Evaluating the Implementation of Smart Specialization Policy

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This is an Accepted Manuscript of an article published by Taylor & Francis in Regional Studies on 13 April 2022, available at: https://doi.org/10.1080/00343404.2022.2047915

To cite this article: Emanuela Marrocu, Raffaele Paci, David Rigby & Stefano Usai (2022): Evaluating the implementation of Smart Specialisation policy, Regional Studies, DOI: 10.1080/00343404.2022.2047915

Abstract

The smart specialisation strategy (S3) is at the core of the 2014-2020 European Cohesion Policy, supporting regions to identify the technologies and economic sectors that might comprise sustainable growth paths. This paper provides an early attempt to assess empirically, for all the EU, whether the choices made by regions in selecting S3 target sectors are consistent with their current or potential specialisation patterns. Results show only a few regions selected S3 paths rooted in both their current specialisations and in related activities, most of them prioritised different combinations of unspecialised or unrelated sectors, thus limiting the growth potential of their S3 policy choices.

Keywords: Smart Specialization Strategy, regional development, capabilities, revealed comparative advantage, relatedness

JEL codes: L52, O18, R11, R58

Acknowledgements: The authors thank two anonymous referees and the associate editor of the journal for helpful suggestions and insights. They also thank Donato Iacobucci for helpful comments on an earlier version of this paper.

Funding: David Rigby acknowledges funding from the Visiting Professor programme, sponsored by the Regione Autonoma della Sardegna (RAS), for his visiting period at the University of Cagliari in February 2020.

Introduction

The European Union (EU) assigned a central role to the Smart Specialisation Strategy (S3) within the Europe 2020 development agenda promoting smart, sustainable and inclusive growth (European Commission, 2012). The Regional Operational Programme 2014-2020, and especially the European Regional Development Fund (ERDF), incorporated S3 policy in their agendas, devoting significant financial resources to implement the new approach envisaged by the program. Over the period 2014-2016, all EU regions defined their S3 policy priorities after prolonged negotiations with local stakeholders and European Commission (EC) officers. These priorities are currently being implemented through public calls and other administrative procedures.

Almost immediately, operationalization of the S3 programme, and its "bottom-up" process of identifying regional targets of economic transformation through an "entrepreneurial discovery logic" were criticised (see the recent review by Aranguren et al., 2019). Early concerns focused on the risks of ineffective implementation, especially in peripheral regions that face additional developmental constraints (Boschma, 2014; Morgan, 2015; Iacobucci and Guzzini, 2016). Quality of governance questions, weak regional innovation systems, the lack of capacity in specific knowledge-based sectors, and concerns with the potential integration of local markets into global value chains have been highlighted as potential policy limitations (Capello and Kroll, 2016). Broader issues with the appropriate spatial scale of policy actions, of regional "lock-in" and the complex interplay between tangible and intangible knowledge production assets, and their territorial distribution, have also been raised. Hassink and Gong (2019) remain ardent sceptics, prompting renewed defence by Foray (2019).

It is important to highlight that the current debate around S3, although very intense, has remained mostly speculative, with limited evidence-based analysis. Only recently, a few studies have started assessment of the implementation of S3, focusing on adherence of actual policy actions to the conceptual framework of smart specialisation directly. Among others, D'Adda et al. (2020) for Italian regions, Gianelle et al. (2020b) for the Italian and Polish case, Trippl et al. (2020) for a set of 15 regions in 14 countries, Di Cataldo et al. (2021) and Deegan et al. (2021) for a set of the EU regions, and Biagi et al. (2021) for S3 in the tourism sector. None of these papers cover the entire geographical domain that S3 targets or evaluate the adherence of the actual strategies to the EC guidelines.

In this paper, we address the partial lack of evidence-based systematic and comprehensive analysis on S3 operationalisation for the EU as a whole. We propose a novel empirical framework to examine the coherence of regional policy-makers' choices with the theoretical foundations of S3 and related EC recommendations for defining smart specialisation strategies. It is clearly stated that S3 should prioritise domains, and economic activities that "build on each country's/region’s strengths, competitive advantages and potential for excellence" (European Commission, 2012, p. 8). In order to test whether and to what extent the practice of S3 policy is coherent with these recommendations we build an empirical representation of the policy choices selected by all EU regions. For each region, we match the S3 sectors targeted to their current pattern of economic specialisation and to the potential for local knowledge-driven growth identified by the relatedness of the S3 targets to the existing economic base. We then compute a composite S3 policy coherence indicator to assess, through econometric analysis, whether the S3 selection process is associated with the institutional, economic and structural characteristics of EU regions overall.

Results show that regions across the EU have identified S3 priority sectors that vary significantly in terms of their connection to host economies. Relatively few regions have chosen smart specialization "by the book", targeting sectors in which they already have competitive advantage or in which they show clear potential to develop such. Most regions have chosen to distribute S3 funds across industries in which they exhibit only tangential evidence of building new growth trajectories on existing sets of capabilities. These findings sum to a rather grim diagnosis of the likely success of the S3 policy programme. Finally, estimation results indicate that S3 choices are robustly associated with the quality of local governments. High quality institutions have focused S3 policy choices on EC guidelines by promoting regional strategies more closely related to current patterns of specialization or to sectors closely related to existing capabilities.

The rest of this paper is organised as follows. The second section provides a brief overview of the smart specialization literature, highlighting recent evaluation of the policy rollout and the model of regional branching and related diversification upon which the programme rests. The core research questions that we examine are derived from this discussion. The third section outlines the construction and description of data with a special focus on identification of S3 target sectors. The first and the second research hypotheses are analysed in fourth and fifth sections, respectively. In the sixth section we combine analysis of our two research hypotheses and employ an econometric model to link the choice of S3 target sectors to the institutional and economic characteristics of EU regions. The last section provides some concluding remarks and policy implications.

