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Spatial determinants of regional economic resilience: evidence from EU NUTS 2 regions

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ABSTRACT

Over the last decade, European Union regions experienced two systemic but dissimilar shocks, raising questions about whether own-region and neighbouring characteristics support resilience consistently across crises and adjustment stages. This study identifies recurrent pre-crisis correlates of regional economic resilience in an interdependent regional system and tests whether these associations remain stable across crises and dimensions. Five dimension-specific sensitivity indices measure resistance, recovery, reorientation, and renewal for 244 EU NUTS 2 regions during the Great Financial and Sovereign Debt Crisis and the COVID-19 pandemic. These indices are aligned: higher values indicate stronger performance, without aggregation into a composite score. A pooled Spatial Durbin model estimates associations with time-weighted pre-crisis characteristics, decomposing direct, indirect, and total impacts; crisis- and dimension-interacted specifications test stability. Relative specialisation and R&D intensity show the strongest positive system-wide associations, while investment intensity shows the strongest negative association. Industrial concentration is negatively associated with resilience, while social and health conditions are positively associated, mainly through local channels. Strong spatial dependence confirms that resilience also reflects the characteristics of connected regions. However, recurrent factors vary in magnitude and spatial channels across crises and resilience dimensions. Policy should therefore strengthen recurrent capacities while remaining spatially coordinated and stage-specific.

IMPACT STATEMENT

Understanding why some regions withstand and recover from economic crises more successfully than others is essential for reducing regional disparities and designing effective development policies. This study addresses an important gap in existing research by examining whether the same regional characteristics support economic resilience across different crises and stages of adjustment, while accounting for inter-regional interdependencies. Using evidence from 244 EU NUTS 2 regions, the findings identify recurrent resilience-related factors, particularly innovation intensity and relative specialisation, but demonstrate that their associations vary across crises and resilience dimensions. The study also highlights that regional resilience depends not only on local characteristics but also on the capacities of connected regions. These findings advance understanding of the context-dependent and spatial nature of economic resilience and provide evidence to inform more targeted, spatially coordinated EU cohesion and regional development policies aimed at strengthening long-term regional resilience and reducing regional disparities.

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1. Introduction

Within little more than a decade, European Union regions were hit by two systemic yet fundamentally different shocks, the Great Financial and Sovereign Debt Crisis of 2008–2013 and the COVID-19

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pandemic, followed by energy-price and geopolitical disruptions. Their regional consequences were strikingly uneven: some regions absorbed the shocks and recovered quickly, while others experienced prolonged stagnation and had not regained pre-crisis output levels years after the shock, deepening core–periphery disparities within the EU (Bănică et al., 2024; Davies, 2011; Gong et al., 2020). This experience of repeated, dissimilar crises is the development that motivates the present study. Its scope is regional economic resilience, the capacity of a regional economy to withstand, recover from, and adapt to shocks and renew, as observed in labour-market and output outcomes, rather than financial resilience, which concerns the stability of financial institutions and markets. It matters because the costs of weak resilience are borne locally and because EU cohesion and recovery policies are increasingly place-based. Accordingly, regional economic resilience is conceptualised not as a single regional attribute, but as a temporally differentiated process through which regions resist, recover, reorient, and renew after economic shocks. This distinction is essential because the determinants that reduce the initial depth of a downturn are not necessarily the same as those that support post-crisis recovery or longer-term structural transformation; the classical "bounce-back" interpretation has been criticised precisely for separating short-term recovery from longer-term evolutionary change and for masking regional lock-in into obsolete development paths (Boschma, 2015; Martin, 2012; Simmie & Martin, 2010).

The European Union provides an informative setting for examining whether determinants of regional resilience recur across dissimilar crises. The single market establishes a shared framework for cross-border economic activity (European Union, 2012, Art. 26), while Cohesion Policy combines common development objectives with programming and implementation involving multiple levels of government (European Parliament & Council of the European Union, 2021, Arts. 5 and 8). Within this supranational framework, national policy systems and regional administrative capacities remain heterogeneous, and substantial differences in government quality persist both between and within Member States (European Commission: Directorate-General for Regional and Urban Policy and Durán Laguna, J, 2024). These institutional differences may influence the mobilisation of resources, the implementation of support measures and the coordination of adjustment following shocks. The combination of economic integration and institutional diversity, therefore, provides a relevant setting for investigating recurrent resilience capacities alongside crisis-specific and spatially differentiated associations. NUTS 2 regions are selected for the research because this territorial level combines regional policy relevance with a harmonised statistical framework. Eurostat identifies NUTS 2 as the basic level for regional policies, and the classification is used to determine regional eligibility for Cohesion Policy support (Eurostat, n.d.). For the present study, this level supports the joint analysis of employment, technology- and knowledge-intensive activity, GDP per capita and regional explanatory characteristics, while retaining territorial variation that national aggregates would obscure. Examining these units across two crises also enables the distinction between own-region associations and associations involving connected regions, directly supporting the study's spatial perspective. The analysis covers 244 regions in the present EU27 using the NUTS 2024 classification. NUTS regions differ in administrative status and should not be assumed to possess equivalent policy responsibilities (European Parliament & Council of the European Union, 2003, Art. 3). Accordingly, the empirical design incorporates country fixed effects and a measure of within-country governance differences to account for selected aspects of institutional heterogeneity.

A key limitation of existing research is that regional economic resilience has often been analysed in terms of single crises, single outcomes, or relatively short time horizons. While resistance and immediate recovery can usually be measured within a few post-shock years, reorientation and renewal require longer temporal observation because they concern structural adaptation and the emergence of new development paths (Pudelko et al., 2018; Sensier et al., 2016). Moreover, resilience is shock-specific: the determinants that mitigate a financial or demand-side crisis may not operate in the same way during a public health crisis, a technological disruption, or an energy-price shock (Gong et al., 2020; Sutton et al., 2025). This tension constitutes a genuine and still unresolved debate rather than a search for influential factors. One position in the literature, consistent with the notion of general adaptive capacity, holds that a stable set of regional attributes, economic diversity, human capital, institutional capacity, innovation, social capital, and infrastructure supports resilience irrespective of the type of shock (Fratesi & Perucca, 2018). A rival evolutionary position holds that determinants of resilience are inherently shock- and dimension-specific because each crisis activates distinct mechanisms of exposure and adjustment

(Boschma, 2015; Gong et al., 2020; Martin et al., 2016). Existing evidence cannot adjudicate between these positions: the relevant factors are rarely examined within an explicitly multi-crisis, multi-dimensional framework, and recent studies explicitly leave the universality of determinants across shocks as an open question (Sutton et al., 2025). The central question of this paper is therefore debatable by construction: are the determinants of regional economic resilience common across crises and resilience dimensions, or are their effects context-specific? If the first position holds, determinant effects should remain stable across the GFC and COVID-19 and across resistance, recovery, reorientation, and renewal; if the second holds, crisis- and dimension-specific interactions should dominate.

The recent literature on successive and distinct systemic shocks reinforces this point. The COVID-19 pandemic demonstrated how a public health crisis could simultaneously generate labour-market disruption, sectoral asymmetries, institutional stress and uneven spatial impacts (Fan et al., 2024; Gong et al., 2020; He & Sheng, 2024; Partridge et al., 2022; Tuysuz et al., 2022). Successive systemic shocks create spatially heterogeneous outcomes, non-additive interactions, and recovery paths in which progress in one dimension may be undermined by continuing vulnerability in another (Borsekova & Korony, 2023; Chen et al., 2024; Di Caro & Fratesi, 2023; Pontarollo & Serpieri, 2020; Sánchez & Cuadrado-Roura, 2024; Tsvirko et al., 2026). Therefore, a multi-crisis perspective requires moving beyond a list of determinants towards a framework that distinguishes between shock-specific vulnerability, cross-crisis capacities and dimension-specific mechanisms.

Prevailing regional economic resilience measures often focus on a single crisis or outcome, emphasise resistance and immediate recovery, or aggregate dimensions in ways that allow strong performance in one stage to conceal weakness in another. This study instead uses five direction-aligned, dimension-specific sensitivity indices for four distinct dimensions. The measurement framework is comprehensive in its coverage of the resilience process, but it is not composite in its aggregation. The indices facilitate cross-shock comparison while preserving distinctions among recovery, resistance, reorientation, employment renewal, and output renewal. They help researchers assess transferability across shocks and help policymakers diagnose the stage at which a region is vulnerable. However, they remain analytical benchmarks rather than complete welfare measures or causal policy scores.

The study, therefore, pursues two objectives. The first is to identify pre-crisis regional characteristics that are recurrently associated with economic resilience within an interdependent EU regional system. The second is to establish whether those associations are stable across the two crises and the five resilience indices, or whether their magnitude and spatial channel are context-specific. Our contribution is positioned against the three strands of literature reviewed in Section 2. First, whereas existing cross-crisis comparisons examine resilience outcomes or single determinant domains across shocks without testing a common determinant set (Di Caro & Fratesi, 2023; Ileanu & Pana, 2024; Sánchez & Cuadrado-Roura, 2024; Sensier et al., 2016), we synthesise this fragmented evidence into a framework of eight factor groups and test their effects jointly across two crises. Second, whereas multidimensional studies distinguish resilience dimensions within a single crisis (Martini, 2020; Pudelko et al., 2018), we operationalise four dimensions through direction-aligned, dimension-specific sensitivity indices estimated jointly across crises. Third, whereas determinant studies typically treat regions as isolated observations, we respond to calls to account explicitly for the spatial dependence underlying regional resilience (Sutton & Sutton, 2024) by embedding the determinants in a multi-crisis Spatial Durbin framework with time-weighted pre-crisis determinants and direct–indirect impact decompositions, distinguishing own-region effects from spatial spillovers. Together, these elements make it possible to assess directly whether resilience determinants are common, crisis-specific, or dimension-specific – the question that each strand leaves open individually.

The paper is organised so that each objective is traceable from theory to evidence. Section 2 develops the theoretical framework and derives the competing general-capability and contextual-activation expectations, together with the spatial mechanisms they imply. Section 3 translates these expectations into measurement and estimation: the baseline pooled Spatial Durbin model addresses the first objective, and the crisis- and dimension-interacted specifications address the second. Section 4 reports the baseline results, their robustness, and the heterogeneity tests in the same order, and Sections 5 and 6 present the policy implications and conclusions.

