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SPECIAL ISSUE PAPER

Strengths and weaknesses of EU regional reactivity to shocks

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Abstract
This study introduces the novel concept of regional reactivity to shocks. A region is considered to be much more reactive if it bounced back to the level of labour productivity achieved before a shock in the same or less time than it took to reach the pre-2008 economic crisis peak from an equivalent lower bound. The analysis of the reactivity of the EU-NUTS2 regions reveals a clear spatial pattern. By using a spatial lag model selected via a Bayesian comparison approach, we show that tertiary education and institutional quality are key to promote reactivity. On the other hand, population density acts in the opposite direction. Our results are potentially useful for defining policy strategies that emphasise or refocus the strengths of each region in light of current territorial trends and emerging challenges.

JEL Classification R11 · R12 · C21 · C25

1 Introduction

Current mega trends and emerging global challenges, such as the COVID-19 pandemic, are pushing scholars and policy makers to understand the relevance of economic resilience. In recent years, however, the global economic crisis has been extensively studied in the literature on regional economic resilience, as it altered the growth trajectory and equilibrium of the world economy and affected the stability of administrations at various levels.

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The notion of economic resilience is multi-faceted and can have different policy implications depending on the specific aspects considered. Martin's seminal 2012 paper identifies four main dimensions of regional resilience. Resistance measures the sensitivity of regional economic systems to shocks, recovery investigates the speed with which a region bounces back from a specific shock with respect to the national average, and reorientation is defined as the adaptation of a regional economy after a shock because of resource reallocation. Finally, renewal examines the extent to which a region renews its growth path in the post-crisis period.

This study contributes to the literature by offering a further perspective on regional recovery by proposing a new indicator that examines the timing and strength of regions' response to the crisis compared to past performances, which we define as reactivity. Moreover, after mapping our indicator and formally testing whether it exhibits a significant spatial pattern, we rely on a spatial autoregressive model, chosen via a Bayesian comparison approach (LeSage 2014; 2015) to test the most relevant variables identified in the resilience literature to determine which ones facilitated European regions' early reaction to the global crisis.

Accordingly, a region is considered to be much more reactive if it bounced back to the level of economic performance achieved before a shock in the same or less time than it took to reach the pre-shock peak from an equivalent lower bound. This approach has several advantages as it overcomes some of the limitations of the widely used measurement of recovery, namely that medium- and long-term trends are linearly approximated and that the period considered for the calculation of the average growth identified a priori. Furthermore, unlike Martin et al. (2016), our indicator relates the post-shock interval to the corresponding pre-shock interval, rather than considering only the expansionary movements or the recessionary contractions separately. Moreover, the resistance and recovery indicators are often rescaled or compared to the national or European average (Martin et al. 2016), although authors such as Crescenzi et al. (2016a, b), Annoni et al. (2019) and Cutrini (2023) did not. Although national contexts undoubtedly influence regional resilience, we chose to do not apply any kind of "standardisation" or rescaling factor.[1] There are several reasons for this. First, since, unlike most of the previous literature on resilience, we do not rely on only one phase, i.e. the pre- or post-shock time interval, but we consider both, we did not want to add further complexity to our indicator, with the aim of creating an easily interpretable measure. A similar approach has already been used by Pontarollo and Serpieri (2019; 2021), whose indicator compares pre- and post-shock periods. Second, several European countries have only one or a few regions. In addition, even if possible for large countries, cantering or scaling variables at the national level as in Martin et al. (2016) would risk to artificially removing possible cross-border spill-over effects. This may be a problem as spatial dependence is a well-known feature of regional economic resilience, regardless of its measure. Recent examples include Cutrini (2023) who finds high spatial dependence in the average annual growth rate of per capita GDP between 2010 and 2016

[1] The specific country characteristics are considered in the estimation strategy, as it will be shown in the rest of the paper.

and emphasises the positive role of institutional quality. Ezcurra and Rios (2019) and Giannakis and Papadas (2021) confirm the spatial dependence for the resistance dimension. While the former again highlight the role of institutional quality, the latter emphasise the importance of markets accessibility. Spatial dependence is also confirmed for regional renewal by Pontarollo and Serpieri (2019; 2021), who find that diversification and tertiary education contributed to the renewal of the growth path of European regions, while gender gap in unemployment had a negative effect. Strong positive regional spill-overs exist also in the resistance and recovery of Eastern European regions from the COVID-19 pandemic (Brada et al. 2021).

The remainder of this paper is organised as follows. The next section introduces the concept of reactivity. The third section presents the empirical estimation technique and the data employed. The fourth section details the results of the empirical analysis. Finally, we conclude and provide policy implications in the closing section.

2 Reactivity capacity

Previous research evaluates several dimensions of regional resilience by comparing indices and rates. Martin et al. (2016) measured resistance as the ratio of decline in employment or output in a region to the respective decline in the country as a whole; therefore, a region is considered resistant if it ranks higher than other regions or the national average. Instead, Ezcurra and Rios (2019) use the average European level as a benchmark. The main limitation of this method is that it only focuses on a region's capacity to limit economic decline but not the recovery in subsequent years. Notably, according always to Martin et al. (2016), recovery is achieved if the average growth rate after a shock is better than that before the shock, both of which are measured in the medium term and rescaled with respect to the national or European average. The limitations of this method are that it only works over a reasonably long time period of time (or with high-frequency data), and it requires identifying a priori the period to be considered for the calculation of the average growth.

The renewal dimension, theoretically introduced by Martin (2012), is operationalised by Pontarollo and Serpieri (2021) as the difference between the slopes of the trends before and after the crisis. As for recovery, this dimension is measured assuming that the trends in the medium term are approximated linearly and tend to be stable. This simplification could lead to ambiguous results regarding the real growth trajectory and economic level reached after the shock. However, this conceptualisation uses neither national nor European benchmarks.

The novel measure of reactivity herein proposed can be considered a more comprehensive facet of recovery within the broader resilience literature. It is computed as the ratio between the post-shock interval, identified with the time span needed to return to pre-crisis GDP per employee rates and the pre-shock interval, defined by the timing to reach the pre-crisis GDP per employee peak, starting from the same lower bound. If the first time interval is equal or lower (greater) than the second one, a region is considered as (less) much reactive. Reactivity is thus a positive continuous variable, with values greater than one indicating that a region took longer to react to the shock under analysis than in the past and, conversely, values equal to (less than) one indicating the same (stronger) reaction than in the past.

Unlike resistance or recovery, reactivity uses information about both the post- and pre-shock intervals, and unlike renewal, it does not require a priori identification of time spans to calculate pre- and post-shock trends. The graphical representation in Fig. 1 illustrates the scenarios to better determine whether and how much regions react.

The x-axis represents the time, and the y-axis denotes the level of GDP per employee. The black curve illustrates the evolution of the GDP per employee across time in three different cases. Starting from the beginning of the time period under analysis (in t_0), the first upward movement illustrates the economic growth of a region prior to the exogenous shock, which causes the regional GDP per employee level to reach the minimum at t_0'. The time needed to reach the positive economic peak is represented by the time period t_0T.

From t_0' onwards, three different representative reactivity patterns are presented. In case 1, a region is strongly reactive as it took less time to reach the pre-shock economic level compared to the time needed to reach the same economic level prior to the crisis (i.e. $t_0'T_1 < t_0T$). In case 2, the two time intervals are equal; thus, the region is considered reactive but to a lesser extent than before, while in the third case, given that $t_0'T_3 > t_0T$, where T_3 is the end of the period under analysis, the region has not yet reacted.

Figure 1 is only illustrative given that, as a consequence of the economic crisis, different regions naturally experience different negative peaks in time, which corresponds to the t_0' for each region, and strength. Therefore, the relevant t_0 for each region is identified going backwards in time from t_0' to obtain the approximately equivalent lower bound.

