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Industrial dynamics in Brazilian mesoregions: The relevance of technological intensity

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Abstract This study examines the factors influencing industrial location in Brazil during two periods: 2006–2014 and 2014–2019. Using multilevel logit regressions, the net balance of industrial establishments within mesoregions was considered as the dependent variable. Results indicate that technological development levels significantly determine industrial dynamics. Additionally, industries favor mesoregions with skilled labor and low labor costs. The study also demonstrates that agglomeration economies and market size are crucial determinants in the creation of manufacturing industries. The multilevel analysis provides a clear understanding of the importance of local characteristics for the establishment of industries with varying technological levels.

Keywords Mesoregional analysis · Industrial location · Technological levels

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1 Introduction

The location of productive activities, specifically industries, has been a key area of study in economics since the foundational works of Von Thünen's "concentric circles" and Alfred Weber's "Isolated State." Given the inherent complexity of this topic, the empirical literature has produced a significant variety of results (Blair and Premus, 1987; Badri 2007).

Studies on this topic must address different levels of analysis, which vary across communities and countries. Industrial firms face several factors such as wages, taxes, rents, and agglomeration economies. Recently, the importance of technological intensity has also been emphasized as a determining factor. Technological intensity is accessible to varying degrees across individual industries (Guimarães et al. 2000, 2004; Balland and Boschma 2021). Additional literature has shown that technological intensity is essential for creating new investments in local and regional economies. Different phases of the economic cycle impact each industry differently, characterized by the industry's level of technological intensity (Hanson 2005). Effective regional policies also depend on considering the differences in technological intensity among firms (da Silva Leme 1990).

The main objective of this work is to investigate the role of technological intensity in the net balance of industrial establishments (i.e., change in the number of industrial establishments) between two periods in Brazil. The periods covered are from 2006 to 2014 and 2014 to 2019. The first period was marked by economic growth for most Latin American economies, especially Brazil. However, during the second period, the 2008 international banking and financial crisis negatively impacted all economies and their growth dynamics, limiting the expansion plans of businesses and industrial initiatives. Brazil also faced a domestic economic and political crisis during this period. These consequences were particularly noticeable in Brazil from 2014 onwards, resulting in negative growth and a slow recovery, further curtailed by the COVID-19 pandemic in 2020.

This study empirically contributes to the complex debate about the importance of technological intensity in the dynamics of creating or destroying certain industries. We discuss how different regions exhibit heterogeneous net balances of industrial dynamics during periods of growth and crisis. In summary, we conclude that the dynamics of Brazilian industries depend not only on the characteristics of the locations but also on the type of industry and its respective technological intensity.

Discrete choice models enabled the estimation of probabilities of different net balances of industrial establishments, conditional on firms' level of technological intensity. The preferred discrete choice model was the multinomial and logit multilevel, which allowed for control over both the technological level of the industrial segments and the mesoregional determinants (Greene 2003; Paula 2004; Gujarati and Porter 2009; Pindyck and Rubinfeld 2014).

The remainder of this article is composed of the following sections. Section 2 reviews the literature on industrial location in light of the industrial dynamics of regions in Brazil. Section 3 describes the reality of the Brazilian industrial distribution. Section 4 and 5 respectively present the Methodology and discuss the achieved Results. Section 6 concludes the work.

2 Industrial dynamics of Brazil's regions

Much of the dynamics of industrial location in Brazil can be understood by analyzing its industrialization process, which was highly concentrated initially. Industrialization in Brazil began in the Metropolitan Region of São Paulo (RMSP), driven by historical factors and socioeconomic processes linked to the coffee-exporting economy of the late 19th and early 20th centuries. Brazil adopted a policy of import substitution to transform its agro-export economy into an industrial one, aiming to make domestic production efficient and competitive (Suzigan 2022). This policy significantly boosted industrial growth (Negri 1996; Cano 2008; Gremaud et al. 2002; de Souza, 2007), establishing São Paulo as the industrial hub of the nation (Cano 2008; Negri 1996).

However, from the 1970s onwards, Brazil began a gradual process of productive deconcentration, particularly affecting the manufacturing sector (Diniz 1994). Metropolitan regions were the first to receive new industries relocating from São Paulo (Carleial and Valle 1997), a process continuing into the 1980s (Cano 2008). During these two decades, industrial distribution spread as companies moved from São Paulo to other metropolitan areas, particularly in the South and Southeast regions.

In the 1990s, trade liberalization and economic deregulation attracted new investments, further driving industrial deconcentration and relocation due to agglomeration diseconomies. Industries sought to move away from high-density, high-cost labor centers (Ocampo and Porcile 2020), and new investments were attracted by tax incentives offered by states and municipalities distant from the traditional industrial hubs (Carleial and Valle 1997). The appreciation of the exchange rate after 1994 also negatively impacted industrial production, intensifying deconcentration (Cano 2008). The Brazilian economy began showing signs of deindustrialization, which further promoted the dispersal of industry.

Brazil's late industrialization process, driven by its agro-export model, created a microeconomic environment with few high and medium technological industries (Suzigan 1986). For instance, only a third of Brazilian companies were deemed innovative during the 2015–2017 period, a decline of 2.4 percentage points compared to the previous three years (IBGE 2022).

This low level of innovation contributes to Brazil's appearance on lists of countries with the lowest investment and innovation rates. Analyzing the evolution of research and development (R&D) expenditures as a proportion of gross domestic product (GDP) confirms this trend: in 2011, Brazil spent 0.59% of its GDP on R&D, compared to 1.83% in the USA, 1.34% in the Euro Zone, 0.71% in Spain, and 1.39% in China (Koeller et al. 2016). Additionally, income in Brazilian mesoregions tends to be low, with higher income areas coinciding with regions of greater industrial activity and relatively higher technological levels (Ruiz and Domingues 2008; Rocha and Araújo 2021).

Policies fostering investment in innovation and knowledge make technological expenditures in regions like the Euro Zone or the United States more attractive. However, considering Brazil's diverse industrial landscape, it is essential to account for historical constraints and regional differences in technological development that shape the current industrial distribution. This work explores the importance of technological intensity as a determinant of the current distribution of Brazilian industry, offering a novel perspective on this issue.

3 Literature review—the importance of technological intensity in industrial dynamics

3.1 From agglomeration effects to industrial location

The main idea behind location theories is that a company's performance is closely related to the characteristics of the region where it is located. Each region possesses unique attributes such as land use intensity, energy inputs, and human capital requirements. Theoretical and empirical literature strives to generate models that identify locational factors among the numerous spatial alternatives, seeking to better reflect real decisions made by companies (Blair and Premus 1987; Egan 1993).

