I.S.S.N.: 0213-7585

REVISTA DE ESTUDIOS REGIONALES

2ª EPOCA Septiembre-Diciembre 2017

110

SUMARIO

UNIVERSIDADES DE ANDALUCÍA

REVISTA DE ESTUDIOS REGIONALES Nº 110, I.S.S.N.: 0213-7585 (2017), PP. 175-195

Effects of smart specialization on regional economic resilience in EU

Efectos de la especialización inteligente en la resiliencia económica regional en la UE

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Recibido, Noviembre de 2016; Versión final aceptada, Julio de 2017.

Keywords: Regional economic resilience, Smart specialization, EU, Dynamic panel, NUTS regions

Palabras claves: Resiliencia económica regional, UE, Panel dinámico , NUTS regiones

Clasificación JEL: R10, R11 O31, B52

RESUMEN

Recientemente, el término “resiliencia económica regional” (RER) se ha vuelto popular para entender cómo las economías regionales están funcionando debido a las consecuencias de las recientes crisis económicas. Así, el RER ha estado en el foco del investigador, pero falta la investigación empírica sobre sus determinantes. Por lo tanto, este trabajo establece un modelo empírico centrado en el papel de la especialización inteligente para el RER. El análisis empírico se realiza para las regiones NUTS 2 en la UE-27 sobre la base de un enfoque de datos panel para un período de 10 años (2003-2012). Los resultados indican que la especialización inteligente tiene un efecto significativo y positivo en el RER.

ABSTRACT

The regional economic resilience (RER) term has become popular recently and tackles the issue of understanding how regional economies are faring due to the consequences of high levels of economic dynamism. In that way RER becomes the focus of the researchers but there is lack of the empirical investigation of its determinants. Therefore, this paper establishes empirical model focusing on the role of smart specialization on RER. Empirical analysis is performed for NUTS 2 regions in EU-27 based on a panel data approach for a 10-year period (2003-2012). The results indicate that smart specialization has significant and positive effect on RER.

1. INTRODUCTION

Regional economic resilience is multidimensional phenomena that can be differently defined, used and managed, depending on different objectives (Modica and Reggiani, 2015). As phenomenon it has been in the focus of recent empirical research mainly due to the latest economic crises and observed regional differences in both, the vulnerability to economic shocks and ability to adapt to serious disruptions in the economic environment (e.g. Bristow, 2010; Hassink, 2010; Christopherson et al., 2010; Simmie and Martin, 2010; Martin, 2012; Bristow and Healy 2014; Martin and Sunley, 2015; Sensier et al., 2016). Consequently, regional economic resilience has rapidly become important part of regional and local economic studies (e.g. Martin and Sunley, 2015) and a new imperative in policy cycles. Nonetheless, its conceptual framing and empirical implementation remain the subject of considerable academic debate (Bristow and Healy, 2014; Boschma, 2014; Martin and Sunley, 2014; Sensier et al., 2016).

Martin and Sunley (2015) conceptualize regional economic resilience as capacity of regional or local economy to withstand or recover its developmental growth path from market, competitive and environmental shocks by, if necessary, undergoing adaptive changes of its economic structures and its social and institutional arrangements, so as to maintain or restore its previous developmental path, or transit to a new sustainable path characterized by a fuller and more productive use of its physical, human and environmental resources. They also emphasize that there is still substantial ambiguity about what does the concept of regional economic resilience represent, how should it be measured and which are its determinants (Martin and Sunley, 2015).

The focus of the analysis in this paper is in the latest mentioned issue. The notable literature area in regional science is not only looking at specific factors that explain regional employment growth and the long-run developmental path (Mameli et al., 2014; Di Caro, 2015), but also in investigating the determinants of multidimensional phenomena such as regional economic resilience. In this paper the empirical investigation of determinants of regional economic resilience is performed at the EU regional level.

This empirical analysis has no intention to explain the theoretical background for this relationship, but it intends to provide the empirical evidence which stimulates researchers to pay more attention on theoretical explanation of possible channels through which smart specialization can affect regional economic resilience. Thus the results of this paper could have significant benefits for stakeholders. They can provide policy makers with the notion of and better understanding of regional economic resilience. Consequently, the policy makers can create conditions for regional economic resilience to be more robust by, for example, delivering more effective regional policy measures.

In order to empirically investigate the determinants of regional economic resilience (RER) this paper introduces the role of smart specialization (SS). Why SS? The SS is one of the cornerstones of the new place-based approach that characterize regional development interventions in the EU (Rodriguez-Pose et al., 2014). Furthermore, the smart specialization approach offers a range of advantages for the design of appropriate innovation policy-making from a regional policy perspective (McCann and Ortega-Argilés, 2015). Thus, SS approach is compatible with key characteristics of regional economic resilience and investigation of its effects on RER gives new insights in RER literature. Although there is theoretical foundation for the possible link between smart specialization and regional economic resilience, empirical evidence in the literature is still quite limited. Moreover, in the analyzing of the effects of the smart specialization on regional economic resilience, up to the knowledge of the authors, this is the first study attempting this issue. The paper is structured as follows: in Section 2 the various definitions of resilience and their characteristics and links with the smart specialization are provided and described. Section 3 introduces the empirical investigation of the role of smart specialization on regional economic resilience for NUTS II regions in EU during the period 2003-2012. Finally, section 4 concludes the paper with recommendations for future research, highlighting the need for further empirical studies in clarifying the determinants of regional economic resilience.

