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Spatial location and agglomeration economies in exports: empirical evidence by technological intensities in Brazil

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ABSTRACT
This study investigates spatial autocorrelation and the formation of spatial export clusters of Brazilian mesoregions based on technological intensity. It also analyzes how regional knowledge and agglomeration economies explain regional exports, using spatial econometric techniques. Brazilian exports exhibit a stronger spatial autocorrelation. Non-manufacturing sectors, which are less technology-intensive, exhibit lower spatial dependence than manufacturing sectors. The results also show an autocorrelation between exports and R&D expenditure, identifying the formation of clusters in the southeastern and southern regions. R&D expenditure fosters the growth of regional exports and the spatial lag effects of exports and R&D expenditure are significant in the high technology-intensive manufacturing sector.

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Agglomeration economies; exports; R&D expenditure; spillovers

1. Introduction

Agglomeration economies and knowledge spillovers have been used as a theoretical framework to explain the process of economic growth based on their impact on firm productivity (Audretsch & Feldman, 2004; Döring & Schnellenbach, 2006). They are based on the geographical proximity of economic activities and on the possibility of interaction and knowledge transfer among agents, as well as on other locational advantages called externalities (Fugita et al., 2002; Krugman, 1991; Marshall, 1961). Moreover, knowledge exchange between workers and firms, especially through interactive learning, enables technological innovation (Lundvall, 1992).

Thus, one of the determinants of technological innovation is proximity. Firms which are closer to sources of knowledge are able to innovate faster than firms that are further away as they can absorb the knowledge that is shared through the informal exchange of ideas between economic agents (Lambooy, 2010; Storper & Venables, 2004). Externalities that promote the adoption of new technologies are also more important at the regional level than at the national level and depend positively on the proximity of firms (Baptista, 2000). Moreover, social and relational proximity are important channels of knowledge dissemination and generate synergies that drive

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regional growth (Basile et al., 2012). A distinctive feature of relationships between economic agents is that they are not limited by regional administrative boundaries. As for the agglomeration economies resulting from the link between R&D and production, including exports, they are also likely to cross these borders (Coe & Helpman, 1995; Guastella & van Oort, 2015).

By exploring the spatial dimension of exports and R&D, this paper first examines spatial autocorrelation and formation of spatial export clusters of Brazilian mesoregions based on technological intensity. It also examines how regional knowledge and agglomeration economies explain regional exports, using spatial econometric techniques. Regions with higher export concentration are expected to have a greater capacity to form spatial clusters, which may vary depending on the technological intensity of the sectors. Furthermore, a positive spatial autocorrelation between exports and R&D expenditure is expected, with knowledge spillovers crossing administrative boundaries and spreading to neighboring regions, leading to different dynamics between regions.

While many studies have tried to establish a link between innovation and exports at the country level, little is known about this relationship (1) across location of exports within a country (i.e., at regional level), (2) by technological intensity of the export structure, (3) especially in developing countries. By analyzing the location of exports and R&D expenditure by technological intensity sector to characterize the pattern of regional concentration and whether there is a relationship between this pattern and R&D expenditure in 137 Brazilian mesoregions, this study contributes to expanding the range of empirical regional studies and international trade in this issue. In recent years, the structure of Brazilian exports has changed requiring new studies on the determinants of these exports with updated data, since the advantages acquired by firms/regions in international trade are always temporary in terms of technological issues.

Using data on 137 Brazilian mesoregions between 2008 and 2021 and the recent OECD taxonomy of economic activities based on R&D intensity (Galindo-Rueda & Verger, 2016), which includes not only manufacturing but also services, we found that Brazilian exports exhibit spatial autocorrelation. Non-manufacturing sectors (less technologically intensive) exhibit lower spatial dependence than manufacturing. Mesoregions with higher exports of high-manufacturing goods are surrounded by neighboring mesoregions with high R&D expenditure, hinting at the existence of a cluster in the southeastern and southern regions. Finally, using spatial econometric techniques, we found spatial spillover effects of exports (i.e., knowledge diffusion about foreign markets) and R&D expenditure between neighboring regions in the high manufacturing sector. Naturally, these results must be interpreted with caution due to limitations of the study, as there are few variables at the mesoregion level that allow for the best proxy of stock of knowledge and the choice of spatial weighting matrix.

The remainder of the paper is organized as follows. Section 2 provides a brief discussion on agglomeration economies, highlighting the externalities that may arise and the potential knowledge spillover and innovation. Section 3 describes the data source and empirical methodology employed, namely exploratory spatial data analysis and spatial panel data econometric techniques. Section 4 analyzes and discusses the results. The patterns of spatial distribution and clustering of Brazilian exports by technological intensity as well as their spatial relationship with R&D expenditure are highlighted. Finally, Section 5 underscores the main conclusions and possible policy implications.

2. Agglomeration economies, regional knowledge and exports

The literature on agglomeration economies generally highlights the advantages of closely located firms that lead to external economies, in particular productivity growth at the firm level, production growth at the sectoral and regional level, which ultimately foster regional economic growth (van Oort et al., 2012). The benefits can result, first, from internal economies of scale at the firm level, and second, from the scale of geographical concentration of industries, which not only favors internal economies of firms, but also enables external economies (Fugita et al., 2002; Galinari & Lemos, 2007; Hoover, 1937; Jones & Jordan, 2019). As a result, agglomeration economies have become an important element in studies on the location of economic activity (Krugman, 1991). Moreover, the space (within and between geographic areas) seems to determine the performance of firms/regions (Duschl et al., 2015; Tsvetkova et al., 2020).

Agglomeration economies may have origin in the spatial concentration of firms belonging to the same industry, specialization or localization economies, or from the variety and diversity of local economic activities, urbanization or diversity economies. Formal or informal contacts between firms and their workers belonging to the same industry foster productivity gains that are likely to be higher in regions where the industry is more concentrated, the so-called specialization economies (Hoover, 1937). At the local level, supplier-user link occurs due to the specialization in similar or complementary segments of the production process supplying raw materials, goods, and intermediate services.

Geographic proximity also reinforces intensive knowledge spillovers through the exchange of technical and organizational information between firms (Marshall, 1961). Externalities can also arise from the diversity of economic activities, called urbanization or diversity economies (Hoover, 1937). Diversification allows for more creativity and the exchange of information and experience between local industries (Bracalente et al., 2008; Galinari & Lemos, 2007; Góis Sobrinho & Azzoni, 2014).

Knowledge spillovers arise from non-market interactions (Fujita & Thisse, 2013). Therefore, geographical proximity can also be a decisive factor for knowledge exchange and collaborative innovative activities. In this context, the concept of *milieu innovateur*—i.e., a complex network of social and productive relationships in a limited geographical area that intensifies local innovation capacity and productivity growth through collective learning processes – is more meaningful (Camagni, 1991; Capello et al., 2011). Studies show that regions with greater concentration of economic activities and with institutional assets, such as universities, research laboratories and other knowledge organizations, even if not directly linked, are more likely to accelerate knowledge and innovation transfer not only within the region but also to neighboring regions (Kauffeld-Monz & Fritsch, 2013; Zhou et al., 2019). Capello and Lenzi (2013, 2015) have shown that innovation impacts the economic performance not only of those regions with a higher intensity of scientific knowledge creation but also neighboring regions.

It is reasonable to expect that the effects of agglomeration economies and knowledge spillovers also holds for exports. Since exports are key determinants of economic growth, countries adopt economic policies to promote them (Herzer & Nowak-Lehmann, 2006; Neves et al., 2016; Ribeiro et al., 2016). Therefore, it is important to study the spatial location pattern of exports and the formation of clusters, as well as the effects of agglomeration economies and knowledge spillover effects on these activities.

