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EFFECTS OF SMART SPECIALISATION ON REGIONAL LABOUR RESILIENCE[1]

Abstract. The global economy has experienced great volatility and uncertainty during the last decades. Economic effects of global recession in the period 2008-2009 showed to be diverse in terms of territorial impacts. This has raised interest in the empirical investigation of the causes of such territorial differences and supported the increase in literature dealing with the resilience concept and determinants of regional economic resilience. This research addresses literature gaps in understanding the role of smart specialisation process in regional labour resilience, as it is one of the cornerstones of the new place-based regional development policy approach in the European Union (EU). To this end, we have developed a new proxy for smart specialisation and employed the data for EU regional labour resilience for two different periods, recession (2007-2009) and recovery (2009-2014), which is determined based on regional economic performance data. Then, the EU regions were grouped in four categories considering resistance and recovery dimension of the resilience concept. We provide the extension of the existing literature by separately analysing the recovery dimension of the resilience concept in the short and long run. The multinomial logistic model enabled us to examine in detail the differential effects of all relevant resilience determinants. Research results indicate significant and positive effects of smart specialisation on regional labour resilience, especially for regions of the most resilient group. Furthermore, our study confirmed the significance of other determinants for regional labour resilience, such as stage of regional development, regional economic structure, population and education. The findings could be used for establishing the theoretical background for important socio-economic channels through which smart specialisation affects regional labour resilience and creating effective regional development policy measures.

Keywords: regional labour resilience, smart specialisation, resistance, recovery, EU, regional development, multinomial logistic model, economic structure, institutions, human capital

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ИССЛЕДОВАТЕЛЬСКАЯ СТАТЬЯ

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Влияние умной специализации на региональную устойчивость рабочей силы

Аннотация. Характерными чертами мировой экономики в последние десятилетия являются непостоянство и неопределенность. Поскольку экономические последствия глобальной рецессии в период 2008-2009 гг. различным образом повлияли на развитие территорий, возрос интерес к эмпирическому исследованию причин таких различий. Также увеличилось количество научных работ, посвященных концепции устойчивости и детерминантам экономической устойчивости на уровне регионов. В представленной статье описывается роль умной специализации и ее влияние на региональную устойчивость рабочей силы. Умная специализация — один из наиболее важных элементов новой региональной политики Европейского союза, опирающейся на возможности мест (*place-based policy*). Для проведения анализа был разработан авторский показатель умной специализации и использованы данные о региональной устойчивости рабочей силы ЕС за два разных периода: рецессии (2007–2009 гг.) и восстановления (2009–2014 гг.). Затем регионы ЕС были сгруппированы в четыре категории с учетом их устойчивости и скорости восстановления. Опираясь на существующую литературу, мы расширили подход, проанализировав скорость восстановления как в краткосрочной, так и в долгосрочной перспективе. Для детального изучения дифференциальных эффектов всех соответствующих детерминант устойчивости была использована мультиномиальная логистическая модель. Результаты анализа свидетельствуют о значительном положительном влиянии умной специализации на региональную устойчивость рабочей силы, особенно в регионах, принадлежащих к группе с наиболее высокими показателями. Кроме того, была подтверждена значимость других детерминант региональной устойчивости рабочей силы, таких как этап развития региона, экономическая структура, численность населения и образование. Полученные выводы могут быть использованы для теоретического обоснования социально-экономических каналов влияния умной специализации на региональную устойчивость рабочей силы и разработки эффективных мер политики регионального развития.

Ключевые слова: региональная устойчивость рабочей силы, умная специализация, устойчивость, восстановление, ЕС, региональное развитие, мультиномиальная логистическая модель, экономическая структура, институты, человеческий капитал

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Introduction

Severe global economic volatility with structural breaks manifested during recent financial and global crisis have raised the interest in regional economic fluctuations and the concept of resilience (Hill et al., 2008; Pike et al., 2010; Bristow, 2010; Hassink, 2010; Christopherson et al., 2010; OECD, 2012a; Mitchell & Harris, 2012; Martin, 2012; Bristow & Healy, 2014; Boschma, 2015; Martin & Sunley, 2015; Sensier et al., 2016; Nyström, 2018; OECD; 2012b).

In addition, the concept of labour market resilience has been used by OECD (2012b) to analyse the fundamental effects of the global economic downturn, defining regional labour resilience as "an extent to which labour markets withstand through economic downturns with limited social costs". This definition elevated a key research question in empirical literature. What determinants enlighten a capacity of a region to withstand, adjust or even renovate in better direction after external shock?

The literature provides several attempts in defining the determinants of regional labour resilience. Among different concepts, Bigos et al. (2013) emphasise the importance of two determinants on regional labour resilience, the policy innovations and the outcomes of the labour markets. This is in line with OECD (2012a) paper which illuminates that the empirical evidences based on the labour market resilience concept are vital, since they effectively capture the influence of economic downturns on workers' well-being. Finally, this also goes together with general consensus among researchers, which postulates the key role of the structural policy settings in determining labour market outcomes (OECD, 2012a; Bigos et al., 2013).

Since smart specialisation is an innovative approach in dealing with the place-based dimension of regional development in EU (Rodríguez-Pose et al., 2014), our goal is to empirically investigate the role of smart specialisation in the resilience of regional labour market.

The paper is organised as follows. In the next section, theoretical foundations of the link between smart specialisation and regional labour resilience are presented. Section 3 presents the data, the empirical strategy with results. Section 4 offers concluding remarks.