The pioneering studies of Von Thünen (1910), Weber (1962), Christaller (1933), Hoover (1948), Lösch (1954), Isard (1960), and Marshall (2009 [1985]) laid the foundation for location theory. The theoretical framework of the New Economic Geography (NGE) provided significant advances, particularly influenced by Marshall. NGE theorists attribute a central role to external economies in location decisions. Budget specifications, prices, resources, geographic distribution of the population, technology supply and demand, and other determinants are included in NGE models. This allows NGE to address the economies and diseconomies of agglomeration and identify the tension between centripetal and centrifugal forces that attract or repel productive activities in a given location (Kaldor 1957; Hirschman 1958; Nakamura 1985, 2005; Henderson 1986; Krugman 1991, 1992, 1997, 1998; Gallup et al. 1999; Fujita et al. 2001).

Agglomeration effects can positively or negatively impact on firm's dynamics. Positive impacts occur when communication and information spillovers, skilled labor, and proximity to suppliers are significant. Conversely, agglomeration can discourage investors due to negative externalities like congestion, pollution, and rising land prices (Florida 1994; Cieślik and Ryan 2005; Galinari et al. 2007; Arauzo-Carod and Viladecans-Marsal 2009; Arauzo-Carod et al. 2010). For NGE, economies and diseconomies of scale are related to centripetal and centrifugal forces, often associated with market size effects and local linkages that promote geographic concentration on one hand and immobile elements working against this concentration on the other (Krugman 1991, 1992, 1997, 1998).

In recent decades, empirical studies have increased interest in investigating the forces influencing locational decisions of productive activities, especially in industries. These studies have provided important methodological advances, particularly regarding utility maximization functions. For example, Walker (1989) and Florida (1994) analyzed profit maximization in industries considering a trade-off between low costs and skilled labor. Recent contributions to location theory have presented new evidence on determinants such as taxes, wages, transportation costs, and agglomeration economies. For instance, location choice may include factors related to the demand for industrial products and the supply of inputs, reflecting potential regional demand through market size estimates (Flanagan et al. 2023). As industries create demand for inputs, the supply is expected to respond to the size of a regional economic base (Head and Ries 1996).

Much of the new evidence results from the availability of new datasets and different econometric specifications with new variables or sampling changes. Some studies focus on particular regions and reach conclusions that differ from national-level studies. Research on new industries and new plants also shows varied results. Determinants are not static over time and change as production conditions evolve (Blair and Premus 1987; Ellison and Glaeser 1997; Midelfart-Knarvik et al. 2000; Figueiredo et al. 2002; De Bruyne 2003; Cieślik and Ryan 2005; Badri 2007; Arauzo-Carod et al. 2010).

Empirical studies have analyzed industrial concentration in Brazil using concentration indices like the Hirshman-Herfindahl index (Biderman 2004; Lautert and Araújo 2007; Vignandi et al. 2014). However, studies on industrial location in Brazil are still limited. Notable examples include Silva and Neto (2009), who considered NGE, and Rocha and Araujo (2021), who analyzed industrial distribution dynamics from 2002 to 2014 using decomposition suggested by Dumais et al. (2002). Rocha and Araújo (2021) also estimated migratory flows of companies by technological level. However, the role of technological intensity has not been adequately explored, as will be shown in the next subsection.

3.2 The relevant role of technological intensity

When examining the body of work focused on industrial distribution in Brazil, it becomes evident that most studies have overlooked the role of technological intensity. Technological intensity refers to the importance of technology in the operations of each firm and industry, encompassing the acquisition, development, and utilization of advanced instruments and techniques.

Several factors contribute to this gap in the Brazilian literature. First, there was an assumption that technological intensity functioned as a public good equally accessible to most industries. However, technological offerings vary significantly in terms of accessibility, with different industries accessing varying levels of technology. Globalized industries and companies, supported by departments of research and development, tend to adopt more innovative technological standards. In contrast, industries with substantial investments in existing equipment often view new technologies as less of a priority.

Additionally, dominant trends in the literature identified other factors as primary determinants of industrial concentration or distribution across a given territory. The classic factors of labor and capital costs influenced by geography overshadowed the view of technology and related technological intensity. Only with the recognition of technological development as a driver of economic growth did the academic discourse begin to focus on technological intensity as a crucial factor in differentiating industrial locations.

There was also a misconception that phases of the economic cycle affected all industrial sectors equally. It was assumed that entire industry segments responded uniformly to economic stimuli. However, more recent understandings reveal that low-tech segments respond differently to economic crises than high-tech segments, which react distinctively to periods of economic growth. This realization opened new opportunities for considering technological intensity as a relevant factor in firms' location decisions.

Attention has also turned to the design of state and regional policies. In the past, regional industrial policies tended to benefit all industrial sectors equally within the same area. Later studies suggested that different industrial sectors required differentiated policies to be effective, as uniform policies could result in suboptimal outcomes.

In the fight against unemployment and social inequalities, Badri (2007) found that industries with different technological bases varied in their capacity to generate employment and value. Thus, the importance of studying industrial sectors based on differences in technological intensity has been strongly emphasized.

Our research aims to fill the gap in studies on industrial locations in Brazil. We analyze two distinct periods: 2006 to 2014, a period of economic growth, and 2014 to 2019, a period of crisis. We focus on technological intensity as a critical factor in the dynamics of industrial firms' creation or destruction.

4 Methodology

4.1 Theoretical model of industrial location

Industrial location is a long-term investment decision where a company aims to establish itself in a location with the highest net present value of its production. If a company's revenue is not significantly affected by its location, the profit maximization would be where costs are minimized. For example, if savings from low wages compensate for a smaller market area, the company would select that location (Carlton 1979; Blair and Premus 1987).

Empirically, the profit maximization assumption is often expressed through the Random Utility Maximization (RUM) approach. This posits that a company seeking a new location calculates the maximum profit for each potential location, considering its production function and the prices of inputs and outputs. The company then chooses the location where profits would be maximized. The model for the location of an industry *i* begins as a profit function, with K different industrial sectors, (k = 1,..., K). There are *N* investors (i = 1,..., *N*) who independently select a location *j* from a set of *J* potential locations (j = 1,..., J) (Hansen 1987). The profit that investors will obtain if they select sector k located in area j is given by Eq. 1:

$$\pi_{ijk} = \gamma x_k + \theta y_j + \beta z_{jk} + \varepsilon_{ijk} \tag{1}$$

In this equation, γ, θ, and β are vectors of unknown parameters, x_k is a vector of sector-specific variables (e.g., barriers to entry or concentration rates), y_j is a vector of location-specific variables (e.g., agglomeration economies, land costs, or local taxes), z_{jk} is a vector of explanatory variables that change by region and sector (e.g., wages or location economies), and ε_{ijk} is the error term representing attributes not observed in the model.

For studies on industrial location, this approach to profit maximization provides a theoretical basis that has led to the development of a vast set of empirical results. In this research, the profit maximization hypothesis is maintained using variables that express the importance of reducing costs and increasing revenue in specific industries. Therefore, it is assumed that a company's decision to establish a business in a particular location reflects the optimization of its profit maximization problem.

