric approach based on Malmquist decomposition (subsection 3.3). Section 4 presents the estimations for the long panel data (parametric approach). Section 5 presents the estimations related to DEA analysis and section 5.1 presents the Malmquist decomposition for the Brazilian case. Finally, in the section 6, are the drawn the concluding remarks.

2. ECONOMIC GROWTH, MANUFACTURING, AND ECONOMIC COMPLEXITY

The issue of countries' economic growth plays a central role in development economics and macroeconomics, regardless of the approach taken. In general, in the neoclassical growth models, the underlining idea of diminishing returns on capital, predict that those countries with low *per capita* income should grow faster than the richest, eventually reaching them (BOIANOVSKY; HOOVER, 2009).

However, the *per capita* income convergence among countries would result not only from their respective initial conditions, but from changes in the determinants of the long-term growth path (ROMER, 2012), such as human capital, institutions, Research and Development (R&D) investments, among other factors. Both in the first and in the second generation of neoclassical models, the expansion of the long-term growth is due to the increase in productivity or the availability of resources (mainly capital and labor), supply-led, whereas the non-conventional models such as of Keynesian, Kaldorian or/and Structuralist framework are characterized by a growth considered demand-led (SETTERFIELD, 2009). Moreover, the distinction between growth rates is not caused by the initial and intrinsic conditions of countries, such as geographical, cultural, climatic conditions, and so on (ROS, 2013).

In the work developed by Rodrik (2013a), what differentiate the countries' performance is the ability to rapidly expand value added and manufacturing employment (as GDP share), given that for emerging countries there is an unconditional convergence of the productivity in this sector. Moreover, Gabriel and Missio (2018)´s empirical findings suggest that manufacturing also plays an important role on the countries' economic complexity, mainly emerging countries. Part of this dynamic is a consequence of the productive linkages and spillover effects, which are stronger in manufacturing industries. Therefore, manufacturing industries positively influences emerging countries' catching up process.

However, the behavior of unconditional convergence of manufacturing productivity would not be sufficient to have an aggregate effect on the emerging economies. There are three justifications for this: the other sectors of the economy do not tend to converge; in poor countries, the share of manufacturing is relatively small, compared to other sectors in the economy; and the effect of relocating workers to this sector is not large enough or systematic for low-income countries (RODRIK, 2013b).

Rodrik (2013b) states that the structural transformation for the expansion of manufacturing is difficult, given that there are failures in the market (such as problems of coordination and learning externalities) and in government (such as barriers to entry, high taxes on formal companies), whose effect on investment varies according to the intensity of this scenario in each country. Therefore, depending on the country, the return of modern industries will not always be attractive to investors. The most effective way to correct market or government failures may be to compensate for them indirectly, rather than trying to eliminate them. For alternatives of this type, Rodrik (2013a) classifies them as second-best strategies,

[6] Brazil is a middle-income country in terms of *per capita* income, the 7th largest economy in the world and it has the equivalent to more than 40% of Latin America's GDP. Nassif, Feijó and Araújo (2014) conclude that Brazil has embarked on a trajectory of falling behind relative to the world economy and the international economic frontier and in the absence of appropriate policies, may lower growth rates in the long run. The author´s results was based on Kaldorian–Thirlwallian approach. In sections 2, 3 and 4 we explain our analysis' methods and how we deepen on this question.

which can alleviate obstacles to growth present in the economy, such as, for example the direct subsidies to industrial exports adopted in South Korea and Taiwan.

The structural change process also occurs in the various subsectors in manufacture. Haraguchi (2016) divides the economies into four stages of income levels. The first stage corresponds to a low level of income, there are usually three labor-intensive industries that dominate the manufacturing sector in terms of value added: food and beverages, textiles, and clothing. Labor-intensive industries reduce their share in the economy as the manufacturing structure gradually shifts toward capital-intensive industries, which occurs in the second stage.

In the third stage, capital-intensive industries, which include processing resources such as basic and manufactured metals, and those that process materials to make final products (including electrical machinery), become dominant in terms of relative share. In the fourth stage, except for food and beverages, there is a decline in capital intensive industries, in this stage manufacturing production would be dominated by chemical products, machinery and equipment as well as electrical appliances, technology and knowledge intensive industries.

This structural change within manufacturing vary according to the level of income *per capita* of the economy so that the relationship between the two occurs in an inverted U format (RODRIK, 2013a; HERRENDORF; ROGERSON; VALENTINYI, 2014). Moreover, the composition of demand changes as income increases. The income effect means that, at low levels of *per capita* income, household consumption is destined for essential goods, in the case of labor-intensive industries, at higher levels, families tend to consume more elastic goods, as in the case of capital-intensive industries (MORCEIRO, 2018). Haraguchi (2016) also points out that in the initial stages of development, the performance of manufacturing is relatively more uncertain, since at this stage countries acquire technology from advanced economies, at the high-income stage, countries are successful in inventions and innovations, which can sustain high growth in some manufacturing industries like machinery and equipment.

According to Gabriel and Missio (2018) there are different impacts of economic sectors, as well as their sub-sectors, on income growth. In addition, these lines of activity have an intrinsic relationship with the measure of complexity of the economy, defined based on their productive capacities in Hidalgo *et al.* (2007) and Hidalgo and Hausmann (2009). Regarding manufacturing, empirical evidence suggests that the share of this sector in developing countries exhibits more positive and significant effects on the level of economic complexity when compared to other economic sectors (Gabriel and Missio, 2018). In this regard, Hidalgo and Hausmann (2009) highlight that countries tend to converge to the level of income dictated by the complexity of their productive structure. [7]

Felipe *et al*. (2012) pointed out that the ten most complex products in the economy belonged to the sub-sector of machinery, chemicals, and metallic products, while the least complex are from agricultural production, raw materials and commodities, such as wood and textiles. The authors also highlighted the relationship between the level of income and the complexity of exported products. The biggest exporters of the ten most complex products are high-income countries - with an average income *per capita* of $ 34,000. Those whose export basket is dominated by less complex products, are low- or middle-income countries, with an average *per capita* income of $ 10,000, at constant 2005 prices, considering purchasing power parity (PPP).

Gala *et al.* (2018)´s findings on this issue also verified a positive relationship between the allocation of work in more sophisticated branches of the economy and complexity. Based on the recent structuralist theory, the authors considered that the sophisticated services sector started to share characteristics similar to those of the industry and showed that the level of long-term economic complexity depends on the country's ability to generate jobs in both branches.

[7] The level of economic complexity is assessed by determining three indexes that are interrelated: the index of revealed comparative advantage (RCA), and the diversity and ubiquity. Hausmann *et al.* (2013) state that diversity and ubiquity are rudimentary approximations to the variability of capacities required by a product or available in a country. Diversity can be used to correct ubiquity and vice versa, the process converges after some interactions and represents the quantitative measurement of complexity.

