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ORIGINAL PAPER

Labour productivity and regional labour markets resilience in Europe

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Abstract
This paper conceptualizes and empirically explores the resilience of European Union regional labour markets in terms of labour productivity growth. We assess the effect of pre-crisis region-specific factors on regional labour markets resilience controlling for the effect of exogenous technological change and substitution between capital and labour. Regional input–output models are developed to estimate supplies and sales linkages across the European Union NUTS-2 regional economies. Spatial Durbin Error Model estimates suggest that regional labour markets characterised by a higher level of economic pull capabilities of the Construction sector and a higher level of industrial concentration can better withstand the effects of the negative shock and recover faster. Place-based policies building on regions' competitive strengths can smooth out the negative effect of the economic shock and accelerate the recovery of regional labour markets, while policy interventions promoting capital investment can further enhance labour productivity in European Union regions.

JEL Classification C67 · E24 · R11 · R12 · R15

1 Introduction

The spatial labour markets have experienced great volatility and uncertainty during the last two decades. The severe and asymmetric territorial impacts of the recent financial, political and health events across local labour markets, from the Great Recession to Brexit and the current corona pandemic crisis, have provided new

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stimuli to regional scientists to understand the varying ability of spatial labour markets to withstand, react and recover from exogenous shocks.

Several methodologies have been developed to explore the resilience of regional labour markets to external perturbations, ranging from short-term responses to absorb an external shock (Giannakis and Bruggeman 2017a) to long-term adaptability to develop new growth paths (Pontarollo and Serpieri 2020a). The increasing use of the notion of resilience in analysing spatial labour markets performance, as in other fields of application, has brought more clarity on the definition of the concept, but no consensus has yet been reached (Boschma 2015). The theorization and subsequently the empirical operationalization of the resilience concept is still under development (Martin and Sunley 2015; Tsiapa et al. 2018).

Local labour markets resilience features are usually measured in terms of employment growth rates, either absolute or relative, e.g., versus EU average (Lagravinese 2015; Giannakis and Bruggeman 2017b). Several studies suggest that labour productivity is positively associated with employment, i.e., higher labour productivity growth induces lower unemployment rates (Mortensen and Pissarides 1998; Miyamoto and Takahashi 2011). In this study, we conceptualize and measure the resilience of regional labour markets in terms of labour productivity growth, which is equal to regional economic output growth minus the labour input growth.

The behaviour of labour productivity has been widely studied both across European regions (Cuadrado-Roura et al. 2000; Ezcurra et al. 2007) and within individual countries, e.g., across Italian (Giacinto and Nuzzo 2006), British (Gardiner et al. 2020) and Greek (Christopoulos and Tsionas 2004) regions. Filippetti and Peyrache (2015) assessed the role of the technology gap, capital deepening, exogenous technical change, and efficiency change in explaining labour productivity differences in European regions. Basile et al. (2008) analysed the relationship between regional unemployment, wages, and labour productivity differentials in Europe. Tsiapa et al. (2018) explored how EU regions' pre-crisis path-dependence productivity changes influenced their resilience levels during the economic crisis period, 2008–2013.

Our resilience concept compares the labour productivity growth rate of a regional labour market to the labour productivity growth rate of a reference regional labour market. Region-specific characteristics and growth paths before the onset of the economic downturn have been found to strongly affect the performance of spatial labour markets during and after exogenous shocks (Di Caro and Fratesi 2018). Our framework aims to consistently estimate the effect of pre-crisis conditions on the resilience of spatial labour markets, controlling for the effect of exogenous technological change and substitution of labour with capital.

Various region-specific factors have been linked to the ability of spatial labour markets to resist negative exogenous shocks (Crescenzi et al. 2016). However, little research has been conducted on the role of industrial linkages and interdependencies in shaping spatial labour markets resilience capabilities. The industrial structure of a region has been considered a major determinant for the resilience of regional labour markets to external perturbations (Cainelli et al. 2019a). A major area of debate has been whether a diverse economic structure provides greater regional resilience to negative exogenous shocks than a more specialised structure (Martin 2012; Martin and Sunley 2015). However, precisely how a diversified or specialised regional economy reacts to recession strongly depends on the degree of direct and indirect sectoral interdependencies (Martin 2012).

Input–output (IO) models have been applied in the regional resilience literature to analyse the interdependence of economic sectors and simulate how an exogenous shock propagates in spatial economies through supplies and sales linkages (Acemoglu et al. 2016; Galbusera and Giannopoulos 2018). However, most of the applications have been employed in individual countries. For instance, IO models have been employed to explore the resilience of regional labour markets to economic shocks in the Netherlands (Diodato and Weterings 2015), the UK (Kitsos et al. 2019), and Greece (Giannakis and Bruggeman 2017a).

The contribution of the paper is twofold. First, we develop a theoretical model, which is based on the theory of production, for the operationalization and empirical measurement of regional labour markets resilience. Second, we empirically explore the relationship between a set of pre-crisis region-specific factors, namely, industrial interconnectedness, industrial concentration, agglomeration economies and human capital factors, and the ability of labour markets to resist and recover from the impact of exogenous shocks. Industrial interconnectedness indicators are not available at the regional level, thus we constructed regional input–output models to estimate sectoral backward and forward linkages across the European Union (EU) NUTS-2 regions.

2 Theoretical model

We define labour productivity growth of a region i as the logarithmic ratio of output produced to labour at period t over the ratio of output produced to labour at period $t-s$ as follows:

$$\ell_{\mathrm{it}} = \ln\frac{\frac{y_{\mathrm{it}}}{L_{\mathrm{it}}}}{\frac{y_{\mathrm{it}-s}}{L_{\mathrm{it}-s}}} = \ln\frac{y_{\mathrm{it}}}{y_{\mathrm{it}-s}} - \ln\frac{L_{\mathrm{it}}}{L_{\mathrm{it}-s}} \tag{1}$$

where y_{it}, L_{it} are the output and labour input of region i at period t, respectively.

