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Identifying Critical Areas in Industrial Employment: Emerging Hot Spot Analysis of Workforce Expectations

Abstract. *This paper investigates the spatiotemporal distribution of employment expectations in industry (BS-IEME-BAL) between 1992 and 2025, using DG ECFIN Business and Consumer Surveys (BCS) data. The main aim is to identify areas with critical dynamics of the industrial labour market and to assess regional trends in labour fluctuations. The method used is based on Emerging Hot Spot Analysis (EHSA) in GIS, which allows the detection of regions where employment growth or decline has a persistent, oscillating, or emerging trend. The algorithm classifies areas according to the intensity and persistence of variations, allowing for anticipation of the impact of economic transformations on the industrial labour market. The study highlights critical regions where public policies can intervene to mitigate the negative effects or to support sustainable employment growth. Identifying hot spots in the industry contributes to the development of adaptive territorial strategies, based on spatial data, for the efficient management of structural changes in the labour market.*

Keywords: *Hot spot analysis, Space-Time Cube, industry, labour market, public policies.*

JEL Classification: J23, R11, C55, O18, E24.

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1. Introduction

The advancement in technology, the changing world of economics as well as those of the hiring employees are making the industries redefine how they operate and at what places they work at. Industries change with changes in skills, attitudes, and behaviour of workers, which provide new challenges and opportunities to both the policies maker and the employers, as well as regional planners. Although the vast literature is available on labour markets, there is a necessity to consider how the industrial change mirrors the wider tendencies in the state and technology within the territory of the region.

One of the main questions in the realm of the modern labour markets research is to determine areas of too slow or too fast adaptation of the workforce. Special attention should be paid to regions that have a high economic potential or constant structural weaknesses. Hot spot analysis and spatial clustering provide useful methods that could be used to identify trends and patterns in the regional job market. With behavioural and institutional information on the workforce, they can offer a more dynamic perception of local labour market strength and weakness.

This research paper fills this gap by focusing on understanding the ability of managers to focus on potential future industrial labour in terms of regions and also determining the highlighted patterns in future staff composition. Based on the studies on labour economy, urban economics, and industrial policy, the paper identifies the critical influence of regional contexts on the creation of job opportunities. The mutual influence of vocational training, educational systems and values of labour market is referred to with particular attention.

The main objective is to examine spatial-temporal changes in the industrial employment expectations in Europe through the Emerging Hot Spot Analysis (EHSA) technique on the Employment Expectations Index (EEI). This strategy outlines both short-term and long-term tendencies and their recent changes which provide information on structural weaknesses and possibilities of reindustrialisation in case of Industry 4.0.

Although the broader objective refers to industrial employment dynamics in Europe, the empirical analysis covers only the 13 EU Member States for which the DG ECFIN Employment Expectations Index (EEI) provides complete and harmonised monthly series for the entire 1992–2025 period. This restriction ensures temporal consistency across countries and prevents biases caused by missing or discontinuous data in the remaining EU countries.

2. Literature review

2.1 Regional Disparities and Hot Spot Analysis in Industrial Employment

Infrastructure, education, the framework of policy, and history are involved in industrial employment in a region. Spatial inequality means the structural difference in the rate of providing employment, resilience in labour markets, and expectations of the workforce. More researchers use the methods of spatial econometrics and GIS to determine which areas experience an increase or decrease in employment (Prakoso et al., 2021; Pirciog et al., 2023).

As an illustration, studies reveal that industrial investments do not equally impact rural areas since some areas do not have the preconditions to generate employment opportunities. Green and sustainable employment is awarded to cities with an assortment of enterprises and innovation networks. Tools such as emerging hotspot analysis assist in tracing employment patterns over time. Jing et al. (2023) in Southeast Asia also apply GMM models to show that regional disparities cause unemployment trends, thus promoting geographically specific policy actions.

A major role is also performed by the planning in cities. According to Liu and Liu (2018) in China, urban development enhances the creation of jobs in non-metropolitan cities by decentralising the jobs positions. Kane et al. (2018) observes that in the U.S, employment sub-centres improve congestion and encourage new labour markets. In general, spatial analysis and hot spot detection enables better focused and efficient employment planning through alignment of training, infrastructure, and innovation with regional needs.

2.2 Technological Disruption and Workforce Adaptation

Industrial work as well as the skills one needs to be employed are being reshaped by automation, artificial intelligence, and digitalisation. These changes cause labour markets and institutions problems with the protection and preparation of workers (Prananta et al., 2022). The using of digital technologies changes not only efficiency but also the interaction between the teams and the way their tasks are performed.

The situation is more challenging in the emerging economies where there is a lack of access to structural, and digital skills training. Hammer and Karmakar (2021) describe in India that the tendency is to increasingly offer jobs based on cognitive skills, but with poor institutions and education systems, this cannot be generalised. Proactive reskilling to the Industry 4.0 requirements is essential to avoid the pitfall of the skill mismatch. Technology alters the manner in which individuals seek employment and retain the jobs. Labor platforms based on the digital realm augment the flexibility of the working ruling but regularly decrease job security by the least vulnerable classes. Also, the investment in digital is focused on the cities, and it increases the regional inequality (Jing et al., 2023). In order to overcome this gap, it is vital that there are inclusive innovation policies.

2.3 Employment Expectations, Equity, and Workforce Behaviour

With changing industry, expectations, attitudes and behaviours of workers also change. The labour force of today is no longer interested in simply stability, but in flexibility, purpose, and self-fulfilment. Such changes affect the labour flows, the shift of jobs, and the necessity of new training corresponding to the new technologies and the new norms of labour productivity, the values towards work are influenced by generational differences. Gauffin (2020) exemplifies how precarity in Sweden is an expression of instability in the economy, while career development and work life balance in response to environmental changes is analysed by Dima et al (2023).