Literature Review

The labour market resilience promoted by Bigos et al. (2013) refers to basic labour market outcomes, i. e. unemployment and employment rates, primarily driven by institutional, socio-economic and structural-demographic conditions.

Institutional factors affecting labour market outcomes are unemployment benefits (Sengenberger, 2011), active labour market policies (Bonoli, 2010), employment protection legislation (McCann et al., 2012), labour contracts (Holman, 2013), working hours (Bell et al., 2012), waging setting institutions and minimum wages (OECD, 2004) and finally labour taxation (OECD, 2007). The different sets of these policies and regulations are essential for understanding heterogeneous labour market outcomes across countries/regions (Eichhorst et al., 2010).

The socio-economic conditions are also important for labour market resilience such as the firm size, current regional inequalities and industry structure (Bigos et al., 2013). Those socio-economic factors help explain the persistence of regional disparities and the differences between regional unemployment and employment rates.

The third group of factors are demographic characteristics (Bigos et al., 2013). The age structure, educational skills and migration patterns are of significant importance in the context of labour market outcomes.

The reduction in current public funds, which address regional labour issues with long-term public perspective, occurred due to both the economic downturn in 2008–2009 and arisen global problems (urge in addressing health care, climate change or inequality issues). Addressing regional labour outcomes through research and development (R&D) and innovation has become progressively salient.

Smart specialisation, coined as a strategic proposal in 2009 (European Commission, 2009), was the result of the EU initiative aimed to find more effective public policy that will produce synergy effects among public investments in education, research and innovation and public support to businesses. The specialisation, which combines innovation activities and specific competitive advantage at the national or regional level, should result in the resilient regional labour outcomes.

In other words, smart specialisation affects regulations and policies, which are part of the institutional framework, already elaborated as one of the drivers of labour market outcomes. Furthermore, the second group of important labour market drivers such as firm size, industry structures and regional development disparities are also in the focus of smart specialisation strategy and processes, offering specific opportunities for less developed and peripheral regions (Rodríguez-Pose et al., 2014). In addition, smart specialisation focuses on the development of local human capital and consequently, affects human capital endowment at the regional level. This should support the rise of new technologies implementation among traditional regional industries (David et al., 2009). Therefore, smart specialisation process should be promoted on all governmental levels, especially on the regional level, so as to support regional development and resilience of regional labour.

Data and Methodology

This part of the paper tries to empirically test the importance of smart specialisation for regional labour resilience in NUTS2 European Union regions.[1]

The study is based on the hypothesis that "the smart specialisation positively affects regional labour resilience."

The data are taken from Eurostat[2], Regional Innovation Scoreboard (RIS)[3] and from World Governance Indicators (WGI), adopted from the World Bank[4] dataset.

The exiting empirical studies promote different ways to find resilience proxy, ranging from descriptive and interpretative case studies to econometric models, e.g. papers by Martin (2012), Sensier et al. (2016), Simmie and Martin (2010), Fingleton et al. (2012), Cowell (2013).

In this paper, we have decided to follow and extend the approach presented in the paper of Faggian et al. (2018). The authors define regional

[1] Due to data availability, the dataset covers the period 2006-2014. However, latest NUTS 2013 classification is used in selection of NUTS 2 regions.

[2] Eurostat. Retrieved from: https://ec.europa.eu/eurostat (Date of access: 13.10.2017).

[3] Regional Innovation Scoreboard. Retrieved from: https://ec.europa.eu/growth/industry/policy/innovation/regional_en (Date of access: 13.10.2017).

[4] World Bank, WGI indicators. Retrieved from: https://info.worldbank.org/governance/wgi/ (Date of access: 13.10.2017).

labour resilience as the combination of the resistance and recovery phases needed to overcome crisis periods; therefore, they separately examine the recessionary period by implementing resistance proxy and pre-recessionary period by measuring employment growth.

Thus, to express resistance, we have decided to use Faggian et al. (2018) adaptation of formula for sensitivity index (*SnI*) that was originally presented by Martin (2012):

$$SnI = \frac{E_{r,t}}{E_{r,t-1}} / \frac{E_{EU,t}}{E_{EU,t-1}}, \quad (1)$$

in which E_r represents total employment in region (r) and E_{EU} represents total employment in European Union. Period t represents the recessionary period and $t-1$ is the pre-recessionary period. To deduct recessionary and pre-recessionary period on the total EU-28 level, we ran quarterly gross domestic product (GDP) (chain linked volumes). The crisis is identified if the observation of GDP showed its downturn for 3 quarters in a row and the recovery is identified when the data for GDP showed that it has been ascending 3 quarters in a row. The analysis of data on GDP showed that it dropped considerably in 2008 and continued to decline during 2009 (recessionary years). Hence, we calculate the values of the sensitivity indexes for two periods. For the first period (SnI_1), we take into consideration employment data for 2007 and 2008, while in the second case (SnI_2), we deal with the data for 2008 and 2009. Considering those facts, our sensitivity index (*SnI*) is set on the average level of two indexes that measure resistance: SnI_1 and SnI_2.

SnI_1, SnI_2 and SnI are defined as:

$$SnI_1 = \frac{E_{r,2008}}{E_{r,2007}} / \frac{E_{EU,2008}}{E_{EU,2007}},$$

$$SnI_2 = \frac{E_{r,2009}}{E_{r,2008}} / \frac{E_{EU,2009}}{E_{EU,2008}},$$

$$SnI = \left(SnI_1 + SnI_2\right) / 2. \quad (2)$$

Sensitivity index (*SnI*) is centred around 1 and if the value is above 1 that means that the region was more resistant in comparison to the EU-28 while otherwise it suggests that the region was vigorously hit by recession.