Literature review and theoretical background

The S3 program represents a radical shift in EU Cohesion Policy, a clear break with the industrial policy of the past few decades and an embrace of place-based reforms that target national and regional economic development strategies and allied institutional reforms (Barca, 2009; McCann and Ortega-Argilés, 2013). Envisaged largely as a ‘bottom-up’ initiative, the S3 platform seeks both to renew and widen the knowledge and industrial base of regions, at different spatial scales, leveraging existing capabilities to support innovation and new trajectories of growth (Kroll, 2015). This smart specialization agenda emerged out of the *Knowledge for Growth Expert Group* (Foray et al., 2009) that emphasized 'entrepreneurial discovery' to identify those research domains, sectors and institutional structures in which regions possessed existing strengths, alongside a vision that that long-run competitive advantage would result from scaling core activities through processes of diversification and complementary innovation.

For many, the policy ambition of Foray and colleagues is woefully under-developed. Indeed, the authors themselves admit as much in their 2011 paper (Foray et al., 2011) that did little to dampen the enthusiasm of their critics. Early concerns raised by McCann and Ortega-Argiles (2015) question whether lagging regions have the potential to develop effective smart specialization policy. This theme is echoed by Rodriguez-Pose et al. (2014) who note the absence of effective governance and the institutional supports vital for innovation policy to succeed in peripheral regions of Europe. Moodysson et al. (2015), building on Borras (2011), argue that S3 fails to connect required innovations in the policy environment, reaching across multiple spatial scales, that successful implementation of regional economic innovation and new path creation will demand. Veugeleurs (2015) is in broad agreement, doubting whether there is sufficient scope for heterogeneity within smart specialization policy at all. Kroll (2015) laments the lack of integration between place-based theoretical development of innovation systems in economic geography and S3, and finds the focus on local techno-economic potentials "somewhat chaotic". He is joined by Pugh (2018) and Gianelle et al. (2020a) in questioning whether S3 policy is flexible enough to operate across the heterogeneous institutional environments found in EU regions. Morgan (2015) is more direct, claiming that S3 lacks any empirical foundations. For Nauwelaers et al. (2014), S3 constitutes a rushed application of under-developed theoretical ideas and an inadequate assessment framework. Boschma (2014) recognizes some of the same theoretical failings and attempts to shore-up the policy framework by closer integration with the concept of related variety. Hassink and Gong (2019) summarize many of the criticisms levelled against the S3 program spurring a spirited defense by Foray (2019).

At its core, S3 is a regional policy framework built around identification of competitive, local specializations and on extending the capabilities existing within those specializations to diversify economies along new, innovative pathways (McCann and Ortega-Argiles, 2013; Hassink and Gong, 2019). In many respects, this policy model sits squarely on top of the economic geography literature that focuses on the generation and maintenance of regional competitive advantage (see Maskell and Malmberg, 1999). It recognizes the importance of innovation to long-run growth and imagines innovation as growing out of the capabilities, the sets of tangible and intangible assets, that support competitive clusters of economic activity found in different locations. In this way, regions are not expected to follow a "one-size fits all" model of development (Tödtling and Trippl, 2005), but rather to chart their own course, giving rise to greater differentiation across the EU economic landscape. Operationalization of this framework requires identification of local/regional capabilities upon which existing competitive industrial specializations have been developed and a model of diversification that is explicitly linked to the evolution of those capabilities.

Identification of existing regional capabilities is the role of the entrepreneurial discovery process (EDP) of the S3. Local economic actors are seen as having the place-specific knowledge of industrial organization, institutions, innovation systems and markets around which regional forms of competitive advantage have been created (McCann and Ortega-Argiles, 2013; Boschma, 2014). The concept of self-discovery of capabilities is a cornerstone of the development models of Hausmann and Rodrik (2003). They also see state support for resulting policy choices as critical to economic growth, helping to offset market failures in terms of the absence of investment in new growth possibilities and too much diversification that may diffuse productive potentials. Other concerns regarding EDP have focused on the self-interest of local entrepreneurs and on whether they have the ability to detect the "right stuff" on which self-sustaining growth depends, especially in peripheral regions (Sotarauta, 2018). Hassink and Gong (2019) raise further concerns related to regional "lock-in" and the inability to make radical structural transformations under the EDP.

Boschma and Gianelle (2014) offer the clearest model of diversification linked to smart specialization policy. They view diversification as key to the process of knowledge-based economic transformation, as a process of building new growth paths out of existing national and regional capabilities. At the core of the diversification process ishow to leverage the existing capabilities of the region into new ventures. These capabilities, as mentioned early, are the tangible and intangible assets that are most effectively deployed within the region in the creation of value. They may be distinct pools of tacit knowledge, modes of organizing firms and entire industries, the formal and informal institutional supports that undergird local networks of education, learning, knowledge production, its diffusion and effective absorption. One of the most difficult questions that the EDP must face in identifying these capabilities is which of them are actually place-based and thus provide a platform to generate further growth at the local/regional level. The success of diversification is likely to depend upon the strength of existing capabilities within the region and upon the possibilities for deploying those capabilities in new domains of economic growth. In this sense, related diversification is critical for successful regional branching (Frenken and Boschma, 2007; Neffke et al., 2011). Related diversification occurs when the capabilities that support specific kinds of economic activity are successfully redeployed to support other activities. The hope is that over time, sets of regional capabilities will be broadened as each type of economic activity rests, at least to some extent, on slightly different skills, technologies, organizational and institutional structures. Larger, more developed regions have a relatively easy time diversifying their economies as they already possess many sets of related and unrelated capabilities and thus can branch into many different activities. Less developed economies have smaller sets of capabilities and their options for related diversification are therefore limited. At the same time, Grillitsch et al. (2018) argue that regions that focus just on related sectors may hinder long-run growth due to potential lock-in, whilst unrelated diversification may ensure long-term competitive advantages.

It is important to highlight that the current debate around smart specialization, although very intense, has remained mostly speculative, with limited evidence-based analysis. An exception is Balland et al. (2019), who develop a theoretical framework to assess the S3 policy, but not its implementation, using patent data to compute measures of relatedness and complexity. Rigby et al. (2019) take the same analytical framework and use historical data to assess whether regions that followed a technological trajectory coherent with the S3 approach enjoyed improved economic performance. Along this same research path, Balland and Boschma (2020) explore the relevance of inter-regional linkages, especially in complementary capabilities, on the potential process of S3 diversification. While important, none of these studies directly tackle assessment of the actual implementation of S3. Only recently, a few studies assess the adherence of real policy actions to the smart specialisation conceptual framework directly: D'Adda et al. (2020) for Italian regions, Gianelle et al. (2020b) for the Italian and Polish case, Trippl et al. (2020) for a set of 15 regions in 14 EU countries. Other contributions have targeted an ample set of European regions. Di Cataldo et al. (2021) focus on the frequencies of economic/scientific domains and policy objectives, which are found loosely connected with the intrinsic conditions of each region. Biagi et al. (2021) concentrate on tourism priorities and show no relationship between tourism concentration and the choice of tourism as their S3 priority. Finally, Deegan et al. (2021) explore the relatedness and complexity of actual S3 policy choices for a set of countries and regions.

