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ARTICLES

Technological intensity patterns and job polarization in Brazil's manufacturing industry

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ABSTRACT

Although studies on the innovation-employment nexus are longstanding in economics, current investigations are focused on the effects of digital technologies on the labor market. This paper examines how technological intensity affects job polarization in Brazil's manufacturing industry. Utilizing the technological standardization methodology by Galindo-Rueda and Verger (2016), data were grouped using the Fisher-Jenks algorithm at the two-digit sectoral level. To measure job polarization, the Routine Task Intensity Index (RTI) by Autor and Dorn (2013) was employed. A pattern of production concentration in sectors with lower innovation relative to value added can be observed. According to the RTI, employment in the industry sectors is polarized; however, the hypothesis that higher technological intensity leads to greater job polarization was not observed in some sectors of the Brazilian manufacturing industry.

KEYWORDS | Technological intensity; Intensity R&D; Job polarization; Manufacturing industry

1. Introduction

Technological advances, while enabling the development of new skills, also promote an increase in job automation. Current technologies, such as digital ones, require higher worker qualifications, as individuals with higher levels of education adapt better to new technologies, thereby increasing productivity. In contrast, less qualified workers are more affected by the costs of digital development, which can intensify employment polarization.

The concept of job polarization was introduced by Autor, Levy and Murnane (2003), an approach that later became dominant in economic science. The authors observed changes in employment patterns in the United States due to the adoption of technologies. Polarization refers to the shift of tasks from the middle of the occupational distribution (middle-wage jobs) to one end, specifically the lower end, where non-routine abstract tasks (high qualification) are concentrated.

This theoretical framework of the innovation-employment nexus, as well as the trade-off between employment and technological change in the labor market, is based on the hypothesis that the higher the technological intensity of economic sectors, the greater the likelihood of intensified employment polarization. This study seeks to answer the following question: Do Brazilian manufacturing sectors with greater technological intensity also show higher levels of employment polarization?

This paper aims to analyze the relationship between the technological intensity patterns of sectors in the Brazilian manufacturing industry and their respective job polarization intensities. The methodology of Galindo-Rueda and Verger (2016) will be applied to identify technological patterns and organize them into groups of high, medium-high, medium, and medium-low technological intensity. The taxonomy considers the relationship between Research and Development (R&D) expenditure and Value Added. To reflect sectoral distances in terms of R&D efforts, the Fisher-Jenks algorithm will be used for data clustering.

To investigate the intensification of job polarization in the distribution of occupational skills, the Routine Task Intensity Index (RTI) proposed by Autor and Dorn (2013) will be used. Most of the literature analyzes job polarization by considering both occupational skills and wages, assuming a cause-and-effect relationship. This work will focus solely on the distribution of occupational skills. Technological advances enable technologies to take over routine tasks (low skill level), causing changes in the rewards for certain skill levels and the allocation of skills to tasks.

This paper is divided into five sections, including this introduction. The second section presents the literature review. The third section describes the methodology for constructing the classification of sectors in the manufacturing industry by technological intensity and the RTI. In the fourth section, the research results are presented and discussed. Finally, in the fifth section, the concluding remarks are presented.

2. Literature review

2.1 Sectoral taxonomies and classifications

The evolutionary theory, also known as neo-Schumpeterian theory, aims to identify inter-sectoral differences in how innovations are sought, introduced, used, and diffused in capitalist dynamics, in other words, the technological pattern in which companies operate. Various proposals for taxonomies based on indicators of technological efforts have emerged to explain such sectoral patterns and to synthesize characteristics of the productive structure from a relatively small number of categories (SILVA, 2018).

In the 1990s, methodologies aiming at the technological standardization of companies from a systemic perspective of the innovation process stand out, as proposed by OECD studies, the Oslo Manual, and the Frascati Manual. According to Tessarin (2018), these instruments were widely disseminated in innovation economics studies and served as the basis for the formulation of national innovation research. An example is the Technological Innovation Survey (PINTEC) elaborated by the Brazilian Institute of Geography and Statistics (IBGE), which follows the definitions and recommendations of the Oslo Manual (ORGANIZATION FOR ECONOMIC CO-OPERATION AND DEVELOPMENT, 2005) and the innovation surveys of OECD countries (ORGANIZATION FOR ECONOMIC CO-OPERATION AND DEVELOPMENT, 2015).

The OECD's taxonomy has been subjected to revisions in order to refine it. The first version from 1984, based on R&D intensity for the manufacturing industry following the International Standard Industrial Classification (ISIC), divided sectors into three categories: high, medium, and low technology (ORGANIZATION FOR ECONOMIC CO-OPERATION AND DEVELOPMENT, 1984). In the 1990s, Hatzichronoglou (1997) reformulated this classification, grouping industries into four categories: high, medium-high, medium-low, and low technology. This reformulation combined measures of internal R&D intensity, R&D acquired indirectly through purchases of national and imported intermediate production factors, and capital goods. In 2003, the OECD updated the classification based solely on R&D intensity but continued to refer to it as a technological classification (GALINDO-RUEDA; VERGER, 2016).

Considering this, the Organization for Economic Co-Operation and Development (2011) proposed aggregating industrial sectors according to their technological intensity, based on the degree of innovative effort present in each sector. This classification divides sectors into four groups: high, medium-high, medium-low, and low technological intensity. In 2016, Galindo-Rueda and Verger (2016) revised this taxonomy, adding value-added data from both manufacturing and non-manufacturing sectors (including services, extractive industries, and agriculture), based on the ISIC Revision 4. This revision covers virtually all sectors of economic activity, considering both external and internal R&D expenditures, along with a measure of output, typically Gross Value Added (GVA) or Gross Domestic Product (GDP).

The taxonomy by Galindo-Rueda and Verger (2016) was applied in 27 OECD member countries, as well as Singapore and Taipei, encompassing 29 countries. This approach encompasses the structural and technological heterogeneity of various national production arrangements and their impacts on R&D indicators. In this version, sectors are grouped into five categories of R&D intensity: high, medium-high, medium, medium-low, and low. The results of this new taxonomy show that all manufacturing industries are present in the high and medium R&D intensity categories, while non-manufacturing industries are more dispersed, ranging from high to low intensity.

Even though Brazil is an associate nation of the OECD, Galindo-Rueda and Verger (2016) did not include the country in the sample to calculate the new taxonomy. According to the authors, it was not possible to construct measures of R&D intensity at a detailed industrial level on a global basis, as there was a risk of underestimating or overestimating this measure in the global context. The methodology of Galindo-Rueda and Verger (2016) was reproduced for the Brazilian economy in Morceiro (2018).