Considering that Faggian et al. (2018) were focused on analysing short-run recovery on Italian local labour markets for the period 2007–2011, during which the recovery period was recorded only in 2011, we have decided to extended our analysis and test not only the short run recovery but also the long run recovery.

For the short-run recovery we use regional percentage change in the employment in 2010 as follows:

$$REC_{r2010} = \left(\frac{E_{r2010} - E_{r2009}}{E_{r2009}}\right)100, \quad (3)$$

year 2010 is taken as recovery year, since by all criteria it is first year when GDP has showed an upward trend for 3 consecutive quarters on EU-28 level. If $REC_{r2010} > REC_{EU28\_2010}$, the spatial units stand as fast recovery and opposite as slow recovery region.

For the long-run recovery we use regional percentage change in employment in the period 2009–2014 as following:

$$REC_{r2014} = \left(\frac{E_{r2014} - E_{r2009}}{E_{r2009}}\right)100. \quad (4)$$

If $REC_{r2014} > REC_{EU28\_2014}$, the region is defined as fast recovery and opposite as slow recovery region.

According to Faggian et al. (2018) and their analysis of the sample of Italian local labour markets regions, we divided EU NUTS2 regions into 4 categories (groups) based on resistance and recovery indicators:

1. High resistance/fast recovery (group I);
2. High resistance/slow recovery (group II);
3. Low resistance/slow recovery (group III);
4. Low resistance/fast recovery (group IV).

Consequently, the dependent variable is consisted of those four groups and multinomial logit model where structural characteristics of each NUTS 2 region determine the probability of belonging to one of these four group, or more formally:

$$Pr(y = m \mid x) = \frac{e^{x\beta_{m/III}}}{\sum_j e^{x\beta_{j/III}}}. \quad (5)$$

Furthermore, the equation (5) stands for the probability of a region (in our case NUTS 2 region) to be part of the defined group relative to group III (base group), as a function of characteristics summarised by the x vector. Group III is used as the base group as it consists of low resistance and slow recovery regions which are therefore defined as worst performers.

The x vector consists of variables that have been defined as potential regional labour determinants in the existing literature. The GDP level represents proxy for socio-economic conditions. Higher regional attractiveness is usually associated with the high level of the GDP. These regions are able to provide more business opportunities, which leads to additional openings for employment for displaced workers (Nyström, 2018). It could also result in more effective job-search pro-

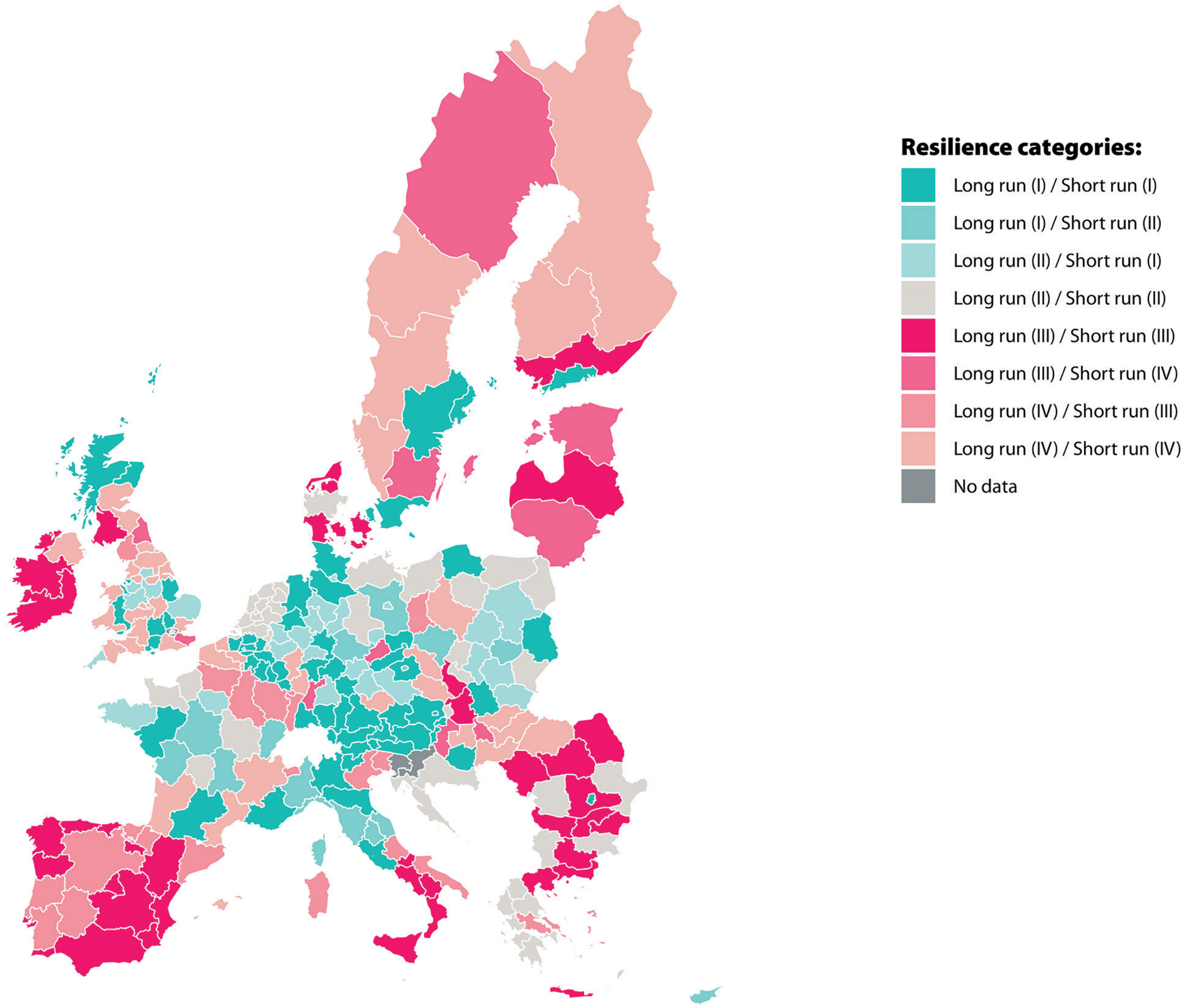

Fig. 1. *Map of regions and associated groups of resilience for the short and long run*

