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Intersectoral Labour Mobility in Europe as a Driver of Resilience and Innovation: Evidence from Granularity and Spatio-Temporal Modelling

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Abstract

Intersectoral labour mobility is a key driver of economic resilience and innovation in Europe. The redistribution of workers across sectors and regions enables economies to adapt to shocks, create flexibility and increase the rate of structural change. However, the dynamics of mobility have not been adequately investigated across varying scales of sectoral granularity and spatio-temporal dimensions. This paper applies the Intersectoral Mobility Index (MI) to all European NUTS-2 areas from 2008 to 2020, utilising Eurostat Structural Business Statistics. Two levels of sectoral aggregation (NACE Rev. 2, 1-digit and 2-digit) are employed to compute MI, capturing both broad and fine-grained reallocations. Classical indices of structural change (NAV, Krugman, Shorrocks) are combined with spatio-temporal modelling in ArcGIS Pro, employing Space–Time Cubes, time-series exponential smoothing forecasts, time-series clustering and emerging hot spot analysis. Results indicate that MI distributions are positively skewed and heavy-tailed, with peaks coinciding with systemic crises (2009–2011, 2020). At the 2-digit level, MI values are significantly higher, revealing intra-sectoral changes obscured in aggregated data. A statistically significant downward trend in mobility suggests an increasing structural rigidity following the global financial crisis. Regional clustering highlights heterogeneity: a small number of regions, such as Bremen, Madeira and the Southern Great Plain, have sustained high or unstable mobility, while most exhibit convergent mobility and low reallocation. This paper contributes to the conceptualisation of MI as a dual measure of resilience and innovation preparedness. It underscores the importance of multi-scalar and spatio-temporal methods in monitoring labour market flexibility. The findings have policy implications, including the design of targeted reskilling programmes, proactive labour market policies and just transition plans to maintain regional resilience during the EU's green and digital transitions.

Keywords: labour market; intersectoral mobility; structural change; sectoral granularity; resilience; innovation; sustainability

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Academic Editor: Grigorios L. Kyriakopoulos

Received: 7 October 2025
Revised: 10 November 2025
Accepted: 10 November 2025
Published: 18 November 2025

Citation: Lincaru, C.; Pirciog, C.S.; Grigorescu, A.; Mladen-Macovei, L. Intersectoral Labour Mobility in Europe as a Driver of Resilience and Innovation: Evidence from Granularity and Spatio-Temporal Modelling. *Sustainability* **2025**, *17*, 10333. https://doi.org/10.3390/su172210333

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1. Introduction

The Intersectoral Mobility Index (MI) quantifies the annual reallocation of employment shares across sectors within a region. Low MI values indicate structural stability, while

higher values signal substantial labour reallocation. However, MI must be interpreted within context; the same value may reflect either vulnerability to shocks in narrowly specialised regions or positive adaptability in advanced, innovation-driven economies. Filippetti et al. [1] demonstrates that innovative regions maintained employment resilience during crises, while Braunerhjelm et al. [2] shows that mobility among knowledge workers fosters firm-level innovation. Thus, MI is best understood as a dual indicator of both resilience and innovation readiness.

Intersectoral labour mobility is influenced by a range of forces operating at economic, technological, institutional and demographic levels. Economic factors include productivity differentials, business-cycle shocks and sectoral wage gaps that encourage industry reallocation [3,4]. Technological change serves as a structural stimulus, replacing labour in declining industries with employment in digital, green and knowledge-based sectors [5,6]. The presence of institutional and policy frameworks affects the nature of these transitions, either facilitating or hindering labour redeployment through employment protection, training systems and innovation policies [7,8]. Additionally, demographic changes, such as ageing and migration, alter the flexibility of regional labour markets, thereby influencing mobility pressures [9]. In this context, the MI reflects the responsiveness of regional labour ecosystems to these counteracting forces and structural transformations.

Based on this understanding, the updated conceptual framework broadens the interpretation of intersectoral labour mobility from a structural adjustment tool to a systemic ecosystem indicator, acknowledging the processes of innovation diffusion and resilience within the regional labour market. In this paper, 'ecosystem' refers to the network of firms, workers, educational institutions and policy actors engaged in continuous interaction and learning. These learning systems facilitate knowledge sharing, skill reallocation and adaptive innovation. Consequently, the MI serves as an indicator of the capacity of the regional learning ecosystem to absorb shocks and transform them into opportunities for innovation through labour reallocation. This perspective aligns with the learning economy concept [10] and recent Organization for Economic Co-operation and Development (OECD) models, which assert that regional innovation ecosystems are crucial for resilience and inclusive transitions [7].

Although the literature on labour mobility and innovation has been expanding, few studies have explored how the temporal and spatial dimensions of intersectoral mobility influence innovation preparedness at the regional level. Current practices often regard mobility as a consequence of structural change rather than a process of learning and adaptation. This study addresses the identified research gap by demonstrating that intersectoral mobility trajectories reflect regions' ability to innovate and their resilience in the face of ongoing crises.

MI introduced in this study operates at the ecosystem level, linking various structural reallocation dynamics with the functioning of regional innovation systems. It captures not just changes in employment sectors but also adaptive capacity, knowledge diffusion and learning processes that underpin resilience and innovation preparedness [1,2,11]. This approach aligns with recent studies suggesting that innovation diffusion results from the interplay among labour mobility, absorptive capacity and technological preparedness [12,13]. Through this multi-scalar ecosystem framework, the analysis integrates MI into regional contexts, emphasising structural flexibility and the redeployment of human capital to facilitate sustainable transformation and policy adaptability [14–17].

Yet, MI is not meaningful when interpreted as a static number alone. Its significance emerges only when placed in a temporal and spatial context. Over time, MI trajectories reveal whether a region undergoes persistent restructuring, cyclical adjustments or shock-induced spikes (e.g., 2009–2011, 2020). Across space, the same MI level may represent

positive flexibility in advanced economies (e.g., innovation-driven Ireland) or structural fragility in vulnerable economies (e.g., Greece or outermost regions). Spatio-temporal modelling approaches (such as the Space–Time Cube, clustering and hot spot analysis) operationalise this principle, demonstrating how regional labour markets evolve differently under common shocks [1,2,12,13].

This paper applies MI across all European NUTS-2 regions from 2008 to 2020 using Eurostat's Structural Business Statistics [14–16]. Grounded in classical measures of structural change (NAV, Krugman, Shorrocks) [3,18,19] and informed by contextual evidence of innovation and mobility [1,2,20–22], our analysis extends by implementing spatio-temporal modelling and forecasting using ArcGIS Pro tools [12,13].

The paper aims to achieve three objectives:

(i) To establish intersectoral labour mobility (MI) between all European regions from 2008 to 2020 using the NUTS-2 regions and to identify patterns of structural change over time and space;
(ii) To project these mobility patterns onto the regional learning ecosystems, evaluating the encouragement of innovation diffusion and adaptability;
(iii) To reflect on the policy implications of transition management towards digital and green economies.

The organisation of the paper is as follows: Section 2 contains the conceptual background and hypotheses, Section 3 details the data and methodology, Section 4 reports the empirical results, Section 5 discusses the policy implications and Section 6 concludes with the limitations and future research directions.

2. Literature Review

2.1. Baseline of Intersectoral Labour Mobility

Intersectoral labour mobility refers to the movement of labour between different sectors of the economy, such as from manufacturing to services or from agriculture to industry. This mobility is a crucial element in economic growth and development, as it enables the effective distribution of labour in response to evolving economic conditions and technological changes.

Intersectoral labour mobility is underpinned by several economic theories and models. Neoclassical models, including the Harris–Todaro model [23], emphasise the importance of wage differentials. Migrant workers leave low-wage (rural, traditional) sectors and move to high-wage (urban, modern) sectors to increase their expected income until equilibrium is reached across industries, while also considering the risk of unemployment.

According to Human Capital Theory [24], a change in sectors is viewed as an investment: mobility will be observed in areas where there is a high level of expected returns on skills and education. This highlights the relevance of education and the transferability of skills. Search and Matching models introduce friction into the labour market, acknowledging that a change in jobs does not occur immediately but relies on matching efficiency, the availability of information and the duration of unemployment.

In contrast, Segmented Labour Market Theory [25,26] posits that labour markets are divided into distinct sectors with different wages, terms and security. Institutional barriers may limit the mobility of these segments, discrimination may hinder their movement, or there may be a mismatch in skills, indicating that structural issues can impede the free movement of labour.

However, intersectoral labour mobility is not frictionless [4,27,28]. As shown by [18], firm-level heterogeneity (a concept referred to as granularity) and exposure to trade can significantly impact patterns of sectoral reallocation. Their model identifies that the wage impacts of trade shocks are sensitive to the level of labour mobility. In cases of limited

mobility, trade impacts are concentrated only in a small number of sectors, leading to further distributional effects.

Foster-McGregor and Verspagen [28] decompose labour productivity growth into within-sector and between-sector factors for a panel of developing economies. They conclude that, in most instances, productivity growth has been primarily driven by within-sector improvements rather than by reallocation across sectors. They discuss the effect of job automation risk exposure in their subsequent paper [27] and demonstrate that a country's sectoral employment structure is closely associated with its vulnerability. Global trade may drive structural change, necessitating consideration of automation risk in developed economies.

Krugman [29] illustrates that intersectoral and inter-regional mobility has actively transformed economic geography: core–periphery patterns of development can emerge through labour movements from agriculture to industry, driven by wage differentials and scale effects. Sassen [30] situates labour mobility within the broader socio-political context of globalisation, arguing that mobility trends are influenced not only by wages and productivity but also by institutional and political systems.

The Norm of Absolute Values (NAV), also known as the index of structural change, is the sum of absolute differences between sectoral shares in two periods, representing a simple measure of the magnitude of change [31]. The Krugman Specialisation Index measures the economic organisation of a region or country compared to a reference, often used to assess convergence or divergence over time [29]. Mobility or fluidity between categories is measured by the Shorrocks Index [19], which has been modified to account for the structural reallocation of labour. Lastly, the Duncan and Duncan Index of Dissimilarity [18] represents the percentage of change in categories that workers would need to make to equalise two distributions over time; thus, it is a classic measure of structural change. These measures collectively provide complementary perspectives on the magnitude and flow of structural change, whether in terms of simple comparisons of shares or mobility and segregation views.

2.2. Previous Methodological Approaches to Measuring Structural Change

Intersectoral measures of mobility and specialisation extend classical measures such as the Norm of Absolute Values (NAV), Krugman-type measures of dissimilarity and mobility/segregation schemes like the Shorrocks Index [19] and the Duncan and Duncan Index [18]. These serve as a starting point for quantifying the scale of reallocations in the sector and structural divergence. Further formulations build on this foundation to include entropy-based and Theil-based indicators, which are concentrated-sector dependent and diversity-dependent, providing an information-theoretic view of structural dynamics [15].

One key methodological challenge is sectoral granularity. Within-sector adjustments (e.g., retail sub-branches, construction specialisations or employment services) that are obscured at aggregate levels are revealed through indexes that capture broad reallocation between macro-sectors at coarser levels (e.g., NACE 1-digit) and facilitate cross-country comparability at finer levels (e.g., NACE 2-digit) [28,29]. In practical terms, findings are scale-dependent and conclusions can vary across levels of aggregation—especially around crises and turning points [4,27,28,32].

Comparative research also emphasises that the process of structural change is not usually continuous; rather, it consists of bursts of reallocation followed by periods of stasis or even turnover [20,21]. These findings relate to core–periphery models [28] and institutional perspectives [30], highlighting the importance of considering mobility measures in both spatial and policy contexts. This body of literature supports a multi-metric, multi-scale approach: combining distance-based (L1/total variation) and mobility/segregation indicators

and presenting the results at both 1-digit and 2-digit NACE levels to prevent aggregation bias and to elucidate the actual channels of intersectoral reallocation [18,19,28].

2.3. Intersectoral Mobility, Resilience, and Regional Labour Markets

One significant mechanism of regional economic resilience is intersectoral mobility, which can be described as a region's ability to absorb, adapt and recover from regional shocks, such as recessions, industry-specific downturns or systemic shocks [33,34].

As a large sector contracts—by closing factories, halting construction or slowing tourism—workers in less affected areas have the opportunity to transition to an expanding industry, thereby avoiding prolonged economic depression and accelerating recovery. High intersectoral mobility thus acts as a shock absorber, facilitating the reallocation of resources and enabling knowledge spillovers that foster new industries and productivity gains [27,33].

The extent of mobility, and consequently resilience, systematically depends on the following:

Skill-relatedness: Reallocation is facilitated when sectors have similar skill requirements, providing displaced workers with viable career options [34].

Human capital and education: A better-educated workforce is more mobile and adaptable, as transferable skills enhance retraining opportunities [35]. Institutions in the labour market, such as flexible labour legislation, retraining policies and efficient matching mechanisms, favour transitions, while inflexible regulation retards adjustment [35,36].

The composition of industries: Regional economies characterised by associated variety are more resilient to shocks compared to those dominated by a single sector [34].

Empirical research has established a positive relationship between mobility-based adjustment and the pace of recovery in regions following a crisis. The analysis of the 2008–2009 Great Recession revealed that areas in the EU with greater intersectoral and inter-occupational mobility experienced quicker employment recovery [33], whereas regions with rigid labour markets (e.g., Greece, Spain) faced persistent unemployment and skills loss [36,37]. Labour market institutions, such as short-time work arrangements in Germany, contributed to shock buffering by ensuring firm-worker compatibility and diminishing the scale of reallocation that would otherwise be substantial [36]. Meanwhile, the movement of people across borders within the EU served as a partial adjustment policy but also resulted in a drain of skills from Southern and Northern Europe [37].

The COVID-19 crisis revealed new dimensions of mobility. Remote working emerged as a form of virtual mobility, enabling employees to remain productive even in the presence of spatial immobility. Regions with teleworkable jobs, particularly capital cities reliant on services, demonstrated greater resilience during the initial phases of the pandemic [5,11].