Morceiro (2018) follows the sectoral aggregation of ISIC4 to apply the R&D intensity index in the National Classification of Economic Activities (CNAE 2.0), considering only private sectors, as in the original study. This was possible because the classification of ISIC4 is compatible with CNAE 2.0, allowing for an identical sectoral aggregation as that of Galindo-Rueda and Verger (2016). The results obtained for Brazilian sectors, considering data from 2011, are practically the same as those found in the study by Galindo-Rueda and Verger (2016), but in smaller proportions.

It is worth noting that Galindo-Rueda and Verger (2016) understand that innovations cannot be fully explained by R&D intensity, as the innovative performance of companies is not necessarily directly related to formal R&D activities. Many innovations originate from the appropriation of knowledge generated outside the firm's environment.

Consequently, from this theoretical perspective, the OECD moved to embrace “R&D intensity”.

It’s important to point out that “technological intensity” and “R&D intensity” can be employed interchangeably without losing the ability to analyze sectoral innovation movements effectively. Although networks of tacit knowledge exchange and the formation of technological learning capabilities cannot be expressed solely in R&D investments, the collection of statistical data on intangible factors and socioeconomic relationships is complex in terms of treatment, collection, systematization, and comparability (ORGANIZATION FOR ECONOMIC CO-OPERATION AND DEVELOPMENT, 2017). For this reason, R&D statistics still dominate in characterizing the degree of technology embedded in sectors (ORGANIZATION FOR ECONOMIC CO-OPERATION AND DEVELOPMENT, 2018). Therefore, in this paper, the term “technological intensity” will be adopted.

The taxonomy proposed by Galindo-Rueda and Verger (2016) provides a methodological synthesis that allows the construction of categories of technological intensity according to statistical criteria for data clustering, being more efficient for the objectives of this research.

2.2 Job polarization

In studies on the man-machine relationship, the dominant methodology is the task-based approach, popularized by Autor, Levy, and Murnane (2003). The authors explain that the adoption of computer technology (software and hardware) by companies has modified the tasks performed by workers and the demand for qualifications, known as the routinization hypothesis. Routinization suggests that computer capital (computer technologies) substitutes workers in the execution of a set of routine tasks and complements them in the execution of non-routine tasks, through price dynamics. In other words, the impact of computer technologies on routine jobs stems from the fall in the price of these technologies (AUTOR; LEVY; MURNANE, 2003).

The change in skill returns and the evolution of wage inequalities presented by Autor, Levy and Murnane (2003) are based on the canonical model, which treats technology as exogenous and there is no distinction between skills and tasks, meaning high and low-skilled workers produce two imperfectly substitutable goods. The analysis of employment trends is performed by estimating the effects of workers' tasks to obtain consistent estimates for the trends of each wage-task premium. Thus, job polarization is characterized by employment growth at the lower and upper ends of the income distribution, with technical change being naturally biased (ROCHA, 2021).

Acemoglu and Autor (2011) propose a methodology to enrich the canonical model, allowing a more effective analysis of modern markets, highlighting the importance of differentiating between skills and tasks. The authors define a task as a unit of work activity that produces goods and services, while skill is a set of resources that a worker possesses to perform various tasks. Thus, workers apply their skills to tasks in exchange for wages, and the applied skills produce outcomes. The analysis of job polarization can be identified in the changes that occur in the distributions of occupational skills and wages, where the supply of skills (low, medium, and high) corresponds to the comparative advantage of different skill groups among tasks. Given the wages for different types of skills in the market, technologies embodied in capital, trade, and outsourcing contribute to competition in performing various tasks, applied under equilibrium conditions that depend on costs and comparative advantages.

Thus, based on the hypothesis of Autor, Levy and Murnane (2003), Acemoglu and Autor (2011) characterize the content of tasks performed by workers in the United States of America (USA) using descriptors from the *Occupational Information Network* (O*NET)[1] and allocating specific skills to each task. The following categories are considered:

[1] The primary source of occupational information in the USA, created to ensure that all users of occupational data classify workers in the same way.

- **Cognitive routine tasks**: Activities such as accounting and office work are characterized as low-skilled.
- **Manual routine tasks**: Repetitive and production line monitoring work, which requires low skills.
- **Non-routine manual tasks**: Activities involving visual recognition and personal interaction, requiring skills that cannot be described in a set of programmable rules. Such skills include detailed knowledge of local traffic and the ability to decipher difficult handwriting. Therefore, these activities are considered non-routine and require intermediate qualifications (ROCHA, 2021).
- **Abstract non-routine tasks**: Require problem-solving abilities, intuition, and creativity, such as in the role of a company director. These tasks demand high qualifications (ROCHA, 2021).

Building upon the routinization hypothesis and using the methodology of Acemoglu and Autor (2011), Autor and Dorn (2013) developed the Routine Task Intensity Index (RTI). In this index, technological changes are considered endogenous, assuming that the polarization results from the interaction between consumer preferences (entrepreneurs demanding labor for service provision and preferring variety over specialization) and the decreasing cost of automating routine and codifiable tasks (ROCHA, 2021).

All the studies cited in this section have been applied in the USA economy, where the results indicate job polarization due to the adoption of technologies in production and management processes in companies. Polarization has been exacerbated over the years due to advances in digital technologies and artificial intelligence, which make the production process more efficient (AUTOR, 2015). In this approach, it is considered that sectors or companies that are more technology-intensive are more likely to shift labor from productive activities to other sectors of the economy or to other countries.

In Brazil, this literature has been addressed in several works, such as those of Sulzbach (2020) and Rocha (2021). The results indicate that job polarization in the country has low intensity, meaning that the technologies adopted by Brazilian companies are not causing an intense displacement of labor when compared to developed countries.

3. Methodology and data source

3.1 Technological intensity

The sectoral aggregation proposed by Galindo-Rueda and Verger (2016) considers the sectoral division (manufacturing and non-manufacturing) at the two-digit level. However, in some cases, industrial sectors were grouped into just one higher category due to their homogeneity in terms of R&D intensity, such as sectors 10, 11, and 12 of ISIC 4 (food, beverages, and tobacco, respectively). In other cases, sub-industries (three-digit level) were considered due to their significant heterogeneity. As mentioned in section 2.1, Morceiro (2018) applied the method of Galindo-Ruega and Verger (2016) to the Brazilian case, obtaining an aggregation identical to the original study.

