**Regional manufacturing bases in the EU an their relevance for income and growth.**


## Abstract

The objective of the study was to evaluate the spatial spillover growth effects initiated by regions with a robust manufacturing base. Contrary to expectations rooted in Location Theory and Industrial Agglomeration Theory, the findings indicate a negative association between measured manufacturing proxy variables (manufacturing employment per square kilometre, share of GVA in manufacturing) when controlling for labour stock and population density. Spatial spillovers were confirmed only in the Spatial Error Model (SEM), suggesting that unobserved regional factors, rather than manufacturing intensity, were driving the spatial dependence. The Spatial Lag Model (SLM) did not confirm the existence of significant spatial dependence in regional GDP growth within the EU's regional structure. Neither regional hubs in terms of employment in manufacturing nor regions with a higher share of GVA in manufacturing have significantly outperformed other regions in economic growth; hence, the growth spillovers to neighbouring regions were not confirmed. The findings suggest that the current EU industrial base is facing structural constraints, characterised by an outdated and high-cost manufacturing structure that is unable to drive growth or generate positive spillovers. From a policy perspective, future EU strategies should be more regionally adaptive, involving the local institutions and stakeholders in the acceleration of the dismantling of obsolete technologies and industrial structures, while supporting the diversification and gentrification of industrial areas.



**Key words:** manufacturing hubs, manufacturing deserts, economic growth, spatial spillover effects, spatial dependence, regional policy


## Introduction

Restoring the competitiveness of the European manufacturing sector and closing the innovation gap with the US and China remain key priorities for the EU. The European Commission, as the EU's principal executive body, primarily relies on regulatory simplification and reforms in fiscal, labour, and industrial policies, implemented mainly at the member-state level (Competitiveness Compass for the EU, 2025).

The EU has long called for an *'Industrial Renaissance'*. In 2014, the European Commission, in its communication, challenged the EU's commitment to *'For a European Industrial Renaissance,'* citing the industry's outsized role in the EU economy. EC reported that the EU industry accounts for over 80% of Europe's exports and 80% of private research and innovation (EC, 2014).

The following geopolitical events, such as the COVID-19 pandemic and the war in Ukraine, brought a broad range of repercussions onto the EU economy. On the backdrop of these events, the EC presented and updated document '*A New Industrial Strategy for Europe'* – a comprehensive plan aiming to shore up flagging European competitiveness towards the main non-European competitors, like the US and China The EU also observes such a plan as an opportunity for the EU's world-leading industry to lead twin green and digital transitions against the backdrop of other pressing issues like climate change and the phasing out of Russian fossil fuels (EC, 2021; EC, 2023).

However, the EU industrial anaemia has continued to put further strain on the European economy. In more recent reports, Enrico Letta (Letta, 2024) cites several factors which are eroding the EU's position on the world stage. 1) The global demographic and economic landscape: over the past three decades, the EU's share of the global economy has diminished in favour of rising Asian economies. The leading cause is the shrinking and ageing European population; 2) The rule-based international order: wars and trade conflicts increasingly undermine the principles of a rule-based international system; 3) The perimeter of the Single Market: there are still sectors kept outside of the integration process, like finance, electronic communication and energy. Initially designed to protect domestic industries, national markets now represent a significant brake to growth and innovation in sectors where global competition has become increasingly important. Furthermore, Mario Draghi (Draghi, 2024) highlighted the slowing of EU productivity growth and the failure to close the innovation gap with the US and China, especially in advanced technologies. Among the essential causes, the report cites a static European industrial structure with few new companies rising to develop new growth engines. The EU generally lags behind the US in R&D spending, translating innovation into commercialisation in overseas markets, thereby propelling EU trade competitors.

The paper's research goal is to investigate potential spatial spillover growth effects between regions with significant industrial clustering that diffuses into neighbouring regions. This paper revisits traditional location-based theories to explain regional competitiveness in the EU manufacturing sector, emphasizing the role of industrial density in shaping economic performance. Their relevance in the case of the EU industry will be questioned. That raises questions about whether traditional industrial bases located in the EU's heartland still deliver economic growth or have become a liability due to their difficult adaptability and stiff competition.

There is considerable variation in industrial density among the EU member states on the regional level. Traditionally, large industrial bases are often cited as the backbone of the economy and, therefore, have a significant presence in regional theories. There is evidence that regions with significant manufacturing bases are prone to innovation and retain a competitiveness advantage in the global environment (Porter, 1990, 1998), able to attract skilled workers with significant spillover effects (Marshall, 1890) and realise economies of scale (Krugman, 1991).

The central focus of the study is the relationship between regional manufacturing hubs and economic growth in the EU. The regional hub is considered a region with significant representation of manufacturing employment, operationalized as the number of workers per square kilometre (e.g. manufacturing density) at the regional NUTS3 level. This level of observation prevents the blurring of subtle regional differences, that would occur at higher spatial unit. To frame the structural variation, the study considers three type of regions:

- Manufacturing hubs – regions with high manufacturing density and activity
- Manufacturing average – regions with moderate density
- Manufacturing deserts - regions with the low density, reflecting industrial decline or underdevelopment areas.

The study examines the geographical distribution and clustering of manufacturing hubs using spatial analysis methods. For this purpose, the Incremental Spatial Autocorrelation method was adopted. Finally, the diffusion of potential spatial growth effects of manufacturing hubs into neighbouring regions will be evaluated by using the spatial autoregression model.

While most existing studies emphasise firm-level externalities and their effects on local space, this study uniquely investigates spatial spillovers of manufacturing hubs at the regional level across the EU. The novelty of this research lies in extending the concept of spillovers beyond firms to the regional scale, bringing evidence on whether regions with substantial manufacturing concentrations stimulate growth in adjacent areas. There are well-elaborated theories concerning spatial spillovers between the firms in the area, thereby realising scale economies from local externalities. The presence of knowledge, technology, and innovation spillovers between firms is already supported by evidence, but little is known about their diffusion. By addressing this gap, the study provides insights into the growth prospects of regions retaining robust manufacturing sectors and offers policy implications for fostering the regional development.

## The theoretical background

### *The manufacturing geography of EU*

There is a common consensus about the role of industrialisation in a nation's economic development. Proponents often cite manufacturing's productivity advantage over the other sectors and the higher externalities that can arise from manufacturing growth (Haraguchi et al., 2019).