In a broad perspective, economic complexity is not just a consequence of increased income, but a particularly important input. Countries in which the level of complexity is higher than expected, given their income, grow faster when compared to those that have an income greater than their complexity (HIDALGO; HAUSMANN, 2009).

According to Morceiro (2018) and Gabriel and Ribeiro (2019) the manufacturing subsectors diverge in terms of technology; income elasticity of demand; dynamism of international trade; sector links; inputs used; intensity of physical and human capital; degree of assembly and commercialization with the outside; and, exchange rate sensitivity. Therefore, it is important to verify whether the positive effect of structural change favorable to manufacturing differs among its subsectors in terms of their results for economic complexity.

In order to fulfill the empirical analysis of the present work, two methods are used: the parametric, using long panel econometric models, and the non-parametric, using the Data Envelopment Analysis (DEA) and the Malmquist decomposition method. In this context, the next topic presents the database that will be used for empirical analysis. Moreover, in the next subsection the above mentioned method are explained: long panel data in section 3.1; DEA in section 3.2 and Malmquist decomposition in section 3.3.

3. DATABASE AND PARAMETRIC AND NON-PARAMETRIC APPROACH

Table 1 presents the variables used in the empirical models, a brief description, and its sources.

Table 1- Description of the variables

Variable	Brief Description	Source
ECI	Economic complexity index – normalized	Atlas of Economic Complexity
Highemp	Employment share in high R&D - % *	UNIDO
Lowemp	Employment share in low R&D - % *	UNIDO
Mediumhigh	Employment share in medium high R&D - % *	UNIDO
Mediumlow	Employment share in medium low R&D - % *	UNIDO
GDP gap	Ratio of each country *per capita* income in relation to USA *per capita* income– in real terms	WDI
Pop	Country population	PWT (9.1)
Govexp	Government spending (% of GDP)	WDI
Human capital	Human capital index – Barro & Lee (2013)	PWT (9.1)
Inv	Gross fixed capital formation as a proportion of annual GDP - %	WDI

Source: Authors´ elaboration

Note: WDI (*World Development Indicators*) – World Bank; PWT (*Penn World Table* 9.1) and *United Nations Industrial Development Organization* (UNIDO). * - Within manufacturing.

Given the availability and consistency of the data in the INDSTAT 2 2015, ISIC *Revision* 3 da UNIDO (*United Nations Industrial Development Organization*), twenty advanced countries were considered: Australia (AUS), Austria (AUT), Belgium (BEL), Canada (CAN), Denmark (DNK), Spain (ESP), Finland (FIN), France (FRA), United Kingdom (GBR), Greece (GRC), Israel (ISR), Italy (ITA), Japan (JPN), South Korea (KOR), Netherlands (NLD), Norway (NOR), Portugal (PRT), Singapore (SGP), Sweden (SWE) and the United States (USA). And, eight emerging countries: Brazil (BRA), Chile (CHL), Colombia (COL), Ecuador (ECU), India (IND), Iran (IRN), Malawi (MWI) and Turkey (TUR). The classification of countries was based on the IMF World Economic Outlook Database, made available in October 2019.

The manufacturing sub-sectors were divided according Research and Development (R&D) level, the division was carried out based on the OECD classification (2011). The choice for this classification is due to the importance of the technological effort to determine productivity growth and international competitiveness (OECD, 2011). Greater technological opportunities are caused by a greater share of intensive activities in R&D, fostering innovations, which, consequently, increases the demand for new products, including in international trade, decreasing the Balance of Payment Constraint to Growth (GABRIEL; MISSIO, 2018).

Table 2 presents the subsectors for the empirical analysis in this work, classified in terms of R&D.

Table 2 - Classification of the activity branches by R&D level - Manufacturing

ISIC Description	R&D Level
Manufacture of food products and beverages Manufacture of furniture; manufacturing n.e.c. Manufacture of tanning and dressing of leather; manufacture of luggage, handbags, saddlery, harness, and footwear Manufacture of paper and paper products Publishing, printing, and reproduction of recorded media Recycling Manufacture of textiles Manufacture of tobacco products Manufacture of wearing apparel; dressing and dyeing of fur Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	Low
Manufacture of basic metals Manufacture of coke, refined petroleum products and nuclear fuel Manufacture of fabricated metal products, except machinery and Equipment Manufacture of other non-metallic mineral products Manufacture of radio, television, and communication equipment and Apparatus Manufacture of rubber and plastic products	Medium Low
Manufacture of chemicals and chemical products Manufacture of electrical machinery and apparatus n.e.c. Manufacture of machinery and equipment n.e.c. Manufacture of motor vehicles, trailers, and semi-trailers Manufacture of other transport equipment	Medium High
Manufacture of medical, precision, and optical instruments, watches and clocks Manufacture of office, accounting, and computing machinery	High

Source: Authors´ elaboration based on UNIDO (2015) and OCDE (2011).

3.1. PARAMETRIC APPROACH: LONG PANEL DATA ANALYSIS

The data analyzed in the survey are 28 countries (*n*) arranged over 50 years (T), a sample collected from 1963 to 2012, being, therefore, a long panel. A long temporality for panel data generated two strands of work in the econometric literature: the first rejects the homogeneity of the regression patterns implicit in a grouped model, being favorable to heterogeneous regressions, that is, one for each country; a second strand defends the application of time series procedures to verify non-stationarity, spurious regressions and cointegration relations (BALTAGI, 2005).

Based on the second strand, unit root tests were performed. It is noteworthy that the unit root tests have a low confidence, the panel data can increase the reliability of these tests because they are compounded of time series and several cross sections, in addition, these tests may be relevant for the subsequent cointegration results (CAMERON; TRIVEDI, 2009, p. 273). Levin, Lin, and Chu - LLC (2002), Im, Pesaran and Shin (2003) and Maddala and Wu (1999) tests were performed.

Baltagi (2005) highlights that the linear combination of two or more non-stationary series can form cointegrated series and, thus, non-spurious analysis. In order to verify the cointegration of the series, the Pedroni (1999, 2004) and Kao (1999) tests were performed. The Pedroni cointegration test allows the heterogeneity of the coefficients, in addition, it considers that the autoregressive coefficients (AR) vary between the panels. The Kao test considers the same AR for all panels.