cess as region with higher GDP can have higher arrival rate of job offers and better match on job market (Neffke et al., 2018). As a result, the positive influence of GDP on labour resilience is expected. Institutional framework represents a large spectrum of formal and informal ways of organising economic activity (Donnellan et al., 2012; Martin et al., 2016) and shaping labour market conditions (Bigos et al., 2013). More precisely, by determining wage and occupational flexibility and labour mobility, the institutional framework may be an important driver for regional labour resilience.

The human capital should also be considered a relevant factor of regional labour resilience (Nyström, 2018). The regions with the higher share of well-educated people are more capable to create or adopt new solutions during and after economic crisis that will result in more employment opportunity and resilient economy (Martin, 2012; Nyström, 2018; Glaeser et al., 2014).

Literature also emphasises agglomeration effects as important drivers of resilience (Nyström, 2018; Neffke et al., 2018). In first place, larger urban areas are generating better conditions for economic activity creation through the competition or knowledge creation and, therefore, larger population should have a positive effect on regional labour resilience (Chapple & Lester, 2010). The structure of regional economies should also be recognised as an important factor. The more diverse economic structure, represented mostly by industries at different stages of the product life cycle and with different demand conditions, should not be affected by larger employment uncertainty and job losses (Nyström, 2018; Chapple & Lester, 2010; Markusen, 1985).

Finally, considering that the role of smart specialisation is the focus of the paper, the key question is how to measure the smart specialisation at the regional level? Although there are several authors indicating the strong need for the smart specialisation indicators (David et al., 2009; Barca & McCann, 2011; Santoalha, 2019), the empirical studies related to regional smart specialisation are rare (Iacobucci, 2014; Caragliu & Del Bo, 2013) with the limited importance to the existing regional structure (Santoalha, 2019). On this matter, there are several important features to be considered.

First, smart specialisation is a relatively old term but a rather new concept in the context of the implementation process. Thus, gathering the data on the smart specialisation outcomes is almost an impossible task. As indicated in the paper by Balland et al. (2018), operationalisation of smart specialisation has been recognised as a "perfect example of policy running ahead of theory (Foray et al., 2011; Boschma, 2014), as an example for lacking of an 'evidence base' (Morgan, 2015; Unterlass et al., 2015) and building on 'anecdotal evidence rather than the application of theoretically grounded methodologies' (Santoalha, 2019; Iacobucci & Guzzini 2016).

However, the smart specialisation indicators should not be limited only on the outcomes, but they should also represent the broader picture. As indicated in the handbook by Gianelle et al. (2016), the monitoring system of the smart specialisation should not only assess "whether expected changes are taking place, in what direction and with what intensity" but also "how policy measures are contributing to those changes" or in other words, the monitoring system should reflect the smart specialisation logic of intervention. The same approach has been implemented in this paper. Instead of trying to do "the impossible task" and construct the measure for smart specialisation outcomes, we focus on constructing the measure for the implementation of smart specialisation processes on the regional level, i. e. smart specialisation logic. By testing the smart specialisation process, we provide the logic behind the transmission channel that shows the effects of the smart specialisation implementation. Our approach represents the perfect match with the purpose of the monitoring system of smart specialisation and it should be seen as a part of 'learning-by-monitoring' process with significant impression and guidance of the smart specialisation strategy management (Gianelle et al, 2016). Thus, for complete presentation of smart specialisation logic, the proxy (index) should integrate several important features presented by the European Commission[1].

The influence of smart specialisation on national and regional innovation systems is reflected in: (a) Governance and institutional changes, (b) The Entrepreneurial Discovery Process, (c) Monitoring, (d) Economic transformation, new technological and market opportunities, (e) Behavioural changes in universities and research centres and (f) Cooperation. Consequently, the smart specialisation proxy should include all these dimensions. Finally, we believe that the proxy should provide good balance between "keep it simple" principle, limitations in regional data and persevering the bond with the key elements of smart specialisation logic.

We believe that the proxy presented in the paper tackles all previously mentioned issues by combining specific indicators from the Regional Innovation scoreboard 2017.

(i) Governance and Institutional Changes

The implementation of smart specialisation implies adoption and modification of the governance and institutional framework of the innovation ecosystem at the national, regional and local level. Two indicators will be used to capture these changes: (a) Public-private co-publications per million population giving the number of public-private co-authored research publications, (b) R&D expenditure in the public sector as percentage of GDP, measuring all R&D expenditures in the government sector and the higher education sector.

