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REGIONAL PATTERNS OF THE MANUFACTURING INDUSTRY IN THE BALTIC REGIONS OF RUSSIA: A MORAN'S I SPATIAL ANALYSIS

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The manufacturing industry of Russia's Baltic regions has faced major global challenges in recent years, including the COVID-19 pandemic and Western sanctions. This study aims to identify the spatiotemporal effects of these external shocks on industrial dynamics in Saint Petersburg, Leningrad and Kaliningrad regions, and to identify local clusters of industrial growth and decline. The methodological framework of the study is spatial analysis based on differential global and local Moran's I statistics, which allows for the assessment of spatial autocorrelation in changes in industrial output at the municipal level during 2019–2023. Official Rosstat data, normalized (deflated) to pre-crisis levels, serve as the empirical basis of the study. The findings reveal pronounced heterogeneity in regional responses. In the Kaliningrad region, extensive zones of industrial decline emerged, reflecting the region's high dependence on imports. By contrast, several municipalities in the Leningrad region demonstrated growth, supported by production diversification and government measures. These results make it possible to identify local poles of decline and growth, highlighting significant spatial disparities in the resilience of the manufacturing sector across Russia's Baltic regions.

Keywords:

Baltic regions, Russia, manufacturing industry, municipalities, spatiotemporal autocorrelation, pandemic, sanctions

Introduction

The Baltic regions of Russia (the city of Saint Petersburg, the Leningrad and Kaliningrad regions) have traditionally played a pivotal role in the national economy. Saint Petersburg serves as a major industrial, scientific, and transport hub on Russia's Baltic coast. Leningrad region, adjacent to Saint Petersburg, is distinguished by its well-developed engineering sector and agro-industrial

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complex, while the Kaliningrad region, a Russian coastal exclave, specializes in shipbuilding, food processing, and light industry. All three regions are characterized by highly developed manufacturing industries and active foreign trade relations (in particular, Kaliningrad is a resident of a special economic zone with intensive external trade) [1].

In recent years, Russia's manufacturing sector has encountered two major external shocks: the COVID-19 pandemic and unprecedented sanctions imposed by Western countries. The pandemic disrupted global supply chains and depressed demand (for example, in 2020–2021, global GDP and industrial output contracted) [2]. At the same time, lockdowns curtailed enterprise activity, while sanctions-related pressures further limited access to foreign technologies and capital, resulting in significant disruptions to imports, particularly of high-technology goods and intermediate components [3]. As a result, in 2022–2023, Russian industries displayed divergent trajectories: while some regions and sectors (notably extractive and high-technology) experienced growth, others (including mechanical engineering) faced significant difficulties.

The relevance of this study stems from the need to identify the spatial patterns in how the manufacturing sector responds to systemic external shocks, specifically the COVID-19 pandemic and sanctions-related pressures. The Baltic regions constitute important industrial hubs and zones of external economic activity, deeply integrated into global production and logistics chains. Amid the abrupt disruption of global and regional production chains, issues of resilience in territories with differing industrial structures and logistical positions became particularly acute. Moreover, regional economies often display marked spatial heterogeneity in their responses to crises, underscoring the need for spatial analytical approaches capable of identifying both centres of contraction and poles of growth. The integration of geo-analytical methods with municipal-level data allows for a more nuanced understanding of regional crisis dynamics and supports the development of targeted industrial policy measures.

The present study seeks to assess the spatio-temporal effects of external shocks on the manufacturing sector's dynamics in Russia's Baltic regions, and to identify local clusters of industrial growth and decline at the municipal level using spatial analysis techniques, particularly the differential Moran's Index (Moran's I).

To achieve this aim, the following research objectives were formulated:

- to review theoretical and methodological approaches to spatial analysis applicable to the study of industrial dynamics at the regional and municipal levels;
- to evaluate the spatio-temporal autocorrelation of changes in industrial output using the differential Local Indicators of Spatial Association (LISA), and to identify clusters of growth and decline at the municipal level;
- to formulate recommendations for territorially differentiated industrial policy aimed at overcoming the consequences of crises and enhancing the resilience of the manufacturing sector in the Baltic regions.

It should be noted that the present study has several limitations. First, the spatial autocorrelation analysis is based on aggregate data for the manufacturing sector, without disaggregation by individual industries. Second, a single regional deflator was applied uniformly across municipalities, as local consumer price indices are unavailable at the municipal level. Third, the differential local Moran's I used in the analysis identifies spatial patterns of change but does not reveal the underlying determinants of the observed differences, thereby necessitating further investigation. These limitations outline the directions for future research.

Theoretical review

The global manufacturing sector experienced substantial losses as a result of the COVID-19 pandemic. Studies indicate that the pandemic led to severe disruptions in supply chains, temporary plant shutdowns, and significant logistical delays. The impact was highly uneven: while some sectors (e.g., personal protective equipment and electronic components) experienced explosive growth, others (such as the automotive and aerospace industries) witnessed a sharp decline. At the same time, as governments and businesses adapted, the severity of the crisis gradually diminished [2]. IMF reports emphasized that industrial output began to recover as early as the second half of 2021, with particularly strong resilience observed in China and Russia.¹

In Russia, the effects of the pandemic across regions were heterogeneous. Large metropolitan areas such as Moscow and Saint Petersburg, despite high infection rates and the vulnerability of the service sector, demonstrated relative economic resilience due to diversified economies, strong innovation potential, and well-developed digital infrastructure. This allowed declines in some sectors to be offset by growth in others, particularly in IT and pharmaceuticals. In contrast, regions with narrow industrial specialization, especially those reliant on the automotive industry and the fuel and energy complex, experienced a deeper economic downturn as a result of falling global demand [5]. Structural features of the Russian economy—including a low share of non-productive services and small businesses, as well as limited development of the financial sector—helped to mitigate the overall negative impact of the crisis. Moreover, less stringent restrictions in industries such as agriculture, construction, and extractive sectors helped sustain economic activity in several regions [6].