The platform economy makes employment difficult to define. Gig and crowd work diminish job security, career advancement, and peer encouragement spill taking the chance of employment out of associations and into individuals. The pressure, especially in the context of work, encourages self-branding and acting like entrepreneurs, but much less institutional reinforcement comes across (Murgia et al., 2020). Research of these developing labour relations is fundamental to the development of equitable, broad-based, and receptive employment policies.

2.4 Urbanisation, Industrial Clusters, and Polycentric Growth

The patterns of industrial employment are intimately related with the strategies of the urban and rural development. Whereas centre cities tended to have attracted and supported high concentration of the infrastructure, qualified labour and innovation, lately planning has been concentrated into distributed growth as a means of encouraging regional equity in terms of employment. The study by Kane et al. (2018) demonstrates that sub-centres of employment in the periphery limit congestion and increase access to jobs by peripheral population, and this promotes economic inclusivity in cities. According to (Dima et al., 2019), telework creates a better work–life balance and becomes a valid option for large cities where the time spent on travel is high.

Munshi et al. (2018) state that industrial corridors are the main driver of innovations, infrastructure development, and formal employment through reducing cost to business and promoting local knowledge sharing. Such agglomerations that are not in central cities usually have these benefits. As Petrov (2021) emphasises, the rural regions of Bulgaria still experience negative employment prospects even in times when the whole country develops industries despite the lack of policies at the national level. Spatial employment is complicated by digitalisation as the production process remains place-oriented, whereas the tech and service jobs become more mobile. Taken together, the combination of urban planning tools such as polycentric development and industrial clustering and localised region policies may align distribution of industrial jobs and contribute to more inclusive labour markets.

2.5 Industrial Policy, Sustainability, and Green Transitions

Greening of the work force is also forcing industries to modify their workforce systems with the aim of developing environmental friendly economies. The current trend in green industrial policies is to mitigate the possibility of carbon emissions, contribution to employment growth, innovation, and social upheavals are minimised. Johnstone et al. (2021) demonstrate the policies of European countries that facilitate clean energy transitions by investing and employee training. Li et al. (2023) highlight the improvement of employment in developing markets due to green innovation with the help of supportive institutions that could link the environmental strategy with labour policies.

An inclusive environmental change occurs within the framework of a just transition. Instead, Kronenberg and Fuchs (2022) suggest that place-based plans concentrated on equity should prevent job displacement, particularly in susceptible areas. In the absence of such strategies, green restructuring can only end up worsening labour disparities. Trends in sustainability also transform labour in such industries as tourism, manufacturing, and logistics where a new set of regulations and consumer demands requires new skills. On the one hand, high technologies enhance efficiency, whereas, on the other hand, they pose a threat of taking away high-carbon job. In order to make a process of the workforce transition smooth and equitable, it is vital to consider integrating green skills into vocational training. Dima et al. (2019) discusses the sustainable social implications of telework, providing a long-term solution to the problems of the communities**.** The future policies should consider both environmental, economic aspects and social dimensions in a bid to create a sustainable inclusive industrial labour force.

3. Model specification

The literature review reveals a high interest in the labour market context, evolution, shifts, and challenges; however, it still lacks geographical models and global perspectives compared to local (national) analysis and trends evaluation. This complex environment, along with the challenges faced by the labour market in general and from our study's perspective in the industry, should be addressed through integrated policies and strategies. We develop a space-time analysis using Emerging Hot Spot Analysis (EHSA) and temporal zoom to identify the geographic area with positive, negative, or significant volatility in industrial employment.

The research questions we are addressing are: 1) How do the spatiotemporal dynamics of managerial expectations regarding employment in industry reflect the process of European industrial transition in the period 1992–2024? 2) Which are the emerging European regions as leaders or vulnerable in the transition to Industry 4.0, identified through the temporal zoom 2009–2022 and the spatiotemporal analysis of managerial expectations?

We formulate the following hypothesis to be verified by the proposed model:

H0 (methodological): The use of spatio-temporal analysis through Emerging Hot Spot Analysis (EHSA), with the integration of seasonality and regional interdependencies, represents an effective tool for the early identification of risks and opportunities in the European industrial transition process.

H1: The period 1992–2024 captures a process of industrial transition at the European level, characterised by spatial polarisation between regions with traditional industrialisation and those with high potential for adaptation to Industry 4.0.

H2: In the time window 2009–2022, emerging leaders in the transition to Industry 4.0 are identified through Oscillating Hot Spot patterns and positive trends in managerial expectations regarding employment in industry, exemplified by the case of Denmark.

H3: Eastern European regions, such as Romania and Bulgaria, although marked by an initial process of energy-intensive and inefficient industrialisation in the 1990s, show potential for reindustrialisation, visible through oscillating patterns and signals of recovery in managerial expectations.

3.1 Mathematical Specification of the EHSA Model

The Emerging Hot Spot Analysis (EHSA) is based on two quantitative elements:
(1) the statistic of spatial clustering Getis-Ord Gi, and (2) which is calculated on a time-by-time basis.
(2) the temporal statistic relying on the Mann-Kendall test, on the sequence of Gi*s at each location.
In order to ascertain methodological transparency, the mathematical relations of the model are described in this subsection.

(1) The Getis–Ord Gi* statistic

For a spatial process with $n$locations, the Gi* statistic for location $i$and distance band $d$is defined as:

$$G_i^*(d) = \frac{\sum_{j=1}^{n} w_{ij}(d)x_j - \bar{X}\sum_{j=1}^{n} w_{ij}(d)}{S\sqrt{\frac{n\sum_{j=1}^{n} w_{ij}^2(d) - (\sum_{j=1}^{n} w_{ij}(d))^2}{n-1}}}$$

where:

- x_j= value of the Employment Expectations Index (EEI) at location j;
- $w_{ij}(d)$= spatial weight between $i$and $j$for distance d;
- $\bar{X}$= global mean of the EEI;
- S= global standard deviation.