Conversely, long-term scarring can occur in regions with minimal movement due to repeated trauma. A paradigmatic example is the U.S. Rust Belt, where limited labour mobility has led to chronic unemployment, city decay and loss of human capital [38,39]. These issues continue to affect former coal and shipbuilding areas in Europe and non-urbanised Central and Eastern Europe, where internal migration is impeded by structural obstacles such as housing, infrastructure and institutional inflexibilities [6,40].

Such structural limitations create inequalities among regions and cannot be rectified solely through labour reallocation, underscoring the importance of policies that promote intersectoral and inter-regional mobility [41,42].

2.4. Intersectoral Mobility and Innovation Capacity

Intersectoral labour mobility has been extensively cited as a source of innovation potential, as it encourages the transfer of skills, knowledge and tacit know-how between

firms and sectors. The mobility of talented workers, including scientists, engineers and managers, generates knowledge spillovers and professional networks, thereby accelerating learning and technological diffusion [1,11]. This aligns with the Schumpeterian definition of creative destruction: labour moves out of the failing, less productive parts of the economy into new sectors, triggering dynamics in firms and competitive forces that drive innovation.

Theoretically, intersectoral labour mobility can lead to innovation through knowledge transfer and absorptive capacity, which determines the extent to which regions and firms can convert labour reallocation into learning and productivity benefits. In this context, it is essential to differentiate between adaptive mobility, which reflects proactive skill redeployment and is beneficial for innovation and reactive churn, which results from economic shocks or structural weaknesses that create short-term movements of workers without accumulating benefits [10,24,25]. The potential of mobility within the learning economy framework relies on the institutional capacity to absorb, recombine and exploit new flows of knowledge [7,10].

MI is interpreted through the lens of adaptive mobility and reactive churn, which are empirically distinct. Stable and goal-oriented labour reallocation towards knowledge-based or technology-focused industries indicates learning and innovation in resilient ecosystems, representing adaptive mobility [1,2,7,10]. In contrast, reactive churn refers to sudden or unplanned movements due to economic shocks or institutional weaknesses, often associated with job losses and declines in productivity [40,43]. Thus, adaptive transformation and reactive instability can be represented by the same MI value, depending on the regional context and additional indicators of R&D, education and employment.

MI possesses a dual nature, as it is contingent upon the structures and institutions within which mobility occurs. A high MI indicates adaptive flexibility and dynamic relocation of human capital to productive, technology-intensive sectors in advanced, innovation-driven areas, supported by robust learning and policy ecosystems [1,2,10]. Conversely, in peripheral or structurally dependent sectors, parallel MI scales tend to indicate reactive churn—regular reallocations due to shocks, industrial decline or unstable policies that do not yield cumulative innovation [4,7,43]. This context sensitivity is why MI may be viewed as a context-dependent, relative measure of adaptability or resilience rather than an absolute one.

In addition to individual firm-level factors, the innovative capabilities associated with intersectoral mobility depend on systemic facilitators, including policy coordination, institutional quality and technological preparedness. Recent reports indicate that coherent policy frameworks and improved digital infrastructure in a region significantly increase the likelihood that labour mobility will lead to cumulative innovation rather than stagnation. Jahanbakht and Ahmadi [44] demonstrate that technological and non-technological enablers influence adaptive and reactive mobility outcomes, while Roumboutsos et al. [45] consider mobility as central to ecosystem-based innovation models. Similarly, Zhang et al. [46] provide empirical evidence that organisational and technological relationships within regional innovation ecosystems enhance adaptability and resilience during structural change.

Mobility enables expanding companies to acquire valuable human resources from shrinking industries, particularly relevant during digital and green transitions, where emerging industries demand a diverse range of skills [5,6]. Labour flows positively contribute to the formation of innovation clusters by facilitating geographic concentration of talent, increasing face-to-face interactions and developing dense ecosystems that enhance the likelihood of subsequent waves of innovation and entrepreneurship [47].

These mechanisms are upheld by empirical evidence. In European firms, Filippetti et al. [1] observes that inter-firm labour mobility has a positive and significant relationship with the outcomes of innovation (patents, product introductions). This impact is more

pronounced in cases of external mobility, which brings new ideas and perspectives, and is maximised in firms with a high absorptive capacity. According to Braunerhjelm et al. [2], entrepreneurial mobility, or the movement of experienced founders when moving or initiating new ventures, is associated with increased firm formation and technological advancement, especially in high-technology industries.

The insights highlight the necessity for policies that eliminate mobility restrictions (e.g., non-compete clauses) and provide reskilling opportunities to prepare workers for new industries. Special programmes can aid in the redistribution of labour from declining, carbon-intensive or low-tech sectors to those driving the digital economy (data science, automation, software) and the green transition (renewable energy, circular manufacturing). Ensuring that such transitions are socially inclusive—through regional diversification policies and just transition schemes—maximises both innovation potential and social resilience [40,48].

Recent studies on resilience and transition strategies demonstrate that limited or developing economies are devising mechanisms that integrate technological use with institutional learning. According to Tondro, Jahanbakht, and Ozay [8], adaptive technology-acquisition systems can stimulate socio-economic growth through incremental digital innovation and local entrepreneurship in emerging contexts, consistent with the dual role of intersectoral mobility as both a stabiliser and a driver of renewal. Similarly, Zheng and Cai [49] highlight that integrating technological, human capital and institutional elements through public policy can transform innovation systems into interconnected ecosystems. This systemic perspective supports the view that MI serves as a diagnostic tool to assess the capacity of regional ecosystems to adapt to technology, coordinate institutional patterns and undergo policy-driven transformation [8,49].

Beyond mechanisms at the individual or firm level, intersectoral mobility acts as a systemic facilitator of learning processes within the regional ecosystem. It promotes skills development, institutional learning and knowledge diffusion across interrelated sectors, linking human capital mobility with the flexibility of innovation systems [7,10]. In this framework, regions with high absorptive capacity and effective policy coordination could transform labour reallocation into a process of cumulative innovation and resilience.

2.5. Policy Context and Sustainability Perspectives

Intersectoral labour mobility is closely aligned with the United Nations Sustainable Development Goals (SDGs), particularly SDG 8 (Decent Work and Economic Growth) and SDG 10 (Reduced Inequalities). SDG 8 calls for sustainable, inclusive and productive economic growth and complete, productive employment. The ability to reallocate labour between low-productivity and high-productivity sectors is a primary source of GDP growth and a crucial means of achieving SDG 8.1 [5,50]. Furthermore, mobility supports SDG 8.5 on decent work and productive employment, as it enables workers to transition from precarious, informal jobs to formal, better-paying positions [40].

The second SDG 10.2, which aims to ensure the social, economic and political inclusion of all individuals, also involves labour mobility. The capacity of workers, particularly those from underprivileged groups, to transition to industries that offer better pay and greater job security helps reduce income and opportunity disparities between regions [47,48]. Conversely, low mobility can confine employees in low-income, low-productivity industries, perpetuating inequality [6].

From a policy perspective, mobility is central to just transition policies, regional diversification and territorial resilience [2,51]. To facilitate an effective transition to a low-carbon economy, policies should cover the following:

- Offer reskilling and upskilling programmes to prepare workers for roles in renewable energy, sustainable manufacturing and green infrastructure;
- Ensure social security and mobility of benefits to mitigate the risks associated with sectoral developments;
- Engage stakeholders (governments, unions, employers, communities) to ensure that processes are fair and inclusive.

Policies for regional diversification should be less restrictive regarding labour mobility, create new local opportunities and tailor education systems to meet emerging labour market demands [52,53]. The concept of mobility is becoming a key component of the framework for territorial resilience, recognising that flexibility in the labour force enables regions to withstand shocks and recover more swiftly [43,54].

2.6. Research Questions and Hypothesis

Considering the gaps identified in the existing literature and the need for measuring intersectoral mobility at the national level from an integrated perspective, we formulate the research questions (RQs) for this study.

Building on the objectives outlined above, this study addresses the following RQs:

- RQ1. How does MI vary across European NUTS-2 regions from 2008 to 2020, what are its distributional properties and does it exhibit a statistically significant trend?
- RQ2. To what extent does sectoral granularity (1-digit vs. 2-digit NACE) affect the measurement and interpretation of MI, and how do the difference (Δ) and ratio (ρ) diagnostics behave over time?
- RQ3. How can MI be interpreted within a space–time framework, distinguishing between crisis shocks, recovery phases and stability, as well as between advanced and vulnerable regions?
- RQ4. Does a high MI primarily indicate resilience and innovation capacity in advanced economies, or structural fragility in vulnerable economies?
- RQ5. What are the implications of MI patterns for EU cohesion and labour market policies, particularly in the context of green and digital transitions, and can space–time approaches provide early-warning signals for policy?
- RQ6. Are MI trajectories sufficiently persistent to allow for short-term forecasting, and what is the uncertainty associated with one-step-ahead predictions?

To clarify the logical structure of the research design, Figure 1 and the accompanying summary present a question-to-hypothesis map that links the conceptual and analytical components of this study. Each RQ corresponds to a specific analytical dimension and an associated hypothesis (H), ensuring coherence between theoretical framing and empirical testing:

- RQ1–RQ3 examine the temporal and spatial characteristics of MI, establishing the descriptive foundation for subsequent trend and distribution analyses.
- RQ4–RQ5 connect mobility interpretation to innovation and resilience outcomes, aligning with the conceptual hypotheses H1–H3 introduced in Section 2.4 and empirically tested through clustering and spatio-temporal modelling.
- RQ6 focuses on predictive assessment, addressing MI persistence and short-term forecasting (H6).

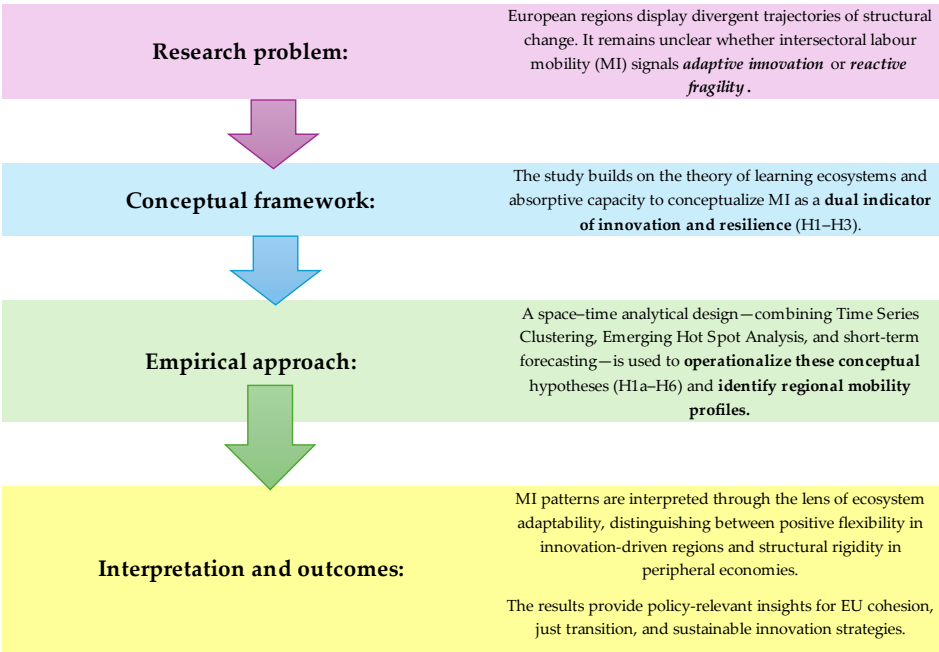

Figure 1. Conceptual–Empirical Research Framework Linking Intersectoral Labour Mobility (MI), Innovation, and Resilience. Source: Authors' elaboration based on the proposed conceptual–empirical framework.

Building on the conceptual framework outlined above, this study tests the following overarching hypotheses linking intersectoral labour mobility (MI) to innovation diffusion and adaptability:

H1. *Regions with higher levels of intersectoral labour mobility (MI) demonstrate stronger innovation performance and resilience, indicative of adaptive rather than reactive mobility.*

H2. *The relationship between MI and innovation outcomes is mediated by regional absorptive capacity and knowledge diffusion mechanisms.*

H3. *Sustained increases in MI are associated with enhanced structural adaptability and a greater potential for sustainable transformation under ongoing digital and green transitions.*

The subsequent operational hypotheses (H1a–H6) delineate the empirical testing procedures used to evaluate these conceptual relationships.

The three conceptual hypotheses (H1–H3) outlined above establish the theoretical foundation of the study, linking intersectoral labour mobility to processes of innovation diffusion and adaptive capacity. The following operational hypotheses (H1a–H6) specify the empirical procedures through which these conceptual relationships are tested. Together, they constitute an integrated question–hypothesis framework that connects the theoretical rationale to measurable outcomes within a space–time analytical design:

H1a (distribution). *MI distributions are non-normal, positively skewed and heavy-tailed, with outlier regions driving structural change during crisis periods.*

H1b (trend). *At the EU NUTS-2 level, MI displays a statistically significant downward trend over 2009–2020, indicating progressive structural rigidification.*

H2a (level effect). *MI measured at the 2-digit level is systematically higher than at the 1-digit level, as it captures intra-sectoral reallocations that are obscured in aggregated data.*

H2b (granularity diagnostics). *The ratio $\rho = MI_{2d}/MI_{1d}$ exceeds 1 on average, while the difference $\Delta = MI_{2d} - MI_{1d}$ is close to zero in the mean but exhibits high variance and outliers during crisis years; extreme ρ values occur when MI1d $\approx$ 0.*

H3a (shocks and fragility). *During systemic shocks (e.g., 2009–2011, 2020), MI spikes are concentrated in fragile or narrowly specialised regions, which emerge as mobility hot spots.*

H3b (stability in cores). *Cold spots and flat trajectories are observed in advanced industrial cores (e.g., DE, AT), where low MI indicates structural stability rather than weakness.*

H3c (temporal profiles). *DTW/Fourier time-series clustering identifies profiles with significant downward trends even among historically high-mobility regions, suggesting increasing rigidity.*

H4 (dual meaning of high MI). *In innovation-driven regions (e.g., Ireland, 2013–2014), high MI reflects adaptive capacity and innovation readiness, whereas comparable magnitudes in peripheral areas denote structural vulnerability.*

H5 (framework utility). *The multi-scalar (1d + 2d) and space–time analytical framework (STC, clustering, hot spots) differentiates between 'positive' flexibility and 'negative' fragility and provides early-warning signals for policy intervention.*

H6 (forecastability). *One-step-ahead exponential-smoothing forecasts yield low average RMSE values, with higher errors occurring in regions characterised by extreme mobility dynamics.*

3. Materials and Methods

3.1. Dataset and Variables

The Eurostat Structural Business Statistics (SBS) regional dataset (NUTS 2 level) created by NACE Rev. 2 classification (code sbs_r_nuts06_r2) was employed, using the indicator V16110—Persons employed (number) at an annual frequency for the period 2008–2020 [14,15]. Territorial units correspond to NUTS-2 regions as defined by Eurostat, including Extra-Regio areas where applicable. Because Eurostat periodically revises the NUTS nomenclature (2006, 2010, 2013, 2016 and 2021), the number of available regions per year varies (typically $\approx$ 240–290 NUTS-2 regions per year) owing to boundary adjustments and occasional data gaps [16].