In the early months of the pandemic, enterprises faced supply disruptions, shortages of components, and sharp declines in demand. Experts note that the labour market in the Kaliningrad region was particularly weakened by restrictive measures, with manufacturing, transport, and logistics sectors suffering the most [7]. According to World Bank estimates, approximately 1.78 million jobs were lost in Russia in 2020, with a significant share of these losses occurring in

¹ TASS, 2025. The IMF stated that the global economy is recovering faster than expected, URL: <https://tass.ru/ekonomika/10955549> (accessed 25.04.2025).

manufacturing.¹ In Saint Petersburg and the Leningrad region, although lockdown measures were somewhat less restrictive, many enterprises—especially in mechanical engineering and the automotive industry—also reported production declines.

During 2020–2021, growth rates of industrial production varied significantly across regions. In the Kaliningrad region, for instance, industrial output fell by almost 27 % over the first two years of the crisis, whereas in some other regions production grew (e.g., Bryansk Region recorded +38 % over the same period) [4]. These differences were largely explained by industrial specialization: the largest declines (beyond Kaliningrad) occurred in traditionally export-oriented sectors, including wood processing, metallurgy, and particularly automotive manufacturing. As noted by Zubarevich, among regions with developed automotive industries, the Kaliningrad region suffered the most severe contraction [8]. This was linked to the cessation of imported components essential for car assembly, with parallel imports unable to fully compensate for the disruption. Overall, production declines were most acute in regions with high external dependence.

The sanctions of 2022–2023 constituted an even more profound shock. Even before 2022, Russia's manufacturing sector had been under sanctions-related pressure, but following the events of February 2022, the situation deteriorated sharply. Studies show that manufacturing has been disproportionately affected compared with other sectors due to its integration into global value chains. For example, Stepanov et al. identified the complex impact of sanctions on industrial dynamics across regions and described scenarios of import substitution and logistical restructuring [3].

Declines in imports of components and equipment exacerbated the difficulties of enterprises in the Baltic regions, which are deeply embedded in global production networks. Research indicates that Kaliningrad and Leningrad regions exhibit high levels of import dependence in mechanical engineering, particularly in the automotive sector, due to their integration into global supply chains [9]. In 2022, this led to significant disruptions in cooperation: enterprises were forced to reconfigure logistics, seek new suppliers, and redirect production toward the domestic market (particularly in the context of growing demand for domestically produced goods) [10]. A notable consequence was the restructuring of regional economies: in the Kaliningrad region, authorities pursued radical changes in foreign economic relations and industrial policy to minimize losses.

By 2022–2023, however, a process of adaptation had begun. According to research [11], the overall dependence of Russian industrial production on imports had decreased by nearly 1.5 times by the end of 2023 compared with early 2022. This reflects large-scale import substitution, with enterprises in the Baltic regions increasingly producing goods from domestic components. The geography of

¹ World Bank Group, 2025, *How has Russia's economy fared in the pandemic era?*, URL: <https://www.worldbank.org/en/news/opinion/2021/06/08/how-has-russia-s-economy-fared-in-the-pandemic-era> (accessed 25.04.2025).

dependency also shifted: instead of assembly plants with high import intensity (as in the automotive sector), new leaders in import dependence emerged—namely, territories with projects involving foreign participation and substantial reliance on imported equipment. For example, in Saint Petersburg, certain pharmaceutical producers (e.g., Biocad, Cytomed, Solopharm) demonstrate high import dependence due to reliance on foreign equipment, while in the Leningrad region, several chemical enterprises with foreign participation (e.g., Poliplast North-West, EuroChem North-West, Fosforit) fall into this category. At the same time, industrial dependence on imports declined by 57.5 percentage points in the Kaliningrad region and by 17.9 percentage points in the Leningrad region [11]. This sharp reconfiguration indicates that regions are pursuing broad-based import substitution and developing local supply chains.

Nevertheless, the pace of change has been uneven. In the export-oriented territories of the Northwest—Saint Petersburg, Kaliningrad, and Leningrad regions—the sanctions shock of 2022 was expected to trigger a substantial decline in economic activity. Estimates suggest that the Northwest (including the Kaliningrad region) was more severely affected than the Russian average in 2022: in May—June, many surveyed enterprises reported the urgent need to overhaul supplier networks and redirect production to the domestic market [12]. From January to autumn 2023, however, these impacts weakened significantly as adaptation measures—including logistical restructuring, the development of new markets, and expanded state support—helped to alleviate the sanctions shock.

Government intervention and the development of regional industrial policies played a crucial role. During 2022–2023, regional authorities intensified measures to stimulate local production (through clusters, industrial parks, subsidies, and special tax regimes), thereby enhancing industrial resilience. Studies indicate that by 2023, the share of manufacturing in regional GRP had become an important factor in industrial growth. Increased state participation (via higher public ownership and fiscal injections) also played a stabilizing role in supporting industrial development during the crisis [4]. Import substitution and policies aimed at strengthening the real sector delivered tangible results: although the decline in imports of components was inevitable, the gap was increasingly offset through local cooperation and parallel supply schemes.

Thus, the pandemic and sanctions exerted heterogeneous effects on the manufacturing sector of the Baltic regions. On the one hand, sharp contractions were observed, particularly in sectors with high import intensity (e.g., Kaliningrad's automotive industry and export-oriented enterprises). On the other hand, by 2022–2023, significant structural adjustments were underway: the decline in industrial activity was less severe than initially expected due to the push toward import substitution and localization. As a result, reliance on foreign components diminished across all key sectors.