To further clarify, imagine that a region i reaches a GDP per employee of 15,000 in 2008. As a consequence of the crisis, it falls to 12,000 in 2010 and then starts to grow again reaching 15,000 in 2016, i.e. it takes 6 years to recover to the pre-crisis

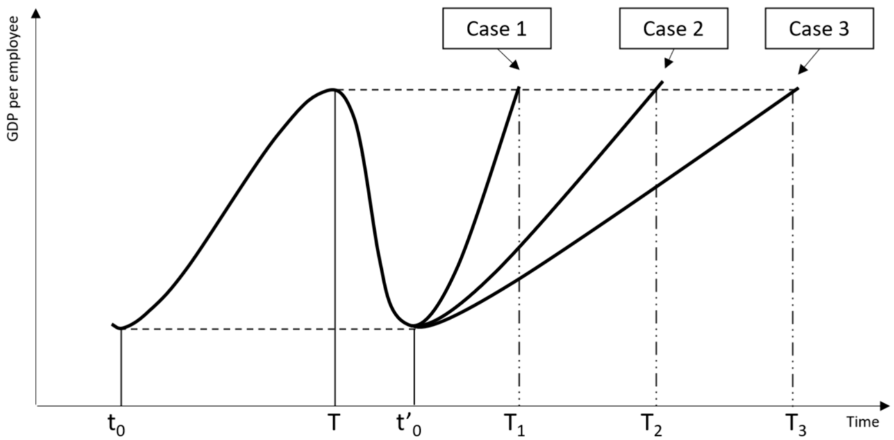

Fig. 1 Reactivity capacity (colour figure online)

level. Now we have to go back in time to identify the year before the positive peak of 2008 when the same region had a GDP per employee of approximately 12,000. Let's suppose 2004. The pre-crisis time span is thus 2004–2008, a 4-year interval. We compute reactivity as the ratio between the post-shock interval and the corresponding pre-shock. In the example, the value corresponds to $6/4 = 1.5$, meaning that the region took 50% more time to reach the same level of GDP per employee as before the global financial crisis.

Our approach departs from Martin et al. (2016)[2] by considering two different time intervals where the past is assumed to be the counterfactual, attempting to somehow incorporate the persistence of regional responsiveness and thus some dynamics into the resilience process that is formulated through learning over time. It is worth noting that the approach, although novel, suffers from the limitation of not considering the heterogeneity of different shocks that have occurred over time. In particular, the factors that helped regions respond to the financial crisis in the past may not necessarily react with the same intensity in the aftermath of the COVID-19 pandemic crisis, which has been configured as an exogenous shock with absolutely unique characteristics. In addition to this, we let to future research the attempt to investigate regional reactivity to COVID-19, which, due to the non-availability of data for a sufficiently long time horizon, is out of the scope of the present paper since it requires different Machine Learning forecasting techniques.

A preliminary exploratory analysis of the regional reactivity dynamics is provided in Fig. 2. The red (yellow) colour illustrates regions that were less (more) able to react to the 2008 crisis than the past. Spain, Germany, Poland, and Sweden are the countries where the majority of regions strongly reacted. In contrast, regions of Italy (apart from Lombardy), France, Finland, Greece, and the Baltics poorly react.

The comparison of our reactivity measure with the newly developed regional development trap indicator (DT1) by Diemer et al. (2022) shows that many of the reactive regions correspond to those in the development trap. This confirms the goodness of fit our indicator, as it is conceivable that trapped regions are less able to react expediently to shocks.

3 Methodology and data

Given the spatial pattern visually identified in the previous section, we check its statistical significance by using the Moran's I. It is equal to 0.403 (p-value < 0.01), indicating that regions with similar levels of reactivity are located close to each other.[3] This spatial dependence will be accounted for in the econometric specification. Precisely, in addition to the standard Lagrange Multiplier (LM) test, we rely on a more recent and sophisticated Bayesian comparison approach (LeSage 2014; 2015) to identify the type

[2] As mentioned above, Martin et al. (2016) consider the expected nationwide expansion (contraction) as a counterfactual to the average regional growth after (from) the shock and focus only on single episodes.

[3] Moran's I is based on a row-standardised k nearest neighbour of order 10 spatial weight matrix **W**. As is customary, the matrix **W** is row-standardised by row and vary between − 1 and 1.

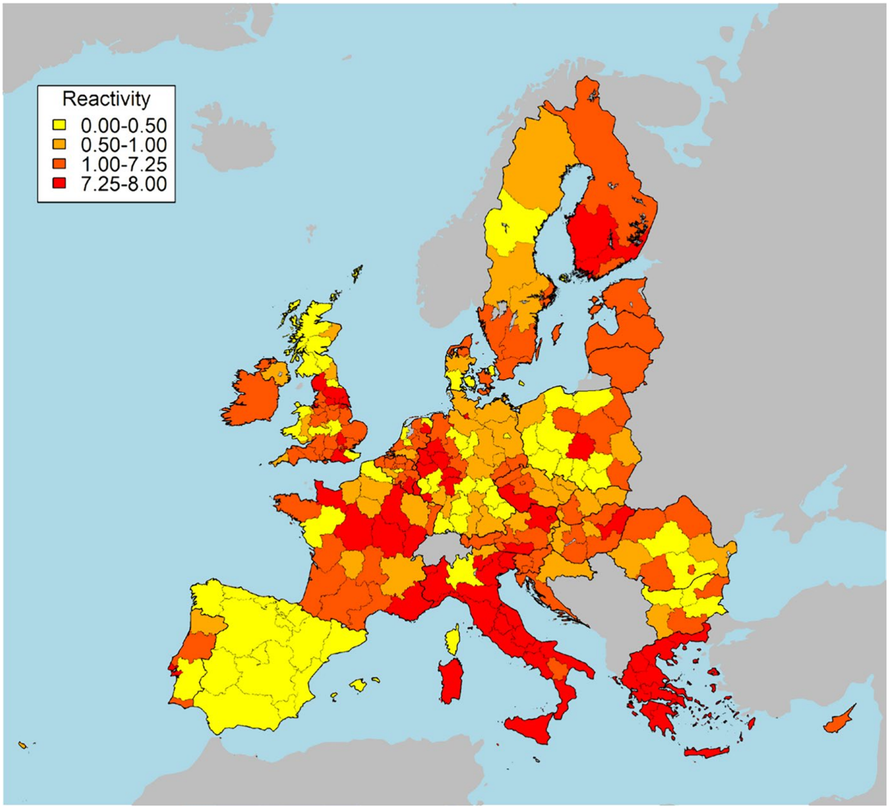

Fig. 2 Reactivity capacity in the GDP per employee of EU-NUTS2 region over the 2000–2017 period (colour figure online)

of spatial dependence to be modelled. We compare five alternative models: a spatial lag model (SLM), a model with spatial lags of explanatory variables (SLX), a spatial error model (SEM), a spatial Durbin model (SDM), with spatial lags of explanatory variables plus spatial lagged values of the dependent variable, and a spatial Durbin error model (SDEM) that combines spatial lags of explanatory variables and spatial dependence in the model disturbances. The log-marginal likelihood is the key metric that allows us to compare various spatial models. The probabilities, based on the log-marginal likelihood obtained by integrating all the parameters of the model over the entire parameter space on which they are defined, are normalised to 1, with the normalisation being based on the (nonlinear) property of the Bayesian posterior approach. As it will be shown in the section dedicated to the empirical results, the model that best suits the data is a SLM:

$$\text{Reactivity}_i = \zeta + \rho \boldsymbol{W}\text{Reactivity}_i + \delta \boldsymbol{X} + \varepsilon_i \tag{1}$$

where Reactivity$_i$ is a vector of size ($N\times 1$), $i=1,\ldots$, and N is the number of regions.[4] *Reactivity* is measured using GDP per employee in 2005 constant euro prices as a measure of labour productivity. The rationale for selecting GDP per employee as dependent variable rather than GDP per capita relies on the fact that employment rather than population experiments more pronounced cyclical movements and adjustments in recessionary contractions. In addition, productivity is a key economic indicator that has not been thoroughly examined by the regional economic resilience literature. Furthermore, the aim is to provide broader policy implications as well-designed and complementary policies may intervene on different sectors and markets without limiting the analysis to the labour market, as would be the case if employment were chosen as the dependent variable. Finally, we select GDP per employee also in line with recent interesting publications by Crescenzi et al. (2016a, b) and Giannakis and Mamuneas (2022) who use the same dependent variable in the context of economic resilience.

The exogenous $N\times N$ row-standardised spatial weight matrix $\boldsymbol{W}$, as mentioned above, is based on a k nearest neighbour of order 10. ρ is the spatial autoregressive coefficient and, as we use a row-normalised weight matrix, it is bounded between -1 and 1. δ is a ($k\times 1$) vector of parameters associated with the ($N\times k$) data matrix $\boldsymbol{X}$, which we will specify below. The error term (ε_i) is assumed to be normally distributed with a mean of 0 and unit variance. Equation (1) is estimated with a standard maximum likelihood approach (ML) (Anselin 1988).