The focus of this paper is on examining whether the adoption of technologies leads to stronger job polarization in technology-intensive sectors of the manufacturing industry. For the purpose of comparing the two indices used in this study, sectoral aggregation entirely at the two-digit level is adopted, and the R&D intensity index is calculated based on Galindo-Rueda and Verger (2016). This aggregation did not impair the analysis of R&D intensity, as can be observed in section 4.1 below, where sectors 10, 11, and 12 of CNAE 2.0/ISIC 4 in 2017 do not show very homogeneous results.

The choice to focus on the manufacturing industry stems from the hypothesis that these sectors are more dynamic in terms of productivity levels and technical progress. Following Galindo-Rueda and Verger (2016), the indices are constructed by considering the amount of expenditure on internal and external R&D by companies in each sector of the manufacturing industry, regardless of the origin of their funding, whether public, private, or from the company itself.

These data refer to companies that have implemented product and/or process innovations. Technological intensity is calculated as:

$$I_t = \left(\sum_i^n RD_i\right) / VA_t) \qquad (1)$$

in which, I_t represents the technological intensity in a given sector, $\left(\sum_i^n RD_i\right)$ is the sum of expenditure on R&D (internal and external) in group i (sector of the manufacturing industry), and VA_t is the share of the value added of group i in the total value added of the sector.

Once I_t is calculated, the sectors are grouped according to their categories of technological intensity: high, medium-high, medium, and medium-low. The category of low technological intensity was excluded, as it is characteristic of non-manufacturing sectors, as discussed in section 2.1 in the studies by Galindo-Rueda and Verger (2016) and Morceiro (2018), not falling within the manufacturing industry sector.

Galindo-Rueda e Verger (2016) applied the k-means algorithm to perform data clustering into five categories of technological intensity. In this method, clusters are defined by spatial regions based on a principal value or characteristic for each cluster (K) determined by the researcher. The within-cluster variance is minimized by assigning data points to clusters in such a way that the average squared distance is reduced. This method is used in both unidimensional and multidimensional datasets, but it is in the latter where this algorithm proves to be more powerful. In the study by Galindo-Rueda and Verger (2016), 29 countries were considered in the analysis, thus the database has a dimensional nature, making the analysis by spatial regions more suitable. In this paper, the data are unidimensional because only the R&D intensity for the Brazilian manufacturing industry is analyzed. Although the k-means algorithm is efficient for unidimensional data, the Fisher-Jenks algorithm is more advisable, being a more rigorous method. Thus, the Fisher-Jenks method was opted, considering four categories of technological intensity, inspired by the Acca (2021) study.

Fisher (1958) proposed a data clustering method into value intervals that maximize the difference between classes, reflecting the distances between the clusters. Later, Bivand (2018) incorporated Jenks' method into this algorithm, which aims to group the projected data to determine the best arrangement without arbitrary definition, distributing the values into different classes. The 'Jenks Natural Breaks' classification minimizes the variance within each interval so that the values within each interval are as close to each other as possible. In this way, the Fisher-Jenks method maximizes the difference between groups and minimizes the variance within each group, providing a data clustering into categories that form homogeneous groups in terms of the variance within each of these categories. This approach allows identifying the boundary between the last point of one category and the first point of the subsequent category.

The data on R&D are extracted from PINTEC and the Value Added from the Annual Industrial Survey - Enterprises (PIA-Empresas), both surveys conducted by IBGE for the year 2017 (the last year with available PINTEC data during the development of this research). Therefore, it is necessary to cross-reference two surveys with different samples of manufacturing industry companies to calculate the technological intensity.

3.2 Routine task-intensity index (rti)

Autor and Dorn (2013) developed the Routine Task Intensity Index (RTI), based on the hypothesis of routinization and considering technological changes as endogenous. Thus, the index assumes that polarization results from the interaction between consumer preferences (with employers demanding labor for service provision and preferring variety over specialization) and the decreasing cost of automating routine and codifiable tasks (ROCHA, 2021).

The authors discriminate occupations into different levels of intensity, grouping these measures to create a summarized measure of RTI at the occupational level, calculated as:

$$RTI_k = ln\left(T_{k,t}^{R}\right) - ln\left(T_{k,t}^{M}\right) - ln\left(T_{k,t}^{A}\right) \tag{2}$$

where $T^R_{k,t}$, $T^M_{k,t}$ and $T^A_{k,t}$ are, respectively, the employment links performing routine (R), non-routine manual (M), and abstract (A) tasks in each occupation k in year t.

In this index, large occupational groups are created in which the RTI increases according to the importance of routine tasks in each occupation and declines in the importance of non-routine manual and abstract tasks. Thus, when the RTI is negative, the occupations presented are mostly inherent to non-routine manual and/or abstract tasks, and when it is positive, there is a greater number of routine tasks.

However, in this paper, the RTI was adapted to evaluate the variation in the degree of routine tasks at the level of the manufacturing industry sector, instead of being applied to each occupational group, as follows:

$$RTI_s = ln\left(T^R_{s,t}\right) - ln\left(T^M_{s,t}\right) - ln\left(T^A_{s,t}\right) \tag{3}$$

where $T^R_{s,t}$, $T^M_{s,t}$ and $T^A_{s,t}$ represent, respectively, the quantity of employment links performing routine, non-routine manual, and abstract tasks in each sector s in year t. Thus, the average RTI for each sector of the manufacturing industry is obtained.

Additionally, the RTI assumes an inverted U-shape in occupational skill. This occurs if the elasticity of production exceeds the elasticity of consumption, resulting in increases in wages for low-skilled workers in manual tasks relative to wages for routine tasks. This increases the flows of low-skilled labor to meet occupations at the lower end of the occupational skill distribution, polarizing the lower tails of wage and employment distributions (AUTOR; DORN, 2013).

3.2.1 Classification of occupations according to task type

To calculate the RTI, it is necessary to classify occupations into task categories based on each occupation in the Brazilian Classification of Occupations (CBO2002). This exercise was conducted in Brazil in Rocha's study (2021), which is adhered to in this paper.

Rocha (2021) adopts the task typology proposed by Acemoglu and Autor (2011). The limitation encountered in implementing this methodology in CBO2002 arises because the codes of the *Standard Occupational Classification* (SOC)[2] and O*NET are not perfectly corresponding to CBO2002. Given this issue, the author implements the method of refining the correspondence between SOC codes and the International Standard Classification of Occupations (ISCO88), considering this typology, as presented by Fonseca et al. (2018) for Portugal, which provides an exact correspondence of most occupations with SOC codes. This method was feasible to adopt because CBO2002 has comparability with ISCO88, aligning the Brazilian classification with the typology of Acemoglu and Autor (2011), which is more suitable for assessing the effects of current technologies.