Local experts note that over the course of two years, revised procurement strategies and restructured logistics chains helped partially offset the adverse

effects of sanctions. Following the withdrawal of foreign automotive giants, new ventures emerged: for instance, local automobile production (e.g., Solaris replacing Hyundai) was launched at vacated facilities.¹ The Izmeron plant, operated by Bronka Group, secured 2 billion rubles in 2023 to expand oil and gas equipment capacities, reflecting a re-engineering shift toward high-tech niches.² In the Kaliningrad region, adaptation progressed through the Vostok programme relaunched in early 2025, which doubled concessional loan limits to stimulate new industries in the eastern zone.³ In the Chernyakhovsk industrial park, DMS Vostok invested approximately 2.3 billion roubles in a deep dairy processing plant producing milk powder and butter, with export plans covering 40–60 % of output and operations scheduled to begin in 2025. The Leningrad region experienced growth driven by chemical enterprises redirecting activities to the domestic market and to Asian partners. Localization of anticorrosion coatings began in late 2022, while fertiliser producers (EuroChem, Fosforit) adapted through the adoption of domestic equipment and reconfigured internal supply chains.

Overall, the industrial complex of Saint Petersburg, the Leningrad region, and the Kaliningrad region ultimately demonstrated considerable adaptability: despite severe shocks, authorities and businesses identified new niches (both in the domestic market and within the pivot to Asia) and continued the development of manufacturing industries.

Alongside these empirical findings, it is essential to review methodological approaches for analyzing the structures and dynamics of manufacturing. In recent decades, economic geography and regional studies have employed a broad range of spatial modelling methods to study industrial structures and trends.

Classical regression models (e.g., OLS regression) assume independence of observations and fail to account for spatial autocorrelation. In spatial econometrics, traditional methods often yield biased results when spatial autocorrelation is present [13]. To address this issue, spatial regression models have been developed. The spatial lag model (SAR) incorporates the influence of neighbouring regions on the dependent variable by including a spatially lagged term [14]. The spatial error model (SEM) captures spatial structure in the error term [15]. Both approaches formalize the phenomenon of interdependence among geographically proximate regions and produce more reliable estimates of production factors. However, they require the construction of a spatial weight matrix and complicate econometric interpretation (e.g., the presence of multiplicative effects). A further extension

¹ RIA Novosti, 2025. *Car production of Solaris launched in Saint Petersburg*, URL: <https://ria.ru/20240222/avto-1928999404.html> (accessed 25.06.2025).

² Delovoy Peterburg, 2025. *With new conditions: the main investment projects of the year in Saint Petersburg*, URL: https://www.dp.ru/a/2023/01/11/S_novimi_vvodnimi (accessed 25.06.2025).

³ RBC, 2025. *The «Vostok» business support program resumed in Kaliningrad*, URL: <https://kaliningrad.rbc.ru/kaliningrad/31/03/2025/67ea65c29a79472b8f09f70d> (accessed 25.06.2025).

is the spatial Durbin model (SDM), which accounts for spatial lags of both dependent and independent variables [16]. This increases flexibility in modelling interregional interactions but also expands the parameter space and raises issues of multicollinearity.

An alternative approach involves regression models with spatial non-stationarity [17]. Geographically Weighted Regression (GWR) allows model coefficients to vary by location, thereby capturing local heterogeneity. In GWR, a separate OLS regression is estimated for each location based on nearby observations, thus relaxing the assumption of spatially constant relationships [18]. This approach improves model fit in the presence of substantial regional heterogeneity and facilitates the interpretation of local effects. According to Mamontov and Ostrovskaya, GWR's advantages include computational simplicity and interpretability under conditions of pronounced regional diversity. Its drawbacks include reduced generalizability—since the model no longer produces a single global relationship—and risks of multicollinearity and complex model diagnostics. Nonetheless, the authors conclude that for analyzing Russian regional convergence, GWR is the most suitable modelling method due to the strong interregional disparities [19]. For the study of industrial production, this implies that GWR reveals spatially localized dependencies among variables.

Another group of methods consists of tools for analyzing spatial autocorrelation, which measure the similarity of values across neighbouring territories. The principal methodological approaches here are global and local indices of spatial autocorrelation, including Moran's I [20], Geary's C [21], and the Getis—Ord statistics (G and G_i^*) [22; 23]. The global Moran's I assesses the overall tendency toward clustering across the study area: positive values indicate that neighbouring regions exhibit similar levels of the studied variable (either high or low), while negative values suggest alternating high and low values. For example, a study of the spatial distribution of manufacturing enterprises demonstrated significant positive autocorrelation: production sites are not randomly distributed but cluster spatially [24]. The drawback of these global measures lies in their generality: they identify clustering across the entire study area but not its precise locations.

To locate clusters, local indices are applied, particularly the Local Moran's I (LISA, Anselin's Local Moran's I). This method identifies 'hot spots' (concentrations of high values), 'cold spots' (concentrations of low values), as well as spatial outliers — regions with unusually high values surrounded by low ones (or vice versa). Results, however, are sensitive to the choice of spatial weights matrix and the scale of analysis. In addition to Moran's I, Getis—Ord statistics (for hot/cold spot detection) and Geary's C (an alternative global autocorrelation measure) are sometimes used. Such methods are widely applied in GIS-based spatial analysis. For instance, Hassan et al. combined kernel density, Ripley's K function, and global and local Moran's indices to study enterprise activity, identifying clear clustering patterns in several industries and a strong relationship between firm locations and infrastructure access [25].

Geoinformation methods complement statistical analysis: GIS systems enable visualization of spatial patterns, overlaying and analyzing multiple map layers, buffering, and data aggregation within specified boundaries. However, GIS analysis is often descriptive in nature: it highlights local clusters but does not fully capture causal relationships. Moreover, results depend heavily on data quality, which must be taken into account during interpretation.

For analyzing temporal changes in production volumes, standard spatial indices are not directly applicable, as they assess static autocorrelation. For comparisons across two time points, spatial-temporal statistics are more useful. One such tool is the differential local Moran's I, which calculates local Moran's I based on the changes in a variable between two periods. Unlike the conventional local Moran's I, which uses absolute values, the differential index uses differences (e.g., increases or decreases in regional production) to construct the statistic [26]. This method refines global indices: while the global differential Moran's I captures overall clustering trends, the local differential index pinpoints specific areas with significant changes.