Following studies such as Arauzo-Carod and Viladecans-Marsal (2009), the choice of location , with a certain probability, is correlated with the opportunity to obtain the maximum possible profit for the firm or industry. This assumption transforms Eq. 1 into the probabilistic Eq. 2 discussed next subsection.

4.2 The empirical model

The literature and the type of data available led us to opt for a multinomial logit model expressed by Eq. 2 (Greene 2003):

$$Prob\left(Y_i = j\right) = \frac{e^{\beta'_j X_i}}{\sum_{k=0}^{4} e^{\beta'_k X_i}}, j = 0{,}1, 2{,}3 \tag{2}$$

The estimation of Eq. 2 results in a set of probabilities for j + 1 choices. In this model, the assumption of irrelevance of independent alternatives is respected. Such an assumption is important as it implies that decision-makers see all locations as similar from the start.

According to Arauzo-Carod and Viladecans-Marsal (2009), the locational determinants of the industry can differ depending on the technological level of the industrial segment. The multinomial and multilevel logit model meets the objective of identifying locational determinants while considering differences among industrial subsectors by technological level. This model is characterized by an ordered categorical response on more than one level, assuming at least two hierarchical structures.

The success of the location decision depends on both regional characteristics and those of the industrial segment. According to Christaller's (1933) interpretation, certain activities will not be located in some areas due to a hierarchy of goods, services, and business locations. One approach to addressing this hierarchical structure is multilevel analysis. A regression model is considered multilevel when the explanatory variables have a hierarchical structure with a random effect that influences the variables at the first level. Thus, interactions between covariances measured at different levels affect the outcome of the dependent variable. In these models, the intercept and/or slope vary for units considered at level 2 (Riani 2005).

Ignoring the multilevel structure can result in biased parameter estimates. When the group structure in the data is ignored and the independence assumption is violated, classical regression models tend to underestimate standard errors (Guo and

Zhao 2000; Peugh 2010). In the multilevel logit model, the general equation with several explanatory variables has the following composition (Eq. 3):

$$\eta_{zj} = ln\left(\frac{\pi_{zj}}{1-\pi_{zj}}\right)\gamma_{00}+\gamma_{10}.x_{1zj}+\gamma_{01}.Z_j+\gamma_{11}.Z_j.X_{1zj}+u_{1j}.x_{1zj}+u_{0j}+e_{zj} \quad (3)$$

Where: η_{zj} is the logarithmic probability of success and π_{zj} is the probability of success for industry z.

Considering the conceptual RUM model and the functional model given by Eq. 1, the multilevel estimation (at two levels) allows for analyzing the probability of a manufacturing industry z of a given industrial segment among 24 sectors to be located in one of the 137 Brazilian mesoregions j. We considered four levels of technological intensity assigned to the first level of Eq. 3. The second level contains independent variables that represent the characteristics of the mesoregions. The dependent variable thus relates to the net balance of industrial establishments in each Brazilian mesoregion between the two periods—2006–2014 and 2014–2019.

Equations 4, 5, 6, 7, 8 and 9 express the multinomial logit model to be estimated for the two periods:

Level 1—Characteristics of industrial sectors—technological intensity

$$ln\left[\frac{P\,(0)}{P\,(3)}\right] = \beta_0\,(0)+\beta_1\,(0)\,.Tech_{\text{medH}}+\beta_2\,(0)\,.Tech_{\text{medL}}+\beta_3\,(0)\,.Tech_{\text{low}} \quad (4)$$

$$ln\left[\frac{P\,(1)}{P\,(3)}\right] = \beta_0\,(1)+\beta_1\,(1)\,.Tech_{\text{medH}}+\beta_2\,(1)\,.Tech_{\text{medL}}+\beta_3\,(1)\,.Tech_{\text{low}} \quad (5)$$

$$ln\left[\frac{P\,(2)}{P\,(3)}\right] = \beta_0\,(2)+\beta_1\,(2)\,.Tech_{\text{medH}}+\beta_2\,(2)\,.Tech_{\text{medL}}+\beta_3\,(2)\,.Tech_{\text{low}} \quad (6)$$

Level 2—Mesoregional features

$$\begin{aligned}\beta_0\,(0) = {} & \gamma_{00}\,(0)+\gamma_{01}\,(0)\,.Edu_{\text{null}}+\gamma_{02}\,(0)\,.Edu_{\text{elem}}+\gamma_{03}\,(0)\,.Edu_{\text{secon}} \\ & +\gamma_{04}\,(0)\,.IHH+\gamma_{05}\,(0)\,.\mathit{Distance}+\gamma_{06}\,(0)\,.\mathit{Income} \\ & +\gamma_{07}\,(0)\,.ln_{\text{GDP}}+u_0\,(0)\end{aligned} \quad (7)$$

$$\begin{aligned}\beta_0\,(1) = {} & \gamma_{00}\,(1)+\gamma_{01}\,(1)\,.Edu_{\text{null}}+\gamma_{02}\,(1)\,.Edu_{\text{elem}}+\gamma_{03}\,(1)\,.Edu_{\text{secon}} \\ & +\gamma_{04}\,(1)\,.IHH+\gamma_{05}\,(1)\,.\mathit{Distance}+\gamma_{06}\,(1)\,.\mathit{Income} \\ & +\gamma_{07}\,(1)\,.ln\text{GDP}+u_0\,(1)\end{aligned} \quad (8)$$

$$\begin{aligned}\beta_0\,(2) = {} & \gamma_{00}\,(2)+\gamma_{01}\,(2)\,.Edu_{\text{null}}+\gamma_{02}\,(2)\,.Edu_{\text{elem}}+\gamma_{03}\,(2)\,.Edu_{\text{secon}} \\ & +\gamma_{04}\,(2)\,.IHH+\gamma_{05}\,(2)\,.\mathit{Distance}+\gamma_{06}\,(2)\,.\mathit{Income} \\ & +\gamma_{07}\,(2)\,.ln\text{GDP}+u_0\,(2)\end{aligned} \quad (9)$$

Multinomial regression is conducted by taking a category as a reference. In this case, for the dependent variable, the reference category is the net balance of industrial establishments being greater than or equal to fifty (category 3).