Once the existence of cointegration is determined, it is possible to estimate the cointegration vector. Developed by Kao and Chiang (2000), the Dynamic Ordinary Least Squares (DOLS) estimator presents a better performance than the Ordinary Least Squares OLS in cointegrated series because they allow a correction of the endogeneity and the correlation between its regressors (RAMOS, 2011). In Panel-Dynamic Ordinary Least Squares (PDOLS), DOLS regression is conducted for each individual and the results are combined across the panel following the "Pedroni group mean" approach. The estimator has a good performance for small samples and the statistical inferences of the cointegration vector parameters are facilitated by the fact that the *t* statistics of the estimated coefficients have an asymptotic normal distribution, even with endogenous regressors (FRECKLETON; WRIGHT; CRAIGWELL, 2012).

PDOLS has the advantage of allowing heterogeneity between individuals in relation to the specific time trend for each observation, individual fixed effects, and specific time effects. These characteristics allow the estimator, which provides long-term results, to be suitable for macroeconomic studies in which the existence of a long panel predominates, so that it is more accurate than single equation estimators (MARK; SUL, 2003). For this reason, the PDOLS calculation was chosen.

The econometric model to be estimated has the following functional form in view of the database in Table 1 and the aggregation of data performed in Table 2:

$$ECI_{i,t} = \beta_0 + \beta_1 high\_emp_{i,t} + \beta_2 mediumhigh\_emp_{i,t} + \beta_3 mediumlow\_emp_{i,t} + \beta_4 low\_emp_{i,t} + \gamma \sum_{j=5}^{K} Z_{i,t} + \mu_{i,t} \quad (05)$$

Where $ECI_{i,t}$ represents the economic complexity index of country "i" at time "t". The $\beta_1, \beta_2, \beta_3, \beta_4$, coefficients are related, respectively, with the variables that represent employee shares, in relation to the total number of workers in manufacturing, in the high R&D subsectors ($high\_emp_{i,t}$), low R&D subsectors ($low\_emp_{i,t}$), medium high R&D subsectors ($mediumhigh\_emp_{i,t}$) and medium low R&D subsectors ($mediumlow\_emp_{i,t}$). The set of control variables is indicated by the vector $Z_{i,t}$, which is composed of up to five control variables, such as government spending as a proportion of GDP, GDP gap, population, human capital and gross fixed capital formation as a proportion of annual GDP. Finally, $\mu_{i,t}$ is the idiosyncratic error term.

For the four variables of interest, the proportion of workers allocated in each sub-sector was chosen as a parameter, following the conclusions of Felipe, Mehta and Rhee (2019), for whom the number of workers employed in manufacturing is more relevant to the economic growth than measuring value added in relation to GDP.

The variables referring to government spending in relation to GDP, population and human capital were also used by Gala *et al*. (2017) as controls to verify whether the allocation of jobs in advanced industries (and sophisticated services) positively impacted the countries´ economic complexity. Moreover, population (country size proxy), human capital, and GDP *per capita* were also used as independent variables to verify the sophistication in the export basket, the level of productivity associated with a country's specialization pattern, in the model of Hausmann, Hwang and Rodrik (2007).

After estimating the model (05) for panel data for fixed and random effects, the modified Wald test for heteroscedasticity and the Wooldridge test for autocorrelation were performed and it was verified the existence of heteroscedasticity and autocorrelation at 5% significance level.

Once the heteroscedasticity and the autocorrelation of the samples were verified, two alternative estimators were used. The *Feasible Generalized Least Square* (FGLS) performs well on large samples, adjusting the above problems. Similarly, the *Linear Regression with Panel-Corrected Standard Errors* (PCSE), assumes that the sample has heteroscedastic and autocorrelated errors as well as corrects the estimations for cross section dependence.

All the results of the estimators used are reported and discussed in section 4.

3.2. NONPARAMETRIC APPROACH: DATA ENVELOPMENT ANALYSIS (DEA)

Data Envelopment Analysis (DEA) is a method based on non-parametric mathematical models and aims to define a relative competitive positioning of a set of organizations, or activities, called Decision Making Units (DMUs). In DEA, the comparison of DMUs results in production efficiency indices, which are arranged in the form of an efficiency frontier (FERREIRA; GOMES, 2009).

The performance perspective from which the DMU is assessed can be based on two different approaches: *input* orientation, based on the idea of minimizing the use of inputs in order to produce a specific amount of product; and *product* orientation, which is based on the notion of increasing the quantity produced without increasing the quantity of inputs used (COELLI, 1996). Scale yield variation is another methodological distinction in the DEA. In this approach, the models are classified based on the scale yield, that is, the variation in production that derives from the variation in the use of inputs. More specifically, if the increase in inputs results in a constant proportional increase in production, the constant return to scale model (CRS) is considered. Otherwise, when the change in the input results in a non-proportional change in the generation of the products, the variable returns to scale (VRS) model is used, the underlying idea is to consider a convexity constraint to the CRS model (FERREIRA; GOMES, 2009).

The design of a world production frontier has encouraged works whose methodology is based on the DEA, especially when it is intended to assess the variation in the productivity of countries over time. Ray (2004) points out that, in these cases, the analysis of the increase in product is not enough since it ignores the differences between the inputs. For this reason, studies of the type use index to measure the total productivity of the factors and to incorporate changes in the inputs and products.

Walheer (2018) states that the model based on constant returns to scale, in addition to being the most used in macroeconomic studies, is, through non-parametric tests, the most indicated in this type of analysis. In this regard, the model adopted with product orientation and constant returns to scale is mathematically indicated, according to Coelli (1996), by:

$$max_{\mu v}\ (\mu' y_i), \tag{06}$$

$$\text{Subject to } v' x_i = 1,$$

$$\mu' y - v' x_j \leq 0, j = 1,2,\dots,N,$$

$$\mu, v \geq 0$$

Where *i* represents the countries used as DMU in the sample, *y* is the *output* and indicates the ratio between the value added and the GDP *per capita* of each country (i.e., *y* = value added *per* level of R & D / GDP *per* capita). The input vector for each country is represented by x_i, which are: the capital stock for each country in the sample, at constant prices (base year 2011) and the human capital ratio, given by the multiplication of the human capital index and the number of workers of each economic segment.

The variables used as inputs, as well as the GDP *per capita* at constant prices, were obtained through in Penn World Table 9.1; the value added for each branch of economic activity was obtained the United Nations Industrial Development Organization (UNIDO). These variables were selected from relevant research using the DEA to establish boundaries of productive efficiencies between countries, such as Walheer (2016), Kumar and Russel (2002) and Färe *et al.* (1994). However, the present research differs from the latter by weigh in the value added of each level of R&D by the GDP *per* capita of the respective country, inferring the intensity of the manufacturing share by sub-sector.