2. Theoretical background and literature review

This study is grounded in evolutionary economic geography, which conceptualises regional resilience as a path-dependent process of resistance, recovery, reorientation and renewal rather than as a simple return to equilibrium (Boschma, 2015; Martin, 2012; Simmie & Martin, 2010). From this perspective, productive knowledge, innovation, human resources, and coordinating institutions may constitute capabilities because they can be mobilised in response to different shocks. Their recurrence does not, however, imply invariant effects. Financial and demand crises, pandemic restrictions, and the different tasks of shock absorption, recovery, and structural transformation may activate the same capabilities through different mechanisms and with varying intensities. The theoretical question is therefore whether a common capability structure underlies regional resilience and, if so, whether its magnitude and spatial operation remain conditional on the crisis and resilience dimension.

Existing evidence identifies many determinants, but it cannot resolve this question due to its fragmentation. Single-crisis studies generally explain resistance or short-term recovery through sectoral structure, urbanisation, institutions or policy capacity (Brakman et al., 2015; Cutrini, 2023; Ezcurra & Rios, 2019; Fusillo et al., 2022; Psycharis et al., 2022), while studies of longer-term adjustment examine new specialisations or renewal (Pontarollo & Serpieri, 2020; Xiao et al., 2018). A second strand distinguishes among several resilience phases but remains anchored to a single crisis (Martini, 2020; Nijkamp et al., 2024; Pudelko et al., 2018). A third compares crises but usually focuses on resilience outcomes, Cohesion Policy, or a narrow set of determinants, rather than jointly testing the same pre-crisis characteristics (Di Caro & Fratesi, 2023; Ileanu & Pana, 2024; Sánchez & Cuadrado-Roura, 2024; Sensier et al., 2016). Prior research, therefore, documents plausible determinants and contextual differences, but it does not establish whether any determinant exhibits a consistent association across dissimilar crises and distinct resilience dimensions.

Figure 1 summarises the broad set of determinants considered in the reviewed literature. The evidence is also unevenly distributed: resistance and recovery are studied much more often than reorientation and renewal dimensions. This pattern motivates two competing expectations. The general-capability expectation is that some pre-crisis determinants are sufficiently multifunctional to produce a stable average association across the pooled resilience system (Fratesi & Perucca, 2018). The contextual-activation expectation is that effect sizes, signs or spatial channels vary because each crisis creates different binding constraints and each resilience dimension requires a different adjustment task (Boschma, 2015; Gong et al., 2020; Martin et al., 2016).

A pre-crisis characteristic is potentially common when it relaxes constraints that recur across disturbances, for example, by providing alternative activities, an active labour force, knowledge, coordination capacity, stable demand, or financial capacity, even if it is mobilised differently in each crisis and phase.

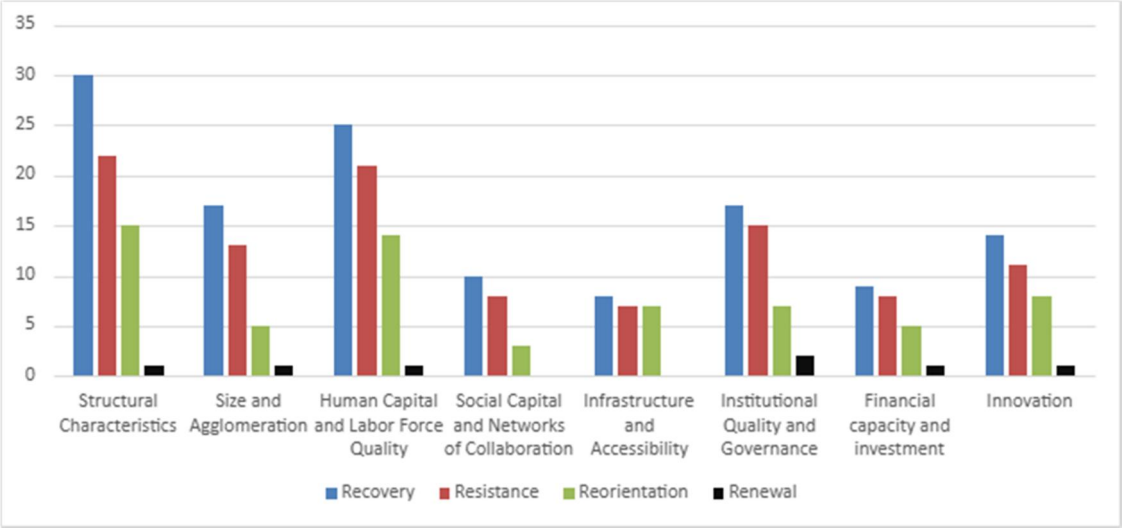

Figure 1. Distribution of resilience determinants across the regional resilience dimensions.
Source: Authors' synthesis based on the analysis of previous research.

The factor groups in Figure 1 are therefore retained as candidate mechanisms whose recurrence must be tested, rather than assumed to have uniform effects.

Institutional quality and labour-market participation illustrate multifunctional but conditional capacities. Effective administration can organise emergency support during resistance, coordinate the restoration of activity during recovery and enable experimentation during reorientation and renewal (Cutrini, 2023; Ezcurra & Rios, 2019; Nijkamp et al., 2024; Rios & Gianmoena, 2020). An active labour force enlarges the pool available for retention, matching and reallocation, although a high participation rate may also expose more workers to an employment-intensive shock (Faggian et al., 2018; Fusillo et al., 2022). The empirical labour-market proxy should therefore be interpreted as an activation proxy rather than a complete measure of education or skills. These capacities may recur across crises while their marginal value changes with the binding constraint.

Productive structure may also contain transferable capacities, but its theoretical interpretation requires separating overall concentration from distinctive specialisation. A region concentrated in only a few broad sectors has limited portfolio protection and fewer alternative adjustment paths if its dominant activities are disrupted. Greater diversity can therefore reduce sector-specific exposure and widen the set of resources available for reallocation (Chen et al., 2024; Martin et al., 2016; Pudelko et al., 2018). Relative specialisation, however, captures a different feature: the presence of a distinctive capability that is over-represented relative to the wider European economy. Such specialisation may embody accumulated know-how, specialised labour, supplier relationships, and institutionalised production competences. These capabilities can support competitiveness and provide a base for post-shock recombination, particularly when specialised activities are technologically coherent and embedded in a broader, diversified regional economy (Cuadrado-Roura & Maroto, 2016; Rocchetta et al., 2022; Xiao et al., 2018). Interregional industrial linkages may further strengthen resilience by enabling regions to draw on complementary industries and capabilities located elsewhere (Li, 2024). Diversity and specialisation are therefore not theoretical opposites: excessive dependence may weaken resilience while distinctive capabilities may strengthen it.

Innovation is another strong candidate for cross-context relevance. R&D capacity supports knowledge creation and absorption, process adjustment, organisational flexibility, and the development of new products and growth paths (Bristow & Healy, 2018; Filippetti et al., 2020; He et al., 2023; Rocchetta et al., 2022). It may improve resistance when innovative firms can modify production or retain skilled labour, support recovery through productivity and knowledge diffusion, and become especially important for reorientation and renewal through technological recombination and branching. Innovation is, nevertheless, complementary rather than self-sufficient: its contribution to resilience depends on human capital, related capabilities, institutional support, and access to external knowledge networks (Fusillo et al., 2022; Tóth et al., 2022; Wen & Fang, 2024). This complementarity makes innovation potentially recurrent across contexts while leaving room for considerable variation in its effect size.

Demographic structure and agglomeration-related conditions may influence regional resilience through labour-market depth, fiscal capacity, demand stability and access to knowledge and infrastructure. However, there is little reason to expect their effects to be invariant. Urban and metropolitan regions generally possess deeper labour markets, larger knowledge pools, more diversified economies, and stronger innovation systems, which can facilitate labour reallocation, firm adaptation, and knowledge diffusion during recovery, reorientation, and renewal (Brakman et al., 2015; Capello et al., 2015; Fratesi & Perucca, 2018). Nevertheless, the same density, connectivity, and concentration of face-to-face activities can increase exposure to specific shocks, as demonstrated by the disruptions experienced by metropolitan and service-intensive regions during COVID-19 (Partridge et al., 2022; Sensier et al., 2024; Tuysuz et al., 2022). Rural and peripheral regions often have thinner labour markets, more limited institutional capacity and less favourable demographic structures, although lower exposure to internationally integrated or contact-intensive activities may strengthen their short-term resistance to some shocks (Bănică et al., 2024; Giannakis & Bruggeman, 2017, 2020; Petkov, 2026). Within this broader spatial context, the demographic dependency ratio used in the present study captures a specific aspect of regional capacity: a relatively small working-age population may constrain labour supply, the fiscal base and the capacity to reallocate workers during recovery and longer-term transformation.

Social and health conditions and institutional quality are plausible general-purpose foundations of resilience, but their mechanisms vary across crises and dimensions. Favourable health conditions support labour supply, household adjustment and economic continuity, while effective governance reduces uncertainty and improves policy coordination (Cutrini, 2023; Ezcurra & Rios, 2019; Rios & Gianmoena, 2020). These factors may support resistance and recovery through immediate crisis management, whereas institutional adaptability and the retention of human resources become more important for reorientation and renewal (Nijkamp et al., 2024; Pontarollo & Serpieri, 2020). The life-expectancy indicator used here captures accumulated social and health conditions rather than social capital or network structure.

Tourism, investment and external openness can represent both capacity and exposure. Tourism generates income and employment but increases vulnerability to mobility and face-to-face restrictions, particularly during COVID-19 (Muštra et al., 2023; Partridge et al., 2022; Sensier et al., 2024). Investment can support demand and productive upgrading, but high pre-crisis intensity may also reflect capital-heavy structures, fixed costs or cyclical overexpansion (Di Caro & Fratesi, 2023; Psycharis et al., 2022). Trade and knowledge-service linkages provide access to markets and technologies while transmitting foreign demand and supply disruptions (Di Pietro et al., 2021). These effects may also spread through production networks, capital flows and service linkages. Their relevance may therefore recur across crises, but their direction, magnitude and spatial channel are likely to remain context-dependent.

The contextual-activation expectation follows the evolutionary argument that a pre-existing characteristic contributes to resilience by addressing a constraint made binding by the shock (Boschma, 2015; Gong et al., 2020; Martin et al., 2016). The Great Financial and Sovereign Debt Crisis originated within the economic and financial system and spread to regions through credit tightening, falling demand and investment, trade contraction, and fiscal stress. It therefore increased the exposure of construction-, finance-, export-manufacturing- and narrowly specialised regions. Productive diversity and public-service demand could cushion the initial contraction, whereas functioning labour markets, innovation and distinctive production competences could support recovery as credit and demand returned. Trade and manufacturing linkages could amplify the initial downturn yet accelerate subsequent recovery, illustrating why the same characteristic may change in magnitude or even sign across dimensions (Begley et al., 2024; Cuadrado-Roura & Maroto, 2016; Martin et al., 2016). COVID-19 activated a different constraint set. Although it became an economic shock, it originated as a public health emergency. It affected regions through mobility restrictions, mandated closures, supply disruptions, and limits on face-to-face production and consumption. Tourism, hospitality, leisure and retail were directly constrained, while public services and many knowledge-intensive activities could continue or reorganise more readily (Partridge et al., 2022; Sánchez & Cuadrado-Roura, 2024; Sensier et al., 2024; Tuysuz et al., 2022). Health conditions, administrative implementation, labour availability and the feasibility of reorganising work therefore became especially salient. Crises do not create regional capabilities; they alter the marginal usefulness of those capabilities by changing the bottleneck that regions must overcome.