For comparative discussion, a multilevel linear model was also estimated for the net balance of industrial establishments in each mesoregion for each period (Raudenbush and Bryk 2002). The specification of the linear model is represented in Eq. 10:

$$\begin{aligned} \text{Industrial}_{\text{net}ij} = {} & \beta_0 + \beta_1.\text{Tec}h_{\text{medH}ij} + \beta_2\text{Tec}h_{\text{medL}ij} + \beta_3\text{Tec}h_{\text{low}ij} \\ & + \beta_4\text{Edu}_{\text{null}ij} + \beta_5.\text{Edu}_{\text{elem}ij} + \beta_6.\text{Edu}_{\text{secon}ij} + \beta_7.\text{IHH}_{,ij} \\ & + \beta_8.\text{Distance}_{ij} + \beta_9.\text{Income}_{ij} + \beta_{10}.ln_{\text{GDP}ij} + u_{0j} + \epsilon_{ij} \end{aligned} \tag{10}$$

4.3 Database and variables

Our dependent variable will identify the dynamics of industries in a region during a given period and by technological level. Considering that we do not have the individual trajectory of each company—births, and closures—we will use a proxy that provides information about the aggregated process, including companies that remain installed and operational. This approach aligns with the studies developed by Figueiredo et al. (2002, 2003) and Guimarães et al. (2000, 2004). The two periods analyzed—2006 to 2014 and 2014 to 2019—were selected because they provide sufficient variability to perform the regressions while being contained enough to avoid multiple structural changes in the economy and the characteristics of the mesoregions. In the first period, Brazil experienced slight economic expansion, whereas in the second period, the national economy entered a crisis, resulting in a reduction in GDP and employment.

The data source for the dependent variable was the largest available database for Brazilian companies and industries: the Annual Social Information Report (RAIS). From this source, the balance of plants in the mesoregions was calculated for all twenty-four sectors of the manufacturing industry according to the National Registry of Economic Activities (CNAE 2.0). The net balance of industrial establishments for the two periods was calculated as the difference between the number of establishments from 2006 to 2014 and from 2014 to 2019. Specifically, it was calculated as the number of active industrial establishments in the final year minus the number of active establishments in the initial year, as shown in Eq. 11.

$$\textit{Net Balance} = \text{Establishments}_{t1} - \text{Establishments}_{t0} \tag{11}$$

This difference was grouped into four categories: negative net balance (category 0), zero net balance (category 1), positive net balance less than 50 (category 2), and positive net balance greater than or equal to 50 (category 3) (Table 1). These categories were adopted in both periods to facilitate comparison. The first period (2006–2014), characterized by greater stability, was used as the basis for adjustment.

Table 1 Detail of the dependent variable (category): net balance of industrial establishments in Brazilian mesoregions, during the periods of 2006–2014 and 2014–2019

Category	Net balance value
0	Balance <0
1	Balance $=0$
2	$0<$ Balance <50
3	Balance ≥ 50

Source: RAIS. Elaborated by the authors

4.3.1 a) First-level explanatory variables

In examining the first level, a set of binary variables was constructed to identify the technological intensity of the industries due to their different interests and production characteristics according to their technological standards. Firms with greater technological content demand more skilled labor, while more traditional sectors demand less skilled labor, hired at a lower cost (Hatzichronoglou 1997; Figueiredo et al. 2002, 2003; Guimarães et al. 2000, 2004; Arauzo-Carod and Viladecans-Marsal 2009; de Lima 2003; Passos and de Lima 1992; Staduto et al. 2008; Schettini 2010).

The technological levels classification of twenty-four sectors of the manufacturing industry—according to the National Classification of Economic Activities 2.0—were grouped into four categories: high, medium-high, medium-low, and low technology. This classification follows the OECD (2005) definition, which categorizes the technological levels of economic sectors based on the relationship between Research and Development (R&D) expenditure and added value, as well as the integration of technology in the procurement of intermediate and capital goods (see Appendix 1).

4.3.2 b) Second-level explanatory variables

On the second level, variables suggested by the literature were considered on a regional scale. The unit of mesoregions was chosen because smaller sampling units, such as micro-regions or municipalities, would not provide sufficient variability in the net balance of industrial establishments. This is due to significant gaps throughout the country caused by high concentrations of population and production in metropolitan regions, particularly in the Southeast and South of Brazil (Cano 2008; Rocha and de Moura 2017; Rocha and Araújo 2021). The mesoregional scale is also small enough to capture the diverse location alternatives in Brazil.

The independent variables are associated with locational factors, as identified in the literature. According to Blair and Premus (1987) and Badri (2007), the factors influencing location decisions can be divided into two broad groups: factors that influence a firm's costs and factors that influence revenue. Variables to capture these two factors were selected based on previous studies.

a. Cost of labor: This dimension was estimated through the mean earnings of employees (salary) and expressed in terms of the number of minimum wages. The mean earning is calculated for formal jobs in the manufacturing industry, being a variable that usually characterizes the cost of labor for each mesoregion (Passos and de Lima 1992; Staduto et al. 2008; Schettini 2010).

b. Transportation costs: Several authors suggest that the industry chooses a location that will minimize these costs (Weber 1929; Hoover 1948; Greenhut and Greenhut 1975; Hoover and Giarratani 1999; Vulevic 2016; Gallo et al. 2020). For this variable, the travel distances between markets were estimated. The municipalities with the highest GDP in each mesoregion were considered the economic and non-geographic central points of the mesoregions because they generally have a greater population and density of services supplied (Crocco et al. 2006; Garcia 2007). In the case of Brazil, this central area would be the capital of each Federation Unit. After defining the central areas, these distances were weighted to correct measurement biases. A mesoregion may be associated with a small transportation cost—due to a shorter distance—concerning the market area of its administrative capital; alternatively, this proxy of distance may have small values because this market area may have little participation in the total national product (Eq. 12), namely:

$$\mathrm{proxydistance}_{ij} = \frac{StateCapitalGDP}{NationalGDP}.\mathrm{distance}_{ij} \tag{12}$$

Where: i are the mesoregions and j are the capitals of Brazilian states. $Distance_{ij}$ is the road distance measured in kilometers from mesoregion i to state capital j. Therefore, more distant state capitals weigh positively on distance costs.

c. Skill of the workforce: Many empirical works, including those using primary data sources, point to the importance of a qualified workforce for industries (Blair and Premus 1987; Badri 2007; Larsen and Hansen 2022). Mesoregions with skilled labor are more attractive; therefore, we used the proportion of employees with a certain level of education k for each mesoregion (Eq. 13).

$$P_{ki} = \frac{\mathrm{Numberofemployees}_{ki}}{\mathrm{TotalNumberofemployees}_{i}} \tag{13}$$

Where: k denotes the education level and i the mesoregion; P_{ki} is the proportion of employees in the mesoregion to hold a certain level of education k. The education levels were divided into illiterate, elementary, high school, and higher education.

d. Agglomeration: Economic agglomerations have effects on urban-industrial wages and affect the growth of regions. However, there is no consensus among agglomeration theories that these effects are caused by external economies of productive specializations, urban agglomeration, or productive diversification (Guimarães 2000; Florida 1994; Galinari et al. 2007; Arauzo-Carod et al. 2010; Dalberto and Staduto 2013; Tao et al. 2019; Raiher 2020). We used the adjusted Hirschman-Herfindahl Index (HHI), which is based on the variability of productive specialization among the mesoregions (Dalberto and Staduto 2013; Naldi and Flamini

2018; Haron et al. 2021). It is calculated using Eq. 14:

$$\mathrm{HHI}_i = \sum\nolimits_{j=i}^{n} \left[\left(\frac{E_{ij}}{E_i} \right) - \left(\frac{E_j}{E_p} \right) \right] \quad (14)$$

The factors in Eq. 14 are as follows:

- E_{ij} is employment in mesoregion i in sector j.
- E_i is the total number of industrial jobs in mesoregion i.
- E_j is the national employment in sector j.
- E_p is the total number of industrial jobs in Brazil.
- $n = 1, 2, 3,..., 24$ are the industrial sectors.