(ii) The Entrepreneurial Discovery Process (EDP)

The Entrepreneurial Discovery promotes the integration of fragmented entrepreneurial knowledge through building networking among key actors[2]. Stakeholder interaction, with small and medium-sized enterprises (SMEs) as a key actor, has proved beneficial to opening up new markets, as well as shaping government decision-making. Having all of this in mind, the five indicators for EDP used in this paper are: (a) SMEs innovating in-house as percentage of SMEs, (b) innovative SMEs collaborating with others as percentage of SMEs, (c) Non-R&D innovation expenditures in SMEs as percentage of turnover, (d) SMEs introducing product or process innovations as percentage of SMEs, (e) SMEs introducing marketing or organisational innovations as percentage of SMEs.

(iii) Monitoring

European Member States have designed smart specialisation as a set of result-oriented policy actions, whose results need to be monitored closely[3].

[1] Smart Specialisation Platform. Retrieved from: https://s3platform.jrc.ec.europa.eu/what-is-smart-specialisation- (Date of access: 12.10.2017)/

[2] Smart Specialisation Platform. Retrieved from: https://s3platform.jrc.ec.europa.eu/entrepreneurial-discovery-edp (Date of access: 12.10.2017).

[3] Smart Specialisation Platform. Retrieved from: https://s3platform.jrc.ec.europa.eu/monitoring (Date of access: 12.10.2017).

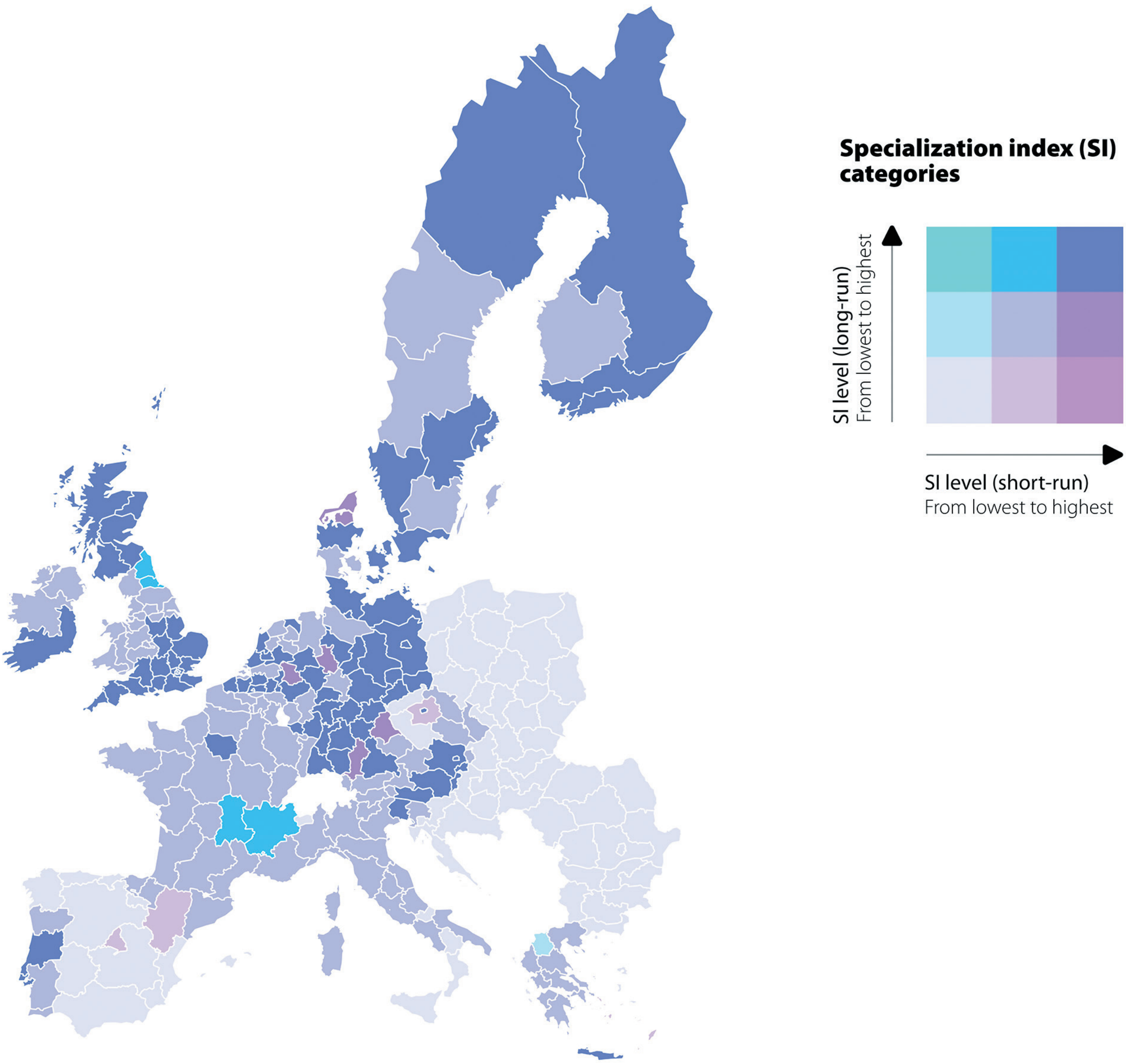

Fig. 2. *Map of regions and associated groups of Smart Specialisation Index (SI) for the short and long run*

Considering that we already underlined the importance of the monitoring process and the link with our approach, the monitoring framework is mainly incorporated in all the indicators represented in our smart specialisation logic index.

(iv) Economic Transformation, New Technological and Market Opportunities

The smart specialisation strategies are essentially focused on regional economic transformation by promoting locally driven knowledge-based growth. The three indicators that capture transformation defined in this paper are: (a) sales of new-to-market and new-to-firm innovations in SMEs as percentage of revenue, (b) SMEs introducing product or process innovations as percentage of SMEs used also for the indication of EDP and (c) SMEs introducing marketing or organisational innovations as percentage of SMEs also already defined as the indicator for EDP.