Resilience dimensions also represent different economic tasks. Resistance depends primarily on exposure, redundancy, stable demand, financial slack and operational continuity. Recovery depends on renewed demand, liquidity, labour-market matching and the mobilisation of existing capacity. Reorientation requires transferable labour, industrial alternatives, knowledge recombination and open networks, whereas renewal requires innovation, productive investment and institutional support for new development paths (Boschma, 2015; Martin, 2012; Sensier et al., 2016; Xiao et al., 2018). These distinctions explain why a recurrent determinant need not have an equal effect across dimensions: the same capability may absorb loss in one phase and enable transformation in another. Reorientation and renewal are therefore qualitatively different from, rather than stronger versions of, recovery.

Production-network and spatial-spillover logic identify two distinct mechanisms through which connected regions influence resilience. First, outcome interdependence arises when common exposure, demand contraction, supply-chain disruption, commuting and feedback transmit resilience or vulnerability across regions; this is the economic mechanism represented by the spatially lagged resilience outcome. Second, capacity spillovers arise when connected regions' pre-crisis characteristics change local access to suppliers and markets, specialised labour, investment, public services and external knowledge; this is the mechanism represented by spatially lagged determinants (Diodato & Weterings, 2015;

Fingleton et al., 2012; Martin & Sunley, 2015; Sutton & Sutton, 2024). These channels can work in opposite directions: integration may weaken resistance by propagating a common shock but strengthen recovery, reorientation and renewal by widening the pool of adaptive resources (Annoni et al., 2019; Crespo et al., 2014; Elekes et al., 2024; Tóth et al., 2022). Geographic proximity, borders, language and institutional similarity facilitate functional interaction; they are not causal mechanisms in themselves. The sign of a neighbouring-region effect, therefore, depends on whether shock transmission, competition or access to adaptive resources dominates in the relevant crisis and dimension. These two mechanisms map directly to Wy and WX in the Spatial Durbin specifications developed in Section 3.5.

Taken together, these arguments yield three linked empirical expectations. First, the general-capability expectation predicts that some multifunctional pre-crisis characteristics will exhibit recurrent average associations across the pooled resilience system. However, this does not require identical crisis- or dimension-specific coefficients. Second, the contextual-activation expectation predicts that the magnitude, sign, or spatial channel of these associations will vary between the GFC and COVID-19, and among resistance, recovery, reorientation, and renewal, because each context imposes different binding constraints. Third, the spatial-interdependence expectation predicts both outcome dependence and capacity spillovers across connected regions. These expectations map directly to the empirical design: the common-effect Spatial Durbin model tests recurrent average associations, the crisis- and dimension-interacted models test contextual activation, and the Wy and WX structure with direct, indirect, and total impacts tests the two spatial mechanisms.

3. Methodology

The empirical design follows directly from Section 2. Sections 3.1-3.3 operationalise the four resilience dimensions and the candidate capabilities, Section 3.4 implements the two spatial mechanisms identified above, and the nested specifications in Section 3.5 test the general-capability expectation in the baseline model and the contextual-activation expectation in the interacted models.

3.1. Regional units, crisis windows, and source variables

The analysis covers 244 NUTS 2 regions (i) in the EU27, defined according to the NUTS 2024 classification (Eurostat, n.d.; Eurostat GISCO, n.d.). Here, EU27 denotes the fixed geographic coverage of the 27 countries belonging to the European Union in 2024, rather than the Union's membership in each observation year. Thus, NUTS 2024 serves as the common spatial reference for observations, enabling comparisons between the two crisis episodes using consistent regional units. The EU benchmarks used to construct the resilience indices and relative specialisation measures refer to the same fixed EU27 composition throughout the observation period.

The empirical design compares two shocks, i.e. crises (c): the Great Financial and Sovereign Debt Crisis (GFC) and the COVID-19 crisis. Following the regional resilience literature on resistance, recovery, reorientation, and renewal by Martin (2012), Martin et al. (2016), Sensier et al. (2016), and Xiao et al. (2018), among others, we measure four dimensions of resilience using five sensitivity indices (d). Let P_c, C_c, and A_c denote the pre-crisis, crisis, and post-crisis periods. The crisis windows are: $P_{GFC} = 2005 - 2008$, $C_{GFC} = 2009 - 2013$, $A_{GFC} = P_{COVID} = 2014 - 2019$, $C_{COVID} = 2020$, $A_{COVID} = 2021 - 2023$. EMP_{it} is the employment rate, $HTER_{it}$ is the share of employed persons in technology and knowledge-intensive sectors, and $GDPpc_{it}$ is GDP per inhabitant at constant 2020 prices. EU subscript denotes the corresponding EU benchmark. Source variables are presented in Table 1, along with their regime summary data in Appendix Table A1.

Table 1. Source variables used to construct sensitivity indices.

Code	Label	Source code in Eurostat	Unit
HTER	Employed persons in technology and knowledge-intensive sectors by NACE Rev. 2 activity and NUTS 2 region (2008–2026) || Employed persons in technology and knowledge-intensive sectors by NACE Rev. 1.1 activity and NUTS 2 region (1999–2008)	htec_emp_reg2 || htec_emp_reg	Percentage of total employment
EMP	Employment rates by NUTS 2 region	lfst_r_lfe2emprt	Percentage
GDPpc	GDP per inhabitant at constant 2020 prices, constructed	nama_10r_2gdp; demo_r_pjangroup; nama_10_gdp	Euro per inhabitant, 2020 prices

Annual employment-rate change and real GDP per capita growth are defined as:

$$\Delta EMP_{it} = EMP_{it} - EMP_{i,t-1} \tag{1}$$

$$gGDPpc_{it} = 100\left[\ln\left(GDPpc_{it}\right) - \ln\left(GDPpc_{i,t-1}\right)\right] \tag{2}$$

The regression observation is a region-crisis-resilience-dimension record, indexed by (i,c,d). With 244 regions, two crises, and five indices, the stacked estimation sample contains 244 x 2 x 5 = 2,440 observations. Calendar year t is used only to construct the pre-crisis proxies and sensitivity indices; it is not a separate regression dimension. The empirical design is therefore a stacked region-crisis-dimension dataset rather than a conventional annual panel.

3.2. Resilience dimensions and sensitivity indices (SIs)

Five direction-aligned sensitivity indices represent four conceptually distinct dimensions of resilience. Resistance is the capacity to limit the initial employment loss during a crisis; recovery is the extent of the employment rebound from the crisis trough; reorientation is a qualitative change in economic composition, operationalised here as a shift in technology- and knowledge-intensive employment; and renewal is a change in the longer-term development trajectory. Renewal is measured separately for employment and GDP per capita because labour-market and output trajectories can diverge. The dimensions are related stages of adjustment, not stronger or weaker versions of a single construct, and they are not aggregated into an omnibus index.

Resistance (RES) captures the capacity to limit the initial employment-rate loss during the crisis relative to the pre-crisis peak:

$$L_{i,c}^{EMP} = \frac{\min_{t\in C_c} EMP_{it} - \max_{t\in P_c} EMP_{it}}{\max_{t\in P_c} EMP_{it}} \tag{3}$$

$$SI_{RES_{i,c}} = \frac{L_{i,c}^{EMP}}{L_{EU,c}^{EMP}} \tag{4}$$

The original resistance sensitivity index has the opposite substantive direction to the other indicators: a higher SI_RES indicates weaker resistance, as it reflects a larger employment loss relative to the EU benchmark. Direction alignment is implemented by the exact transformation $SI_RESI_{i,c} = -SI_RES_{i,c}$. Higher SI_RESI values, therefore, indicate stronger resistance, consistent with the favourable direction of recovery, reorientation, and renewal.

Recovery (REC) captures the extent of the employment-rate rebound from the crisis trough during the post-crisis period:

$$R_{i,c}^{EMP} = \frac{\max_{t\in A_c} EMP_{it} - \min_{t\in C_c} EMP_{it}}{\min_{t\in C_c} EMP_{it}} \tag{5}$$

$$SI_{REC_{i,c}} = \frac{R_{i,c}^{EMP}}{R_{EU,c}^{EMP}}. \tag{6}$$

Reorientation (REO) captures one specific form of qualitative structural change: the post-crisis change in the share of technology- and knowledge-intensive employment relative to its pre-crisis level:

$$Q_{i,c} = \text{mean}_{t\in A_c} HTER_{it} - \text{mean}_{t\in P_c} HTER_{it} \tag{7}$$

$$SI_{REO_{i,c}} = \frac{Q_{i,c}}{Q_{EU,c}} \tag{8}$$

Renewal (REN) captures a change in the longer-term regional development trajectory and is measured as the ratio of the post-crisis to the pre-crisis OLS slope. Employment and GDP per capita are retained as separate renewal indices because labour-market and output trajectories may diverge. For outcome Y in {EMP, GDPpc}, we estimate:

$$Y_{it} = a^{Y}_{i,p} + b^{Y}_{i,p}t + u_{it}, p \in \{P_c, A_c\} \tag{9}$$

The SI for renewal is

$$SI_{REN^{Y}_{i,c}} = \frac{b^{Y}_{i,A_c}/b^{Y}_{i,P_c}}{b^{Y}_{EU,A_c}/b^{Y}_{EU,P_c}} \tag{10}$$

Because the original renewal indices contain extreme values due to small or sign-changing pre-crisis slopes, the models use winsorized renewal variables, REN_EMW and REN_GDPW. Winsorization is pooled within each renewal family at the 2.5th and 97.5th percentiles. The employment-renewal thresholds are −9.30 and 7.95, and the GDP-renewal thresholds are −7.10 and 8.65. Appendix Table A2 provides descriptive statistics. SI correlations are computed after resistance inversion and renewal winsorization (Appendix Table A3). The reorientation indicator captures only technology- and knowledge-intensive employment change rather than every form of structural transformation, while the slope-ratio renewal measures remain sensitive to small or sign-changing pre-crisis trends even after winsorization.