Due to the presence of the spatial autoregressive parameters in the dependent variable, the marginal effect of an explanatory variable X_r belonging to vector $\boldsymbol{X}$ is defined as:

$$\frac{\partial Y}{\partial X_r'} = (\boldsymbol{I} - \rho \boldsymbol{W})^{-1}\boldsymbol{I}\beta_r = \left(\boldsymbol{I} + \rho^2\boldsymbol{W}^2 + \ldots + \rho^N\boldsymbol{W}^N\right)\boldsymbol{I}\beta_r. \tag{2}$$

where $\boldsymbol{I}$ is the identity matrix of size $N\times N$. LeSage and Pace (2009) define the direct effect as the mean of the diagonal elements of (2) and the indirect effect as the mean of the off-diagonal elements, where the off-diagonal row elements are summed up and then an average is taken. The sum of the direct and indirect effects gives the average total effect. $\boldsymbol{X}$ contains a set of explanatory variables which are expressed in 2005 constant euro prices.[5] Given that these variables aim to explain the reactivity after the 'Great Recession' (after 2008), referencing Pontarollo and Serpieri (2021), we take the average annual values between 2000 and 2007.

GDP per employee growth has been included to capture the productivity path prior to the crisis. Whether pre-crisis productivity has a positive or negative effect on the regions' resilience capacity is rarely examined in the literature. We expect that regions with a higher pre-crisis GDP per employee are able to better react to shocks, consistent with the results of Giannakis and Papadas (2021). However, Annoni et al. (2019) and others have found that less developed regions recover and grow faster

[4] Ireland, Cyprus, the Baltic Republics, and Finland are excluded from the sample due to missing data.

[5] See Tables 5 and 6 in Appendix for data sources, descriptive statistics, respectively.

than others. In addition, pre-shock productivity trend serves also to proxy for the parameter of scale.

Another key element, particularly relevant for a monetary union, is the trade openness that we computed as the ratio of the sum of regional exports and imports of goods and services at constant prices over gross value added. In this specific context, trade openness boosts the integration of product markets, thus fostering economic integration, increasing the benefit from a common currency, and synchronising cycles that reduce the cost of giving up independent currencies (McKinnon 1963). Furthermore, international trade also favours the exchange of knowledge (Yanikkaya 2003) and technology (Di Liberto 2005). Referencing Soukiazis and Antunes (2011), international trade gives regions the opportunity to specialise with resulting comparative advantage, in addition to collaborating in innovative investments.

To this regard, however, specialisation can also be problematic as a high degree of specialisation implies that the impact of sector-specific shocks may be relatively big (Kenen 1969), and difficult to be absorbed by regional economies. In fact, a diversified economy guarantees flexibility and adaptability of the regional economic structure as a consequence of more balanced business risk-sharing and workforce distribution across sectors. To this extent, to measure the degree of diversification we rely on the inverse Hirschman–Herfindahl index calculated on six sectors.[6] It takes the maximum value of 6 if workers are equally distributed across sectors, and 1 if they are concentred in just one.

Another variable commonly considered in the context of regional resilience is the capacity to innovate, which can foster productivity. Following Lach (1995), we rely on patent data, as the author found that the contribution of knowledge to productivity is larger than that obtained when knowledge is measured by the R&D stock. Hasan and Tucci (2010) argue that patents highlight both the quantity and quality of modernisation capacity, providing evidence of a positive relationship with countries' economic growth rate. On the other hand, in the context of resilience, Rocchetta et al. (2022) show that regions endowed with technologically coherent capabilities adapted better in times of economic downturn, and that resilience is influenced by a region's capacity to generate new growth paths. In our analysis, to proxy for the regional propensity towards innovation, we follow Crescenzi et al. (2007) by relying on patents per million of active population.

Along the same line, the share of people that have attained secondary and tertiary education proxies for regions' human capital endowment and workforce capabilities (di Liberto 2005). Referencing Bristow and Healy (2018), a well-educated workforce is considered to be an engine of economic growth as it is correlated with the introduction of new technologies. Education is defined by Crescenzi et al. (2016a, b)

[6] The inverse Hirschman–Herfindahl index is the reciprocal of the sum of the square of the sectoral employment share. We consider the following six NACE Rev. 2 sectors: agriculture (A), manufacturing & energy (B–E), construction (F), distribution, communications and transport (G–J), financial & business services (K–N), and non-market services (O–U).

Table 1 Log-marginal likelihood for spatial models

Matrix	SLX	Spatial lag	SDM	Spatial error	SDEM
knn = 10	0	0.733	0	0.267	0

Tests are performed on specification (1) in Table 8

as a soft aspect of human capital, and it is widely recognised as a fundamental driver of resilience and economic growth.

If so far, we have focussed on soft elements essentially related to knowledge and innovation production, we must also consider gross fixed capital formation (as a percentage of GDP), which may influence a prompt responsiveness to the crisis. Investments increase productivity and efficiency by producing more goods and services at a lower cost, which favours economic growth and higher living standards (Solow 1956; Swan 1956). Nevertheless, the evidence of persistent patterns of regional inequality within and between countries challenges this prediction from the neoclassical theory (Iammarino and Storper 2019). In fact, the latter assumes adjustment mechanisms such as the flow of labour and capital to places where these factors are scarce, which are rather weak and limited in the real world. Frictions like institutional frameworks, social norms, regulations, etc., seriously limit the functioning of labour and capital markets across space.

Another potential determinant of resilience as well as economic growth is the share of employment in manufacturing. This sector produces tradable goods and offers the inputs for other fields. Moreover, it also opens the possibility of developing economies of scale (Szirmai and Verspagen 2015).

Population density is also considered among the factors possibly affecting reactivity. It represents agglomeration economies that can lead to higher degrees of innovation and productivity development due to a larger market. As cities usually record a higher population density, this dimension also accounts for the urban–rural divide. Cities tend to have a higher degree of productivity because firms benefit from being located in a denser area (Rodríguez-Pose 2017). In contrast, agglomeration can also result in negative effects such as congestion from higher traffic and higher cost of living (Bosker 2007). However, recent results by Giannakis and Mamuneas (2022) show that agglomeration is positive for resilience in the EU as expressed by labour productivity growth.

Finally, the regional quality of government index is deeply analysed by Ezcurra and Rios (2019) and Cutrini (2023) in the context of resilience. The authors demonstrate its strong correlation with resilience. High-level institutions promote financial stability by regulating capital markets and combatting corruption. They can also affect firms' systematic uncertainty and investment decisions by developing competition rules. Institutional quality has also an impact on judicial systems efficiency. As the regional quality of government index is based on ad hoc surveys that are representative at the regional level and acknowledging that institutional quality changes very slowly over time (North 1990), we rely on 2010 data by Charron et al. (2014; 2015), which is the first to be computed and published at NUTS2 level. Institutional quality is a multidimensional indicator including three sub-indices that account for

Table 2 Regression results—spatial autoregressive model

	(1)	(2)	(3)	(4)
Constant	−22.648***	−19.378***	−20.689***	−19.160**
	(7.672)	(7.371)	(7.809)	(7.571)
Log(GDP per empl.)	2.431***	2.212***	2.191***	2.039***
	(0.756)	(0.731)	(0.766)	(0.743)
Gross Fixed Capital form.	2.289	0.341	1.748	4.676
	(4.682)	(4.716)	(4.741)	(4.753)
Empl. Manufacturing	−0.011	−0.020	−0.013	−0.009
	(0.027)	(0.027)	(0.027)	(0.027)
Log(Patents)	−0.331	−0.282	−0.367	−0.332
	(0.273)	(0.273)	(0.275)	(0.274)
Share sec. edu.	0.218***	0.193***	0.254***	0.167**
	(0.071)	(0.070)	(0.075)	(0.071)
Share sec. edu.^{2}	−0.002***	−0.002***	−0.003***	−0.002**
	(0.001)	(0.001)	(0.001)	(0.001)
Share ter. edu.	−0.168***	−0.156***	−0.183***	−0.160***
	(0.035)	(0.036)	(0.035)	(0.035)
Trend GDP per empl.	−0.011	−0.145	0.053	0.005
	(0.168)	(0.172)	(0.170)	(0.169)
Log(pop. density)	0.397**	0.337*	0.427**	0.463***
	(0.174)	(0.176)	(0.175)	(0.174)
DI	−0.110	−0.080	−0.128	−0.098
	(0.170)	(0.169)	(0.172)	(0.171)
Trade openness	−0.00002	−0.00001	−0.00001	−0.00003
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Reg. QoG	−0.800***			
	(0.238)			
Control of Corruption Axis		−0.943***		
		(0.261)		
Quality Axis			−0.551**	
			(0.227)	
Impart Axis				−0.556**
				(0.222)
Rho	0.3405***	0.3093***	0.4091***	0.4151***
	(0.1011)	(0.1039)	(0.0947)	(0.0951)
AIC	1154.21	1154.21	1154.21	1154.21
Observations	243	243	243	243
Log Likelihood	−558.329	−557.577	−560.833	−560.589
sigma^2	5.733	5.710	5.820	5.805
Akaike Inf. Crit.	1,146.658	1,145.154	1,151.665	1,151.177
Wald Test	11.348***	8.866***	18.668***	19.061***
LR Test	9.556***	7.422***	15.288***	16.242***

Standard errors in brackets

***p < 0.01, **p < 0.05, * < 0.10

the public sector, which include corruption, impartiality in the allocation of public services and the quality of public goods (see Appendix Table 6).