A statistically significant high Gi* (positive Z-score) indicates a **hot spot**, while a significantly low Gi* (negative Z-score) indicates a **cold spot** (Getis & Ord, 1992; Ord & Getis, 1995).

(2) The Mann–Kendall temporal trend test

To classify the temporal evolution of each location, EHSA applies the Mann–Kendall test to the ordered sequence of Gi* statistics. The test statistic is:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \operatorname{sgn}(x_j - x_i)$$

where:

$$\operatorname{sgn}(x_j - x_i) = \begin{cases} 1, & \text{if } x_j > x_i \\ 0, & \text{if } x_j = x_i \\ -1, & \text{if } x_j < x_i \end{cases}$$

The variance of Sunder the null hypothesis of no trend is:

$$\operatorname{Var}(S) = \frac{n(n-1)(2n+5)}{18}$$

The standardised statistic $Z$is computed as:

$$Z = \begin{cases} \dfrac{S-1}{\sqrt{\operatorname{Var}(S)}}, & \text{if } S > 0 \\ 0, & \text{if } S = 0 \\ \dfrac{S+1}{\sqrt{\operatorname{Var}(S)}}, & \text{if } S < 0 \end{cases}$$

Positive and significant Z-values indicate an upward temporal trend, while negative values indicate a downward trend.

(3) EHSA classification

EHSA is a composite statistic that integrates the spatial Gi statistic with the temporal Mann-Kendall trend to categorise each location into 17 categories, which are New Hot Spot, Intensifying Hot Spot, Oscillating Cold Spot, etc. (Esri, 2016) and recent empirical applications (Bayles et al., 2024; Akrofi, 2024). This mathematical specification gives all the quantitative structure of the model of the analysis.

Association of Gi and Mann-Kendall to EHSA Classification.

The 17 EHSA categories are a product of two statistical dimensions:

- ***Spatial clustering (based on the Getis-Ord Gi statistic) within each time slice: a hot spot (cold spot), or not significant.***
- ***Temporal change of these spatial clusters, which was calculated by using the Mann-Kendall trend test of the series of Gi values of every location.***

EHSA has the following classification rules:

- ***A point is termed a New Hot Spot once the latest step includes a substantial positive Gi value initially, and previous steps were not hot.***

- ***An Intensifying Hot Spot entails the constant hot spot condition over the last few steps and a statistically significant positive change over time (Mann-Kendall Z > 0).***
- ***The Persistently Hot Spot is used to show that the location has been very important over a proportion of time, though the trend may not be important.***
- ***An oscillating hot spot is observed when values of Gi are significant and non-significant, with no monotonic pattern.***
- ***Similar regulations are used in Cold Spot categories on the basis of highly negative Gi values.***
- ***When clusters are intermittent and are not time-structured, sporadic categories are used.***
- ***Any pattern found is not associated with a sequence of non-significant values of Gi, which lack any obvious temporal pattern.***

The classification of EHSA is therefore purely based on the statistical behaviour of Gi(t) and the Mann-Kendall Z(t) trend that gives an explicit connection between the mathematical characteristics of the model and the spatiotemporal patterns represented by the maps.

3.2 Explaining the Basics of EHSA and the Approach Taken

Emerging Hot Spot Analysis (EHSA) is a method to identify areas that exhibit similar changes over a specified period. On platforms such as ESRI's ArcGIS, EHSA makes use of the Getis-Ord Gi method within a Space-Time Cube to see spots in data that stand out statistically (ESRI, 2024). EHSA does this by combining locations over time and locations in one place, helping researchers categorise areas as new, persistent, intensifying, diminishing, or sporadic hotspots.

With this methodology, scientists can analyse changes in nature, cities, crime, health situations, and infrastructure. Being able to show how things change in both time and space, GIS allows you to track the results of government policies, the sharing of resources, and different developments in society.

3.3 EHSA Applied in Different Research Fields

In environmental and public health studies, hot spot analysis and spatial-temporal data tools have been used as an effective tool to identify the outbreaks of diseases, pollution, and insect-vectored diseases (Bayles et al., 2024). In more recent years, these instruments found purchase in the world of socio-economic, industrial, and labour market research, as useful in a wide variety of policy areas. Akrofi (2024) developed a spatial hot spot analysis that exposed the concentrations of global carbon credit projects in map projections that assist in green economy planning. Xu et al. (2023) focused on spatial industrial development within the EGS industrial sector in Wuhan, determining the major drivers of transformations. Dang et al. (2024) simulated the pattern of corruption diffusion at different levels of regions. Many fields have put a lot of emphasis on Emerging Hot Spot Analysis (EHSA) within the last ten years, in the sphere of public health, environmental researchers like deforestation and climate risks, urban research, land use, housing vacancies, etc.

3.4 Examining How EHSA Applications are Spread Geographically

The EHSA method is used worldwide, including research in the Americas (Gale & Roy, 2023), Asia (Liu et al., 2023), Africa (Wright & Roy, 2022), and Europe (Memisoglu Baykal, 2023). The EHSA method was used to analyse fire risk in Turkey (Memisoglu Baykal, 2023) and for archaeological research in Slovenia (Štular et al., 2022). Such diversity proves that the approach is useful in many regions, sectors and situations. Nevertheless, research on the socio-economic labour market using EHSA is not widespread. Although many use remote sensing in environmental and health applications, its ability to monitor workforce trends, industry patterns and changes over different places and times has not been fully explored.