The analysis employs two levels of granularity based on the NACE Rev. 2 classification:

(i) One-digit (sections): B–N (excluding K, following SBS coverage), encompassing Mining and quarrying; Manufacturing; Electricity, gas, steam and air-conditioning; Water supply, sewerage, waste and remediation; Construction; Wholesale and retail trade and repair of motor vehicles; Transportation and storage; Accommodation and food; Information and communication; Real estate; Professional, scientific and technical; Administrative and support—a total of 12 sectors [55,56].

(ii) Two-digit (divisions): B05–B09 . . . N82 and S95, comprising 68 divisions in total (e.g., C10–C33 for manufacturing; D35; E36–E39; F41–F43; G45–G47; H49–H53; I55–I56; J58–J63; L68; M69–M75; N77–N82; S95) [55,56].

The SBS domain excludes Agriculture, forestry and fishing (A), Financial and insurance activities (K) and several non-market service activities (O–Q, R, S—except S95). This exclusion is particularly relevant for interpreting cross-regional and temporal patterns [16,55].

The variable under consideration, $E_{r,k,t}$, represents the number of persons employed in region r, sector k and year t, as reported in Eurostat's Structural Business Statistics (SBS) [15]. Regional totals are:

$$\mathrm{Yr,t} = \sum_{j=1}^{K} E_{r,j,t} \tag{1}$$

$$\sum_{k=1}^{K} s_{r,k,t} = 1 \tag{2}$$

We form sectoral employment shares:

$$s_{r,k,t} = \frac{E_{r,k,t}}{\sum_{j=1}^{K} E_{r,j,t}}, \tag{3}$$

following the approach commonly employed in the structural change measurement literature [3,28].

Inter-sectoral mobility is quantified as half the L_1 (total variation) distance between consecutive sectoral structures—a standard structural change or dissimilarity index widely used in regional and labour economics [3,19,29]:

$$\mathrm{MI_{r,t}} = \frac{1}{2}\sum_{k=1}^{K} \left| s_{r,k,t} - s_{r,k,t-1} \right| \in [0,1] \tag{4}$$

We compute (2) at two granularities:

$$\mathrm{MI_{r,t}^{(1d)}} = \frac{1}{2}\sum_{k\in\mathcal{K}_{1d}} \left| s_{r,k,t} - s_{r,k,t-1} \right|, \mathrm{MI_{r,t}^{(2d)}} = \frac{1}{2}\sum_{k\in\mathcal{K}_{2d}} \left| s_{r,k,t} - s_{r,k,t-1} \right| \tag{5}$$

where K is the NACE categories number. The indicator is calculated separately for the two garanularities considered:

- $\mathrm{MI_{r,t}^{(1d)}}$ cu K = 12 (divisions, 1-digit);
- $\mathrm{MI_{r,t}^{(2d)}}$ cu K = 68 (divisions, 2-digit).

The interpretation of MI indicates no change in sectoral structure when MI = 0, progressing to a complete reallocation of employment across all sectors (the theoretical maximum) when MI = 1 [18]. Empirical studies suggest that an annual reallocation of 1–10% is considered normal [3,28].

3.2. Sample Properties and Comparability (1d vs. 2d)

At the NACE 1-digit (1d) level, the valid sample size per year is approximately 174 regions; at the NACE 2-digit (2d) level, it is approximately 173. This difference reflects the listwise deletion of missing cases from the Eurostat SBS dataset [15,16].

Distributional properties: Both MI-1d and MI-2d deviate substantially from normality, as indicated by the Kolmogorov–Smirnov and Shapiro–Wilk tests ($p < 0.001$), exhibiting positive skewness and heavy tails [3,19]. Skewness and kurtosis are higher at the 1d level during 'calm' years (2013–2017), whereas medians are consistently higher at the 2d level, since intra-sectional reallocations are captured only at finer levels of granularity [4,28]. Representative values include the following:

- 2012: median(2d) = 0.0258 vs. median(1d) = 0.0142;
- 2019: median(2d) = 0.0221 vs. median(1d) = 0.0130;
- 2020: median(2d) = 0.0322 vs. median(1d) = 0.0223.

MI is sensitive to sectoral granularity. The 1-digit (macro-sector) MI provides robust cross-national comparability and highlights major structural shifts [29], while the 2-digit MI captures finer reallocations within sections (e.g., construction subsectors, retail branches)

that are invisible at aggregate levels but essential for diagnostic and policy targeting purposes [18,27].

3.3. Comparability Across Granularities and Derived Measures

Because the total-variation sum in Equation (2) increases mechanically with the number of categories K, absolute MI levels are not directly comparable between the 1-digit (12 sections) and 2-digit (68 divisions) classifications. To examine the effect of granularity, we also report difference and ratio measures:

$$\Delta_{r,t} = \mathrm{MI}_{\mathrm{r,t}}^{(\mathrm{2d})} - \mathrm{MI}_{\mathrm{r,t}}^{(\mathrm{1d})} \tag{6}$$

$$\rho_{r,t} = \frac{\mathrm{MI}_{\mathrm{r,t}}^{(\mathrm{2d})}}{\mathrm{MI}_{\mathrm{r,t}}^{(\mathrm{1d})} + \varepsilon}. \tag{7}$$

where $\varepsilon \approx 10^{-6}$ is a small numerical safeguard.

This approach follows standard practices in structural fragmentation and clustering analyses across aggregation levels [3], enabling the separation of scale effects from genuine reallocation dynamics.

Moreover, for within-year comparisons across regions at the same level of granularity $g \in \{1d,2d\}$, we compute standardised scores:

$$z_{r,t}^{(g)} = \frac{MI_{r,t}^{(g)} - \mu_t^{(g)}}{\sigma_t^{(g)}} \tag{8}$$

where $\mu_t^{(g)}$ and $\sigma_t^{(g)}$ are, respectively, the mean and standard deviation of $MI_{r,t}^{(g)}$ across all regions in year t.

$$g \in \{1d, 2d\}$$

This z-score transformation enables the identification of regions exhibiting exceptionally high or low intersectoral mobility relative to the annual distribution, consistent with standard statistical practices in distributional analysis [13,27].

3.4. Research Framework

Annual MI values (2008–2020) were imported into ArcGIS Pro 3.2.2 and structured into a Space–Time Cube using the Create Space Time Cube From Defined Locations tool [12]. This process transformed the regional MI series into a multidimensional lattice indexed by space (NUTS-2 regions) and time (year), thereby enabling temporal pattern mining and visual analytics.

Exponential Smoothing Forecasting was applied to each regional MI series, modelling only the trend components to prevent overfitting to short-term fluctuations. Forecast accuracy was evaluated using the Root Mean Square Error (RMSE) and through visual inspection of residuals [13].

Time Series Clustering (TSC) was then performed on MI trajectories for all NUTS-2 regions using ArcGIS Pro's Time Series Clustering tool [12]. This procedure groups regions with similar temporal evolution patterns and was implemented in three configurations to capture complementary dimensions of similarity.

Although Time Series Clustering (TSC) provides valuable insights into the temporal distribution of structural change, it has several limitations that warrant attention. The results depend on the selected similarity measure (e.g., Dynamic Time Warping) and the length of the temporal window, both of which influence the distinction between short-term and long-term variations. Moreover, the approach is inherently descriptive, identifying

similar patterns rather than uncovering the determinants of mobility dynamics. Therefore, the resulting clusters should be interpreted as representations of regional mobility profiles rather than as causally or statistically determined groupings.

The rationale behind this caveat aligns with Cheng and Adepeju [57], who emphasise that the results of spatio-temporal clustering are context-dependent, as they vary with the choice of time scale and similarity measure, both of which require careful interpretation [20].

By combining Value clustering to capture isolate-level effects, Correlation clustering to identify synchronous temporal responses and Fourier clustering to reveal structural rhythms and long-term cycles, we derive a comprehensive typology of regional mobility dynamics.

This multidimensional approach is recommended in spatio-temporal analytics to prevent misleading conclusions that may arise from reliance on a single similarity metric [13]. It also accords with best practices in economic geography and regional science for detecting latent heterogeneity in structural change processes.

Finally, Emerging Hot Spot Analysis was performed to identify statistically significant clusters of high and low MI values [12].

The overall research framework is illustrated in Figure 2.

Figure 2. Research framework synthesis.

To enhance the interpretative value of the spatial–temporal patterns, the analysis integrates contextual indicators of regional innovation ecosystems. These include R&D intensity (gross domestic expenditure on R&D as a percentage of GDP; Eurostat code rd_e_gerdreg), higher education and STEM graduate density and startup activity per 1000 employed persons, retrieved from Eurostat and OECD Regional Statistics (2023) [7].

As demonstrated by Zhang et al. [46], incorporating organisational, technological and environmental factors provides a more comprehensive understanding of ecosystem resilience. These complementary dimensions enable the identification of clusters not only as mobility regions but also as potential innovation zones, where high MI coincides with strong absorptive capacity and institutional learning potential.

Although these indicators are not directly modelled, they inform the qualitative interpretation of the clusters in Section 4, linking the mobility dynamics identified through clustering and hot spot analysis to regional capacities for knowledge diffusion and innovation resilience [7,58–61].

Robustness and data representativeness.

Following the recommendation of Zhang et al. [46], methodological robustness was clarified by specifying the dimensions along which MI can be meaningfully assessed. By construction, MI measures year-to-year reallocations (t vs. $t - 1$) and therefore does not rely on an external base year. As a practical robustness check, MI values were compared at two aggregation levels (NACE 1-digit and 2-digit) using the ratio $\rho = MI_2d/MI_1d$ and the difference $\Delta = MI_2d - MI_1d$. These were examined alongside clustering results to ensure that observed spatial–temporal patterns are not artefacts of sectoral granularity.

Regarding data coverage, Eurostat's Structural Business Statistics (SBS) [62] provide harmonised and longitudinally consistent data for the non-financial business economy at the NUTS-2 level. Although some public and informal segments fall outside its scope, the SBS remains the most appropriate foundation for analysing intersectoral mobility. Contextual indicators of innovation ecosystems—such as R&D intensity, higher education/STEM

density and startup activity—are used qualitatively to interpret cluster patterns, in line with OECD [60] and Regional Innovation Scoreboard 2025 guidelines [60–62].

4. Results

4.1. Granularity Effect in Intersectoral Mobility

MI is inherently scale-dependent, with results varying according to the level of sectoral aggregation (NACE Rev. 2) [23,28,29]. At the 1-digit level, the index captures broad structural shifts, whereas at the 2-digit level, it reveals more fine-grained reallocations (e.g., F43—specialised construction activities; G47—retail trade; N78—employment activities).

A comparative assessment across these levels shows both overlap—indicating stable and robust drivers of labour mobility—and divergence, where new mobility patterns emerge only at finer resolutions [23,29]. While the overlaps confirm the reliability of certain intersectoral shifts irrespective of classification, the divergences underscore the analytical value of granularity in identifying intra-industry reallocations that would otherwise remain obscured.

Empirically, this effect is evident in the descriptive statistics of *Dif* (MI_2d–MI_1d) and *Rho* (MI_2d/MI_1d) across NUTS2 regions (see Table 1). The mean values of *Dif* remain close to zero, indicating overall consistency between the two scales; however, extreme negative values reveal regions where 2-digit reallocations diverge markedly from broad sectoral trends. In contrast, *Rho* averages between 1.4 and 1.9, confirming that 2-digit mobility is systematically higher, while outliers highlight the sensitivity of ratio measures when 1-digit values approach zero [23,28,29].

Table 1. Descriptive statistics for the difference (Dif) and ratio (Rho) between the Intersectoral Mobility Index calculated at 2-digit and 1-digit levels, NUTS2, EU27+ (2009–2020).

Year	Dif Min	Dif Max	Dif Mean	Dif Stdev	Rho Min	Rho Max	Rho Mean	Rho Stdev
2009	−0.263	0.091	−0.002	0.053	0.149	5.482	1.430	0.709
2010	−0.275	0.097	0.013	0.042	0.149	9.091	1.941	1.234
2011	−0.458	0.086	0.007	0.052	0.062	6.185	1.764	0.769
2012	−0.305	0.087	0.009	0.043	0.080	5.277	1.880	0.691
2013	−0.398	0.047	0.005	0.051	0.083	3.975	1.716	0.590
2014	−0.403	0.241	0.010	0.051	0.094	4.491	1.810	0.677
2015	−0.287	0.099	0.010	0.030	0.113	6.811	1.819	0.752
2016	−0.273	0.071	0.010	0.028	0.089	4.860	1.759	0.640
2017	−0.784	0.164	0.005	0.067	0.169	8.459	1.807	0.773
2018	−0.663	0.129	0.011	0.060	0.166	6.604	1.944	0.807
2019	−0.679	0.085	0.004	0.057	0.132	8.289	1.885	0.844
2020	−0.255	0.070	0.002	0.043	0.137	55,100.000	222.771	3491.726

Note: Values are calculated for NUTS2 regions in EU27+ (2009–2020). Rho2020 shows an extreme outlier (55,100) caused by MI1d ≈ 0 in one region; in subsequent analyses, the indicator was winsorized.