4 Results

In Table 1, the Bayesian posterior model probabilities shows that the preferred model is the spatial lag. This is corroborated by the results of the Lagrange multiplier test shown in Table 9 in Appendix. Table 2 presents the estimates. The spatial lag coefficient (ρ) is always statistically significant and ranges between 0.31 and 0.41; thus, the likelihood of being a reactive region is higher when neighbouring regions are also reactive. Taking as a reference column (1), the spatial multiplier is $1/(1-0.34) \approx 1.50$, i.e. around 50% of the impact of reactivity is correlated with the interaction among neighbours, constituting the so-called indirect effect. This fact is not secondary, indicating that if standard models are mistakenly used instead of spatial models, researchers may risk attributing indirect marginal effects to direct explanatory variables. This could happen when the estimated coefficient is inflated by the fact that it incorporates the indirect spatial effect (see Mobley et al. 2009). Consequently, coefficient estimates cannot be directly interpreted because the partial derivative concerning a given independent variable is an $N \times N$ matrix rather than a scalar, as shown in the previous section; thus, we decompose the marginal effects into direct, indirect and total effects in Table 3.

Before describing the results, it is worth mentioning that if a variable has a positive and significant coefficient, it means that it has a negative impact on reactivity, and vice versa, due to the construction of the reactivity variable (see Sect. 2). Indeed, higher values for the reactivity variable indicate a longer regional recovery time compared to the past.

We observe that the average GDP per employee is positively correlated with regional reactivity mainly via the direct effect. The indirect (or spill-over) effects of (log) GDP per employee are almost half the size and weakly significant. The total effect, representing the sum of the two, is one-third larger than the direct effects. These results demonstrate that initially more productive regions are unable to improve their growth path compared with pre-crisis levels. Furthermore, the trend of GDP per employee, the share of employment in manufacturing and sectoral diversification have no effect on reactivity. After testing for non-linearity in both human capital variables, we found that only secondary education has a concave effect, although tertiary education is key for reactivity. Highly skilled human capital has a strong role in economic growth as well as resilience, regardless of how it is measured (see, among others, Crescenzi et al. 2016a, b). This factor can be considered somewhat sticky, as professional and highly educated people can also migrate as talented individuals seek better economic opportunities, career advancement, or higher quality of life elsewhere. Indeed, the mobility of Europeans is relatively low within the continent.

For instance, around 4% of the labour force was mobile in 2018 and is primarily characterised by middle-skilled workers (EC 2021). Nevertheless, Europe is also experiencing a different complex and dynamic process of "brain drain"

Table 3 Impact estimates

	Direct	Ind	Total	Direct	Ind	Total	Direct	Ind	Total	Direct	Ind	Total
Log(GDP per empl.)	2.460***	1.225*	3.686***	2.232***	1.476*	3.708***	2.079***	1.407*	3.486*	2.233***	0.969*	3.202***
	(0.784)	(0.690)	(1.252)	(0.799)	(0.812)	(1.439)	(0.760)	(0.785)	(1.382)	(0.729)	(0.581)	(1.109)
Gross fixed Capital	2.317	1.154	3.471	1.781	1.178	2.959	4.767	3.227	7.995	0.344	0.149	0.494
	(4.842)	(2.973)	(7.567)	(4.815)	(3.785)	(8.404)	(4.838)	(4.261)	(8.796)	(4.818)	(2.590)	(7.181)
form. Empl. Manuf.	−0.012	−0.006	−0.017	−0.014	−0.009	−0.023	−0.009	−0.006	−0.015	−0.020	−0.009	−0.029
	(0.027)	(0.015)	(0.041)	(0.026)	(0.020)	(0.045)	(0.028)	(0.022)	(0.049)	(0.026)	(0.014)	(0.039)
Log(Patents)	−0.335	−0.167	−0.502	−0.374	−0.247	−0.621	−0.339	−0.229	−0.568	−0.285	−0.124	−0.408
	(0.277)	(0.178)	(0.434)	(0.281)	(0.245)	(0.503)	(0.281)	(0.247)	(0.506)	(0.273)	(0.158)	(0.412)
Share sec. edu.	0.221***	0.110*	0.330***	0.259***	0.171*	0.430***	0.170*	0.115*	0.286*	0.195***	0.084*	0.279***
	(0.068)	(0.054)	(0.101)	(0.074)	(0.076)	(0.126)	(0.072)	(0.062)	(0.121)	(0.071)	(0.045)	(0.098)
Share sec. edu.^{2}	−0.002***	−0.001*	−0.004***	−0.003***	−0.002*	−0.005***	−0.002*	−0.001*	−0.003*	−0.002***	−0.001*	−0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Share ter. edu.	−0.170***	−0.085*	−0.255***	−0.186***	−0.123***	−0.309***	−0.164***	−0.111*	−0.274***	−0.158***	−0.068*	−0.226***
	(0.036)	(0.041)	(0.058)	(0.036)	(0.050)	(0.064)	(0.037)	(0.046)	(0.065)	(0.036)	(0.034)	(0.053)
Trend GDP per empl.	−0.011	−0.006	−0.017	0.054	0.035	0.089	0.005	0.003	0.008	−0.146	−0.064	−0.210
	(0.177)	(0.106)	(0.275)	(0.172)	(0.132)	(0.298)	(0.173)	(0.139)	(0.306)	(0.178)	(0.096)	(0.263)
Log(pop. density)	0.402**	0.200	0.602**	0.435**	0.287*	0.722**	0.472***	0.320*	0.792**	0.340**	0.147	0.487**
	(0.179)	(0.158)	(0.307)	(0.176)	(0.186)	(0.330)	(0.174)	(0.204)	(0.341)	(0.179)	(0.125)	(0.281)
DI	−0.112	−0.056	−0.167	−0.131	−0.086	−0.217	−0.099	−0.067	−0.167	−0.080	−0.035	−0.115
	(0.166)	(0.102)	(0.257)	(0.169)	(0.137)	(0.296)	(0.173)	(0.140)	(0.306)	(0.177)	(0.098)	(0.266)
Trade openness	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Reg. QoG	−0.810s	−0.403*	−1.213***									
	(0.239)	(0.203)	(0.354)									
Quality Axis				−0.562**	−0.371*	−0.933**						
				(0.237)	(0.224)	(0.418)						

Table 3 (continued)

	Direct	Ind	Total	Direct	Ind	Total	Direct	Ind	Total	Direct	Ind	Total
Impart Axis							−0.567**	−0.384*	−0.951**			
							(0.222)	(0.212)	(0.390)			
Control of Corruption Axis										−0.952***	−0.413*	−1.365***
										(0.258)	(0.201)	(0.353)

Standard errors in brackets

***$p < 0.01$, **$p < 0.05$, *< 0.10

("brain gain"), which reflects the movement of highly skilled individuals across borders within the continent or from Eastern to Western Europe (Mayr and Peri 2009). This outflow of human capital has the potential to hinder domestic innovation and economic growth. However, Europe has been lagging behind in its capacity to attract skilled workers, notably from non-EU countries. Implementing effective policies and initiatives to retain talent and encourage knowledge exchange can help alleviate brain drain concerns while maximising the benefits of brain gain for European economies and societies.

However, skilled professionals from other areas in the world could be attracted by European opportunities, academic environment, and living standards, but coordination across the EU in the immigration policies specifically aimed at selecting and attracting highly skilled labour as well as a reasoning in the design of labour market institutions are required to bridging the gap (Boeri 2008). This influx of talent may enrich the resident workforce, foster innovation, and contribute to economic development in host countries.

Furthermore, it is worth mentioning that tertiary education also has a significant indirect and total effect, highlighting that it spill-overs in neighbour regions. Secondary education, on the other hand, has a negative impact (positive coefficient). However, this negative impact is decreasing in size. In contrast, the completely non-sticky factor of patents, which represent firms' innovation capabilities but can be exploited anywhere, does not contribute to making a region more reactive, as in Crescenzi et al. (2016a, b) and Pontarollo and Serpieri (2019), among others. The same reasoning holds for gross fixed capital formation. The direct effect of population density is significantly associated with reactivity. Arguments concerning the benefits of spatial agglomeration on growth, innovation, and productivity have been extensively examined in several disciplines, including economic geography, urban economics, and new economic geography (De Dominicis 2014). Nevertheless, other studies such as Bosker's (2007) and Brülhart and Sbergami (2009) find a negative relationship between agglomeration and growth. In our context, it could be inferred that congestion effects are at play, meaning that population density hampers recovery or improvement in the growth path after the financial crisis.