2. LITERATURE REVIEW

The word resilience comes from Latin “resilire” which means *to rebound or leap back*. This etymology the researchers try to imbed in their definitions of resilience (e.g. Martin, 2012). Modica and Reggiani (2015) argue that the etymology of the word *resilience* is common foundation for all definitions of resilience and for the definitions of regional economic resilience as well. Furthermore, term resilience has been earlier introduced in different scientific fields such as physics and ecology that consequently led to its first differentiation in definition (Modica and Reggiani, 2015).

Markusen (2003) and Swanstrom (2008)(cited by Modica nad Regigiani, 2015) indicate that in economic science resilience has been introduced as boththe fuzzy concept or just conceptual framework. However, resilience in economics and especially in regional economics has recently received huge scientific interest (Christopherson et al. 2010; Simmie and Martin 2010; Martin 2012; Bristow and Healy 2014; Martin and Sunley 2015; Modica and Reggiani 2015).

The scientific research in economic literature offers several different definitions of regional economic resilience that have been widely explained in the papers by Martin and Sunley (2015) and by Modica and Reggiani (2015). First definition lies on the ‘bounce back’ version of the resilience concept. This concept is founded by Holling (1973) where resilience is examined as system’s speed of recovery or return to its pre-shock position. Considering that this definition is mostly used in physical and engineering sciences, it has been called ‘engineering resilience’. This concept implies that “return to normal” and the “normal” could be interpreted as identifiable long-run, path-dependent developmental trajectories. This definition and ability of systems to maintain or regain stability after external perturbations and disturbances has been challenged by implementing new concept defined as ‘ability to absorb“. This concept implies resilience to be “the capacity of a system to absorb disturbance and reorganize while undergoing change so as to still retain essentially the same function, structure, identity and feedbacks” (Walker et al., 2006, p 2.). However, as Martin and Sunley (2015) indicate “this definition is not without ambiguity, since it remains unclear just how much ‘reorganization’ and ‘change’ is permitted for the system to be regarded as still having ‘essentially the same structure, identity and feedbacks’. These doubts offered space for the new concept named „adaptive resilience’. This concept defines resilience as “the ability of the system to withstand either market or environmental shocks without losing the capacity to allocate resources efficiently” (Perrings,2006, p.418). This idea of resilience has led some authors to refer to it as ‘evolutionary resilience’, defined in terms of ‘bounce forward’ concept rather than ‘bounce back’ concept (Simmie and Martin, 2010).

Taking those three main interpretations into consideration it is obvious that defining regional economic resilience is not straightforward. However, Martin and Sunley (2015) introduce the definition that tackles all previously mentioned challenges. They define regional economic resilience as the capacity of a regional or local economy to withstand or recover its developmental growth path from market, competitive and environmental shocks by, if necessary, undergoing adaptive changes of its economic structures and its social and institutional arrangements, so as to maintain or restore its previous developmental path, or transit to a new sustainable path characterized by a fuller and more productive use of its physical, human and environmental resources. As Martin and Sunley (2015) underline, this definition has five crucial elements: vulnerability (the sensitivity or propensity of a region’s firms and workers to different types of shock); shocks (the origin, nature and incidence of a disturbance, and the scale, nature and duration thereof), resistance (the initial impact of the shock on a region’s economy); robustness (how region’s firms, workers and institutions adjust and adapt to shocks, including the role of external mechanisms, and public interventions and support structures); and recoverability (the extent and nature of recovery of the region’s economy from shocks, and the nature of the path to which the region recovers). All these five elements indicate that regional economic resilience is linked with the regional (economic) characteristics, shaping and by being shaped by the reaction of the region’s economy (Simmie and Martin 2010).

Considering that regional (economic) characteristics are noticeably important for fully understanding the regional resilience phenomena and that these characteristics are shaped by research and development actives (e.g. Rodriguez-Pose et al. 2008) this paper emphasizes the role of the smart specialization for regional economic resilience.