Cross-dimensional SI correlations are generally low to moderate rather than high. The largest absolute GFC correlation is RES^{I} with *REO*, −0.382; the largest absolute COVID correlation is RES^{I} with *REC*, −0.311. This supports treating the SI measures as related but distinct resilience dimensions. Same-dimension correlations across crises are very low: 0.143 for resistance, −0.007 for recovery, −0.130 for reorientation, 0.019 for employment renewal, and 0.048 for GDP renewal. This is consistent with crisis-specific regional resilience patterns and supports including COVID interactions rather than assuming that GFC and COVID reveal identical regional capacities.

3.3. Pre-crisis explanatory factors and proxy construction

The explanatory variables are pre-crisis regional factors. GFC models use 2005 – 2008. COVID models use 2014 – 2019. For proxy x, region i, crisis c, and the pre-crisis period P_c, the time-weighted pre-crisis average is:

$$X_{i,c} = \frac{\sum_{t \in P_c} \omega_{t,c} x_{i,t}}{\sum_{t \in P_c} \omega_{t,c}} \tag{11}$$

The weight $\omega_{t,c}$ increases with proximity to the crisis. For the GFC, weights increase linearly from 1 in 2005 to 4 in 2008, so the normalised weights are 0.10, 0.20, 0.30, and 0.40, respectively. For COVID, weights increase linearly from 1 in 2014 to 6 in 2019, yielding normalised weights ranging from 0.048 to 0.286. Thus, the most recent pre-crisis observations receive the largest influence while still retaining information from the full pre-crisis window. If missing values are present, the available non-missing years are used in both the numerator and the denominator.

Right-skewed count and density variables were log-transformed before constructing weighted averages. *INF_TOUR_DENS* was transformed before averaging, with $\ln(1+x)$ since zero values were reported in some cases. The selection of empirical proxies was theory-led. Table 2 operationalises the mechanisms identified in Section 2 using twelve pre-crisis proxies.

Detailed proxy descriptive statistics for crisis-specific pre-crisis periods are presented in Appendix Table A4. The proxy set was selected to ensure that pairwise absolute correlations between proxies from different factor groups would not exceed 0.50 in either the GFC or COVID pre-crisis proxy data. Where more than one proxy came from the same factor group, within-group absolute correlations should not exceed 0.30. This screen reduces multicollinearity before SDM estimation. This restriction was particularly important because the SDM expands the regressor matrix beyond the main proxy variables by adding their spatial lags and, in extended specifications, also includes interactions between crises and SIs with both X and WX. Even moderate correlations among the original proxies can therefore be amplified after constructing WX, COVID × X, COVID × WX, etc., making coefficient estimates less stable and standard errors more sensitive to the chosen specification. The maximum absolute off-diagonal correlation among reported proxies is approximately 0.493 in GFC, 0.480 in COVID, and 0.480 in the pooled pre-crisis data. The pairwise correlations among the pre-crisis proxy variables for the GFC, COVID, and pooled samples are presented in Appendix Figures A1–A3.

Table 2. Pre-crisis proxy definitions.

Factor group	Proxy	Name	Formula and unit	Interpretation	Source note
Structural Characteristics	STR_DIV_HHI	Industrial concentration	$\sum_i s_i^2$, where s_i is the share of total regional GVA in the broad non-overlapping sector i. Unit: 0–1 concentration index.	Higher values mean the economy depends more on a few sectors.	Eurostat nama_10r_3gva; regional sectoral GVA and total GVA.
	STR_SPEC_MAXLQ	Relative specialisation	$\max_i[(\text{regional sector share}_i)/(\text{EU sector share}_i)]$, using broad non-overlapping GVA sectors. Unit: ratio.	Strongest regional sectoral over-representation relative to the EU structure.	Eurostat nama_10r_3gva; regional and EU shares from the same broad sectoral GVA categories.
	STR_SPEC_PUBLIC	Public-service stabilisation	100× public administration, education, health and social-work GVA / total regional GVA. Unit: per cent of GVA.	Measures the public administration, education, health, and social work.	Eurostat nama_10r_3gva, NACE O-Q.
Size and Agglomeration	AGG_DEM_DEP	Demographic dependency	Dependent-age population / working-age population ×100. Unit: per cent.	Ratio of dependent-age population to working-age population.	Eurostat demo_r_pjanind2.
Human Capital and Labour Force Quality	HCL_LM_PART	Labour-market participation	Labour force / working-age population ×100. Unit: per cent.	Labour-market activation proxy.	Eurostat lfst_r_lfp2actrt.
Innovation	INN_RD_GDP	R&D intensity	Intramural R&D expenditure / GDP ×100. Unit: per cent of GDP.	Standard innovation-input intensity measure.	Eurostat tgs00042.
Institutional Quality and Governance	GOV_REG_GAP	Within-country governance advantage	Regional EQI score − country-year average EQI score across regions. Unit: index-point gap.	Within-country governance advantage.	QoG Institute EQI; country-year means.
Infrastructure and Accessibility	INF_TOUR_DENS	Tourism spatial intensity	$\ln(\text{tourist nights}/\text{land area})$. Original unit: nights per square km; empirical proxy stored as natural log.	Logged tourism spatial intensity.	Eurostat tour_occ_nin2.
Social Capital and Networks of Collaboration	SOC_HEALTH_LIFE	Social and health conditions	Life expectancy at selected age and sex definition. Unit: years.	Broad social and health condition measure.	Eurostat demo_r_mlifexp.
Financial Capacity and Investment	FIN_INV_RATE	Investment intensity	100× total regional GFCF / regional GDP. Unit: per cent of GDP.	Investment intensity of the regional economy.	Eurostat nama_10r_2gfcf and nama_10r_2gdp.
	FIN_OPEN_MFGCAP	Goods-trade and manufacturing-capital exposure	$z_t(\text{national goods trade openness}) \times z_t(\text{regional manufacturing share of GFCF})$. Unit: standardised interaction.	Interacts national goods openness with the regional manufacturing investment share.	Eurostat nama_10_gdp and nama_10r_2gfcf.
	FIN_OPEN_KSERVEXP	Services-trade exposure interaction	National services trade openness × regional knowledge-service GVA share. Unit: interaction index.	Combines national services openness with regional knowledge-service orientation.	Eurostat nama_10_gdp and nama_10r_3gva

Before SDM estimation, both the dependent sensitivity indices (SIs) and the proxy variables were standardised using a common z-score transformation:

$$zV_{i,c,m} = \frac{V_{i,c,m} - \overline{V}_m}{s_{V_m}} \tag{12}$$

where $V_{i,c,m}$ denotes either a sensitivity index or a proxy variable, and m denotes the specific SI dimension or proxy variable. The mean $\overline{V}_m$ and standard deviation s_{V_m} are calculated over the relevant pooled region-crisis sample for each variable m.

For the sensitivity indices, standardisation is applied separately within each SI dimension d, pooling GFC and COVID observations for that dimension. Thus, $\overline{V}_m$ and s_{V_m} are calculated over 488 region-crisis observations for each SI dimension: inverted resistance, recovery, reorientation, employment-based renewal, and GDP-based renewal. For the proxy variables, standardisation is applied separately within each proxy variable k, pooling GFC and COVID pre-crisis proxy averages over 488 region-crisis observations. This is because the proxies are measured in heterogeneous units, including percentages, ratios, years, density measures, indices, and interaction terms.

3.4. Spatial weights and descriptive spatial autocorrelation

Spatial estimation is selected because both theoretical considerations and descriptive Moran diagnostics indicate two forms of interdependence. Resilience outcomes may propagate through demand, supply chains, commuting, and feedback, while the pre-crisis capacities of connected regions may alter access to markets, labour, services, knowledge, and investment. A Spatial Durbin model accommodates both channels through Wy and WX and permits the direct, indirect, and total impact decomposition required for substantive interpretation. The three prespecified matrices test whether the findings depend on distance and borders alone or also on language and institutional proximity.

Spatial weight matrices represent theory-based potential interaction, not observed NUTS2-to-NUTS2 flows. All matrices have zero diagonal and are row-standardised:

$$w_{ij} = \frac{a_{ij}}{\sum_{j \neq i} a_{ij}}, w_{ii} = 0 \tag{13}$$

Therefore, *Wy* and *WX* are weighted averages of other regions' outcomes and covariates. The matrices use the 244 EU27 NUTS 2 regions under NUTS 2024. GISCO NUTS 2024 label points/geodata provide the geographical base.

The main matrix is the distance-border matrix W^{DB}:

$$a_{ij}^{DB} = \exp\left[-\gamma D_{ij} - \delta B_{ij}\right] \tag{14}$$

where D_{ij} is the great-circle distance in kilometres between NUTS 2 label points and $B_{ij} = 1$ if regions i and j are in different countries. The parameters are $\gamma = \frac{\ln(2)}{300}$ and $\delta = \ln(2)$, so distance halves raw affinity approximately every 300 km, and crossing a national border halves raw affinity before row-standardisation. The language-augmented matrix adds language proximity to W^{DB} for cross-border links:

$$a_{ij}^{DBL} = a_{ij}^{DB} \exp\left[B_{ij}\left(0.35\ \mathit{Official\ Language}_{ij} + 0.20\ \mathit{Ethnolinguistic\ Language}_{ij}\right)\right] \tag{15}$$

The institutional-proximity matrix adds institutional proximity to W^{DB} for cross-border links:

$$a_{ij}^{DBI} = a_{ij}^{DB} \exp\left[B_{ij}\left(0.15\ EU_{ij} + 0.20\ Euro_{ij} + 0.20\ Schengen_{ij} + 0.25\ Group_{ij}\right)\right] \tag{16}$$

The predefined groups are: Benelux; Nordic EU; Baltic; Nordic-Baltic EU; Visegrad; Iberian; German-speaking core; Former Czechoslovakia; EU Adriatic former-Yugoslavia pair; and Hellenic pair. Institutional variables are averaged over the relevant pre-crisis period: 2005–2008 for GFC and 2014–2019 for COVID. For crisis-pooled models:

$$W^{POOLED} = \mathrm{diag}\left(W^{GFC}, W^{COVID}\right) \tag{17}$$

For all-dimension pooled models, the crisis-pooled matrix is repeated by the SI dimension $W^{ALL} = I_D \otimes W^{POOLED}, D = 5$. This prevents artificial spatial links between crisis episodes and SI dimensions, while allowing comparable construction of spatial lags within each crisis-dimension block.

Global Moran's *I* is reported using the main W^{DB} matrix. It shows whether SIs and proxies are spatially clustered before modelling. Two-sided pseudo-*p* values use 999 random permutations. Detailed Moran's I statistics for the resilience indicators and pre-crisis proxy variables are reported in the Appendix Tables A5a and A5b.