Contrary to expectations, trade openness is not correlated with reactivity. A possible rationale for this null effect may be that even if regions more exposed to international trade are more vulnerable to the transmission of external shocks through the value chain (Röhn et al. 2015), they can also enjoy opportunities. These two effects may counterbalance themselves.

Institutional quality has a crucial role on reactivity. All dimensions are equally significant and all spill-over. Overall, our results confirm the key influence of regional institutional quality on resilience after the global crisis, as Rios and Ezcurra (2019) demonstrate for resistance and Cutrini (2023) shows for economic growth. Policymakers should therefore understand the importance of investing in quality, fairness, and anti-corruption measures within the local institutions. By doing so, they can improve the ability of local governments to respond effectively to economic challenges and promote reactivity.

5 Robustness

To test for the robustness of our results, we ran the estimations by using three additional matrices, namely a Queen matrix, a Gaussian, and an inverse distance decay matrix with a threshold distance at the first quantile. The results of the LM tests and Bayesian posterior model probabilities are shown in Tables 9 and 10 in Appendix, respectively. The choice of the spatial lag model is confirmed as well as the results in Tables from 11, 12, to 13.

Furthermore, we ran the same estimates adding a dummy controlling for financial distressed countries,[7] i.e. Greece, Portugal, Italy, Ireland, and Spain. Results in Table 4 confirm the previous ones and show that the dummy has a negative impact on reactivity (i.e. a positive sign), highlighting that the limited fiscal capacity to support development policies may hinder regional responsiveness. Robustness checks with different spatial weight matrices are performed also in this case, confirming the results (see Tables 15 and 16 for the LM tests and Bayesian posterior model probabilities tests, respectively, and 17, 18, 19 for the results).

6 Conclusions

Our study presents a novel indicator of resilience, called reactivity, that can be considered as another facet of recovery, comparing the timing and strength of regional labour productivity responses to shocks with past performance. We observe that, as for other measures of resilience, there are clusters of regions with similar degrees of reactivity located close to each other. This spatial clustering is statistically significant, leading us to check if and which spatial model better fits our data. The spatial autoregressive model is identified as preferred by both the Bayesian comparison approach (LeSage 2014; 2015) and a LM test. This means that there is evidence of spatial spill-overs across regions; thus, the likelihood of a region being reactive is higher in the presence of reactive neighbours. This has strong consequences in terms of the impact of the regressors. Indeed, a change in a variable that affects the reactivity of a region also affects neighbours (and the neighbours of neighbours and so on) which then returns to the region itself. Given that regions are not isolated islands, this means that (a) a policy applied to a region i will not only affect just region i, and (b) a policy applied by neighbours will also impact region i. As a consequence, horizontal and vertical policy coordination is essential not just in “normal” times, but especially in times of crisis.

Considering the factors that affect the likelihood of being a reactive region, notably the key role of tertiary education spills over to other regions as well. Regions with highly educated and skilled workforces are better equipped to adapt the economy and take advantage of new opportunities. A well-educated workforce is more likely to learn new skills quickly and to use them efficiently, which is critical for

[7] Distressed countries are defined as those countries experiencing a Gross Public debt GDP ratio greater than 100 in the post-crisis years. Data are collected by AMECO.

Table 4 Regression results—spatial autoregressive models with dummy financial distress

	(1)	(2)	(3)	(4)
Constant	− 20.615***	− 17.635**	− 17.059**	− 19.360***
	(7.614)	(7.309)	(7.820)	(7.414)
Log(GDP per empl.)	1.891**	1.698**	1.498*	1.653**
	(0.769)	(0.746)	(0.791)	(0.738)
Gross Fixed Capital form.	− 1.271	− 2.536	− 1.382	0.444
	(4.692)	(4.710)	(4.740)	(4.722)
Empl. Manufacturing	− 0.034	− 0.039	− 0.036	− 0.033
	(0.027)	(0.027)	(0.027)	(0.027)
Log(Patents)	− 0.208	− 0.178	− 0.229	− 0.179
	(0.271)	(0.271)	(0.274)	(0.270)
Share sec. edu.	0.328***	0.300***	0.339***	0.305***
	(0.076)	(0.077)	(0.078)	(0.076)
Share sec. edu.^{2}	− 0.003***	− 0.003***	− 0.003***	− 0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Share ter. edu.	− 0.142***	− 0.134***	− 0.149***	− 0.127***
	(0.036)	(0.036)	(0.037)	(0.036)
Trend GDP per empl.	0.004	− 0.103	0.04	0.025
	(0.164)	(0.170)	(0.167)	(0.164)
Log(pop. density)	0.391**	0.349**	0.428**	0.441***
	(0.171)	(0.174)	(0.172)	(0.169)
DI	− 0.168	− 0.14	− 0.176	− 0.172
	(0.168)	(0.168)	(0.170)	(0.167)
Trade openness	0.0001	0.0001	0.0001	0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Financial distressed countries	2.690***	2.520***	2.710***	3.270***
	(0.812)	(0.824)	(0.844)	(0.800)
Reg. QoG	− 0.671***			
	(0.241)			
Control of Corruption Axis		− 0.744***		
		(0.267)		
Quality Axis			− 0.318	
			(0.238)	
Impart Axis				− 0.650***
				(0.219)
Rho	0.2205**	0.2121*	0.3053***	0.228**
	(0.1086)	(0.1093)	(0.1019)	(0.1069)
AIC	1139.04	1139.04	1139.04	1139.04
Observations	243	243	243	243
Log Likelihood	− 552.74	− 552.81	− 555.54	− 552.22
sigma^2	5.512	5.518	5.616	5.487
Akaike Inf. Crit	1,137.48	1,137.63	1,143.09	1,136.45
Wald Test	4.122**	3.767*	8.980***	4.548**
LR Test	3.568*	3.207*	7.667***	3.980**

Standard errors in brackets

***$p < 0.01$, **$p < 0.05$, * < 0.10

responding to shocks. For this reason, policymakers should be aware of the importance of successful education systems, aligning programmes to high standards. Investments in human capital are shown to be more effective than investments in physical capital because the former has a higher degree of stickiness than the latter. For the same reason, patents likely have no effect on reactivity. Their null impact on resilience is already demonstrated by Fratesi and Perucca (2018) and Pontarollo and Serpieri (2021), showing that if innovation is fundamental for growth in normal times, it is not correlated with expediently bringing a region out of a crisis. Despite this, the finding does not imply that policymakers should not encourage innovation, but that promoting innovation is not the right short-term policy instrument to successfully navigate a crisis. In contrast, a key policy tool would be improving public institutions and governance to provide the necessary conditions and assurances for local actors, including citizens and businesses, to act successfully. Indeed, local institutions are key to set the proper condition for firms to innovate (Barra and Ruggiero 2022), to facilitate the access (Tiganasu and Lupu 2023) and the efficient use (Rodríguez-Pose and Garcilazo 2015) of European funds, to improve infrastructure (Crescenzi et al. 2016a, b) and to reduce transaction costs and make the development of economic activity more viable (Rodríguez-Pose 2013). In economic downturns, they mitigate regional economic contraction (Ezcurra and Rios 2019) and influence positively recovery (Annoni et al. 2019; Cutrini 2023). Our results complement this picture, as we find that all the aspects of local institutions (quality, impartiality and control of corruption) play a role on reactivity. Moreover, thanks to spill-over effects local governments can improve mutual learning and reduce the costs of policy innovation (Mukand & Rodrik 2005; Ward & John 2013). Therefore, policy makers should prioritise measures that promote knowledge sharing among local governments, using spill-over effects to streamline policy innovation processes and minimise associated costs. Establishing transparent governance structures and accountability mechanisms can increase trust in local institutions, foster cooperation, and maximise the impact of stimulus measures. Policymakers should therefore consider allocating resources to strengthen local institutions, promote cooperation between them, and foster an environment leading to innovation and resilience building at the regional level. By doing so, they can enhance the effectiveness of local governments in responding to economic challenges and promoting recovery.

Finally, it is worth noting that, although our indicator is innovative because it compares two different time intervals and thus economic phases, deviating from the standard approaches adopted in the resilience literature, it does not account for the heterogeneity of different shocks experienced over time. Specifically, the factors driving regional recovery from the financial crisis in the past may not exhibit the same level of efficacy in response to the COVID-19 pandemic crisis, which is an external shock with entirely unique attributes. Moreover, our approach has the limitation of not considering a cross-sectional scale parameter as we do not compare regional pre- and post-shock economic performance with the national or European average level. This choice, as already stated in the previous part of the study, was leaded by various considerations. The most relevant is that, given that the conceptualisation of reactivity is not straightforward, we preferred to avoid adding complexity to our indicator to facilitate its interpretation. Further refinements are left to future research.