Taken together, the rankings and distributional statistics indicate that intersectoral labour mobility in Europe is highly uneven and spatially concentrated, displaying pronounced geographical and sectoral patterns. Geographically, high MI values have shifted from core industrial regions in Central and Western Europe toward peripheral, island and outermost regions, where smaller economies recurrently exhibit elevated MI due to greater exposure to shocks [18–21]. Sectorally, mobility remains concentrated within a narrow set of activities: at the 1-digit level, the top three sectors account for 41–64% of annual MI (C, G, F, with growing contributions from N and I), while at the 2-digit level, concentration intensifies around G47, N78, F43 and I56, with occasional entries such as H53 [4,14–16,28].

The granularity effect introduces a critical methodological dimension: whereas 1-digit categories capture broad structural shifts, 2-digit divisions reveal the concrete channels—such as retail, employment agencies, specialised construction, hospitality and logistics—through

which reallocation materialises [4,28,29]. Analysis of *Dif* confirms that, on average, cross-scale differences remain small; however, outliers indicate sharp divergences, particularly during crisis years [20,58,63]. In parallel, *Rho* systematically exceeds 1, suggesting that finer classifications consistently reveal higher mobility, with extreme values emerging when macro-sector values approach zero [64,65].

From a policy perspective, these findings underscore the importance of multi-scalar monitoring and targeted interventions, distinguishing between (i) macro-level volatility in peripheral regions and (ii) fine-grained, intra-industry transitions in core manufacturing hubs. Notably, the temporal analysis indicates that the added value of granularity peaks during periods of crisis and transition (2009–2010, 2017–2019, 2020), when detailed sectoral reallocations provide early signals of structural change that remain obscured at more aggregated levels [1,2,33,34].

4.2. Space–Time Cube and Forecasts

The Space–Time Cube (STC) constructed in ArcGIS Pro illustrates persistent heterogeneity in labour mobility across regions. Emerging trajectories reveal alternating phases of stability and reallocation, with clusters of regions exhibiting parallel paths. Outlier regions—already evident in the distributional statistics of *Dif* and *Rho* (see Appendix A)—appear in the cube as abrupt shifts or discontinuous trajectories, particularly in peripheral or structurally fragile economies.

The spatio-temporal analysis conducted using the *Create Space Time Cube* tool for the MI_1D (Intersectoral Mobility Index) at the NUTS 2 level over the period 2009–2020 reveals a statistically significant decreasing trend in intersectoral mobility. The trend test (statistic = -2.6743; $p = 0.0075$) confirms a steady decline in MI values, indicating a reduction in the pace of labour reallocation across economic sectors. This result suggests a progressive rigidification of the employment structure following the 2008–2010 economic crisis and may reflect both the consolidation of regional specialisations and constraints on the capacity of regional economies to generate major structural shifts during the period under review (see Figure 3).

All maps (Figures 3–7) were generated using harmonised coordinate systems and identical spatial extents, as required by the ArcGIS Pro Space–Time Cube environment. Minor layout adjustments were made to ensure consistent visual framing across figures, without affecting analytical comparability or statistical outputs.

The spatial distribution of forecasted MI values for 2021 reveals a clustered yet diverse pattern across Europe. Regions with the highest forecasted intersectoral mobility ($\geq$0.03) are concentrated in Germany (DE50—Bremen, DEA5—Arnsberg, DEF0—Schleswig-Holstein, DE80—Mecklenburg-Vorpommern), Portugal (PT30—Madeira, PT20—Azores), Malta (MT00), Greece (EL41—North Aegean) and Hungary (HU33—Southern Great Plain).

Notably, Madeira (PT30) ranks highest with a forecasted MI of 0.1005, indicating an exceptionally dynamic labour reallocation process, followed closely by Bremen (DE50) and Arnsberg (DEA5), both exceeding 0.094.

These results indicate that structural mobility dynamics are strongest in small, peripheral and partially insular economies (Madeira, Azores, Malta), as well as in several German Länder, which appear to sustain a momentum of structural transformation even after 2020. Central and Eastern Europe also contribute with notable positive forecasts, particularly in HU33 and selected Romanian regions (RO21, RO41, RO42).

Model accuracy assessment: The average forecast RMSE across all regions is low ($\approx$0.02), with slightly higher values for regions exhibiting extreme mobility (e.g., DEA5, DE50). This suggests that while the model effectively captured historical trends, it faces greater uncertainty in areas undergoing intense structural shifts. The validation RMSE

(≈0.02) confirms the model's generalisability and indicates robust forecasting performance for one-step-ahead predictions.

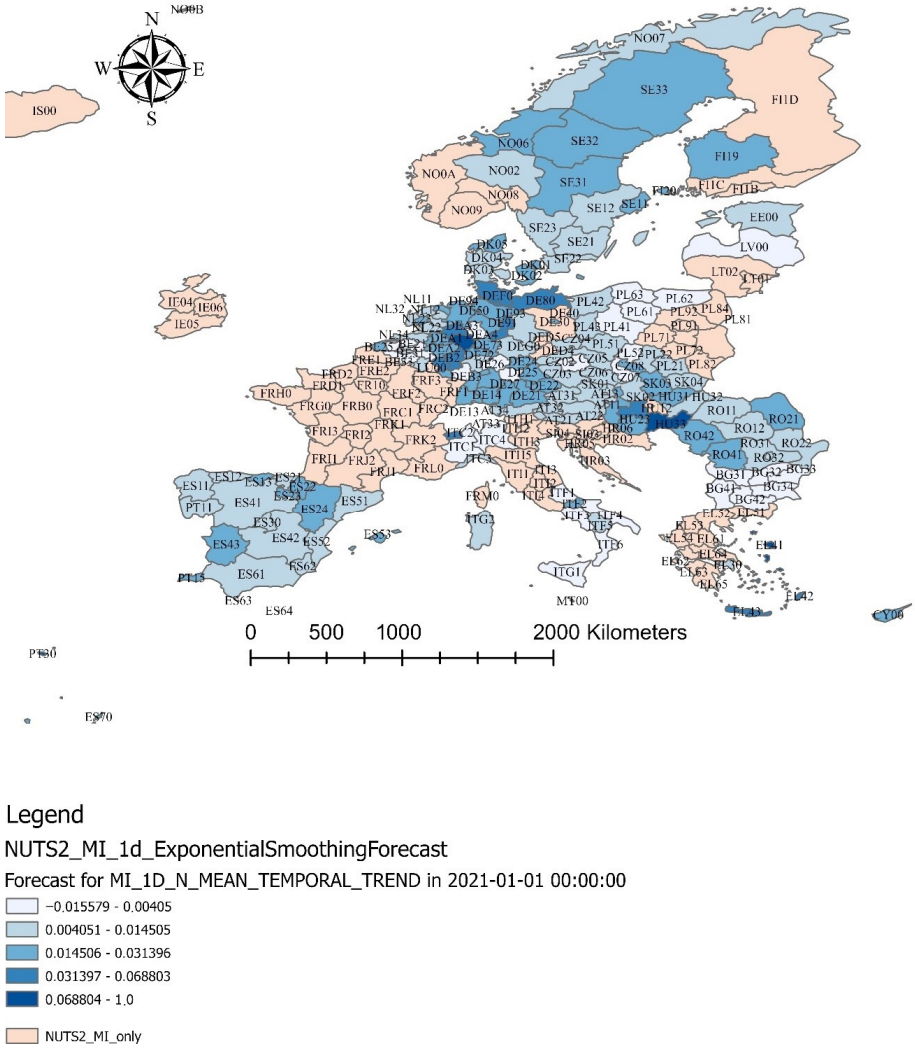

Figure 3. Intersectoral Labour Mobility via Exponential Smoothing Forecast.

Outlier analysis: Approximately 46% of regions contained outliers, with the highest concentration observed in the first time step (2009), likely reflecting the disruptive effects of the global financial crisis on intersectoral reallocation. In most cases, the number of outliers per region was very low (0–1), suggesting localised anomalies rather than systemic inconsistencies. Their presence reinforces the interpretation that shocks such as the 2008–2010 crisis had a measurable yet contained impact on long-term mobility trends.

The time series reveal contrasting dynamics: HU33 (Southern Great Plain) demonstrates a clear and sustained positive trajectory, whereas DE50 (Bremen) and DEA5 (Arnsberg) exhibit wide oscillations between minimum and maximum values, alongside an overall downward tendency, despite a short-term positive forecast for 2021.

4.3. Time Series Clustering by Value, Correlation and Fourier Clustering

Time-series clustering of the Intersectoral Mobility Index (MI_1D) identified two distinct clusters across the 168 NUTS 2 regions, determined by the highest pseudo F-statistic (F = 59.59). Figure 5 presents the corresponding clustering outcomes.

Figure 4. Time series contrast dynamics. Fitted Value (dashed line), Forecasted Value (Solid line).

Cluster 1 comprises the majority of regions (n = 151) and exhibits a generally low and gradually declining MI trajectory over the 2009–2020 period (statistic = −1.85; p = 0.064, not significant at the 5% level).

Cluster 2 includes a smaller subset of 17 regions, concentrated mainly in Germany (DEA3, DEA4, DEA5, DE60, DEF0, DE80), Greece (EL41–EL42, EL61–EL62) and selected high-mobility regions in Spain (ES51, ES61–ES64). This cluster is characterised by systematically higher MI values (often exceeding 0.08 in the early years) and a statistically significant decreasing trend (statistic = −1.99; p = 0.047).

The contrasting trajectories are illustrated in Figure 5. While Cluster 1 remains close to the EU baseline with limited fluctuation, Cluster 2 exhibits pronounced oscillations, peaking in 2011–2013 and followed by a sharp contraction between 2014 and 2018, before a partial rebound in 2020. This pattern indicates that Cluster 2 regions experienced more volatile structural reallocation, with periods of intense mobility interspersed with phases of stabilisation. These findings suggest that structural rigidity is deepening even in regions traditionally characterised by high mobility, raising concerns about the resilience of labour markets to future shocks. The strong early peaks followed by subsequent decline further imply that much of the post-crisis structural adjustment was concentrated in the first half of the decade.

The correlation-based time-series clustering identified five distinct temporal profiles of intersectoral mobility across the 168 NUTS 2 regions (Pseudo F = 121.55, the highest among candidate solutions). This method groups regions not only by the magnitude of MI values but also by the shape and synchronisation of their trajectories over 2009–2020.

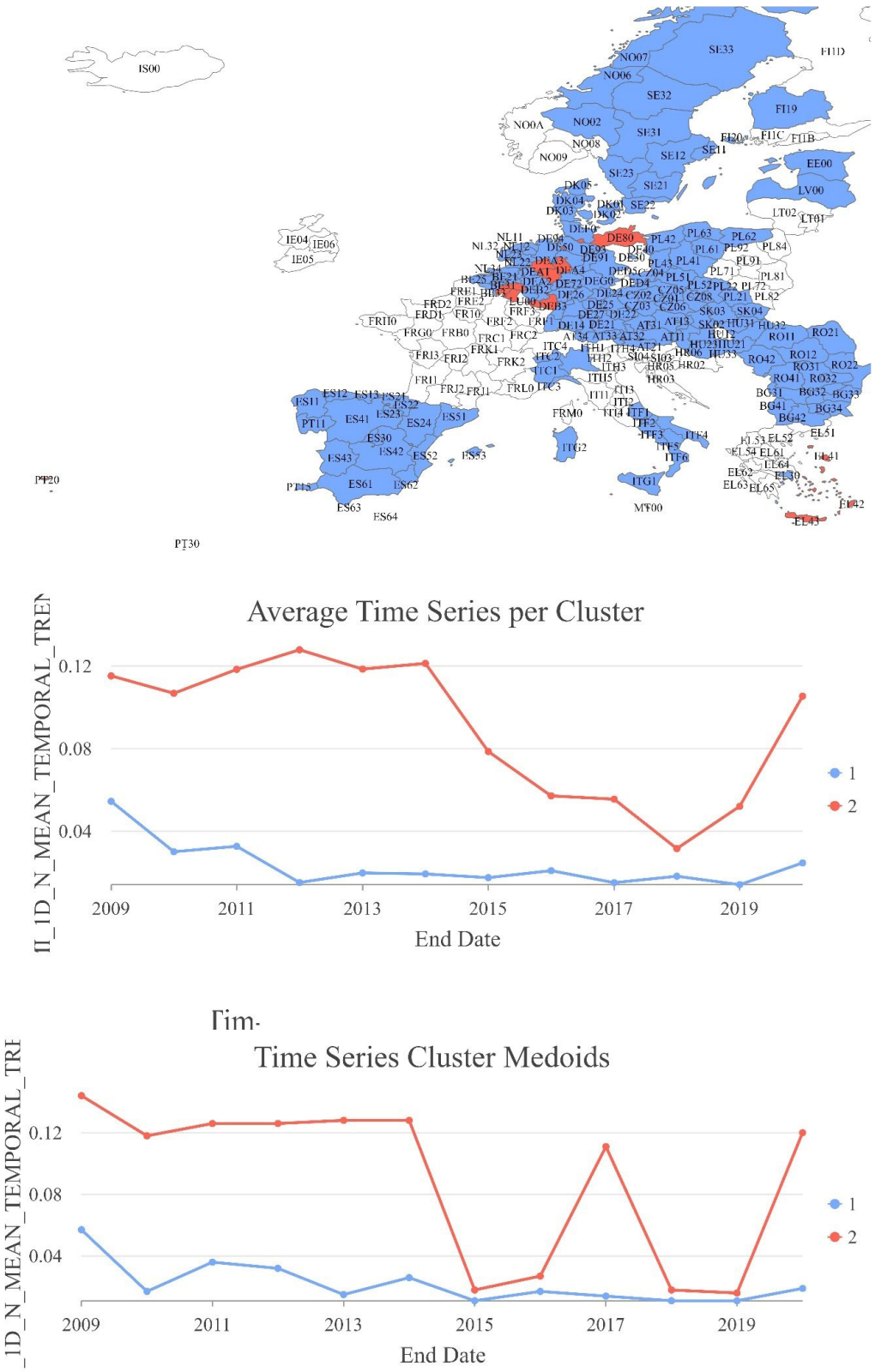

Figure 5. Time series clustering values.