In the process of economic growth, more technology-intensive activities have a greater capacity for innovation and knowledge spillovers. Moreover, the higher the technological intensity content of exports, the larger the positive externalities for other sectors (Herzer & Nowak-Lehmann, 2006). de Almeida et al. (2022) also point out that industries' location patterns and their tendency to cluster vary according to their technological intensity. We have therefore our first hypothesis:

Hypothesis 1: The regional exports of high technology-intensive activities are spatially autocorrelated and form clusters, while the less technology-intensive activities are more randomly distributed.

Regions with an export agenda based on the regional innovative environment are better placed to maintain and expand their international competitiveness (Gama et al., 2018) and consequently achieve higher growth (Neves et al., 2016). Since innovation efforts are often identified as determinants of exports (Neves et al., 2016) and the formation of spatial agglomerations due to patterns of regional concentration and spillovers (Audretsch & Feldman, 2004; Fagerberg, 1996; López-Bazo & Motellón, 2018), our second hypothesis is as follows:

Hypothesis 2: There is a spatial autocorrelation between exports and R&D expenditure in Brazilian mesoregions, forming clusters of export regions with high innovation environment.

As we have seen, innovation impacts the economic performance not only of those regions with a higher intensity of scientific knowledge creation, but also neighboring regions (Capello & Lenzi, 2013, 2015). This brings us to our third hypothesis:

Hypothesis 3: In the high technology-intensive activities, R&D investments benefit not only the exports of own region, but also neighboring regions.

3. Empirical methodology

3.1. Database

The Ministry of Industry, Foreign Trade, and Services of the Brazilian Federal Government is our source of data on exports across 137 mesoregions in Brazil between 2008 and 2021.[1] Such data are provided in accordance with the Mercosur Common Nomenclature (NCM), which is based on the Harmonized Commodity Description and Coding System (HS). A correspondence table between the National Classification of Economic Activities (CNAE) and the NCM was used to match the data by technological intensity sectors (High, Medium-High, Medium and Medium-Low Manufacturing

[1] In 2019 this Ministry was transformed into a Secretariat under the Ministry of Economy.

sectors and also Medium-Low and Low Non-Manufacturing sectors), as proposed by Galindo-Rueda and Verger (2016).[2] Export values are originally reported in U.S. dollars. They were converted into Brazilian real using annual average exchange rates (IPEA-DATA) and deflated by the IGP-DI.[3]

We also used data on R&D expenditure provided by the *National Indicators of Science, Technology and Innovation*, Ministry of Science, Technology, Innovation and Communications, also covering the period 2008–2021.[4] They are in millions of Brazilian real and were deflated by the IGP-DI. However, the data are only available for the 27 Brazilian states (26 states plus the Federal District). To address this shortcoming, we used the mesoregion share of number of researchers and teachers in higher education in each of the 27 Brazilian states to allocate R&D expenditure proportionally among mesoregions.[5] The Frascati Manual (OECD, 2015) identifies research institutes and the higher education sector as critical elements in the innovation efforts of countries and regions. Moreover, the assumption of a high correlation between R&D expenditure and the number of R&D employees is supported by several research works (e.g., Rehman et al., 2020).

3.2. Exploratory spatial data analysis

Regional economic research has emphasized the critical role of spatial proximity by using the econometric technique of Exploratory Spatial Data Analysis (ESDA) to identify spatial autocorrelation and spatial heterogeneity (Anselin, 1988; Anselin et al., 2008; Florax & Nijkamp, 2004; Florax et al., 2003; Raiher et al., 2017; Vogel & Azevedo, 2015). Global Moran's I is the most commonly used test statistic for estimating global spatial autocorrelation of a variable (Anselin, 1996; Moran, 1950). The bivariate Moran's I statistic, in turn, tests the spatial relationship of a variable in a particular region with other variables in surrounding regions.

The Local Indicator of Spatial Association (LISA), also known as Local Moran's I, is used to calculate the individual contribution of each region to the overall Moran statistic. This disaggregated spatial indicator captures both spatial associations and heterogeneities (Miller, 2004). Local Moran's I can be interpreted as a measure of local spatial agglomeration and can be used to identify local clusters (where adjacent regions have similar attribute values) or spatial outliers (areas distinct from their neighbors) using the Moran scatter plot (Anselin, 1995).

Following the same methodology of previous studies (e.g., de Campos et al., 2023; Kopczewska et al., 2017), we have selected for each sector the spatial weight matrix (W) with the best Moran's I scores. Accordingly, we selected the spatial contiguity weight matrix of the Queen type for all technological intensity groups.[6]

[2]Correspondence tables can be found at: https://concla.ibge.gov.br.
[3]IGP-DI – general – centred - end of period – index (Aug. 1994 = 100) Frequency: Annual from 1944 until 2021. Source: Fundação Getúlio Vargas, Conjuntura Econômica – IGP (FGV/Conj. Econ. - IGP), http://www.fgv.br.
[4]The 2020 and 2021 values were obtained using autoregressive techniques of order 1. Source: https://www.mctic.gov.br/mctic/opencms/indicadores/indicadores_cti.html.
[5]The source of this data was RAIS (Annual Social Information Report) from the Ministry of Labor and Employment, based on the Brazilian Classification of Occupations (COB), codes 203 and 234 for Researchers and Higher Education Professors, respectively.
[6]Other nearest neighbor spatial weight matrices (3NN, 5NN, 7NN and 9NN) were also tested, but with less robust results than those obtained with chosen weight matrix (LeSage & Pace, 2014).

3.3. Empirical model and estimation strategy

To estimate the determinants of regional export growth at sector level, we assume that they can be explained by regional R&D expenditure and by two additional sources of knowledge attributable to agglomeration economies: (i) localization economies or intra-industry specialization economies (SPE), resulting from knowledge related to agglomeration of workers in the same sector in the same region[7]; and (ii) diversity economies (DIV), related to knowledge of workers in other sectors in the same region[8]; that is:

$$y_{irt} = \beta_{rd} rd_{rt} + \beta_{spe} spe_{irt} + \beta_{div} div_{irt} + Z_{rt} + \mu_{irt}, \tag{1}$$

where y_{irt} is the exports of sector i, region r, at time t; rd_{rt} is the (log) R&D expenditure, spe_{irt} and div_{irt} are the (log) specialization and diversity economies, respectively[9]; Z_{rt} is a set of control variables that includes size of region (proxied by region's real GDP in log form) and year dummies[10]; and μ_{irt} is the error term. (Table A1 in the Appendix shows the descriptive statistics of variables.)

To estimate the empirical model (1), considering that regional knowledge transmission is not limited by regional boundaries, we adopt an estimation approach that includes spatial interaction effects: endogenous interactions among the dependent variable (Wy), exogenous interactions among the explanatory variables (WX), and interactions among the error terms ($W\mu$). We have considered the following specifications derived from the general nested spatial model (Carreira & Lopes, 2020; Elhorst, 2014; O'Connor et al., 2018; Posada et al., 2018):

i) the *Spatial Durbin Model* (SDM):

$$y = \delta \ Wy + \alpha \ \iota_N + X\beta \ + WX\theta \ + \varepsilon \tag{2}$$

ii) the *Spatial Autoregressive Model* (SAR):

$$y = \delta \ Wy + \alpha \ \iota_N + X\beta \ + \varepsilon \tag{3}$$

iii) the *Spatial Error Model* (SEM):

$$y = \alpha \ \iota_N + X\beta \ + \mu, with\, \mu = \lambda \ W\mu + \varepsilon \tag{4}$$

The model selected is the one that best fits the data.

[7]Formally: $SPE_{irt} = \left(\frac{L_{irt}}{\sum_r L_{irt}}\right) / \left(\frac{\sum_i L_{irt}}{\sum_i \sum_r L_{irt}}\right)$, where L_{irt} is the number of workers in sector i, located in region r, at time t.

[8]Formally: $DIV_{irt} = 1/\sum_{i' = 1, i' \neq i} \left(\frac{L_{i'rt}}{L_{rt} - L_{irt}}\right)^2$, where $i' \neq i$ denotes other sectors.