Thus, four efficiency frontiers were calculated, related to a specific level of R&D considered: high, low, medium high and medium low, comprising the period from 1963 to 2012 of the sample of countries presented in section 2. From this analysis, it was possible to define a ranking among the countries in the sample regarding the efficiency of manufacturing production, in terms of value added, for each level of R&D.

Thereafter, the results found were presented in the form of two figures: for developed and emerging economies, in order to verify the behavior of the level of efficiency obtained over the 50 years observed and the economic complexity index. The results of the estimates and discussion are presented in section 5.

3.3 NONPARAMETRIC APPROACH: MALMQUIST DECOMPOSITION - THE BRAZILIAN CASE

Starting from the idea that the result of efficiency in manufacturing production stems from the particularities of each country and to meet the objective of deepening the analysis of the Brazilian case, a specific analysis was carried out for Brazil using the data referring to the value added of each subsector of the manufacturing industry from UNIDO database.

As the second analysis refers only to Brazil, the DMUs considered were the economic activities analyzed in the country. In this context, the Malmquist decomposition was performed, having as inputs the human capital index, multiplied by the number of workers in the country, and the number of workers in each subsector. The deflated value added was considered as a product, given the availability of the data, the period analyzed comprises the years 1996 to 2011. The years analyzed were grouped in two intervals, 1996 to 2002 and 2003 to 2011 because between 2003 and 2008 America Latina went through a period marked by economic growth, driven by rising commodity prices and favorable conditions for external financing (ABELES; RIVAS, 2011).

The Malmquist index, calculated to verify the variation in the total productivity of the factors, was based on the product orientation having as output, the deflated value added and, two variables as input, the capital stock at constant prices in 2011 and the number of workers in the industry multiplied by the human capital index (see section 3 for a brief description of the variables).

This index makes it possible to analyze productivity growth over time using two components, changes in technical efficiency and changes in technology. Since the index covers any type of scalar return, whether constant or variable returns, the scaling efficiency in each period is due to the ratio of the distance function that satisfies the constant returns to scale and the distance function that satisfies the increasing returns of scale (FÄRE et al., 1994).

Based on this method, the change in technical efficiency (productivity) results from two effects: the catching up effect, i.e., the result of improvement in the production process or products, while maintaining the same technology; and the efficient frontier shift effect, which is based on the production of a superior product, either in quality or quantity, from less use of inputs, characterizing the use of new technologies (FERREIRA; GOMES , 2009).

Mathematically, Cooper, Seiford and Thone (2007) expressed the Malmquist index as:

$$catch-up = \frac{(x_0,y_0)^1 \; efficiency \; in \; relation \; to \; the \; frontier \; in \; period \; 2}{(x_0,y_0)^2 \; efficiency \; in \; relation \; to \; the \; frontier \; in \; period \; 1} \tag{07}$$

Where $(x_0, y_0)^1$ and $(x_0, y_0)^2$ are DMU_0(0=1,..n), to the periods 1 and 2, respectively.

If the result of the catch-up effect is less than 1 it indicates that the productivity has worsened, if greater than 1, the productivity of the DMU has improved, if is equal to 1 it means that the productivity of the DMU has remained the same over time. For the calculation of the innovation effect of the DMU in two periods, $(x_0, y_0)^1$ and $(x_0, y_0)^2$, indicated by the frontier shift effect, it is necessary to consider the effects of displacement of the frontier of each DMU ($\emptyset$), considering two DMUS, Cooper, Seiford and Thone (2007) presents that:

$$\emptyset_1 = \frac{(x_0,y_0)^1 \; efficiency \; in \; relation \; to \; the \; frontier \; in \; period \; 1}{(x_0,y_0)^1 \; efficiency \; in \; relation \; to \; the \; frontier \; in \; period \; 2} \tag{08}$$

$$\emptyset_2 = \frac{(x_0,y_0)^2 \; efficiency \; in \; relation \; to \; the \; frontier \; in \; period \; 1}{e(x_0,y_0)^2 \; efficiency \; in \; relation \; to \; the \; frontier \; in \; period \; 2} \tag{09}$$

$$frontier - shift \; effect = \emptyset = \sqrt{\emptyset_1 \emptyset_2} \tag{10}$$

In the model with product orientation, the technical efficiency of the DMU worsened over time if the calculation of the effect of the displacement of the frontier is less than 1; if it is greater than 1 it means that the technical efficiency of the DMU has improved; and it appears that the technical efficiency of the DMU remained the same, if it is equal to 1.

The Malmquist index is defined by:

$$MI = (\,catch - up\; effect) * (frontier - shift\; effect) \qquad (11)$$

The interpretation of the index coincides with the previous ones: the deterioration of the total factor productivity in the DMU over time is indicated if MI is less than 1; if it has a value equal to or greater than 1, it implies that productivity remained the same or improved, respectively.

4. LONG PANEL DATA ESTIMATIONS

The sample is divided in 20 developed countries, and 8 emerging economies. So, there are two group of countries for long panel data analysis, covering 50-year period. For this reason, tests by Levin and Lin (1992); Im, Pesaran and Shin (1997) and Fisher, proposed by Maddala and Wu (1999) and Choi (1999), for unit root were perfomed. In both tests, the series related to the percentage of workers allocated by each level of R&D are not stationary, the results pointed out by these series are I(1). Notwithstanding, the Pedroni and Kao cointegration´s tests informed that panels are co-integrated, that is, they do not have a spurious relationship, at 1% significance.

After performing the cointegration tests, it is possible to estimate the cointegration vector and, thus, a long-term relationship between the dependent and independent variables using the Panel Dynamic Ordinary Least Squares (PDOLS).

Table 3 presents that in the two samples, all allocations of workers at different levels of R&D were shown to be statistically significant in the long run, when related to the level of economic complexity. However, with different impacts and magnitudes.

Table 3 - PDOLS estimations – 1963 a 2012

ECI	**Developed Countries**	**Emerging Countries**
high R&D	6,839 ***	71,17 ***
	(27,12)	(6,229)
medium low R&D	1,706 ***	-0,001487 ***
	(3,389)	(-21,45)
medium high R&D	-0,1582 ***	0,5443 ***
	(-19,05)	(53,47)
low R&D	-1,32 ***	0,3014 ***
	(-41,84)	(4,128)
GDP gap	-0,8436 ***	-4,049 ***
	(-18,89)	(10,24)
inv	0,01462 ***	0,02902 ***
	(24,24)	(-34,85)
govexp	0,05519 ***	0,02704 ***
	(22,81)	(-50,21)
n	20	8

Source: Authors´ elaboration.
Note: *t* statistics in parentheses. Statistical significance at: *10%, **5%, ***1%.

According to Table 3´s results, in the long run, the percentage of employment in subsectors with high R&D is positively related to the ECI, both in advanced and emerging countries, but this subsector impacts about 10.5 times more emerging economies, in terms of economic complexity.