Furthermore, we also leave to future research the task of examining regional responsiveness to COVID-19, as the unavailability of data over a sufficiently long time period requires alternative approaches such as machine learning forecasting methods that are beyond the scope of this paper.

In conclusion, understanding regional resilience requires a holistic approach, and our research proposes a new and complementary way of measuring it. Human capital and institutional quality are all significant factors contributing to regions' reactivity and spill-over to neighbours. As these factors are essential also for other dimensions of resilience, setting them as priority policy objectives, regions can better prepare the foundations to withstand and recover from shocks, ensuring long-term economic growth.

Appendix

See Tables 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18 and 19.

Table 5 Data source

Variable	Source
GDP per employee	Cambridge Econometrics Regional Database
Exports and Imports	European Commission (JRC) (2020)
Patents	Eurostat
Secondary education	Eurostat
Tertiary education	Eurostat
Gross fixed capital formation	Cambridge Econometrics Regional Database
Employment manufacturing	Cambridge Econometrics Regional Database
Population density	Cambridge Econometrics Regional Database
Diversification index (DI)	Own calculations based on Cambridge Econometrics Regional Database
Regional Quality of Government (QoG)	Quality of Government Institute of the Gothenburg University
Gross Public Debt over GDP	Ameco Database

Table 6 Regional Quality of Government (QoG) components

Axis quality

● How would you rate the quality of the police force in your area? (low/high, 0–10)

● How would you rate the quality of public education in your area? (low/high 0–10)

● How would you rate the quality of the public health care system in your area? (low/high 0–10)

Axis impartiality

● The police force gives special advantages to certain people in my area. (agree/disagree, 0–10)

● All citizens are treated equally by the police force in my area (Agree, rather agree, rather disagree or Disagree, 1–4)

● Certain people are given special advantages in the public education system in my area (agree/disagree, 0–10)

● Certain people are given special advantages in the public health care system in my area. (agree/disagree, 0–10)

● All citizens are treated equally in the public education system in my area (Agree, rather agree, rather disagree or Disagree, 1–4)

● All citizens are treated equally in the public health care system in my area (Agree, rather agree, rather disagree or Disagree, 1–4)

Axis control of corruption

● Corruption is prevalent in the police force in my area (agree/disagree, 0–10)

● Corruption is prevalent in my area's local public school system (agree/disagree, 0–10)

● Corruption is prevalent in the public health care system in my area (agree/disagree, 0–10)

● In the past 12 months have you or anyone living in your household paid a bribe in any form to: Health or medical services? (yes/no)

● In your opinion, how often do you think other citizens in your area use bribery to obtain public services? (never/very often, 0–10)

Aggregation method is equal weighting for each axis. Regional QoG is the aggregation of Quality, Impartiality and Corrupt axes based on equal weighting

Table 7 Descriptive statistics

Variable	Mean	St. Dev.	Min	Max
Reactivity	2.722	3.197	0	8
Log(GDP per empl.)	9.841	0.703	7.700	11.062
Growth GDP per empl.	2.283	1.802	−0.584	9.347
Trade openness	92.16	41.64	39.05	222.49
Log(Patents)	4.335	1.760	−0.936	7.295
Secondary edu.	47.150	15.294	9.637	78.975
Tertiary edu.	21.242	7.914	7.213	43.867
Gross Fixed Cap. Form	22.55	4.376	12.49	38.87
Empl. Manufacturing	37.012	9.312	18.889	74.660
Log(Pop. Density)	4.970	1.106	1.130	8.727
DI	6.573	1.118	3.980	9.380
Reg. QoG	0.173	1.047	−2.962	2.127
Impartiality Index	0.121	0.953	−2.581	2.043
Control of corruption index	0.134	1.053	−3.130	2.221
Quality index	0188	1.011	−3.588	2.034

All the variables are collected for 243 NUT2 regions. Independent variables are averaged over the period 2000–2007. To compute the reactivity indicator, the time period 2000–2017 is considered

Table 8 Regression results—OLS

	(1)	(2)	(3)	(4)
Constant	−29.996***	−24.488***	−29.384***	−26.654***
	(7.394)	(7.203)	(7.923)	(7.449)
Log(GDP per empl.)	3.278***	2.865***	3.181***	2.916***
	(0.707)	(0.687)	(0.760)	(0.710)
Gross Fixed Capital form.	1.451	−1.220	0.265	4.967
	(4.635)	(4.732)	(4.785)	(4.970)
Empl. Manufacturing	−0.016	−0.028	−0.020	−0.013
	(0.027)	(0.026)	(0.028)	(0.027)
Log(Patents)	−0.397	−0.318	−0.478*	−0.425
	(0.280)	(0.285)	(0.286)	(0.287)
Share sec. edu.	0.303***	0.256***	0.391***	0.253***
	(0.063)	(0.065)	(0.064)	(0.069)
Share sec. edu.^{2}	−0.003***	−0.003***	−0.004***	−0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Share ter. edu.	−0.217***	−0.193***	−0.257***	−0.224***
	(0.034)	(0.034)	(0.033)	(0.034)
Trend GDP per empl.	0.024	−0.171	0.141	0.063
	(0.159)	(0.164)	(0.164)	(0.159)
Log(pop. density)	0.367**	0.284	0.405**	0.466***
	(0.168)	(0.176)	(0.169)	(0.168)
DI	−0.080	−0.041	−0.100	−0.047
	(0.158)	(0.158)	(0.165)	(0.158)
Trade openness	−0.00002	−0.00001	−0.00001	−0.00005
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Reg. QoG	−1.176***			
	(0.200)			
Quality axis		−1.342***		
		(0.210)		
Impart axis			−0.910***	
			(0.201)	
Control of corruption axis				−0.880***
				(0.218)
AIC	1154.21	1150.58	1164.95	1165.42
Observations	243	243	243	243
R^2	0.408	0.417	0.381	0.380
Adjusted R^2	0.377	0.386	0.349	0.347

***p < 0.01, ** p < 0.05, * < 0.10. Standard errors in brackets

Table 9 LM tests

	Queen		knn = 10		inv. Distance		Gaussian	
Test	Statistic	*p*-value	Statistic	*p*-value	Statistic	*p*-value	Statistic	*p*-value
LMerr	0.021	0.884	1.351	0.245	0.055	0.814	0.409	0.523
LMlag	4.323	0.038	10.901	0.001	6.713	0.01	5.381	0.02
Rob. LMerr	13.37	0.0003	5.214	0.022	7.717	0.005	7.223	0.007
Rob. LMlag	17.672	0.00003	14.764	0.0001	14.375	0.0001	12.195	0.0005

Tests are performed on specification (1) in Table 1

Table 10 Log-marginal likelihood for spatial models

Matrix	SLX	Spatial lag	SDM	Spatial error	SDEM
Queen	0	0.860	0	0.140	0
Inverse weights	0	0.768	0	0.232	0
Gaussian	0	0.422	0	0.578	0

Tests are performed on specification (1) in Table 8

Table 11 Regression results—spatial autoregressive model, Queen contiguity matrix

	(1)	(2)	(3)	(4)
Constant	−26.763***	−22.443***	−25.507***	−23.041***
	(7.654)	(7.388)	(7.845)	(7.684)
Log(GDP per empl.)	2.911***	2.604***	2.739***	2.506***
	(0.753)	(0.731)	(0.767)	(0.753)
Gross Fixed Capital form.	1.796	−0.538	0.914	4.622
	(4.744)	(4.763)	(4.816)	(4.861)
Empl. Manufacturing	−0.012	−0.022	−0.013	−0.009
	(0.027)	(0.027)	(0.027)	(0.028)
Log(Patents)	−0.407	−0.338	−0.473*	−0.432
	(0.276)	(0.277)	(0.279)	(0.280)
Share sec. edu.	0.265***	0.231***	0.324***	0.216***
	(0.069)	(0.069)	(0.074)	(0.071)
Share sec. edu.^{2}	−0.003***	−0.002***	−0.004***	−0.002***
	(0.001)	(0.001)	(0.001)	(0.001)
Share ter. edu.	−0.188***	−0.172***	−0.209***	−0.186***
	(0.035)	(0.036)	(0.035)	(0.036)
Trend GDP per empl.	−0.010	−0.172	0.072	0.011
	(0.170)	(0.174)	(0.173)	(0.173)
Log(pop. density)	0.346**	0.279	0.365**	0.419**
	(0.176)	(0.178)	(0.178)	(0.178)
DI	−0.091	−0.056	−0.114	−0.068
	(0.172)	(0.171)	(0.174)	(0.174)
Trade openness	−0.00002	−0.00001	−0.00001	−0.00004