Manufacturing growth is often linked with economic growth (Fagerberg et al., 2004; Felipe et al., 2016). One of the foremost theories regarding this relationship posits Kaldor's law as a set of empirical relationships between manufacturing growth and overall economic growth. In its scope, manufacturing is observed as a driver of economic growth, with significant spillover potential for the broader economy. Despite some evidence suggesting a shift in the economic weight of modern economies towards knowledge-based services at the expense of industry, this has not resulted in slower economic growth. Hence, it may be considered that Kaldor's principles are still valid (Quah, 1997; Peneder et al., 2001; Keho, 2018).

When discussing European industrialisation and manufacturing, we begin with their origins. Europe has a number of the world's most important industrial regions. They are located in a north-south belt, starting in Scotland, extending through southern England, and continuing from the mouth of the Rhine River in the Netherlands, through the Ruhr region in Germany, to northern France and northern Italy (Stutz and Warf, 2012).

The largest European manufacturing region today is in northern European lowland countries of Belgium and the Netherlands, northwestern Germany, and northeastern France. The Rhine river, the largest waterway of European commerce, empties into the North Sea in the Rotterdam which became one of the world's largest ports. The Upper Rhine-Alsace-Lorraine region is in south-western Germany and eastern France. This area is well situated to be a distribution hub to population centers throughout Western Europe. The main cities on the German side include Frankfurt, Stuttgart, and Manheim which increasingly become manufacturing hubs for transportation, chemical, pharmaceutical and financial industry. Not far away, the EU manufacturing belt extends to the Po River valley including Turin, Milan and Genoa where roughly 70% of Italian industry is located (Stutz and Warf, 2012).

When examining more detailed industrial datasets (Annexe 1) in the EU, the leading manual-intensive (in terms of job occupations) industry is *the food* industry*,* with a 15.46% share of employment, followed by the *metal manufacturing* industry with a 14.92% employment share. The following two double-digit employment share industries are the *automotive* industry (10.64%) and miscellaneous products (including jewellery, toys, etc.), with a 11.43% share. The lowest job occupation rate is found in the *chemical* industry and associated sectors, such as *coke* and *petroleum* (0.41–0.41%; chemicals 3.73%; pharmaceuticals 2.05 – 2.05%). (Eurostat, 2025).

***The Manufacturing within the scope of regional theory***

In the realm of economic geography and urban planning, understanding the factors that influence industrial location is crucial for policymakers, investors, and businesses alike. The Location Theory, a significant precursor to Regional Development theories, plays a crucial role in identifying the drivers of economic activity in an area and explaining the spatial arrangement of the economy. Its neo-classical foundation underscores its importance in the field of economic geography. In a narrower scope, theories with a focus on industrial location provide a framework for understanding why industries cluster in certain areas and how various factors contribute to their spatial distribution.

Blažek and Uhlíř (2020) speaks about four main developings of location theory: 1) internal and external savings – internal savings can be achieved within the industry and are usually based on specialization or extending the production; external savings are gained externally, like expanding of other companies or public infrastructure improvements; 2) location decision of companies – Hotelling's model of business location, developed by Hoteling (1929) explores how firms choose their locations in a competitive market, considering rather geographic than marker conditions; 3) the third trajectory stressed particularly 'soft' factors like perception and behavioral factors; 4) the fourth trajectory pursued the complex explanation of spatial arrangement of economic activity on the area.

Furthermore, to complex explanation of economic activity spatial arrangement considerably contributed Von Thunen model of agricultural land use around a central market (Encyclopedia Britannica, 2014); Weber's Least-Cost location theory and Christaller's Central Place Theory, examining how and why the arrangement of cities and markets has come to be and providing rationalizations for decision making and service allocation (Murray, 2009).

Models of regional development inspired by the Firm Location Theory largely depended upon the existence of firms in the region. In such models, regional development is a function of the factors which firms consider when looking for a location. Its traditional formulation – influenced by the pioneer works of Weber (1910s), Predohl (1920s) and Losch (1940s) – the firm's location decision problem is modelled as a simple transportation costs problem. Industries seek to minimise the production costs by locating where the costs of inputs – raw materials, labour and transportation costs are lowest (Sousa, 2010).

Hoover (1948) expanded Weber's ideas, introducing the Theory of Industrial Location. Hoover incorporated the role of market actors like the consumer demand into location decisions made by firms. Location theories, within their content, present both advantages and disadvantages in explaining the localisation of economic activity in the region. Among the benefits, the introduction of external economies of scale laid the groundwork for the clustering of firms in the space, thereby generating positive effects such as sharing resources, a specialised pool of workers, and knowledge spillovers. The firm clustering effect was coined as 'the presence of special atmosphere' by Marshall, summing up the most important features that characterise and identify an industrial district. The importance of an atmosphere is underscored by the 'automatic organisation', that is, a high degree of technological complementarities, as well as a continuous interplay between competition and cooperation (Belussi and Caldari, 2009).

Evenly, considering the location theory in the current global context, regional co-locations (clustering) remain a strategic advantage for firms, for example, by providing interconnectivity within and between clusters (van den Heuvel et. al, 2013).

In the current globalisation process, Location Theory is positioned in a global force field. This force field forces the firm to act and adapt rapidly to changing conditions, so that nomadic types of behaviour increasingly replace stable locations. The rapidly emerging technological changes encourage location theory to account for volatility, digitalisation and global dependencies (Mukhopadhyay, 2020). However, the Theory often oversimplifies the complexity of factors influencing the location decisions of individuals and firms. They disregard the existence of other activities or individuals, as well as dichotomous location alternatives, such as urban or non-urban areas, central or peripheral ones, and areas with high or low concentrations of economic activity (Capello, 2011).

Marking a stark departure from the assumptions of neoclassical theory, Keynesian theories assume that regional development is largely demand-driven. One of the foremost examples of different approaches to understanding regional development is Export Base Theory (EBT). The EBT established the importance of regional specialisation and the impact of external demand for a region's products on its growth. The region's export prices determine demand, the income levels of other regions and the price substitutes in external markets. Within the EBT, crucial are the region's export industries, which drive local growth, taking into account a variety of factors influencing prices, such as wages, capital, raw materials, and technology inputs. (Pike, Rodríguez-Pose and Tomaney, 2006).

From a slightly different perspective, the Grow Pole Theory (GPT) was established by Francois Peroux in 1949. The intuitive notion of growth poles identifies a growth pole as an industry or perhaps a group of companies within an industry (Gavrila-Paven and Bele, 2017). Within the GPT, in particular, the inter-industry linkage, multiplier effects, and trickle-down economics are emphasised. Economic growth from a lead or propulsive firm or an industry induces growth in other firms or sectors of an economy through agglomeration economies of positive externalities. Hence, growth poles are at once a theory of development and a regional development strategy or policy application. (Hutchinson, 2010).