[9]To address the problem of zero-valued observations (less than 0.05% of the observations), we replaced all zero values by 0.1 before taking the logarithm. We obtained similar results when we eliminated all zero observations.

[10]We also tested for region-specific effects, but these were found to be statistically insignificant in all specifications, which could be due to the fact that the effect is already controlled by the agglomeration and size variables (note that these variables, by definition, show little variation over time).

4. Empirical results and discussion

4.1. Spatial autocorrelation and export clustering

We used Moran's I statistics to examine the spatial autocorrelation of Brazilian exports by manufacturing and non-manufacturing technological intensity sectors. Overall, Global Moran's I is statistically significant and positive for all technological intensity sectors and for total exports, except in 2008, indicating spatial autocorrelation of exports across Brazilian mesoregions (Table 1).

The breakdown of exports by technology intensity shows that the High Manufacturing (HM) sector has the highest Global Moran's I value (except in 2016, 2018, 2020, and 2021), indicating a greater spatial dependence of exports in this sector than in other sectors. On the other hand, the lowest spatial autocorrelation values are observed in the Medium-Low Non-Manufacturing (MLNM) and Low Non-Manufacturing (LNM) sectors, meaning that export activities with lower technological content are more geographically spread across Brazilian mesoregions.

Thus, our results also confirm that the relationship between the location of exports and the level of technological intensity varies significantly. The OECD taxonomy (Galindo-Rueda & Verger, 2016), which provides a division between manufacturing and non-manufacturing sectors and then a subdivision within manufacturing, is therefore relevant for this type of study, as it allows a better identification and characterization of sectoral differences. Compared to other studies, we obtained Moran's I values in line with those of Raiher et al. (2017), who used a different classification, with a relatively high similarity in the technology-intensive sectors and the non-manufacturing sectors. The left graph in Figure 1 shows the Moran scatterplot and the right map the points of the regions on the scatterplot for exports from 2008 to 2021.

The spatial distribution pattern of Brazilian exports of the High-High type was observed in the southern regions of Brazil, in the state of Rio Grande do Sul with four mesoregions and in the southeastern region, particularly in the states of São Paulo with nine mesoregions and Minas Gerais with three mesoregions (see Tables A2, A3 and , A4 in the Appendix for a list of mesoregions). Thus, two major agglomerations of exports were identified, showing that mesoregions with high exports are surrounded by neighbors with also high exports, confirming the existence of spatial autocorrelation.

The formation of spatial clusters of the Low-Low type was observed in a much larger number of mesoregions, but they are also grouped in two large clusters. The first is located in the northern region of the country, in the states of Roraima with two mesoregions, Amazonas with two mesoregions, and Acre also with two mesoregions. The other agglomeration is located in the northeast, in the states of Rio Grande do Norte, Paraíba, Piauí and Bahia, each with one mesoregion, in the states of Ceará and Alagoas, each with two mesoregions, and in the states of Pernambuco and Sergipe, each with three mesoregions.

Besides the spatial autocorrelation patterns of the High-High and Low-Low types, the patterns of the High-Low type were found in the northern region, in the state of Amazonas with two mesoregions, and in the northeastern region, in the state of Alagoas with one mesoregion. The Low-High autocorrelation pattern was found in the south-eastern region, in the states of Minas Gerais and São Paulo, each with one mesoregion, and in the southern region, in the states of Paraná and Santa Catarina each also with one mesoregion.

Table 1. Global Moran's I for exports by technological intensity, 2008–2021.

	Technological intensity						
Year	HM	MHM	MM	MLM	MLNM	LNM	TOTAL
2008	0.036	0.040	−0.002	0.261***	0.026	−0.002	0.280***
2009	0.483***	0.414***	0.281***	0.381***	0.148***	0.295***	0.330***
2010	0.415***	0.384***	0.350***	0.326***	0.148***	0.303***	0.339***
2011	0.483***	0.425***	0.320***	0.328***	0.238***	0.347***	0.375***
2012	0.458***	0.326***	0.363***	0.375***	0.189***	0.271***	0.309***
2013	0.450***	0.362***	0.328***	0.317***	0.214***	0.332***	0.363***
2014	0.419***	0.307***	0.342***	0.302***	0.235***	0.315***	0.288***
2015	0.477***	0.319***	0.367***	0.401***	0.249***	0.250***	0.355***
2016	0.375***	0.323***	0.389***	0.282***	0.222***	0.246***	0.289***
2017	0.302***	0.242***	0.301***	0.262***	0.198***	0.157***	0.114***
2018	0.369***	0.373***	0.411***	0.298***	0.172***	0.320***	0.335***
2019	0.410***	0.367***	0.403***	0.322***	0.199***	0.302***	0.308***
2020	0.398***	0.364***	0.401***	0.389***	0.241***	0.295***	0.394***
2021	0.312***	0.429***	0.397***	0.406***	0.220***	0.299***	0.369***
2008–21	0.372***	0.394***	0.357***	0.360***	0.202***	0.320***	0.454***

HM: High technological intensity of Manufacturing; MHM: Medium-High technological intensity of Manufacturing; MM: Medium technological intensity of Manufacturing; MLM: Medium-Low technological intensity of Manufacturing; MLNM: Medium-Low technological intensity of Non-Manufacturing; LNM: Low technological intensity of Non-Manufacturing. Empirical pseudo-significance based on 999 random permutations. ***, ** and * statistical significance at the 0.01, 0.05 and 0.10 levels, respectively.

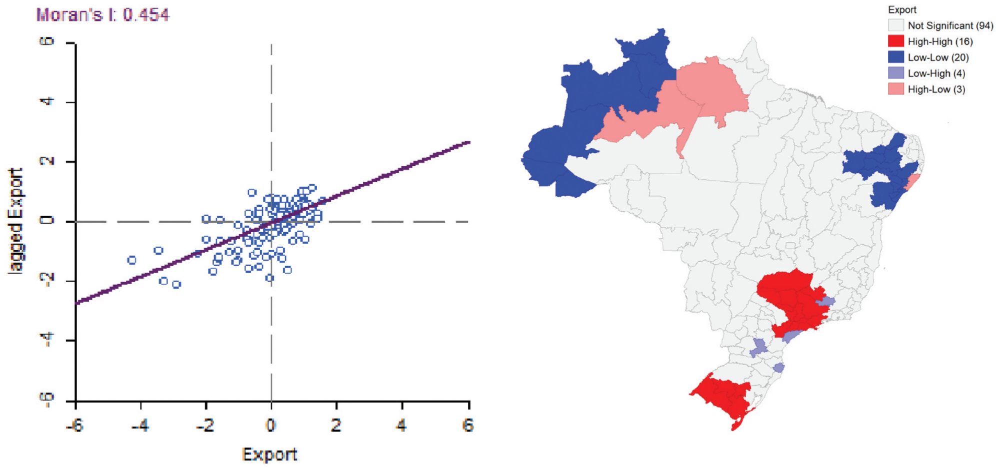

Figure 1. Dispersion diagram of Global Moran's I and LISA cluster map of exports, 2008–2021. *Notes*: Empirical pseudo-significance based on 999 random permutations. Significant Moran's I value at 0.01 level; significant cluster map at 0.05 level.

Similar results were reported by Schettini (2019), showing that the northern and central-western regions of Brazil have little or no industrial agglomeration, while the southern and southeastern regions have the most agglomeration in the country. (Figure A1b in the Appendix presents the dispersion diagram of Global Moran's I and LISA cluster map of exports by technological intensities). Overall, our results therefore show the formation of two types of spatial clusters: a High-High type cluster in the southeastern and southern regions of the country and a Low-Low type cluster in the northern and part of the northeastern regions. The remaining mesoregions of the country show spatial randomness in their exports and thus no spatial interdependence.