The adjusted HHI varies between 0 and 2. If HHI is equal to zero, any mesoregion i will be considered perfectly diversified. For an HHI equal to 2, the opposite will occur, i.e., the mesoregion will be fully specialized (Galinari et al. 2007; Dalberto and Staduto 2013).

e. Market size: According to Hotelling (1990), firms tend to be located in the centers of their respective market areas, benefiting from strategic decisions aimed at optimizing revenue. GDP is a proxy for market size (Jaumotte 2004; Shan, et al. 2018). Markets follow the hierarchical structure between cities and regional poles (Esparza and Krmenec 1996). In Brazil, this structure has remained stable over time, despite the number of municipalities that have been created (Simões and Amaral 2011; Dalberto and Staduto 2013; Agnoletti et al. 2015). This is why the 2010 GDP data was used to reflect this stability between markets. Thus, the higher the GDP of a region, the greater the probability of that region hosting an industrial location as well as investments (Jaumotte 2004; Shan et al. 2018). Therefore, we used the mesoregional GDPs transformed by their natural logarithms.

Table 2 describes the explanatory variables of level 2, accompanied by a brief comment. The data sources used to extract the explanatory variables were: i) The IPEADATA database, published by the Institute of Applied Economic Research;

Table 2 Description and Sources of explanatory variables at level 2

Variable	Description	Source
Edu_null	Proportion of illiterate employees	RAIS
Edu_elem	Proportion of employees with elementary education	RAIS
Edu_secon	Proportion of employees with secondary education	RAIS
Edu_col	Proportion of employees with a college education	RAIS
HHI	Adjusted Hirschman-Herfindahl Index	RAIS
Distance	Distance index (a proxy for transport costs)	Google Maps
Salary	Mean earnings in manufacturing as a multiple of the minimum wage	RAIS
Market	Mesoregional GDP logarithm (a proxy for market size)	IPEA

Source: RAIS. Elaborated by authors

ii) Google Maps (2021) for data on distances, which have been calculated by the authors using the reported distances in kilometers along roads between departure and arrival points for each pair of municipalities; and iii) The Annual List of Social Information (RAIS) published by the Ministry of Labor and Employment.

5 Empirical evidence of determinants of industry net balance variations in Brazil (2006–2014 and 2014–2019)

5.1 Different periods in the Brazilian economy: 2006–2014 and 2014–2019

Table 3 shows the descriptive statistics for the two analyzed periods. Overall, economic variables performed worse in the second period, particularly the net balance of industrial establishments and income. On the other hand, structural variables such as education showed improved statistical performance.

Figure 1 shows the total net balance of industrial establishments per Brazilian mesoregion for the two periods studied. Net balance in these maps is not classified using the categories from the model. Instead, values are grouped by mesoregions, with each mesoregion having a single net balance of industrial establishments. The classification method that allowed for better understanding and visualization was the natural break. The map effectively reflects the deep economic crisis Brazil faced between 2014 and 2019. Although the negative balance was widespread across the country, it was more intense in the South and Southeast regions, where the majority of the Brazilian population and industrial activities are concentrated.

Table 4 summarizes the net balance of industrial establishments by technological intensity and major region of Brazil. The data confirm a significant loss of industrial

Table 3 Descriptive statistics of the variables studied

Variable	2006–2014				2014–2019			
	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max
Balance	24.99	79.34	–305	1662	–10.69	75.67	–2615	365
Balance(categories)	1.62	0.94	0	3	0.77	0.90	0	3
Balance_Cat0	0.182	0.386	0	1	0.528	0.499	0	1
Balance_Cat1	0.156	0.363	0	1	0.184	0.387	0	1
Balance_Cat2	0.523	0.499	0	1	0.273	0.446	0	1
Balance_Cat3	0.139	0.346	0	1	0.015	0.121	0	1
Edu_null	0.005	0.005	0.0006	0.0494	0.005	0.004	0.0002	0.035
Edu_elem	0.255	0.056	0.129	0.394	0.19	0.049	0.080	0.301
Edu_secon	0.541	0.049	0.433	0.683	0.56	0.046	0.453	0.682
Edu_col	0.199	0.046	0.095	0.332	0.239	0.056	0.149	0.456
Salary	2.42	0.67	1.60	5.55	2.32	0.58	1.58	5.17
HHI	0.129	0.097	0.024	0.563	0.124	0.102	0.019	0.700
Distance	5.68	11.63	0	66.01	5.68	11.63	0	66.01
Market	15.43	1.21	12.39	19.62	15.43	1.21	12.39	19.62

Note: *MW* Minimum Wage

Source: RAIS. Elaborated by the authors

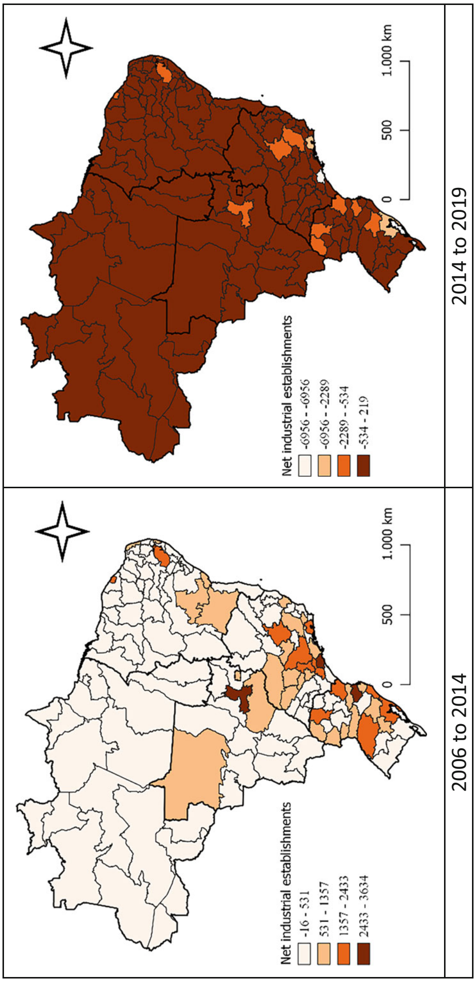

Fig. 1 Net balance of industrial establishments distributed by Brazilian mesoregions for the periods 2006–2014 and 2014–2019. Source: RAIS. Elaborated by the authors

Table 4 Net balance of industrial establishments by the level of technological intensity and major region

Region	Net Balance from 2006 to 2014				Net balance from 2014 to 2019			
	High	Medium-high	Medium-low	Low	High	Medium-high	Medium-low	Low
North	240	248	1494	1033	–113	–113	–267	–839
Northeast	1148	820	6124	8844	–309	–345	–1197	–3154
Midwest	470	689	4021	4160	–179	–64	–115	–1514
Southeast	696	2738	12,539	13,335	–1789	–1672	–3900	–9144
South	1109	2669	8846	10,933	–618	–473	–1079	–5967

Source: RAIS. Elaborated by the authors

establishments across all technological levels, especially in the South and Southeast regions from 2014 to 2019. In contrast, the initial period shows a positive net balance for all major regions and technological levels. Presenting and interpreting the data this way highlights the importance of dividing the analysis into two-time intervals.