Our contribution moves along these same lines, though it is broader in geographical focus, aiming to address the partial lack of evidence-based systematic and comprehensive analysis on S3 operationalization for the whole of Europe. We propose a novel empirical framework to examine the coherence of regional policymakers' choices with the theoretical foundations of S3 and related EC recommendations for defining smart specialization strategies. To illustrate our research question, we start by reconsidering the EU guidelines to the smart strategy definition. In the official S3 platform of the European Commission (EC) it is clearly stated that the regional S3 "should prioritise domains, areas and economic activities where regions or countries have a competitive advantage or have the potential to generate knowledge-driven growth". To test whether and to what extent the practice of

S3 policy is coherent with these recommendations, we articulate our research agenda into two main hypotheses:

H1. Regions selected their S3 targets in domains/areas/activities in which they *currently* exhibit revealed comparative advantage (RCA).

H2. Regions seek to generate knowledge-driven growth by developing new RCA in S3 target sectors that are related to their existing patterns of RCA.

To examine these hypotheses, we build an empirical representation of the policy choices selected by all EU regions. For each of these regions, we match the S3 sectors targeted to their current pattern of economic specialization and to the potential for local knowledge-driven growth identified by the relatedness of the S3 targets to the existing economic base.

The EC has recently reclassified the S3 domains, often declared in creative or hazy ways, by assigning to each priority the complete set of economic sectors involved in its implementation. This allows us to obtain a complete representation of the economic dimension of S3 domains. Mapping the existing economic structure of regions and their potential growth paths utilize existing EU data and measures of relatedness between economic sectors derived from a European production space. Testing H1 is possible by comparing the existing economic specialization of regions, identified using RCA indicators, to the S3 policy priorities selected. Testing H2 is more challenging as we have to deal with the *potential* notion of knowledge-driven growth, likely to be triggered by new specializations. To operationalize this idea, we use the concept of *relatedness density* proposed by Hidalgo et al. (2007). In the context of our analysis, relatedness density measures the degree to which an S3 sector utilizes economic capabilities that are readily available within a region. Higher relatedness density implies that a sector is more likely to be successful in activating growth through diversification. Such density measures are derived from the comprehensive description of the production space based on current and prospective co-specializations that we provide for Europe as a whole.

Data and methods

To investigate our research questions, we need to build three homogeneous blocks of regional data on: (i) S3 selected sectors, (ii) current production specialisation, (iii) potential related production specialisation. In the following paragraphs, data and methods applied to build these blocks are discussed while a descriptive analysis is provided in the online supplemental material.

The Smart Specialization Strategy

As remarked by D'Adda et al. (2019), drilling into the details of regional smart specialisation strategies is not an easy task given the absence of a codified system for the classification of targets. As a result, each region has specified its S3 domains in a flexible and creative way so that comparisons across regions and quantitative evaluations are almost impossible. The EC has developed a S3 platform where information on the regional strategies is gathered.[1] In 2018 the EC has enriched the platform classifying each strategy according to standard taxonomies.[2] We will focus on the economic dimension, based on NACE 2-digit sectors in both manufacturing and services. This implies that S3 targets can be analysed beyond both the "pure" technological domain and the manufacturing perimeter by including services. This is crucial given that several regions based their S3 policy on service activities such as tourism, culture, archaeological heritage and health.

S3 has been implemented at different territorial levels: national and NUTS-1, -2 -3 regional levels.[3] From now on we simply refer to "regions", regardless of the NUTS level. The choice to perform S3 at the national level seems reasonable for small countries while it is more surprising for large countries like Hungary and Bulgaria, given that the policy was originally intended as a local strategy.[4]

According to the EC guidelines, each region was supposed to build its S3 on a limited number of *priorities*, namely the economic activities where the region had a competitive advantage or the potential to generate knowledge-driven growth (Foray, 2015). The key idea of the strategy is to concentrate the managerial and financial resources available in the region on a few well-defined priorities to avoid policy dilution following the EDP (Gianelle et al, 2020b).

We might expect a higher number of priorities by richer regions that have wider technological opportunities and are more likely to face greater requests by local stakeholders. At the same time, less developed regions, where private investments are scarce, might prefer a more flexible and inclusive strategy, enlarging the number and the scope of their priorities to exploit all potential investment opportunities (Trippl et al. 2020). The average number of priorities is 6 with a high variability among regions. Thus, a first consideration is that the number of priorities pursued by many regions seems higher than we would have expected, although the S3 foundations do not provide very clear guidance on this issue.

[1] See: https://s3platform.jrc.ec.europa.eu/home. For a detailed description of the platform see Sörvik and Kleibrink (2015). McCann and Ortega-Argiles (2016) provide a first overview of the regions' choices.
[2] The economic dimension is classified according to the NACE rev2, the scientific dimension thanks to NABS 2007 and the policy dimension by referring to EU objectives.
[3] We have aggregated the S3 defined at the NUTS3 level for Sweden and Finland to the corresponding NUTS2.
[4] In six countries (Austria, Denmark, Germany, Greece, Poland and Portugal) the S3 carried out at the regional level has been complemented with national projects effective to the whole country. We have excluded these national priorities to avoid the overlapping of different decision levels.

According to McCann and Ortega-Argiles (2015) there is no clear rationale to the selections made: regions with similar socio-economic background chose diverse thematic and sectoral priorities both in quantitative and qualitative terms. Looking at the regions according to their geographical location, our results confirm Iacobucci's (2014) prediction and Kroll's (2015) preliminary assessment: Southern regions have a higher number of priorities (on average 7.2) than Central-Northern and Eastern regions (average less than 6). Looking at the economic sectors included they appear as diverse as the nature of the selected priorities with a high regional heterogeneity.