3.5 EHSA for Industrial Employment: A New Use of the System

What makes EHSA special for industrial employment is its ability to explore how labour changes over both space and time. Unlike other statistical models, EHSA displays and sorts regions according to how employment trends are moving up, staying the same, or down. You can use this method to pinpoint locations with a big or small workforce, detect the start of structural issues in the workforce, and help form policies for a region. Since automation and globalisation are bringing about major changes in industry, there is now more demand for ways to find where employee expectations are shifting and what actions are necessary. Analysing data over time gives EHSA the means to observe changes in employment sectors, catch the decline of previous industries, and see when green jobs are on the rise.

Relying on EHSA would also address a major shortcoming when analysing industrial employment in Europe. There is a lot of spatial variety in European labour markets due to EU efforts, differences between regions, and demographic changes. Places that are moving away from heavy industry to focus on high-tech areas, including the Ruhr Valley and Eastern Europe, might use EHSA to direct investments, education, and the building of important infrastructure.

3.6 Policy Implications and Future Research

EHSA often plays a major role in making well-supported government decisions. When emerging employment cold spots are found, governments can help people change careers and encourage them to move or invest in projects that benefit their local economies. Using data on income, education, and age structure together with the method makes labour market diagnostics more detailed.

Besides being adaptable, EHSA is a good fit for assessing how industrial policies like smart specialisation strategies or EU Green Deal projects influence growth. For instance, reporting job numbers in the clean energy field each year might tell us if the transition to sustainability is working. Later work can attempt to combine EHSA with emerging methods like machine learning (Štular et al., 2022) or obtain information from massive datasets contributed by the public. Lab data in various forms of EHSAs and with other administrative or company data could provide even deeper insights into the dynamics of the labour market.

4. Model specification - Hot Spot Analysis Framework

This study constructs a Hot Spot Analysis model to early identify the risks and opportunities in the European industrial transition process. The main methodological steps are presented in Figure 1.

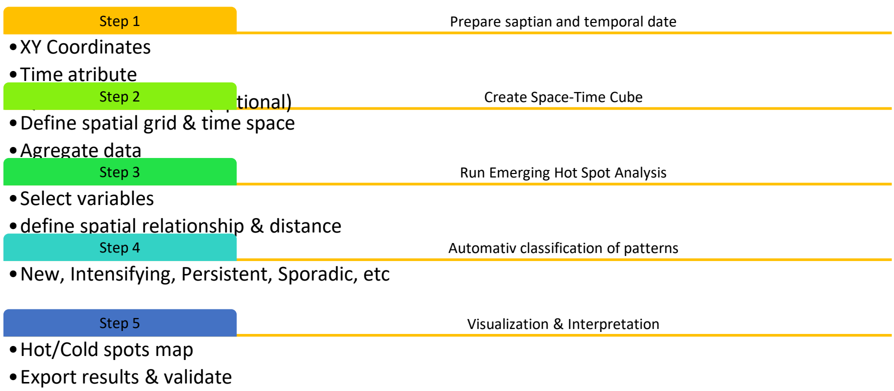

Figure 1. Methodological Approach to Emerging Hot Spot Analysis

Source: Authors' creation based on ESRI ArcGIS Pro documentation (2024).

The EHSA framework integrates the spatial Getis–Ord Gi* statistic with the temporal Mann–Kendall trend test, enabling the detection of statistically significant hot and cold spot patterns across space and time. The analysis is based on the Getis-Ord Gi statistic, which tests the statistical significance of spatial clusters at each time step. Hot spots and cold spots were identified with a 95% confidence level ($z > \pm 1.96$). Missing values were handled by excluding time bins with insufficient data coverage (less than 80% of the expected series length), ensuring consistency across countries and periods. No spatial interpolation was applied.

The dataset used in this study is the Business and Consumer Surveys for 1992-2025, comprising data collected for 13 countries within the EU. An Emerging Hot Spot Analysis has been conducted using a spatio-temporal model with K = 8 Nearest Neighbours and a Neighbourhood Time Step of 12 months, ensuring the integration of regional interdependencies and the seasonal cycle in trend detection at the NUTS 0 level (national level). The Space-Time Cube was created with the characteristics presented in Table 1. Similar STC was created for time-zoom window 2009-2022.

Table 1. Characteristics of the Space-Time Cube for 1992-2025 & 2009-2022

Input Space Time Cube Details

Characteristics	Space-Time Cube for 1992-2025	Time-zoom window (period 2009-2022)
Time step interval	1 month	1 month
Shape Type	Polygon	Polygon
First time step temporal bias	100,00%	0,00%
First time step interval	after 1991-12-01 00:00:00 to on or before 1992-01-01 00:00:00	after 2008-12-01 00:00:00 to on or before 2009-01-01 00:00:00
Last time step temporal bias	0,00%	0,00%
Last time step interval	after 2025-01-01 00:00:00 to on or before 2025-02-01 00:00:00	after 2022-12-01 00:00:00 to on or before 2023-01-01 00:00:00
Number of time steps	398	169
Number of locations analyzed	13	13
Number of space time bins analyzed	5174	2197

Analysis Details

Number of neighbors	8	8
Neighborhood time step intervals	12 (spanning 12 months)	12 (spanning 12 months)

Source: Authors' processing.

The running of the EHSA model offers the possibility of extraction of quantitative fast results, geographical detail results, and a graphic representation of the results.

5. Results and discussion

5.1 Fast Quantitative Results

Considering the summary results of the running EHSA model, the fast results are presented in Table 2, which shows the number of hot and cold spots among the total studied locations. Additionally, they are displayed in eight categories.