Equation (1) defines labour productivity as the difference between the growth rates of output and labour input. Let y_{kt} and L_{kt} be the output and labour input of a reference region k at period t, where the output and labour input are the geometric means of all regions (Caves et al. 1982). Then by using Eq. (1), the labour productivity growth of the reference region k at period t is given by ℓ_{kt}. We define the resilience of a region i, ℓ_i, as the difference in the growth rate of labour productivity between the regions i and k as follows:

$$\ell_i = \ell_{\mathrm{it}} - \ell_{\mathrm{kt}} = \ln\frac{\frac{y_{\mathrm{it}}}{L_{\mathrm{it}}}}{\frac{y_{\mathrm{it}-s}}{L_{\mathrm{it}-s}}} - ln\frac{\frac{y_{\mathrm{kt}}}{L_{\mathrm{kt}}}}{\frac{y_{\mathrm{kt}-s}}{L_{\mathrm{kt}-s}}} \tag{2}$$

Equation (2) can be equivalently interpreted as the growth rate of the difference in labour productivity of regions i and k between periods t and $t-s$.

Following Giannakis et al. (2021), who developed a production function framework to measure regional economic resilience in terms of output growth, and assuming that the production function is given by a first-order logarithmic Taylor series approximation (Cobb–Douglas),[1] we have:

$$\mathrm{lny}_{\mathrm{it}} = -\mathrm{ln}\xi_{\mathrm{it}} + \mathrm{lnA}_{\mathrm{it}} + \alpha\mathrm{lnL}_{\mathrm{it}} + \beta\mathrm{lnK}_{\mathrm{it}} \tag{3}$$

where y, L, K are the output, labour and capital inputs, respectively; A_{it} is the exogenous technical change (Total Factor Productivity); ξ_{it} measures the reduction of output due to the negative shock, when $\xi_{\mathrm{it}} > 1$; when $\xi_{\mathrm{it}} = 1$, the regional economy i has economically fully recovered at time t.

Assuming constant returns to scale ($\alpha + \beta = 1$), labour productivity from Eq. (3) is given as:

$$\mathrm{ln}\frac{y_{\mathrm{it}}}{L_{\mathrm{it}}} = -\mathrm{ln}\xi_{\mathrm{it}} + \mathrm{ln}A_{\mathrm{it}} + \beta\mathrm{ln}\frac{K_{\mathrm{it}}}{L_{\mathrm{it}}} \tag{4}$$

The Eq. (4), from Eq. (1) can be expressed in terms of labour productivity growth between periods t and $t-s$ as follows:

$$\ell_{\mathrm{it}} = -\mathrm{ln}\frac{\xi_{\mathrm{it}}}{\xi_{\mathrm{it}-s}} + \mathrm{ln}\frac{A_{\mathrm{it}}}{A_{\mathrm{it}-s}} + \beta\left(\mathrm{ln}\frac{K_{\mathrm{it}}}{K_{\mathrm{it}-s}} - \mathrm{ln}\frac{L_{\mathrm{it}}}{L_{\mathrm{it}-s}}\right) \tag{5}$$

Equation (5) shows that the labour productivity growth between t and $t-s$ depends on the rate of change of the exogenous shock, the growth rate of the exogenous technical change, and the capital deepening, that is, the growth rate of capital minus the growth rate of labour. Similarly, the labour productivity of the average region k between periods t and $t-s$ can be defined as follows:

$$\ell_{\mathrm{kt}} = -\mathrm{ln}\frac{\xi_{\mathrm{kt}}}{\xi_{\mathrm{kt}-s}} + \mathrm{ln}\frac{A_{\mathrm{kt}}}{A_{\mathrm{kt}-s}} + \beta\left(\mathrm{ln}\frac{K_{\mathrm{kt}}}{K_{\mathrm{kt}-s}} - \mathrm{ln}\frac{L_{\mathrm{kt}}}{L_{\mathrm{kt}-s}}\right) \tag{6}$$

Then Eq. (2) from Eqs. (5) and (6) becomes:

$$\begin{aligned}\ell_{\iota} = &\left(\mathrm{ln}\frac{\xi_{\mathrm{it}-s}}{\xi_{\mathrm{kt}-s}} - \mathrm{ln}\frac{\xi_{\mathrm{it}}}{\xi_{kt}}\right) + \left(\mathrm{ln}\frac{A_{\mathrm{it}}}{A_{\mathrm{it}-s}} - \mathrm{ln}\frac{A_{\mathrm{kt}}}{A_{\mathrm{kt}-s}}\right)\\ &+ \beta\left[\left(\mathrm{ln}\frac{K_{\mathrm{it}}}{K_{\mathrm{it}-s}} - \mathrm{ln}\frac{L_{\mathrm{it}}}{L_{\mathrm{it}-s}}\right) - \left(\mathrm{ln}\frac{K_{\mathrm{kt}}}{K_{\mathrm{kt}-s}} - \mathrm{ln}\frac{L_{\mathrm{kt}}}{L_{\mathrm{kt}-s}}\right)\right]\end{aligned} \tag{7}$$

Equation (7) is not empirically identifiable since the level of exogenous technology and the effect of the negative shock are unknown.

To account for exogenous technical change, we assume that each region has an exponential growth of technology:

[1] Our framework can be defined for any general production function. For simplicity, we use here the Cobb–Douglas function.

$$A_{\mathrm{jt}} = A_{j0}e^{\gamma_j t}, (j = i, k) \tag{8}$$

where A_{jt} is the technology level of region j at time t, A_{j0} is the initial level of technology, γ_j is the exogenous technological rate; when $\gamma_j > 0\left(\gamma_j < 0\right)$ there is technical progress (recess).