The great variability in regional strategies in terms of priorities and sectors was partly expected as an obvious consequence of the S3 general strategy, which aims at avoiding all regions following the same direction. However, it is difficult to understand the S3 selection process in many cases. The choices made do not all appear to be clearly linked to a strategy of evidence-based assessment. At the same time, it is important to remark that each region had to allocate a significant part of its ERDF resources (like firms' financial incentives) to the priorities and sectors indicated in the S3. Therefore, rational behaviour by regional policy-makers was to define priorities in a generic fashion so that a larger set of economic sectors was included in their strategies, thus enhancing private sector investments. Overall, there is little sign of proliferation and widening of specialisation domains, but rather diverse approaches to the decision process, apparently independent from the development status and the institutional setting, and more related to the mode of governance (Kroll, 2015).

Finally, for operational purposes, we consider for each region the entire set of S3 targeted sectors, regardless of the original priorities; this constitutes a sort of regional "unified" S3 strategy, since we have included all the NACE sectors selected at least once in the original priorities. The result is a binary matrix of 169 regions and 82 sectors, where each entry $s3_{ri}$ takes the value of 1 if sector i is included in the S3 strategy of region r and 0 otherwise.

Existing regional production specialisation

The second block of data we need to test H1 entails the drawing of a comprehensive map of economic specialisation across regions in Europe, which can be juxtaposed to the S3 pattern. We provide this representation by computing the RCA index, based on employment in 2016, classified by NACE economic sectors and extracted from Eurostat Structural Business Statistics (SBS).[5] We collect data for 243, mainly NUTS2, regions. In a similar fashion, Balland and Boschma (2019) have

[5] Four macro sectors (A *Agriculture*; K *Financial and insurance services*; O-P *Public administration, education, health*; R-T *Arts, entertainment, recreation*) are not available in SBS, and the corresponding employment levels were retrieved from Eurostat Regional Accounts.

recently explored EU regional specialisation by using a different database, derived from the EU Labour Force Survey. Since our aim is to examine for each region the degree of association between S3 target sectors and the existing production specialisation, we need to match the regional and sectoral dimension of S3 with the employment data. The intersection between the two datasets contains 166 territorial units[6] and 64 sectors listed in Table A1 and A2 of the online Appendix.

Finally, we use the employment data to compute the RCA index and a regions/sectors matrix with entries taking the value of 1 if a region has a comparative advantage (RCA>1) in a given sector and 0 otherwise.

The European production space and regional relatedness density

In the third data block, we provide a measure for the *potential* to activate growth through diversification by computing the *relatedness density* of each S3 target sector to each region's existing economic base. As already mentioned, this measure proxies the availability of local capabilities and it is derived from the empirical representation of the European production space in terms of co-specialisations. We thus provide an alternative measure of such space, complementing existing spaces based on patents, as in Balland et al. (2019) and Rigby et al. (2019). The importance of relatedness for regional innovation and economic development is emphasised by Boschma (2005) and Frenken et al. (2007). The pace and direction of technological dynamics in a region are shaped by the costs and benefits of exploiting new ideas given the existing mix of knowledge and industry. This cost-benefit balance of diversifying from one technology to another is more favourable when two technologies are related. Several studies (Rigby and Essletzbichler 1997; Kogler et al. 2013; Boschma and Iammarino, 2009; Boschma et al., 2015; Rigby, 2015, Maggioni et al., 2019) have shown that knowledge production within regions accumulates in a path dependent fashion going from an existing technology to a related one.

Following Hidalgo et al. (2007), we thus proceed by building a European production space using the employment data. First, we compute the *proximity* matrix for the 64 sectors considered in our analysis. Proximity or relatedness between any two sectors, *i* and *j*, is given by the minimum of the pairwise conditional probability of a region being specialised in the production of sector *i* (*j*) given that it is also specialised in the production of sector *j* (*i*):

$$\varphi_{i,j} = min\{P(RCAs_i|RCAs_j), P(RCAs_j|RCAs_i)\}$$

The proximity parameter $\varphi_{i,j}$ provides a measure of the strength of co-specialisation between sectors *i* and *j* and it is computed using all 243 EU regions for which sectoral employment data are

[6] We excluded three small countries Cyprus, Luxembourg and Malta due to missing data for employment.

available in order to maximise the information on economic co-specialisation.[7] The resulting matrix represents the European production space, which is depicted in Graph 1 as a network. For the sake of visualisation, we aggregate the 64 sectors into 13 macro-sectors. The graph shows the relevance and centrality of services sectors across most EU regions. Economic sectors that cluster together are more highly related than those which are relatively distant. We interpret the relatedness between sectors as an indication of shared capabilities in terms of production requirements. Thus, if a region has the capabilities to produce output in industry *i* it is also likely to own the capabilities also needed to produce output in industry *j* if the industries *i* and *j* are related to one another. In general, the production space based on employment data allows assessment of the interactions among sectors in a more comprehensive way with respect to patents.

The next step is to calculate the 166 regions by 64 sectors *relatedness density* matrix Ω. For sector *j* in region *r* the matrix entry is computed as follows:

$$\omega_{rj} = \frac{\sum_{i \neq j}^{N} I_i^r \phi_{i,j}}{\sum_{i \neq j}^{N} \phi_{i,j}}$$

where I_i^r is an indicator function taking the value of 1 if $RCA_i^r > 1$ and 0 otherwise and $\phi_{i,j}$ is the sectoral proximity parameter discussed above.

Finally, using matrix Ω, we compute two measures of the *average relatedness density* for each region considering: i) *all* sectors of the regional economic structure; ii) the *S3-specific* sectors including only the sectors selected for the region's S3 policy. The average value computed considering *all* economic sectors provides the existing pattern of relatedness density of a region's production structure regardless of the S3 implementation. The correlation between the two regional average relatedness densities is very high (0.98). We return to this finding in the fourth section.