The SI Moran's *I* diagnostics show spatial clustering in several resilience outcomes. GFC resistance, GFC reorientation, GFC recovery, COVID recovery, COVID reorientation, and COVID GDP renewal are positive with permutation $p \leq 0.01$. COVID resistance is weak or marginal, $I = 0.02$, $p = 0.07$. Renewal based on employment or GDP is more mixed, especially in the GFC.

The reported proxies are mostly positively spatially autocorrelated under W^{DB}. Stronger clustering appears for social and health conditions, labour-market participation, public-service specialisation, relative specialisation, demographic dependency, R&D intensity, and logged tourism spatial intensity. GFC investment intensity is weak, $I = 0.01,\ p = 0.17,$ while COVID investment intensity is clearly clustered, $I = 0.17,\ p \leq 0.01$. These diagnostics justify spatial specification and motivate VIF diagnostics because spatially clustered proxies can make local *X* and neighbouring *WX* associations difficult to separate.

3.5. Empirical strategy and spatial Durbin model specifications

The empirical strategy proceeds from a parsimonious pooled model to progressively more flexible tests of heterogeneity. Equation (18) identifies associations that recur, on average, across the two crises and the five sensitivity indices. Equations (19) and (20) test whether these associations vary by crisis or resilience dimension. Equation (21) permits joint crisis-by-dimension heterogeneity and is treated as a diagnostic because of its extensive parameterisation. Equation (22) tests whether the pooled findings are robust to spatial dependence varying across resilience dimensions.

3.5.1. Baseline common-effect SDM

The estimation observation is (*i, c, d*), where *i* denotes a NUTS 2 region, *c* denotes the crisis episode, and *d* denotes the resilience-index dimension. Region *j* is a connected region, *g(i)* is the country containing region *i*, $x_{i,c}$ is the vector of standardised pre-crisis proxies repeated across the five dimensions, $w_{ij}^{(c)}$ is the within-crisis spatial weight, and D_c equals one for COVID and zero for the GFC. Spatial links operate only between regions within the same crisis-dimension block; *W* contains no links across crises or resilience dimensions.

The baseline model imposes common proxy effects and one common spatial autoregressive parameter across crises and dimensions. It includes a COVID indicator, country fixed effects, dimension fixed effects, and COVID-by-dimension fixed effects. These controls absorb the average crisis shift, time-invariant national institutional and macro-regulatory conditions, average differences among the five indices, and dimension-specific crisis shifts. The SDM is preferred to a non-spatial or single-channel model because it estimates both outcome propagation through *Wy* and capacity spillovers through *WX*.

$$y_{icd} = \rho \sum_{j \neq i} w_{ij}^{(c)} y_{jcd} + x_{ic}'\beta + \sum_{j \neq i} w_{ij}^{(c)} x_{jc}'\theta + \delta D_c + \mu_{g(i)} + \lambda_d + \sum_{r \neq d_0} \kappa_r \left[D_c 1(d = r) \right] + \varepsilon_{icd}. \tag{18}$$

Here, ρ captures common spatial autoregressive dependence in the resilience outcome, β contains the common own-region proxy associations, and θ contains the common associations with proxies of connected regions. The country, dimension, COVID, and COVID-by-dimension controls absorb the fixed differences described above. Equation (18) is the primary model for identifying recurrent pooled associations.

3.5.2. Crisis heterogeneity

$$y_{icd} = \rho \sum_{j \neq i} w_{ij}^{(c)} y_{jcd} + x_{ic}'\beta + \sum_{j \neq i} w_{ij}^{(c)} x_{jc}'\theta + D_c \left[x_{ic}'\beta_C + \sum_{j \neq i} w_{ij}^{(c)} x_{jc}'\theta_C \right] + \delta D_c + \mu_{g(i)} + \lambda_d + \sum_{r \neq d_0} \kappa_r \left[D_c 1(d = r) \right] + \varepsilon_{icd}. \tag{19}$$

Equation (19) relaxes the baseline restriction that β and θ are identical across crises by adding COVID interactions with X and WX. It tests crisis activation: beta and theta describe GFC associations, while $\beta + \beta_C$ and $\theta + \theta_C$ describe COVID associations. The common ρ restriction is retained so that crisis heterogeneity is attributed to proxy channels rather than to a separate crisis-specific spatial multiplier.

3.5.3. Resilience-dimension heterogeneity

$$y_{icd} = \rho \sum_{j \neq i} w_{ij}^{(c)} y_{jcd} + x_{ic}'\beta + \sum_{j \neq i} w_{ij}^{(c)} x_{jc}'\theta + \sum_{r \neq d_0} 1(d = r) \left[x_{ic}'\beta_r + \sum_{j \neq i} w_{ij}^{(c)} x_{jc}'\theta_r \right] + \delta D_c + \mu_{g(i)} + \lambda_d + \sum_{r \neq d_0} \kappa_r \left[D_c 1(d = r) \right] + \varepsilon_{icd}. \tag{20}$$

Equation (20) relaxes the baseline restriction that proxy associations are equal across resilience dimensions. It tests whether the same capacity operates differently in resistance, recovery, reorientation, and renewal. For reference dimension d_0, β and θ are the associations; for dimension r, they become $\beta + \beta_r$ and $\theta + \theta_r$.

3.5.4. Joint crisis-dimension heterogeneity

$$y_{icd} = \rho \sum_{j \neq i} w_{ij}^{(c)} y_{jcd} + x_{ic}'\beta + \sum_{j \neq i} w_{ij}^{(c)} x_{jc}'\theta + D_c \left[x_{ic}'\beta_C + \sum_{j \neq i} w_{ij}^{(c)} x_{jc}'\theta_C \right] + \sum_{r \neq d_0} 1(d = r) \left[x_{ic}'\beta_r + \sum_{j \neq i} w_{ij}^{(c)} x_{jc}'\theta_r \right] + \sum_{r \neq d_0} D_c 1(d = r) \left[x_{ic}'\beta_{C,r} + \sum_{j \neq i} w_{ij}^{(c)} x_{jc}'\theta_{C,r} \right] + \delta D_c + \mu_{g(i)} + \lambda_d + \sum_{r \neq d_0} \kappa_r \left[D_c 1(d = r) \right] + \varepsilon_{icd}. \tag{21}$$

Equation (21) jointly relaxes the crisis- and dimension-invariance restrictions and tests whether crisis activation itself differs by resilience dimension. Context-specific associations are obtained by summing the relevant baseline and interaction terms. Because the model partitions the evidence across many crisis-dimension cells and is highly parameterised, it is used as a diagnostic of heterogeneity rather than as the preferred explanatory specification.

3.5.5. Robustness to dimension-specific spatial dependence

$$y_{icd} = \rho_d \sum_{j \neq i} w_{ij}^{(c)} y_{jcd} + x_{ic}'\beta + \sum_{j \neq i} w_{ij}^{(c)} x_{jc}'\theta + \delta D_c + \mu_{g(i)} + \lambda_d + \sum_{r \neq d_0} \kappa_r \left[D_c 1(d = r) \right] + \varepsilon_{icd}. \tag{22}$$

Equation (22) relaxes only the baseline restriction of a common spatial autoregressive parameter by estimating ρ_d for each resilience dimension. The common β and θ coefficients preserve the pooled-factor interpretation, while the model tests whether that interpretation depends on the assumption of equal outcome propagation across dimensions. The ρ_d parameters remain common across crises for stability.

3.6. Estimation, inference, diagnostics, and interpretation of impacts

The SDMs are estimated by maximum likelihood because *Wy* is determined simultaneously with *y*; ordinary least squares would not appropriately account for this spatial dependence. Country fixed effects control for shared national institutional and macro-regulatory conditions, dimension fixed effects absorb average scale and level differences across the five indices, and COVID-by-dimension fixed effects absorb

dimension-specific shifts between crises. Primary inference uses paired region-cluster bootstrap standard errors with 499 replications, resampling NUTS 2 regions and retaining all ten crisis-dimension observations of each sampled region. This procedure addresses the within-region dependence created by the stacked design. Region-clustered standard errors, White/sandwich heteroskedasticity-robust standard errors for the transformed equation y-ρ Wy = Zeta + epsilon, and full joint ML/Hessian standard errors obtained from the numerically inverted joint Hessian are reported as sensitivity checks rather than co-equal inferential standards (Cameron et al., 2008; Cameron & Miller, 2015; White, 1980).

For each proxy k in an SDM with common ρ, the impact matrix is

$$S_k(W) = (I - \rho W)^{-1}(\beta_k I + \theta_k W) \tag{23}$$

The average direct effect is:

$$ADE_k = n^{-1}\mathrm{tr}[S_k(W)] \tag{24}$$

The average total effect is:

$$ATE_k = n^{-1}\mathbf{1}'S_k(W)\mathbf{1} \tag{25}$$

The average indirect effect is:

$$AIE_k = ATE_k - ADE_k \tag{26}$$

For interacted models, impacts use the relevant context-specific coefficient sums. For example, a COVID impact uses $\beta_k + \beta_{C,k}$ and $\theta_k + \theta_{C,k}$. Because both the resilience indices and explanatory proxies are standardised, impacts are comparable across factors. The average direct effect is the within-region association, including feedback through the spatial multiplier; the average indirect effect is the cumulative spillover association transmitted through connected regions; and the total effect is their sum. Large total effects reflect system-wide spatial propagation rather than a change of that magnitude in one isolated region. All impacts remain conditional associations and are not interpreted as causal effects.

4. Results and discussion

4.1. Baseline pooled spatial model

The baseline common-effect SDM using W_DB identifies a compact set of recurrent spatial associations. Relative specialisation and R&D intensity have the largest positive total effects; investment intensity has the largest negative total effect; industrial concentration is negatively associated with resilience primarily within regions; and social and health conditions show a positive local association. Table 3 reports the direct, indirect, and total impacts that provide the substantive basis for comparing these factors.

The spatial autoregressive parameter is 0.792 with a region-cluster bootstrap standard error of 0.079, indicating strong outcome propagation across connected regions. The own-region X block and spatially lagged WX block are jointly significant, while the near-zero residual Moran's I indicates little remaining spatial autocorrelation after estimation. Full coefficient and alternative-inference results are reported in Appendix Table B1, with diagnostics in Appendix Tables B2-B5.

Under W_DB, investment intensity has the largest robust negative system-wide association, with a total effect of −5.266. Relative specialisation and R&D intensity have the largest positive total effects, 5.262 and 4.588, respectively. Industrial concentration has a direct negative effect of −0.117, while social and health conditions have the strongest stable positive local effect of 0.154. Public-service specialisation has a positive total effect of 2.556, but its sensitivity to the spatial matrix makes it secondary to the three largest system-wide effects.