The allocation of employment in medium-low R&D subsectors had a negative relationship, but remarkably close to zero in the complexity of emerging economies. However, in advanced economies, the effect was positive. The allocation of employment in medium-high R&D subsectors has a negative effect on the ECI variable in advanced countries, but positive in emerging countries.

Finally, the allocation of workers in low R&D is negatively related in advanced countries and positively related to ECI in emerging countries, in the long run.

When the econometric model (1) was estimated for fixed and random effects, problems of heteroscedasticity were detected using the modified Wald test and also autocorrelation was detected by the Wooldridge test for panel data, both at the level of 1% significance. Thus, analyzes based on the Linear Regression with Panel-Corrected Standard Errors (PCSE) and the Feasible Generalized Least Square (GLS) were considered for advanced and emerging countries. The results are shown in table 4.

As Cameron and Trivedi (2005) presents, the Prais–Winsten transformation in the PCSE estimations removes the heteroskedasticity and autocorrelation, and the results are unbiased coefficients and consistent panel corrected standard errors. Furthermore, when calculating the standard errors and the variance-covariance matrix it is assumed that the errors are heteroskedastic and contemporaneously correlated between panels.

Table 4 – PCSE and FGLS estimations – Developed and Emerging countries – 1963 a 2012.

	Developed Countries		**Emerging Countries**	
lneci	**PCSE**	**FGLS**	**PCSE**	**FGLS**
Lnhigh R&D	0.25977 ***	0.002	0.9316 ***	0.68517 ***
	(4.43)	(0.14)	(3.28)	(2.92)
Lnmedhigh R&D	0.6311 ***	0.031	4.1046	3.09556
	(2.76)	(0.33)	(1.58)	(1.59)
Lnmedlow R&D	-0.096	0.017	0.9416 *	0.82255 **
	-(0.43)	(0.19)	(1.94)	(2.23)
Lnlow R&D	-0.79172 ***	-0.007	10.635 *	8.12773 **
	-(3.04)	-(0.06)	(1.84)	(2.11)
Lngovexp	1.29653 ***	0.067	-0.2249	0.22521
	(4.93)	(1.00)	-(0.39)	(0.58)
LnGDPgap	0.21598 *	0.1779 ***	0.3274	0.32492 **
	(1.78)	(2.92)	(1.05)	(1.96)
Lnpop	0.36172 ***	0.0663 ***	0.0733	0.11492
	(7.18)	(2.82)	(0.35)	(0.78)
LnHK	-4.70082 ***	0.156	-1.1158 *	-1.2756 **
	-(6.82)	(0.90)	-(1.64)	-(2.16)
_cons	-4.3322 **	-1.1038 *	12.4452 *	7.60893
	-(2.15)	-(1.66)	(1.90)	(1.46)
n	20	20	8	8

Source: Authors´ elaboration
Note: *t* statistics in parentheses. Statistical significance at: *10%, **5%, ***1%.

In the case of advanced economies, Table 4 shows that the PCSE model has more statistically significant variables than the GLS model. This result implies that the panels in this sample are contemporaneously correlated between themselves. Regarding the employment allocation variables in manufacturing, only in the PCSE model these prove to be significant, the results show that only the allocation of labor in sectors of high and medium high R&D contributes to the increase in the level of economic complexity. On the other hand, in this model the allocation of labor in low R&D would negatively affect the level of ECI in advanced economies, *coeteris paribus*, 10% increase in the proportion of workers allocated to low R&D manufactures would result in a reduction of 7.9 % in the ECI index of developed countries.

For the sample of emerging economies, the results of the PCSE and FGLS estimation methods were remarkably similar in terms of the economic subsectors. The allocation of labor in low-R&D subsectors has a positive effect on the level of complexity for both estimated models, as well as on the allocation in low-R&D and high-R&D sectors. In addition, the greatest impact on the economic complexity of this sample of countries is in the low R&D and medium high R&D sectors.

Such results corroborate the idea that structural change presents certain patterns that can vary between different nations according to the level of development (HARAGUCHI, 2016; WEISS; JALILIAN, 2016). Moreover, the structural change in the economic sectors´ share, linked to the countries' income level, also occurs within the branches of activity belonging to the manufacture, as the showed results in terms of its impacts on economic complexity.

In general, in the first stage of development, corresponding to low-income countries, labor-intensive industries dominate the manufacturing sector, and gradually greater share moves to capital-intensive industries in the second stage. In the third stage, such industries, the processing of basic metals resources (classified in the present research as low R&D), become dominant in terms of relative share. Finally, in the fourth stage, there is an increase in the share of technology and knowledge intensive industries, such as those classified as medium high R&D and high R&D (HARAGUCHI, 2016).

In addition, as countries develop, the composition of economies' demand changes. The income effect means that, at low levels of *per capita* income, household consumption is destined for essential goods, in the case of labor-intensive industries, at higher levels, families tend to consume more elastic goods, as in the case of capital-intensive industries (GABRIEL, 2016 and MORCEIRO, 2018).

Table 4 also shows that the magnitude of the impact of manufacturing employment allocation at the ECI level is greater in the case of emerging economies. One of the justifications for this result lies on the fact that the industry share in the GDP can vary according to the level of *per capita* income of the economy so that the relationship between the two occurs in an inverted U format (RODRIK, 2013a; HERRENDORF; ROGERSON; VALENTINYI, 2014).

As exposed throughout the theoretical and empirical discussion, a greater allocation of employment in manufacturing tends to increase the level of economic complexity in the country and, consequently, its *per capita* income over time. The results of this section expand this analysis by empirically demonstrating that the level of R&D of the manufacturing sub-sectors, in terms of employment, has different impacts on the country's economic complexity, and such impacts are distinguished from particular characteristics of each group of economies. In general, for advanced countries, the proportion of jobs in the low R&D subsectors contributes negatively to their respective complexity, however, the same does not occur in emerging countries.

5. NON-PARAMETRIC APPROACH: DATA ENVELOPMENT ANALYSIS (DEA)´S RESULTS

Given that the particularities of each country, or group of countries, differentiate the way in which the structural change between the manufacturing sub-sectors impacts on economic complexity, it is correct to infer that the efficiency in generating jobs differs between the different economies. In this subsection, the results obtained by the data envelopment analysis (DEA) are presented, observing the relationship between the efficiency in generating jobs and the level of economic complexity. The data envelopment analysis was calculated as a product orientation in which the ratio between the value added in each type of R&D and the GDP *per capita* at constant prices was considered as output and as inputs the human capital index (multiplied by the number workers) and the capital stock (see section 2 for more details of the methodology).