The negative shock function $\left(\xi_{jt}\right)$ of region j, which depends on the common to each region shock and a vector of region-specific factors, can be formulated as follows:

$$\xi_{\mathrm{jt}} = \xi_0(t)e^{\mathrm{bz_{jt}}}, (j = i, k) \tag{9}$$

where $\xi_0(t)$ is the common exogenous shock to each region and it is a function of time; z_{jt} is a set of regional characteristics at time t. If $b < 0$, the characteristics z_j observed in region j will reduce the baseline negative effect of the shock $\left(\xi_0(t)\right)$ and therefore they will have a positive effect on the recovery of the regional economy.

Assuming that at time t there is a full recovery of the economy, $\xi_{jt} = 1$; substituting in Eq. (7), the Eqs. (8) and (9), we have:

$$\ell_i = \left(\gamma_i - \gamma_k\right) \cdot s + b\left(z_{\mathrm{it}-s} - z_{\mathrm{kt}-s}\right) + \beta\left(x_i - x_k\right) \tag{10}$$

where $x_j = \left(\ln\frac{K_{\mathrm{jt}}}{K_{\mathrm{jt}-s}} - \ln\frac{L_{\mathrm{jt}}}{L_{\mathrm{jt}-s}}\right)(j = i, k)$ is the capital deepening of region j.

Equation (10) shows that the difference in the labour productivity growth $\left(\ell_i\right)$ between region i and a reference region k, i.e., our metric to operationalize the resilience of regional labour markets, depends on the difference in the growth rate of the exogenous technical change, the difference on the levels of the region-specific factors and the difference in the growth rate of the capital-labour ratio (capital deepening) between the two regions.

The main channels affecting the resilience of regional labour markets include changes in capital-labour ratio, either through capital accumulation or changes in the quantity and quality of the labour force; and second, shifts of the production function, either through changes in technology or negative shock. All other factors held equal, investment in capital that favours capital-labour substitution and technological progress increases the resilience of regional labour markets. On the contrary, negative shock reduces labour productivity growth due to a reduction in output. However, higher levels of pre-crisis region-specific factors like industrial interconnectedness, industrial concentration, agglomeration economies, and human capital, mitigate the negative shock and therefore accelerate the recovery of regional labour markets.

3 Methods and data

3.1 Empirical model

The empirical model of the paper is based on Eq. (10). However, considering that the resilience of regional labour markets might depend not only on their own characteristics but also on features of neighbouring regions (Pontarollo and Serpieri 2020a; Ezcurra and Rios 2019; Cainelli et al. 2019b), we apply spatial regression models to explore the effect of spatial spillovers on regional labour markets resilience. Two of the most popular spatial regression specifications to account for the effect of spatial spillovers are: (a) global spillover models that include a spatial lag of the dependent variable and (b) local spillover models including spatial lags of the explanatory variables (LeSage 2015). LeSage (2014a) argues that there are two main spatial model specifications that need to be considered when there is uncertainty about the optimal model to use, namely, the spatial Durbin global spillover model (SDM) and the spatial Durbin error local spillover model (SDEM). The spatially lagged X model (SLX) is another local spillover specification, which is nested to both SDM and SDEM. Following this line of reasoning, similar to Cainelli et al. (2019b), we apply the SDM, SDEM and SLX cross-sectional models to estimate Eq. (10).

The SDM, which captures global spatial spillovers through spatial lag terms of both the dependent variable and the explanatory variables, takes the form (LeSage 2014b):

$$\ell_i = a_i + Z_i b + \beta X_i + W\Phi_i \pi + \rho W \ell_i + \varepsilon_i \tag{11}$$

where $a_i = (\gamma_i - \gamma_k) \cdot s$ is the constant term that captures the difference in the productivity growth between region i and region k; $Z_i = (z_i - z_k)$ is a $n \times m$ matrix of the difference in the region-specific factors between region i and the average of all regions (identified with index k); $X_i = (x_i - x_k)$ is a $n \times 1$ vector of the difference in the capital deepening between region i and region k; b is a $mx1$ vector of coefficients that captures the effect of region-specific factors on regional resilience; β captures the effect of capital deepening; W is a $n \times n$ row-standardized spatial weights matrix used to model spillover effects across regions; $\Phi_i = (Z_i, X_i)$ is a $n \times (m+1)$ matrix of the region-specific factors and the capital deepening; π is a $(m+1) \times 1$ vector of spatial parameters referring to the spatially lagged region-specific factors and the spatially lagged capital deepening; ρ is the spatial autoregressive parameter; $W\ell_i$ is a $nx1$ vector of the spatially lagged dependent variable ℓ; ε_i is a $n \times 1$ vector of error terms.

The SDEM captures local spillovers to immediate neighbouring regions but also allows for global diffusion of shocks to the model disturbances, i.e., the effect of a change in the disturbance of a given region on disturbances of neighbouring regions (LeSage 2014b). The SDEM takes the form:

$$\ell_i = a_i + Z_i b + \beta X_i + W\Phi_i \pi + \mu_i \tag{12}$$

with $\mu_i = \lambda W \mu_i + \varepsilon_i$, where λ is the spatial error parameter.

The SLX model, which captures local spatial spillovers to neighbouring regions through spatial lag terms for the explanatory variables, takes the form (LeSage 2014b):

$$\ell_i = a_i + Z_i b + \beta X_i + W\Phi_i \pi + \varepsilon_i \tag{13}$$

We apply a Bayesian model selection approach to choose between the three models (LeSage 2014a). The model selection procedure is based on the comparison of the log-marginal likelihood values of the different models using alternative row-standardised spatial weight matrices. The MATLAB algorithms developed by LeSage (2015) were used to calculate spatial weight matrices and log-marginal likelihood values. Details about the theoretical foundation of the applied Bayesian approach can be found in LeSage (2014a).