5.2 Dynamics affecting the net balance of industrial establishments (2006–2014)

We can infer the existence of a random effect on the average net balance of industrial establishments, indicated by the statistical significance of the intercept in Table 5, that is, the two-level estimation was adequate. This approach controls for data dispersion, as significant differences exist in mesoregion characteristics according to technological intensity. Therefore, technological intensity influences the location of firms, with the location of Brazilian industries varying based on their technological intensity.

Table 5 shows that coefficients of the medium-high, medium-low, and low-technology companies were significant and lower likelihood for net balances less than zero compared to high-technology companies. Medium-low and low-technology companies, with significant and negative coefficients for net balances of zero and between zero and 50, had lower likelihood of these net balances compared to high-technology companies. Low and medium-low technology companies had a positive probability of having net balances greater than fifty, whereas high technology

Table 5 Multinomial and multilevel logit model for categories of net balance for industrial establishments in Brazil, 2006 to 2014

Explanatory variable	Dependent variable (Category 3 omitted)		
	Category 0: Balance <0	Category 1: Balance = 0	Category 2: 0 < Balance <50
Industrial level (High-technology omitted)			
Medium-high technology	–0.549***	–0.109	0.428
Medium-low technology	–2.03*	–2.750*	–1.865*
Low technology	–1.290*	–2.022*	–1.189*
Mesoregional Level			
Edu_null	4.475	14.698	15.992**
Edu_elem	3.015	2.816	2.607
Edu_secon	6.332**	6.249**	5.824*
HHI	2.327***	3.595*	2.127***
Distance	0.007	0.001	0.003
Salary	0.871***	1.128***	0.821***
Market	–0.873***	–2.093***	–1.1471***
	Level 1 coefficient	Level 2 coefficient	
Intercept 1(0)	0.935***	0.983***	
Intercept 1(1)	0.388***	0.353*	
Intercept 1(2)	2.043***	2.098***	

Note: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. LogLikelihood = –0.27712

Source: RAIS. Elaborated by the authors

Table 6 Probability results for each level of technological intensity, 2006 to 2014

Intensity level	Category 0	Category 1	Category 2	Category 3	Sum
Low	0.353	0.088	0.212	0.344	*1.000*
Medium-low	0.241	0.114	0.266	0.379	*1.000*
Medium-high	0.291	0.207	0.176	0.325	*1.000*
High	0.331	0.280	0.198	0.190	*1.000*

Source: RAIS. Elaborated by the authors

companies had a lower probability of such high net balances. This suggests that low to medium-low technology companies were more likely to expand during the most dynamic period. However, low and medium-low technology industries have lower capital intensity and are mostly associated with labor-intensive transformation industries of the agricultural and livestock chains (Santos 2014). In Brazil, an accelerated deindustrialization process is particularly affecting high-technology companies (Oreiro and Feijó 2010; Koeller et al. 2016; Souza and Veríssimo 2019).

The probability matrix of each technological intensity level having each of the four types of net balances is given in Table 6 (derived from Table 5). The results indicate that industrial segments with a greater probability of a positive net balance or a net balance greater than 50 between 2006 and 2014 were the least technology-intensive. This was expected since these establishments require less initial capital and are associated with the transformation chains of agricultural and livestock products. Other studies (e.g., Schettini 2010) support this finding, showing greater growth of low and medium-low technology industries in Brazilian mesoregions during this period.

At the second level, we explored the characteristics of mesoregions that explain the observed net balance of industrial establishments during the dynamic economic period (Table 5). Mesoregions with a higher proportion of illiterate workers were more likely to have net balances above zero and below 50 units (category 2) compared to those with net balance exceeding 50 units, as well as compared to those employing a greater proportion of workers with higher education. Medium-high and high-technology industries tend to be located in the latter mesoregions, while low and medium-low-technology industries are found in mesoregions with a higher proportion of illiterate workers. In mesoregions with a higher proportion of workers with primary education, the coefficients were not significant. However, mesoregions with a higher proportion of workers with secondary education showed a higher probability of having negative, zero, or less than 50 net balances, and a lower probability of net balances greater than 50 compared to mesoregions with a higher proportion of workers with higher education. Mesoregions with more workers with higher education are more likely to have net balances greater than 50.

The significant coefficient of the HHI variable reveals that agglomeration economies impact the net balance of industrial establishments. The positive coefficient for categories 0, 1, and 2 indicates that the probability of a negative, zero, or positive net balance of less than 50 units increases with the HHI coefficient. Conversely, an increase in the HHI coefficient reduces the probability of a net balance greater than 50. In most mesoregions, specialization economies predomi-

Table 7 Multilevel linear regression model results for variations in net balance for industrial establishment in Brazil, 2006 to 2014

Explanatory variable	Coef	Z	*P*>z
Technology level (High-technology omitted)			
Medium-high technology	0.56	0.60	0.546
Medium-low technology	1.37	1.10	0.272
Low technology	0.85	0.81	0.419
Mesoregional Level			
Edu_null	21.04	2.08	0.038
Edu_elem	–3.49	–3.18	0.001
Edu_secon	–2.14	–2.03	0.042
HHI	–0.27	–0.67	0.506
Distance	–0.00	–0.35	0.729
Salary	–0.46	–5.75	0.000
Market	0.63	4.29	0.000
Constant	923.83	214.26	0.000

Source: RAIS. Elaborated by the authors

nate, with little evidence of productive diversification (Dalberto and Staduto 2013; Raiher 2020), particularly in the interior regions where most industries are low and medium-low technology (Dalberto and Staduto 2013; Schettini 2010). Deindustrialization is more pronounced among high-technology industries, which tend to be located in the oldest industrialized mesoregions, particularly in the South and Southeast regions' metropolitan areas (Fig. 1).