(v) Behavioural Changes in Universities and Research Centres

Universities have an important role in the design and implementation of regional smart specialisation logic (Kempton et al., 2014). Their role goes beyond the role of research generators. Therefore, the measurement of their role and scope in translating knowledge and research outputs into benefits for local businesses and the local economy is ambiguous. We have used two indicators for those measurements: (a) scientific publications among the top-10 % most cited publications worldwide as percentage of total scientific publications of the region, (b) public-private co-publications per million population used for the measurement of the governance and institutional changes and for cooperation.

(vi) Cooperation

Cooperation has been recognised as outward-looking specialisation. Key elements of cooperation lie in the identification of niches, cross-sectoral innovation and value chain linkages dedicated to challenge societal issues. It also reflects the need to identify international partners for the realisation of potential advantages on global markets. Cooperation should involve key actors from academia, business, but also policymakers on the regional level.

Therefore, the three indicators that capture cooperation used in our paper are: (a) international scientific co-publications per million population, (b) innovative SMEs collaborating with others as percentage of SMEs used also for measurement of EDP, (c) public-private co-publications per million population used for the measurement of both governance and institutional changes and behavioural changes in universities and research centres. Finally, the Smart Specialisation Index (SI) is calculated as the average of the chosen indicators for the periods 2007–2010 and 2007–2014, regarding short-term and long-term analysis, respectively[1].

The value of Smart Specialisation Index (*SI*) is between 0 and 1, and based on those values we have classified regions into 3 categories of the implementation of smart specialisation process, i. e. development of smart specialisation logic at the regional level:

SI value up to 0.36 — regions with the lowest level regarding smart specialisation logic

SI between 0.36 and 0.48 — regions with the moderate level regarding smart specialisation logic

SI above 0.48 — regions with the highest level regarding smart specialisation logic

To sum it up, in our model we use variables population (*POP*) — number of inhabitants in region (in 000 000) as of 1 January (average 2007–2010 for short term / average 2007–2014 for long term), *GDP* — GDP PPS per inhabitant, Education (*EDU*) — percentage of persons with tertiary education in total group of inhabitants between 25 and 64 years, *WGI* — as there are no data at regional level for the whole period as an appropriate proxy for institutional quality, the data are used at the national level and therefore we allocate the particular level of WGI of specific country to each NUTS 2 region of a certain country (for example, Italy's WGI was given to all Italian NUTS2 regions). WGI is adopted by calculating the average of the values (percentile rank) for six dimensions of WGI[2] and these values were used to form different categories of institutional quality. The 3 different categories were formed:

1. Inferior institutional quality — average percentile rank under 75 %
2. Moderate institutional quality — percentile rank between 75 % and 90 %
3. Best institutional quality — percentile rank above 90 %

Specification indices — the proxy used for regional industry specialisation is a dummy variable derived on the basis of the index of specialisation presented by Martin (2003) as follows:

$$SPEC\_INDEXshort = \\ = \frac{GVA_{r,i\,avg\_2007-2010}}{GVA_{r,i\,avg\_2007-2010}} / \frac{GVA_{EU,i\,avg\_2007-2010}}{GVA_{EUi\,avg\_2007-2010}}, \qquad (6)$$

$$SPEC\_INDEXlong = \\ = \frac{GVA_{r,i\,avg\_2007-2014}}{GVA_{r,i\,avg\_2007-2014}} / \frac{GVA_{EU,i\,avg\_2007-2014}}{GVA_{EUi\,avg\_2007-2014}}, \qquad (7)$$

where $GVA_{r,i}$ stands for gross value added of specific sector by NACE classification[3] of region and $GVA_{EU,i}$ is gross value added of specific sector by NACE classification in whole European Union. *GVA* total is total gross value added of region or European Union. If *SPEC_INDEX* is higher than 1.1, we associated value 1 to that region meaning that there is the presence of specialisation in that NACE category.

Results and Discussion

Finally, to test the importance of smart specialisation for regional labour resilience, we run Multinomial logistic regression models with regional labour resilience as the dependent variable. The results are reported in Table 1 for the short

[1] INTERN_CO_PUBLICATIONS, MOST_CITED_PUBLICATIONS, PUB_RD, NON_R&D_INN_EXP, PROD_PROCES_INN, MARK_ORG_INN, SME_INHOUSE, INN_SME_COLLAB and NEW_MARKET_FIRM_SALES are average values of 2008 and 2010 year in the short run and average values of 2008, 2010, 2012 and 2014 in the long run, while PUB_PRIVATE_COPUB values are average in 2007 and 2009 in the short run and average in 2007, 2009, 2011 and 2014 in the long run.

[2] 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*)

[3] NACE 2 classification: A — Agriculture, forestry and fishing; B-E — Industry (except construction); C — Manufacturing; F — Construction; G-I — Wholesale and retail trade, transport, accommodation and food service activities; J — Information and communication; K — Financial and insurance activities; L –Real estate activities; M-N — Professional, scientific and technical activities; administrative and support service activities; O-Q — Public administration, defence, education, human health and social work activities; R-U — Arts, entertainment and recreation; other service activities; activities of household and extraterritorial organisations and bodies.