GPT itself brings seeds of regional inequality. As the Cumulative Causation theory, pioneered by Kaldor (1950s-1960s), notes that scale economies present in Growth poles guarantee that the economy does not equilibrate. Social aspects of theory were highlighted by Myrdal (1957), who pointed to global inequality fueled by both internal and external economies. Poorer regions suffered 'backwash effects' due to the loss of population, ageing, low income levels, and outflow of capital, among other factors. Then, 'Spread effects' disseminate prosperity of growing regions, but far weaker than backwash effects. However, according to Hirschman's view (1958), inter-industry linkages among firms expand together in mutually supportive relationships (Jackson, 2020). Such attractions are equal in both directions. The backwards linkage is important mainly to the supplying activity. Therefore, a market-oriented activity is attracted by the presence of an activity to which it can sell its products or services. In turn, Forward linkage means that the impact of change is transmitted to an activity further along the sequence of operations. Backwards linkages promote the supply of inputs into industry, and forward linkages promote the processing, distribution and retailing of new, semi-finished products. The stronger the inter-industry linkages, the faster regional growth will be (Hoover and Giarratani, 2020).

The global application of the growth pole policies was reviewed by Frick and Rodríguez-Pose (2025). Several common characteristics were formulated: 1) the core of any growth pole strategy is the activation of pre-existing or nascent economic potential; 2) the policies aim to generate spill-over effects from the growth pole into surrounding areas; 3) successful growth pole strategy require an interconnected set of interventions and coordination between a broad range of subjects; 4) growth pole policy follow a spatially targeted approach, with interventions aimed at specific locations. In conclusion, the analysis of prosperous and less successful cases shows that while growth poles are not a cure-all for comprehensive development in emerging countries, they can oftentimes become a highly effective tool for boosting economic dynamism in cities and regions (Frick and Rodríguez-Pose, 2025).

New Economic Geography and Endogenous Growth models in the 1990s-2000s departed the industry, innovation, and agglomeration, but with micro-foundations. Notably, increasing mobility of production factors, goods and services was integrated into the economic growth of space. The presence of increasing returns and transport costs creates the circular logic of activities' agglomeration in space (noted as centripetal effects). A region with a large market offers advantages for firms which achieve scale economies. These types of firms can reduce costs by concentrating production at one site and serving other markets from that particular site. Large markets favour vertical linkages (backwardsboth backwards and forward linkages) between producers (upstream) and users (downstream) of intermediate inputs. Firms take advantage of such a location because of access to labour and a variety of inputs. The high number of different firms and their proximity enable the diffusion of knowledge and technology sharing (knowledge spillovers), further fostering market attractiveness. In turn, immobility of others – like land, natural resources and also labour implies the centrifugal effects. Other factors, such as stifling competition and congestion effects (e.g., pollution, price bubbles), impede further concentration and promote dispersion. (Krugman, 1998; Helmut and Fernanda, 2004; Buček et al., 2010; Capello and Nijkamp, 2011).

Krugman (1991) developed a theoretical model of endogenous industry location choice and in given conditions a spatial distribution of economic activity with core and periphery would develop. It suggests that the evolution of industrial structure and spatial configuration are endogenous which makes the model more effective than New Trade Theory in explaining the location choices about international trade and FDI (Fengru and Guitang, 2019).

Among others, the NEG takes credit for explaining why industries tend to cluster and also uneven development (through the influence of centripetal and centrifugal forces. The emergence of economic agglomeration is naturally associated with the emergence of inequalities across locations, regions or nations. Since, in general, the locations do not operate as 'autarkies' and economic activities are not perfectly divisible, the transport of some goods between some places becomes unavoidable. In this case, the Spatial Impossibility Theorem tells us that no competitive equilibrium exists ( Perrons, 2004; Fujita and Thisse, 2009).

The NEG was augmented by the New Growth Theory, which represents an interconnected framework. The agglomeration of industries is inevitably linked to the incidence of spillover effects of all kinds and may also be explicitly associated with knowledge spillovers. Henderson et al (2001) talk about dynamic externality, which relates the economic activity of an area with the past and present.

Two kinds of dynamic externalities can be distinguised: 1) category derived from Marshall (1890), Arrow (1962) and Romer (1990) based on the geographical proximity of firms in the area and; 2) the second category relates to the diversity and hence the spread of knowledge across different sectors (Boschma et al., 2011; Jacobs, 1969; Beaundry and Schiffauer, 2009). Extensive evidence suggests that innovation has both direct and indirect effects on people and firms located in clusters (Feldman, 1994; Baptista and Swann, 1998). The effect of knowledge and information spillovers between spatially concentrated firms in the same industry is to facilitate growth and innovation. The knowledge spillovers, as measured by the 'knowledge production function', were used to assess the effects of R&D investment on economic growth. Anselin et al. (2000), Acs et al. (2002) found evidence of spillover effects between universities and certain industries, using patent applications as a proxy indicator. Glaeser, et al.(1992) found that employment grows faster in diversified than specialised cities, which supports linkages over information spillovers as the primary force in agglomeration. However, Feldman and Audretsch's (1999) findings pointed out that regional specialisation promotes growth and development. Ellison and Glaeser (1999) studied the reasons for industries to concentrate in space and found that just 10-20% of clustering industrial patterns can be explained by natural endowments (ores and minerals, access to ports or navigable rivers), while the remaining 80-90% is due to intra-industry spillovers.

The role of industrial organisation was neglected mainly in NEG, which later became a focus point for institutional economics, exploring the contribution of organisation and institutions to economic growth.

Pioneering work led to Michael Porter's model of industrial organisation, often referred to as the Five Forces model, which determines factors affecting market entrants or the strategic reorientation of existing companies. The model is based on four parameters in the peripheral environment of industry participants. The two parameters, suppliers and customers, are considered part of the value chain and are relevant for both product or service provision and sales. The substitution factor is the possibility for market participants to exclude a product from their purchase decision by purchasing another product that offers the same benefits as its characteristics (Grant, 2016; Porter, 1985, Porter, 2010). Aghion et al. (1999) hinted about possible relevance of organizational changes for economic growth. However, organizational changes are not considered as main enabler of economic growth and innovation. Its role may contribute to process optimization resulting in productivity increase.