Cluster 1 (n = 29): Regions with moderate MI values and relative stability over time, exhibiting only minor fluctuations around the EU mean.

Cluster 2 (n = 9): Regions with persistently high MI levels during the first half of the period, followed by a pronounced decline after 2014, indicating substantial post-crisis adjustments.

Cluster 3 (n = 41): Regions with low baseline MI values but marked cyclical peaks, particularly around 2011–2013, suggesting heightened sensitivity to short-term shocks.
Cluster 4 (n = 65): The largest group, characterised by consistently low and flat trajectories with no statistically significant trend—representing structurally stable or stagnant labour markets.
Cluster 5 (n = 24): Regions with historically elevated MI values but a statistically significant downward trend (statistic = −1.99, $p = 0.047$), reflecting progressive structural rigidification despite earlier dynamism.

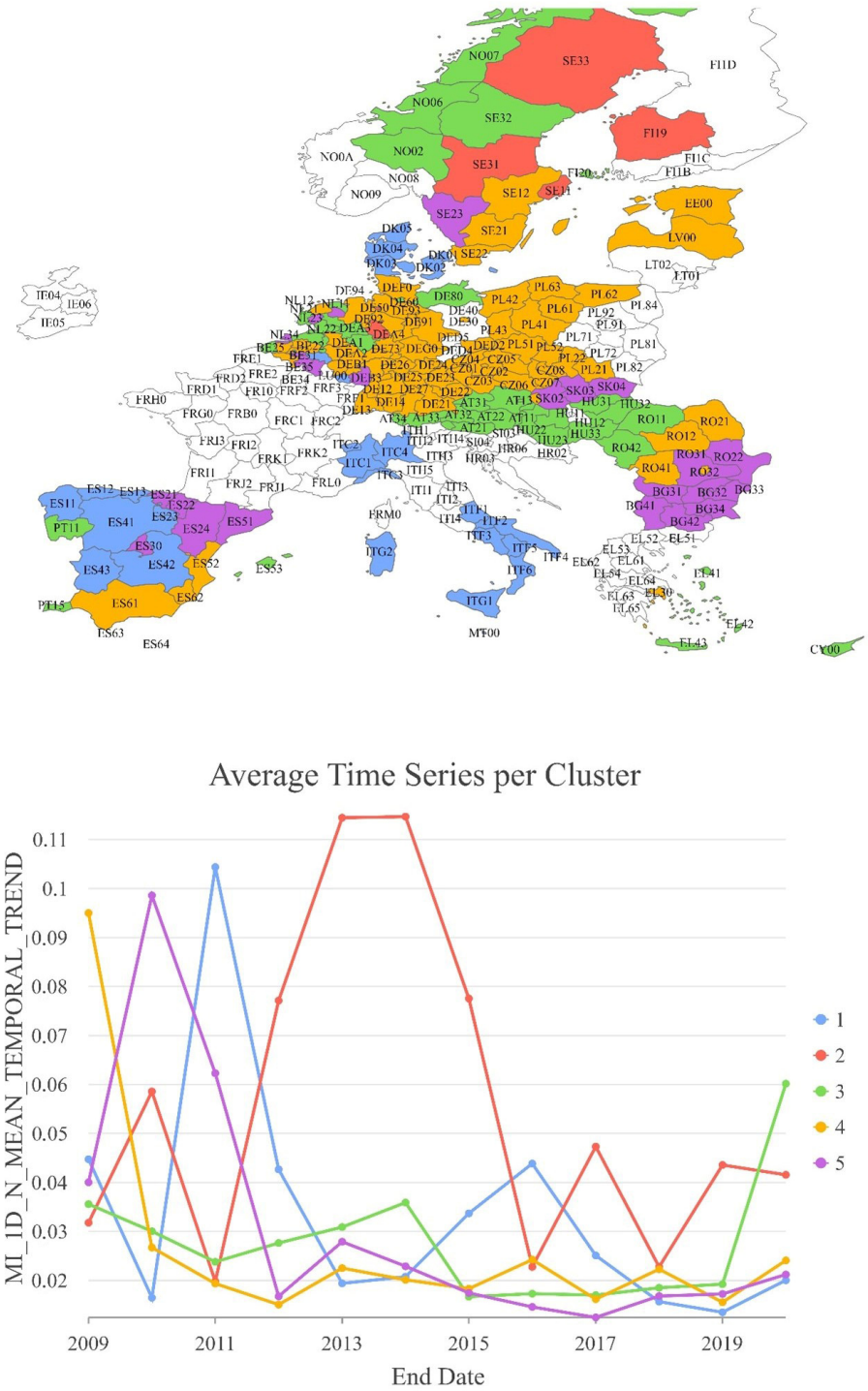

Figure 6. Time series clustering correlations.

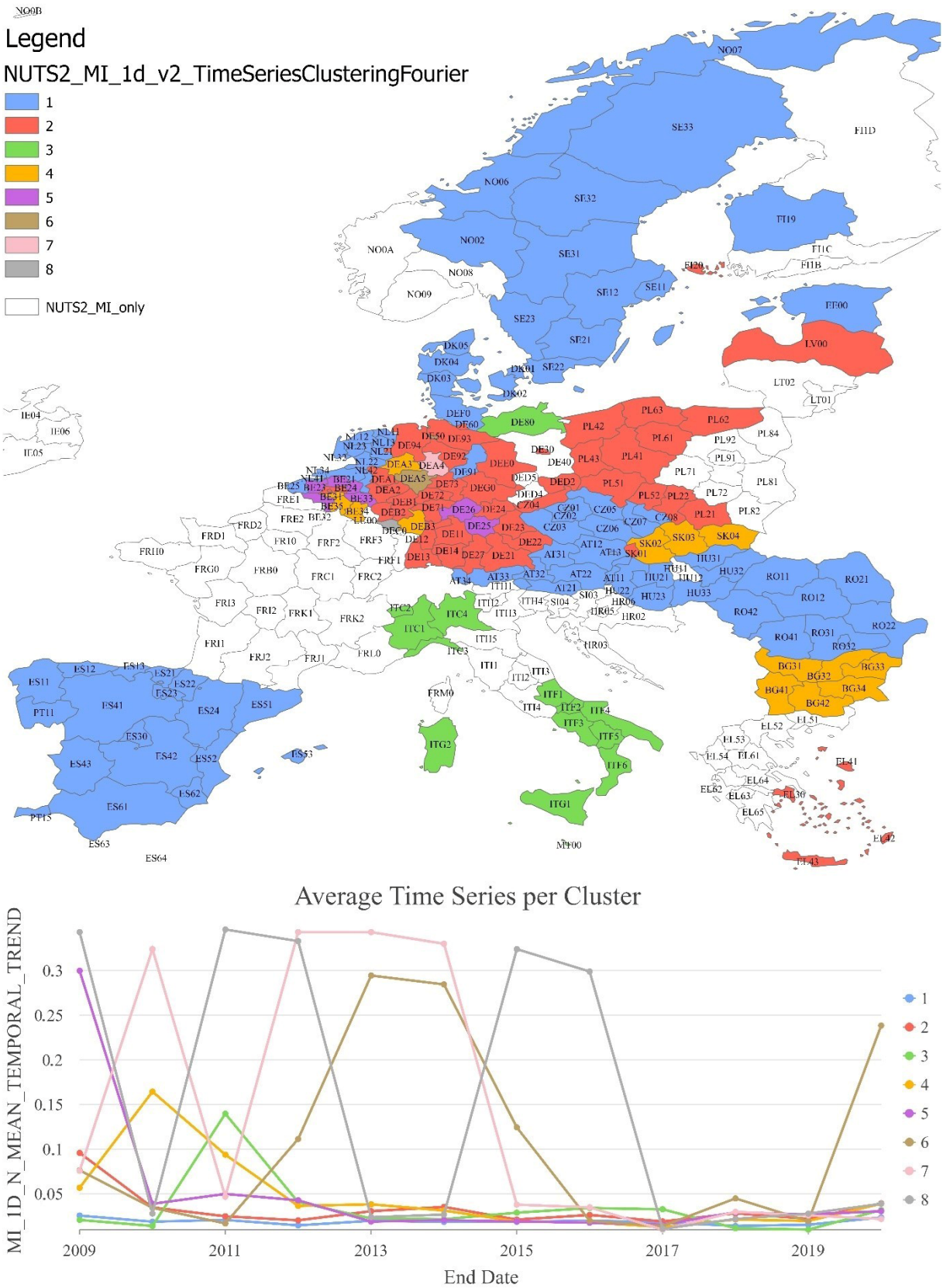

Figure 7. Time Series Clustering Fourier.

Together, these five profiles capture the heterogeneity of labour mobility dynamics across Europe, revealing that most regions converge toward low or stable mobility (Clusters 1 and 4),

while a smaller subset (Clusters 2 and 5) undergo intense restructuring phases that ultimately culminate in exhaustion or rigidity.

The Fourier-based time series clustering of the *MI_1D_N_MEAN_TEMPORAL_TREND* indicator across 168 NUTS-2 regions identified eight spatio-temporal clusters (Pseudo F = 42.58, the highest value). This method groups regions based on the similarity of their spectral profiles, capturing shared periodicities, trends and shape components in their trajectories, rather than relying solely on pointwise distance measures [56] (Figure 7).

Cluster 1 (n = 85) comprises most Northern and Western European regions, characterised by moderate MI values and no statistically significant trend, indicating structural stability and mature labour markets.
Cluster 2 (n = 44) includes a substantial share of Central and Eastern European regions, exhibiting moderate yet statistically insignificant fluctuations, which suggest slow and partial structural transitions.
Clusters 4 (n = 14) and 7 (n = 1) are the only groups displaying a statistically significant decreasing trend ($p < 0.05$), pointing to a gradual rigidification of the employment structure and the reduced pace of sectoral reallocation. These clusters encompass several highly industrialised regions in Poland, Slovakia and Germany.
Clusters 5, 6 and 8 represent exceptional cases, showing pronounced peaks in intersectoral mobility immediately after the 2008–2010 crisis, followed by sharp declines. This indicates that most structural adjustments were concentrated in the first half of the study period.

Overall, the cluster mean profiles reveal that the highest mobility occurred during 2009–2013, followed by convergence towards lower values after 2015. This pattern suggests that the bulk of structural adjustment took place early in the decade, followed by subsequent stabilisation and, in many cases, a gradual decline in mobility.

The temporal clustering results—covering value-based, correlation-based and Fourier-based profiles—consistently reinforce the central finding of this study: intersectoral labour mobility in Europe is on a declining trajectory, with only a few regions maintaining dynamic reallocation patterns. The identification of clusters exhibiting statistically significant downward trends serves as a warning sign of emerging structural rigidities, particularly in the industrial regions of Central and Eastern Europe (Figure 8).

From a policy perspective, these findings underscore the need to:

- Support occupational transitions and targeted re-skilling in regions experiencing declining mobility.
- Ensure continuous, multi-scalar monitoring (at both 1-digit and 2-digit levels) to detect early signals of structural shifts.
- Promote labour market flexibility as a mechanism for enhancing resilience to future shocks and facilitating green and digital transitions.

Integrating these spatio-temporal clustering approaches provides not only a descriptive assessment but also a forward-looking perspective, thereby enabling evidence-based policy recommendations for sustainable regional development.

The NUTS2 region DEA4 is classified as a Sporadic Hot Spot, indicating that it recorded statistically significant high values of intersectoral mobility during several isolated periods between 2009 and 2020. This pattern reflects episodic rather than continuous surges in labour reallocation, likely driven by short-term sectoral shocks or temporary employment restructuring within the region.

In contrast to Consecutive or Persistent Hot Spots, which signify sustained structural transformation, the sporadic pattern observed in DEA4 suggests that its elevated mobility episodes are intermittent and context-specific, rather than indicative of a stable, long-term trend.

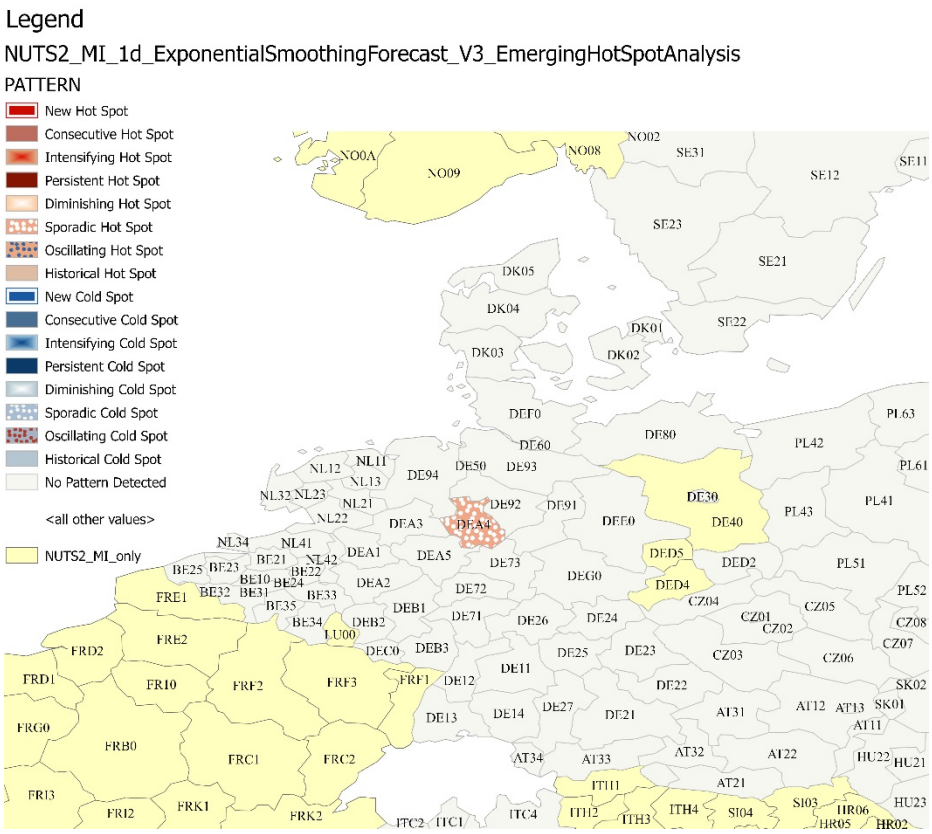

Figure 8. Emerging Hot Spot Analysis to identify statistically significant clusters of high/low MI.