In summary, a review of existing methodological approaches demonstrates that the use of the differential local Moran's I is the most appropriate for studying industrial dynamics in the Baltic regions. This method is specifically designed to assess spatial-temporal autocorrelation of changes, thereby identifying local clusters of industrial growth or decline. Given the objectives of this study—analyzing spatial-temporal changes in manufacturing output and formulating policy recommendations—this approach ensures the necessary level of detail and statistical rigour.

Research methodology

This study employs the local indicator of spatial autocorrelation (LISA) developed by Anselin, adapted for assessing two-period differences of the indicator — the differential Moran's I [13]. This index makes it possible to determine the extent to which changes in a given variable at a specific location depend on similar changes in neighbouring territories. Put simply, it identifies clusters of municipalities with similar rates of industrial production growth or decline over the study period.

At the first stage, global spatial autocorrelation was assessed using the global Moran's I [20]:

$$I = \frac{N}{W} \cdot \frac{\sum_{i=1}^N \sum_{j=1}^N w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^N (x_i - \bar{x})^2}, \quad (1)$$

where N — the total number of territorial units;

x_i — the indicator value for territory i (volume of shipped own-produced manufacturing goods in the municipality, expressed in constant 2019 prices);

$\bar{x}$ — the mean value of the indicator across all territories;

w_{ij} — an element of the spatial weight matrix, defining the degree of neighbourhood between i and j ;

$\sum_{i=1}^N (x_i - \bar{x})^2$ — the variance of the indicator across all units.

A positive index value (ranging from 0.01 to 1.0) indicates positive spatial autocorrelation (clustering of territories with similar values—either high or low). The closer the value is to 0.01, the weaker the spatial association; the closer to 1.0, the stronger the spatial dependence and the more stable the clusters. Negative values (–0.01 to –1.0) indicate negative autocorrelation (adjacency of territories with contrasting values). Values close to –0.01 imply weak spatial association, whereas those near –1.0 reflect strong spatial disintegration, where growth in one territory coincides with decline in another. Values near zero (–0.01 to 0.01) suggest randomness and absence of spatial structure.

The spatial weights matrix w_{ij} of size $N \times N$ (where $N = 167$) was constructed based on distances between the geographic administrative centres of municipalities, calculated using Euclidean distance from latitude and longitude coordinates. Diagonal elements were set to zero $w_{ij} = 0$, since a municipality does not influence itself. After determining the initial weights, the matrix was row-standardized, ensuring that the sum of all elements in each row equalled one. This normalization guaranteed the comparability and validity of the subsequent spatial analysis. A linear distance-based weights matrix was used in this study, reflecting the uneven distribution of municipalities in terms of area, population density, presence of large urban agglomerations, and disparities in economic development. Such heterogeneity makes simple binary contiguity matrices inadequate, as they ignore interaction intensity between non-adjacent municipalities.

In this article, the terms ‘territory’, ‘municipality’, and ‘district’ are used interchangeably to denote municipal units (urban okrugs and municipal districts) of the three regions under study (167 units in total). A cluster is defined as a group of municipalities exhibiting similar industrial production dynamics.

Next, the local Moran’s I was calculated for each municipality:

$$I_i = c (x_{i,t} - x_{i,t-1}) \sum_j w_{ij} (x_{j,t} - x_{j,t-1}), \quad (2)$$

where c — is a scaling coefficient, calculated as the inverse variance of changes in manufacturing output to ensure comparability; t — denotes the time period.

The local index takes positive values when changes in a given municipality coincide with those in its neighbours (either jointly exceeding the average—forming a growth cluster—or jointly declining). Negative values indicate that the dynamics of a municipality diverge sharply from those of its neighbours, i.e., the municipality functions as a spatial outlier.

The statistical significance of local indices was determined using a permutation test with 999 permutations (significance level $p < 0,05$). Based on results, municipalities were classified into categories of spatial autocorrelation (LISA):

- High—High (HH): high dynamics in a municipality and its neighbours, growth cluster (marked in yellow in Figures 2, 4);
- Low—Low (LL): low dynamics in a municipality and its neighbours, decline cluster (marked in blue in Figures 2—4);
- High—Low (HL): a municipality with high growth surrounded by low-growth neighbours, growth pole (marked in red in Figures 1—4);
- Low—High (LH): a municipality with low dynamics surrounded by high-growth neighbours, depression island (marked in green in Figures 3, 4);
- all other municipalities with insignificant indices (no pronounced spatial dependence).

The Moran's I was calculated separately for each municipality, allowing the analysis to focus on the spatial distribution of changes in manufacturing output (growth or decline), rather than static levels of the indicator. All computations were carried out by the author; cluster maps were prepared using GeoDa and QGIS software.

Data and preparation

This study draws upon municipal-level data on the dynamics of manufacturing output for the years 2019—2021 and 2023. The year 2019 was selected as the baseline (pre-crisis) period to normalize the data and ensure comparability of indicators. Two crisis stages were examined: the pandemic-related restrictions (2020—2021) and the period of sanctions pressure (2022—2023). The primary source of data is the official statistical materials of Rosstat for the municipalities of Saint Petersburg,¹ the Leningrad region² and the Kaliningrad region.³

To reduce the effect of inflation, all monetary indicators for 2021 and 2023 were converted to 2019 constant prices by deflating with consumer price indices, thereby allowing calculations in real terms. Unified regional deflators were applied, without disaggregation to the municipal level.

The first crisis stage (2019—2021) was marked by strict restrictions associated with the COVID-19 pandemic, leading to enterprise closures and disruptions in production chains (particularly in the light industry and automotive manufacturing). The second crisis stage (2022—2023) reflects the impact of international sanctions and associated economic counter-shocks, manifested in

¹ Rosstat, 2025. *Database of municipal formations of Saint Petersburg*, URL: <https://rosstat.gov.ru/dbscripts/munst/munst40/DBInet.cgi> (accessed 25.04.2025).