The development of smart specialization concept started within the broad empirical literature examining the transatlantic productivity gap, i.e. the productivity gap between the US and Europe, that has been evident since 1995 (van Ark et al., 2008). The empirical analysis of the factors which have generated those differences was especially related to the differences in labour markets (Gu et al., 2002; Gu and Wang, 2004; Bloom et al., 2005; Gordon and Dew-Becker, 2005; Gomez-Salvador et al., 2006; Crespi et al., 2007) and the differences in industrial performance (McCann and Ortega-Argilés, 2015). The differences in industrial performance have been explained via two broad themes. The first one originating from the differences in industrial structure where according to Mathieu and van Pottelsberghe de la Potterie (2008) European traditional, middle and low-tech sectors are far more ineffective in translation of R&D into productivity gains. The second one goes deeper in sectoral analysis finding out that even within the same sectors European firms exhibit a lower ability to translate R&D into productivity gains or other type of investment (Erken and van Es, 2007). The common theme that has emerged from these explanations is that information and communication technologies (ICTs) play a critical role in productivity gap explanations (McCann and Ortega-Argilés, 2015). Finally, revealed technological disadvantage of EU relative to the US has been seen in ICT-related explanations, proxied by ICT-based R&D investment (Foray, David and Hall, 2009). Nevertheless, the shift from the role of R&D intensity to the role of dissemination of new technologies across the wider economy in explaining the growth potentials has emerged recently in the literature (McCann and Ortega-Argilés, 2015). The rationale for smart specialisation strategy is seen in encouraging investment in programs that will complement the country's additional productive assets to create future domestic capability and interregional comparative advantage (Foray, David and Hall, 2009). Thus the importance of adoption, dissemination and the adaptation of new ICTs across the wider economy has been emphasized (Jorenson, 2001; Jorgenson et al., 2005; Stiroh, 2002; Timmer and van Ark, 2005; O'Mahoy and van Ark, 2003; Gordon, 2004; Draca et al., 2006; Wilson, 2009). This resulted in the adaptation of smart specialisation concept originally developed in sectoral dimension to the regional dimension where the straightforward shift from smart specialisation concept to a regional context is quite difficult and rather more complex that it at first appears (McCann and Ortega-Argilés, 2015). Rodriguez-Pose et al. (2014) explain that the development of smart specialisation concept on a regional basis is based on the recognition that successful development and innovation strategies cannot be replicated mechanically in each and every different regional context. They also argue that rather than trying to generate 'technology miracles' in economically disadvantaged areas, the best way to close the gap between less innovative regions and technology hubs is to try to identify the unique assets that make the potential for innovation in a peripheral region (Rodriguez-Pose et al., 2014). According to Foray, David and Hall (2009) national public policy has an important role in supporting and accompanying emerging trends in smart specialisation. The role is seen in supplying incentives to encourage entrepreneurs and other organizations (higher education, research laboratories) to become involved in the discovery of the regions' respective specialisations. Thus, in contrast of the traditional linear model of devoting more resources into R&D, research and innovation strategies for smart specialisation (RIS3) require a much higher effort in planning, as policy measures are not transposed from the best performers, but they are the result of a careful examination of a region's weaknesses and potential strengths (Rodriguez-Pose et al., 2014). Consequently, the initialisation of the usual policy tools to support R&D and innovation should begin after depicting of the potential of a particular technology to regenerate the targeted economic domain (production or services) through the co-invention of applications, and after examining whether the size of this domain is large enough (the size refers here not to GDP but to the size of the relevant sectors in the economy, that is, those sectors that could potentially benefit from the knowledge spillovers from the initial development of applications (Foray, David and Hall, 2009). Finally, according to McCann and Ortega-Argilés (2015) an increasing emphasis on enhancing the linkages between knowledge generation processes in all their forms (including R&D) and the promotion and dissemination of entrepreneurship and innovation across all sectors, activities and occupations within the context of global value chains is present nowadays in regional and smart specialisation development strategies.

All these elements of smart specialization should rather than pursuing 'one-size fits-all' skills-training policies or alternatively always prioritizing high-technology sectors over others, foster human capital formation for the new 'knowledge needs' in the region's traditional industries which are starting to adapt to new technologies and applying them (David et al., 2009). Moreover, stimulating a local skills base helps the facilitation of widespread local incremental improvements across a range of the region's economic activities. Furthermore, those activities develop more specialized application technologies in the region that could result in decreased region's vulnerability and increased region's resistance, increased robustness and increased recoverability. Those three increased elements are the key elements for higher levels of regional economic resilience.

3. EMPIRICAL RESEARCH

Since the aim of the paper is to investigate the effects of smart specialization on regional economic resilience those two variables are of particular importance for study. In the process of choosing proxies for these two variables the papers by Martin and Sunley (2015), Rodriguez-Pose et al. (2014), Moddica and Reggiani (2015) and Sensier et al. (2016) have been considered. Regional economic resilience is a phenomenon with quite difficult measurement approach. The literature offers several different ways to proxy the variable for its measurement, ranging from descriptive and interpretative case studies to econometric models (e.g. Simmie and Martin, 2010; Martin, 2012, Fingleton et al., 2012; Cowell, 2013; Sensier et al., 2016). Each of these methods and approaches has certain limitation(s) and in principle there are no reasons why different methods could not be combined (Martin and Sunley, 2015). In this paper the aspects of measuring regional resilience and its determinants are analysed using panel data model. This econometric approach uses quantitative data for proxy variables, while interpretative and descriptive case study approach is not applied.

The panel data model formed in this paper uses sensitivity index (*RES*) as an indicator for dependent variable (regional economic resilience). The sensitivity index has been usually calculated based on employment data (see Martin (2012) and Finleton et al. (2012)) or GDP data. The current literature indicates that employment is more appropriate measure for sensitivity index calculation than GDP (see Coyle(2014) and Sensier et al. (2016)) since employment data are less prone to revision. Thus, sensitivity index in this paper gauges the percentage change in employment in one region (E_r) compared with the EU-27 average change in employment (E_{EU-27}). The formula used for its calculation is presented in following paragraph:

$$RES = \frac{(\frac{\Delta E_r}{E_r})}{(\frac{\Delta E_{EU-27}}{E_{EU-27}})} \tag{1}$$

In equation (1) stands for employment[1] change in region *i* in period *t* compared to period *t-1* while is employment in region *i* in period *t.* The symbol $_{EU\text{-}27}$ stands for employment change in EU 27 in period *t* compared to period *t-1,* while EU 27 represents employment in period t.

Second important variable in this empirical research is smart specialization (SS). For defining its proxy, the approach implemented by Rodriguez-Pose et al. (2014) has been followed. Thus, the natural logarithm of patents application filled to the European Patent Office (EPO) per million inhabitants in region is used as a proxy for SS. Furthermore, to check robustness, the natural logarithm of patent applications to the EPO per millions of active population, is also used.