Considerably higher attention has been drawn to the potency of institutions and institutional changes in stimulating economic growth and boosting innovation. The causal link between institutional quality and economic performance was provided by Acemoglu et al. (2001) on the example of cross-country income differences. At the regional level, Viturka (2007) introduced the concept of economic-social regional clusters, known as the 'third Italy' (Tuscany, Emilia-Romagna, and others), as an example of best practices. These clusters have experienced extensive economic growth through concerted efforts among local small and medium-sized enterprises. In such an environment, where endogenous resources and social capital are mobilised through the nexus of cooperative relations, inducing agglomeration effects that ultimately become the bedrock of local economic competition (Maskell et al., 1998). Cooperation and work of institutions, even at the regional level, have become an inherent part of the Place-based development theory, which emphasises the community, endogenous resources, and their challenges, which should form the foundation for its development strategy. Place-Based is a relatively policy framework built on the postulates of earlier development theories (NEG, endogenous growth theory, Institutional economics, and others).

Place-Based Theory underscores the importance of interactions between communities and local institutions within the locality itself, which demands that policymakers take the place specifics into account in their tailored approach to development (Beer at al., 2020). Such approaches to regional development are highly advocated by the EU, UN and OECD (Barca 2009 ; UN-HABITAT, 2005; OECD, 2025).

**Data and Methods**

The paper aims to find evidence on regional growth spillovers diffusing from manufacturing hubs into adjacent regions. For study purposes, the following variables were employed:

- Regional GDP growth rate
- Regional labour stock growth rate
- Manufacturing density – the logarithm of employees in manufacturing per square km
- Manufacturing output – GVA share of manufacturing on total regional GVA
- Population density – the logarithm of population per square km

A cautionary approach has been adopted, surrendering to outright causation, because a range of factors influences the complex reality. The principal data source is Eurostat. Manufacturing is represented in the set of national accounts (ESA, 2010), the C category (NACE), which differs from the broader category of industry. The industry also includes categories B – mining and quarrying, D – electricity and gas, and E – water supply. The spatial analysis and model estimation are supported by the ArcGIS Pro 3.2 program and STATA.

The research period focused on short- to medium-term trends in manufacturing over the 2018-2022 span to mitigate out volatilities (pandemic COVID-19, energy shocks) that had a detrimental impact on the industry. The DATA post 2022 has not been available yet. All variables represent the mean value for the research period. The basic observation unit, the region at the NUTS3 level, was selected. The sample in total represents $n = 1140$ units. Such a level of nomenclature prevents the blur of subtle regional differences if a higher regional unit were considered. Manufacturing density was log-transformed prior to analysis to reduce skewness.

The sample mean was computed and 95% CI on the log scale using $t-$distribution ($x \pm t_{\alpha,n-1}\frac{s_n}{\sqrt{n}}$); regions above the upper CI were labelled as *manufacturing hubs*, below the lower bound are *manufacturing deserts.*

Next, the geographical distribution and the potential clustering of manufacturing centres in the regions are investigated using spatial analysis methods. For this purpose, only manufacturing hubs (included in the upper CI) were selected for *the application of the Incremental Spatial Autocorrelation (ISA)* tool. This method determines the distance or scale at which spatial clustering is most pronounced by computing a global spatial autocorrelation statistic (typically Moran's I) across a series of increasing distance bands. When more than one statistically significant peak is present, clustering is pronounced at each of those distances. Often, it is the first significant peak which is decisive. The Beginning Distance (BD) and Distance Increment (DI) represent the critical input. For the study purposes, the *Average Nearest Neighbour (ANN)* method was applied to determine empirically based search distances (BD, DI) for the ISA. The use of the method appears adequate, as the research encompasses spatially heterogeneous NUTS3 regions, which ensures that the ISA tests distances that accurately reflect the spatial arrangement of regions.

Let $z_i$ denotes value at location $i$, than $\bar{z}$ denotes the mean value of $z_i$, $n$ denotes the number of observations and $w_{ij}(d)$ denotes the spatial weight between $i$ and $j$ given a threshold distance $d$ (1 if distance$\leq d$, 0 otherwise). The distance thresholds are defined as a sequence $d_1 < d_2 < \cdots < d_k$, means increment as $\Delta d = d_{m+1} - d_m$ is constant. For each distance threshold $d_m$, Global Moran's I is computed

$$I(d_m) = \frac{n}{S_0(d_m)} \times \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(d_m)(z_i-\bar{z})(z_j-\bar{z})}{\sum_{i=1}^{n}(z_i-\bar{z})^2} \tag{1.0}$$

Where $S_0(d_m) = \sum_{j=1}^{n} w_{ij}(d_m)$ (1.1)

Expected value under spatial randomness

$$E[I] = -\frac{1}{n-1} \tag{1.2}$$

Variance and $Z$-score for each $d_m$

$$Z(d_m) = \frac{I(d_m)-E[I]}{\sqrt{Var[I(d_m)]}} \tag{1.3}$$

The distance $d^*$ with the highest statistically significant positive score indicates the distance at which spatial clustering is most intense. The paper aims to analyse the association between manufacturing (employment density, GVA) and economic growth, adjusted for labour stock growth and population density, against the backdrop of regional data. However, the assumptions of traditional linear regression models are often violated when using spatial data. When spatial autocorrelation is contained in the dataset, estimates may be biased and lead to inconsistent results. Spatial regression can be used to estimate a regression model that is robust enough in the presence of spatial dependence and heteroscedasticity, as well as to measure spatial spillovers. There are several options for implementing the measurement. The Spatial Error Model (SEM) is designed to address situations in which there is spatial autocorrelation in the residuals of a regression model. In SEM's, the spatial dependence is viewed as a nuisance parameter. The SEM eventually filters out spatial autocorrelation from each of the variables in the model and performs a regression on the spatially filtered variables. This approach appears to be suitable for our purpose, as the estimates will not be influenced by spatial autocorrelation in each variable. Formally, the SEM may be defined as:

$$y = x\beta + u, u = \lambda Wu + \epsilon \tag{2.0}$$

Where $y$ is dependent variable (economic growth), which is predicted by set of explanatory variables $x$. The residual term $u$ is modeled as separate regression equation. The second equation predicts the residual using spatial autoregressive parameter $\lambda$ and a spatial weight matrix $W$, along with its own residual term $\epsilon$. The $\lambda$ quantifies the strength of spatial dependence in the error term and measures how much one location's error term influences the error terms of its neighbors.