Following most of the literature, cognitive routine tasks and manual routine tasks are combined into a single category, encompassing all routine work to facilitate analysis. Rocha (2021) emphasizes the importance of separating these subcategories, especially cognitive routine tasks in the service and manufacturing sectors. In the case of the Brazilian manufacturing industry, cognitive routine tasks do not have a significant representation, which does not hinder the analysis.

The database used for calculating the RTI comprises the editions of RAIS for the years 2017 and 2021. The first year was chosen due to the necessity to correlate it to the results obtained on technological intensity, as the latest available data are from this year. Meanwhile, 2021 the last year with available data during the development of this research, allowing us to assess the progression of the phenomenon in current years.

The analysis domain was restricted to workers aged between 16 and 65 years old, working between 30 and 44 hours per week, with permanent employment contracts in private sector companies.

[2] The SOC is the occupational classification of the United States and encompasses all occupations in which work is performed for pay or profit.

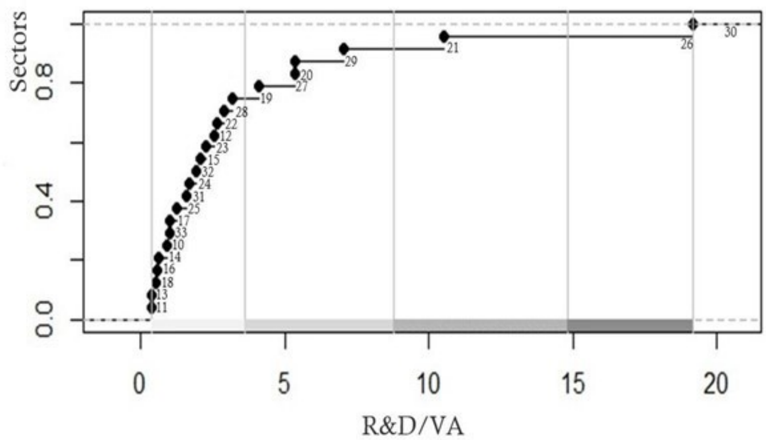
The final sample contained 8,713,938 observations in 2017 and 9,148,227 observations in the year 2021.

4. Results

4.1 Analysis of technological intensity

The results, obtained through the Fisher-Jenks algorithm, show that only two sectors engage in R&D investments that exceed the two-digit mark of sectoral value added: Manufacture of other transport equipment, except motor vehicles (19.17%) and Manufacture of computer, electronic, and optical products (10.51%). Most other sectors have R&D intensities that do not exceed 3% of sectoral value added. There is a significant gap, in terms of innovative efforts, in the Manufacture of other transport equipment sector, which includes the aerospace sector, compared to the other 23 sectors, as observed in Figure 1.

FIGURE 1
Clustering of manufacturing industry sectors according to their level of technological intensity (R&D/VA). Brazil, 2017.



Source: Own elaboration based on PINTEC and PIA 2017 data.

As already observed in the literature on the subject (CAVALCANTE, 2014; BRIGANTE, 2018; MORCEIRO, 2018), the results in Figure 1 reinforce a pattern of concentration of low technological effort in Brazilian industrial sectors.

Through Table 1, it is possible to identify the intensities of each group by their relative shares, observing the structural innovative heterogeneity of the Brazilian manufacturing industry. Sectors with high and medium-high technological intensity account for only 4.1% of total value added, while representing about 20% of R&D investments. This result is consistent with the data obtained by Brigante (2018), in which, although these groups have higher technological intensity indicators, they have relatively small shares in total value added.

About 53% of total R&D investments originate from sectors with medium technological intensity, which concentrate approximately 35% of total value added. This group is the one that contributes the most to the average formation of technological intensity in the manufacturing industry. This indicates that the volume of effort needed to achieve the same levels of aggregated R&D intensity is lower for the medium group compared to the other groups.

The medium-low technological intensity group concentrates the majority of sectors in the manufacturing industry, making up approximately 61% of total value added and 27% of total R&D intensity. Observing the sectors individually, all of them exhibit an R&D intensity of less than 3% of sectoral value added.

In Brazil, most of the manufacturing industry comprises sectors with medium and medium-low technological intensity, representing 95% of the total value added in the industry. The segment of medium technological intensity alone accounts for more than half of the country's R&D efforts, as shown in Table 1.

According to Brigante (2018), the Brazilian productive structure, focused on sectors with lower technological intensity, explains the low level of investment in R&D by Brazilian industrial companies, as "the intensity of R&D in a country is also a reflection of its industrial structure" (BRIGANTE, 2018, p. 530, own translation). This means

TABLE 1
Technological intensity (R&D/VA) of sectors in the manufacturing industry. Brazil, 2017

Aggregation CNAE 2.0	Activities of the manufacturing industry	R&D/ VA (%)	Technological intensity	R&D Share (%)	VA Share (%)
30	Manufacture of other transport equipment, except motor vehicles	19.17	High	11.35	1.83
26	Manufacture of computer, electronic, and optical products	10.51	Medium-high	8.91	2.62
21	Manufacture of pharmaceuticals and pharmaceutical chemicals	7.05	Medium	52.81	34.66
29	Manufacture of motor vehicles, trailers, and bodies	5.36			
20	Manufacture of chemicals	5.36			
27	Manufacture of machinery, electrical equipment, and materials	4.09			
19	Manufacture of coke, petroleum products, and biofuels	3.19			
28	Manufacture of machinery and equipment	2.88	Medium-low	26.93	60.90
22	Manufacture of rubber and plastic products	2.67			
12	Manufacture of tobacco products	2.55			
23	Manufacture of non-metallic mineral products	2.28			
15	Tanning and dressing of leather; manufacture of luggage, handbags, saddlery, harness, and footwear	2.07			
32	Manufacture of other products	1.95			
24	Metallurgy	1.69			
31	Furniture manufacturing	1.59			
25	Manufacture of metal products, except machinery and equipment	1.25			
17	Manufacture of pulp, paper, and paper products	1.03			
33	Maintenance, repair, and installation of machinery and equipment	1.01			
10	Manufacture of food products	0.93			
14	Manufacture of wearing apparel and accessories	0.61			
16	Manufacture of wood products	0.60			
18	Printing and reproduction of recorded media	0.54			
13	Manufacture of textiles	0.41			
11	Manufacture of beverages	0.41			

Source: Own elaboration based on PINTEC and PIA 2017 data.

that the lower the country's capacity to make R&D efforts, the lower the demand for work in the industrial sector that requires the use of non-routine tasks, both manual and abstract. This contributes to the low degree of job polarization intensity found in Brazil (Rocha, 2021).