The assumption that regional economic resilience is influenced only by the smart specialization is rather restrictive and results could potentially suffer from the omission of other (possibly) significant determinants. Hence, this paper analyses whether the relationship between regional economic resilience and smart specialization holds when additional explanatory variables are included in the model.

Before indicating other important determinants, it should be emphasized that understanding the determinants of regional economic resilience is complex process, with many factors being simultaneously important (Fingleton et al., 2012; Martin et al, 2016). Consequently, the current literature indicates different variables that could possibly determine regional economic resilience and that could be used as control variables in empirical models (e.g. Fingleton and Palombi, 2013; Brakman et al., 2014; Di Caro, 2014; Diodato

1 Employment rates 15+

and Waterings, 2014; Martin and Sunley, 2015; Holm and Østergaard, 2015; Sedita et al., 2016; Nystrom, 2017). For instance, Martin and Sunley (2015) indicate five basic groups of regional economic resilience determinants: (i) industrial and business structure, (ii) labour market conditions, (iii) agency and decision-making, (iv) financial arrangements and (v) governance arrangements. Sedita et al. (2016) recognize related and unrelated varieties, population density, macro-geographical area, industrial districts and degree of exporting as relevant determinants. Finally, Nystrom (2017) underlines five areas of determinants of regional resilience : (i) regional closures, (ii) individuals in the region, (iii) regional industry, (iv) regional economy and (v) regional attractiveness.

The inclusion of all potential determinants indicated in the abovementioned literature in this paper could be ultimate. But it is not straightforward task since the regional data on stated aspects (determinants) are rarely available and/or of poor quality. Therefore, the focus of this paper has been on a limited number of available variables. Taking into consideration these limitations, the following variables are considered: GDP, labor force participation, education, institutional quality, infrastructure, population, unemployment and specialization indexes.

The GDP level as determinant of regional economic resilience has been included by several reasons. Regions with the high level of the GDP usually have higher regional attractiveness that has been recognized as important determinant of regional economic resilience by Nystrom (2017). The author indicates that more attractive region might generate more opportunities, which also generate additional openings for employment or entrepreneurship for displaced workers. Furthermore, this facet is important for demographic fluctuations. More precisely, the regions with higher levels of GDP could affect job-search process. Neffke et al. (2016) indicate that bigger economy can have higher arrival rate of job offers. Also, this higher number of job offers can improve the possibilities for better match. Finally, social networks can affect the process of finding jobs after displacement. Thus, the superior possibility of higher level of economic resilience is expected to be in large economies.

Labor market conditions have been indicated as important determinants of regional economic resilience according to Martin and Sunley (2015) and Martin et al. (2016). Labor market conditions incorporate different dimensions of labor market characteristics among which occupational, wage and hour's flexibility and mobility on labor market have been usually related with the higher levels of *labor force participation*. Therefore, the labor force participation is considered to be the determinant of regional economic resilience and it is expected to have positive effects on regional resilience.

The skills of labor force and the characteristics of human capital may not be only the important element of regional resilience (Di Caro, 2014; Martin and Sunley, 2015 and Martin et al., 2016) but, moreover, the key determinant of regional resilience (Nystrom, 2017). The notable number of the empirical studies indicate that higher level of human capital decreases regional shocks and therefore makes regional economy more resilient (e.g. Martin, 2012; Glaeser, Ponzetto and Tobio, 2014; Nystrom, 2017). This is the reason why this study introduces the *educational level of labor force* as one of the determinants of regional economic resilience and it is expected that higher educational level of the work force makes the region more resilient.

Many of the factors that have been previously mentioned as relevant determinants of resilience might be described as 'institutional' (labor market, financial systems and governance arrangements) as they represent more durable patterns and combinations of formal and informal ways of organizing economic activity (Martin et al., 2016). Therefore, the effective *institutional framework* is considered to be a determinant which improves productivity and creativity in regional economy and thus increases regional resilience. Furthermore, it can increase the level of mutual confidence and consequently reduce transaction costs which finally increase regional economic resilience.

A large number of empirical studies have tried to assess the impact of infrastructure on economic growth and many of them find a positive and important contribution of *infrastructure provision* to economic growth (European Commission, EC, 2014). There are several most relevant channels of infrastructural influence explained in report by EC (2014). First channel through which infrastructure effects economic growth is seen through the production function and effects of transport infrastructure on production costs (Pradhan and Bagchi, 2013). Second channel indicates that effective infrastructure may boost capital accumulation by providing opportunities for capital developments (Kirkpatrick, 2004). Furthermore, the provision of infrastructure stimulates aggregate demand by increasing expenditure in construction and maintenance operations (e.g. Pradhan and Bagchi, 2013). Finally, infrastructural development induces other investments in the economy by providing economic/development signals to key sectors in the economy (Fedderke and Garlick, 2008).

Nystrom (2017) follows Neffke et al. (2016) and indicates the reasons why *population* of the region should be considered as determinant of regional economic resilience. Accordingly, the larger region improves the possibilities for a better competition and therefore the population number should increase the resilience. At the same time, social networks, which are often local, are expected to affect the process of finding a job after displacement. Finally, according to Chapple and Lester (2010) the larger region meets greater potentials in terms of new firm creation and labor mobility.