3.2 Measuring regional labour markets resilience

We empirically measure the resilience of regional labour markets $\left(\ell_i\right)$ across the EU-28 NUTS-2 regions, based on Eqs. (1) and (2), as follows:

$$\ell_i = \left(\ln\frac{\mathrm{GVA}_{i2016}}{\mathrm{GVA}_{i2008}} - \ln\frac{\mathrm{GVA}_{k2016}}{\mathrm{GVA}_{k2008}}\right) - \left(\ln\frac{L_{i2016}}{L_{i2008}} - \ln\frac{L_{k2016}}{L_{k2008}}\right) \tag{14}$$

where i identifies the NUTS-2 regional labour markets, $i = 1, 276$; k is a reference regional labour market which represents the geometric mean of all regional labour markets; GVA_i is the gross value added in region i in 2008, that is, the starting year of the crisis period and 2016, that is, the end year of the economic period at constant 2010 prices (euro); L_i is the compensation of employment (employees and self-employed persons expressed in hours of work) at constant 2010 prices (euro).

The compensation of employment is the sum of the compensation of employees (Eurostat 2020a, 2021) and the compensation of the self-employed. Eurostat is the source for the annual regional GVA data (Eurostat 2020a). Eurostat is also the source for the regional compensation of employees data (Eurostat 2020b) and the regional employment data per professional status (Eurostat 2020c).

The spatial distribution of regional labour markets resilience, which is portrayed in Fig. 1, highlights the uneven ability of regional labour markets to withstand, react and recover from the economic shock. The geography of the regional labour markets resilience is clearly influenced by national patterns. Clusters of low resilient labour markets are observed in countries such as Italy and Greece as a result of the relatively higher employment growth rates compared to the output growth rates. For example, although it is well known that the northern regions in Italy are more developed than the southern regions (Lagravinese 2015), the growth rate of the labour productivity in almost all Italian regions is lower than the labour productivity growth rate of the reference region. On the contrary, high-resilient labour markets surrounded by high-resilient labour markets are present in countries such as Spain, Romania and Bulgaria. A heterogeneous pattern of resilience can also be observed within countries. This is particularly evident in countries such as Germany, France, Netherlands, and UK.

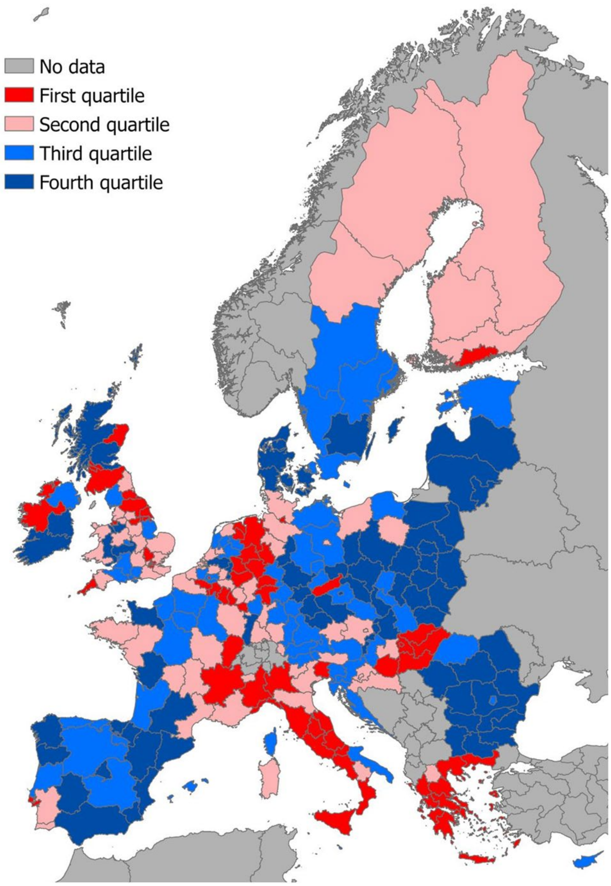

Fig. 1 Regional labour markets resilience across EU-28 NUTS-2 regions for the 2008–2016 period

3.3 Capital deepening

The capital deepening (x_i) equals the growth rate of capital minus the growth rate of labour between 2008 and 2016. The perpetual inventory method was applied to construct capital stock series for each region (see Appendix A). The regional gross fixed capital formation data (Eurostat 2020d) were used to construct the regional capital stock series for the period 2000–2017.

3.4 Region-specific factors

The pre-crisis region-specific factors (z_i) included in the empirical model for the year 2007 are: (1) industrial interconnectedness, (2) industrial concentration, (3) agglomeration economies, and (4) human capital factors.

3.4.1 Industrial interconnectedness

We applied the IO modelling framework to empirically measure the interdependences between economic sectors via backward and forward linkages. The backward linkages of a certain sector j $\left(BL_j\right)$ measure the effects of a change in the final demand of the sector j on the output of all sectors. Backward linkages are given by the column sums of the Leontief-inverse matrix based on the technical input coefficients that relate the intermediate inputs of a sector to the sector's total inputs (Rasmussen 1956). The forward linkages of a certain sector i $\left(FL_i\right)$ measure the effects of a change in the primary inputs of the sector i on the output of all sectors. Forward linkages are given by the row sums of the output-inverse matrix based on the technical output coefficients that relate the intermediate sales of a sector to the sector's total sales (Jones 1976).

The national symmetric IO tables for the 28 EU countries for the year 2007, which were derived from the WIOD database (Timmer et al. 2015), were used to construct 276 regional IO models for the EU-28 NUTS-2 regions. The initial 56-sector classification of the EU-28 national IO tables was aggregated to 8-sector regional schemes including (a) Agriculture, (b) Manufacturing, (c) Construction, (d) Trade, Transport, Accommodation, (e) Finance, (f) Real Estate, (g) Public Administration, Health, Education, (h) Others (Table B1). The methodology for the construction of the regional IO tables is described in Appendix B.