² Rosstat, 2025. *Database of municipal formations of Leningrad Region*, URL: <https://rosstat.gov.ru/dbscripts/munst/munst41/DBInet.cgi> (accessed 25.04.2025).

³ Rosstat, 2025. *Database of municipal formations of Kaliningrad Region*, URL: <https://rosstat.gov.ru/dbscripts/munst/munst27/DBInet.cgi> (accessed 25.04.2025).

shortages of imported equipment and components. Despite the import substitution programs introduced from 2022 onward, regional recovery was uneven, while technological shortages contributed to inflationary pressures.

The results of the study

Before conducting spatial clustering of manufacturing in the Baltic regions, the differential Moran's I was analyzed for the period 2019–2020. The resulting value of -0.016 indicates weak negative spatial autocorrelation, reflecting only minor spatial heterogeneity among municipalities in terms of manufacturing dynamics. Statistically significant spatial clusters were extremely rare: only two municipalities of Leningrad region—Slantsevsky municipal district and Boksitogorsk municipal district (MD) (HL-type clusters) (Fig. 1).

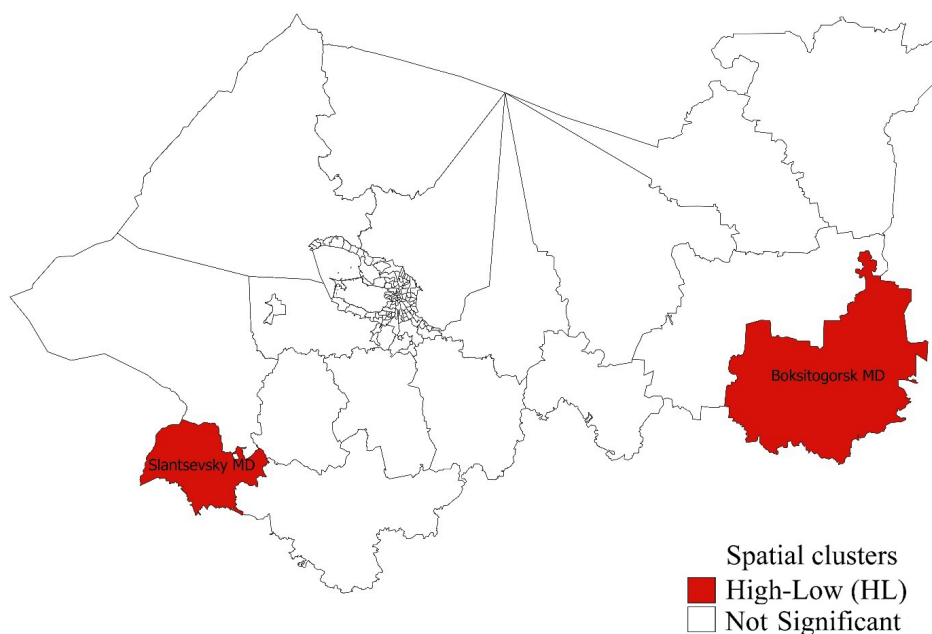


Fig. 1. Spatial clustering of manufacturing in the Baltic regions, 2019–2020

Note: The Kaliningrad region is not shown due to the absence of statistically significant municipalities. Calculations are based on Rosstat data.

These clusters are characterized by high values of manufacturing output in the given municipalities surrounded by neighbours with low values. Altogether, the two significant clusters represent just 1.2 % of all municipalities. This supports the overall conclusion that the pandemic crisis of 2020 was predominantly absolute in nature, affecting municipalities uniformly without the formation of stable spatial groupings of growth or decline [27].

A subsequent analysis of the differential Moran's I for 2019–2021 revealed similar tendencies. The value of -0.011 again confirmed weak negative spatial autocorrelation, i.e., minimal stratification in the development of manufacturing across municipalities in the Baltic regions (Fig. 2).

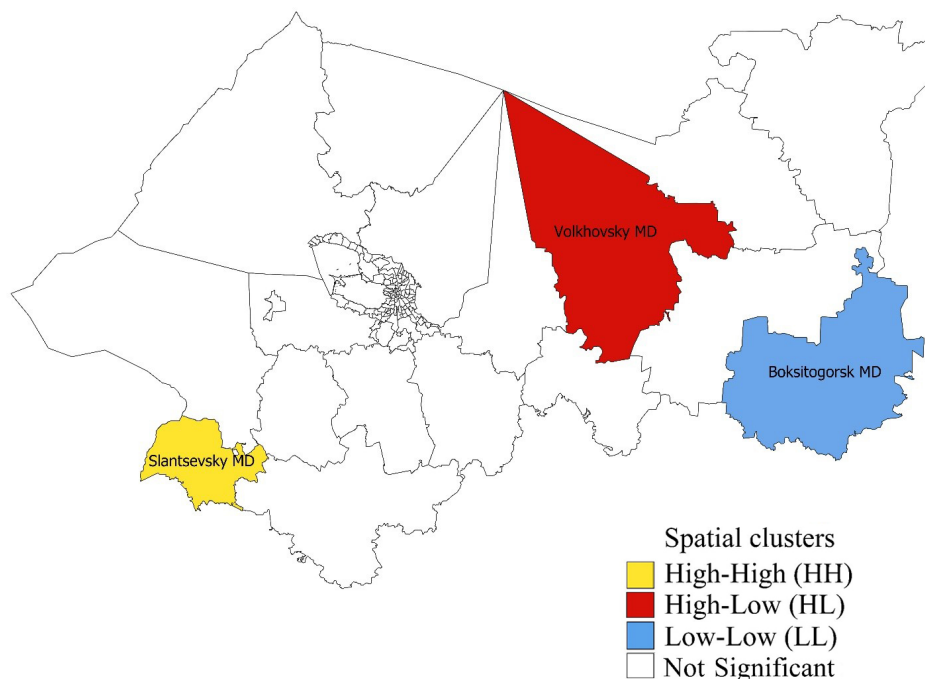


Fig. 2. Spatial clustering of manufacturing in the Leningrad region and Saint Petersburg, 2019–2021

Note: the Kaliningrad region is not shown due to the absence of statistically significant municipalities. Calculations are based on Rosstat data.