Table 2. Summary results of EHSA for 1992-2025 and 2009-2022

Summary of Results

	1992-2025*		2009-2022**	
	HOT	COLD	HOT	COLD
New	0	0	0	0
Consecutive	0	0	0	0
Intensifying	0	0	0	0
Persistent	0	0	0	0
Diminishing	0	0	0	0
Sporadic	0	0	0	4
Oscillating	2	3	1	6
Historical	0	0	0	0

*All locations with hot or cold spot trends: 5 of 13
*All locations with hot or cold spot trends: 11 of 13

Source: Authors' processing.

We can see that for a longer period (1992-2025), the number of hot/cold spots is lower than for the shorter period (2009-2022). In our case, the most frequent types are oscillating.

5.2 Detailed results for 1992-2025

The used spatiotemporal data (K=8 Nearest Neighbors and 12 months step) combines complete seasonality and area interactions, which makes it a steady-as-you-go identification of the long-term tendencies in the perception of industry managers towards employment.

There were identified patterns and new trends. Denmark (DK) is placed under the category of Oscillating Cold Spot. It is in this category because of the high share of Cold Spot (61.56) despite its positive z-score (2.40, p=0.02). Interpretation: The Danish industry is strongly oscillative, and recoveries among the locals are significantly dominated by employment pessimism periods. Finland (FI) and Sweden (SE) boast very good z-scores (8.84, p=0.00) and are in the domain of Cold Spot with large portions of cold periods. It would imply that despite the positive trend in recent months, the entire history of the negative trend influences the whole process and means that industrial recovery would be slow. Romania and Bulgaria are found to belong to the Oscillating Hot Spot with a weakly low z score (-1.87, p=0.06). This interpretation indicates critical swings and periods of industrial optimism, although there is no significant trend of consolidation. South-West Zone (Spain, France, Portugal, Italy, Greece) The countries of this region have extremely low z-scores (Spain, France, Portugal: -14.03, p=0.00) and there is no clear-cut pattern. This means a structural deterioration in industrial confidence in South-West Europe and a lack of emerging trends and affirms the deindustrialisation process in which a clear deterioration occurred.

Weak and pessimistic Luxembourg, Netherlands, and Belgium have a negative value of z-score (-3.63, p=0.00) with large variations, and their variation shows no pattern. This interpretation points out one weak point that lies in the industrial sectors, which are characterised by instability and failure to contract positive expectations.

5.3 Graphic representation

The map (Figure 2) presents the spatial distribution of emerging hot and cold spots in industrial employment expectations across Europe, as revealed by the Emerging Hot Spot Analysis (EHSA) applied to the Employment Expectations Index (EEI). It identifies areas where statistically significant trends are observed over time.

Regions such as Sweden, Finland, and Denmark exhibit a red cross-hatched pattern, indicating Oscillating Hot Spots – zones with employment expectations that have undergone consistent and significant temporal variability. Similar patterns appear in parts of Romania and Bulgaria, where the light orange shading marks Consecutive Hot Spots, reflecting recent sustained increases in positive employment expectations. The map legend distinguishes between several categories of emerging trends: New, Persistent, Intensifying, and Sporadic hot (positive trend) and cold (negative trend) spots. Notably, much of Western and Central Europe (e.g., France, Germany, Italy) shows no statistically significant temporal pattern, suggesting relative stability in industrial employment expectations or the absence of clear directional shifts during the assessed timeframe.

Overall, the map reveals a north-eastern and south-eastern clustering of dynamic labour market transitions, with the Nordic and Balkan regions experiencing greater structural fluctuations. This type of spatial-temporal analysis offers essential insights for shaping industrial policy and targeted labour strategies aligned with reindustrialisation and just transition objectives.