It is worth noting that a country's industrial structure is the result of a complex process involving historical, economic, social, cultural, and organizational factors. Brazil, as a peripheral country, is technologically dependent on central countries. According to Toledo (2019), since the 1970s, while several Latin American countries were incorporating, albeit with decades of delay, process technologies for large-scale production, central countries were advancing in information and communication technologies. Thus, Brazil failed to update its productive structure and lost dynamism and industrial complexity.

Based on the results obtained in this section, it is expected that the most technology-intensive sectors will exhibit a more pronounced job polarization, as they are more likely to incorporate automation technologies.

4.2 Analysis of job polarization

4.2.1 Descriptive analysis of the data

As presented in sections 2.2 and 3.2.1, occupations are categorized into tasks to analyze job polarization. Table 2 shows the distribution of occupations by tasks in the technological intensity groups. As expected, the medium-high (30.4% in 2017 and 30% in 2021), high (24.1% in 2017 and 23.5% in 2021), and medium (21.9% in 2017 and 22% in 2021) technological intensity groups respectively concentrated the highest number of abstract workers in both years studied. Except for the high-intensity group, the others show stability in the participation of workers performing this task between 2017 and 2021.

The largest share of workers performing non-routine manual tasks conglomerated in the high (49.5% in 2017 and 45.9% in 2021) and medium (39.2% in 2017 and 40.6% in 2021) technological intensity groups. This type of task increased its participation in almost all groups over the years studied. This result was expected, as the literature suggests that job polarization in Brazil occurs mainly due to the displacement of workers performing routine tasks to non-routine manual tasks (ROCHA, 2021).

TABLE 2
Distribution (%) of employment links in subsectors of the manufacturing industry according to type of task performed. Brazil, 2017-2021

Aggregation CNAE 2.0	Technological intensity	Tasks					
		Abstract (%)		Manual (%)		Routine (%)	
		2017	2021	2017	2021	2017	2021
30	High	24.1	23.5	49.5	45.9	26.4	30,6
26	Medium-high	30.4	30.0	18.6	19.4	51.1	50.6
21; 29; 20; 27; 19	Medium	21.9	22.0	39.2	40.6	39.0	37.4
28; 22; 12; 23; 15; 32; 24; 31; 25; 17; 33; 10; 14; 16; 18; 13; 11	Medium-low	12.6	12.3	34.2	35.8	53.2	51.9

Source: Own elaboration based on microdata from RAIS 2017 and 2021.

Routine tasks predominate in the medium-low (53.2% in 2017 and 51.9% in 2021) and medium-high (51.1% in 2017 and 50.6% in 2021) technological intensity groups. Analyzing the manufacturing industry in aggregate, these tasks have the highest participation in the composition of occupations, but their contribution has decreased. This reduction is observed in almost all technological intensity groups, as shown in Table 2.

The only exception is in the high technological intensity group, where abstract and non-routine manual tasks decreased their participation from 2017 to 2021, while routine tasks increased. Since routine tasks are codifiable and can be performed by machines, this suggests an increase in the cost of automating these tasks in this sector. This may reflect the economic crisis experienced by Brazil, exacerbated by the COVID-19 pandemic.

Section 2.2 discussed that routine tasks are often performed by low-skilled workers, non-routine manual tasks by workers with intermediate qualifications, and abstract tasks are executed by individuals with high qualifications. According to Table 3, in 2017, the majority of workers performing abstract tasks had a higher education degree (46.2%). However, in 2021, workers with a high school education became the majority of those performing this type of task (48.74%).

TABLE 3
Distribution (%) of employment links in the manufacturing industry according to level of education, by type of task. Brazil, 2017 and 2021

Education Level	Tasks					
	Abstract (%)		Manual (%)		Routine (%)	
	2017	2021	2017	2021	2017	2021
Illiterate or Incomplete Elementary Education	2.21	1.72	19.43	16.03	13.23	11.17
Completed Elementary Education	6.21	5.22	22.18	20.67	21.27	18.62
Completed High School	45.38	48.74	55.97	61.31	58.46	63.41
Completed Higher Education	46.20	44.32	2.42	1.99	7.03	6.79
Total	100.00	100.00	100.00	100.00	100.00	100.00

Source: Own elaboration based on microdata from RAIS 2017 and 2021.

As for non-routine manual and routine tasks, the percentages of workers with a higher education degree are low and have decreased even further from 2017 to 2021.

Notably, there is a higher proportion of workers with secondary education performing all tasks. This can be attributed to the expansion of technical high school education in the 2000s. However, the reduction in the participation of workers with higher education in the manufacturing industry suggests that the phenomenon of mismatch may be occurring, where the supply of workers with higher educational levels is not perfectly aligned with demand. In other words, there is no matching between the qualifications demanded by companies and those offered by workers, causing imbalance in the labor market (REIS, 2012; ROCHA, 2021).

Although the distribution of skills in each task presents a slightly different behavior from that established by Autor, Levy and Murnane (2003), the results still confirm the hypothesis of the characteristic qualifications of each task.

In section 4.1, it was observed that the industrial structure influences R&D skills, usually associated with highly skilled workers. The reduction in the participation of workers with higher education performing abstract tasks can be explained by the decreased requirements for the qualification level of the workforce employed in the Brazilian industry between 2017 and 2021. This may indicate a reduction in technological intensity, since R&D statistics are an important characterization of the degree of technology incorporated in sectors.

Based on Human Capital theory, which explains that more qualified workers receive a higher wage differential compared to unskilled workers, Autor and Dorn (2013) assume that workers performing abstract tasks have higher salaries than those performing non-routine manual tasks, who, in turn, earn more than those performing routine tasks.

Table 4 shows that workers performing abstract tasks received the highest wages in the industry, concentrated in the salary ranges of 2.01 to 5 minimum wages (40,43% in 2017[3] and 43,21% in 2021[4]), followed by those earning between 5.01 and 10 minimum wages (22.60% in 2017 and 20.34% in 2021) in both years studied. They also have a significant share of those earning more than 10.01 minimum wages. As for workers performing non-routine manual tasks (56.66% in 2017 and 57.03% in 2021) and routine tasks (61.58% in 2017 and 58.43% in 2021), they predominantly earned between 1.01 and 2 minimum wages. It is also noted that, regardless of the type of task, between 2017 and 2021, the participation of workers in higher pay range decreased, while the participation of those in lower pay range increased. This result may also reflect the economic crisis experienced by the country, exacerbated by the COVID-19 pandemic, affecting the financial effort exerted by sectors of the manufacturing industry.