Map 1 presents the density measure considering all economic sectors and the regional value of aggregate relatedness density appears highly differentiated across Europe. Overall, the average relatedness density is equal to 0.35 and ranges from a minimum of 0.14 (Nord-Est in Romania) to a maximum 0.61 (in Hungary). As expected, the higher levels of relatedness density are found for regions identified at the national scale: Hungary, Czech Republic, Slovakia, Slovenia, Croatia and the three Baltic states. The portfolio of specialisations at the country level is in general wider than at the regional level, thus it is more likely for a given sector to be surrounded by many related sectors. High values are also found in well-developed regions, such as Lombardia in Italy, Île de France, Hessen in Germany, while only few of them are developing regions like Dolnoslaskie and

[7] The use of the entire set of 243 regions allows us to get a more accurate measure of the proximity parameters, which however does not differ remarkably (correlation coefficient 0.94) when it is computed using the set of 166 regions involved in the S3 policy.

Malopolskie in Poland. In contrast, the lowest levels of relatedness density are detected in the small and less developed areas of Greece, Romania and Southern Italy because of the weak and sparse production space of these regions, where co-specialisations are rare. Interestingly, a low relatedness density is also shown by several French regions (Languedoc-Roussillon, Bretagne, Lorraine, Basse-Normandie) signalling strong territorial specialisation of the French production space.

In general, both the overall and the S3-specific relatedness densities largely depend on the size of the economy and on to the specialisation pattern of the production structure. Countries and rich regions show the highest aggregate relatedness densities while less developed and small regions lie in the low part of the ranking. This implies that the initial conditions of each region are highly differentiated: the higher the overall relatedness density exhibited by a region due to its sectoral specialisation, the more likely that region will reach a higher S3 relatedness density, given the number of S3 target sectors. Thus, in the fourth section we use the general and S3-specific densities to compute a new measure suitable to assess the relationship between S3 choices and the extent of potential growth.

S3 and regional production specialisation

The purpose of this section is to address the first research question by examining whether sectors selected in the S3 regional strategies are those in which regions exhibit comparative advantage. Using the two binary matrices presented in the previous section, as a preliminary step in our analysis, we compute the share of S3 sectors in which each region currently exhibits RCA>1. We find 48 regions with a share below 33% and only 16 regions with shares higher than 66%. On average, regions have RCA in 43% of the target sectors they have chosen to prioritise for their smart specialisation policy, indicating that the degree of coherence between current specialisations and S3 sectors is relatively low.

We proceed by formally testing the degree of association between the two sectoral distributions, that in which the region already has RCA and that reflecting regional S3 policy choices. The first remarkable result is that the average of the estimated correlation coefficients between these distributions is rather low: 0.13.[8] To test this association we also computed the Pearson's chi-squared test. It is worth recalling (Guilford, 1936) that for the case of two binary variables the Pearson correlation coefficient is equal to the mean square contingency coefficient ϕ (with $\phi = \sqrt{\chi^2/n}$ where χ^2 is Pearson's chi-squared test and n=64 is the number of sectors). We find that that in 107 out of

[8] Results are robust with respect to the use of the RCA values rather than their transformation into binary values: the correlation with the S3 matrix is 0.15.

166 regions the null hypothesis of the test (no association) is not rejected at conventional significance levels.[9] This means that, on average, there is little association between the S3 target sectors and the actual production specialisation of most regions.

Looking at the geographic representation of the degree of association, as depicted in Map 2, we observe a positive and statistically significant association in some Greek regions. Indeed, four out of the six regions with the highest correlation coefficients belong to Greece. Among the top ten regions, we find two from Poland and one from Romania, France and Spain. The same differentiated scenario emerges also for the regions with the lowest association. Overall, the regional variability in the correlation coefficients does not seem to exhibit any clear spatial pattern (Moran's *I* test equal to 1.19, *p*-value 0.233).

The novel evidence provided so far seems to clearly reject our research hypothesis H1. On average, while designing their S3 policy, regions have not selected those sectors where they already have comparative advantage. This result stands in stark contrast with the theoretical recommendations and relative guidelines for the favourable implementation of the smart specialisation strategy in Europe. It is clear that S3 policy is built around diversification. With the aggregate nature of the sectors identified in this analysis, it should be clear that there is plenty of scope for diversification across individual industry and product lines within, as well as beyond, each of these sectors. Thus, the relatively low share of priority S3 sectors corresponding with existing regional specializations is rather worrisome.

S3 and regional production relatedness

The purpose of this section is to address research question H2 by assessing the relatedness between the sectors selected in the smart specialisation strategy and the existing economic cores of the regions examined. More precisely, we want to measure the degree to which a sector included in a region's S3 policy utilises economic and knowledge capabilities that are readily available within that region. For this, we build on the two measures of regional average relatedness density previously discussed, the aggregate density score for all existing sectors in a region and the density score focused only on the S3 target sectors.

It is worth noting that if we compare the average relatedness density scores for the existing sectors in a region and the aggregate S3-specific densities they are very similar for most regions. Indeed, across regions, the average density score for existing sectors is equal to 0.3453 whereas the S3 density score averages 0.3544. This is a first indication that regions have not targeted their most

[9] Similar results are obtained by estimating the conditional probability of selecting an S3 sector given the current RCA based on logit models.

highly related sectors in their S3 policy but have tended to replicate the mean underlying features of their current production structure. This could be the result of rational choices made by policy-makers, as already anticipated above. Those policy-makers may have paid more attention to the requests of local stakeholders and/or to the chances of attracting private investment flows for the economy as a whole, rather than trying to exploit as much as possible the growth potential of their own region's economic base.

In order to measure the extent of the loss in terms of unexploited relatedness density (and ultimately in terms of growth opportunities), we rank for each region in decreasing order *all* the sectors according to their relatedness density values. Then, we calculate the *average maximum potential relatedness density* (from now on *max-potential*) achievable given the number of sectors the region has selected in its smart strategy. For example, the max-potential relatedness density attainable by a region with, say, ten S3 sectors is the average of the relatedness density values for its ten sectors with the highest relatedness density. Finally, we evaluate how close the region has come in its actual S3 choices to this benchmark by calculating the difference between the average S3-specific relatedness density and the max-potential. In order to take into account starting conditions (i.e. having a specialised or diversified production space), we compare regions on the basis of the percentage ratio of the difference computed above with respect to the max-potential.