The Spatial Lag Model (SLM) can be used to account for analyzing spatial spillover effects (spatial endogeneity), such as spreading effects of economic growth between the regions while accounting for spatial dependence. The SDM can be defined as:

$$y = \rho Wy + XB + \varepsilon \tag{3.0}$$

Where $y$ is dependent variable (economic growth), $Wy$ represent endogenous spillover – influence of neighbour's dependent variable, and $WX$ represent exogenous spillover - influence of neighbour's explanatory variable.

Finally, there is Spatial Autoregressive Combined model (SAC) which includes spatial autoregressive parameter $\lambda$ and $\rho$ from the spatial error and spatial lag models, respectively. The SAC model is used to identify spatiall spillovers effects in the dependent variable while also addressing the spatial dependence of the error term. Formally, the SAC model ca be defined as:

$$y = \rho Wy + XB + u, u = \lambda Wu + \epsilon \tag{4.0}$$

For the study purpose, SEM and SDM will be proved. Choosing the appropriate model will depend on the model's diagnostic tests and model fit statistics. In the case of indecision, the SAC model will be applied. The application of the spatial regression method addresses the issues of spatial endogeneity and spatial autocorrelation, thereby enabling consistent parameter estimation and correct statistical inferences.

## Results

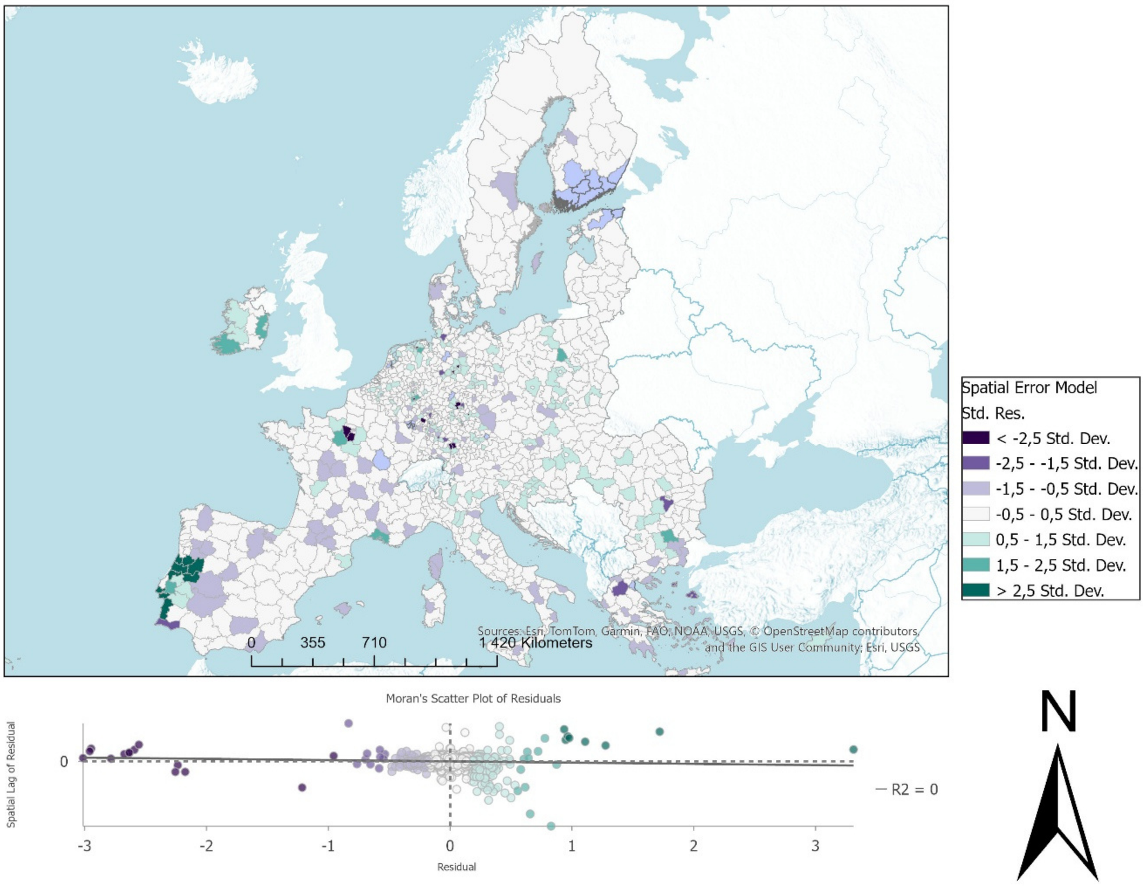
The analysis begins with patterns that show the geographical distribution of manufacturing density at the regional NUTS3 level. For study purposes, only manufacturing hubs (e.g., those with the highest manufacturing density) are elaborated. Based on the results of implementing the ANN method, we used an initial distance of 35 km (as observed by the ANN) and, after consideration, an incremental distance of 6 km, divided into 25 distance bands. (ESRI, 2025).

Fig.1 (Annexe 2) shows the results of Incremental Spatial Autocorrelation. The analysis reveals a statistically significant maximum peak at approximately 41 km distance, with a Moran's index value of 0.1665 and $z$-score of 3.452 ($p$-value < 0.05). The result suggests that the highest degree of spatial clustering occurs when compared locations are within a 41 km radius. The results may correspond with the extent of manufacturing agglomerations where the mutual proximity of companies enhances vertical linkages, supply-chain relations, and other location externalities.

Next, the series of Spatial regression models is performed. The optimal model is selected based on diagnostics and model fit. When plugging the model, the same systematic approach has been applied. For the spatial weight matrix, we used the nearest neighbour method, choosing eight neighbours, as suggested in the literature (Anselin & Rey, 2014). As a local weighting scheme, the *bisquare* option was selected, where weights decline with distance (nearby units receive more weight, while far ones receive near-zero weight), which seems to be appropriate.

Fig. 2 displays the choropleth map, which projects the application of the SEM, showing the map of residuals where the dependent variable is still underestimated or overestimated after accounting for both explanatory variables and the spatial error process. In Figure 2, Moran's scatterplot displays an $R^2$ value of 0, indicating that spatial autocorrelations are removed mainly. However, the map plot shows several places where high or low values are clustering (e.g., Portugal, Finland), which suggests that the spatial error process might not fully capture the actual spatial dependence. The reasons may vary, hence the diagnostics of the model could be undertaken.