Table 1

Results of Multinomial logistic regression — base category Quadrant 3 (low/slow) (odds ratio)

	SHORT RUN			LONG RUN		
Variables	**Q1 (high/fast)**	**Q2 (high/slow)**	**Q4 (low/fast)**	**Q1 (high/fast)**	**Q2 (high/slow)**	**Q4 (low/fast)**
Specialisation index						
SI_2	8.326** (6.883)	5.684** (4.491)	8.321** (6.150)	4.278** (3.163)	4.169** (3.041)	6.767** (5.654)
SI_3	8.852** (8.807)	3.733 (3.764)	6.774** (6.299)	5.249* (4.510)	1.794 (1.734)	7.827** (7.732)
Main control variables						
Population	0.949** (0.019)	0.957 (0.020)	0.982 (0.0174)	0.969* (0.018)	0.928** (0.021)	0.993 (0.021)
Education	0.880** (0.042)	0.955 (0.043)	0.982 (0.044)	0.926* (0.0384)	0.892** (0.039)	1.033 (0.048)
GDP	1.200** (0.080)	1.041** (0.063)	1.026 (0.065)	1.070 (0.058)	1.006 (0.052)	0.810** (0.060)
Institutional quality						
WGI_2	2.100 (1.716)	0.441 (0.343)	2.549 (1.832)	1.592 (1.253)	0.920 (0.684)	3.197 (2.865)
WGI_3	0.309 (0.360)	0.316 (0.369)	0.226 (0.267)	2.043 (2.299)	3.872 (4.467)	13.620* (18.749)
Sectors specialisation (GVA of NACE sectors)						
A	0.417 (0.273)	1.653 (1.191)	0.584 (0.361)	0.374 (0.233)	0.934 (0.718)	0.335 (0.226)
B-E	2.339 (2.265)	0.674 (0.628)	1.405 (1.326)	1.424 (1.178)	0.876 (0.748)	1.151 (1.053)
C	0.948 (0.861)	0.663 (0.579)	2.047 (1.793)	0.210* (0.170)	0.242* (0.198)	0.224* (0.195)
F	0.897 (0.504)	0.590 (0.313)	0.5318 (0.270)	1.070 (0.594)	0.401* (0.217)	0.573 (0.3198)
G-I	1.031 (0.747)	0.560 (0.389)	1.056 (0.750)	0.207** (0.136)	0.435 (0.272)	0.071** (0.056)
J	8.454 (11.494)	1.998 (2.405)	0.534 (0.690)	2.143 (2.704)	7.322 (9.49)	1.729 (2.382)
K	0.084** (0.10)	1.408 (2.405)	0.540 (0.489)	0.210 (0.228)	1.560 (1.794)	0.399 (0.412)
L	3.162* (2.176)	1.462 (2.405)	1.788 (1.100)	0.469 (0.3077)	2.434 (1.644)	0.412 (0.263)
M-N	8.718** (9.453)	7.104** (7.560)	2.536 (2.9093)	51.388** (72.614)	42.740** (62.628)	19.675** (29.150)
O-Q	1.650 (1.189)	0.730 (0.501)	0.869 (0.584)	0.487 (0.326)	0.712 (0.464)	0.182** (0.134)
R-U	0.435 (0.346)	0.330 (0.249)	0.666 (0.471)	1.465 (1.096)	0.439 (0.323)	1.606 (1.272)
_cons	0.090 (0.173)	2.294 (3.928)	0.401 (0.636)	2.965 (5.221)	27.318* (52.010)	79.598** (139.750)
Number of obs	201					
Log likelihood	−211.66665					
LR chi2(51)	131.31					
Prob > chi2	0.0000					
Pseudo R^2	0.2367					

Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Source: authors' calculation using software Stata.

run (columns 1–3) and for the long run (columns 4–6).

Before we interpret the results, we should introduce diagnostic test outcomes. As it can be noticed in Table 1, LR chi2 (51) is significant at the level of 5 %, indicating that model has good predicting ability. In addition, as (Faggian et al., 2018) indicate the values of McFadden pseudo-R^2 between 0.2 and 0.4 represent an excellent fit (see also McFadden, 1977) and therefore the values of the McFadden pseudo-R^2 of 0.2367 and 0.2705 indicate that the models perform well.

Results for the short run (columns 1–3) show that smart specialisation has a positive impact on regional labour resilience. Regions belonging to the group with the moderate level of the implementation of smart specialisation logic (SI_2) have more chances (compared to low specialised regions — SI_1) to have higher resilience, or more precisely, to belong to high/fast (column 1), high/slow (column 2), or low/fast group (column 3) instead of being in low/slow group of regions. Furthermore, if a region belongs to the group of regions with the highest value of smart specialisation (SI_3), it has higher chances comparing to low specialised regions (SI_1) to belong to high/fast (column 1), and low/fast group (column 3). However, it seems that it is not case for regions belonging to high resistance and slow recovery group (column 2) in the short run. This last result could indicate that smart specialisation does not have a significantly positive effect on regions that have only one dimension of resilience (high resistance) and slow recovery in the short run. Finally, it should be stressed that there is a higher probability to belong to the most resilient regions (high resistance and fast recovery) if a region belongs to the group of regions with the highest value (SI_3) comparing to the regions with the moderate level of the implementation of smart specialisation logic (SI_2).