The formation of spatial clusters can also be observed by technological intensity sectors. We only highlight High Manufacturing (HM) in the High-High pattern due to the scale of the task. The High Manufacturing (HM) sector is particularly important because it consists of technology-intensive activities with relatively high levels of knowledge, which generate more regional dynamics and greater knowledge spillovers. We found clusters with the High-High pattern in the southern states Rio Grande do Sul with one mesoregion, Santa Catarina with four mesoregions, and Paraná with three mesoregions. Clustering was also observed in the Southeast region, in the states of São Paulo with 12 mesoregions, Rio de Janeiro with one mesoregion, and Minas Gerais with two mesoregions.

Our results for exports by technological intensity seem to confirm the spatial pattern of innovative activities (i.e., North-South polarization) observed by Gonçalves (2007). The author reported a spatial autocorrelation showing spatial heterogeneity with High-High patterns for the southern region and Low-Low patterns for the northern region.

In short, spatial autocorrelation is associated with manufacturing activities, while non-manufacturing activities, which are less technologically intensive, are more randomly distributed. Thus, the first hypothesis of the study was confirmed, as the formation of a spatial cluster was observed for the southeastern and southern regions, led by the regions of São Paulo, Rio de Janeiro, Minas Gerais and Rio Grande do Sul, which definitely have more technology-intensive export activities.

4.2. Autocorrelation and spatial cluster formation in exports and R&D expenditure

In this section, we use the univariate and bivariate Global Moran's I and LISA to identify the formation of spatial clusters and to test the occurrence of spatial autocorrelation first in R&D expenditure and then in exports. Several studies have shown that high technology-intensive exports are associated with higher levels of innovation (Audretsch & Feldman, 2004; Fagerberg, 1988; Guarascio et al., 2016; López-Bazo & Motellón, 2018).

First, we looked into the existence of spatial autocorrelation of R&D expenditure between Brazilian mesoregions (univariate Moran's I). As can be seen in Table 2, the values are statistically significant throughout the period of analysis, rejecting the hypothesis that there is no spatial autocorrelation. Figure 2 confirms that R&D expenditure shows spatial interdependence between mesoregions, with the formation of spatial clusters in both the southeastern region (states of São Paulo, Rio de Janeiro and Minas Gerais) and the southern region (state of Santa Catarina). These results confirm previous studies that have found a concentration of patents and innovative activities in Brazil (Araújo & Garcia, 2019; Gonçalves et al., 2019).

In terms of spatial autocorrelation patterns, the High-High type prevailed, meaning that mesoregions with high R&D expenditure were surrounded by mesoregions with high R&D expenditure (Figure 2). Twenty mesoregions with a High-High pattern shape a large region with the states of São Paulo with 15 mesoregions, Rio de Janeiro with three mesoregions, and Santa Catarina and Minas Gerais with one mesoregion each, forming a large spatial agglomeration of mesoregions with high R&D expenditure. Twelve mesoregions show a Low-Low pattern in the northern region (the states of Amazonas with two mesoregions and Roraima, Pará, Amapá, Acre, and Rondônia with one mesoregion each) and northeastern region (states of Sergipe with two mesoregions and Maranhão, Piauí, and Bahia with one mesoregion each). The rest of the country shows a random pattern (spatial heterogeneity). Moreover, only the state of Amazonas, in the northern region of Brazil, shows a High-Low pattern in one mesoregion, while the Low-High pattern was also only found in one mesoregion in the state of Paraná.

Bivariate analysis of the spatial autocorrelation between total exports and R&D expenditure shows that all Moran's I values are positive and statistically significant (Table 2). Medium Low Manufacturing (MLM) intensity and R&D expenditure have the highest Moran's I values, followed by Medium High Manufacturing (MHM) and R&D expenditure, suggesting the existence of spatial autocorrelation.

The most technology-intensive export activities (High Manufacturing, HM) are spatially correlated with R&D expenditure. This result supports previous studies that have shown that technological development strongly depends on spatial spillovers (e.g., Gonçalves et al., 2019). The importance of local knowledge spillovers has also been highlighted as an explanation for firms' productivity (Carreira & Lopes, 2018).

Regions in Brazil that are more specialized in high-tech and invest more in R&D tend to internalize knowledge and extract gains from the innovation process (de Almeida et al., 2021). Thus, corroborating previous studies (Braja & Gemzik-Salwach, 2019; Neves et al., 2016), the relationship between exports and R&D is more intense in production activities with MLM and HM intensity (Table 2).

Table 2. Global Moran's univariate I for R&D expenditure and Global Moran's bivariate I for exports and R&D expenditure by technological intensity, 2008–2021.

	Technological intensities and R&D							
Year	R&D	HM-R&D	MHM-R&D	MM-R&D	MLM-R&D	MLNM-R&D	LNM-R&D	Total-R&D
2008	0.425***	0.373***	0.311***	0.263***	0.194***	0.145***	0.204***	0.242***
2009	0.442***	0.422***	0.354***	0.290***	0.227***	0.158***	0.241***	0.256***
2010	0.441***	0.401***	0.355***	0.337***	0.246***	0.202***	0.240***	0.276***
2011	0.479***	0.428***	0.388***	0.350***	0.258***	0.264***	0.262***	0.293***
2012	0.465***	0.392***	0.365***	0.337***	0.262***	0.177***	0.230***	0.286***
2013	0.453***	0.360***	0.352***	0.291***	0.238***	0.132***	0.231***	0.321***
2014	0.464***	0.353***	0.350***	0.290***	0.233***	0.175***	0.219***	0.248***
2015	0.455***	0.420***	0.339***	0.288***	0.228***	0.198***	0.198***	0.280***
2016	0.435***	0.355***	0.348***	0.274***	0.208***	0.178***	0.227***	0.277***
2017	0.460***	0.322***	0.335***	0.315***	0.231***	0.240***	0.199***	0.302***
2018	0.452***	0.318***	0.331***	0.268***	0.210***	0.146***	0.203***	0.254***
2019	0.408***	0.304***	0.313***	0.283***	0.200***	0.126***	0.198***	0.264***
2020	0.409***	0.303***	0.300***	0.259***	0.194***	0.091**	0.185***	0.282***
2021	0.417***	0.277***	0.315***	0.257***	0.211***	0.102***	0.168***	0.273***
2008–21	0.435***	0.342***	0.355***	0.265***	0.234***	0.133***	0.189***	0.309***

See notes to Table 1. ***, ** and * statistical significance at the 0.01, 0.05 and 0.10 levels, respectively.

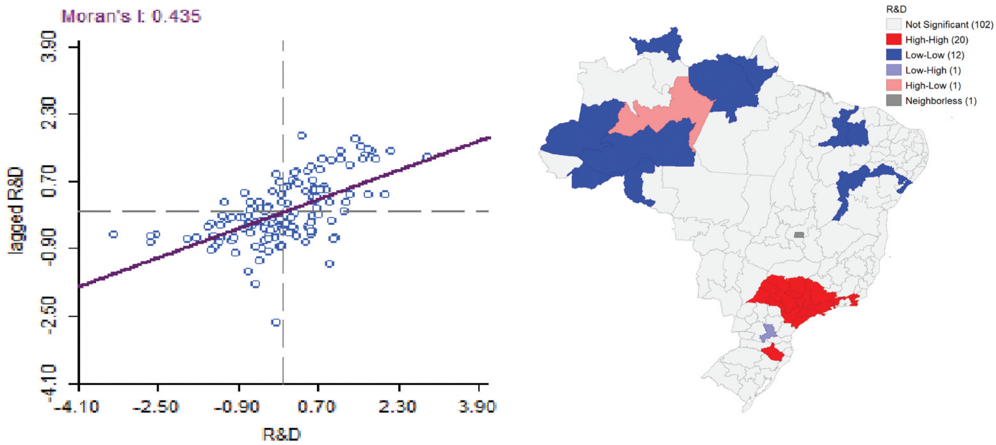

Figure 2. Dispersion diagram of Global Moran's I and LISA cluster map of total R&D expenditure in Brazil, 2008–2021. *Notes*: Empirical pseudo-significance based on 999 random permutations. Significant Moran's I value at 0.01 level; Significant cluster map at 0.05 level.