The percentage ratio is a measure of the "loss" in terms of economic growth potential that a region may experience related to its S3 sectoral policy choices. If the loss is approximately zero it means that a region has targeted S3 sectors that maximise relatedness density to its current economic structure. The larger the loss, the more distant is the focal region choice from the "maximising" S3 strategy, given initial production conditions. This loss measure provides an appropriate indicator to assess our research question H2. Given the value of the max-potential, a small loss implies that the region chose S3 sectors with a better "fit" to the regional economy and, as a result, it enables higher potential economic growth through diversification across sectors. In other words, the higher a sector's relatedness density to the economic core of a region, the lower the costs and risks for the region of developing that sector. This is because as the relatedness density of a target sector increases within a region, the more likely the pool of capabilities, skills and knowledge required in that sector is already locally available.

Map 3 shows that the loss in S3 relatedness density is highly spatially differentiated, though clear spatial patterns are barely discernible with a Moran’s I test statistic equal to -1.86 (p-value 0.062). The region, which comes closest to maximising its S3 relatedness density, given the available potential in the region, is Mazowieckie in Poland with a loss of just -1.6%, followed by three Italian regions Veneto, Toscana and Campania, and then Östra Mellansverige in Sweden and Etelä-Suomi in Finland. Interestingly, among the best performers we find regions with a high max-potential like Veneto (0.53) together with regions where it is quite low, like Campania (0.29) and the Greek Peloponnisos (0.21). These regions, although characterised by very different production structures and specialisation patterns were all able to choose S3 target sectors with high relatedness density. Similarly, the territorial composition at the low end of the ranking is highly differentiated: the highest loss, -35%, is presented by Bulgaria, followed by the South East of the UK, Hovedstaden in Denmark, Helsinki-Uusimaa in Finland and Podkarpackie in Poland. Again, the loss seems independent from the starting conditions in terms of max-potential. Helsinki presents a loss of -28% starting from a high max-potential (0.63), while a similar loss (-27%) is found in Sud-Vest Oltenia in Romania, which had a much lower max-potential (0.24).

If we apply the geographical topology to explore the distribution of these results, one interesting outcome arises. Southern regions have chosen relatively densely related sectors among those available, with an average loss of -10.3% and quite similar is the performance of the Central-Northern regions (-11.8%). In contrast, Eastern regions, despite the presence of several territorial units at the country level, are on average the most distant from their max-potential, with a loss of -15.1%.[10]

The evidence provided in this section for testing the research hypothesis H2 shows a highly differentiated behaviour by regional policymakers. Only 17 regions have a loss smaller than 5%. A loss higher than 10% is found for 92 regions, and in 19 regions losses exceed 20%. Thus, it appears that many regions have selected their S3 sectors without considering the available local core of knowledge, and thus with little attention to the risk that unrelated diversification poses for potential future growth. It is worth considering that this might have been the result of political choices based on different grounds or of policymakers lacking relevant and readily usable information on the production features of their own regions and an adequate benchmarking system.

[10] This distribution may explain why Deegan et al. (2021) find that regions in their subsample (with all Southern countries and Romania) are inclined to choose related diversification strategies.

A comprehensive evaluation framework

Combining the two research hypotheses

Our main results indicate that the S3 policy choices of EU regions have not, in general, tended to target sectors in which they have an existing comparative advantage or in which they have significant potential to develop new specialisations. We have shown that in their implementation of S3, regions across the EU exhibit considerable heterogeneity and, most importantly, that heterogeneity does not closely reflect the recommendations of smart specialisation theory or EC guidelines. The evidence presented raises concerns regarding the likelihood that smart specialisation target sectors will stimulate successful growth trajectories that leverage existing or related regional capabilities. This finding does not imply any kind of judgement on the choices made by regional policymakers, or that the policy will necessarily result in ineffective outcomes. However, growth strategies that are relatively unrelated to a region's current and prospective assets are riskier and do seem inconsistent with the bottom-up, evidence-based policy framework at the heart of the smart specialisation programme.

In order to highlight the S3 trajectories that emerged from the evidence gathered in testing our two hypotheses, Graph 2 locates EU regions in a two-space that indicates their relative location in terms of the correlation of their S3 targets and the existing sectors in which they exhibit RCA (Hypothesis 1 on the vertical axis) and in terms of the percentage relatedness density loss associated with their S3 policy choices (Hypothesis 2 on the horizontal axis). Note that intercepts of the horizontal and vertical lines in the graph are set at median values across the regions (0.123 for H1 and -10.8 for H2). Thus, Graph 2 plots simultaneously how many regions have targeted S3 sectors linked to their existing RCA core and/or to other parts of the regional economy that are high related to that core. Four possible scenarios are identified, varying in terms of their association with the existing economic core of the region and the potential of the region to be able to leverage growth in related activities. See also Map 4 for the distribution of the European regions in the four quadrants of Graph 2.

In the upper right part of the graph Q1 are regions that have chosen a "virtuous path" as their targeted S3 sectors are closely linked with their current specialisation patterns in terms of sectoral overlap and relatedness. If, for instance, we consider the subset of regions with a correlation higher than 0.24 (significant at the 5% level) for H1 and below the 8% loss for H2, we end up with 15 regions (the green area in Graph 2). Among them four Spanish regions (País Vasco, La Rioja, Illes Balears, Andalucía), three Greek regions (Notio Aigaio, Sterea Ellada, Peloponnisos), Wien and Oberösterreich in Austria and one region in Italy, Portugal, Sweden, Finland, Denmark and Germany. These regions have good chances of developing new comparative advantages because they have selected S3 sectors that are both related to their current specialisation and to the core of available knowledge, hence they are less hazardous to develop. The territorial composition of this subset is quite differentiated though it may be remarked that no Eastern European countries or regions are included.

In the bottom right quadrant Q2 are regions that we classify as "out of the beaten path". The S3 targets of these regions do not overlap closely with the current pattern of RCA, though these targets are relatively highly related to existing specialisations in the regions. Interestingly, in this portion of the diagram we find several rich German and Swedish regions together with some innovative regions, such as Lombardy and Emilia Romagna in Italy, and Cataluna in Spain. At the same time, this quadrant includes developing regions that are trying to diversify their production specialisation towards new sectors related to their economic cores. Among these, it is interesting to mention the case of Sicily, which has explicitly stated its intention to exploit S3 opportunities to radically renew its strategic orientation (Bellini et al. 2021).