Values need to be deflated to make a wage comparison between the years. The nominal value of the minimum wage was deflated using the National Consumer Price Index (INPC), with 2021 as the base. Real minimum wages in 2021 are slightly higher (about R$ 163,00) compared to 2017.

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3 The minimum wage in force in 2017 was R$937.00, according to the Departamento Intersindical de Estatística e Estudos Socioeconômicos (2024).

4 In 2021, the prevailing minimum wage was R$1,100.00, according to Departamento Intersindical de Estatística e Estudos Socioeconômicos (2024).

TABLE 4
Distribution (%) of employment links in the manufacturing industry according to ranges of annual average remuneration (in minimum wages), by type of task. Brazil, 2017 and 2021

Wage Ranges	Tasks					
	Abstract (%)		Manual (%)		Routine (%)	
	2017	2021	2017	2021	2017	2021
0,5 a 1 MW	0.93	2.56	3.75	10.98	4.03	10.67
1,01 a 2 MW	19.63	22.45	56.66	57.03	61.58	58.43
2,01 a 5 MW	40.43	43.21	34.85	28.73	28.63	26.52
5,01 a 10 SM	22.66	20.34	4.09	2.91	4.38	3.52
≥ 10,01 MW	16.36	11.43	0.65	0.35	1.39	0.86
Total	100.00	100.00	100.00	100.00	100.00	100.00

Source: Own elaboration based on microdata from RAIS 2017 and 2021.

4.2.2 RTI analysis

The average RTI of each sector of the manufacturing industry showed negative values, indicating that occupations in these sectors are mostly related to non-routine manual and/or abstract tasks. This is mainly due to the presence of non-routine manual tasks, suggesting polarization of employment due to the adoption of technologies.

The initial hypothesis of this research, based on Autor, Levy and Murnane (2003), considers that the higher the technological intensity of a country's economic sectors, the greater the likelihood of intensifying job polarization. However, the results from Table 5 show a different behavior in the activities of the Brazilian manufacturing industry. The sectors with the highest intensity of job polarization in the studied years are of medium-low technological intensity, namely: Manufacture of food products (-12.04 in 2017 and -12.19 in 2021), Maintenance, repair and installation of machinery and equipment (-11.64 in 2017 and -11.77 in 2021), and Manufacture of metal products, except machinery and equipment (-11.59 in 2017 and -11.65 in 2021), observing an increase in the job polarization intensification from 2017 to 2021. In these sectors, workers predominantly engage in

TABLE 5
Average task intensity of divisions in the manufacturing industry. Brazil, 2017 and 2021

Manufacturing industry activities	Technological intensity	Medium RTI	
		2017	2021
Manufacture of food products	Medium-low	-12.04	-12.19
Maintenance, repair, and installation of machinery and equipment	Medium-low	-11.64	-11.77
Manufacture of metal products, except machinery and equipment	Medium-low	-11.59	-11.65
Manufacture of coke, petroleum products, and biofuels	Medium	-11.5	-11.61
Manufacture of machinery and equipment	Medium-low	-11.53	-11.61
Manufacture of motor vehicles, trailers, and semi-trailers	Medium	-11.46	-11.55
Manufacture of chemical products	Medium	-10.94	-10.98
Manufacture of rubber and plastic articles	Medium-low	-10.72	-10.85
Metallurgy	Medium-low	-10.71	-10.83
Manufacture of non-metallic mineral products	Medium-low	-10.6	-10.67
Manufacture of machinery, appliances, and electrical equipment	Medium	-10.28	-10.52
Manufacture of pulp, paper, and paper products	Medium-low	-10.01	-10.3
Manufacture of other transport equipment, except motor vehicles	High	-10.58	-10.27
Manufacture of various products	Medium-low	-9.97	-10.1
Manufacture of pharmaceuticals and pharmaceutical chemicals	Medium	-9.82	-10.05
Manufacture of beverages	Medium-low	-9.85	-9.95
Manufacture of computer, electronic, and optical products	Medium-high	-9.7	-9.74
Manufacture of wood products	Medium-low	-9.38	-9.58
Manufacture of furniture	Medium-low	-9.27	-9.43
Manufacture of textiles	Medium-low	-9.33	-9.41
Manufacture of wearing apparel and accessories	Medium-low	-8.79	-8.8
Printing and reproduction of recorded media	Medium-low	-8.52	-8.56
Preparation of leather and manufacture of leather goods, travel accessories, and footwear	Medium-low	-7.9	-8.04
Manufacture of tobacco products	Medium-low	-6.51	-6.31

Source: Own elaboration based on microdata from RAIS 2017 and 2021.

non-routine manual tasks, suggesting adoption of technologies that automate routine tasks and consequently displace labor.

This result is aligned with the findings of Santos, Rapini and Mendes (2020). When analyzing the consequences of tax incentives, such as the Law of Good (Law Nº. 11,196/2005), and public financing on business expenditures on R&D through the Innovation Law (Law Nº. 10,973/2004), they identified that in sectors of medium-low technological intensity, these incentives had a positive impact on the introduction of new processes to the market rather than the introduction of existing processes (imitation). In other words, companies covered by the laws tended to innovate with processes that had a higher degree of novelty.

It is worth noting that the intensity of job polarization found in these sectors is an exception within the group of medium-low technological intensity. Most sectors present results corresponding to the initial hypothesis of this study. An example is the sector of Manufacture of tobacco products, which shows the lowest intensity of job polarization in the manufacturing industry, with a downward trend (-6.51 in 2017 and -6.31 in 2021). This sector had about 70% of workers performing routine tasks.

Consequently, the results of the high and medium-high technological intensity sectors were different from expected. In the case of the high technological intensity sector, Manufacture of other transport equipment, except motor vehicles (-10.58 in 2017 and -10.27 in 2021), it was observed that the intensity of job polarization weakened from 2017 to 2021, which along with the sector of Manufacture of tobacco products (medium-low) are the only sectors in the manufacturing industry to exhibit this behavior. This corroborates with the findings of Table 2, where there is an increase in the presence of workers performing routine tasks as the participation of non-routine manual and abstract tasks decreases, suggesting an increase in the cost of automating these tasks in this sector. According to Santos, Rapini and Mendes (2020), there is no consensus in the literature regarding the real effects of tax incentives on Brazilian innovative dynamics, especially in high-tech sectors, where the statistical coefficients are not significant.