3.4.2 Industrial concentration

A Herfindahl–Hirschman index $\left(Hindex_{it}\right)$ was constructed, using GVA data, to measure the industrial concentration across regions as follows:

$$\mathrm{Hindex}_{\mathrm{it}} = \sum_{j=1}^{n} S_{\mathrm{ijt}}^{2} \tag{15}$$

where S_{ijt}^2 is the gross value added share in region i in sector j in year t (t = 2007) (Eurostat 2020a). The higher the value of the $Hindex_{it}$, the higher the sectoral concentration of the regional labour market in question.

3.4.3 Agglomeration economies

A measure of employment density (thousand persons per square kilometre) was used to capture the effect of agglomeration forces in regional resilience (Eurostat 2020e; 2020f).

Table 1 Data descriptive statistics for the 276 EU-28 NUTS-2 regions

	Mean	Std. Dev	Min	Max
Labour productivity growth	0.047	0.095	−0.346	0.415
BL Agriculture	1.580	0.161	1.000	1.855
BL Manufacturing	1.673	0.162	1.230	2.027
BL Construction	1.793	0.204	1.332	2.289
BL Trade, Transportation, Accommodation	1.593	0.091	1.302	1.768
BL Finance	1.664	0.191	1.225	2.085
BL Real Estate	1.318	0.133	1.000	1.674
BL Public Administration, Health, Education	1.331	0.072	1.106	1.489
FL Agriculture	1.751	0.236	1.192	2.379
FL Manufacturing	1.502	0.175	1.200	1.992
FL Construction	1.494	0.182	1.132	1.913
FL Trade, Transportation, Accommodation	1.676	0.148	1.255	2.010
FL Finance	1.945	0.216	1.253	2.521
FL Real Estate	1.427	0.162	1.000	1.761
FL Public Administration, Health, Education	1.114	0.048	1.034	1.206
Hindex	0.234	0.029	0.188	0.389
Employment Density	0.191	0.493	0.001	4.866
Secondary Education	0.473	0.153	0.107	0.796
Tertiary Education	0.234	0.089	0.073	0.608
Age3049	0.291	0.019	0.248	0.353
Age5064	0.185	0.019	0.097	0.239
Age65 +	0.170	0.033	0.038	0.270
Capital deepening	0.264	0.139	-0.028	0.871

BL Backward Linkages; *FL* Forward Linkages

3.4.4 Human capital

The share of population with secondary or tertiary education was used to capture the educational effects in regional labour markets resilience (Eurostat 2020g). Several age cohorts were introduced in the analysis to capture the effect of age structure, that is, share of population aged 30–49, share of population aged 50–64, and share of population older than 65 years (Eurostat 2020h).

Table 1 presents the descriptive statistics of the data used in the empirical analysis. A correlation matrix of the explanatory variables is presented in Appendix C (Table C1)

4 Results and discussion

Table 2 reports the log-marginal likelihood values and the posterior model probabilities calculated for the SLX model, the SDM and the SDEM with respect to a broad range of alternative spatial weight matrices, including matrices based on the

Table 2 Spatial Bayesian model selection: log-marginal likelihood (LML) values and posterior model probabilities (p)

Spatial weights matrix ($\boldsymbol{W}$)	SLX		SDM		SDEM	
	LML	p	LML	p	LML	p
8-nearest neighbours	331.759	0.000	331.619	0.000	335.640	0.000
9-nearest neighbours	333.555	0.000	333.376	0.000	338.215	0.006
10-nearest neighbours	336.622	0.001	336.306	0.001	339.000	0.013
11-nearest neighbours	336.872	0.002	336.668	0.001	340.520	0.058
12-nearest neighbours	335.582	0.000	335.432	0.000	339.247	0.016
13-nearest neighbours	338.091	0.005	337.929	0.004	342.551	0.442
14-nearest neighbours	338.766	0.010	338.909	0.012	342.164	0.301
15-nearest neighbours	338.660	0.009	339.053	0.013	340.510	0.058
16-nearest neighbours	337.803	0.004	337.847	0.004	340.071	0.037
Contiguity	328.508	0.000	328.413	0.000	328.101	0.000
$1/d^2$, cut-off at Q1	330.132	0.000	330.521	0.000	329.998	0.000
$1/d^2$, cut-off at Q2	335.337	0.000	335.599	0.000	335.711	0.001
$1/d^2$, cut-off at Q3	335.337	0.000	335.599	0.000	335.711	0.001
$e^{-0.02d}$, cut-off at Q1	323.371	0.000	322.895	0.000	323.030	0.000
$e^{-0.02d}$, cut-off at Q2	326.428	0.000	325.954	0.000	326.032	0.000
$e^{-0.02d}$, cut-off at Q3	326.428	0.000	325.954	0.000	326.032	0.000
$e^{-0.05d}$, cut-off at Q1	316.414	0.000	316.246	0.000	316.209	0.000
$e^{-0.05d}$, cut-off at Q2	318.546	0.000	318.433	0.000	318.285	0.000
$e^{-0.05d}$, cut-off at Q3	318.546	0.000	318.433	0.000	318.285	0.000

Q1, Q2 and Q3 are, respectively, the first, second and third quartiles of the distribution of distances; d is the distance between the centroids of the regions

k-nearest neighbours, the inverse of the squared distance, and the exponential decay function with different cut-offs. All matrices are row-standardized. The results of the Bayesian model selection procedure suggest that the SDEM is the preferred spatial specification. Specifically, a 13 nearest neighbours spatial weight matrix is associated with the 'best' SDEM specification (posterior model probability, $p = 0.442$).