Table 11 (continued)

	(1)	(2)	(3)	(4)
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Reg. QoG	− 0.988***			
	(0.233)			
Quality axis		− 1.150***		
		(0.252)		
Impart axis			− 0.747***	
			(0.227)	
Control of corruption axis				− 0.678***
				(0.225)
Rho	0.1612***	0.1384***	0.2189***	0.2048***
	(0.0738)	(0.075)	(0.0716)	(0.0729)
AIC	1154.21	1154.21	1154.21	1154.21
Observations	243	243	243	243
Log Likelihood	− 560.896	− 559.707	− 564.085	− 565.068
$sigma^2$	5.884	5.837	6.008	6.065
Akaike Inf. Crit.	1,151.791	1,149.414	1,158.171	1,160.135
Wald Test	4.766**	3.410*	9.338***	7.892***
LR Test	4.423**	3.161*	8.783***	7.283***

Standard errors in brackets

***$p < 0.01$, **$p < 0.05$, * < 0.10

Table 12 Regression results—spatial autoregressive model, inverse distance

	(1)	(2)	(3)	(4)
Constant	− 22.648***	− 19.378***	− 20.689***	− 19.160**
	(7.672)	(7.371)	(7.809)	(7.571)
Log(GDP per empl.)	2.669***	2.434***	2.410***	2.268***
	(0.760)	(0.733)	(0.770)	(0.748)
Gross Fixed Capital form.	1.495	− 0.499	0.825	3.714
	(4.728)	(4.749)	(4.794)	(4.807)
Empl. Manufacturing	− 0.011	− 0.020	− 0.013	− 0.008
	(0.027)	(0.027)	(0.027)	(0.027)
Log(Patents)	− 0.335	− 0.283	− 0.367	− 0.331
	(0.276)	(0.275)	(0.278)	(0.278)
Share sec. edu.	0.216***	0.190***	0.243***	0.156**
	(0.072)	(0.072)	(0.077)	(0.072)
Share sec. edu.^{2}	− 0.002***	− 0.002***	− 0.003***	− 0.002**
	(0.001)	(0.001)	(0.001)	(0.001)
Share ter. edu.	− 0.181***	− 0.167***	− 0.196***	− 0.173***
	(0.035)	(0.036)	(0.035)	(0.035)
Trend GDP per empl.	0.015	− 0.129	0.082	0.035
	(0.169)	(0.174)	(0.172)	(0.170)
Log(pop. density)	0.359**	0.298*	0.383**	0.417**
	(0.176)	(0.177)	(0.177)	(0.176)
DI	− 0.103	− 0.071	− 0.120	− 0.090
	(0.171)	(0.171)	(0.174)	(0.173)
Trade openness	− 0.00002	− 0.00001	− 0.00001	− 0.00004
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Reg. QoG	− 0.830***			
	(0.243			
Control of corruption axis		− 0.997***		
		(0.232)		
Quality axis			− 0.541**	
			(0.232)	
Impart axis				− 0.556**
				(0.225)
Rho	0.3579***	0.3191***	0.4601***	0.4705***
AIC	(0.1306)	(0.1334)	(0.1217)	(0.1212)
Observations	1154.21	1154.21	1154.21	1154.21
Log Likelihood	243	243	243	243
sigma^2	− 560.028	− 558.928	− 562.761	− 562.384
Akaike Inf. Crit.	5.846	5.801	5.954	5.933
Wald Test	1,150.056	1,147.857	1,155.522	1,154.767
LR Test	7.512***	5.721**	14.293***	15.067***

Standard errors in brackets

***p < 0.01, **p < 0.05, * < 0.10

Table 13 Regression results—spatial autoregressive model, gaussian distance

	(1)	(2)	(3)	(4)
Constant	−25.678***	−22.033***	−23.313***	−22.081***
	(7.711)	(7.387)	(7.876)	(7.630)
Log(GDP per empl.)	2.841***	2.583***	2.584***	2.461***
	(0.759)	(0.731)	(0.772)	(0.747)
Gross Fixed Capital form.	1.144	−0.889	0.381	3.279
	(4.748)	(4.764)	(4.824)	(4.831)
Empl. Manufacturing	−0.013	−0.022	−0.015	−0.009
	(0.027)	(0.027)	(0.027)	(0.027)
Log(Patents)	−0.354	−0.297	−0.39	−0.353
	(0.277)	(0.276)	(0.280)	(0.279)
Share sec. edu.	0.221***	0.194***	0.245***	0.156**
	(0.073)	(0.072)	(0.077)	(0.073)
Share sec. edu.^{2}	−0.002***	−0.002***	−0.003***	−0.002**
	(0.001)	(0.001)	(0.001)	(0.001)
Share ter. edu.	−0.191***	−0.175***	−0.208***	−0.184***
	(0.035)	(0.035)	(0.035)	(0.035)
Trend GDP per empl.	0.029	−0.122	0.101	0.055
	(0.170)	(0.175)	(0.173)	(0.171)
Log(pop. density)	0.354**	0.29	0.377**	0.409**
	(0.177)	(0.178)	(0.178)	(0.177)
DI	−0.096	−0.065	−0.111	−0.083
	(0.172)	(0.171)	(0.175)	(0.174)
Trade openness	− 2E−05	− 1E−05	−1E−05	−4E−05
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Reg. QoG	−0.858***			
	(0.248)			
Control of corruption axis		−1.033***		
		(0.267)		
Quality axis			−0.535**	
			(0.236)	
Impart axis				−0.571**
				(0.226)
Rho	0.3348***	0.2973***	0.4511***	0.4683***
	(0.1471)	(0.1477)	(0.1379)	(0.1349)
AIC	1154.21	1154.21	1154.21	1154.21
Observations	243	243	243	243
Log Likelihood	−560.78	−559.47	−563.82	−563.13
sigma^2	5.896	5.837	6.026	5.989
Akaike Inf. Crit.	1,151.55	1,148.94	1,157.63	1,156.27
Wald Test	5.181**	4.054**	10.697***	12.052***
LR Test	4.660**	3.631*	9.324***	11.153***

Standard errors in brackets

***p < 0.01, **p < 0.05, * < 0.10

Table 14 Regression results—models with dummy financial distress—OLS

	(1)	(2)	(3)	(4)
Constant	−24.485***	−20.573***	−21.891***	−22.778***
	(7.182)	(6.932)	(7.809)	(7.077)
Log(GDP per empl.)	2.279***	2.025***	1.969**	1.963***
	(0.723)	(0.692)	(0.788)	(0.702)
Gross Fixed Capital form.	−2.441	−4.01	−3.27	−0.356
	(4.488)	(4.552)	(4.583)	(4.603)
Empl. Manufacturing	−0.04	−0.047*	−0.047*	−0.041*
	(0.025)	(0.024)	(0.026)	(0.025)
Log(Patents)	−0.223	−0.183	−0.265	−0.187
	(0.273)	(0.277)	(0.281)	(0.274)
Share sec. edu.	0.399***	0.358***	0.456***	0.374***
	(0.055)	(0.058)	(0.056)	(0.057)
Share sec. edu.^{2}	−0.004***	−0.003***	−0.005***	−0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Share ter. edu.	−0.165***	−0.154***	−0.190***	−0.148***
	(0.032)	(0.032)	(0.034)	(0.033)
Trend GDP per empl.	0.027	−0.112	0.097	0.055
	(0.155)	(0.160)	(0.156)	(0.152)
Log(pop. density)	0.373**	0.317*	0.413**	0.437***
	(0.171)	(0.178)	(0.171)	(0.167)
DI	−0.162	−0.125	−0.171	−0.166
	(0.150)	(0.150)	(0.155)	(0.148)
Trade openness	0.0001	0.0001	0.0001	0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Financial distressed countries	3.206***	2.947***	3.479***	3.990***
	(0.730)	(0.738)	(0.761)	(0.661)
Reg. QoG	−0.864***			
	(0.208)			
Quality axis		−0.963***		
		(0.226)		
Impart axis			−0.494**	
			(0.208)	
Control of corruption axis				−0.816***
				(0.202)
AIC	1139.04	1138.83	1148.75	1138.43
Observations	243	243	243	243
R^2	0.448	0.449	0.426	0.45
Adjusted R^2	0.417	0.417	0.393	0.418

Standard errors in brackets

***p < 0.01, **p < 0.05, * < 0.10

Table 15 Log-marginal likelihood for spatial models with dummy financial distress