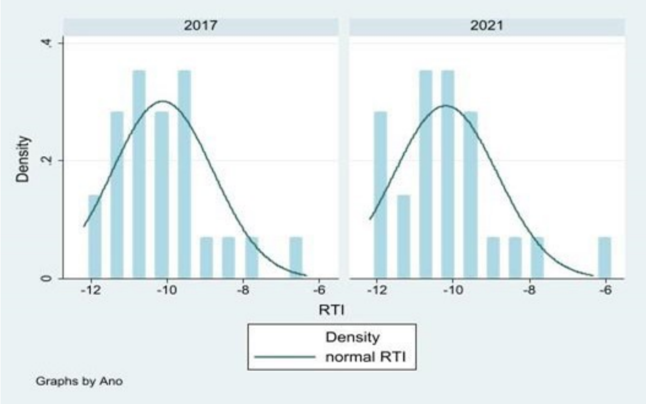
Also noteworthy is the sector of medium technological intensity, Manufacture of pharmaceutical and pharmaceutical chemicals, which shows one of the most significant intensifications of job polarization in the sample (-9.85 in 2017 and -10.10 in 2021). In the study by Santos, Rapini and Mendes (2020), they show that tax incentives benefited the innovation of new products in this sector, which requires highly skilled labor. This is consistent with our findings in Table 2 on the increased participation of workers performing abstract and non-routine manual tasks.

Although there are some results different from what was expected, most segments present average RTI values consistent with the literature on technological intensity. It's also noticeable that, in most cases, the average RTI values decreased, albeit modestly, from 2017 to 2021, indicating an intensification of job polarization.

In Figure 2, it's possible to see more clearly the shift of workers from routine-intensive tasks to non-routine manual tasks in the manufacturing industry in the years under study, where the intensity of routine tasks is higher in the middle of the occupation distribution. In the lower part of the distribution, where non-routine manual and abstract tasks are located, it's evident that the tail is denser, mainly due to manual tasks. This is in line with the hypothesis of Autor and Dorn (2013), which suggests that the elasticity of substitution in production (between computational capital and routine labor) exceeds the elasticity of substitution in consumption (between goods and services) in the Brazilian manufacturing industry. Consequently, the wages of low-skilled workers in manual tasks increase compared to the wages of routine tasks, leading to increased low-skilled labor flows to meet occupations at the lower end of the occupational skill distribution, polarizing the tails of wage and employment distributions.

The difference between the histograms is almost imperceptible because between 2017 and 2021, the intensification of polarization was low, with an average RTI of -13.62 in 2017 and -13.76 in 2021 in the manufacturing industry. However, in 2021, there is a greater concentration of workers in the middle of the distribution (where routine tasks are located) compared to 2017, indicating that, if this trend continues, there may be a reduction in the intensity of job polarization in the coming

FIGURE 2
Density of RTI in the manufacturing industry. Brazil, 2017 and 2021.



Source: Own elaboration based on microdata from RAIS 2017 and 2021.

years. According to Rocha (2021), job polarization in the Brazilian manufacturing industry is largely associated with the declining price of computational capital (software and hardware) rather than with the adoption of digital technologies. These patters are similar to those observed in more advanced countries, such as the United States and Germany in the 1980s. In other words, the Brazilian manufacturing industry lags behind technological advancements.

5. Conclusion

Patterns of technological intensity and their effect on job polarization in Brazil's manufacturing industry were investigated in this study. The OECD taxonomy proposed by Galindo-Rueda and Verger (2016) was applied to classify sectors into four levels of technological intensity (high, medium-high, medium, and medium-low), considering the ratio of R&D to Total Value Added. The Fisher-Jenks algorithm was also used to group one-dimensional data and identify sectoral distances regarding R&D efforts, classifying them according to their technological boundaries. To analyze the intensity of job polarization, the Routine Task Intensity (RTI) index by Autor and Dorn (2013) was employed.

Through the RTI, a shift was observed from routine task-intensive workers (low skill) to non-routine manual tasks (intermediate and low skill), polarizing the distribution of occupational skills. The main results of this research are highlighted below.

The technological patterns found in the manufacturing industry reinforce the concentration of production in sectors with lower innovation levels relative to total value added. This makes sectors of high and medium-high technological intensity a rarity in the Brazilian productive structure, remaining considerably distant from other sectors (medium and medium-low). This concentration of production once again highlights Brazil's technological dependency on developed countries.

The task-based approach was used to investigate job polarization in the distribution of occupational skills, hypothesizing a direct relationship between higher technological intensity and greater job polarization. However, some results found do not corroborate this hypothesis, as sectors with the highest intensity of job polarization belong to the group of medium-low technological intensity, in both years studied. This could be explained by the fiscal incentives aimed at innovation, which enabled sectors with medium-low technological intensity to adopt innovations in new processes. It is worth noting that the intensity of job polarization found in these sectors is an exception, as most of the medium-low group showed results consistent with the initial hypothesis.

Another factor that presents results different from the initial hypothesis is precisely in the group of high technological intensity. The participation of workers performing abstract and non-routine manual tasks decreased between 2017 and 2021, meaning there was a reduction of qualified professionals who facilitate the generation and absorption of new knowledge in the production system. At the same time, workers performing routine tasks increased, reducing the intensity of job polarization in the analyzed period. This suggests that there has been an increase in the cost of automating routine tasks in this sector.

In general, the Brazilian manufacturing industry has undergone recent job polarization, where technologies adopted by industries replace low-skilled workers in performing routine tasks and complement intermediate and high-skilled workers in non-routine manual and abstract tasks. This is evidenced by the negative values of RTI in all years studied, indicating that employment relationships are predominantly related to abstract tasks and/or, mainly, non-routine manual tasks. Job polarization shows low intensity, similar to patterns observed in more advanced countries in the 1980s.

It's important to acknowledge some limitations of this research. Firstly, the OECD taxonomy doesn't identify other essential socio-economic agents in the technological innovation process, such as intersectoral flows of technology. Additionally, the lack of data on innovation corresponding to the most recent years complicates the analysis of the real innovative scenario in the country and its effects on employment dynamics.

References

ACCA, R. S. Tipologias de intensidade tecnológica: revisão metodológica e aplicação para a análise da estrutura produtiva do estado de São Paulo. São Paulo: SEADE Metodologia, 2021.

ACEMOGLU, D.; AUTOR, D. H. Skills, tasks and technologies: implications for employment and earnings. In: ASHENFELTER, O.; CARD, D. (Eds.), Handbook of labor economics. Amsterdam: Elsevier Inc, 2011, v. 4, p. 1043-1171.