Figure 2: Application of Spatial Error Model



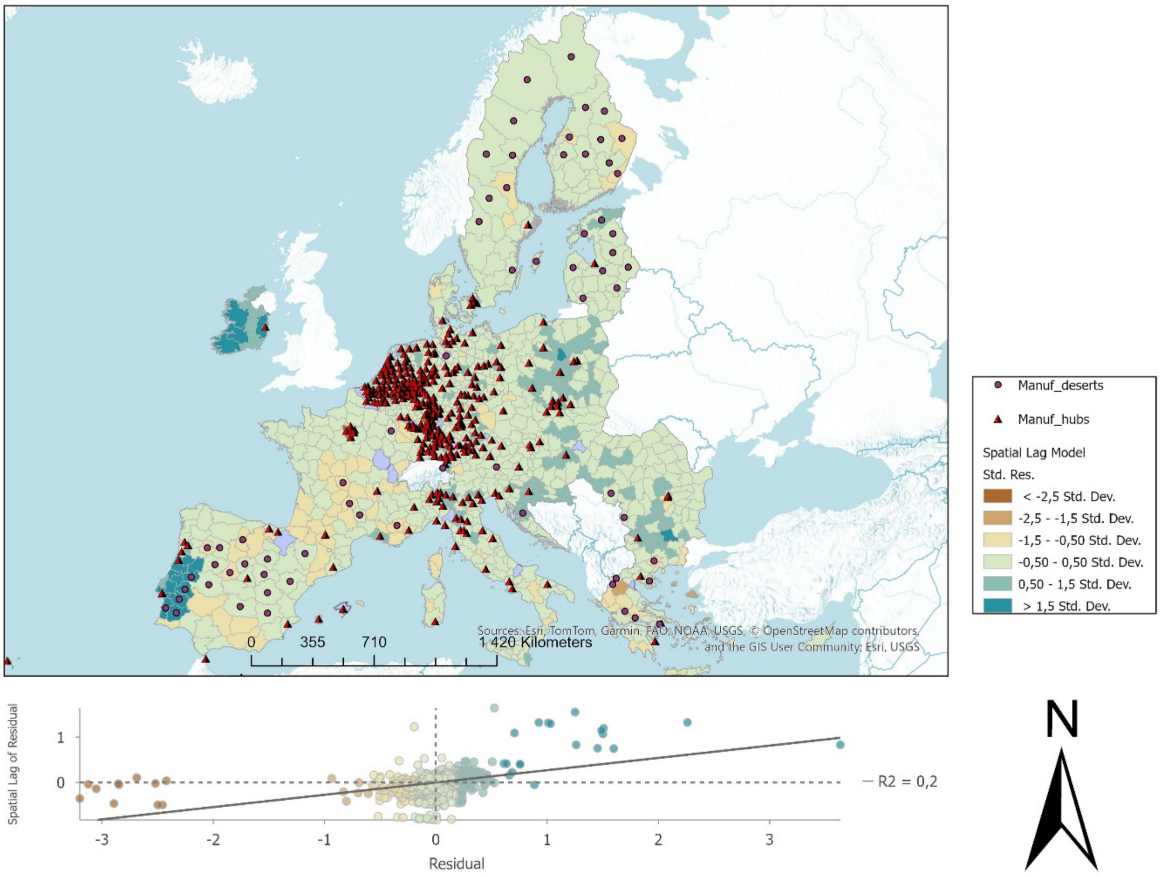

Tab. 2, Tab. 3, and Tab. 4 (Annexe 3) show model diagnostics. The Lagrange multiplier (LM) error and lag became statistically significant, suggesting that both spatial autocorrelation in the error term and spatial dependence in the dependent variable are present. Moreover, the Robust LM error became significant, which strengthens the case for remaining spatial autocorrelation in the error term. Since the Robust LM lag is insignificant, there is less evidence that the spatial lag model is necessary. However, LM combined became significant, which suggests that some form of spatial dependence is present (in the error term, lag, or both).

Estimated model parameters became significant (except the population density) and negative. Here, the interpretation needs to be cautious. At first, there is no inconsistency between the model parameters. Also, the collinearity between variables can be excluded. The results indicate a negative association between the higher concentration of manufacturing employment density relative to area/population, and lower GDP growth (after adjusting for other factors).

Additionally, regions with a higher share of GDP in manufacturing exhibit lower GDP growth. Both results suggest structural rigidity and overreliance on already mature industries in the EU. Labour stock growth also became negative and significant, which can be surprising. It may indicate a labour market mismatch or a predominance of job occupations with lower added value. Finally, the spatial error coefficient (lambda) became positive and significant. The result suggests that there are some unobserved spatially correlated shocks affecting the dependent variable. The model likely suffers from the omitted variable problem, meaning variables that are not factored into the model (such as infrastructure and policies), and are difficult to observe at a given spatial level. However, the SEM controls for bias by introducing a spatial error term (lambda), which makes the results more consistent.

Next, the results of the Spatial Lag Model (SLM) are presented. Fig. 3 shows the choropleth map projecting the application of the model (showing the std. deviations from the dependent variable – economic growth). The first impression shows a relatively uniform pattern of regional growth (most regions exhibit variations between -½ and +1,5 standard deviations from the overall mean growth. However, the map shows a few clusters exhibiting robust economic growth (Portugal, Ireland) and more dispersed regions in the EU's east (Poland, Slovakia, Hungary, Romania, etc.). Moreover, the pictograms depict the regional manufacturing bases (manufacturing hubs) and regions with an underrepresentation of manufacturing (manufacturing deserts are projected). Visually, the presence of either *manufacturing hub* or *a desert* does not automatically lead to economic growth or stagnation. Moran's scatterplot value shows an R-squared value of 0,2, indicating the presence of spatial autocorrelation in the regional data.

Figure 3: Spatial Error Model with manufacturing distribution pattern




Tab. 5, Tab. 6, and Tab. 7 (Annexe 3) provide further model diagnostics. The model predictors show mixed results. The share of GVA in manufacturing became statistically insignificant, as did the lag Y (rho) – spatial lag coefficient, indicating insufficient evidence of direct spatial spillovers in GDP across regions. Instead, the spatial dependence seems to operate through unobserved spatially correlated shocks – in such a case, the Spatial Error Model is more appropriate. In Table 6, a measure called impacts is reported. Impacts help measure the effect of spatial spillovers for each explanatory variable. They are broken down into direct, indirect, and total impacts. The direct impact measures how much a one-unit change in an explanatory variable (e.g., manufacturing density, GVA share, labour stock, or population density) affects the value of the dependent variable at the location itself. Whereas the indirect impact measures how much a one unit change in a variable affects the dependent variable (GDP growth) in its neighbouring locations.