The local analysis identified only three significant clusters in the Leningrad region. Slantsevsky municipal district fell into the HH-type cluster, where both the municipality and its neighbours showed strong positive dynamics. This was driven by the relative resilience of major chemical enterprises, as confirmed by sectoral statistics. In contrast, Boksitogorsk municipal district formed an LL-type cluster with declining dynamics both locally and in surrounding municipalities, due to structural weakness and dependence on industries most affected by the pandemic (such as extractive industries and construction materials). Volkhovsky municipal district was identified as a growth pole (HL-type), outperforming its neighbours thanks to investment projects, notably the construction of a PhosAgro plant producing nitrogen-phosphate fertilizers.

In Saint Petersburg and the Kaliningrad region, no significant spatial clusters were identified for these periods. This can be explained by the relatively balanced structure of manufacturing and the uniform impact of crisis factors such as

disrupted logistics and enterprise shutdowns. In the Leningrad region, more pronounced clustering reflected the structural heterogeneity of its industrial base, where some districts depended on a narrow set of industries and enterprises that adapted differently to external shocks.

For the period 2021 – 2023, the differential global Moran’s I was close to zero (0.001), suggesting almost no spatial autocorrelation and hence weak or absent spatial interdependencies in the distribution of manufacturing (Fig. 3).

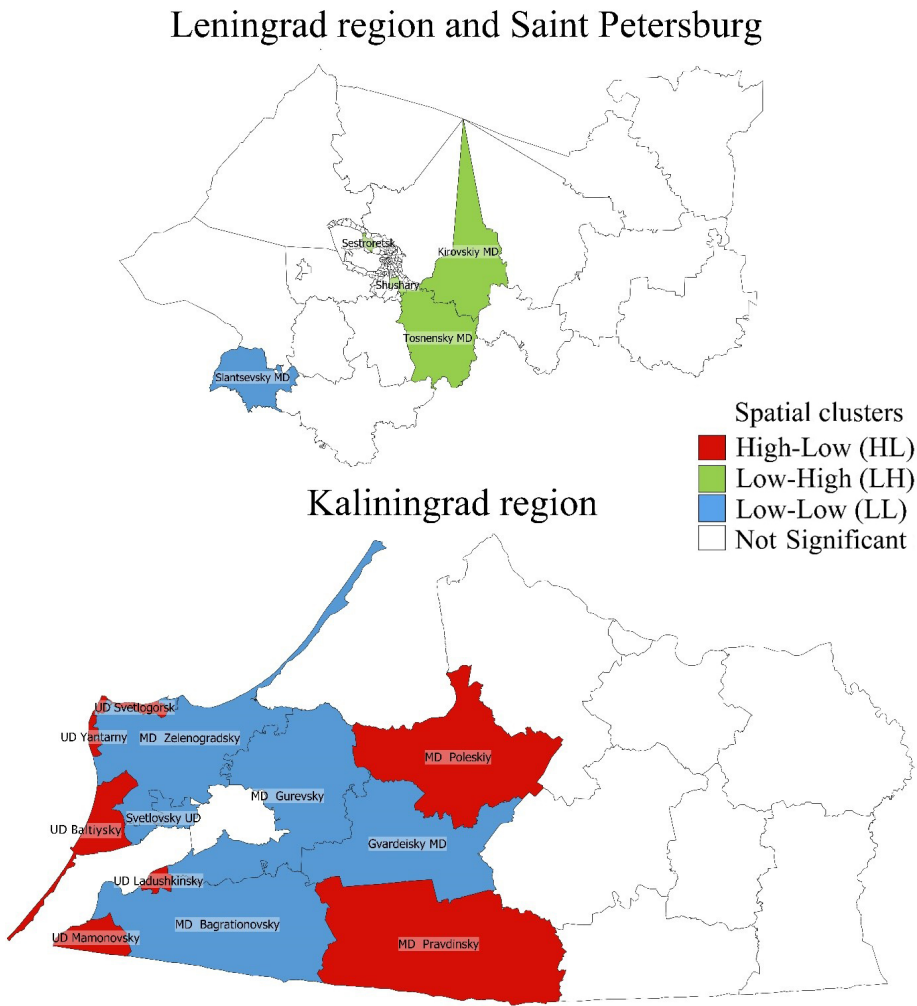


Fig. 3. Spatial clustering of manufacturing in the Baltic regions, 2021 – 2023

Calculations are based on Rosstat data.

However, the number of significant clusters increased markedly. Of 167 municipalities, 26 (16 %) were statistically significant: 21 in the Kaliningrad region, three in the Leningrad region, and two in Saint Petersburg.

In the Kaliningrad region, a large zone of decline was identified: Svetlovsky urban district (UD), Gvardeisky, Bagrationovsky, Guryevsky, and Zelenogradsky municipal districts—all exhibiting low production dynamics alongside neighbouring municipalities with similarly weak performance. At the same time, growth poles (HL-type clusters) were identified Polesky MD, Pravdinsky MD, Ladushkinsky UD, Svetlogorsk UD, Mamonovsky UD, Yantarny UD and Baltiysky UD. Overall, a large LL-type cluster of decline encompassed much of the Kaliningrad region, linked to the loss of transit corridors and dependence on external trade. For example, in spring 2022, Lithuania banned rail transit of coal, metals, cement, timber, and construction materials to Kaliningrad, affecting 40–50 % of the region's cargo. Simultaneously, Avtotor suspended car production for BMW, Hyundai, and Kia, resuming only in late 2022 with Chinese brands. Experts estimate that in 2024, Kaliningrad's industrial output was 23 % lower than in 2021. Yet, local HL-type growth poles also emerged, supported by successful enterprises or subsidies (e.g., agricultural machinery, food industry).