AUTOR, D. H. Why Are There Still So Many Jobs? The History and Future of Workplace Automation. The Journal of Economic Perspectives, v. 29, n. 3, p. 3-30, 2015. http://doi.org/10.1257/jep.29.3.3.

AUTOR, D. H.; DORN, D. The growth of low-skill service jobs and the polarization of the US Labor Market. The American Economic Review, Nashville, v. 103, n. 5, p. 1553-1597, 2013.

AUTOR, D. H.; LEVY, F.; MURNANE, R. J. The skill content of recent technological change: an empirical exploration. The Quarterly Journal of Economics, Oxford, v. 118, n. 4, p. 1279-1333, 2003.

BIVAND, R. ClassInt: choose univariate class intervals. 2018. Available from: https://cran.r-project.org/web/packages/classInt/index.html. Access in: 15 Jan. 2023.

BRIGANTE, P. C. Análise dos indicadores de intensidade de P&D: entendendo os efeitos da estrutura industrial e dos gastos setoriais. Nova Economia, Belo Horizonte, v. 28, n. 2, p. 523-548, 2018. http://doi.org/10.1590/0103-6351/3409.

CAVALCANTE, L. R. An analysis of the business enterprise research and development expenditures composition in Brazil. Revista Brasileira de Inovação, Rio de Janeiro, v. 13, n. 2, p. 433-458, 2014.

DEPARTAMENTO INTERSINDICAL DE ESTATÍSTICA E ESTUDOS SOCIOECONÔMICOS. Pesquisa nacional da Cesta Básica de Alimentos: Salário mínimo nominal e necessário. Available at: https://www.dieese.org.br/analisecestabasica/salarioMinimo.html. Accessed on: April 15, 2024.

FISHER, W. D. On grouping for maximum homogeneity. Journal of the American Statistical Association, Alexandria, n. 53, p. 789-798, 1958.

FONSECA, T.; LIMA, F.; PEREIRA, S. C. Job polarization, technological change and routinization: Evidence for Portugal. Labour Economics, v. 51, n. C, p. 317-339, 2018. http://doi.org/10.1016/j.labeco.2018.02.003.

GALINDO-RUEDA, F.; VERGER, F. OECD taxonomy of economic activities based on R&D intensity. Paris: OCDE, 2016. http://dx.doi.org/10.1787/5jlv73sqqp8r.

HATZICHRONOGLOU, T. Revision of the High-Technology Sector and Product Classification, OECD Science, Technology and Industry Working Papers. Paris: OECD Publishing, 1997. http://dx.doi.org/10.1787/134337307632

MORCEIRO, P. C. A indústria brasileira no limiar do século XXI: uma análise da sua evolução estrutural, comercial e tecnológica. 2018, Tese (Doutorado) - Faculdade de Economia, Administração e Contabilidade, Universidade de São Paulo, São Paulo, 2018.

ORGANIZATION FOR ECONOMIC CO-OPERATION AND DEVELOPMENT. Frascati Manual 2015: guidelines for collecting and reporting data on research and experimental development. Paris: OECD publishing, 2015.

ORGANIZATION FOR ECONOMIC CO-OPERATION AND DEVELOPMENT. ISIC Rev 3. Technology intensity definition. Paris: OCDE, 2011.

ORGANIZATION FOR ECONOMIC CO-OPERATION AND DEVELOPMENT. OECD science, technology, and industry scoreboard 2017: the digital transformation. Paris: OECD, 2017.

ORGANIZATION FOR ECONOMIC CO-OPERATION AND DEVELOPMENT. Oslo manual: guidelines for collecting and interpreting innovation data. 3. ed. Paris: OECD; Eurostat, 2005.

ORGANIZATION FOR ECONOMIC CO-OPERATION AND DEVELOPMENT. Oslo Manual 2018: guidelines for collecting, reporting, and using data on innovation. Paris; Luxembourg: OECD Publishing; Eurostat, 2018.

ORGANIZATION FOR ECONOMIC CO-OPERATION AND DEVELOPMENT. Specialization and competitiveness in high, medium and low R&D intensity manufacturing industries: general trends (internal OECD memorandum). Paris: OECD, 1984.

REIS, S. M. Incompatibilidades entre Educação e Ocupação: Uma Análise Regionalizada do Mercado de Trabalho Brasileiro. 2012. Tese (Doutorado) - Faculdade de Ciências Econômicas, Universidade Federal de Minas Gerais, Belo Horizonte, 2012.

ROCHA, G. R. Mudança tecnológica e polarização do emprego no Brasil. 2021. Dissertação (Mestrado) - Escola Paulista de Política, Economia e Negócios, Universidade Federal de São Paulo, Osasco, 2021. Available from: https://repositorio.unifesp.br/handle/11600/61471. Access in: 12 Jan. 2023.

SANTOS, U. P.; RAPINI, M. S.; MENDES, P. S. Impactos dos incentivos fiscais na inovação de grandes empresas: uma avaliação a partir da pesquisa Sondagem de Inovação da ABDI. Nova Economia, Belo Horizonte, v. 30, n. 3, p. 803-832, 2020. http://dx.doi.org/10.1590/0103-6351/5687

SILVA, F. Q. Fluxo de Tecnologia Intersetorial e Produtividade no Brasil. Tese (Doutorado) - Instituto de Economia, Universidade Federal do Rio de Janeiro, Rio de Janeiro, 2018. Available from: https://www.ie.ufrj.br/pos-graduacao-j/pos-graduacao-em-politicas-publicas/dissertacoes-e-teses.html#mestrado. Access in: 15 July, 2023.

SULZBACH, V. N. Essays on job polarization in the Brazilian labor market. 2020. Tese (Doutorado) - Faculdade de Ciências Econômicas, Universidade Federal do Rio Grande do Sul (UFRGS), Porto Alegre, 2020. Available from: https://lume.ufrgs.br/handle/10183/213635. Access in: 12 Jan. 2023.

TESSARIN, M. S. O papel da inovação, diversificação e vizinhança setorial no desenvolvimento industrial recente do Brasil. 2018. Tese (Doutorado) - Faculdade de Economia, Administração e Contabilidade, Universidade de São Paulo, São Paulo, 2018. http://dx.doi.org/10.11606/T.12.2019.tde-20122018-183108

TOLEDO, D. G. C. Aspectos históricos e conceituais da dependência tecnológica da América Latina sob o novo neocolonialismo. Revista OIKOS, Rio de Janeiro, v. 18, n. 3, pp. 41-56, 2019. Available from: http://www.revistaoikos.org. Access in: 20 Jan. 2023.

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