The spatial autocorrelation pattern is of High-High type for exports associated to R&D expenditure, forming a cluster of 22 mesoregions with high export values associated to high values of R&D in their neighboring mesoregions. There is also spatial autocorrelation in the Low-Low patterns in 11 mesoregions, although more geographically spread out. On the other hand, a large part of Brazil showed spatial randomness in exports and R&D expenditure (Figure 3), consistent with previous studies (Araújo & Garcia, 2019; Gonçalves & Almeida, 2009).

Overall, we found the existence of spatial autocorrelation of exports and R&D expenditure between Brazilian mesoregions, mainly for manufacturing activities, confirming the second hypothesis. The results also reveal the existence of a cluster with a High-High pattern for a large area of the country in the southeastern and southern regions. The mesoregions that comprise this cluster have nationally and internationally recognized teaching and research institutions, namely the University of São Paulo (USP), the University of Campinas (UNICAMP), the Federal University of Rio de Janeiro (UFRJ), and the Federal University of Paraná (UFPR), with relevant interaction and cooperation with the productive sector of the economy. In fact, enhancement of the university-industry relationship has been reported, particularly among the twelve largest universities located in the southern and southeastern regions of Brazil (Bastos & Britto, 2017; Fischer et al., 2019). Moreover, more university research is positively correlated with higher levels of innovation in the respective region (Araújo & Garcia, 2019).

4.3. Knowledge and agglomeration effects measurement

In this section, we estimate the determinants of regional exports by technological intensity, considering regional R&D expenditure and two sources of knowledge explained by agglomeration economies, specialization economies and diversity economies, assuming that there are spatial effects. We also consider regional real GDP to control for the region size and year dummies.

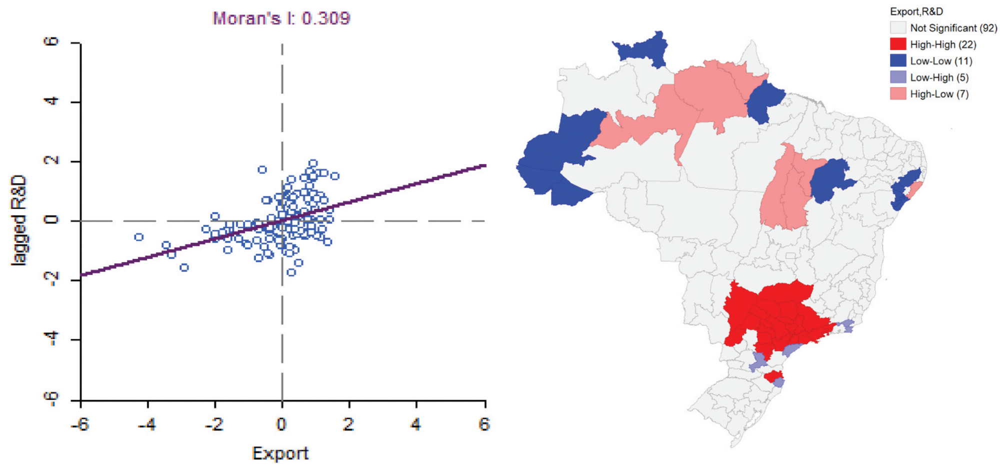

Figure 3. Dispersion diagram of bivariate Global Moran's I and LISA cluster map of exports and R&D expenditure, 2008–2021. *Notes*: Empirical pseudo-significance based on 999 random permutations. Significant Moran's I value at 0.01 level; Significant cluster map at 0.05 level.

Table 3 shows the estimates of model (1) without spatial interactions, using the fixed effects estimator with time fixed effects. We observe a positive impact of R&D on exports in the MM and ML sectors. Surprisingly, R&D does not seem to have any impact on the HM sector. Specialization economies have a positive effect in the MHM, MLM, MLNM and LNM sectors and a negative effect in the HM sector. In turn, the effect of diversification economies has only a significantly positive impact in the HM and MM sectors and a negative impact in the MLM sector.

To account for spatial effects in our analysis, we first performed diagnostic tests to select the most appropriate spatial panel model to fit the data for each sector (Table 4). In all sectors, random effects were rejected according to the Hausman test and, consequently, fixed effects were used. The most appropriate spatial panel model that fits our data was selected according to the strategy used by LeSage and Pace (2009, 2011), Elhorst (2010), and Belotti et al. (2016). As can also be seen in Table 4, the spatial model to be applied to the HM and LNM sectors is the Spatial Durbin Model (SDM), while the Spatial

Table 3. Regression results using fixed effect (without spatial interactions).

	HM	MHM	MM	MLM	MLNM	LNM
rd	0.000	−0.328	0.668***	0.287**	0.484**	0.005
	(0.227)	(0.222)	(0.190)	(0.124)	(0.204)	(0.000)
spe	−0.209**	0.750***	0.072	0.998***	0.459**	1.376**
	(0.084)	(0.198)	(0.230)	(0.318)	(0.224)	(0.682)
div	0.264***	−0.392	4.846***	−1.408**	−0.810	−0.299
	(0.865)	(1.587)	(1.408)	(0.706)	(1.442)	(0.870)
real gdp	2.535***	2.124**	1.782**	1.252***	2.456***	1.713***
	(0.865)	(0.842)	(0.723)	(0.475)	(0.781)	(0.574)
Observations	1918	1918	1918	1918	1918	1918
Wald test	12.15***	6.6***	5.75***	7.43***	9.13***	7.56***

rd, *spe*, *div* and *real gdp* denote R&D employment, localization economies, diversity economies and real GDP (all in log forms), respectively. Coefficients of time (2008–2021) dummies not reported. Standard errors are given in parentheses. ***, ** and * statistical significance at the 0.01, 0.05 and 0.10 levels, respectively.

Table 4. Diagnostic tests.

		HM	MHM	MM	MLM	MLNM	LNM
i) Spatial distance matrix		Contiguity	Contiguity	Contiguity	Contiguity	Contiguity	Contiguity
ii) Test to choose between random and fixed effects							
Hausman test		52.34***	66.12***	55.00***	21.67***	23.96***	17.06***
		FE	FE	FE	FE	FE	FE
iii) Tests to choose the most appropriate spatial panel model							
SAR vs SDM	Wald test	26.48***	3.16	2.76	.64	5.08	26.99***
SEM vs SDM	Wald test	26.43***	3.12	2.75	.64	5.14	26.88***
SAR	AIC	9669.090	9669.090	9122.568	7606.394	9385.688	8282.522
	BIC	9774.712	9774.712	9228.190	7712.016	9491.310	8388.144
SEM	AIC	9669.118	9669.118	9123.493	7606.188	9385.671	8282.352
	BIC	9774.740	9774.740	9229.450	7711.810	9491.293	8387.974
SDM	AIC	9737.836	9671.930	9125.809	7611.753	9386.613	8261.737
	BIC	9860.135	9794.229	9248.108	7734.052	9508.912	8384.035
Most appropriate model		SDM	SAR	SAR	SEM	SEM	SDM

In the SAR vs. SDM model, the null of being SAR is tested using the Wald test. In the SEM vs. SDM model, the null of being SEM is tested using the Wald test. If both SAR and SEM are not rejected, against SDM and being non-nested, the most appropriate model is the one with the lowest Akaike's and Schwarz's Bayesian information criterion. ***, ** and * Statistical significance at the 0.01, 0.05 and 0.10 levels, respectively.

Autoregressive Model (SAR) is applied to the MHM and MM, and the Spatial Error Model (SEM) to the MLM and MLNM sectors.