Table 5 presents the position of countries in a ranking that considers their efficiency in producing for each level of R&D among the sub-sectors.

Table 5 – Efficiency *Ranking* disaggregated in terms of R&D - 1997;2003 a 2008.

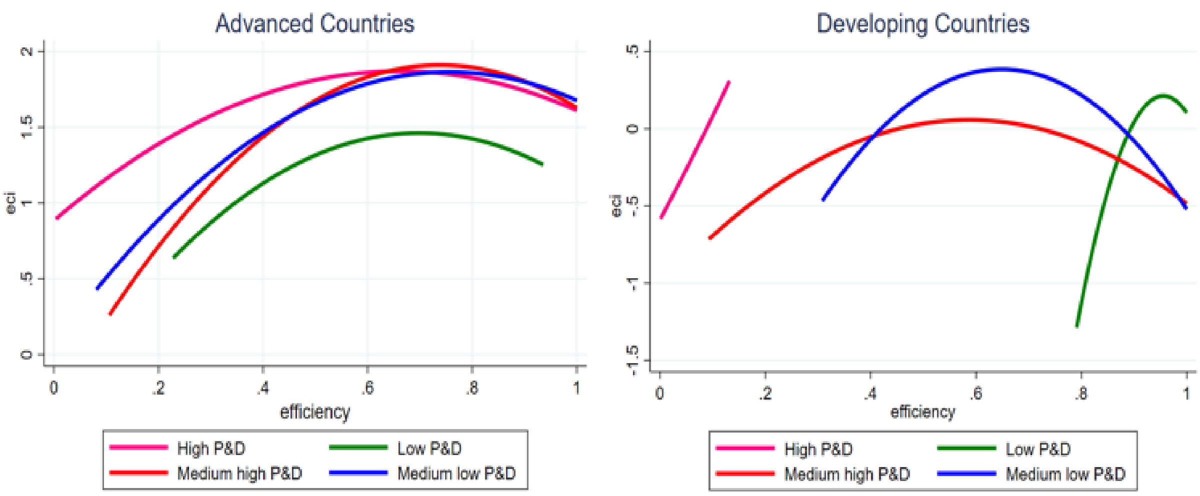
Country	High R&D	Medium High R&D	Medium Low R&D	Low R&D
Singapore	1°	3°	4°	24°

South Korea	2°	1°	1°	3°
Israel	3°	20°	14°	22°
USA	4°	11°	15°	17°
Japan	5°	7°	6°	16°
United Kingdom	6°	16°	20°	13°
India	7°	1°	1°	1°
France	8°	13°	19°	18°
Sweden	9°	9°	11°	14°
Finland	10°	15°	8°	8°
Brazil	11°	4°	7°	5°
Canada	12°	17°	22°	19°
Colombia	13°	14°	9°	4°
Italy	14°	10°	10°	11°
Netherlands	15°	21°	23°	23°
Denmark	16°	22°	25°	21°
Austria	17°	18°	17°	15°
Spain	18°	12°	13°	10°
Chile	19°	6°	18°	1°
Iran	20°	2°	2°	7°
Australia	21°	23°	21°	20°
Belgium	22°	8°	5°	12°
Norway	23°	22°	25°	21°
Turkey	24°	5°	3°	2°
Portugal	25°	19°	16°	6°
Greece	26°	25°	24°	25°
Ecuador	27°	26°	12°	9°

Source: Authors´ elaboration based on DEA´s results on efficiency.

Singapore leads the efficiency ranking in the high-level R&D sub-sectors. Regarding the medium high R&D, the country moves to the third position, Brazil occupies the fourth position, and the ranking is led by South Korea and India. The last two countries also lead the ranking of medium low R&D. The one with the lowest R&D, is led by India and Chile, in this classification Brazil occupies the 5th position.

Figure 1 - Relationship between efficiency and economic complexity



Source: Authors´ elaboration based on DEA´s results on efficiency.

Figure 1 presents the relationship between the efficiency indexes obtained (between the years 1997, 2003, 2004, 2005, 2006, 2007 and 2008) and the level of economic complexity by group of countries (each group divided by R&D level). Figure 1 shows different relationships between the efficiency found by the DEA method and the economic complexity (ECI) for advanced and emerging economies.

For advanced economies, the relationship between efficiencies for each level of R&D and the complexity index behaves as an inverted U format. The greatest relative gain, in terms of complexity, occurs with the advance of efficiency in countries furthest from the technological frontier, after reaching an average efficiency, the gain in complexity tends to be reduced in the levels of R&D. As expected, the gain from increasing efficiency in low R&D is relatively reduced.

For emerging countries there is a linear and monotonic relationship between ECI and efficiency regarding high levels of R&D. This means that the increase in efficiency is related to a greater growth of the economic complexity index in this subsector. The other levels of R&D operate in an inverted U format.

Furthermore, the increasing shape of the high R&D curve in emerging economies is an indication that the effect of these sub-sectors on the level of complexity is relatively greater in lower income countries, compared to advanced economies. Furthermore, the result of this curve for high R&D is in accordance with the impacts estimated in section 4 (Tables 3 and 4). Therefore, this result corroborates what was indicated in the literature by other method of analysis, according to Abeles and Rivas (2011) and Tribe and Weiss (2016).

It´s worth mentioning that Brazil (especially) has gone through an intense process of premature deindustrialization, measured at constant and current prices (MORCEIRO, 2018). This process occurred mainly in relation to the industrial sectors with the highest technological content. This loss of dynamism in this sector has negatively influenced the rates of economic growth in the last decades, that is, the manufacturing industry has ceased to function as an “engine of growth” (GABRIEL; RIBEIRO, 2019).

Based on these considerations, the next topic makes efforts to analyze the variation in productivity between the manufacturing sectors, focusing on the Brazilian case.

5.1 NONPARAMETRIC APPROACH: MALMQUIST DECOMPOSITION - THE BRAZILIAN CASE

As shown in Table 5, Brazil achieved median levels of efficiency in all cases analyzed. In order to better understand the evolution of the Brazilian case, a second efficiency model was estimated. Due to the availability and consistency of data, the period of time analyzed corresponded to the years 1996 to 2011, grouped in two intervals, 1996 to 2002 and 2003 to 2011, given the period of increase in commodity prices and favorable conditions for external financing, which boosted growth in Latin America from 2003 to 2008 (ABELES; RIVAS, 2011).

Twenty sub-sectors of the sample were considered, listed in table 7 and 8, as DMUS. Table 6 shows the average annual result of the Malmquist index, which represents the variation in the total factor productivity, as discussed in section 3.3.

Table 6 – Average Malmquist index – 1996 a 2002.