Table 3 reports the results of the maximum likelihood estimation of the SDEM associated with a 13 nearest neighbours spatial weight matrix. In addition to the Bayesian model selection procedure, standard Wald tests, which are reported in Table 3, confirm the validity of the SDEM specification. The hypothesis that the spatially lagged explanatory variables and the spatial lag of the error term are jointly equal to zero ($\lambda = \pi = 0$) is decisively rejected. Similarly, the hypotheses that $\lambda = 0$ (SLX) and $\pi = 0$ (Spatial Error Model) are also rejected (Table 3). The spatial error parameter (λ) is negative and statistically significant indicating the diffusion of global shocks, through changes in disturbances, in regional labour markets.

Table 3 Regression estimates of the pre-crisis (2007) determinants of regional labour markets resilience for the Spatial Durbin Error Model (SDEM) for the 276 EU-28 NUTS-2 regions

	Direct effects		Indirect effects ($W \times \Phi$)	
	Coef	Robust Std. Err	Coef	Robust Std. Err
BL Agriculture	−0.022	0.050	0.165	0.187
BL Manufacturing	0.037	0.162	0.132	0.395
BL Construction	−0.291*	0.115	−0.547	0.345
BL Trade, Transportation, Accommodation	−0.131	0.246	0.946*	0.431
BL Finance	−0.315	0.190	−0.208	0.175
BL Real Estate	−0.044	0.153	0.560*	0.261
BL Public Administration, Health, Education	0.409	0.303	−0.162	0.341
FL Agriculture	0.013	0.045	0.140	0.158
FL Manufacturing	−0.271	0.262	−0.035	0.458
FL Construction	0.427*	0.189	0.659*	0.271
FL Trade, Transportation, Accommodation	0.177	0.160	−0.148	0.209
FL Finance	0.054	0.065	0.031	0.142
FL Real Estate	0.097	0.121	−0.123	0.218
FL Public Administration, Health, Education	−0.160	1.024	−2.260**	0.736
Hindex	−0.983**	0.222	−1.625	0.992
Employment Density	−0.009	0.013	−0.030	0.041
Secondary Education	0.032	0.109	−0.048	0.201
Tertiary Education	0.174	0.096	0.508*	0.232
Age3049	−0.637	0.474	−2.179	1.162
Age5064	−0.542	0.472	−3.517**	1.279
Age65+	−0.166	0.299	0.942	0.732
Capital Deepening	0.293**	0.037	−0.213	0.164
Constant	−0.065	0.070		
Spatial error parameter λ	−0.761**	0.216		
Country dummies	Yes			
Pseudo R-squared	0.731			
Log-likelihood	445.44			
Hypotheses	Wald tests			
$\lambda = \pi = 0$	$\chi^2_{23} = 82.40^{**}$			
$\lambda = 0$	$\chi^2_{1} = 12.40^{**}$			
$\pi = 0$	$\chi^2_{22} = 69.96^{**}$			
Country dummies = 0	$\chi^2_{27} = 60.66^{**}$			

*$p < 0.05$; **$p < 0.01$

BL Backward Linkages; *FL* Forward Linkages

First, we consider the effects of region-specific factors that reduce the baseline negative effect of economic shock. Note that a negative sign of the coefficient *b* reduces the negative effect of the shock and thus it positively influences the recovery of regional labour markets. Our empirical results indicate that intersectoral linkages create a diverse effect on regional labour markets resilience. The backward linkages of the Construction sector are positively associated with the resilience of labour markets, i.e., the higher the pre-crisis supplies linkages of the Construction sector in the local economy the higher the resilience of the labour market to economic shocks. On the contrary, the forward linkages of the Construction sector are negatively associated with the resilience of the labour markets, i.e., the higher the pre-crisis sales linkages of the Construction sector in the local economy the weaker the resilience of the labour markets to economic shocks. The effect of backward and forward linkages of the remaining economic sectors, either positive or negative, is not statistically significant.[2]

Grabner et al (2020) explored the role of regional economic embeddedness on the resilience of the EU NUTS-2 labour markets during 2000–2010. The findings of the study, in line with our results, indicate that regions with high supplies (backward) embeddedness of the Construction sector were more resilient to economic shocks. On the contrary, regions with strong sales (forward) embeddedness of the Construction sector were less resilient to economic disruptions. Similar results about the importance of the Construction sector's embeddedness in the resilience of the UK NUTS-2 regions are reported by Kitsos et al. (2019). Klimek et al. (2019) using input–output models showed that the Construction sector in the USA had the fastest rebound from economic shocks during the period 2000–2014. Giannakis and Bruggeman (2017a) found that backward linkages of the Construction sector in Greek NUTS-2 regions increased by 16% between 2004 and 2011.

The Construction sector generally exhibits a higher economic pull (backward) than push (forward) effect. This is due to the nature of the construction operations that need many different inputs from a large number of economic sectors and due to the nature of the demand for the construction outputs that are considered derived demand from other economic activities (Pietroforte and Gregori 2003; Liu and He 2016). Specifically, the Construction sector cannot itself create demand for its output, thus if other sectors cannot absorb the construction outputs or the sector expands beyond the adaptive capacity of the economy, it negatively impacts the economy (Pietroforte and Gregori 2003; Song and Liu 2006).

Our findings indicate that the pre-crisis industrial concentration (Hindex) has a positive effect on the ability of regional labour markets to withstand and recover from exogenous shocks. Giannakis and Bruggeman (2017b) showed that European regional economies with more specialized labour markets (i.e., high

[2] We re-estimated the model by dropping the explanatory variables with correlation coefficients greater than 0.60 (Table C1) and the results remained the same. In addition, we estimated the effect of the aggregated industrial interconnectedness (weighted by the output sectoral shares) on regional labour markets resilience. The estimated parameter for the aggregated interconnectedness was not statistically significant but the rest of the parameters remained similar.

Herfindahl–Hirschman index) relative to EU-28 were more likely to withstand the impact of the 2008 economic crisis compared to regions with more diversified labour markets. Van Oort et al. (2015) found a positive relationship between specialization and productivity growth across EU NUTS-2 regions between 2000 and 2010, particularly for large urban and capital regions. On the contrary, Cainelli et al. (2019a) found that industrial concentration had a negative effect across the EU during the 2008–2012 crisis period. Similarly, Holl (2018) and Di Caro (2017), in their studies of regional resilience in Spain and Italy, respectively, emphasize greater resilience in regions with a large diversity of employment.