Table 5 shows the regression results by sector using the selected spatial model. As expected, the estimated coefficients vary by sector. In what concerns non-spatially lagged variables, the estimated coefficients for R&D are positive and statistically significant in the MM, MLM and MLNM sectors, but not in the HM sector (the interpretation of this result is provided below). The effect of specialization economies is statistically significant and positive in the MHM, MLM, MLNM and LNM sectors, while it is negative in the HM sector. The negative sign in this sector could be explained by the congestion effect (i.e., negative externalities of agglomeration). In fact, Góis Sobrinho and Azzoni (2014) found industrial agglomerations, namely in the motor vehicle industry (technology-intensive industry) in the southeast (São Paulo and Minas Gerais) and southern (Paraná and Rio Grande do Sul) regions. In contrast, the authors found that medium and medium-low technology-intensive sectors are more spatially dispersed. Finally, the effect of diversity economies is significantly positive in the MM sector and negative in the MLM sector.

Given the spatial autocorrelation of exports observed in Section 4.1, it is not surprising that there are significant and positive global spatial spillover effects of exports in the HM sector. That is, it seems that the regional knowledge on foreign markets spill over between regions. Andersson and Weiss (2012) also found that the probability of a Swedish firm exporting is positively related to the local presence of exporters, with the effect being more important in contract-intensive industries – the contract-intensive industries are essentially skill intensive (Nunn, 2007), whose knowledge on foreign markets tends to be more important due to high entry costs. The knowledge on foreign market tends to spill over to local firms, lowering their entry costs (Andersson & Weiss, 2012). Conversely, in the case of the MM sector, exporting of surrounding regions will tend to reduce the export activity in its own region.

Regarding the spatial interaction effects of R&D expenditure, we observe that R&D has a positive statistically significant effect in the cases of the HM and LNM sectors. This result is not surprising in Brazil, considering that, as we had seen in Section 4.2, innovative knowledge resulting from investments in R&D tends to be concentrated in a large export area in the southeastern and southern regions with a relevant number of nationally and internationally recognized universities and research institutions (Figure 3). The university-

Table 5. Regression results using spatial panel specification.

	HM	MHM	MM	MLM	MLNM	LNM
Spatial model	SDM	SAR	SAR	SEM	SEM	SDM
Spatial distance matrix			Contiguity			
rd	−0.099	−0.326	0.671***	0.296**	0.486**	−0.036
spe	−0.211**	0.749***	0.084	0.971***	0.460**	1.241*
div	0.127	−0.387	4.822***	−1.362*	−0.811	−0.317
real gdp	2.063**	2.125**	1.769**	1.282***	2.456***	1.509***
spatially lagged exports	0.056*	−0.006	−0.066**			−0.019
spatially lagged rd	1.306***					1.228***
spatially lagged spe	−0.320**					−0.405
spatially lagged div	−8.185***					0.063
spatially lagged error				0.107***	−0.005	
Observations	1918	1918	1918	1918	1918	1918
Wald test	243.56***	113.41***	103.04***	107.59***	157.89***	158.82***
Wald test of spatial terms	31.15***	.04	4.11**	11.18***	0.02	27.02***

See notes to Table 3. Coefficients of time dummies not reported. ***, ** and * denotes statistical significance at the 0.01, 0.05 and 0.10 levels, respectively.

industry relationship is more compelling in the high technology-intensive sector than in other sectors (Araújo & Garcia, 2019; Bastos & Britto, 2017; Fischer et al., 2019). Thus, it is more important for an export region of HM goods to be surrounded by areas with high R&D expenditure than for that region to make its own R&D investments, which is not the case for less technology-intensive goods – note that the R&D coefficient in the HM sector is not statically significant, which is not the case of medium and medium-low technology-intensive sectors where the coefficients are significantly positive. When we estimate the model (3) at the state level (i.e., at a more aggregate level), the R&D coefficient in the HM sector is now positive and statistically significant, which seems to confirm our conclusion (the result is available from the authors upon request).

We also found negative effects for spatially lagged specialization and diversity economies in the case of the HM sector. This could possibly be due to the mobility of workers between regions, which is relatively high in Brazil, as noted by Gonçalves et al. (2016), who analyzed the impact of the migration of highly skilled workers between regions on innovation in the destination region. Ruesga et al. (2014) and Lameira et al. (2020) also observed high worker mobility in Brazil.

Table 6. Direct, spatial spillover and feedback effects.

	HM	MHM	MM	MLM	MLNM	LNM
Spatial model	SDM	SAR	SAR	SEM	SEM	SDM
Spatial distance matrix			Contiguity			
Coefficient						
rd	−0.099	−0.326	0.671***	0.297**	0.486**	−0.036
spe	−0.211**	0.749***	0.084	0.971***	0.460**	1.241*
div	0.127	−0.387	4.822***	−1.362*	−0.811	−0.317
real gdp	2.063**	2.125**	1.769**	1.282***	0.456 ***	1.509***
Direct effect						
rd	−0.081	−0.326	0.671***	0.297**	0.486**	−0.041
spe	−0.216***	0.749***	0.845	0.971***	0.460**	1.243*
div	0.018	−0.387	4.823***	−1.362	−0.811	−0.317
real gdp	2.064**	2.012	1.770**	1.282***	0.456 ***	1.501***
Indirect effect						
rd	1.350***	0.002	−0.042*			1.203***
spe	−0.344**	−0.004	−0.005			−0.420
div	−8.489***	0.002	−0.300*			0.068
real gdp	0.120	−0.012	−0.110			−0.028
Total effect						
rd	1.269***	−0.325	0.630***	0.297**	0.486**	1.161***
spe	−0.559***	0.745***	0.079	0.971***	0.460**	0.823
div	−8.471***	−0.385	4.527***	−1.362*	−0.811	−0.250
real gdp	2.184**	2.113**	1.661**	1.282***	0.456 ***	1.481***
Feedback effect in the own region						
rd			0.000			
spe	−0.005	0.000				0.002
div			0.001			
real gdp	0.001		0.001			−0.008
Feedback effect in the own region as a percentage of the estimated coefficient						
rd			0.099%			
spe	−2.370%	0.001%				0.161%
div			0.021%			
real gdp	0.048%		0.057%			−0.530%

See notes to Table 3. ***, ** and * Statistical significance at the 0.01, 0.05 and 0.10 levels, respectively.

Finally, Table 6 shows the spatial exogenous effects, namely the direct, indirect and total effects of each independent variable, as well as the feedback effect. In the case of the HM sector, the results seem to confirm the previous conclusion that R&D expenditure of neighbor regions is determinant for exports of the region (the indirect and total effect are positive and statically significant, while the direct effect is not statically significant), favoring the formation of clusters, as we observed in section 4.2.

The effects of the remaining independent variables and sectors are consistent with the previous results. In the MM sector, for example, we found significant positive direct effects of R&D and diversity economies, which are moderated by the indirect negative effects of neighboring regions. The feedback effect is also positive and statically significant for the two variables. (The feedback effect measures the impact on the dependent variable of a given region as a result of a change in an independent variable of that region affecting the dependent variable of other regions, which in turn exerts a feedback effect on the dependent variable of the region where the first change occurred.)

5. Conclusions

This study investigated the spatial autocorrelation patterns of regional exports in Brazil and their determinants by technological intensity. It was argued that regions with higher export intensity and higher R&D expenditure are more likely to form spatial clusters, particularly of the High-High type, indicating a greater capacity for knowledge transfer between regions.

The results show that Brazilian exports exhibit spatial autocorrelation, particularly in the High Manufacturing (HM), Medium High Manufacturing (MHM), and Medium Manufacturing (MM) sectors. Non-manufacturing sectors, which are less technology-intensive, show lower spatial dependence than manufacturing sectors. The results also show the formation of mainly two types of spatial clusters: a High-High type cluster in the southeastern and southern regions of Brazil and a Low-Low type cluster in the northern and part of the northeastern regions. The remaining mesoregions of the country show spatial randomness in their exports and thus no spatial interdependence.