In the Leningrad region, the following territories were identified: Slantsevsky municipal district once again fell into an LL-type zone—by 2023, even the region's chemical enterprises faced declining demand and export difficulties, resulting in dynamics similar to those of neighbouring municipalities. Tosnensky and Kirovsky municipal districts became 'depression islands' (LH-type): their own growth rates remained low compared with surrounding areas. In Tosnensky MD, earlier projects in reinforced concrete and household chemical production encountered shortages of imported components and falling domestic demand. The key industrial sectors of Kirovsky MD, such as shipbuilding and mechanical engineering, suffered from declining investment and difficulties in equipment supply.

In Saint Petersburg, the following 'depression islands' were identified: Shushary and Sestroretsk, both classified as LH-type clusters. This indicates that their industries grew more slowly than those of the surrounding territories. Shushary, a major industrial zone in southern Saint Petersburg (cement, chemical, and light industries), was hit by logistic disruptions and demand contraction. At the same time, other districts of the city benefited from state defense contracts: for example, shipbuilding and defense orders supported industrial growth, improving overall performance.

For the combined period 2019–2023, the global differential Moran's I amounted to -0.013 , indicating negative spatial autocorrelation and a tendency toward divergence in manufacturing development among neighboring municipalities (Fig. 4).

A total of 25 municipalities were statistically significant: 21 in the Kaliningrad region, three in the Leningrad region, and one in Saint Petersburg. Almost all Kaliningrad municipalities once again formed a large LL-type cluster

(low dynamics across the region), confirming persistent industrial depression. In the Leningrad region, an HH-type cluster was identified for Kirovsky municipal district, which displayed relatively strong growth, whereas Tosnensky and Kirishi municipal districts remained LH-type (underperforming compared to neighbours). This reflects the fact that Kirovsky municipal district specializes in shipbuilding, supported by state defense orders, while Tosnensky and Kirishi MD depend on construction and refining industries, which were more strongly affected by sanctions and shrinking demand. In Saint Petersburg, only Shushary was classified as LH, lagging behind positive dynamics in the surrounding districts.

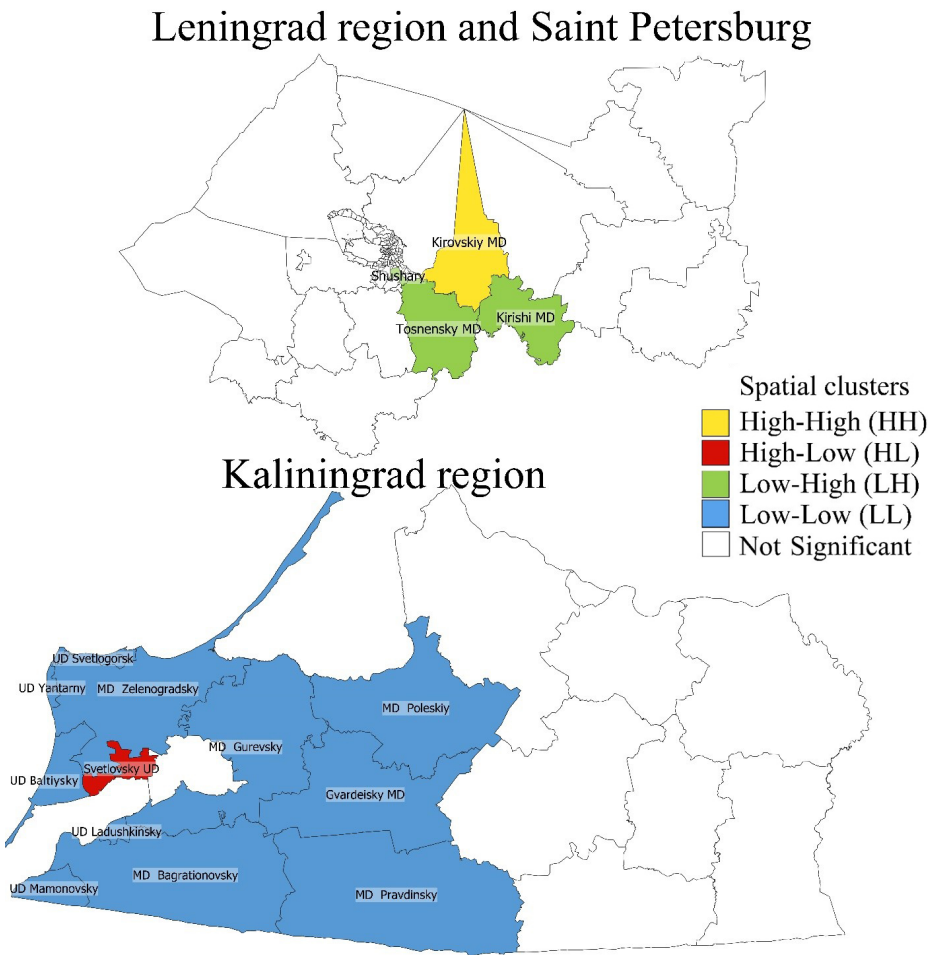


Fig. 4. Spatial clustering of manufacturing in the Baltic regions, 2019–2023.

Calculations are based on Rosstat data.

Thus, the spatial structure of industrial change in the Baltic regions reveals distinct clusters: the Kaliningrad region consistently emerged as a zone of

decline across both crises, most strikingly in 2023 when an LL-type cluster encompassed the majority of the region. This corresponds with Kaliningrad's dependence on foreign trade and limited access to technology. By contrast, Kirovsky municipal district in the Leningrad region became a growth pole over 2019–2023. HL-type clusters are also visible in the Kaliningrad region (e.g., Svetlovsky urban district in 2023 became a growth pole, showing growth against a backdrop of decline in neighbouring municipalities), pointing to the role of successful enterprises or subsidies in certain areas. In the Leningrad region, LH-type clusters (Tosnensky and Kirishi MD) and LL-type clusters (Slantsevsky MD) reflect spatial heterogeneity: some districts performed worse, while their neighbours expanded.