		1996- 2002	
Year	**Technical Efficiency - Δ**	**Technological – Δ**	**Total Factor Productivity (TFP) - Δ**
1997	1,057	2,225	2,351
1998	0,945	1,557	1,472
1999	0,846	0,555	0,47
2000	0,964	1,703	1,641
2001	1,086	0,552	0,599
2002	0,988	0,747	0,738
Média	**0,978**	**1,051**	**1,028**
		2003 – 2011	
Ano	**Technical Efficiency - Δ**	**Technological – Δ**	**Total Factor Productivity (TFP) - Δ**
2004	1,029	2,022	2,081

2005	0,837	1,498	1,254
2006	1,009	1,284	1,296
2007	1,105	1,177	1,301
2008	1,028	0,862	0,886
2009	1,058	0,973	1,029
2010	0,995	1,131	1,126
2011	0,963	1,157	1,114
Média	**1,000**	**1,224**	**1,224**

Source: Authors´ elaboration based on DEA´s results.

Table 6 indicates that 1999, 2001, 2002 and 2008 were the years in which the total factor productivity - that is, the weighted average between the variation in technical efficiency and the technological variation - decreased in relation to the respective previous year , given that the amount reached was less than 1.

The results obtained corroborate those estimated by Veloso, Matos and Peruchetti (2020), who calculated the TFP in relation to labor productivity and the efficiency of capital use. The results pointed out by the authors presents the decrease in Brazilian TFP in the years 1999, 2000, 2001, as well as the improvement in the performance of TFP between 2004 and 2013. It is noteworthy that the analysis made by the authors was quarterly, while the one shown in the Table 6 is annual.

In Morceiro (2018) we can see that in the 1990s there was a process of absolute and relative deindustrialization of employment in Brazil. There was a mini cycle industrialization between 1985 and 1997, in which more technological equipment was replaced (reducing costs of production and workforce demand), which may explain the increase in FTP in 1997 and 1998.

In January 1999 there was an abrupt change in the exchange rate regime amid an international crisis. The floating exchange rate regime was introduced in Brazil, amid currency overshooting by January. This forced the Central Bank of Brazil to increase the basic interest rate to ease the flight of international capital and the inflationary pass through along the year (BARBOSA FILHO, 2008). In this scenario, the exchange rate change caused a direct increase in the costs of activities that import inputs, and, indirectly increased it, due to the intermediate consumption structure of the sectors, that is, the domestic supplier also demanded imported products (PEREIRA, CARVALHO; 2000). Additionally, the economy was in a recessive environment, due to the Russian crisis and its contagious effect in the second half of 1998 (GABRIEL, 2005). In addition, in 1999, inflationary targets were implemented, and the new fiscal regime was put forth, which aimed at stabilizing the ratio between public debt and GDP by maintaining a high primary surplus. All these factors contextualized a year in which gross physical capital formation suffered a negative impact (OLIVEIRA; TUROLLA, 2003), justifying the low results obtained in terms of efficiency.

Oliveira and Turolla (2003) also indicated that there was a negative impact on the series of gross physical capital formation in the years 2001 and 2002, a damage caused by the crisis of the so-called “electrical blackout” and the pre- and post-election tension, respectively. In 2001, a crisis in Argentina also contributed to the outflow of capital and the depreciation of Brazilian exchange rates, increasing the prices of imported goods, the effects of the inflationary increase in 2002 and continued in 2003 (BARBOSA FILHO, 2008). Moreover, in 2003 there was a reduction in the proportion of government spending as a share of GDP, in order to avoid an increase in the country's net public debt (BARBOSA FILHO, 2008).

Regarding the year 2008, Morceiro (2018) points that the international crisis fomented by the breakdown of the Lehman Brothers caused a decrease in the global demand which had repercussions in the international trade of manufacture. The author also explains that from 2009 to 2015 there was a reduction in both the share of manufacturing in GDP and in the share of employment. Table 6, however, shows that as of 2009, the total factor productivity increased a little, even though there was a decrease in technological variation.

The period of continuous growth in the variation of the total factor productivity in Brazil was between 2004 to 2007, which coincides with the period of growth of knowledge-intensive industries. According to Abeles and Rivas (2011) the increase of these industries in Brazil, between 2003 and 2007 was 8.7%.

Table 7 presents the estimations and decomposition of the Malmquist index between the years 1996 to 2002 for Brazil.

Table 7 - Average Malmquist index for manufacturing - 1996 a 2002.

1996-2002				
P&D	**DMUS**	**Technical Efficiency Δ**	**Technological Δ**	**Total Factor Productivity (TFP) Δ**
High	Manufacture of office, accounting, and computing machinery	0,742	0,682	0,506
Medium high	Manufacture of chemicals and chemical products	1	0,757	0,757
Medium high	Manufacture of electrical machinery and apparatus n.e.c.	1,023	0,756	0,774
Medium high	Manufacture of electrical machinery and apparatus n.e.c.	0,8	0,757	0,605
Medium high	Manufacture of motor vehicles, trailers, and semi-trailers	1,074	0,757	0,813
Medium high	Manufacture of other transport equipment	1,014	0,756	0,767
Medium low	Manufacture of coke, refined petroleum products and nuclear fuel	1	0,718	0,718
Medium low	Manufacture of rubber and plastics products	1,008	0,757	0,763
Medium low	Manufacture of other non-metallic mineral products	1,016	0,757	0,77
Medium low	Manufacture of basic metals	1,142	0,757	0,864
Medium low	Manufacture of fabricated metal products, except machinery and Equipment	0,938	0,757	0,71
Low	Manufacture of food products and beverages	1	0,753	0,753
Low	Manufacture of tobacco products	1,104	0,682	0,753
Low	Manufacture of textiles	0,967	0,757	0,732
Low	Manufacture of wearing apparel; dressing and dyeing of fur	0,879	0,755	0,664
Low	Couro, produtos de couro e calçados	1,037	0,756	0,784
Low	Manufacture of wood and of products of wood and cork	1,125	0,757	0,851
Low	Manufacture of paper and paper products	1,164	0,757	0,881
Low	Publishing, printing, and reproduction of recorded media	0,887	0,757	0,671
Low	Manufacture of furniture; manufacturing n.e.c.	0,964	0,757	0,73
Média		0,988	0,747	0,738

Source: Authors´ elaboration based on DEA´s results.

The average results show that in the period from 1996 to 2002, there was a relative worsening in the total productivity of the factors, when calculated by subsector. In the period, both the change in technical efficiency and the technological change showed averages below 1. The reduction was greater in the activity of high R&D, whose total factor productivity has been reduced by 50% over these years.