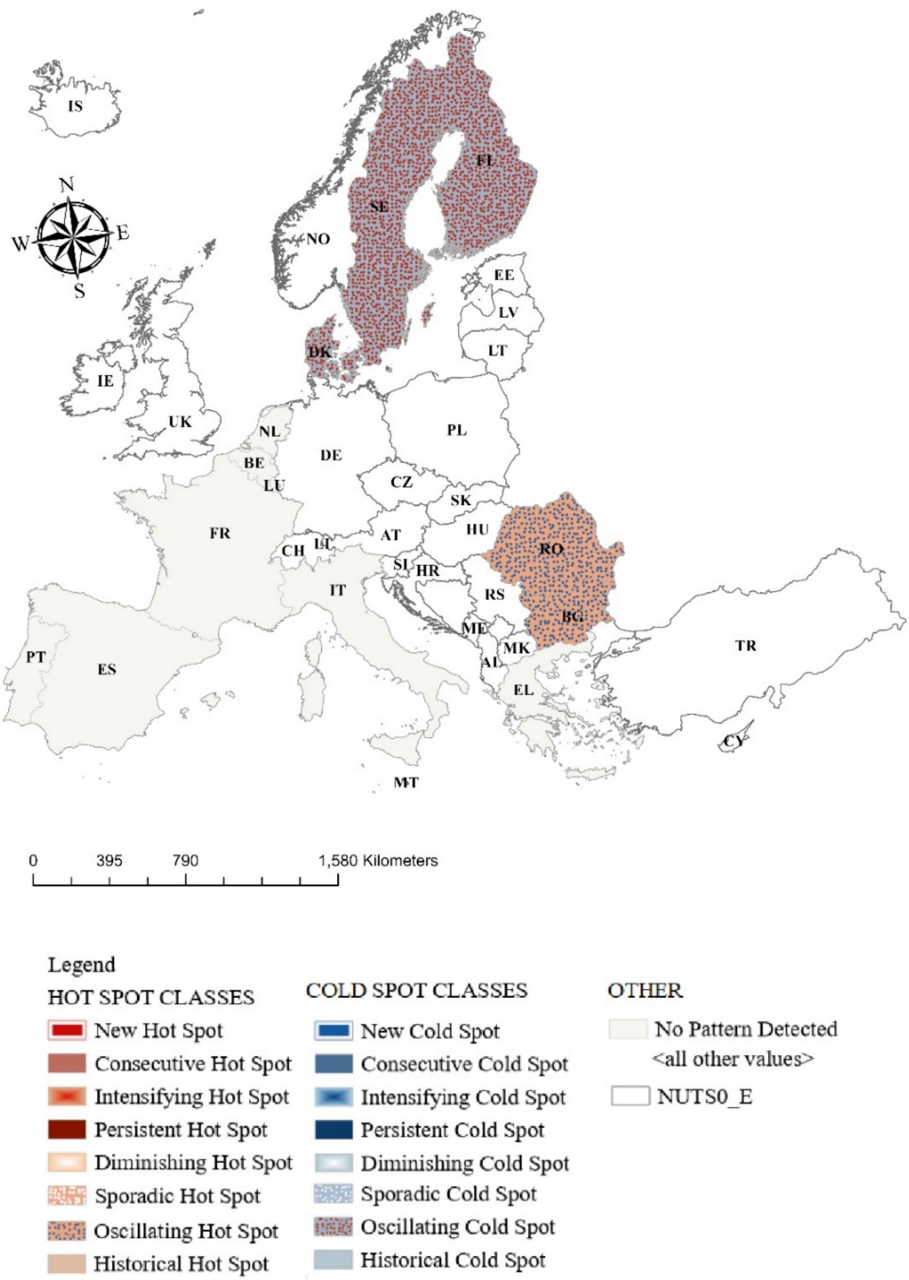

Figure 2. Emerging Hot Spot Analysis for STC 1992-2025
Source: Authors' processing on Esri ArcGIS Pro.

5.4 Subset STC 2009-2022 temporal zoom results

The space-time indicator of EEI reflects the dynamics of the managerial anticipations of employment in the European industrial sector during the period of 2009 to 2022. Since EEI is an economic sentiment indicator that is based on the direct perception of managers, it represents the initial changes in economic cycles and the labour market. Attributing the uniform spatiotemporal sequences of the EEI industry to the Emerging Hot Spot Analysis (EHSA), pertinent trends of accumulation, entrenchment, erosion, or wobbling of such anticipations at the national scale have been observed (Figure 3).

In this sense, the analysis will be able to identify areas where confidence in employment growth is increased or reduced, attributed to the industrial managers, as a proxy for the strength and momentum of the European industrial sector over time. According to the arising spatial patterns of industrial employment confidence in Europe, it is possible to observe different regional processes, which indicate diverse results in the indicators of industrial resilience, volatility, and fragility.

A pattern of Oscillating Cold Spot, along with supremely ill Z-scores (-6.99 in both Belgium and Luxembourg), generates a signified structural instability in the industrial sector in Belgium, Luxembourg, and the Netherlands. The situations in such countries are in a period of interchanging moderate optimism and a sharp fall of managerial confidence concerning the situation at industrial employment. This high volatility is perhaps due to the mix of factors such as industrial relocation, a continued shift in technology, and more immediate upheavals, such as the energy crisis. These variations suggest that the region has been unable to establish a consistent industrial direction, which may indicate difficulties in aligning with global industry trends and international competition.

On the contrary, the situation in Southern and Southeastern Europe, particularly in Romania, Bulgaria, Greece, and Italy, exhibits both scattered and persistent cold spots. The scores (Z-scores) in both Romania and Bulgaria are very low score (e.g., -4.14 in the Romanian case), with Bulgaria exhibiting a pattern of Sporadic Cold Spot. This underscores an ongoing decline in trust in industrial employment, perhaps stimulated by underlying economic frailties, aging industrial bases, and the inability to attract investment in newer, dynamic, emerging sectors. There is a slight negative Z-score of -2.96, indicating higher levels of pessimism and industrial stagnation in Greece and Italy, which are statistically relevant to other countries. In these countries, an overreliance on established sectors, relatively little investment in low-carbon, high-tech ones, and the pressure exerted by industrial transfers outside Western Europe compose a wider story of industrial decline and dislocation.