Another indicator presented in paper by Neffke et al. (2016) is the *regional unemployment level*. In case that regional unemployment represents an unfavorable economic situation in the region, higher regional unemployment might decrease the regional resilience. However, it could also represent higher supply of labor force and therefore higher opportunities for re-employment (Nyström, 2007). In addition, Nystrom (2017) indicates that the newly displaced workers might be in a better position than already unemployed workers indicating negative effects of regional unemployment on regional resilience. Although the presented empirical literature offers foundation for recognizing the importance of population and unemployment as two determinants for regional economic resilience the direction of the relationship is still not clear from both theoretical and empirical perspectives.

The structure of regional and local economies has a significant effect on economic activity in analyzed region or area. Nystrom (2017) and Martin & Sunley (2006) indicate that an excessively narrow regional specialization could decrease the probability of radical innovation and renewal of the economy. Likewise, regions with more diverse industries are less likely to experience large changes in employment. The literature offers two main explanations for such postulations. It could stand because those regions are less affected by exogenous changes in demand for their products (Chapple and Lester, 2010) or because they are more likely to have diverse industries at different stages of the product life cycle (Markusen, 1985). As a result, regions with greater variety of unrelated industries could have greater level of regional resilience. However, regions with a high degree of inter related industries may imply greater regional competitiveness and, hence, greater ability to absorb displacement (Nystrom, 2017). Obviously, *structure of regional economy* might represent the relevant factor for regional economic resilience but the directions of the effects are still not clear. Consequently, *regional specialization* has been indicated as a relevant variable for regional economic resilience. The proxy used for regional industry specialization is the index of specialisation (SI_{ij}). It is calculated on the basis of the following equation (European Commission, 2012):

$$SI_{ijt} = \frac{E_{ijt}}{\sum_{j=1}^{n} E_{ijt}} \Big/ \frac{\sum_{i=1}^{m} E_{ijt}}{\sum_{j=1}^{n} \sum_{i=1}^{m} E_{ijt}}$$

where *i* refers to the region, *j* to the sector and E stands for employment in period *t*. In case that region *i* has higher level of employment concentration in sector *j* than EU27 average, this implies that the region is specialized in this sector (ie. value of SI index is higher than one). The sectors, or sector groups, chosen to define regional specialisation are composed on the basis of NACE classification[2].

Finally, the regional economic resilience depends on its past values. Thus the panel data model formed for the analysis includes dynamic behavior of dependent variable presented by lagged dependent variable.

2 Nace 2 classification:
A Agriculture, forestry and fishing (AGR); B-E Industry (except construction) (IND); F Construction (CON); G-I Wholesale and retail trade, transport, accommodation and food service activities (TRD); J Information and communication (INF); K Financial and insurance activities (FIN); L Real estate activities (EST); M-N Professional, scientific and technical activities; administrative and support service activities (SER); O-Q Public administration, defence, education, human health and social work activities (PUB); R-U Arts, entertainment and recreation; other service activities; activities of household and extra-territorial organizations and bodies (ART); Data for period 2003-2012 were obtained from Eurostat: http://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=nama_10r_3empers&lang=en

3.1. Model and the results

The final model formed for the analysis in this paper is given by following equation:

$$RES_{it} = \mu + \gamma RES_{i,t-1} + \beta_1 SS_{it} + \beta_2 GDPpc_{it} + \beta_3 EDU_{it} + \beta_4 PART_{it} + \beta_5 WGI_{it} + \beta_6 RAIL_{it} + \beta_7 POP_{it} + \beta_8 UNEMP_{it} + SI_{it}\delta + \alpha_i + \varepsilon_{it} \quad (2)$$

where *i* stands for NUTS2 region and *t* is one-year period. μ is an intercept, γ is a parameter of lagged dependent variable and $\beta_1, \beta_2,\ldots, \beta_8$ are the parameters of exogenous variables. $SI_{it} = [SI_{it1}, SI_{it2}\ldots SI_{itK}]$ where 1xK is matrix of control variables of specialization indexes. δ is Kx1 vector of parameters. It is assumed that ε_{it} are IID(0,). α_i is unobservable individual-specific effect that is time invariant and it accounts for any individuals.

Besides already presented proxy variables for RES, SS and SI, the presented model uses gross domestic product per capita (*GDPpc*) (GDP at current market prices, PPS per inhabitant) as proxy for independent variable GDP. As proxy for labor force participation (*PART*) labor force participation rate is used (or economic activity rate - population from 15 to 64 years) while education (*EDU*) is approximated by percentage of people with tertiary education in population between 25 and 64 years. Indicator for infrastructure *(RAIL)* uses total railway lines (kilometre/1000 square km) in a specific country. Since there are no data at regional level to depict institutional quality the paper uses common proxy for institutional quality at national level. Thus the national WGI is adopted by calculating the average of the values for six dimensions of WGI[3], and these values have been presented as proxy for institutional quality at regional level in given country. Furthermore, indicator for population is population density (*POP*) in the region (average population per square kilometre) while indicator for unemployment (*UNEMP*) is total unemployment rate of people aged 25+ years.

Data for GDP, education, infrastructure, population and unemployment have been collected from QoG EU Regional dataset (Charron et al., 2016), while labor force participation data and data for calculation of specialization indexes are collected from Eurostat database. Data for governance indicators have been collected from World Bank dataset (WGI, 2015). The model data cover period from 2003 till 2012.

The yearly basis data for all variables in all regions (276) are collected but their complete availability for analyzed time period 2003-2012 at regional level had interruptions (evident in the Table 1 where for some variables availability for all years counted only 179 regions (variable RAILsq) while for some other variables the data was available for entire time period and in all regions (variable WGIp)). To have balanced final models the number of 122 regions (groups) were used in estimation.