This result is corroborated by that obtained by Abeles and Rivas (2011), who highlighted that the country lost productivity in manufacturing between the years 1998 to 2002 and the relative increase in the number of workers in manufacturing during this period.

According to Table 7, among the 20 activities analyzed, 10 showed positive changes in the catch-up effect. In comparison with the rest of the evaluated manufacturing activity, the activities related to the production of paper, basic metals and wood products were the ones that most advanced towards the efficiency frontier of Brazilian manufacturing.

Table 8 presents the results of the Malmquist index for the years 2003 to 2011.

Table 8 – Average Malmquist index for manufacturing - 2003 a 2011.

2003 – 2011				
P&D	**DMUS**	**Technical Efficiency Δ**	**Technological Δ**	**Total Factor Productivity (TFP) Δ**
High	Manufacture of office, accounting, and computing machinery	1,143	1,209	1,382
Medium high	Manufacture of chemicals and chemical products	0,981	1,232	1,208
Medium high	Manufacture of electrical machinery and apparatus n.e.c.	1,009	1,23	1,241
Medium high	Manufacture of electrical machinery and apparatus n.e.c.	1,036	1,231	1,275
Medium high	Manufacture of motor vehicles, trailers, and semi-trailers	1,036	1,231	1,275
Medium high	Manufacture of other transport equipment	0,989	1,23	1,216
Medium low	Manufacture of coke, refined petroleum products and nuclear fuel	1	1,195	1,195
Medium low	Manufacture of rubber and plastics products	0,991	1,229	1,218
Medium low	Manufacture of other non-metallic mineral products	0,998	1,23	1,227
Medium low	Manufacture of basic metals	0,953	1,23	1,172
Medium low	Manufacture of fabricated metal products, except machinery and	1,025	1,23	1,261

	Equipment			
Low	Manufacture of food products and beverages	1	1,237	1,237
Low	Manufacture of tobacco products	1,032	1,159	1,197
Low	Manufacture of textiles	0,973	1,228	1,195
Low	Manufacture of wearing apparel; dressing and dyeing of fur	1,068	1,23	1,314
Low	Couro, produtos de couro e calçados	0,971	1,227	1,192
Low	Manufacture of wood and of products of wood and cork	0,947	1,228	1,163
Low	Manufacture of paper and paper products	0,959	1,23	1,18
Low	Publishing, printing, and reproduction of recorded media	0,882	1,227	1,082
Low	Manufacture of furniture; manufacturing n.e.c.	1,04	1,23	1,279
Média		1,000	1,224	1,224

Source: Authors´ elaboration based on DEA´s results.

The results in Table 8 show that, between the period 2003 to 2011, there was an increase in the total productivity of the factors, however, the catch-up effect, represented by the change in technical efficiency, remained on average without changes. From this interpretation, it can be inferred that the increase in average manufacturing productivity in this period was mainly due to the effect of shifting the frontier (technological change) - resulting from the production of a superior product through less use of inputs, a potential result of the use of new technologies. Among the listed industries, the one that obtained the greatest increase in productivity was that of office, accounting, and computing machinery, which uses a high level of R&D.

The lines of activities related to high R&D and medium high R&D showed a relatively high increase in the total factor productivity change, of these groups, only the chemical products and other transportation equipment sector received a value less than 1 in the change index in technical efficiency. In this regard, Abeles and Rivas (2011) point out that Brazilian industrial growth between 2003 and 2007 was driven by capital-intensive activities.

However, despite the increase in productivity when compared to national manufacture, Brazil still has a strong external dependence on the supply of intermediate inputs in intensive R&D, given that the country is far from the technological frontier, as pointed out by Morceiro (2018).

When comparing the sectors of Brazilian manufacturing, even though there was an increase in the total productivity of the factors as, for example, in the sectors with the highest levels of R&D, in the most recent period of the sample, it is noted that the catch up effect was not predominant. Such a result can be justified by the fact that these sectors, in Brazil, have little capacity to radiate dynamism in the economy since some high-tech activities do not follow a trajectory of robust industrialization and have low GDP´s share (MORCEIRO, 2018).

6. FINAL REMARKS

The main objective of this work was to carry out an empirical analysis of how the manufacturing industry influences the level of complexity and, therefore, the level of income of an economy, in terms of its sub-sectors, aggregated for R&D level.

The more conventional models were not sufficient to explain the uneven growth rates among nations, that is, the lack of *per* capita income convergence. It was argued that economic growth can be better explained by structural change. Still, as pointed out by the literature, the importance of structural transformation is also supported by the possibility of unconditional convergence, characteristic of manufacturing, as its production allows the transfer and absorption of technology, so that productivity growth accelerates.

Using subsectoral information from the United Nations Industrial Development Organization (UNIDO) data from a sample of 28 countries, between the years 1963 to 2012, and 23 subsectors divided into four classifications were analyzed: high R&D, medium high R&D, medium low R&D and low R&D. Additionally, the efficiency of these countries in each classification was verified, in order to relate the results with the level of complexity.

In general, the results of the present work point out the relevance of the relative share of the workforce in the manufacturing activities of high R&D in the level of economic complexity, and consequently, in the income, for both advanced and emerging countries.

The econometric results indicated that the importance of the manufacturing sector, in terms of its subsectors, is greater for emerging countries than for advanced ones, both in the short and long term, corroborating with the literature that points out the relative importance of the manufacturing industry on *per capita* income in the form of an inverted U.

The results obtained from the data envelopment analysis allowed us to verify that this relationship also remains with regard to efficiency. It can be noted that the most efficient countries in manufacturing activities with a higher level of R&D also present a significant increase in the level of economic complexity, as Singapore, South Korea and Israel, among others. Furthermore, it was observed that the efficiency in the generation of value added and the economic complexity also behaves in an inverted U shape. However, in high R&D activities for emerging countries, the trajectory remained upward, which is consistent with econometric analyzes.

Brazil presented an intermediate position with regard to the DEA analysis, with emphasis on Medium High R&D, in which the country occupied the 4th place for the years evaluated.

The calculation of the Malmquist index allowed us to verify that the increase in the total factor productivity in the country occurred especially between the years 2003 to 2011, being mainly driven by technological change, and not by the increase in technical efficiency (catch up effect). Manufacturing in Brazil has a small (and decreasing) share in the country's productive structure, low investment in research and development - compared to other developed countries - which contributes to its dependence on external technological inputs importation, although being closer to technological frontier and efficiency.

Finally, it is worth mentioning that the dynamic process of structural change requires more than the growth of the manufacturing sector as a whole as, verified in this work. This process also involves both the ability to develop new economic activities as well as the capacity of existing activities to integrate domestically from intra and inter-sectoral linkages. In this sense, further analysis is needed in this perspective in future works.

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