The results for transportation costs are also noteworthy. It was expected that greater distances from market areas would increase transportation costs and negatively impact the number of industries in a region. However, the coefficients for this variable were not significant. This result does not necessarily indicate a zero impact of transportation costs on industrial location decisions in Brazil. It may reflect a failure of the variable to accurately represent real transportation costs or the possibility that industrial establishments primarily serve local markets, making transportation costs less relevant. An alternative transportation cost proxy, the distance of each mesoregion from São Paulo, dynamic center of the country, was tested but also yielded non-significant results and worsened the model's fit.

Significant and positive coefficients for the salary variable in the three net balance categories (0, 1, and 2) show that mesoregions with lower average wages are more likely to have a net balance greater than or equal to 50 (category 3). This suggests that, in Brazil, industrial locations tend to favor mesoregions with lower wages, aligning with profit maximization studies that indicate a trade-off between low cost and skilled labor (e.g., Walker 1989; Florida 1994).

Market area size (measured by regional GDP) was found to be statistically significant (Head and Ries 1996). Mesoregions with higher GDP values are less likely to have a negative or zero net balance. The largest markets are in the South and Southeast regions, which have greater productive and population agglomerations.

Next, we compare the estimates in Table 5 with the multilevel linear regression results in Table 7. Table 7 presents the results of Eq. 10 with more robust analyses. Once again, the importance of the market area's effect (suggested by the logarithm of regional GDP) on identifying higher net balances of industrial units is noted. Additionally, mesoregions with lower levels of education had worse net balances, confirming that skilled labor is crucial in firm location decisions, as found in studies applied to Japan, the United States, Portugal, France, and China (Florida 1994; Figueiredo et al. 2002, 2003; Guimarães et al. 2000, 2004; Wu and Liu 2021). Higher salaries corresponded to lower net balances of industrial establishments, corroborating the observations in Table 5.

The results in Tables 5 and 7 indicate a higher probability of a greater net balance of industrial establishments in mesoregions characterized by higher GDP. This is supported by theoretical bases suggesting industries are attracted to regions with large local markets (Krugman 1992; Fujita et al. 2001; Hanson 1998, 2005; Flanagan et al. 2023).

Summarizing the evidence on technological intensity, low, medium-low, and medium-high technologically intensive industries were the most dynamic in industrial creation across Brazilian mesoregions during the observed period.

5.3 Dynamics of net balance in industrial establishments (2014–2019)

We conducted the empirical analysis described in Sect. 5.2 again in this Sect. 5.3, this time focusing on data from the 2014–2019 period. The adequacy of the two-level estimation was confirmed (Table 8). We can deduce the presence of a random effect on the average net balance of industrial establishments, as evidenced by the statistical significance of the regression intercept shown in Table 8.

Companies in medium-high technology industries were less likely to report a net balance between zero and fifty and more likely to exceed fifty than those in high-technology sectors. Additionally, firms in low-technology intensity industries demonstrated a lower likelihood of achieving a net balance of zero, suggesting a higher probability of exceeding fifty compared to high-technology industries. This pattern indicates that the Brazilian economic crisis has impacted high-technology companies most severely. However, it has also affected industries across low, medium-low, and medium-high technology sectors (see Fig. 1). High-technology companies were already experiencing a structural decline; however, industries that are less technology-intensive and more labor-intensive were facing a worrisome yet slower decline. Part of this industrial contraction may be attributed to the economic crisis, reflecting the adverse situation (Morceiro and Guilhoto 2019; Araujo et al. 2023).

Table 9, derived from Table 8, describes the probability matrix for each level of technological intensity across the four types of net balances. The results indicate that industrial segments with the highest probability of a positive net balance exceeding fifty in Brazilian mesoregions, between 2014 and 2019, were medium-low and medium-high technology-intensive industries. In contrast, low and high-technology-intensive industries had the worst net balances during the crisis period.

At the second level, we examined the characteristics of mesoregions that explain the observed net balance of industrial establishments during the crisis period. Education did not significantly influence the net balance of industries in times of economic slowdown, except for the variable representing the proportion of employees with an

Table 8 Multinomial and multilevel logit model for categories of net balance for industrial establishments in Brazil, 2014 to 2019

Explanatory variable	Dependent variable (Category 3 omitted)		
	Category 0: Balance <0	Category 1: Balance = 0	Category 2: 0 < Balance <50
Industrial level (High-technology omitted)			
Medium-high technology	–0.111	–0.452	–0.614***
Medium-low technology	0.153	–1.198	–0.353
Low technology	0.026	–1.368*	–0.473
Mesoregional Level			
Edu_null	4.485	12.628	4.222
Edu_elem	–1.744	–1.097	–2.404*
Edu_secon	–0.879	–0.613	–0.582
HHI	–0.879**	1.649**	1.239**
Distance	–6 × 10^(–5)***	–2 × 10^(–5)	7 × 10^(–5)
Salary	–86.375	3.076	40.755
Market	0.577***	–1.149***	0.116
	Level 1 coefficient	*Level 2 coefficient*	
Intercept 1(0)	0.558***	0.887**	
Intercept 1(1)	0.388***	0.518*	
Intercept 1(2)	0.044**	0.097***	

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. LogLikelihood = –1260.071
Source: RAIS. Elaborated by the authors

Table 9 Probability results for each level of technological intensity, 2014 to 2019

Intensity level	Category 0	Category 1	Category 2	Category 3	Sum
Low	0.200	0.116	0.606	0.079	1.000
Medium-low	0.161	0.077	0.178	0.584	1.000
Medium-high	0.097	0.047	0.115	0.741	1.000
High	0.144	0.224	0.383	0.249	1.000

Source: RAIS. Elaborated by the authors

elementary school education, which significantly affected the net balance greater than zero and less than 50 (category 2) with a negative sign.

The HHI was significant for the three net balance categories, underscoring the importance of agglomeration economies even during the crisis. However, the insights from this dataset differ from previous ones. The negative coefficient for negative balances and positive coefficients for zero and between zero and 50 reveal a greater probability of specialized mesoregions were less impacted by the economic crisis. In Brazil, the specialization economy is prevalent across mesoregions, as noted by Galinari et al. (2007), Dalberto and Staduto (2013), Lira (2016), and Raiher (2020). Raiher (2020) noted that low and medium-low technology industries dominate 77% of Brazilian municipalities, indicating that these mesoregions specialize predominantly in primary products requiring low levels of capital. Furthermore, these regions are linked to global value chains, which were not affected by the economic crisis during this period, as the crisis was predominantly domestic.