The effect of agglomeration forces, here proxied by employment density, is positive for the resilience of regional labour markets, but this relationship is not statistically significant. Similarly, the effect of human capital variables, i.e., education and age structure, is not statistically significant.

Next, our estimates show, as it was expected, that the coefficient of capital deepening is statistically significant and close to the capital revenue share observed in the data. Several authors have stressed the importance of capital deepening in labour productivity growth (Filippetti and Peyrache 2015; Christopoulos and Tsionas 2004). Since we consider only two periods in our analysis, we cannot estimate exogenous technical change differences across regions. However, we introduce country dummies to capture exogenous technical change differences across countries. Country dummies are jointly significant at 1% and therefore we can reject the null hypothesis that the coefficients of the dummy variables are zero (Table 3).

The statistically significant spatial lags of several independent variables in the second part of Table 3 show the spatial spillover effects of changes in neighbouring regions on own-region labour market resilience. Specifically, the statistically significant coefficients of the spatially lagged backward linkages of the Trade, Transportation, Accommodation and Real Estate sectors indicate that high linkages of those sectors in neighbouring regional labour markets reduce the own-region labour market resilience. Similarly, the indirect effect associated with the forward linkages of the Construction sector is negative revealing negative spillovers from neighbouring labour markets on own-labour market resilience. On the contrary, high forward linkages of the Public Administration, Health and Education sector in neighbouring labour markets increase own-labour market resilience. Interestingly, the indirect effect associated with the share of population with tertiary education is negative indicating negative spillover effects arising from the neighbouring regional markets due to the effects of competition between labour markets. Finally, a high share of the population aged between 50 and 64 in neighbouring labour markets increases own-labour market resilience.

5 Conclusions

This paper conceptualizes and empirically measures the resilience of EU regional labour markets in terms of labour productivity growth. Our analysis assesses the effect of pre-crisis region-specific factors on the resilience of spatial labour markets controlling for the effect of exogenous technological change and substitution of labour with capital across European regions.

The empirical analysis of the paper reveals a positive association between the pre-crisis economic pull capabilities of the Construction sector and the resilience of regional labour markets, which derives from the reduction of baseline negative shock. As such, the Construction sector can play an important role in the recovery of EU regions and it should be a key priority of the current (e.g., the Next Generation EU instrument for economic recovery from the coronavirus pandemic) and future stimulus packages for overcoming the adverse effects of negative shocks. However, the negative association of the push capabilities of the sector with the resilience of labour markets indicate that the Construction sector can positively affect the recovery of labour markets when there is sufficient demand from other sectors to absorb the outputs of the sector. An over-expansion of construction operations may generate inflationary pressures and thus negatively affect the stability of regional economies.

Our findings indicate that pre-crisis industrial concentration has a positive effect on regional labour markets resilience, which derives again from the reduction of baseline negative shock. Place-based policies building on regions' competitive strengths can smooth out the negative effect of exogenous shock, and thus allow a faster recovery of regional economies. Finally, our study confirms the importance of capital deepening in labour productivity growth. As such, policy interventions promoting capital investment in digital transformation, research and development, competitiveness, and innovation included in the current EU Recovery and Resilience Plan, can further enhance labour productivity in EU regions.

Appendix A: Construction of capital stock series for EU-28 NUTS-2 regions

The perpetual inventory method was used to construct capital stock series for each EU-28 NUTS-2 region i as follows (OECD 2009):

$$K_t = K_{t-1} + I_{t-1} - D_{t-1} \tag{A.1}$$

where K_t is the net capital stock at period t; K_{t-1} is the net capital stock at the previous period $t-1$; I_{t-1} is the gross investment in the previous period $t-1$; D_t is the depreciation in the current period t. Assuming that all regions have geometric depreciation rate, Equation (A.1) can be written as follows:

$$K_t = (1-\delta)K_{t-1} + I_{t-1} \tag{A.2}$$

The gross fixed capital formation data, available from Eurostat (2020d), are used as a proxy for investment (I) to construct a capital stock series (K) for the period 2000–2017. We further assume δ equals 0.07 (Levenko et al. 2019). The initial capital stock $\left(\mathrm{K}_{2000}\right)$ is computed as follows (OECD 2009):

$$K_{2000} = \frac{I_{2000}}{g + \delta} \tag{A.3}$$

where g is the growth rate of investment which is proxied here by the average growth rate of gross domestic product for the period 1995–1999.

Appendix B: Construction of regional input-output tables for EU-28 NUTS-2 regions

In this study, we used non-survey techniques to construct regional IO tables. The non-survey techniques involve the representation of the structure of the regional economy through the modification of the national technical coefficients (Giannakis and Bruggeman 2017a).

The regional IO technical coefficients a_{ij}^R can be estimated as follows (Tohmo 2004):

$$a_{\mathrm{ij}}^R = t_{\mathrm{ij}}^R \cdot a_{\mathrm{ij}}^N \tag{B.1}$$

where a_{ij}^N are the national IO coefficients ($N = 1, 28$); t_{ij}^R are the regional trading coefficients and i and j identify the sectors.

The regional trading coefficients $\left(t_{ij}^R\right)$ are typically estimated via the application of employment-based location quotients (LQ) (Flegg and Tohmo 2013). Here, we apply the cross industry location quotients (CILQ) formula as follows (Giannakis and Bruggeman 2017a):

$$\mathrm{CILQ}_{\mathrm{ij}}^R = \left[\frac{E_i^R / E_i^N}{E_j^R / E_j^N}\right] \tag{B.2}$$

where E_i^R and E_j^R are employment in sectors i and j in region R; E_i^N and E_j^N are employment in sectors i and j in country N.