The results indicate that the spatial lag coefficient is statistically insignificant; therefore, these indirect effects are likely to be very weak or insignificant. Tab. 5 shows the additional properties of the model. The spatial pseudo R-squared value is low, indicating limited improvement of the model compared to the null. So far, the model results suggest that spatial dependence is introduced through the error term, making the Spatial Error Model a more suitable alternative to the Spatial Lag Model. Hence, the spatial spillovers of GDP growth are not due to regions directly influencing each other's growth, but rather to the omitted or unobserved factors that are spatially correlated. The robust LM Lag in both models failed to become significant, and the spatial lag term (rho) also failed to do so. Therefore, the last type of spatial model—the Spatial Autoregressive Combined Model (SAC) —is not necessary to introduce.

## Discussion

The objective of the paper was to investigate the association between the regional economic growth and the underlying economic structure, especially the manufacturing base of regions. Regional development theories (e.g., Theory of Location, NEG, others) suggest that industrial clusters have strong development potential for regional development, due to regional specialisation, knowledge and innovation spillovers, and other factors. Regional manufacturing became the centrepiece of the study. Initially, regions with the highest manufacturing density (measured as manufacturing employment per square kilometre) were identified. The application of the Incremental Spatial Autocorrelation (ISA) tool revealed the highest manufacturing clustering at relatively short distances (with a maximum peak within a 41 km radius), which corresponds with the theory regarding the ability to gain external economies of scale. Moreover, the results of spatial analysis (especially the SEM applied) found evidence of cross-regional spillovers impacting regional growth. However, based on the model diagnostics, the spatial dependence arises mainly from unobserved regional heterogeneity and spatially correlated factors, rather than from direct interaction between regions' growth rates.

However, focusing solely on manufacturing industries, they failed to outperform in terms of economic growth. Hence, regions with a substantial manufacturing presence did not exhibit higher economic growth compared to regions with an average or lower manufacturing base and often lag. The key model parameters, manufacturing density, and share of GVA in manufacturing, which are controlled by labour stock growth and population density, were negatively associated with regional GDP growth. Such a finding is often in contrast with the theory or prior evidence. However, recently, there is growing evidence about the other side of the industrial clusters, especially at the EU regional level.

Diseconomies of industrial clustering are also an object of interest from the viewpoint of economists and management scholars. It refers to decreased benefits for incumbent firms as each additional firm joins the cluster. Economies and diseconomies can arise on both the demand and supply sides of the market. On the demand side, congestion and competition in output markets can lead to lower prices, which in turn result in lower profits. Also, a cluster specialized in a particular technology can go into decline if that technology is substituted (Swan et al., 1998). On the supply side, congestion and competition in input markets can lead to higher wages and rents, which in turn may result in movement out of the cluster (Pandit et al., 2002).

On the other hand, the industry itself may suffer from a range of factors that lead to a productivity slowdown and an impediment to economic growth. In recent years, the EU industrial sector has been exposed to a combination of structural headwinds and specific shocks, nurturing fears that Europe might embark on a path of de-industrialisation. The root-causes of headwinds which are straining the EU manufacturing may be listed: 1) increased energy costs – hurt all manufacturing activities; 2) subdued demand for the sectors in the upstream part of manufacturing; 3) significant global overcapacity – mainly due to the expansion of Chinese production; 4) growing competition of China in area of complex products with higher added value; 5)labor shortages – lower skilled workers, labor market mis-match, etc. (Heikkonen, Listl and Reuter, 2025).

Together, Draghi (2024) and Letta (2024) criticise the outdated structure of the EU industry, which relies primarily on mature technologies with low innovation potential and significant overhead costs, posing a further challenge to European competitiveness. Grashof (2025) promotes the importance of a diverse industrial cluster portfolio, whereas a few large specialised industries exhibit size-related negative externalities. None of the above-mentioned factors which put the EU manufacturing industry at a disadvantage seems to be a quick fix. Dealing with such constraints requires strategic planning, a long-term window with a sizable budget and policy tools, and a willingness to face trade-offs related to implementing the policies.

## Conclusion

The paper investigates the presence of spatial spillover growth effects initiated by regions with a robust manufacturing base at the EU NUTS3 level. The focal points of the study are the contribution of manufacturing density and the share of GVA in manufacturing, controlled by the labour stock and population density, to regional GDP growth. The results demonstrate insufficient evidence of direct spatial spillovers in GDP across regions. Applying the Spatial econometric model, the findings showed the negative association between the investigated variables and economic growth. This negative association suggests that despite the apparent benefits of agglomeration clustering, an intense concentration of manufacturing may also be linked to significant structural constraints, such as lower productivity dynamics, limited diversification and saturation of mature industrial regions. In contrast, regions with less manufacturing dependence may benefit more from growth driven by services, innovation-driven sectors and more flexible labour markets.

Such a statement needs to be interpreted with caution. We are discussing findings at the level of association, not causation. The model diagnostics indicate that spatial dependence primarily enters through the error term, suggesting unobserved spatial heterogeneity and a likely sizable influence of additional factors on regional growth.

The study also has some limitations. There is a set of omitted factors that may have a potentially sizable impact on the results. Additionally, the observed period is relatively short, only five years, indicating a short-to-medium-term perspective. Nevertheless, these conditions were set intentionally. The focus point of the study is the EU manufacturing industry and the association between overrepresented manufacturing in regions and economic growth. Additionally, the limited period reflects the recent trend and points to a loss of momentum in the EU industry.

From a policy perspective, the findings imply that future EU industrial and regional policies should be highly adaptive to local contexts. The processes aimed at dismantling obsolete technologies and industrial structures should be accelerated. Involving regional institutions from the local government can create new platforms for area gentrification and explore new economic uses for industrial areas.