We also found a spatial autocorrelation of exports and R&D expenditure between Brazilian mesoregions, especially for manufacturing sectors. Mesoregions with high export values were surrounded by neighboring mesoregions with high R&D expenditure, revealing the existence of a cluster with a High-High pattern in the southeastern and southern regions.

Estimates of the determinants of regional exports by technological intensity using spatial econometric techniques confirm the existence of a spatial spillover effect of exports between neighboring regions in the HM sector. In addition, we also found a spatial spillover effect of R&D expenditure. That is, an increase in R&D expenditure in a neighboring region increases the region's export of HM goods.

These results have helped broaden the range of empirical studies that have found a relationship between exports and R&D expenditure. As far as structural policies are concerned, our results recommend not only incentives for regional R&D investments but, more importantly, measures to improve the mechanisms of regional spillovers, especially through cooperation and productive complementarity between regions. In this sense, regional policies to strengthen partnerships through support networks, such as the Quadruple Helix (Carayannis & Campbell, 2009), seem to be the most promising way to improve the competitiveness of the Brazilian export sector.

The results of this study also reveal some limitations, namely the fact that more variables are not available at the mesoregion level to better represent the stock of knowledge. It should be noted that future studies should focus on the interactions between universities (and research laboratories) and industries and examine the correlation between exports and the level of technological intensity. In addition, the selection of the spatial weighting matrix provided new insights that could contribute to future studies using this econometric tool. However, further research on this topic is needed (Corrado & Fingleton, 2012). These limitations open opportunities for future research.

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Appendix

Table A1. Descriptive statistics, 2008–2021.

Variable	Mean	Std. Dev.	Minimum	Maximum
Exports (10^9 reals)				
HH	0.30	1.66	0	30.10
MHM	1.02	3.14	0	39.90
MM	0.72	2.03	0	18.90
MLM	2.79	6.66	0	137.00
MLNM	0.89	6.25	0	131.00
LNM	1.02	2.69	0	39.70
R&D (10^3 reals)	1.71	4.51	0	19.90
Specialization economies				
HH	0.40	1.09	0.00	11.64
MHM	2.44	2.86	0.00	13.33
MM	4.49	3.02	0.00	19.47
MLM	15.47	6.69	0.25	33.81
MLNM	1.48	2.42	0.00	19.09
LNM	17.07	7.46	3.85	41.36
Diversity economies				
HH	2.62	0.63	1.03	4.65
MHM	2.41	0.52	1.03	4.09
MM	2.23	0.50	1.02	4.08
MLM	2.15	0.83	1.00	5.07
MLNM	2.52	0.65	1.03	4.85
LNM	2.10	0.65	1.00	4.02
GDP (10^6 reals)	61.90	152.00	0.95	1670.00

Notes: Pooled yearly values over the period 2008–2021. Monetary variables are measured in constant Brazilian reals. Zero-values were replaced by 0.1 before the log transformation. HM: High technological intensity of Manufacturing; MHM: Medium-High technological intensity of Manufacturing; MM: Medium technological intensity of Manufacturing; MLM: Medium-Low technological intensity of Manufacturing; MLNM: Medium-Low technological intensity of Non-Manufacturing; LNM: Low technological intensity of Non-Manufacturing.

Table A2. Spatial auto-correlation pattern (High-High and Low-Low) of total exports, 2008–2021.

High-High		Low-Low	
States (Region) and Mesorregions		States (Region) and Mesorregions	
Rio Grande do Sul (S)	Centro Ocidental Rio-grandense; Centro Oriental Rio-grandense; Sudoeste Rio-grandense; Sudeste Rio-grandense	Roraima (N)	Norte de Roraima; Sul de Roraima.
São Paulo (SE)	São José do Rio Preto; Ribeirão Preto; Vale do Paraíba Paulista; Metropolitana de São Paulo; Macro Metropolitana Paulista; Campinas; Itapetininga; Piracicaba; Araraquara.	Amazonas (N)	Sudoeste Amazonense; Norte Amazonense.
Minas Gerais (SE)	Triângulo Mineiro/Alto Paranaíba; Sul/Sudoeste de Minas; Oeste de Minas.	Acre (N)	Vale do Juruá; Vale do Acre.
		Rio Grande do Norte (NE)	Oeste Potiguar.
		Paraíba (NE)	Sertão Paraibano.
		Piauí (NE)	Sudeste Piauiense.
		Bahia (NE)	Nordeste Baiano.
		Ceará (NE)	Centro-Sul Cearense; Sul Cearense.
		Alagoas (NE)	Agreste Alagoano; Sertão Alagoano.
		Pernambuco (NE)	Sertão pernambucano; São Francisco Pernambucano; Agreste Pernambucano.
		Sergipe (NE)	Sertão Sergipano; Agreste Sergipano; Leste Sergipano.
High-Low		**Low- High**	
States (Region) and Mesorregions		**States (Region) and Mesorregions**	
Amazonas (N)	Centro Amazonense; Baixo Amazonense.	Minas Gerais (SE)	Campo das Vertentes.
Alagoas (NE)	Leste Alagoano.	São Paulo (SE)	Litoral Sul Paulista.
		Paraná (S)	Sudeste Paranaense.
		Santa Catarina (S)	Grande Florianópolis.

Note: (N): North; (NE): Northeast; (CO): Centre-West; (SE): Southeast; (S): South.

Table A3. Spatial auto-correlation pattern of total exports, of the technological intensity of High Manufacturing (HM), for the High-High pattern, 2008–2021.

High-High	
States (Region) and Mesorregions	
Rio Grande do Sul (S)	Centro Ocidental Rio-grandense.
Santa Catarina (S)	Norte Catarinense; Oeste Catarinense; Serrana; Sul Catarinense.
Paraná (S)	Centro Oriental Paranaense; Centro-Sul Paranaense; Sudeste Paranaense.
São Paulo (SE)	Vale do Paraíba Paulista; Ribeirão Preto; Araçatuba; São José do Rio Preto; Araraquara; Bauru; Macro Metropolitana Paulista; Itapetininga; Litoral Sul Paulista; Piracicaba; Campinas; Assis.
Rio de Janeiro (SE)	Sul Fluminense.
Minas Gerais (SE)	Sul/Sudoeste de Minas; Oeste de Minas.

Table A4. Spatial auto-correlation pattern (High-High and Low-Low) of R&D expenditures, 2008–2021.

High-High		Low-Low	
States (Region) and Mesorregions		States (Region) and Mesorregions	
São Paulo(SE)	São José do Rio Preto; Ribeirão Preto; Vale do Paraíba Paulista; Metropolitana de São Paulo; Assis; Litoral Sul Paulista; Macro Metropolitana Paulista; Campinas; Itapetininga; Piracicaba; Marília; Bauru; Araraquara; Presidente Prudente; Araçatuba.	Amazonas (N)	Sudoeste Amazonense; Sul Amazonense.
Rio de Janeiro (SE)	Sul Fluminense; Centro Fluminense; Baixadas.	Roraima (N)	Norte de Roraima.
Santa Catarina (S)	Serrana.	Pará (N)	Baixo Amazonas.
Minas Gerais (SE)	Sul/Sudoeste de Minas.	Amapá (N)	Sul do Amapá.
		Acre (N)	Vale do Acre.
		Rondônia (N)	Madeira Guaporé.
		Sergipe (NE)	Sertão Sergipano; Leste Sergipano.
		Maranhão (NE)	Leste Maranhense.
		Piauí (NE)	Centro-Norte Piauiense.
		Bahia (NE)	Vale São Francisco da Bahia.
High-Low		**Low-High**	
States (Region) and Mesorregions		**States (Region) and Mesorregions**	
Amazonas (N)	Centro Amazonense.	Paraná (S)	Sudeste Paranaense.

Note: (N): North; (NE): Northeast; (CO): Centre-West; (SE): Southeast; (S): South.