5. Discussion

Synthesis of Space–Time Cube and Forecast Results

The spatio-temporal analysis confirms that intersectoral labour mobility in Europe is characterised by persistent heterogeneity, alternating phases of stability and reallocation and a statistically significant downward trend over 2009–2020 (trend statistic = −2.67, p = 0.0075) [12,58]. This pattern indicates a progressive rigidification of employment structures, consistent with the consolidation of regional specialisation patterns and a declining capacity for large-scale structural adjustment following the 2008–2010 crisis [4,22].

Exponential smoothing forecasts for 2021 show that the highest mobility is concentrated in small, peripheral and insular economies—Madeira, the Azores and Malta—as well as selected German Länder (Bremen, Arnsberg), indicating continued structural transformation momentum in these territories [12]. Time-series clustering reveals a bifurcation between a majority of regions with low and gradually declining mobility and a minority of high-mobility regions exhibiting strong early peaks followed by structural exhaustion [4,27,28]. Fourier-based clustering corroborates these findings, showing that most structural adjustment occurred between 2009 and 2013, followed by convergence towards lower MI levels [5].

From a policy perspective, these results highlight the need to strengthen re-skilling initiatives and active labour market policies in regions where MI is declining, maintain multi-scalar monitoring (1-digit and 2-digit) and promote labour market flexibility to support resilience and enable digital and green transitions [9].

To better illustrate these findings, Table 2 presents a synthesis of the results.

Table 2. Answers to Research Questions and Hypotheses.

Research Question (RQ)	Hypothesis (H)	Answer (Based on Results)	Instrument/Method
RQ1. Variation and distribution of MI across NUTS-2 regions (2008–2020).	**H1a (distribution):** MI distributions are non-normal, positively skewed and heavy-tailed, with outlier regions driving structural change during crises.	**Confirmed:** Both MI-1d and MI-2d deviate significantly from normality ($p < 0.001$), exhibiting positive skewness and heavy tails. Peaks occur in 2009–2011 and 2020, consistent with crisis-induced restructuring.	Descriptive statistics (Skewness, Kurtosis), K-S and Shapiro–Wilk tests
	H1b (trend): At the EU NUTS-2 level, MI shows a statistically significant downward trend (2009–2020), indicating progressive structural rigidification.	**Confirmed:** The space–time trend test yields a statistic of -2.67 ($p = 0.0075$), indicating declining mobility and gradual consolidation of employment structures.	ArcGIS Pro Space–Time Cube (Mann–Kendall test for trend)
RQ2. Effect of sectoral granularity (1d vs. 2d).	**H2a (level effect):** MI-2d > MI-1d, capturing intra-sector reallocations.	**Confirmed:** The median MI is systematically higher at 2d (e.g., 2020 median: 0.0322 vs. 0.0223 at 1d), confirming that finer granularity reveals within-sector adjustments.	Comparative analysis of MI medians (1d vs. 2d)
	H2b (granularity diagnostics): The ratio $\boldsymbol{\rho = MI_{2d}/MI_{1d}}$ exceeds 1 on average, while the difference $\boldsymbol{\Delta = MI_{2d} - MI_{1d}}$ is close to zero in the mean but shows high variance and outliers in crisis years; extreme $\boldsymbol{\rho}$ values arise when $\mathbf{MI1d \approx 0}$.	**Confirmed:** Rho averages 1.4–1.9; extreme values (>8) appear when MI1d ≈ 0, particularly in 2017–2020. The difference shows a near-zero mean but large variance, capturing hidden reallocations during shocks.	Derived measures (Δ, ρ) + Winsorised analysis for outliers
RQ3. Interpretation in a space–time framework.	**H3a (shocks and fragility):** Crisis spikes concentrate in fragile or specialised regions.	**Confirmed:** Hot spot analysis identifies significant clusters in Greek and outermost regions, reflecting vulnerability during 2009–2011 and 2020.	ArcGIS Pro Emerging Hot Spot Analysis
	H3b (stability in cores): Cold spots occur in advanced industrial cores.	**Confirmed:** Germany, Austria and Northern Italy display persistent cold spots, where low MI represents stable, resilient structures.	ArcGIS Pro Emerging Hot Spot Analysis
	H3c (temporal profiles): Clustering reveals significant downward trends even in historically high-mobility regions.	**Confirmed:** DTW/Fourier clustering shows a long-run decline for Cluster 2 and 5 regions (e.g., DE50 Bremen, DEA5 Arnsberg), signalling structural rigidification after initial post-crisis adjustments.	ArcGIS Pro Time-Series Clustering (DTW + Fourier)
RQ4. Does high MI signal resilience/innovation in advanced economies?	**H4 (dual meaning of high MI):** High MI can indicate adaptability/innovation (advanced regions) or fragility (peripheries).	**Confirmed:** Ireland (2013–2014) exemplifies adaptive reallocation and innovation readiness. Conversely, Greek and outermost regions exhibit high MI due to structural vulnerability.	Combined interpretation of MI + regional typology (advanced vs. peripheral)

Table 2. *Cont.*

Research Question (RQ)	Hypothesis (H)	Answer (Based on Results)	Instrument/Method
RQ5. Policy implications.	**H5 (framework utility):** A multi-scalar and spatio-temporal approach enables differentiation between 'positive' flexibility and 'negative' fragility.	**Confirmed:** 1d is suitable for EU-wide benchmarking, while 2d is necessary for fine-grained policy targeting. Space–time cube and clustering provide early-warning signals for cohesion and just-transition policies.	Multi-scalar comparative framework + GIS-based monitoring
RQ6. Forecastability of MI trajectories.	**H6 (forecastability):** MI trajectories are sufficiently persistent to allow short-term forecasting, with uncertainty highest in extreme regions.	**Confirmed:** Exponential smoothing forecasts yield low RMSE (≈0.02) overall, with slightly higher errors in regions with extreme volatility (e.g., Madeira, Bremen).	ArcGIS Pro Exponential Smoothing Forecast (RMSE validation)

To synthesise the empirical results in relation to the RQs, Table 2 summarises the testing of operational hypotheses (H1a–H6), which derive from the three overarching conceptual hypotheses (H1–H3) linking intersectoral mobility (MI) to innovation diffusion and adaptability.

Taken together, these results confirm that MI is a context-sensitive and multi-dimensional indicator. Its distributional properties highlight that structural change is concentrated in a few regions and amplified during crises, while its temporal trajectory shows a statistically significant decline, indicating progressive rigidification of European labour markets. Granularity diagnostics reveal that 2-digit analysis is indispensable for uncovering hidden reallocations, particularly during shock years, whereas 1-digit analysis remains robust for cross-country benchmarking. Spatio-temporal modelling and clustering allow us to distinguish between positive mobility (adaptive, innovation-driven regions) and negative mobility (shock-driven, fragile regions). Together, these findings underpin the policy discussion in Section 5 and the conclusions in Section 6, providing a strong argument for multi-scalar, spatially explicit monitoring frameworks as tools for EU cohesion policy, just transition strategies and preparedness for future crises.

6. Conclusions

This study advances the measurement and interpretation of intersectoral labour mobility by combining classical structural change indices with a multi-scalar, spatio-temporal analytical framework. By comparing 1-digit and 2-digit NACE levels, we demonstrate that a significant share of structural reallocation occurs within broad sectors, remaining hidden in more aggregated data. The results show that mobility distributions are systematically skewed and heavy-tailed, with crisis years (2009–2011, 2020) amplifying outliers and reshaping regional hierarchies. Importantly, our analysis finds a statistically significant downward trend in MI, indicating a gradual rigidification of the European employment structure and a declining pace of sectoral reallocation.

These findings carry important policy implications for European cohesion, just transition and innovation strategies. MI should be used as a dual indicator, distinguishing 'positive' flexibility in innovation-driven regions from 'negative' fragility in peripheral economies. Policymakers should combine EU-wide monitoring at the 1-digit level with fine-grained diagnostics at the 2-digit level to identify vulnerable labour markets early and design targeted Active Labour Market Policies (ALMPs), reskilling programmes and diversification initiatives. By integrating MI into a continuous monitoring system, Europe

can better anticipate structural pressures, support inclusive growth and enhance resilience to shocks—ensuring that no region is left behind in the green and digital transitions.

6.1. Synthesis of Space–Time Cube and Forecast Results

This paper presents the first systematic comparison of MI at two levels of sectoral granularity (1-digit vs. 2-digit NACE), demonstrating how hidden reallocations become apparent only at finer scales. It situates MI in a spatio-temporal framework using ArcGIS Pro tools (Space–Time Cube, forecasting, clustering, hot spot analysis), enabling the assessment of regional trajectories of structural change in dynamic rather than static terms [20,58,63].

Simultaneously, the study enhances the conceptual understanding of MI as a dual indicator, capturing both resilience to shocks and innovation capacity, thereby bridging debates on labour market adaptability and regional innovation systems [1,2].

It illustrates that MI values cannot be interpreted in isolation but must be understood in relation to the space–time context of regions—distinguishing positive flexibility in advanced economies from structural fragility in vulnerable ones [3,18–21]. The findings provide policy-relevant insights for the European Union, highlighting the varying capacities of regions to adapt to crises and transitions, with direct implications for SDG 8 (Decent Work and Economic Growth) and SDG 10 (Reduced Inequalities) [9,59].

While the increased projectability of the employment system is a positive sign of reduced sectoral reallocation, it may also increase reactive labour mobility when regions face asymmetric shocks or high levels of policy uncertainty. The financial crisis of 2009–2011 and the pandemic of 2020 illustrate that sudden, brief bursts of mobility were common outcomes of sharp shifts in demand and production, indicating a stress-related and non-adaptive reallocation.

As Bloom [66] and Adao et al. [67] note, aggregate employment shocks and economic policy uncertainty can redefine the degree and spatial distribution of labour mobility, generating cyclical spikes that obscure structural rigidity. Therefore, instantaneous intervals of MI should be interpreted with caution, as they not only indicate elasticity but also reveal tensions within weakened regional ecosystems.

Importantly, our results confirm that MI serves a dual role. On one hand, it functions as an early-warning indicator of resilience, detecting regional stress during crises. On the other hand, it acts as a proxy for adaptive capacity and innovation, as regions able to reallocate labour into expanding or knowledge-intensive sectors demonstrate stronger innovation potential and readiness for transitions. This interpretation is supported by [1], which shows that innovative regions maintained greater labour resilience during shocks, and by Braunerhjelm et al. [2], who demonstrate that knowledge-worker mobility directly fosters firm-level innovation.

The significance of MI, however, emerges fully only when embedded in a space–time perspective. Temporally, it distinguishes between crisis shocks, recovery phases and periods of stability. Spatially, the same MI level may signal flexibility in advanced economies or fragility in vulnerable ones [9,59]. Spatio-temporal analysis thus provides the necessary framework to interpret MI as both a stress test and a signal of structural adaptability (OECD, 2022) [4,20,22,27,58,63].

In addition to their descriptive quality, the spatial and temporal patterns identified during the analysis have strategic implications for innovation diffusion, reskilling and regional adaptability. High and sustained MI clusters indicate territories where the reallocation of labour and knowledge streams mutually reinforce each other, signifying dynamic learning ecosystems. Conversely, regions that experience frequent low or fluctuating MI are typically associated with low absorptive capacity and insufficient skill regeneration, reflecting institutional rigidity and diminished innovativeness.

From a policy perspective, these results suggest that tracking MI patterns can help to identify areas where training, mobility incentives or intersectoral collaboration are most needed. Regions with adaptive mobility patterns can serve as exemplars of innovation diffusion, while those with reactivity churn may require targeted support for skill development and institutional resilience. The spatial logic of structural change is linked to the dynamics of human capital in this study, which aids in understanding mobility as both a driver and an indicator of regional preparedness to innovate [1,2,7,8,10,49,54,55].

MI thus complements other indices of specialisation and structural change [8,18,19]. It offers valuable insights for EU cohesion and labour market policies, particularly in the context of the green and digital transitions, supporting SDG 8 (Decent Work and Economic Growth) and SDG 10 (Reduced Inequalities) [9,59]. Future research should extend this framework to incorporate productivity, wages and value-added indicators and test alternative measures of labour mobility in a comparative perspective, explicitly linking them to innovation outcomes [1,2].

There are three original contributions made in this paper: First, it provides a systematic comparison of MI between two levels of sectoral granularity (1-digit vs. 2-digit NACE), indicating that hidden reallocations become apparent only at smaller scales [4,14–16,27,28]. Second, it integrates MI into a space–time analytical platform based on ArcGIS Pro capabilities (Space–Time Cube, forecasting, clustering, hot spot detection), offering a methodological toolkit that can be replicated to study regional labour markets and it allows for a dynamic evaluation of structural change. Third, it further develops the theoretical understanding of MI as a dual measure, representing resilience to shocks and capacity for innovation, and explicitly correlates the measurement of structural change with the EU's green and digital transition agenda.