In the upper left quadrant Q4, we find regions that have chosen a "conservative" or safe path, as their S3 strategy is shaped by existing RCA-based specialisations though not by high levels of relatedness to new sectors. This scenario might bolster existing strengths, in line with EC recommendations, but it also elevates the risk of getting locked into the current pattern of specialisation. This might be the case for the developing regions of Poland, Romania, Greece and Spain included in this quadrant, which risk the perpetuation of a weak equilibrium.

Finally, regions in the lower left quadrant Q3, have chosen a quite different and "risky" path: they have designed their S3 policy targets with little regard to existing patterns of specialisation and, at the same time, away from those sectors that are closely related to existing specialisations. These unrelated diversification scenarios depend almost entirely on external capabilities, or on a broad transformation of local capabilities. This strategy is very risky for the regions involved. Regions in this group appear to be quite heterogeneous including Berlin and Lazio (Rome's region) together with several French (8), Polish (6) and UK (5) NUTS areas.

Looking for the determinants of regions' S3 choices

Is the selection process that identifies S3 target sectors associated with the institutional, economic or structural characteristics of NUTS regions? To investigate this issue, we compute an S3 policy "coherence" indicator as a dependent variable and then regress that on a comprehensive set of potential covariates. To build the coherence indicator, the two measures adopted to test hypotheses H1 and H2 were standardized using the min-max procedure and then averaged. We assign equal weights to the two measures because the EC recommendations (see statement reported above, page

2) places the development of actual (H1) and potential (H2) competitive strategies on the same footing.

As S3 is still clearly a "policy running ahead of theory" (Foray et al., 2011), we cannot proceed by testing theoretical propositions to single out the main determinants of the S3 regional choices. However, given the bottom-up nature of the policy, regional government authorities and local authors played a key role in selecting the priorities. Therefore, we expect the overall coherence of the policy to be positively related to the quality of local institutions. We maintain that high-quality local institutions are less likely to be influenced by external conditions and more likely to follow EU Guidelines. Hence, they are more capable of designing S3 policy to maximise their own region's growth (Capello and Kroll, 2016; D'adda et al. 2020). It is also possible that weaker regional institutions may be "captured" by local stakeholders with specific sectoral interests. In this case, the number of S3 targets may proliferate, reflecting pressure from local firms rather than the exploitation of real growth opportunities. In our analysis, we proxy the quality of local institutions by the European Quality of Government Index (EQI), a multidimensional metric resulting from the combinations of three indices: high impartiality, quality of public service delivery and low corruption (Charron et al. 2015).[11]

As a possible driver of S3 policy coherence, we also considered the general level of regional economic activity, measured by GDP per capita. In this case, the expected association is less straightforward. On the one hand, wealthy regions have more opportunities to diversify since their production structure is wider and more articulated. Moreover, such regions host a larger number of firms, likely to be involved in the strategy and implementation of S3 funding calls. On the other hand, lagging regions with a weak production structure have fewer investment opportunities. These regions may select a relatively large number of S3 targets, simply hoping that at least one of them delivers. In general, we expect a positive association between regional GDP and the S3 policy coherence indicator.

We add two more intangible factors to our model: human capital and technological capital. Human capital is measured by the share of the population aged 25-64 with a university degree (ISCEED 5-8). Technological capital is proxied by R&D expenditure per inhabitant or, alternatively, by the number of patent applications to the European Patent Office (EPO) per million inhabitants. Although we expect these intangible assets to complement and reinforce S3 effects once the policy is implemented, we have no clear-cut expectation on the direction of association with the S3 coherence indicator.

[11] Table A3 reports detailed information on variable definitions and data sources.

We control for the level of agglomeration by including population density in the econometric model. We also add a measure of the structure of the regional economy by including specialisation indices for low-technology manufacturing and knowledge-intensive services.[12] Finally, we include two territorial dummies to account for additional economic, institutional, and social features not entirely accounted for by the variables mentioned above. A "southern" dummy flags the southern regions of Greece, Italy, Spain and Portugal and a "new" dummy flags the 11 new accession countries in the European Union.[13]

Before carrying out the regression analysis, we test the coherence indicator, as well as each standardised indicator, for spatial autocorrelation. The Moran's *I* test computed by using the max-eigenvalue normalised inverse distance matrix returned no significant results.

The main results are reported in Table 1. As for the coherence indicator (columns 1-3), we find evidence of significant positive association with respect to the Quality of Government variable. GDP per capita exhibits a significant positive coefficient only when the model excludes the EQI variable (column 3). The two variables are highly collinear (correlation coefficient 0.70); thus, when both are included in the model (column 1) a multicollinearity problem arises. No other variables seem to play a significant role as possible drivers of regional S3 choices except for the Southern regions dummy. It is worth noting that human capital and technological capital – either proxied by R&D or patents per capita – do not exhibit significant coefficients even in specifications in which they are included one at a time as the main S3 policy driver (EQI and GDP per capita excluded, controls for productive structure and territorial features included).[14] These results are in line with those in Di Cataldo et al. (2021), where the authors find weak evidence for technological capacity and no evidence at all for human capital as drivers of S3 development axes, economic or scientific domains and policy priorities. This could be due to human capital having no direct effects, rather only indirect ones through the quality of government. As for technological capital, it is reasonable to expect a direct effect on the scientific domains rather than on the selection of productive sectors; as discussed in the previous sections, their set is rather heterogeneous and includes also traditional and low-tech economic activities. Overall, although the empirical literature on regional performance has provided extensive and robust evidence on the role played by intangible assets, such as human and

[12] We have also included additional indicators for the production structure, for example, the specialization in high and medium tech manufacturing, but the results remain unchanged.

[13] In a preliminary analysis, we replaced the two territorial dummies with a set of 15 national dummies for the largest countries included in the sample. Although the results are remarkably similar, we opt to report in Table 1 the more parsimonious specification with the two territorial dummies described above.