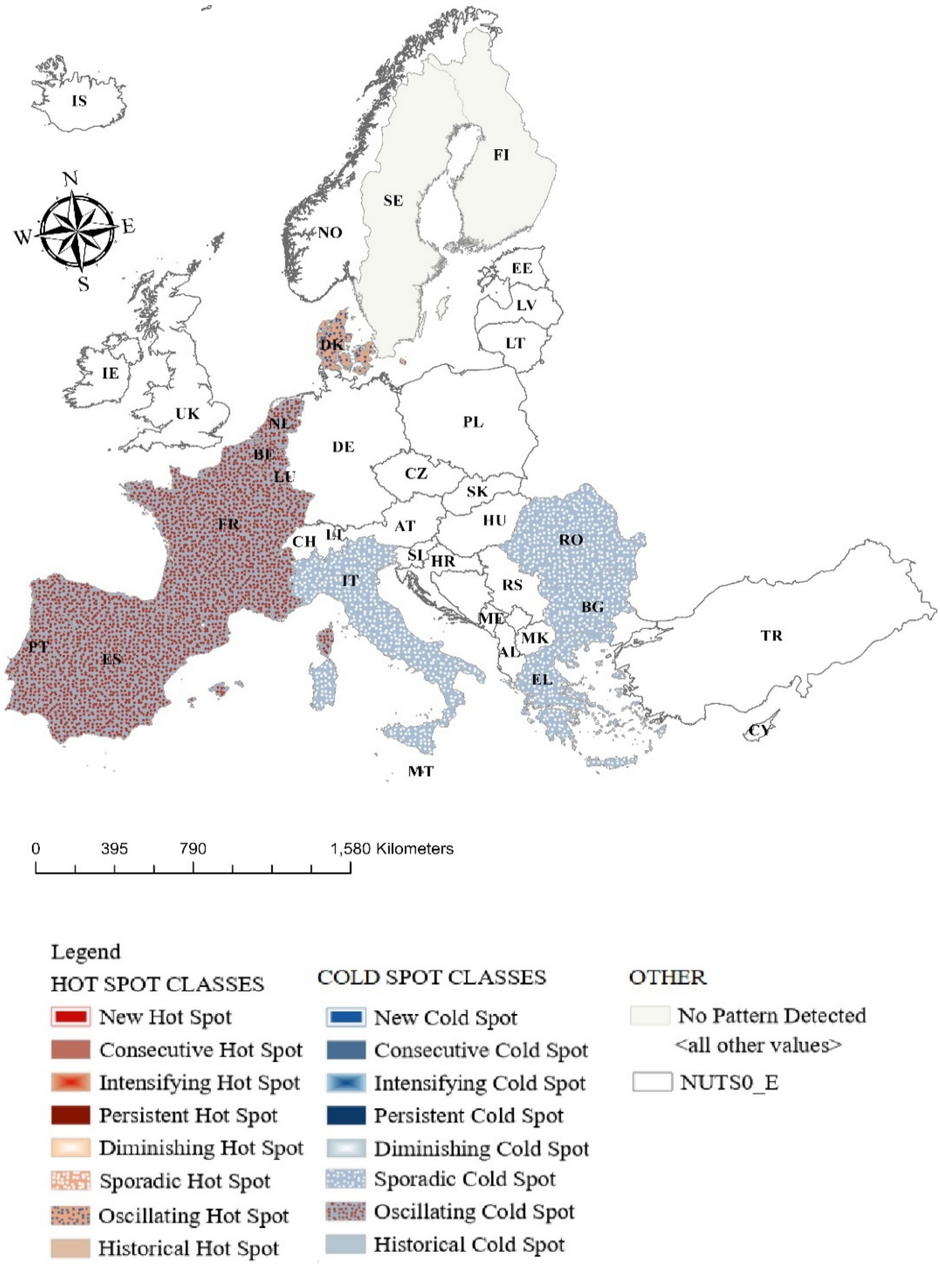

Figure 3. Emerging Hot Spot Analysis for STC 2009-2022
Source: Authors' processing on Esri ArcGIS Pro.

Weak signs of primitiveness emanate in Western European countries like France, Spain, and Portugal. These have negative values of Z-scores, although they are not significant at spatiotemporal (e.g., Spain and Portugal: Z = -1.11, p = 0.27). This implies that despite the absence of a trend of consistent decrease in its values, there still exists a threat of industrial instability. The sensitivity of such economies to changes in the world economic environment may be particularly vulnerable due to the overall context of changes in supply chains and green transition, which involve the need to have strong industrial innovation.

Having a brighter note, Denmark can also be seen as a possible example of resilience. It is the single nation that cannot only have a positive Z-score (+1.68), but also the pattern of Oscillating Hot Spot, i.e., controlled fluctuations with a changing industrial structure. This is an indication of a progressive industrial policy with roots in digitalisation, investment in high-tech, and building green industry. Whilst the statistical results are marginal, their trend is encouraging with the value of p = 0.09, which suggests that Denmark is successfully handling the transition to a more sustainable and technologically advanced industrial foundation.

Lastly, there is the Nordic region, Sweden, and Finland, which does not indicate any spatial-temporal trend, which is indicative of some stability in the expectation of industrial jobs. This neutrality can capture the case with the already established mature industrial systems that can integrate well into the global value chains and are stable against external shocks.

On the whole, the map highlights a disaggregated state of affairs in industrial Europe, as there are areas that are split between insecurity, constant pessimism, and budding strength.

6. Conclusions

6.1 Methodological limitations and future research

This study has a few methodological limitations. First, the spatial analysis is conducted at the NUTS 0 (national) level because the DG ECFIN Employment Expectations Index (EEI) provides only full, harmonised, and continuous monthly series at this level and throughout the period (1992-2025). This necessarily obliterates subnational heterogeneity and does not allow for reliable calibration of EHSA to NUTS 2 or NUTS 3, where the data are not continuous; subsequent research will improve the spatial resolution of the model once consistent regional datasets of EEI become available. Second, the sensitivity of the results is to the parametrisation of the EHSA model, such as the eight nearest neighbours and 12-month temporal step that smooths the short-term variation and cannot capture very recent shifts in employment expectations. Third, it analyses only 13 EU Member States, which is limited by data and relies on an expectations-based indicator that is not as detailed at the sectoral/occupational level. These aspects, to some extent, limit the trustworthiness and applicability of the results and warrant caution in applying the findings to the creation of specific policy interventions. The model should be recreated in future studies on a greater number of countries, on both more spatial and temporal scales, and with other indicators of industrial transformation and labour market adaptation factored in.

6.2 Synthesis of findings and policy implications

The given model of EHSA allows for the integration of the analysis of the workforce expectations between 1992 and 2024, focusing on 2009-2022, which signifies the shift toward Industry 4.0 in Europe. This is the time of structural transformation of the traditional, resource- and energy-intensive industries to digital-oriented, automated, and sustainable ones. The model reflects the transformation of regional restructuring and polarisation as an outcome on the basis of the ability of a given country to respond to the effect of technology and competition.

The 2009-2022 window offers a zoomed picture of fast and slow premises in such a change. Denmark is one of the most impressive emerging leaders which are characterised as Oscillating Hot Spot due to the persistently positive expectations of industrial change. Its leadership is supported by the fact that it ranks highest in the Digital Economy and Society Index (DESI), and thus it can spearhead the Industry 4.0 transition.