If $\mathrm{CILQ}_{\mathrm{ij}}^R < 1$, it is assumed that some of the needs of sector j for input from sector i have to be imported from another region, and the national coefficients will be adjusted downwards by multiplying them by the $\mathrm{CILQ}_{\mathrm{ij}}^R$. If $\mathrm{CILQ}_{\mathrm{ij}}^R \geq 1$, it is assumed that all needs of sector j for input from sector i can be met within the region. Thus, the regional IO coefficients can be computed as follows:

$$a_{\mathrm{ij}}^R = \left\{ \begin{array}{l} a_{\mathrm{ij}}^N \mathrm{CILQ}_{\mathrm{ij}}^R \text{ if } \mathrm{CILQ}_{\mathrm{ij}}^R < 1 \\ a_{\mathrm{ij}}^N \text{ if } \mathrm{CILQ}_{\mathrm{ij}}^R \geq 1 \end{array} \right\} \tag{B.3}$$

Table B1 presents the aggregated 8-sector classification of the 276 EU-28 NUTS-2 regional IO tables for the year 2007.

See Table B1

Table B1 NACE (Statistical classification of economic activities in the European Union) codes of the sectors of economic activity for the 276 EU-28 NUTS-2 regions

n/n	Sector	NACE code
1	Agriculture	A01-A03
2	Manufacturing	C10-C33
3	Construction	F
4	Trade, Transport, Accommodation	G45-G47, H50-H53, I
5	Finance	K64-K66
6	Real Estate	L68
7	Public administration, Health, Education	O84, P85, Q
8	Others	B, D35, E36-E39, J58-J63, M69-M75, N, R, S, T, U

Source: Eurostat (2008)

Appendix C: Correlation matrix

See Table C1

Table C1 Correlation matrix of the explanatory variables

		[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
BL Agriculture	[1]	1									
BL Manufacturing	[2]	0.00	1								
BL Construction	[3]	0.01	0.65	1							
BL Trade, Transportation, Accommodation	[4]	0.29	0.55	0.64	1						
BL Finance	[5]	0.40	0.06	−0.07	0.38	1					
BL Real Estate	[6]	0.28	−0.21	0.00	0.04	−0.02	1				
BL Public Administration	[7]	0.11	0.15	0.30	0.32	−0.05	0.25	1			
FL Agriculture	[8]	0.07	0.08	−0.06	0.16	0.27	−0.21	−0.19	1		
FL Manufacturing	[9]	0.05	0.05	0.06	−0.12	0.11	−0.15	−0.20	0.20	1	
FL Construction	[10]	0.15	−0.29	−0.15	−0.16	0.06	0.38	0.13	−0.10	0.30	1
FL Trade, Transportation, Accommodation	[11]	0.26	−0.17	−0.07	−0.01	−0.02	0.34	−0.07	0.16	0.33	0.36
FL Finance	[12]	0.16	0.18	0.15	0.15	0.11	−0.23	−0.26	0.21	0.23	−0.15
FL Real Estate	[13]	0.00	0.07	0.03	0.01	−0.21	0.01	−0.45	−0.03	−0.12	−0.24
FL Public Administration	[14]	0.19	0.15	0.04	0.21	0.36	0.27	0.49	−0.02	−0.02	0.37
Hindex	[15]	0.02	0.02	−0.20	−0.09	0.29	−0.22	−0.27	0.11	0.05	0.04
Employment Density	[16]	−0.15	−0.01	−0.01	−0.07	0.00	−0.04	0.13	0.05	0.02	0.13
Secondary Education	[17]	0.40	−0.26	−0.31	0.03	0.18	0.51	0.07	−0.05	−0.25	0.08
Tertiary Education	[18]	−0.07	−0.12	−0.10	0.01	0.09	0.05	0.26	0.06	0.01	0.16
Age3049	[19]	−0.10	0.29	0.38	−0.01	−0.19	−0.17	0.04	−0.05	0.09	−0.11
Age5064	[20]	0.18	−0.22	−0.08	0.13	−0.02	0.23	0.20	−0.11	−0.20	−0.01
Age65	[21]	−0.14	0.26	0.09	0.23	0.01	−0.33	0.04	0.00	−0.19	−0.29
Capital Deepening	[22]	0.11	−0.06	−0.02	−0.01	−0.13	0.31	0.01	0.00	0.04	0.14

Table C1 (continued)

	[11]	[12]	[13]	[14]	[15]	[16]	[17]	[18]	[19]	[20]	[21]	[22]
BL Agriculture												
BL Manufacturing												
BL Construction												
BL Trade, Transportation, Accommodation												
BL Finance												
BL Real Estate												
BL Public Administration												
FL Agriculture												
FL Manufacturing												
FL Construction												
FL Trade, Transportation, Accommodation	1											
FL Finance	0.29	1										
FL Real Estate	0.19	0.44	1									
FL Public Administration	0.14	−0.32	−0.50	1								
Hindex	−0.06	0.14	−0.07	0.08	1							
Employment Density	−0.09	−0.17	−0.19	0.21	0.28	1						
Secondary Education	0.26	0.02	0.06	0.08	−0.15	−0.16	1					
Tertiary Education	−0.07	−0.22	−0.11	0.26	0.14	0.42	−0.30	1				
Age3049	−0.08	0.14	0.16	−0.09	−0.02	0.36	−0.24	0.10	1			
Age5064	0.15	0.03	0.06	−0.10	−0.27	−0.37	0.39	−0.07	−0.49	1		
Age65	−0.16	0.15	0.26	−0.12	−0.29	−0.28	−0.02	−0.12	−0.15	0.40	1	
Capital Deepening	0.09	−0.17	−0.03	−0.10	−0.15	−0.10	0.25	0.04	−0.17	0.15	−0.26	1

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