6.2. Theoretical Implications

This research contributes to the theoretical framework of intersectoral labour mobility (MI) by framing the concept as a dual indicator of innovation capacity and resilience in the face of shocks. The findings underscore that mobility patterns cannot be understood as standalone variables; they must be contextualised within both spatial and temporal dynamics, as parallel MI values may indicate mobility flexibility in developed economies and instability in vulnerable ones [9,58]. The introduction of MI within a spatio-temporal analytical framework enables the study to extend structural change theory, which emphasises the need to consider cyclical shocks, reallocation during crises and the long-term ghettoisation of labour markets [4,28]. Additionally, results support the Schumpeterian views on creative destruction by demonstrating that intersectoral mobility enhances knowledge spillovers and innovation by reallocating human capital within the digital and green transitions, making labour reallocations productive [5,40]. Recent work highlights how mobility is particularly crucial in the digital and green transitions, as reskilling and absorptive capacity can contribute to productivity gains or structural stress during labour reallocations. In theory, this research advances the conceptualisation of MI beyond a merely descriptive measure of reallocation, positioning it as a proxy for adaptive capacity and innovation preparedness, consistent with recent discussions on regional resilience and sustainable development. The combination of MI with the SDGs (especially SDG 8 and SDG 10) further situates it in the wider policy and sustainability context, emphasising the role of mobility-based adaptation as a driver of inclusive development and spatial cohesion [43,54,59].

6.3. Practical Implications

This research has several practical implications for policymakers, employers and authorities responsible for regional development: Firstly, the finding that intersectoral mobility reinforces resilience and innovation underscores the necessity of implementing policies that actively mitigate obstacles to the reallocation of workers. This can be achieved by eliminating institutional constraints, such as non-compete agreements or incompatible credentialing systems, to promote more seamless labour mobility between contracting and growing sectors [9,58].

Secondly, the outcomes highlight the importance of reskilling and upskilling initiatives for industries contributing to the digital and green transitions. Training in relation to renewable energy, automation and ICT should be used to enhance the absorptive capacity of firms and increase the innovation potential of reallocated employees [5,43]. Furthermore, it is also necessary to implement regional diversification policies in sensitive areas, such as former coal and industrial regions, where mobility limitations may lead to long-term scarring and social exclusion [6].

Lastly, incorporating intersectoral mobility analysis into regional and national planning systems provides a tool for predicting structural bottlenecks and fostering territorial resilience. MI trends can assist policymakers develop adaptive strategies that optimise the balance between economic efficiency and social inclusiveness, as these trends serve as early warnings of labour mismatches [4,54].

The study operationalises these findings by identifying a set of ecosystem-level levers that can be employed to improve adaptive mobility and innovation diffusion within European regions. These include the following:

- Establishing regional exchange systems among companies, educational institutions and local governments to organise reskilling and job-matching programmes;
- Forming cross-sectoral consortia to pilot labour redeployment projects in digital and green industries;
- Implementing geographical fiscal or innovation incentives in regional innovation centres to stimulate the flow of skills and entrepreneurship.

Additionally, MI can serve as an indicator of structural stress or adaptability in advance. Irregularities in long-term MI trends or abrupt accelerations may indicate areas prone to labour mismatches or economic stagnation. These signals should be integrated into regional observatories or EU cohesion dashboards, enabling policymakers to anticipate vulnerabilities and construct timely, place-sensitive interventions consistent with OECD [60] and Regional Innovation Scoreboard (2025) frameworks [7,51,58–61].

6.4. Limitations

Although the empirical framework is well-built and replicative, one should consider a number of methodological limitations. To begin with, the analysis is based on aggregated regional data, which does not allow making causal conclusions about the mechanisms underlying the relationship between intersectoral mobility and innovation outcomes. The method establishes associations and structural patterns as opposed to direct cause-effect relationships. Second, the temporal smoothing that is introduced by using yearly MI computation can reduce short-term shocks or micro-adjustments that are found in sub-annual cycles. Third, the findings are also aggregation-sensitive (1- vs. 2-digit NACE) because the degree of granularity impacts the observation of concealed reallocations and can impact the magnitude of the observed patterns. Awareness of these constraints will provide transparency and the future study will be directed to multi source, micro level and causal extensions of analysis [3,14–16,18,19,60,62].

This study also faces several limitations: The SBS dataset excludes agriculture (A), finance (K), and most public services (O–Q, R except S95), which constrains full comparability across regions where these activities are substantial. NUTS boundary revisions between 2008 and 2020 may introduce breaks in regional time series [12].

Furthermore, MI captures only the extent of labour reallocation (share changes), not the quality of adjustment (e.g., productivity, wages, value added), meaning that high MI can indicate either positive adaptation or structural stress [14–16].

6.5. Further Developments

This study opens several avenues for future research on intersectoral labour mobility and its implications for regional resilience and innovation capacity. Firstly, given that the present analysis relies exclusively on Eurostat SBS data [14–16], future work should integrate complementary datasets such as EU-LFS microdata or productivity and wage statistics to capture the quality of reallocation (e.g., value added, wage dynamics, job quality). This would allow for disentangling whether high MI values reflect desirable productivity-enhancing reallocations or precarious labour churning.

Secondly, the modelling framework could be extended beyond descriptive statistics to causal inference approaches, employing panel regression or spatial econometrics to identify the determinants of MI variation across regions (e.g., innovation intensity, ALMP expenditure, digitalisation level). Exploring the interaction between MI and structural transformation drivers such as automation risk, global value chain participation and human capital endowments would deepen the understanding of resilience mechanisms [27].

Thirdly, there is potential to develop multi-scalar models that integrate MI at both 1-digit and 2-digit levels with occupational mobility indicators, thereby bridging sectoral and task-based approaches to structural change. This could help detect 'hidden' reallocations within knowledge-intensive services or green sectors that may not be visible in aggregated classifications.

Fourthly, future studies could experiment with advanced spatio-temporal techniques, such as Bayesian hierarchical models, machine learning-based forecasting or network-based representations of sectoral flows, to capture nonlinearities and cross-regional spillovers.

Finally, future research could connect MI dynamics more explicitly to policy evaluation, assessing how specific EU and national interventions (e.g., Just Transition Mechanism, ESF+ funded reskilling programmes) influence labour reallocation patterns over time. This would enable the transformation of MI from a descriptive indicator into a real-time monitoring tool for policy design and impact assessment.

Author Contributions: Conceptualization, C.L., A.G. and C.S.P.; methodology, C.L., C.S.P. and A.G.; software, C.L.; validation, A.G. and L.M.-M.; formal analysis, C.L. and C.S.P.; investigation, C.L. and L.M.-M.; resources, C.S.P.; data curation, C.L. and L.M.-M.; writing—original draft preparation, C.L., A.G., C.S.P. and L.M.-M.; writing—review and editing, A.G. and C.S.P.; visualisation, C.L. and A.G.; supervision, A.G. and C.S.P.; project administration, A.G.; funding acquisition, C.S.P. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Romanian Ministry of Research, Innovation, and Digitalization, Program NUCLEU, 2022–2026, Spatio-temporal forecasting of local labour markets through GIS modelling [P5] PN 22_10_0105.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are openly available in Eurostat. SBS Data by NUTS 2 Region and NACE Rev.2 (2008–2020). Dataset code: sbs_r_nuts06_r2. Available online: https://ec.europa.eu/eurostat/web/structural-business-statistics (accessed on 31 August 2025).

Acknowledgments: This work was supported by a grant from the Romanian Ministry of Research, Innovation, and Digitalization, Program NUCLEU, 2022–2026, Spatio-temporal forecasting of local labour markets through GIS modelling [P5] PN 22_10_0105.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Temporal Correlations of Granularity Indicators (Dif and Rho), NUTS2, EU27+ (2009–2020)

This appendix reports the Pearson correlations among *Dif* (MI_2d–MI_1d) and *Rho* (MI_2d/MI_1d) for 2009–2020 across NUTS2 regions. The matrix highlights high adjacent-year consistency for *Dif* and clustered moderate correlations for *Rho*, supporting the temporal structuring of the granularity effect discussed in Section 4.2.

Correlations

		Dif2009	Dif2010	Dif2011	Dif2012	Dif2013	Dif2014	Dif2015	Dif2016	Dif2017	Dif2018	Dif2019	Dif2020	Rho2009	Rho2010	Rho2011	Rho2012	Rho2013	Rho2014	Rho2015	Rho2016	Rho2017	Rho2018	Rho2019	Rho2020
Dif2009	Pearson Correlation	1	0.022	0.228**	0.219**	0.014	−0.004	0.255**	0.310**	0.110	0.100	0.086	−0.004	0.625**	0.043	−0.047	0.145*	0.102	0.016	0.052	0.114	0.115	0.143*	0.186*	0.028
	Sig. (2-tailed)		0.732	0.000	0.001	0.837	0.948	0.000	0.000	0.115	0.153	0.263	0.958	0.000	0.502	0.478	0.027	0.133	0.810	0.447	0.101	0.097	0.040	0.014	0.711
	N	251	251	233	233	220	220	220	208	208	208	173	173	251	251	233	233	220	220	220	208	208	208	173	173
Dif2010	Pearson Correlation	0.022	1	0.396**	0.397**	0.322**	0.204**	0.033	0.043	0.079	−0.010	−0.078	0.141	−0.022	0.562**	0.240**	0.178**	0.189**	0.112	0.035	0.059	0.004	−0.020	−0.029	0.118
	Sig. (2-tailed)	0.732		0.000	0.000	0.000	0.002	0.622	0.536	0.256	0.884	0.309	0.064	0.729	0.000	0.000	0.006	0.005	0.095	0.605	0.393	0.957	0.777	0.704	0.120
	N	251	252	234	234	221	221	221	209	209	209	174	174	251	252	234	234	221	221	221	209	209	209	174	174
Dif2011	Pearson Correlation	0.228**	0.396**	1	0.394**	0.145*	0.076	0.348**	0.375**	0.013	0.012	−0.088	0.067	0.025	0.096	0.575**	0.244**	0.133*	0.109	0.154*	0.171*	0.092	0.071	−0.118	0.034
	Sig. (2-tailed)	0.000	0.000		0.000	0.023	0.235	0.000	0.000	0.849	0.865	0.245	0.373	0.705	0.142	0.000	0.000	0.036	0.086	0.015	0.012	0.177	0.299	0.118	0.652
	N	233	234	265	265	248	248	248	215	215	215	178	178	233	234	265	265	248	248	248	215	215	215	178	178
Dif2012	Pearson Correlation	0.219**	0.397**	0.394**	1	0.285**	0.276**	0.548**	0.442**	0.097	0.063	−0.043	0.443**	0.066	0.113	0.231**	0.564**	0.252**	0.221**	0.221**	0.243**	0.028	0.168*	0.022	0.262**
	Sig. (2-tailed)	0.001	0.000	0.000		0.000	0.000	0.000	0.000	0.146	0.343	0.558	0.000	0.314	0.086	0.000	0.000	0.000	0.000	0.000	0.000	0.675	0.011	0.765	0.000
	N	233	234	265	278	261	261	261	228	228	228	190	190	233	234	265	278	261	261	261	228	228	228	190	190
Dif2013	Pearson Correlation	0.014	0.322**	0.145*	0.285**	1	0.879**	0.177**	0.041	0.115	0.032	0.167*	0.384**	0.099	0.084	0.014	0.150*	0.529**	0.403**	0.169**	0.097	0.099	0.122	0.046	0.247**
	Sig. (2-tailed)	0.837	0.000	0.023	0.000		0.000	0.004	0.542	0.084	0.633	0.021	0.000	0.143	0.216	0.823	0.015	0.000	0.000	0.006	0.143	0.138	0.066	0.528	0.001
	N	220	221	248	261	261	261	261	228	228	228	190	190	220	221	248	261	261	261	261	228	228	228	190	190
Dif2014	Pearson Correlation	−0.004	0.204**	0.076	0.276**	0.879**	1	0.249**	0.004	−0.090	−0.180**	0.263**	0.316**	0.095	0.051	−0.009	0.144*	0.410**	0.531**	0.166**	0.067	0.085	0.074	0.138	0.253**
	Sig. (2-tailed)	0.948	0.002	0.235	0.000	0.000		0.000	0.956	0.161	0.005	0.000	0.000	0.160	0.449	0.882	0.020	0.000	0.000	0.005	0.295	0.186	0.247	0.051	0.000
	N	220	221	248	261	261	281	281	244	244	244	201	201	220	221	248	261	261	281	281	244	244	244	201	201
Dif2015	Pearson Correlation	0.255**	0.033	0.348**	0.548**	0.177**	0.249**	1	0.574**	0.153*	0.079	0.253**	0.045	0.035	0.048	0.131*	0.259**	0.176**	0.238**	0.548**	0.264**	0.148*	0.172**	0.123	0.123
	Sig. (2-tailed)	0.000	0.622	0.000	0.000	0.004	0.000		0.000	0.016	0.217	0.000	0.526	0.610	0.475	0.039	0.000	0.004	0.000	0.000	0.000	0.020	0.007	0.081	0.082
	N	220	221	248	261	261	281	284	247	247	247	202	202	220	221	248	261	261	281	284	247	247	247	202	202
Dif2016	Pearson Correlation	0.310**	0.043	0.375**	0.442**	0.041	0.004	0.574**	1	0.457**	0.316**	0.026	0.126	0.029	0.038	0.201**	0.209**	0.085	0.086	0.276**	0.482**	0.332**	0.119	0.018	0.095
	Sig. (2-tailed)	0.000	0.536	0.000	0.000	0.542	0.956	0.000		0.000	0.000	0.717	0.073	0.683	0.580	0.003	0.001	0.199	0.180	0.000	0.000	0.000	0.062	0.794	0.181
	N	208	209	215	228	228	244	247	248	248	248	202	202	208	209	215	228	228	244	247	248	248	248	202	202
Dif2017	Pearson Correlation	0.110	0.079	0.013	0.097	0.115	−0.090	0.153*	0.457**	1	0.931**	0.313**	0.204**	0.020	0.064	0.087	0.151*	0.185**	0.075	0.184**	0.244**	0.446**	0.296**	0.082	0.190**
	Sig. (2-tailed)	0.115	0.256	0.849	0.146	0.084	0.161	0.016	0.000		0.000	0.000	0.001	0.775	0.358	0.204	0.023	0.005	0.244	0.004	0.000	0.000	0.000	0.207	0.003
	N	208	209	215	228	228	244	247	248	290	290	241	241	208	209	215	228	228	244	247	248	290	290	241	241