Relative specialisation has a direct effect of 0.132, an indirect effect of 5.131, and a total effect of 5.262 under W_DB, all significant at $p < 0.01$. The dominance of the indirect component indicates that distinctive regional capabilities are associated with resilience mainly through the connected regional system rather than solely within the originating region.

R&D intensity has a direct effect of 0.096, an indirect effect of 4.492, and a total effect of 4.588 under W_DB. The spillover magnitude dominates the local association, consistent with knowledge diffusion, supplier and customer learning, shared labour pools, and institutional learning across connected regions.

Table 3. Common-effect SDM direct, indirect, and total impacts across W matrices.

	Direct effect			Indirect effect			Total effect		
Proxy	W^{DB}	W^{DBL}	W^{DBI}	W^{DB}	W^{DBL}	W^{DBI}	W^{DB}	W^{DBL}	W^{DBI}
Industrial concentration (STR_DIV_HHI)	**−0.117** **<0.043>***	−0.118 <0.047>**	−0.100 <0.041>**	**−2.633** **<1.469>***	−2.693 <1.639>	−2.177 <1.495>	**−2.750** **<1.506>***	−2.811 <1.681>*	−2.277 <1.530>
Relative specialisation (STR_SPEC_MAXLQ)	**0.132** **<0.043>***	0.135 <0.044>***	0.119 <0.039>***	**5.131** **<1.532>***	5.293 <1.570>***	4.745 <1.360>***	**5.262** **<1.567>***	5.428 <1.605>***	4.864 <1.389>***
Public-service stabilisation (STR_SPEC_PUBLIC)	**0.058** **<0.045>**	0.058 <0.048>	0.042 <0.042>	**2.498** **<1.392>***	2.510 <1.482>*	2.051 <1.252>	**2.556** **<1.418>***	2.568 <1.513>*	2.093 <1.277>
Demographic dependency (AGG_DEM_DEP)	**−0.023** **<0.042>**	−0.021 <0.042>	−0.001 <0.042>	**−1.266** **<1.505>**	−1.261 <1.495>	−1.149 <1.367>	**−1.288** **<1.527>**	−1.283 <1.518>	−1.150 <1.391>
Labour-market participation (HCL_LM_PART)	**−0.080** **<0.056>**	−0.079 <0.058>	−0.091 <0.052>*	**1.063** **<1.397>**	1.153 <1.378>	0.982 <1.236>	**0.983** **<1.421>**	1.074 <1.404>	0.891 <1.254>
R&D intensity (INN_RD_GDP)	**0.096** **<0.046>****	0.097 <0.047>**	0.082 <0.041>**	**4.492** **<2.041>****	4.679 <2.071>**	4.456 <1.919>**	**4.588** **<2.084>****	4.776 <2.113>**	4.539 <1.955>**
Within-country governance advantage (GOV_REG_GAP)	**0.021** **<0.037>**	0.021 <0.038>	0.014 <0.037>	**1.307** **<1.482>**	1.311 <1.509>	0.948 <1.416>	**1.328** **<1.510>**	1.332 <1.537>	0.963 <1.443>
Tourism spatial intensity (INF_TOUR_DENS)	**−0.009** **<0.043>**	−0.009 <0.040>	0.005 <0.035>	**−0.447** **<1.808>**	−0.499 <1.668>	−0.098 <1.449>	**−0.455** **<1.841>**	−0.508 <1.700>	−0.093 <1.472>
Social and health conditions (SOC_HEALTH_LIFE)	**0.154** **<0.082>***	0.152 <0.084>*	0.172 <0.080>**	**0.007** **<1.561>**	−0.031 <1.620>	−0.205 <1.501>	**0.161** **<1.575>**	0.120 <1.641>	−0.033 <1.517>
Investment intensity (FIN_INV_RATE)	**−0.106** **<0.050>****	−0.106 <0.052>**	−0.093 <0.040>**	**−5.160** **<1.885>*****	−5.153 <1.993>***	−4.302 <1.685>**	**−5.266** **<1.927>*****	−5.259 <2.038>***	−4.396 <1.716>**
Goods-trade and manufacturing-capital exposure (FIN_OPEN_MFGCAP)	**0.060** **<0.056>**	0.063 <0.057>	0.041 <0.048>	**3.062** **<2.028>**	3.233 <2.224>	2.349 <1.884>	**3.121** **<2.076>**	3.296 <2.273>	2.390 <1.924>
Services-trade exposure interaction (FIN_OPEN_KSERVEXP)	**−0.096** **<0.086>**	−0.100 <0.092>	−0.100 <0.093>	**0.803** **<2.622>**	0.534 <2.371>	0.322 <2.180>	**0.707** **<2.667>**	0.434 <2.417>	0.222 <2.209>

Note. Cells report the impact estimate and region-cluster bootstrap standard error. The shaded W_DB columns are the prespecified baseline; W_DBL and W_DBI are spatial-connectivity robustness checks. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. In the pooled pre-crisis data, one standard deviation equals 0.030 HHI points for industrial concentration, 1.167 ratio units for relative specialisation, 6.060 percentage points for public-service specialisation, 1.087 percentage points of GDP for R&D intensity, 2.818 years for social and health conditions, and 10.011 percentage points of GDP for investment intensity.

The R&D result is consistent with the view that innovation capacity increases regional adaptability, absorptive capacity, and the ability to reorganise economic activity after shocks (Bristow & Healy, 2018; Filippetti et al., 2020; Nijkamp et al., 2024; Rios & Gianmoena, 2020). Previous work on regional resilience has emphasised that adaptation and renewal depend on knowledge bases and the capacity to develop new activities rather than to restore pre-shock output levels (Martin, 2012; Martin et al., 2016; Xiao et al., 2018). The spillover evidence in Table 3 suggests that this capacity is not confined to administrative boundaries. Regions embedded in innovation-intensive neighbourhoods or connected spatial systems may benefit from knowledge diffusion, supplier and customer learning, shared labour pools, and institutional learning. This interpretation is also consistent with spatial-econometric theory because the SDM indirect effect captures the association between connected regions' characteristics and a region's outcome, after accounting for feedback through the spatial multiplier.

Industrial concentration has a negative direct effect of −0.117 under W_DB. Its indirect effect is −2.633, and its total effect is −2.750, both supported only at the 10% level. The evidence is therefore strongest for a local penalty from concentration, with weaker support for a system-wide spillover.

The industrial-concentration evidence therefore supports a robust direct association between lower concentration and stronger resilience, while providing weaker evidence of spatial spillovers. This finding aligns with a major strand of resilience literature, which argues that diversified regional economies are less exposed to sector-specific downturns and may have greater scope for reallocation after shocks (Martin, 2012; Martin et al., 2016; Sensier et al., 2016). At the same time, the simultaneous positive result for relative specialisation shows that diversification and specialisation are not simple opposites. Concentration in a few broad sectors is negatively associated with resilience, but distinctive sectoral over-representation is positively associated with resilience. This combination is substantively plausible: a region may benefit from a strong specialised capability if it is not locked into an excessively concentrated structural profile.

Investment intensity has the largest negative system-wide magnitude: a direct effect of −0.106, an indirect effect of −5.160, and a total effect of −5.266 under W_DB. The result is driven mainly by the spillover component. It is consistent with capital-heavy exposure, cyclical overexpansion, or investment patterns vulnerable to demand and credit shocks rather than with investment quality itself.

The negative investment-intensity result should be interpreted as an association with exposure or vulnerability rather than as evidence that investment is undesirable. The proxy measures pre-crisis investment intensity, not investment quality, productivity, or sectoral allocation. High values may therefore reflect capital-heavy regional structures, construction or asset-cycle exposure, overheated local demand, or investment patterns that are more vulnerable to credit tightening and demand shocks. This interpretation is consistent with crisis-context arguments that pre-crisis growth dynamics can amplify subsequent vulnerability when expansion is linked to cyclical or debt-sensitive activities (Cutrini, 2023; Di Pietro et al., 2021; Wang & Wei, 2021). The large negative indirect effects in Table 3 also suggest that investment-intensive spatial environments may transmit vulnerability across connected regions. This is a distinctive spatial finding: the negative association is not merely an own-region relationship, but a system-level association operating through connected regions.

Social and health conditions have a positive direct effect of 0.154 under W_DB, while the indirect and total effects are not significant. The association is therefore local rather than system-wide, consistent with a healthier labour supply, household adjustment capacity, and more favourable accumulated social conditions within the region.

Public-service specialisation has no significant direct effect under W_DB, but its indirect effect of 2.498 and total effect of 2.556 are weakly significant. The pattern is compatible with spatially distributed stabilisation through public administration, education, health, and social work, but it is treated as secondary because the robustness checks show sensitivity to W.

Demographic dependency, labour-market participation, within-country governance advantage, logged tourism spatial intensity, goods-trade and manufacturing-capital exposure, and services-trade exposure interaction do not have significant direct, indirect, or total effects under the baseline bootstrap criterion. Their isolated significance under alternative standard error estimates is insufficient to classify them as recurrent pooled factors.

4.2. Robustness to spatial-connectivity and inference choices

The W_DBL and W_DBI estimates preserve the principal ranking. Relative specialisation and R&D intensity remain positive in both the indirect and total effects, while investment intensity remains negative. The negative direct effect of industrial concentration and the positive direct effect of social and health conditions also persist. Public-service specialisation is the main qualification because its spillover evidence weakens under W_DBI. Table 3 presents these robustness estimates alongside the visually emphasised W_DB baseline.

The full coefficient results in Appendix Table B1 compare ML/Hessian, heteroskedasticity-robust, region-clustered, and region-cluster bootstrap standard errors. The bootstrap is the primary benchmark, while the other variants show whether conclusions depend on the covariance estimator. The spatial autoregressive estimate remains large under W_DBL (0.792) and W_DBI (0.759), supporting the baseline conclusion that resilience is spatially interdependent.

Diagnostics in Appendix Tables B2–B5 show near-zero residual Moran's I and joint significance of the X and WX blocks. Collinearity is limited within the own-region X block, where the maximum VIF is 1.883, but higher in the combined X-WX block, with maximum VIFs of 21.175 under W_DB, 21.034 under W_DBL, and 24.626 under W_DBI. This supports emphasis on impact decompositions and joint evidence rather than isolated WX coefficients.

4.3. Stability across crises and resilience dimensions

4.3.1. Crisis heterogeneity

The COVID-interacted model (based on Eq. 19) shows that the common-effect results cannot be interpreted as crisis-invariant. Appendix Table B3 reports that the joint COVID x proxy block is significant at $p < 0.01$ across all W. The heterogeneity is especially pronounced for the spatially lagged terms. The joint COVID x WX block is significant across all three matrices, while the COVID x X block is not significant under W^{DB} or W^{DBL} and is significant only under W^{DBI}. This pattern indicates that the main difference between the GFC and COVID specifications lies less in the direct own-region effects of regional attributes and more in how spatially connected regional attributes condition resilience across crises.