3 Voice and Accountability (VOI), Political Stability and Absence of Violence (POL), Government Effectiveness (GOV), Regulatory Quality (REG), Rule of Law (LAW) and Control of Corruption (COR)

The model presented for this study postures several advantages. According to Pablo-Romero and Molina (2013) panel data methodology allows larger number of explanatory variables, larger sample of countries, longer time periods under analysis and greater depth in the relationships between variables. Furthermore, Seetaram and Petit (2012) specify that one of the most important advantages is that panel data modelling allows for the control of heterogeneity in the sample. Thus, in order to control heterogeneity in this paper all variables that are given in relative ratios are transferred to natural logarithms (except WGI which is special in percentile rank term, ranging from 0 (lowest rank) to 100 (highest rank)).

Descriptive statistics of the model is presented in the Table 1. It provides intuition and foundation for understanding of this empirical investigation. It can be noticed that regional economic resilience measured by Sensitivity index (RES) has mean 0.78 and standard deviation 14.55 which suggests that this variable has high variations.

TABLE 1
DESCRIPTIVE STATISTICS

Variable	Mean	Std. Dev.	Min	Max	i	N
RES	0.788622	14.55571	-192.1568	111.4465	268	2517
SSinh	99.48189	122.3132	0.018	783.677	264	2524
SSact	207.7437	381.9851	0.05	3341.41	264	2560
GDPpc	23938.25	10976.62	4400	146500	274	2740
EDU	71.07169	15.41041	15.2	97	266	2614
LABOR	70.82707	6.415376	46.3	84.4	275	2556
WGIp	82.03851	10.70807	50.31963	99.75804	276	2760
RAILsq	67.88973	77.21147	0	708	179	1578
POPsq	391.3615	961.357	2.3	10294.8	267	2627
UNEMP	7.450754	4.543807	1.5	33.4	274	2585
SI_AGR	1.077376	1.415496	0	9.740266	266	2621
SI_IND	0.966123	0.394798	0.125309	2.290581	266	2621
SI_CON	0.997585	0.260324	0.347811	2.038058	266	2621
SI_TRD	1.414915	0.262464	0.596811	2.748457	202	1985
SI_INF	1.246334	0.814419	0.141007	4.646315	202	1985
SI_FIN	1.321929	0.915617	0.228803	7.272462	202	1985
SI_EST	1.328903	0.795763	0	6.112902	202	1985
SI_SCI	1.328106	0.652063	0.217471	3.545266	202	1985
SI_PUB	1.276334	0.369015	0.373233	2.762825	228	2241
SI_ART	1.268108	0.554014	0.343839	3.551939	202	1985

Note: i-the number of regions for which the data for variable is available; N – the number of observations in the analyzed period 2003-2012. Source: compiled by the authors using software Stata 13.0

Next step in the modeling of dynamic panel data is the test of multicollinearity (see Baltagi, 2008). The pair wise correlation matrix with Pearson's correlation coefficients is given in Table 2.

TABLE 2
PAIR WISE CORRELATIONS MATRIX

Variable	RES	L2.RES	L.logSSi	L.logSSa	L.GDPpc	L.EDU	L.PART
RES	1.0000						
L2.RES	0.0046	1.0000					
L.logSSinh	0.0559	-0.0460	1.0000				
L.logSSact	0.0643	-0.0514	0.9168	1.0000			
L.logGDPpc	0.0421	0.0039	0.7982	0.6958	1.0000		
L.EDU	0.0086	-0.1270	0.2335	0.2470	0.0346	1.0000	
L.PART	0.0124	-0.0418	0.5872	0.4866	0.5786	0.3146	1.0000
L.WGIp	0.0569	-0.0397	0.7576	0.6089	0.6052	0.2256	0.6524
L.logRAILsq	0.0107	-0.1169	0.2213	0.2835	0.2126	0.4798	0.0603
L.logPOPsq	-0.0095	-0.0461	0.1840	0.1870	0.1763	0.1577	0.1488
L.UNEMP	-0.0119	-0.0257	-0.0235	0.0382	-0.0348	-0.0515	-0.0602
L.SI_AGR	-0.0884	-0.0203	-0.7126	-0.6490	-0.7037	-0.0944	-0.4269
L.SI_IND	0.0266	-0.0567	-0.1360	-0.0673	-0.3372	0.3791	-0.1360
L.SI_CON	-0.0150	0.1622	-0.2401	-0.2588	-0.0684	-0.3808	-0.0908
L.SI_TRD	-0.0044	0.1163	0.1166	0.0392	0.2831	-0.2984	0.1844
L.SI_INF	0.0372	0.0067	0.4706	0.5235	0.6108	0.2637	0.4500
L.SI_FIN	0.0213	-0.0149	0.4106	0.4218	0.5952	0.0555	0.2715
L.SI_EST	0.0197	-0.0605	0.3036	0.3490	0.3542	0.5311	0.4321
L.SI_SCI	0.0196	-0.0068	0.6349	0.6086	0.6990	-0.0101	0.3472
L.SI_PUB	0.0402	-0.0057	0.4981	0.3753	0.2698	-0.0091	0.2555
L.SI_ART	0.0726	0.1172	0.2448	0.2983	0.4357	-0.6106	-0.1219
Variable	L.WGIp	L.logRAIL	L.logPOP	L.UNEMP	L.SI_AGR	L.SI_IND	L.SI_CON
L.WGIp	1.0000						
L.logRAILsq	0.1306	1.0000					
L.logPOPsq	0.2272	0.2250	1.0000				
L.UNEMP	-0.0319	0.0730	-0.0793	1.0000			
L.SI_AGR	-0.6490	-0.3423	-0.1884	-0.0148	1.0000		
L.SI_IND	-0.2573	0.1289	-0.0886	-0.0977	0.1655	1.0000	
L.SI_CON	-0.1282	-0.3285	-0.1639	-0.1109	-0.0565	-0.0846	1.0000
L.SI_TRD	0.0638	0.0320	-0.0222	0.0252	-0.3263	-0.3932	0.3471
L.SI_INF	0.3906	0.3760	0.3107	-0.0250	-0.4909	-0.4065	-0.1648