Matrix	SLX	Spatial lag	SDM	Spatial error	SDEM
knn = 10	0	0.706	0	0.294	0
Queen	0	0.857	0	0.143	0
inv. weights	0	0.787	0	0.213	0
Gaussian	0	0.667	0	0.333	0

Tests are performed on specification (1) in Table 14

Table 16 LM tests for models with dummy financial distress

	Queen		knn = 10		inv. Distance		Gaussian	
Test	Statistic	*p*-value	Statistic	*p*-value	Statistic	*p*-value	Statistic	*p*-value
LMerr	0.018	0.894	0.521	0.470	0.223	0.637	0.620	0.431
LMlag	1.742	0.187	3.658	0.056	1.495	0.222	0.814	0.367
Rob. LMerr	4.616	0.032	1.376	0.241	2.989	0.084	2.815	0.093
Rob. LMlag	6.340	0.012	4.513	0.034	4.260	0.039	3.009	0.083

Tests are performed on specification (1) in Table 14

Table 17 Regression results—spatial autoregressive models with dummy financial distress—Queen W

	(1)	(2)	(3)	(4)
Constant	−22.788***	−19.376***	−19.953**	−21.340***
	(7.545)	(7.285)	(7.809)	(7.393)
Log(GDP per empl.)	2.112***	1.891**	1.790**	1.837**
	(0.764)	(0.744)	(0.791)	(0.737)
Gross Fixed Capital form.	−1.955	−3.384	−2.384	−0.132
	(4.706)	(4.717)	(4.766)	(4.748)
Empl. Manufacturing	−0.036	−0.043	−0.039	−0.036
	(0.027)	(0.027)	(0.027)	(0.027)
Log(Patents)	−0.241	−0.204	−0.286	−0.208
	(0.272)	(0.273)	(0.276)	(0.272)
Share sec. edu.	0.368***	0.334***	0.399***	0.348***
	(0.073)	(0.075)	(0.075)	(0.074)
Share sec. edu.^{2}	−0.004***	−0.003***	−0.004***	−0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Share ter. edu.	−0.150***	−0.141***	−0.162***	−0.135***
	(0.036)	(0.036)	(0.037)	(0.036)
Trend GDP per empl.	0.005	−0.116	0.052	0.032
	(0.165)	(0.170)	(0.169)	(0.165)
Log(pop. density)	0.359**	0.312*	0.383**	0.417**
	(0.172)	(0.174)	(0.173)	(0.170)
DI	−0.164	−0.131	−0.173	−0.167
	(0.168)	(0.169)	(0.171)	(0.168)
Trade openness	0.0001	0.0001	0.0001	0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Financial distressed countries	2.988***	2.783***	3.072***	3.699***
	(0.791)	(0.807)	(0.829)	(0.767)
Reg. QoG	−0.764***			
	(0.234)			
Quality axis		−0.851***		
		(0.260)		
Impart axis			−0.424*	
			(0.237)	
Control of corruption axis				−0.725***
				(0.216)
Rho	0.1033	0.0957	0.159***	0.0975
	(0.0746)	(0.0751)	(0.0729)	(0.0745)
AIC	1139.04	1139.04	1139.04	1139.04
Observations	243	243	243	243
Log Likelihood	−553.62	−553.66	−557.1	−553.42
sigma^2	5.563	5.567	5.704	5.555
Akaike Inf. Crit.	1,139.24	1,139.32	1,146.20	1,138.84
Wald Test	1.916	1.625	4.758**	1.715
LR Test	1.8	1.512	4.551**	1.587

Standard errors in brackets

***p < 0.01, **p < 0.05, * < 0.10

Table 18 Regression results—spatial autoregressive models with dummy financial distress—inverse distance

	(1)	(2)	(3)	(4)
Constant	−22.064***	−18.868***	−18.064**	−20.641***
	(7.608)	(7.297)	(7.838)	(7.410)
Log(GDP per empl.)	2.060***	1.854**	1.636**	1.801**
	(0.769)	(0.745)	(0.794)	(0.738)
Gross Fixed Capital form.	−2.011	−3.32	−2.275	−0.216
	(4.712)	(4.725)	(4.769)	(4.744)
Empl. Manufacturing	−0.035	−0.041	−0.038	−0.035
	(0.027)	(0.027)	(0.027)	(0.027)
Log(Patents)	−0.208	−0.175	−0.223	−0.177
	(0.272)	(0.272)	(0.276)	(0.272)
Share sec. edu.	0.343***	0.309***	0.341***	0.316***
	(0.079)	(0.079)	(0.080)	(0.078)
Share sec. edu.^{2}	−0.003***	−0.003***	−0.003***	−0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Share ter. edu.	−0.151***	−0.142***	−0.158***	−0.135***
	(0.036)	(0.036)	(0.037)	(0.036)
Trend GDP per empl.	0.022	−0.093	0.063	0.044
	(0.165)	(0.171)	(0.169)	(0.165)
Log(pop. density)	0.368**	0.322*	0.396**	0.419**
	(0.172)	(0.174)	(0.173)	(0.170)
DI	−0.166	−0.135	−0.172	−0.169
	(0.169)	(0.169)	(0.171)	(0.168)
Trade openness	0.0001	0.0001	0.0001	0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Financial distressed countries	2.871***	2.662***	2.886***	3.471***
	(0.820)	(0.829)	(0.847)	(0.812)
Reg. QoG	−0.713***			
	(0.246)			
Control of corruption axis		−0.798***		
		(0.272)		
Quality axis			−0.307	
			(0.243)	
Impart axis				−0.682***
				(0.223)
Rho	0.1901	0.1866	0.3221***	0.2074
AIC	(0.1402)	(0.1398)	(0.1307)	(0.1367)
Observations	1139.04	1139.04	1139.04	1139.04
Log Likelihood	243	243	243	243
sigma^2	−553.74	−553.67	−556.82	−553.22
Akaike Inf. Crit.	5.575	5.571	5.701	5.549
Wald Test	1,139.48	1,139.34	1,145.65	1,138.44
LR Test	1.839	1.782	6.071**	2.3

Standard errors in brackets

***p < 0.01, **p < 0.05, * < 0.10

Table 19 Regression results—spatial autoregressive models with dummy financial distress—gaussian distance

	(1)	(2)	(3)	(4)
Constant	−23.010***	−19.615***	−18.923**	−21.460***
	(7.600)	(7.282)	(7.853)	(7.396)
Log(GDP per empl.)	2.163***	1.944***	1.744**	1.892**
	(0.769)	(0.744)	(0.796)	(0.737)
Gross Fixed Capital form.	−2.284	−3.636	−2.692	−0.431
	(4.721)	(4.733)	(4.787)	(4.752)
Empl. Manufacturing	−0.037	−0.043	−0.04	−0.036
	(0.027)	(0.027)	(0.028)	(0.027)
Log(Patents)	−0.217	−0.183	−0.237	−0.185
	(0.273)	(0.273)	(0.277)	(0.272)
Share sec. edu.	0.356***	0.319***	0.350***	0.325***
	(0.079)	(0.079)	(0.081)	(0.078)
Share sec. edu.^{2}	−0.003***	−0.003***	−0.003***	−0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Share ter. Edu.	−0.158***	−0.148***	−0.166***	−0.141***
	(0.035)	(0.036)	(0.037)	(0.036)
Trend GDP per empl.	0.029	−0.091	0.076	0.053
	(0.166)	(0.171)	(0.169)	(0.165)
Log(pop. Density)	0.367**	0.318*	0.393**	0.419**
	(0.172)	(0.174)	(0.174)	(0.170)
DI	−0.163	−0.131	−0.168	−0.167
	(0.169)	(0.169)	(0.172)	(0.169)
Trade openness	0.0001	0.0001	0.0001	0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Financial distressed countries	2.966***	2.729***	2.987***	3.569***
	(0.822)	(0.831)	(0.846)	(0.817)
Reg. QoG	−0.748***			
	(0.251)			
Control of corruption axis		−0.834***		
		(0.274)		
Quality Axis			−0.304	
			(0.248)	
Impart Axis				−0.706***
				(0.225)
Rho	0.1464	0.1511	0.2994***	0.1769
	(0.1572)	(0.1542)	(0.1471)	(0.1514)
AIC	1139.04	1139.04	1139.04	1139.04
Observations	243	243	243	243
Log Likelihood	−554.12	−553.98	−557.48	−553.57
sigma^2	5.597	5.59	5.742	5.57
Akaike Inf. Crit.	1,140.24	1,139.96	1,146.97	1,139.14
Wald Test	0.867	0.96	4.142**	1.365
LR Test	0.805	0.874	3.789*	1.291

Standard errors in brackets

***$p < 0.01$, **$p < 0.05$, * < 0.10

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