This finding is consistent with the wider regional resilience literature (Di Caro & Fratesi, 2023; C. He & Sheng, 2024; Sutton & Sutton, 2024), which emphasises that different shocks activate different mechanisms of exposure and adjustment. The GFC and sovereign debt crisis were closely linked to financial conditions, demand contraction, industrial exposure, and fiscal stress, while mobility restrictions, public health constraints, sectoral shutdowns, and uneven service-sector exposure shaped the COVID-19 shock. It is therefore plausible that the same pre-crisis factor can matter differently across crises, especially through spatial channels. The joint-test evidence in Appendix Table B3 confirms that the pooled common-effect model is averaging over meaningful crisis-specific variation.

The crisis-specific impact evidence in Appendix Table B6 provides the substantive detail. Relative specialisation remains positively associated with resilience in the GFC specification through spillover and total effects. Under WDB, the GFC indirect effect is 5.488, and the GFC total effect is 5.586, both significant at $p < 0.05$. The same pattern holds under WDBL and WDBI. By contrast, the corresponding COVID-specific relative-specialisation impacts are not significant. This suggests that specialised regional capabilities were more strongly associated with resilience during the GFC than during the COVID context. A plausible interpretation is that the GFC rewarded accumulated production capabilities, tradable-sector positioning, and interregional production linkages. In contrast, COVID disrupted activity through restrictions and public health measures that did not map directly onto pre-crisis sectoral specialisation. This is consistent with studies arguing that regional resilience is shock-specific and that structural advantages in one crisis do not necessarily translate mechanically into another (Martin et al., 2016; Sensier et al., 2016; Webber et al., 2018).

R&D intensity shows a similar crisis-specific pattern. Appendix Table B6 reports that, under W^{DB}, the GFC direct effect is 0.132, the indirect effect is 6.450, and the total effect is 6.582. The indirect and total GFC effects remain partly supportive under W^{DBI}, while the COVID-specific R&D impacts are not significant. The result suggests that innovation capacity is a strong common factor in the pooled model, but

its crisis-specific expression is more visible in the GFC specification. This may reflect the role of innovation and absorptive capacity in restructuring production, adapting firms, and supporting medium-term adjustment after a financial and demand shock. During COVID, by contrast, short-term resilience may have depended more on restrictions, public health conditions, remote work capacity, emergency policy support, and the sectoral feasibility of continued activity. This does not contradict the common-effect result in Table 3. Rather, it clarifies that the pooled positive R&D association is not equally strong across all crisis-specific decompositions.

Investment intensity exhibits a different profile of heterogeneity. In the common-effect model, Table 3 shows that investment intensity is negative mainly through indirect and total effects. In Appendix Table B6, the clearest COVID-specific evidence is a negative direct effect under W^{DB} and W^{DBI}, while the GFC-specific investment-intensity impacts are not significant. This suggests that investment intensity may have captured a more direct vulnerability within its own region during COVID. One possible interpretation is that investment-intensive regions were more exposed to fixed-capital adjustment, construction-cycle disruptions, or capital-intensive sectors affected by mobility and supply constraints. The spatial spillover channel that dominates the pooled model remains important in Table 3, but the COVID-interacted model indicates that the crisis-specific channel was more local and direct.

Services-trade exposure interaction is also crisis-sensitive. Appendix Table B6 shows negative GFC-related evidence under W^{DB} and a negative COVID direct effect under W^{DB}, but the evidence is not stable across W^{DBL} and W^{DBI}. The services-trade interaction may capture heterogeneous regional exposure to tradable services and knowledge-service structures, but the coefficient and impact evidence are too W-sensitive to classify it as a robust common factor. This is consistent with the broader caution in resilience studies that openness can operate both as a source of opportunity and as a channel of vulnerability, depending on the nature of the shock, the sectoral composition of trade, and the capacity for adjustment (Di Pietro et al., 2021; Eraydin, 2016; Pontarollo & Serpieri, 2020; Tupy et al., 2021; Tuysuz et al., 2022).

The crisis-specific impact results in Appendix Table B6 show that some factors may matter in particular crises without qualifying as common factors. Services-trade exposure, for example, shows selected negative crisis-specific effects, but these results are sensitive to the spatial weight matrix and are not supported by a robust total effect in the common-effect model (Table 3). Social and health conditions also exhibit selected crisis-specific direct effects but, unlike services-trade exposure, retain a stable positive direct association in the common-effect model. Appendix Table B9 provides additional context-specific evidence for public-service stabilisation in selected recovery and reorientation outcomes.

Overall, the crisis-heterogeneity evidence supports a qualified interpretation of common regional factors. The common-effect model identifies factors that recur broadly across the full pooled system. However, Appendix Table B6 and Appendix Table B3 show that their strength and spatial channels differ between the GFC and COVID. This finding is consistent with the conceptual distinction between resilience as a general regional capacity and resilience as a shock-specific outcome (Martin, 2012; Martin et al., 2016). The empirical results, therefore, support common-average relevance rather than literal crisis invariance.

4.3.2. Resilience-dimension heterogeneity

The SI-dimension-interacted model (Eq. 20) provides strong evidence that resilience determinants differ across dimensions. Appendix Table B3 shows that the SI-dimension x X block, the SI-dimension x WX block, and the combined SI-dimension proxy-interaction block are all jointly significant across all W. These tests indicate that resistance, recovery, reorientation, employment-based renewal, and GDP per capita-based renewal are not governed by identical factor structures. This is consistent with the multidimensional view of regional resilience, in which the capacity to withstand a shock, recover from it, reorient economic activity, and generate renewal may depend on different underlying regional attributes (Martin, 2012; Sensier et al., 2016; Webber et al., 2018; Xiao et al., 2018).

The dimension-specific impacts in Appendix Table B7 show that the main common factors reappear across dimensions, but not uniformly. Relative specialisation is most visible in recovery and renewal. In the recovery dimension, Appendix Table B7 reports positive direct, indirect, and total effects across all W. Employment-based renewal shows the same robust pattern, with positive direct, indirect, and total

effects across all three W matrices. GDP per capita-based renewal also shows positive spillover and total effects. These results indicate that specialised capabilities are particularly relevant for post-shock adjustment and renewal, rather than for all dimensions equally. This finding is consistent with evolutionary resilience arguments that renewal depends on the capacity to redeploy existing capabilities into new or reconfigured activities (Martin, 2012; Xiao et al., 2018). Specialisation appears less as a generic shield against shocks and more as a capability base for recovery and renewal.

R&D intensity also has a dimension-specific profile. Appendix Table B7 shows the positive resistance direct effects, the positive recovery indirect and total effects, and the positive employment-renewal direct, indirect, and total effects. This suggests that innovation capacity contributes to both immediate resilience and longer-run adjustment, but through different channels across dimensions. The resistance result indicates that innovation-intensive regions may be better positioned before the shock, perhaps because they have more productive firms, more adaptable organisations, or stronger knowledge infrastructures. The recovery and renewal results suggest a more dynamic role in which innovation capacity supports reorganisation, diffusion, and labour-market adjustment. These findings complement the common-effect evidence in Table 3 and reinforce the interpretation of R&D intensity as one of the most robust positive factors.

Investment intensity remains negative across several dimensions. Appendix Table B7 reports persistently negative effects on resistance, recovery, and GDP-per-capita-based renewal, particularly through indirect and total channels. This strengthens the interpretation from Table 3, which holds that investment intensity captures exposure or vulnerability rather than resilience-enhancing capacity. The dimension-specific results are important because they show that the negative association is not confined to one outcome type. It appears in the ability to resist, recover, and renew GDP per capita performance. The spatial spillover nature of the effect in Appendix Table B7 suggests that investment-related vulnerability may be embedded in broader regional systems, possibly through shared sectoral cycles, connected capital markets, or interregional demand linkages.

Industrial concentration is negatively associated with specific dimensions. Appendix Table B7 shows negative recovery direct effects and negative reorientation indirect and total effects. This indicates that concentration is most clearly associated with weaker post-shock recovery and weaker capacity for structural reorientation. This finding fits the argument that diversified economies may have more alternative adjustment paths, while concentrated economies may face greater lock-in when the dominant activity is adversely affected (Martin et al., 2016; Sensier et al., 2016). The common-effect direct concentration result in Table 3 is therefore not merely an average association. Appendix Table B7 suggests that the negative concentration-resilience link is especially relevant for recovery and reorientation.

Social and health conditions are most visible in the renewal dimensions. Appendix Table B7 shows positive direct effects for employment renewal and GDP per capita-based renewal. This suggests that favourable social and health conditions may be particularly important for longer-run regional renewal rather than for all forms of resilience equally. The result is consistent with the idea that healthier and socially stronger regions may sustain labour-force participation, institutional capacity, and human capital retention during prolonged adjustment (Giannakis & Bruggeman, 2020; Martin et al., 2016; Muštra et al., 2023; Sabatino, 2019; Stanickova & Melecký, 2018). The common-effect result in Table 3 already shows a positive direct association, and Appendix Table B7 clarifies that this association is concentrated in renewal-related dimensions.

Goods-trade and manufacturing-capital exposure shows a dimension-specific result that does not appear as a robust common factor in Table 3. Appendix Table B7 reports positive recovery direct, indirect, and total effects across W matrices. This suggests that, although goods trade and manufacturing capital exposure are not common-pooled factors, they may matter specifically for recovery. This is plausible because manufacturing capital and goods-trade linkages can support a rebound when demand returns, even if they also expose regions to international cycles. The absence of a robust common-effect impact in Table 3 indicates that this recovery-specific association does not generalise across all resilience dimensions.

Services-trade exposure interaction is also dimension-specific. Appendix Table B7 shows negative direct effects for GDP per capita-based renewal across W matrices. However, the corresponding indirect and total effects are not significant. This suggests a local negative association with one renewal

dimension, but not a broader spatial or pooled pattern. The evidence is therefore more consistent with specific exposure than with a general resilience factor.

4.3.3. Robustness to dimension-specific spatial dependence

The SI-specific-rho model (Eq. 22) reinforces the conclusion that spatial dependence itself varies across resilience dimensions. Equality of the SI-specific rho terms is rejected across all W matrices (Appendix Table B3). Resistance and reorientation have the largest spatial autoregressive parameters, while employment-based renewal has the weakest and least robust spatial dependence.