TABLE 2
PAIR WISE CORRELATIONS MATRIX (CONCLUSIÓN)

L.SI_FIN	0.3432	0.3391	0.2459	-0.0398	-0.4176	-0.4138	-0.0592
L.SI_EST	0.3439	0.5158	0.2480	-0.1631	-0.4201	-0.0055	-0.0675
L.SI_SCI	0.4954	0.3333	0.1820	0.1311	-0.5824	-0.4196	-0.2198
L.SI_PUB	0.6289	-0.0473	0.1949	0.0283	-0.5168	-0.4827	-0.1669
L.SI_ART	-0.0337	-0.1475	-0.1341	0.1032	-0.3838	-0.3715	0.2750
Variable	L.SI_TRD	L.SI_INF	L.SI_FIN	L.SI_EST	L.SI_SCI	L.SI_PUB	L.SI_ART
L.SI_TRD	1.0000						
L.SI_INF	0.0643	1.0000					
L.SI_FIN	0.0956	0.6677	1.0000				
L.SI_EST	0.0093	0.5520	0.3716	1.0000			
L.SI_SCI	0.0592	0.5502	0.4590	0.2645	1.0000		
L.SI_PUB	-0.0799	0.2398	0.1687	0.1381	0.2655	1.0000	
L.SI_ART	0.2779	0.2023	0.2029	-0.0468	0.2784	0.0414	1.0000

Source: compiled by the authors using software Stata 13.0

Gujarati and Porter (2008) clarify that problem of multicollinearity exists when Pearson's correlation coefficients between independent variables in the dynamic panel data model exceed the 0.8 threshold. The model presented in this paper showed the problem of multicollinearity among two independent variables (it is the correlation of 0.9168 between two smart specialization indicators) which has been solved by using those variables separately in two models. As presented in Table 2, all other coefficients are lower than critical value of 0.8. and consequently, the empirical analysis of the model is completed.

The dynamic panel data model is estimated on the basis of Blundell and Bond two step estimator. Blundell and Bond (1998) GMM (generalized methods of moments) is an improved version of Arellano and Bond (1991) GMM estimator and is the appropriate choice considering paper sample characteristics (data sample containing more cross than time observations and large number of regions). Blundell and Bond two step estimator was chosen over one step estimator because the latter assumes the error terms to be independent and homoscedastic across countries and over time while two step estimator relaxes the assumption of independence and homoscedasticity.

Finally, following Blundell-Bond (1998), panel data model with lagged variables was estimated:

$$RES_{it} = \mu + \gamma_1 RES_{i.t-2} + \gamma_2 RES_{i.t-1} + \beta_1 logSS_{i,t-1} + \beta_2 logGDPpc_{i,t-1} + \beta_3 EDU_{i,t-1} + \beta_4 PART_{i,t-1} + \beta_5 WGIp_{i,t-1} + \beta_6 logRAILsq_{i.t-1} + \beta_7 logPOPsq_{i.t-1} + \beta_8 UNEMP_{i,t-1} + SI_{i,t-1}\delta + \alpha_i + \varepsilon_{it} \quad (3)$$

The model in equation (3) was tested in two different defined models. In both models all previous mentioned control variables are included (level of GDP - GDPpc, labor force participation - PART, education - EDU, modified institutional quality - WGI, infrastructure quality - RAIL and specialization indexes - SI). Difference between two models is in proxy variable for smart specialization. Model 1 includes number of patents per million of inhabitants as indicator of SS while in Model 2, for additional robustness check, indicator for SS is number of patents per million of active population.

TABLE 3
ESTIMATION RESULTS (BLUNDEL AND BOND GMM SYSTEM ESTIMATOR) FOR MODEL OF REGIONAL RESILIENCE

Variable	Model 1	Model 2
L.RES	-0.340***	-0.336***
	(0.0410)	(0.0417)
L2.RES	-0.0982***	-0.0960***
	(0.0229)	(0.0234)
L.logSSinh	-0.978**	
	(0.426)	
L.logSSact		-1.146***
		(0.432)
L.logGDPpc	-8.036**	-7.806**
	(3.930)	(3.936)
L.EDU	0.369**	0.375**
	(0.152)	(0.152)
L.PART	-0.622**	-0.643**
	(0.278)	(0.281)
L.WGIp	0.635***	0.631***
	(0.114)	(0.115)
L.logRAILsq	-5.209**	-5.075**
	(2.543)	(2.519)
L.logPOPsq	-23.95**	-23.88**
	(9.850)	(10.06)
L.UNEMP	-0.565***	-0.559***
	(0.194)	(0.195)
L.SI_AGR	-3.640	-3.734
	(2.750)	(2.762)
L.SI_IND	5.872	5.609
	(7.313)	(7.388)