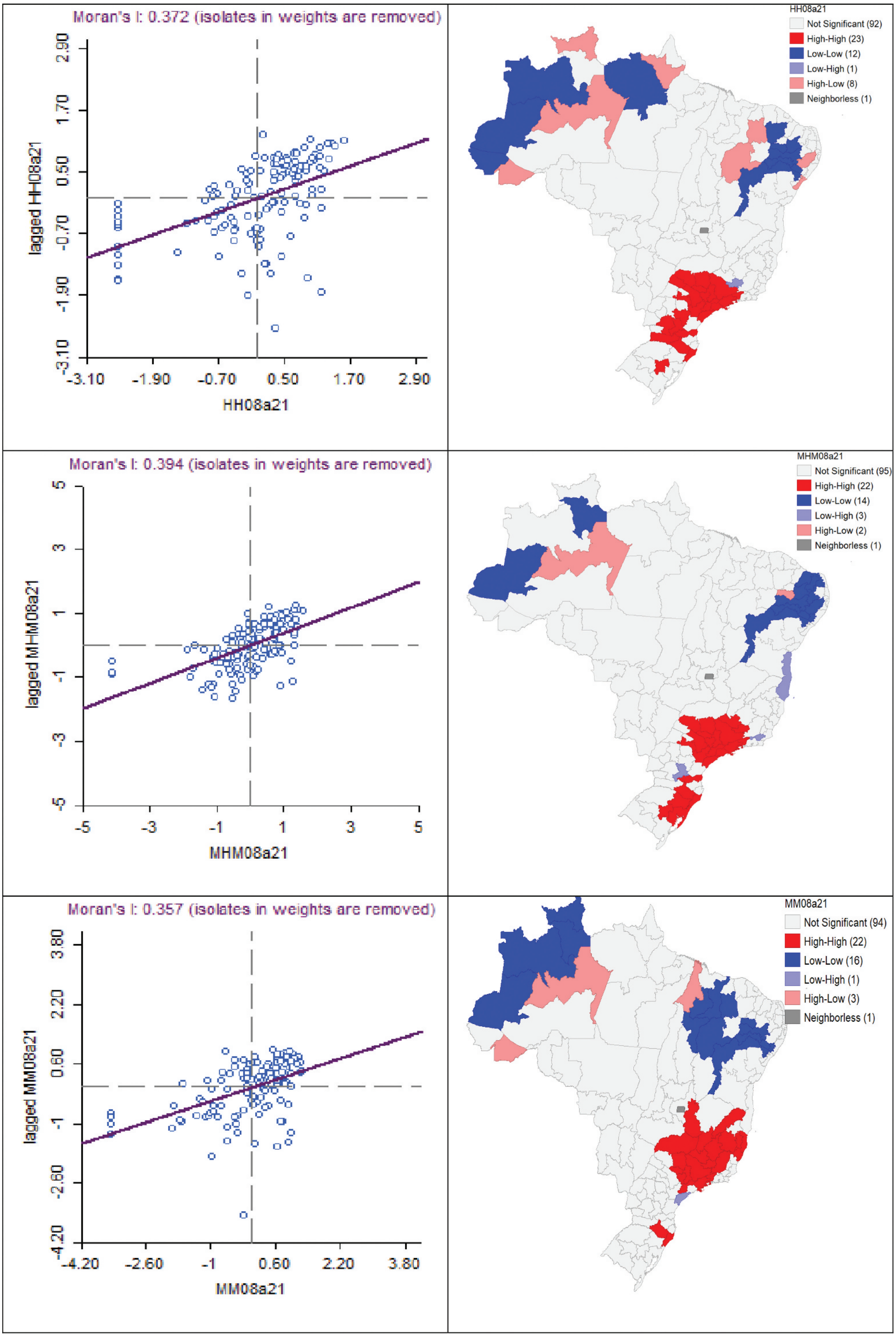

Figure A1. Dispersion diagram of Global Moran's I and LISA cluster map of exports, by technological intensities, 2008–2021. Notes: Empirical pseudo-significance based on 999 random permutations. Significant Moran's I value at 0.01 level; Significant cluster map at 0.05 level.

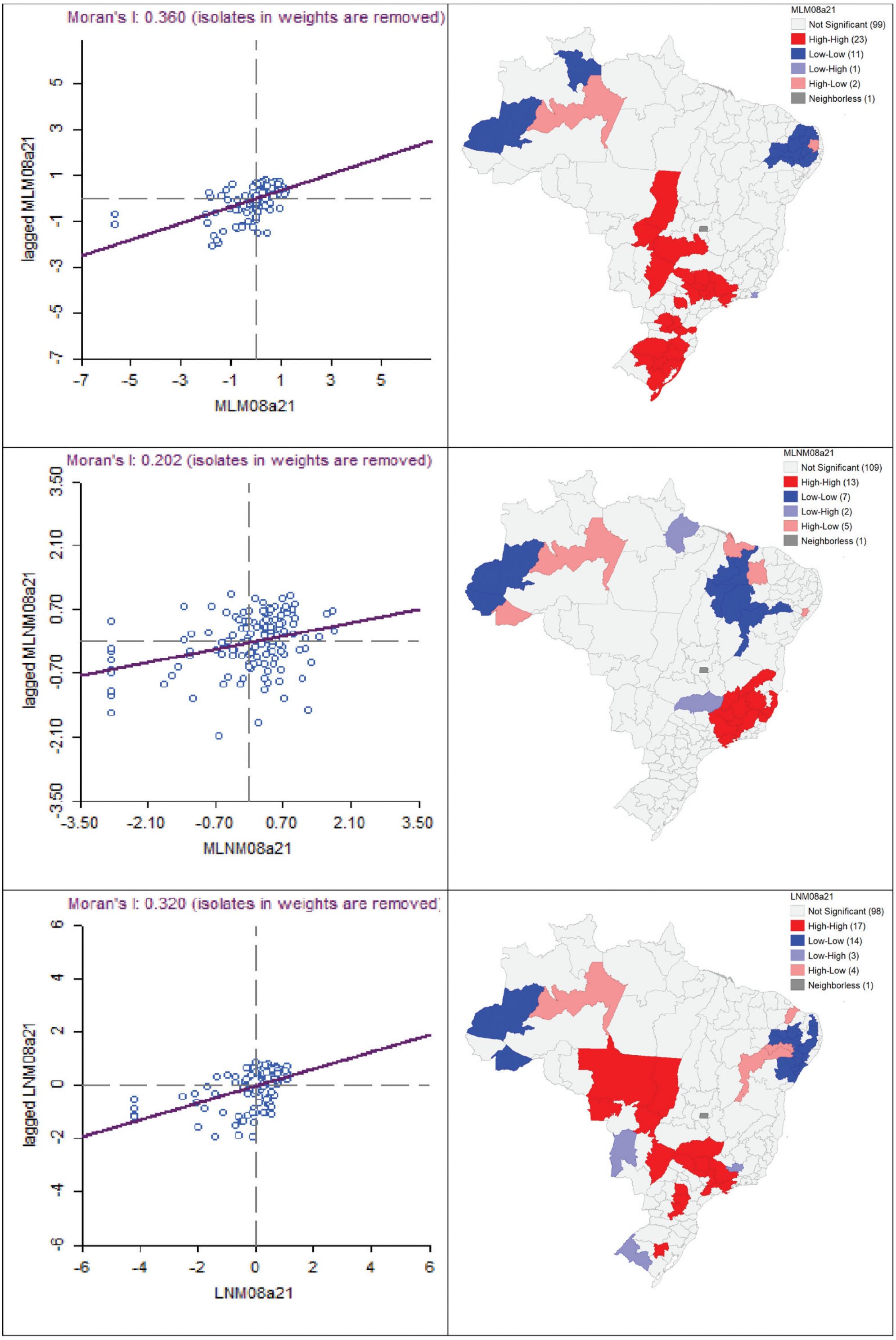

Figure A1. (Continued).