Crucially, Appendix Table B8 also shows that the main common factors survive this more flexible spatial-dependence structure. Relative specialisation retains strong positive total effects across all five dimensions. R&D intensity also shows positive total effects across dimensions, while investment intensity shows negative total effects. Social and health conditions continue to have positive direct effects. This is important because it demonstrates that the common-effect findings in Table 3 are not artefacts of imposing a single ρ across all resilience dimensions. Even when spatial autoregressive dependence is allowed to differ by dimension, the main associations remain consistent.

The dimension-heterogeneity results, therefore, sharpen the paper's central claim. Common factors exist, but they do not operate identically across resistance, recovery, reorientation, and renewal. Relative specialisation and R&D intensity are most strongly linked to recovery and renewal channels. Industrial concentration is most clearly detrimental for recovery and reorientation. Investment intensity is a broad vulnerability factor, particularly through spatial and total channels. Social and health conditions are a local renewal-related factor. This interpretation aligns with multidimensional resilience research, which treats resilience not as a single outcome but as a family of related adjustment processes (Martin, 2012; Sensier et al., 2016; Webber et al., 2018).

4.4. Joint crisis-dimension heterogeneity diagnostic

The full COVID x SI-dimension interacted model provides a useful diagnostic check, but it is not treated as the primary basis for interpretation. Appendix Table B9 reports selected robust impacts, while Appendix Table B3 reports strong joint significance for the COVID x SI interaction blocks. The joint COVID x SI x X block, the joint COVID x SI x WX block, and the combined COVID x SI proxy-interaction block are all significant across all W. This confirms that the factor-resilience associations vary jointly by crisis and resilience dimension. The evidence is therefore incompatible with a strict invariance interpretation.

At the same time, Appendix Table B4 shows that the full COVID x SI-dimension interacted specification is highly parameterised and affected by severe multicollinearity. The maximum VIF in the full proxy-related block is 176.581 under W^{DB}, 168.978 under W^{DBL}, and 272.534 under W^{DBI}. These values are much larger than those in the common-effect model and the SI-specific-ρ model. The residual Moran's I values in Appendix Table B2 are again close to zero, indicating that the spatial specification absorbs residual spatial autocorrelation. However, the bootstrap evidence for ρ is weak in the full interacted model. This combination implies that the model is valuable for detecting heterogeneity, but less reliable for ranking individual factor effects.

The full interacted impacts in Appendix Table B9 nevertheless provide useful triangulation. Some patterns from the main and intermediate models reappear. R&D intensity is positive across several GFC-related contexts, particularly in the context of resistance. Relative specialisation shows a positive association with selected GFC resistance effects. Public-service stabilisation is positive in reorientation-related contexts. Investment intensity remains negative in selected COVID recovery and reorientation contexts. The services-trade exposure interaction is negative for the COVID GDP per capita-based renewal. These patterns are compatible with the broader interpretation from Table 3, Appendix Table B6, and Appendix Table B7. However, they are more fragmented because the full interaction model divides the evidence into many crisis-by-dimension blocks.

The full COVID x SI-dimension interacted model also shows why the common-effect results should be understood as average-pooled regularities. A factor can be robust in the common-effect model because it has a strong average association across the full resilience system, yet appears only in selected crisis-

dimension blocks. Conversely, a factor can matter in a particular crisis-dimension context without becoming a robust common factor. Goods-trade and manufacturing-capital exposure, services-trade exposure interaction, labour-market participation, and public-service stabilisation illustrate this distinction. They appear in some heterogeneity checks, but they do not have stable direct, indirect, or total effects in the common-effect model.

The evidence supports a common resilience-factor structure, but not a fully invariant one. Table 3 and Appendix Table B1 identify the main pooled associations. Appendix Table B6 shows that crisis-specific channels differ, particularly in the spatially lagged factors. Appendix Table B7 shows that the determinants vary across resistance, recovery, reorientation, and renewal. Appendix Table B9 confirms deeper crisis-by-dimension heterogeneity, but with severe multicollinearity. Appendix Table B8 shows that the main conclusions hold when ρ differs across resilience dimensions.

Across these layers of evidence, relative specialisation and R&D intensity are the most robust positive factors. Their strongest associations are spatial, as shown by the large indirect and total effects in Table 3 and their persistence across WDBL and WDBI. Industrial concentration is negatively associated with resilience, primarily through direct effects (see Table 3), with additional dimension-specific evidence in Appendix Table B7. Investment intensity is consistently negative, especially in the indirect and total effects (see Table 3), and this negative association reappears across several dimension-specific results (see Appendix Table B7). Social and health conditions provide a stable, positive, direct association (see Table 3 and Appendix Table B8), with the strongest dimension-specific evidence in renewal outcomes. Public-service stabilisation has positive but W-sensitive spillover evidence and should be treated as a not-very-robust result.

By contrast, within-country governance advantage, tourism spatial intensity, demographic dependency, goods trade and manufacturing-capital exposure, and the interaction between services trade exposure and these factors do not qualify as robust common-pooled factors. Some of these variables appear in selected crisis- or dimension-specific specifications, but the evidence on their impact in Table 3 does not support a stable, common interpretation. The results do not suggest that only a few variables ever matter for resilience. Rather, they show which factors are sufficiently stable across the pooled multi-crisis, multi-dimensional system to be interpreted as broadly recurrent resilience factors.

The overall pattern fits the core message of contemporary regional resilience research. Resilience is not a single property, and regions do not respond to all crises through the same mechanisms. Structural composition, specialised capabilities, innovation capacity, social conditions, and investment exposure all matter, but their effects are mediated by spatial interdependence and by the type of resilience outcome considered. The empirical contribution of the SDM framework is that it separates own-region associations from spillover and total effects, showing that several of the most important factors, especially relative specialisation, R&D intensity, and investment intensity, operate predominantly through spatially mediated channels. This reinforces the view that regional resilience is relational as well as local, and that common factors should be understood as recurrent conditional associations within an interdependent regional system rather than as universal constants.

These findings provide qualified support for the general-capability expectation and strong support for contextual activation and spatial interdependence. The baseline model identifies recurrent average associations for relative specialisation, R&D intensity, industrial concentration, investment intensity, and social and health conditions. However, the significant crisis-and-resilience-dimension interaction blocks indicate that these associations are not invariant in magnitude or spatial channel. The large spatial autoregressive parameter and indirect effects further demonstrate that regional resilience is relational: both resilience outcomes and pre-crisis capacities are connected across regions. The results therefore answer the central research question by identifying a common but contextually activated and spatially mediated resilience-factor structure.

5. Policy implications

First, the negative association between industrial concentration and resilience supports the importance of diversification and strategies that reduce excessive structural dependence. At the same time, it does not imply that all forms of specialisation are undesirable, since the positive evidence for relative

specialisation points to a more selective policy. Since the strongest results operate through indirect and total effects, suggesting that specialised regional capabilities may be resilience-enhancing when embedded in a wider spatial system, the relevant policy issue is therefore not a simple diversification-versus-specialisation trade-off, but the quality, complementarity, and connectivity of specialised activities.

Second, R&D intensity has one of the clearest positive profiles. Its direct, indirect, and total impacts are positive in the common-effect model, and the spillover evidence is particularly strong. This supports policies that strengthen regional innovation capacity while also facilitating interregional diffusion, knowledge exchange, and absorptive links. The spatial evidence cautions against treating innovation policy as purely local.

Third, the negative impacts of investment intensity are large and robust, especially through spillover and total effects. This pattern does not warrant a generic reduction in investment. Rather, it suggests that pre-crisis investment intensity may capture several forms of regional exposure, including cyclical sensitivity, capital-allocation vulnerability, overheating, and spatially transmitted competitive pressures. The negative spillover effects also allow for an interpretation in terms of neighbouring-region displacement or attraction effects: investment-intensive connected regions may draw firms, labour, demand, or capital away from other regions, thereby reducing the resilience potential of surrounding or economically linked territories. At the same time, the negative direct effects indicate that this is not only a zero-sum interregional competition mechanism; high investment intensity may also reflect local vulnerability within the investing region itself. Policy attention should therefore focus less on reducing investment per se and more on improving investment quality, avoiding spatially uneven or overheated capital formation, and coordinating investment strategies across connected regions so that investment strengthens system-wide resilience rather than redistributing resilience capacity between neighbouring regions.

Fourth, social and health conditions exhibit a stable, positive, direct association. This supports the view that favourable social and health environments are part of regional resilience capacity, but the weak evidence of spillover implies that these benefits are mainly local in the pooled specification.

6. Conclusion

This paper identifies pre-crisis regional characteristics with recurrent spatial associations across the pooled resilience system. Then it tests the stability of those associations across the Great Financial and Sovereign Debt Crisis, COVID-19, and five resilience indices. The SDM impact framework distinguishes among local associations, spatial spillovers, and system-wide effects.

The evidence supports a common resilience-factor structure, but not a fully invariant one. Relative specialisation and R&D intensity emerge as the clearest positive recurrent factors, particularly in their indirect and total effects. Industrial concentration is negatively associated with resilience, indicating that more diversified structures are generally favourable in the pooled system. Investment intensity is consistently negative, particularly through spillover and total channels, suggesting that high pre-crisis investment intensity may proxy exposure or cyclical vulnerability. Social and health conditions show a positive, direct association, whereas public-service stabilisation provides weaker, W-sensitive evidence of spillover. Several factors that may be relevant in specific contexts, including governance advantage, tourism spatial intensity, demographic dependency, goods trade and manufacturing-capital exposure, and the interaction of services trade exposure, do not qualify as robust common factors in the pooled model.

The heterogeneity checks refine this conclusion. Crisis interactions and SI-dimension interactions are jointly significant, and SI-specific spatial dependence differs across resilience dimensions. The full interacted model confirms extensive heterogeneity but is affected by severe multicollinearity, so it is treated as diagnostic evidence. Overall, "universal" factors should therefore be understood as broadly recurrent and statistically stable across the pooled resilience system, not as identical across every crisis, outcome dimension, and spatial channel.

The main limitations follow from the observational design, the reliance on pre-crisis proxy measures, and the sensitivity of highly interacted models to multicollinearity. The five sensitivity indices are direction-aligned analytical benchmarks rather than a composite welfare measure or causal policy score; the

reorientation indicator captures one specific structural shift, and slope-ratio renewal remains sensitive to small or sign-changing pre-crisis trends. Future research should test alternative proxy sets and spatial structures, explicitly examine endogeneity, and connect spillovers to labour-market networks, supply chains, innovation systems, and institutional coordination.

Author contributions

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Data availability statement

The data supporting the findings of this study are available in the supplementary materials accompanying this article. Additional data and materials are available from the corresponding author upon reasonable request.

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