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# Annexes

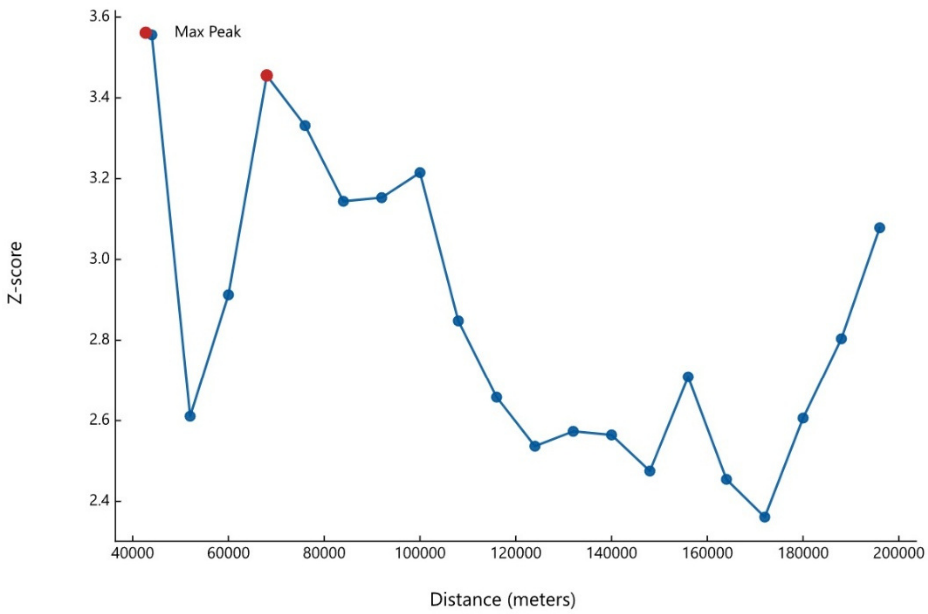
## Annexe 1

Tab.1: Detailed composition of EU manfacturing

| Industry | Av.no.of workers in thd. | Relative share of workers | share on GVA |
|---|---|---|---|
| Manufacture of food products; beverages and tobacco products | 4651 | 15,46% | 1,94 |
| Manufacture of textiles, wearing apparel, leather and related products | 1998 | 6,64% | 0,54 |
| Manufacture of wood, paper, printing and reproduction | 2181 | 7,25% | 0,9 |
| Manufacture of coke and refined petroleum products | 124 | 0,41% | N/A |
| Manufacture of chemicals and chemical products | 1122 | 3,73% | N/A |
| Manufacture of basic pharmaceutical products and pharmaceutical preparations | 616 | 2,05% | N/A |
| Manufacture of rubber and plastic products and other non-metallic mineral products | 2792 | 9,28% | 1,28 |
| Manufacture of basic metals and fabricated metal products, except machinery and equip-ment | 4487 | 14,92% | 2 |
| Manufacture of computer, electronic and optical products | 1067 | 3,55% | N/A |
| Manufacture of electrical equipment | 1489 | 4,95% | 0,8 |
| Manufacture of machinery and equipment n.e.c. | 2915 | 9,69% | N/A |
| Manufacture of motor vehicles, trailers, semi-trailers and of other transport equipment | 3201 | 10,64% | 2,26 |
| Manufacture of furniture; jewellery, musical instruments, toys | 3438 | 11,43% | N/A |
| Total | 30081 | 100,00% | X |

## Annexe 2

Fig.1: Manufacturing density plot of spatial autocorrelation by distance



Source: own research

**Annexe 2**

Table 2: Lagrange Multiplier test diagnostic

| LM Test Results | | |
|---|---|---|
| **Test** | **Statistic** | **p-value** |
| LM Error | 193,775013 | 0 |
| LM Lag | 172,324081 | 0 |
| Robust LM Error | 23,11382 | 0,000002 |
| Robust LM Lag | 1,662888 | 0,197214 |
| LM Combined | 195,437901 | 0 |

Source: own research

Table 3: Spatial error model diagnostics

| Summary of SAR Results (Spatial Error Model) | | | | |
|---|---|---|---|---|
| **Variable** | **Coefficient** | **StdError (White)** | **z-Statistic** | **Probability** |
| Intercept | 1,966198 | 0,066052 | 29,767228 | 0,000000* |
| LN_POPDENS | 0,000019 | 0,00002 | 0,957076 | 0,338529 |
| LN_MANEMP_SQ | -0,058326 | 0,016594 | -3,51491 | 0,000440* |
| GVA_SHARE | -0,662533 | 0,331663 | -1,997607 | 0,045759* |
| LABOR_GR | -5,342126 | 1,308274 | -4,083339 | 0,000044* |
| Lag Residual (lambda) | 0,407079 | 0,045328 | 8,98073 | 0,000000* |

* An asterisk next to a number indicates a statistically significant p-value ($p < 0,05$).

Source: own research

Tab. 4: Model diagnostics

| Model Diagnostics | |
|---|---|
| Dependent Variable | GDP_G |
| Number of Features | 1136 |
| Degrees of Freedom | 1131 |
| Model Used | ERROR |
| Pseudo R2 | 0,088378 |
| Jarque-Bera Statistic (value, p-value) | 70755,38, 0,000000* |

Source: own research

**Annexe 3**

Tab. 5: Spatial error model diagnostics

| Summary of SAR Results [Spatial Lag Model (User-Specified)] | | | | |
|---|---|---|---|---|
| **Variable** | **Coefficient** | **StdError (White)** | **z-Statistic** | **Probability** |
| Intercept | 1,227314 | 0,475287 | 2,582259 | 0,009816* |
| LN_POPDENS | 0,000006 | 0,000016 | 0,391832 | 0,695182 |
| LN_MANEMP_SQ | -0,040666 | 0,012873 | -3,159145 | 0,001582* |
| GVA_SHARE | -0,366325 | 0,281521 | -1,301234 | 0,193178 |
| LABOR_GR | -2,732319 | 1,100304 | -2,483239 | 0,013019* |
| Lag Y (rho) | 0,381479 | 0,246145 | 1,549811 | 0,121187 |

Source: own research

Tab. 6: Spatial error coefficient effects summary

| Coefficient Effects Summary | | | |
|---|---|---|---|
| Variable | Direct | Indirect | Total |
| Intercept | 1,227314 | 0,756958 | 1,984271 |
| LN_POPDENS | 0,000006 | 0,000004 | 0,00001 |
| LN_MA-NEMP_SQ | -0,040666 | -0,025081 | -0,065747 |
| GVA_SHARE | -0,366325 | -0,225934 | -0,592259 |
| LABOR_GR | -2,732319 | -1,685184 | -4,417503 |

Source: own research

Tab.7: Model diagnostics

| Model Diagnostics | |
|---|---|
| Dependent Variable | GDP_g |
| Number of Features | 1120 |
| Degrees of Freedom | 1114 |
| Model Used | LAG |
| Pseudo R2 | 0,229956 |
| Spatial Pseudo R2 | 0,073711 |
| Anselin-Kelejian Test (value, p-value) | 0,867 0,351 |
| Jarque-Bera Statistic (value, p-value) | 63545,05, 0,000000* |

Source: own research