Alternatively, Southeastern Europe (Romania and Bulgaria), which were formed on the basis of an ineffective and energy-intensive industrial base, also demonstrate Oscillating Hot Spot patterns that connote the potential of transformation as well as vulnerability. The regions risk not continuing with development without long term investments and consistent policies.

The results highlight the necessity of various strategic measures to alleviate the regional diversities and favour a certain, inclusive shift to Industry 4.0 in the European industrial estate.

The hypotheses of the study were confirmed by the EHSA model (see Table 3).

Table 3. Hypotheses validation

Hypothesis	Content	Validation & results
H0	EHSA is efficient in detecting risks and opportunities	Confirmed – The proposed model clearly identified the relevant space-time patterns
H1	Spatial polarisation between regions with traditional industrialisation and that adapted to Industry 4.0	Confirmed – West and South in decline, North and East with different potential
H2	Identifying emerging leaders for the period 2009–2022	Confirmed – Denmark looks like an emerging industrial leader
H3	Romania and Bulgaria have reindustrialisation potential, but they risk being marginalised	Confirmed – Oscillation between potential and vulnerability

Source: Authors' processing.

EHSA findings are dependent in the first place on the way spatial neighbourhood is measured: selecting among others eight close neighbors of each unit of analysis is arbitrary and may substantially affect the pattern identified. In addition, it is at the granularity level of spatial aggregation at NUTS0 (i.e. at the national level) that lost granularity lies since subnational heterogeneity is obscured when aggregated by country; potentially, not all locally or regionally thick points or regional variations will be detected. More than that, to minimise the fluctuations (within short periods as well as seasonality) of monthly data, a 12-month time step (annual resolution) may be used, which will not allow for highlighting very short-term trends or tracking very recent changes. Therefore, the instability of the temporal data and the sensitivity to the parameters of the analysis restrict, in part, the reliability and the interpretability of EHSA outcomes.

Response to Research Question 1: *What do the spatio-temporal dynamics of managerial expectations about industrial jobs indicate about the European process of industrial transition of the period 1992-2025?*

According to the data of spatio-temporal analysis, the polarisation of European industrial dynamics on the long-term scale (1992-2024) occurs. Northern nations such as Sweden, Finland, and Denmark display Oscillating Cold Spot patterns and this trend suggests the diminishing managerial confidence in industrial employment based on structural reorganisation, loss of traditional industry in addition to challenges faced in the process of changing to new production models. In their turn, Romania and Bulgaria turn into Oscillating Hot Spots, which indicates the movement towards industrial optimism. This is testimony to the history of the 1990s industrialisation as well as to the availability of new opportunities of repositioning due to strategic investment and policy support which show the possibility of new industrial growth in the new world of euro economics.

Response to Research Question 2: *Which are the new leaders or vulnerable European regions in the passage to Industry 4.0, furthermore, confirmed by the time-zoom 2009-2022 combined in the spatiotemporal analysis of the expected management?*

Denmark became a leader in Industry 4.0 between 2009 and 2022, and its Oscillating Hot Spot pattern had performance close to the top on the DESI scale. Romania and Bulgaria, on the contrary, continue to be Sporadic Cold Spots, experiencing structural weaknesses as legacies of energy-intensive historical paths of industrialisation inefficiencies. Causing a risk of industrial competitiveness, declining trends in Southern and Western Europe are also indicated. The cycle of 1992-2025 shows not only the deindustrialisation of older Western and Northern industrial centres but also the non-even or uneven reindustrialisation of Eastern Europe. Such unequal regional activities in adopting Industry 4.0 indicate the potential opportunities and the threats existing in a new industrial versatile terrain on the continent.

The Emerging Hot Spot Analysis (EHSA) model offers data-oriented answers that are highly applicable to the domain of policy and industrial strategy. Among the conclusions there is an urgent necessity of the reindustrialisation strategy in South-East Europe, active surveillance over the Benelux region and the potential of Northern Europe as the source of resilience models and best practices in transition to the Industry 4.0. EHSA with 8 nearest neighbour and 12-month distances proves its usefulness in following managerial expectations that are very vital in a responsive national and European economic policies.

Methodologically, the implementation of EHSA on the Employment Expectations Index (EEI) of 2009 to 2022 is associated with a couple of limitations. Its spatial analysis is founded on the NUTS0 level and is therefore quite limited in its granularity, and its temporal scale is not robust against short-term fluctuations. They could be assessed at a finer spatial and monthly time scales, where comparisons made at the local level would be more appropriate, and play a better role in seasonal or sudden changes. Moreover, the research involves only 13 countries of the EU, and the subjective and averaging character of the EEI prevents any information on the sectoral or regional peculiarities and the real size of employment.

Interpretation of policy should be made by taking caution. Although EHSA is good at recognising employment expectation patterns, it fails to elaborate on the causes of these patterns or include enough details that would allow focused interventions. Nevertheless, findings prove that there is a structural change taking place in the European industry whereby the gaps between the rising stars and the vulnerable regions are increasing. Denmark is a good example of Industry 4.0 adaptation, and Eastern and Southern Europe need logical assistance to prevent marginalisation of their economies.

Further studies ought to extend the model to a wider number of the EU countries and add measurable indicators of industrial change. Reproducing of the model at more spatial resolutions would bring the neighbouring influences about workforce attraction and regional competitiveness. The research design adds the EEI to the Space-Time Cube structure, helps find statistically significant trends in industrial anticipation all over Europe, and provides a repeatable workflow based on GIS. Geographic polarisation is evident in its results and makes it clear that reindustrialisation should be differentiated, that cohesion policies need to be refocused, and that planning the workforce should be based on the European Green Deal and Digital Agenda.

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