Table 10 Multilevel linear regression model results for variations in net balance for industrial establishments in Brazil, 2014 to 2019

Explanatory variable	Coef	Z	*P*>z
Technology level (High-technology omitted)			
Medium-high technology	1.545	0.20	0.844
Medium-low technology	32.214	1.71	0.087
Low technology	19.668	1.53	0.127
Mesoregional Level			
Edu_null	168.130	0.85	0.394
Edu_elem	–50.077	–3.58	0.000
Edu_secon	10.889	0.28	0.776
HHI	36.312	1.59	0.112
Distance	–0.001	–1.24	0.217
Salary	–10.032	–2.81	0.005
Market	23.313	3.06	0.002
Constant	–323.024	–2.50	0.013

Source: RAIS. Elaborated by the authors

The variable measuring distance only showed a significant and negative coefficient for the negative net balance category, despite its small magnitude (close to zero). Conversely, market size (measured by the log of regional GDP) was an important variable during the economic crisis, as it increased the probability of a negative net balance (category 0) in mesoregions with large markets, indicating the highest number of firm failures during these periods. These companies are concentrated in the wealthiest areas of Brazil, namely the metropolitan mesoregions of the South and Southeast (Lira 2016; Raiher 2020).

Following the analytical pattern discussed in relation to Table 5, where estimates were compared with their multilevel linear regressions from Table 7 for the period 2006 to 2014, we now compare the results of Table 8 with the regressions in Table 10 for the period 2014 to 2019. Table 10 presents the outcomes of estimating Eq. 10 using data from 2014 to 2019, affirming the continued significance of medium-low technologically intense industries, as observed in the earlier period. During this time, mesoregions supported by workers with primarily elementary education reported poorer net balances compared to those with a higher proportion of more educated workers, reinforcing the findings from Tables 5 and 8, and 9. The salary coefficient was significant and negative, suggesting that higher wages in mesoregions correlate with lower net balances of industrial establishments, highlighting labor costs as a critical factor in the decision to maintain or close these entities.

The importance of market size (logarithm of regional GDP) is underscored once again, showing higher net balances in the observed mesoregions (Table 10). However, these results do not align precisely with those in Table 8, possibly due to the disaggregation by net balance category affecting the outcomes. Additionally, mesoregions in the South and Southeast regions of Brazil, which host the largest markets, are the most complex and diversified, housing a broad spectrum of industries across all technological levels. In contrast, mesoregions in other areas predominantly feature specialization economies with a prevalence of low and medium-low technological-level industries.

6 Final considerations, implications, and future work

Our primary goal was to examine the influence of technological intensity on new firm creation across two distinct periods in Brazil, using the net balance of industrial establishments as a proxy. These periods range from 2006 to 2014, a time of economic growth, and from 2014 to 2019, marked by economic contraction. We utilized multinomial and multilevel probabilistic logit models, along with multilevel linear regressions, to analyze determinants at two levels: technological intensities and mesoregional characteristics. Despite previous literature often overlooking the role of technological intensity in industrial dynamics, our findings indicate that industries with varying technological intensities possess different capacities to navigate economic cycles.

Previous studies encountered challenges with smaller geographic units due to the increased likelihood of unobservable location characteristics. Therefore, researchers have frequently responded by working with smaller samples or using aggregated data, which unfortunately omits valuable information and leads to less efficient estimates. Our methodological approach mitigates these issues, enabling more realistic scenario analyses.

Moreover, controlling for factors that influence location at both the industrial and mesoregional levels enhances the accuracy of parameter estimates and facilitates analysis of how explanatory variables at one level affect those at another. Technological levels significantly impact industrial location, with variations evident across different mesoregions. Overlooking the multilevel structure of these relationships can lead to biased estimates. A key contribution of this study is demonstrating the importance of technological intensity in locational decisions within industries.

Despite its specific focus on Brazilian mesoregions, a major contribution of this study is the demonstration that technological intensity is crucial. It influences the capacity for new firm creation across regions, attributes of industrial resilience, and the effects of industrial policies. According to our multinomial and multilevel regression analyses, low to medium-low technology companies were more likely to expand during the dynamic period. Conversely, the Brazilian economic crisis disproportionately affected high-technology companies, though it also impacted industries across low, medium-low, and medium-high technology levels. There was an ongoing structural decline in high-technology industries, while less technology-intensive and more labor-intensive companies faced a slower decline. This industry contraction may reflect the broader economic downturn.

The main findings from the second level of our multinomial and multilevel probabilistic logit models indicate that industries are more often established in regions with more qualified labor and lower labor costs. Agglomeration economies play a significant role in the dynamics of manufacturing industries, with specialization exerting a strong influence on industrial location within Brazil. During the 2014–2019 crisis period, the industrial sector in diversified mesoregions exhibited greater resilience. Market size also emerged as a crucial factor for industrial location. Mesoregions with higher GDP are more likely to have a greater net balance of industrial establishments, particularly during economic growth periods.

We propose four avenues for future research. First, we suggest estimating multi-level ‘ordered logit’ regressions for the ordinal variables that classify the different net balances of industrial units by period. This approach would provide more detailed insights than those presented here. Second, we recommend expanding the database to include periods before 2006 as soon as official sources permit, allowing us to explore additional dimensions. Third, conducting spatial regression analyses with the data collected would help determine the influence of similar and dissimilar features in the surrounding areas on observed dynamics. The geographic characteristics of this study, specifically the location of firms across various mesoregions, highlight the need for an in-depth analysis of spatial dependence. Spatial dependence is frequently observed in location models and can significantly impact the accuracy of statistical models that do not account for it. Enhancing the spatial analysis approach could refine our understanding of firm location patterns in Brazilian mesoregions. Additionally, numerous studies emphasize the importance of spatial autocorrelation in this research field. Thus, it is widely agreed upon that including spatial lag variables in future models is crucial, following a thorough literature review of discrete models and spatial analysis to ascertain the relevance of incorporating these dimensions into the current model.

7 Appendix

Table 11 Classification of twenty-four sectors within the manufacturing industry based on technological intensity

High Technology	Manufacturing of Pharmachemicals and Pharmaceutical Products
	Printing and Reproduction of Recorded Media
	Manufacture of IT, Electronic, and Optical Products
Medium-high Technology	Manufacturing of Electrical Machines, Devices, and Materials
	Manufacturing of Machinery and Equipment
	Manufacturing of Motor Vehicles, Trailers, and Bodies
	Manufacturing of Chemicals
	Manufacturing of Other Transport Equipment, Except Motor Vehicles
Medium-low Technology	Maintenance, Repair, and Installation of Machinery and Equipment
	Manufacturing of Rubber and Plastic Products
	Manufacturing of Coke, Petroleum Products, and Biofuels
	Manufacturing of Non-Metallic Mineral Products
	Manufacturing of Metal Products, Except Machinery and Equipment
	Metallurgy
Low Tech	Manufacturing of Miscellaneous Products
	Manufacturing of Pulp, Paper, and Paper Products
	Manufacturing of Wooden Products
	Manufacturing of Food Products
	Manufacturing of Beverages
	Manufacturing of Tobacco Products
	Manufacturing of Textile Products
	Production of clothing items and accessories
	Preparation of Leather and Manufacture of Leather Articles, Travel Articles, and Footwear
	Manufacturing of Furniture

Source: National Classification of Economic Activities 2.0. Clustering based on OECD criteria

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