Correlations

		Dif2009	Dif2010	Dif2011	Dif2012	Dif2013	Dif2014	Dif2015	Dif2016	Dif2017	Dif2018	Dif2019	Dif2020	Rho2009	Rho2010	Rho2011	Rho2012	Rho2013	Rho2014	Rho2015	Rho2016	Rho2017	Rho2018	Rho2019	Rho2020
Dif2018	Pearson Correlation	0.100	−0.010	0.012	0.063	0.032	−0.180**	0.079	0.316**	0.931**	1	0.368**	0.176**	0.097	−0.135	0.102	0.100	0.126	−0.003	0.086	0.125*	0.294**	0.366**	0.008	0.098
	Sig. (2-tailed)	0.153	0.884	0.865	0.343	0.633	0.005	0.217	0.000	0.000		0.000	0.006	0.162	0.051	0.137	0.132	0.058	0.963	0.178	0.049	0.000	0.000	0.904	0.131
	N	208	209	215	228	228	244	247	248	290	290	241	241	208	209	215	228	228	244	247	248	290	290	241	241
Dif2019	Pearson Correlation	0.086	−0.078	−0.088	−0.043	0.167*	0.263**	0.253**	0.026	0.313**	0.368**	1	0.414**	0.118	0.018	−0.013	0.078	0.216**	0.241**	0.201**	0.085	0.199**	0.201**	0.341**	0.257**
	Sig. (2-tailed)	0.263	0.309	0.245	0.558	0.021	0.000	0.000	0.717	0.000	0.000		0.000	0.122	0.816	0.865	0.285	0.003	0.001	0.004	0.229	0.002	0.002	0.000	0.000
	N	173	174	178	190	190	201	202	202	241	241	241	241	173	174	178	190	190	201	202	202	241	241	241	241
Dif2020	Pearson Correlation	−0.004	0.141	0.067	0.443**	0.384**	0.316**	0.045	0.126	0.204**	0.176**	0.414**	1	0.110	0.087	0.072	0.308**	0.317**	0.274**	0.202**	0.235**	0.177**	0.171**	0.173**	0.080
	Sig. (2-tailed)	0.958	0.064	0.373	0.000	0.000	0.000	0.526	0.073	0.001	0.006	0.000		0.151	0.251	0.339	0.000	0.000	0.000	0.004	0.001	0.006	0.008	0.007	0.210
	N	173	174	178	190	190	201	202	202	241	241	241	249	173	174	178	190	190	201	202	202	241	241	241	249
Rho2009	Pearson Correlation	0.625**	−0.022	0.025	0.066	0.099	0.095	0.035	0.029	0.020	0.097	0.118	0.110	1	−0.083	−0.082	0.111	0.162*	0.099	−0.029	0.135	−0.016	0.143*	0.088	0.054
	Sig. (2-tailed)	0.000	0.729	0.705	0.314	0.143	0.160	0.610	0.683	0.775	0.162	0.122	0.151		0.188	0.211	0.092	0.016	0.143	0.671	0.052	0.813	0.039	0.251	0.478
	N	251	251	233	233	220	220	220	208	208	208	173	173	251	251	233	233	220	220	220	208	208	208	173	173
Rho2010	Pearson Correlation	0.043	0.562**	0.096	0.113	0.084	0.051	0.048	0.038	0.064	−0.135	0.018	0.087	−0.083	1	−0.020	−0.008	0.069	0.040	0.027	−0.007	0.045	−0.068	0.042	0.114
	Sig. (2-tailed)	0.502	0.000	0.142	0.086	0.216	0.449	0.475	0.580	0.358	0.051	0.816	0.251	0.188		0.756	0.900	0.306	0.552	0.691	0.923	0.517	0.329	0.584	0.133
	N	251	252	234	234	221	221	221	209	209	209	174	174	251	252	234	234	221	221	221	209	209	209	174	174
Rho2011	Pearson Correlation	−0.047	0.240**	0.575**	0.231**	0.014	−0.009	0.131*	0.201**	0.087	0.102	−0.013	0.072	−0.082	−0.020	1	0.244**	0.040	0.126*	0.069	0.066	0.080	0.070	−0.094	−0.012
	Sig. (2-tailed)	0.478	0.000	0.000	0.000	0.823	0.882	0.039	0.003	0.204	0.137	0.865	0.339	0.211	0.756		0.000	0.535	0.047	0.277	0.336	0.241	0.308	0.213	0.873
	N	233	234	265	265	248	248	248	215	215	215	178	178	233	234	265	265	248	248	248	215	215	215	178	178
Rho2012	Pearson Correlation	0.145*	0.178**	0.244**	0.564**	0.150*	0.144*	0.259**	0.209**	0.151*	0.100	0.078	0.308**	0.111	−0.008	0.244**	1	0.247**	0.274**	0.118	0.171**	0.079	0.234**	0.058	0.167*
	Sig. (2-tailed)	0.027	0.006	0.000	0.000	0.015	0.020	0.000	0.001	0.023	0.132	0.285	0.000	0.092	0.900	0.000		0.000	0.000	0.056	0.010	0.235	0.000	0.430	0.022
	N	233	234	265	278	261	261	261	228	228	228	190	190	233	234	265	278	261	261	261	228	228	228	190	190
Rho2013	Pearson Correlation	0.102	0.189**	0.133*	0.252**	0.529**	0.410**	0.176**	0.085	0.185**	0.126	0.216**	0.317**	0.162*	0.069	0.040	0.247**	1	0.435**	0.174**	0.226**	0.209**	0.304**	0.096	0.302**
	Sig. (2-tailed)	0.133	0.005	0.036	0.000	0.000	0.000	0.004	0.199	0.005	0.058	0.003	0.000	0.016	0.306	0.535	0.000		0.000	0.005	0.001	0.002	0.000	0.186	0.000
	N	220	221	248	261	261	261	261	228	228	228	190	190	220	221	248	261	261	261	261	228	228	228	190	190
Rho2014	Pearson Correlation	0.016	0.112	0.109	0.221**	0.403**	0.531**	0.238**	0.086	0.075	−0.003	0.241**	0.274**	0.099	0.040	0.126*	0.274**	0.435**	1	0.175**	0.128*	0.256**	0.179**	0.115	0.318**
	Sig. (2-tailed)	0.810	0.095	0.086	0.000	0.000	0.000	0.000	0.180	0.244	0.963	0.001	0.000	0.143	0.552	0.047	0.000	0.000		0.003	0.046	0.000	0.005	0.105	0.000
	N	220	221	248	261	261	281	281	244	244	244	201	201	220	221	248	261	261	281	281	244	244	244	201	201

Correlations

		Dif2009	Dif2010	Dif2011	Dif2012	Dif2013	Dif2014	Dif2015	Dif2016	Dif2017	Dif2018	Dif2019	Dif2020	Rho2009	Rho2010	Rho2011	Rho2012	Rho2013	Rho2014	Rho2015	Rho2016	Rho2017	Rho2018	Rho2019	Rho2020
Rho2015	Pearson Correlation	0.052	0.035	0.154*	0.221**	0.169**	0.166**	0.548**	0.276**	0.184**	0.086	0.201**	0.202**	−0.029	0.027	0.069	0.118	0.174**	0.175**	1	0.222**	0.213**	0.118	0.096	0.337**
	Sig. (2-tailed)	0.447	0.605	0.015	0.000	0.006	0.005	0.000	0.000	0.004	0.178	0.004	0.004	0.671	0.691	0.277	0.056	0.005	0.003		0.000	0.001	0.063	0.176	0.000
	N	220	221	248	261	261	281	284	247	247	247	202	202	220	221	248	261	261	281	284	247	247	247	202	202
Rho2016	Pearson Correlation	0.114	0.059	0.171*	0.243**	0.097	0.067	0.264**	0.482**	0.244**	0.125*	0.085	0.235**	0.135	−0.007	0.066	0.171**	0.226**	0.128*	0.222**	1	0.447**	0.178**	0.041	0.230**
	Sig. (2-tailed)	0.101	0.393	0.012	0.000	0.143	0.295	0.000	0.000	0.000	0.049	0.229	0.001	0.052	0.923	0.336	0.010	0.001	0.046	0.000		0.000	0.005	0.561	0.001
	N	208	209	215	228	228	244	247	248	248	248	202	202	208	209	215	228	228	244	247	248	248	248	202	202
Rho2017	Pearson Correlation	0.115	0.004	0.092	0.028	0.099	0.085	0.148*	0.332**	0.446**	0.294**	0.199**	0.177**	−0.016	0.045	0.080	0.079	0.209**	0.256**	0.213**	0.447**	1	0.338**	0.210**	0.229**
	Sig. (2-tailed)	0.097	0.957	0.177	0.675	0.138	0.186	0.020	0.000	0.000	0.000	0.002	0.006	0.813	0.517	0.241	0.235	0.002	0.000	0.001	0.000		0.000	0.001	0.000
	N	208	209	215	228	228	244	247	248	290	290	241	241	208	209	215	228	228	244	247	248	290	290	241	241
Rho2018	Pearson Correlation	0.143*	−0.020	0.071	0.168*	0.122	0.074	0.172**	0.119	0.296**	0.366**	0.201**	0.171**	0.143*	−0.068	0.070	0.234**	0.304**	0.179**	0.118	0.178**	0.338**	1	0.230**	0.216**
	Sig. (2-tailed)	0.040	0.777	0.299	0.011	0.066	0.247	0.007	0.062	0.000	0.000	0.002	0.008	0.039	0.329	0.308	0.000	0.000	0.005	0.063	0.005	0.000		0.000	0.001
	N	208	209	215	228	228	244	247	248	290	290	241	241	208	209	215	228	228	244	247	248	290	290	241	241
Rho2019	Pearson Correlation	0.186*	−0.029	−0.118	0.022	0.046	0.138	0.123	0.018	0.082	0.008	0.341**	0.173**	0.088	0.042	−0.094	0.058	0.096	0.115	0.096	0.041	0.210**	0.230**	1	0.245**
	Sig. (2-tailed)	0.014	0.704	0.118	0.765	0.528	0.051	0.081	0.794	0.207	0.904	0.000	0.007	0.251	0.584	0.213	0.430	0.186	0.105	0.176	0.561	0.001	0.000		0.000
	N	173	174	178	190	190	201	202	202	241	241	241	241	173	174	178	190	190	201	202	202	241	241	241	241
Rho2020	Pearson Correlation	0.028	0.118	0.034	0.262**	0.247**	0.253**	0.123	0.095	0.190**	0.098	0.257**	0.080	0.054	0.114	−0.012	0.167*	0.302**	0.318**	0.337**	0.230**	0.229**	0.216**	0.245**	1
	Sig. (2-tailed)	0.711	0.120	0.652	0.000	0.001	0.000	0.082	0.181	0.003	0.131	0.000	0.210	0.478	0.133	0.873	0.022	0.000	0.000	0.000	0.001	0.000	0.001	0.000	
	N	173	174	178	190	190	201	202	202	241	241	241	249	173	174	178	190	190	201	202	202	241	241	241	249

** Correlation is significant at the 0.01 level (2-tailed). * Correlation is significant at the 0.05 level (2-tailed).

Table A1. Extended descriptive statistics for the difference (Dif) and ratio (Rho) between MI2d and MI1d, NUTS2, EU27+ (2009–2020).

Year	Variable	Mean	95% CI (Lower–Upper)	Median	Variance	Std. Dev.	Skewness	Kurtosis	Min	Max	N
2009	Dif	−0.004	−0.013–0.004	0.009	0.003	0.056	−3.146	10.326	−0.263	0.091	251
	Rho	1.415	1.300–1.530	1.303	0.586	0.765	2.254	9.201	0.149	5.482	251
2010	Dif	0.009	0.002–0.016	0.011	0.002	0.049	−3.262	14.774	−0.275	0.097	252
	Rho	1.971	1.755–2.187	1.583	2.07	1.439	2.672	9.138	0.149	9.091	252
2011	Dif	−0.001	−0.009–0.006	0.01	0.002	0.049	−3.906	18.773	−0.324	0.073	265
	Rho	1.659	1.536–1.782	1.587	0.672	0.82	1.427	6.21	0.062	6.185	265
2012	Dif	0.002	−0.006–0.009	0.01	0.002	0.048	−4.877	24.519	−0.305	0.044	278
	Rho	1.828	1.720–1.937	1.72	0.522	0.723	0.749	3.459	0.08	5.277	278
2013	Dif	0.002	−0.005–0.009	0.01	0.002	0.045	−5.726	34.878	−0.321	0.039	261
	Rho	1.626	1.543–1.710	1.582	0.31	0.557	0.273	2.765	0.083	3.975	261
2014	Dif	0.005	−0.002–0.011	0.01	0.002	0.041	−5.074	30.501	−0.299	0.097	281
	Rho	1.734	1.638–1.831	1.655	0.415	0.644	0.295	1.06	0.094	3.8	281
2015	Dif	0.005	0.000–0.010	0.009	0.001	0.032	−6.723	51.603	−0.287	0.033	284
	Rho	1.721	1.631–1.811	1.669	0.357	0.597	0.806	4.019	0.113	4.665	284
2016	Dif	0.008	0.004–0.013	0.01	0.001	0.029	−6.752	57.657	−0.273	0.071	248
	Rho	1.767	1.670–1.864	1.642	0.421	0.649	1.122	3.672	0.089	4.86	248
2017	Dif	0.006	0.003–0.010	0.009	0.001	0.023	−4.488	25.888	−0.155	0.081	290
	Rho	1.808	1.712–1.904	1.761	0.412	0.642	0.738	2.682	0.169	4.7	290
2018	Dif	0.013	0.011–0.014	0.01	0	0.01	1.659	6.364	−0.023	0.066	290
	Rho	1.863	1.765–1.962	1.771	0.427	0.654	2.647	10.745	0.562	5.649	290
2019	Dif	0.007	0.004–0.010	0.008	0	0.02	−5.271	34.489	−0.127	0.073	241
	Rho	1.808	1.691–1.925	1.662	0.608	0.779	3.694	27.752	0.132	8.289	241
2020	Dif	0.004	−0.001–0.009	0.008	0.001	0.032	−5.189	30.942	−0.239	0.052	249
	Rho	1.454	1.384–1.524	1.4	0.219	0.468	0.791	3.942	0.143	3.422	249

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