The results for the short-term analysis (Table 1) indicate that population and education have a negative impact on labour resilience. These results are in line with findings of Faggian et al. (2018) and Dijkstra et al. (2014), both indicating that urban regions (with higher share of human capital) are more exposed to the negative effects of crisis than the intermediate and rural regions close to a city. Also, if the share of tertiary level education (of people aged 25–64) increases by one percentage point, chances for being in high/fast group (comparing to low/slow) are lower by 12.02 % (column 1). Although this could be strange at first sight, it can be easily explained by the fact that higher educated people are more mobile and that in case of the economic downturn they will easily emigrate from the region. Also, it should be noted that that education does not have a significant effect on the less resilient regions (columns 2 and 3). Obviously, education has significantly different effects on resilience among different groups of regions and policy makers should take it into account. Results for the short run also indicate that higher level of development (proxied by GDP PPS pc) increases the chances of the region to be more resilient, especially belonging to the most resilient (high/fast) regions. Also, there is no empirical evidence that institutional quality at the national level has a significant influence on regional labour resilience in short period. This should be considered not as an ultimate empirical evidence of the not exiting institutional influence, but as a motivation for providing better dataset of the institutional quality, especially on the regional level and for testing the influence of the institutional quality in the long run. Finally, regarding the specialisation, a region has higher chances to belong to high/fast group then low/slow, in the short run, if it has a higher share of the financial and insurance activities, real estate activities, scientific and technical activities; administrative and support service activities.

For the long run, several important results (presented in Table 1, columns 4–6) should be interpreted. First, results show that smart specialisation has a positive impact on regional labour resilience not only in the short run, but also in the long run. Again, the exception is high resistance and slow recovery group (column 5) confirming that smart specialisation does not have a significantly positive effect on regions that have only one dimension of resilience (high resistance) and slow recovery. Finally, it should be stressed that there is a higher probability to belong to the most resilient regions (high resistance and fast recovery) if a region belongs to the group of regions with the highest value (SI_3) comparing with the regions with the moderate level of the implementation of smart specialisation logic (SI_2).

Although population and education have a negative impact on resilience in the long run, as it has been identified in the short run, several differences should be reported. In first place, magnitude of the influence (or more precisely, chances to belong to a specific group) is smaller in the long run than in the short run. Also, for the regions that have only one dimension of resilience (high resistance) and slow recovery (column 6), population and education do not have a significant influence on the labour resilience. Results also indicate that higher level of development (proxied by GDP PPS pc) does not have a significant influence in the long run except for the regions with the high resistance and slow recovery (column 6).

Institutional quality on the national level has a significant influence on regions with the high resistance and slow recovery (column 6) in the long run, which again raises the importance of providing better dataset on the regional level and investigating the long run effects. Finally, in the long run, specialisation in specific activities has a significant influence on regional labour resilience. More precisely, a region has more chances to be more resilient (to be in the high/fast, high/slow or low/fast then low/slow group) if it is specialised in professional, scientific and technical activities; administrative and support service activities at the significance level of 5 %. On the other side, a region has less chances to be in high/fast or low/fast then low/slow if it is specialised in wholesale and retail trade, transport, accommodation and food service activities. Furthermore, specialisation in public administration, defence, education, human health and social work activities leads to higher chances to be low/slow than low/fast group. At the significance level of 10 %, specialisation in manufacturing leads to less resilience (higher chances to be in low/slow than in all more resilient groups: high/fast, high/slow, low/fast) in the long run. Additionally, at the 10 % significance, specialisation in construction increases chances of being in low/slow instead of high/slow group. Obviously, supporting of specific activities can have significant influence on regional labour resilience.

To sum it up, our results, for the short and long run, provide empirical evidence that implementation of smart specialisation should have a significant influence on regional labour resilience, especially for the most resilient group of regions (with high resistance and slow recovery). At the same time, the results indicate that regional labour resilience is determined also by other factors, primarily by regional economic structure (represented by specialisation in specific activities), population and education characteristics and development stage. These results provide empirical evidence that regional labour resilience is a complex process, with many factors being simultaneously important (Bigos et al., 2013). In addition, we should be fully aware that those factors can further interact with each other and their relative importance changes over time. As a final point, smart specialisation is a policy that not only animates the development of R&D and innovation activities in some targeted domains that offer present or future strengths for the regional economy (OECD, 2013), but also is a policy that tackles all other important factors and can directly and indirectly affect regional labour resilience.

Conclusion

While regional economic fluctuations have been enthroned among the academic community long time ago, there is a lack of knowledge on those phenomena (Bigos et al., 2013; Diodato & Weterings, 2015), especially in case of regional labour resilience.

Therefore, this paper has tried to achieve several objectives. Firstly, it examines and explains the role of the smart specialisation concept for regional labour resilience. Secondly, it empirically tests the short and long term effect from the period of the last economic crisis by dividing EU NUTS2 regions into 4 categories based on resistance and recovery indicators (Faggian et al., 2018) and by introducing the new measure for smart specialisation logic. By testing smart specialisation logic, we provide the transmission channel for testing the implementation of smart specialisation.

Smart specialisation is probably the most ambitious EU policy reflecting key aspects of “place-based” and “people-based” approaches for transforming research activity into business opportunity that will elevate local strengths for dealing regional societal issues directly and indirectly affect labour markets.

The empirical part of the analysis has confirmed this importance by indicating that higher level of smart specialisation increases a chance of belonging to the more resilient group of regions, with the most significant effect for the most resilient group of regions in the short and long run. In period of frequent global disturbances, it is especially important to recognise smart specialisation as an effective shock absorber.

Also, it should be realised that smart specialisation is not a silver bullet for all existing and future challenges. Regional labour resilience is also shaped by other regional characteristics, emphasising it as a multi-dimensional phenomena.

Finally, this paper should stimulate theorists and practitioners to focus not only on further analysis, but especially on joint cooperation that will lead to better understanding and more efficient implementation of smart specialisation policy actions for more robust regional labour outcomes.

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