TABLE 3
ESTIMATION RESULTS (BLUNDEL AND BOND GMM SYSTEM ESTIMATOR) FOR MODEL OF REGIONAL RESILIENCE (CONCLUSIÓN)

Variable	Model 1	Model 2
L.SI_CON	-8.896**	-8.953**
	(3.636)	(3.656)
L.SI_TRD	21.94***	22.20***
	(6.910)	(7.002)
L.SI_INF	5.357*	5.386*
	(2.975)	(2.974)
L.SI_FIN	3.888	4.017
	(3.204)	(3.186)
L.SI_EST	-1.150	-1.090
	(1.822)	(1.843)
L.SI_SCI	11.35**	11.30**
	(4.625)	(4.658)
L.SI_PUB	2.419	2.000
	(9.813)	(9.889)
L.SI_ART	-1.665	-1.375
	(4.764)	(4.774)
_cons	142.6**	141.7**
	(63.13)	(64.24)
Number of observations	786	786
Number of groups	122	122
Number of instruments	62	62
Sargan test (Pvalue)	0.1807	0.1808
m1-test (P-value)	0.0000	0.0000
m2-test (P-value)	0.4081	0.4107

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Source: compiled by the authors using software Stata 13.0

Before the interpretation of empirical results, the validity of the models has been tested by performing Sargan test and tests for serial correlation. The results of those tests are presented in Table 3 and they indicate that model is well specified. The coefficients in the Table 3 are unstandarized.

Taking into consideration the empirical results presented in Table 3, it is firstly possible to notice that all independent variables have significant impact on regional resilience as all variables are statistically significant with significance level of at least 5%. The only exceptions are two specialization indexes (NACE classification C (Construction) and O-Q - (Public administration, defence, education, human health and social work activities) indicating that if the region is specialized in construction activities or in specific public services (NACE O-Q) there is no statistically significant effect on resilience.

Higher level of initial GDP, education, labor force participation and infrastructure quality has negative effect on the sensitivity index and therefore positive impact on regional economic resilience. At the same time, institutional quality has negative impact, but this result should be considered with caution taking into consideration that institutional quality has been proxied by the value of *national institutional quality* (WGI).

The results in analyzed models show that smart specialization (SS), has negative effect on the sensitivity index (RES). In other words, higher level of implementation of smart specialization decreases sensitivity of regional economy and therefore increases regional economic resilience. These results indicate that smart specialization allows "fuller and more productive use of resources" which is crucial for regional economic resilience.

These results are in line with the expectations presented in the report produced by the European Committee of the Regions (2017). This report implements an approach that combines a workshop setting for identifying systemic relations between a policy (smart specialization) and its territorial consequences with a set of indicators describing the sensitivity of European regions with the objective of identifying the future potential territorial impacts of Smart Specialization. The majority of the experts involved in preparing the report indicate that Smart Specialization should have net positive effect on majority socio-economic variables that are at same time important for regional economic resilience. At same time they emphasize a potential territorial differentiated impact. The territorial impact in the report depicts a combination of so-called regional sensitivity and the exposure caused by the implementation of the policy initiative. Thus, the expatiations from the report are in line with our empirical evidence by which higher level of implementation of smart specialization increases regional economic resilience.

In addition, experts in the report expressed their concern that specialization can have ambiguous impacts on a region. This is also in line with our results (for the regions specialized in construction activities or in specific public services (NACE O-Q) there is no statistically significant effect on regional economic resilience)

Finally, by indicating in the report the importance of the effective multilevel governance and importance of the building the capacity on local level and cooperation among different stakeholders on all levels (local, regional, national and EU) we are in position to clearly understand why higher institutional quality (on national level) is not enough not only for the effective implementation of the smart specialization, but in first place for the higher level of regional economic resilience.

4. CONCLUSION

This research provides for the first time empirical investigation of the relationship between smart specialization and regional economic resilience. It offers empirical evidence of the influence of the smart specialization on regional economic resilience. The empirical results indicate that higher level of implementation of smart specialization decreases sensitivity of regional economy and therefore increases regional economic resilience.

The paper designates that increased regional economic resilience can be achieved by realization of the three main operational objectives of smart specialization (maximising "public-private entrepreneurial discoveries"; providing operational facilities for continuous observation, detection and evaluation; and supporting early growth of the prioritised activities (Foray and Rainoldi, 2013). More precisely, this can be achieved by building local entrepreneurial knowledge (including the mobilisation of extra-regional resources), aligning incentives through intelligent policy design, determining the most appropriate method to finance experiments and discoveries and indicating "direction" in which experiments and discoveries should be oriented. According to Foray and Rainoldi (2013) the fine-grained observations of all activities and detection capabilities are also important for achieving positive effect of smart specialization on regional economic resilience. Finally, the crucial factor of success in this is reaching high levels of competence and commitment in the policy making capability at regional level.

Having all of this in mind the results of this research are twofold. They could stimulate researchers in profound analysis of theoretical background for empirical relation between regional economic resilience and smart specialization. They could also be useful for policy makers in raising their consciousness about the positive effects of smart specialization on regional economic resilience.

Finally, the results of this research should have impact on policy measures to raise effectiveness of regional policy. The measures should be based on the integrated policy support to help strengthen the specialisation and regional robustness.

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