In summary, several key trends can be identified. First, the sanctions generated greater spatial heterogeneity in the manufacturing sector than the pandemic. By 2023, clear zones of decline (Kaliningrad region) and resilience (Kirovsky MD in the Leningrad region) had emerged against the general backdrop of recovery. Second, there is a clear link between industrial structure and clustering: industrially developed districts (e.g., Kirovsky MD) managed to sustain growth even during crises, while territories with vulnerable sectors (e.g., Slantsevsky municipal district, dependent on extractive and energy-intensive industries) fell into decline. This confirms the relevance of the concept of spatial resilience of industrial clusters [28]. Third, the identified spatial clusters correspond to well-known structural factors: export-oriented Kaliningrad, heavily impacted by disrupted supplies, became a zone of decline, while the more diversified Leningrad region, exemplified by Kirovsky MD, proved to be a cluster of high performance. Finally, the widespread LL-type cluster in Kaliningrad highlights systemic regional problems, whereas isolated HL/HH clusters illustrate the effects of local initiatives or investments.

On the basis of these findings, several policy implications arise. First, support should be concentrated in clusters of decline. In the Kaliningrad region, specific measures are needed: accelerated import substitution (reorienting enterprises to domestic components), logistical diversification (development of maritime corridors with partner countries), and investment incentives for priority sectors (pharmaceuticals, instrumentation), where other regions have already advanced [29]. Second, in HH-type regions, existing competitive advantages should be reinforced—for example, expanding large-scale industries and clusters (shipbuilding, electronics). Third, in LH-type municipalities such as Tosno and Kirishi, interaction should be stimulated: support for small enterprises, strengthening educational and training programs to improve workforce skills (given that human capital quality is a key growth factor). In addition, continued state support for agglomerations and core enterprises is advisable, since under such conditions the role of state-owned companies becomes especially prominent.

At the strategic level, it is crucial to emphasize that the Baltic regions should leverage their foreign trade connections not for importing scarce technologies but for exporting processed goods. Greater emphasis should be placed on deeper processing, innovation, and digitalization of production. Developing flexible logistics and diversifying export markets (e.g., strengthening cooperation with China, the CIS, and other partner countries) will also minimize risks of external disruptions.

Conclusion

The identified spatial heterogeneity is largely explained by differences in the industrial structure and resilience of municipal economies. The Leningrad region, in particular, exhibits substantial sectoral diversity: in Slantsevsky municipal district (HH-type cluster), the chemical industry dominates, with large enterprises able to weather the crisis relatively smoothly. By contrast, Boksitogorsk municipal district specializes in extractive industries and building materials, which were less resilient during the pandemic and recorded a sharp decline in output (LL-type cluster). Volkhovsky municipal district, on the other hand, displayed higher-than-average local growth, explained by new investment projects such as the PhosAgro fertilizer plant. This unevenness reflects the differing shares of chemicals, mechanical engineering, extractives, and light industry, which create distinct external risks and growth potentials. Regions with developed defense and engineering industries demonstrated stable growth, while resource-based clusters experienced fluctuations and decline. The resilience of large enterprises (metallurgical and chemical) in the Leningrad region generated local ‘islands of stability’, whereas municipalities with more vulnerable industries entered crisis more quickly. Investment projects (fertilizers, shipbuilding) generated HL-type growth poles even against the general backdrop of decline.

The COVID-19 pandemic and subsequent sanctions affected all territories. In Saint Petersburg and the Kaliningrad region, logistics breakdowns, supply chain disruptions, and widespread enterprise shutdowns impacted sectors in a relatively uniform manner. In Kaliningrad, dependence on foreign trade and supply restrictions produced overall industrial decline, reinforcing a region-wide downturn and leading to LL-type clustering across the region—making it one of the few regions that has not recovered from the 2022 contraction.

The Leningrad region differed from its neighbours in that its districts reacted unevenly to the pandemic of 2020—2021. All statistically significant clusters of this period were concentrated there. Slantsevsky municipal district avoided major losses by relying on large chemical enterprises, while Boksitogorsk municipal district suffered a notable decline and entered an LL-type cluster. Volkhovsky municipal district, benefiting from new investment, emerged as a growth pole (HL-type). This indicates strong intra-regional differentiation:

some municipalities possessed consolidated resources and state contracts, while others depended on a narrow set of industries. By contrast, no significant clusters formed in Saint Petersburg and Kaliningrad: their industrial structures were more homogeneous, and crisis factors affected most enterprises in a broadly similar manner. The absence of significant HH or LL clusters means that local changes in production volumes were largely random (with the global Moran's I close to zero). This corresponds to a situation where sectoral shocks are distributed evenly and enterprises share similar structures, preventing the formation of distinct spatial clusters.

The results highlight the necessity of a territorially differentiated approach to industrial policy. In the short and medium term, priority should be given to targeted support for municipalities in decline clusters: developing mechanisms of import substitution, stimulating logistical adaptation, and forming stable production and sales networks oriented toward the domestic market and alternative external destinations. At the same time, municipalities in growth clusters require measures to scale up their production potential and deepen industrial specialization. Moreover, at the interface between growth and decline zones, it is advisable to promote connecting infrastructure, support small and medium-sized enterprises, and develop inter-municipal production chains, thereby contributing to balanced spatial industrial development.

Looking ahead, it is advisable to expand the analytical framework by incorporating additional socio-economic indicators such as investment levels, employment, and innovation activity. Furthermore, applying spatial regression models (including spatial lag and spatial error specifications) would enable a deeper interpretation of the factors underlying territorial disparities in industrial dynamics.

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