[14] All results are available from the authors upon request.

technological capital, in determining economic outcomes, the S3 selection policy does seem to be almost entirely unaffected.[15]

Even though we maintain that to assess the role of regional structural characteristics on S3 choices it is more appropriate to consider the composite coherence indicator, in Table 1 we also report the results for the H1 (columns 4-6) and H2 (columns 7-9) indicators. Results confirm the key role of the Quality of Government in driving the accordance between S3 choices and the EC recommendations for both H1 and H2 indicators. Per capita GDP exhibits a positive coefficient though not significant at conventional levels. Technological capital turns out to be negatively associated with S3 choices targeting sectors with existing comparative advantage, while we find some evidence suggesting that regions might have leveraged existing knowledge and innovative capabilities to develop potential comparative advantage in related sectors (columns 7-8). Population density is positively associated only with H1, whereas no evidence is found for human capital as a driver of S3 choices.

Overall, the estimation results indicate that policy decisions on S3 target sectors are robustly associated only with the quality of local governments. Institutions with high quality are able to lead the regions towards a positive path of potential growth consistent with EC guidelines by adopting more precise and more focused strategies. It appears to be the case that low-quality governments are more prone to fulfil the expectations and requests of local stakeholders. Indeed, the inclusion of a specific sector in the S3 means that private investments in that sector become eligible for EU financial grants. Therefore, the local authorities' choices are likely to be influenced by stakeholder pressures, which might be exerted by pure rent-seekers in the worst cases. Moreover, low-quality institutions might also face more difficulties accessing and processing the necessary information required for the complex and challenging S3 policy agenda.

Conclusions

As the S3 priorities are currently being implemented with the assigned resources to be spent by 2023 (the *n*+3 rule of the 2014-20 EU programmes applies in this case), it will not be possible to evaluate the economic impacts of the smart specialisation programme until at least a certain number of years have elapsed since the end of the term above. Nonetheless, it is possible to assess how regions and countries have interpreted the conceptual framework of S3 and how they have moved from theory to practice. Most countries and regions have included S3 in their development policies and devoted a share of available EU resources to their 2014-2020 Regional Operational Programmes. The strategy

[15] For robustness we also carried out the regression analysis on the composite coherence indicator obtained as the average of the normalized single indicators; results, not reported to save space, are very similar.

has attracted a lot of attention from policy-makers and academics because it represents one of the largest experiments of place-based development policy centred on the selection of local priority sectors. In this paper, we have empirically assessed how much the choices made by regions in selecting S3 sectors are consistent with the EC aim to prioritise economic activities where regions are already specialised or have the potential to generate economic growth through related diversification within and beyond existing specializations.

Our analysis of regional strategies draws from the EC official S3 website, where all regions have disclosed their industrial and technological priorities, and from the employment data in manufacturing and services provided by Eurostat. These data allow us to examine for most EU regions the degree of association between S3 and both *current* and *potential* production specialisations, in terms of competitive advantage and relatedness.

Results show that S3 practice has taken many different routes with respect to the guiding principles stated in the EC guidelines. Only a handful of regions have chosen smart specialisation "by the book". Most regions have only partially targeted sectors in which they have an existing competitive advantage or the potential to develop one. Although our findings do not imply in any way a negative assessment either on policy-makers or on the policy itself, it is important to remark that growth strategies unrelated to a regions' current or prospective specialisations are much riskier and might entail higher implementation costs.

We summarise regional strategies across four different trajectories by matching policy choices with existing and related capabilities within EU regions. These paths are characterised by strengths and weaknesses as much as opportunities and risks. In the future, it will be essential to assess whether the economic performance of regions is linked to the coherence of the S3 trajectory chosen. Unfortunately, the overall effectiveness of S3 policy is going to prove difficult to assess due to the economic impact of the COVID-19 pandemic and the different national responses to it.

Results from a cross-sectional econometric model suggested that individual and composite indicators of regional “coherence” with S3 policy were positively and significantly related to quality of governance. There was also evidence of a positive relationship between S3 policy coherence and regional GDP. A dummy variable also revealed that southern regions of the EU prioritized S3 targets following EU guidelines more closely. Indicators of regional economic structure and human and technological capital were insignificant in the model. Until the results from the regional S3 choices are revealed, highlighting successful policy prescriptions remains impossible.

All in all, results presented here should lead to further reflections on S3 policy from both a theoretical and practical perspective for potential future adjustments and improvements. Regional policy-makers should have a comprehensive and collective base of information to lead the consultation process towards the best possible strategy. We believe that the novel analysis proposed in this paper should be part of the ex-ante information set available to regions in order to make more conscious and possibly more effective decisions for a truly "evidence based" strategy. Moreover, the EU authorities should reflect on the opportunity to provide regional policy-makers with more detailed and strict guidelines for the next operational programmes 2021-2027 and more generally for policies with complex design and implementation criteria, as was the case for the smart specialisation strategy.

There are several prospective research lines that might stem from this contribution. As regions are not independent units, as implicitly considered by the S3 programme, they are more or less connected depending on their geographical and technological proximity, and thus have varying capabilities to monopolize internal capabilities and also exploit external possibilities. More work is needed to assess inter-regional interdependencies, within and between countries. The duplication of S3 policy targets across many regions raises several questions, but also permits interesting research designs given that not all regions chasing the same industrial targets are likely to be equally successful. This calls for coordination efforts at all levels of government – regions, countries, EU – in order to maximise the beneficial effects of the integrated regional potentials.

In the near term, the S3 implementation process has already raised a number of policy-related concerns. While the “bottom-up” initiative of the Entrepreneurial Discover Process is to be lauded for generating flexibility across regions in terms of sectoral targets, that same process raises a number of issues in terms of how effective identification of strategic priorities. First, vested business interests might be pushing rent-seeking interests at the expense of choices that might have broader socio-economic impact. What should be the relative role of entrepreneurs in the EDP vis-à-vis local regional policy-makers and other “experts”? Second, how should countries, and even the EU as a whole, deal with the inevitable duplication of target sectors across different regions? Who chooses, and with what criteria, which regions might be favoured in this process? Third, although diversification is to play a critical role in S3 policy, what is much less clear, given the aggregate priorities listed by many EU regions, is how much diversification might occur within existing sectors relative to developing ones? Furthermore, what are the prospects of recombinant knowledge and broader forms of economic development resulting from growing breadth within existing specializations versus developing new sectors, and is there an optimum number of specializations for regions of different scales?

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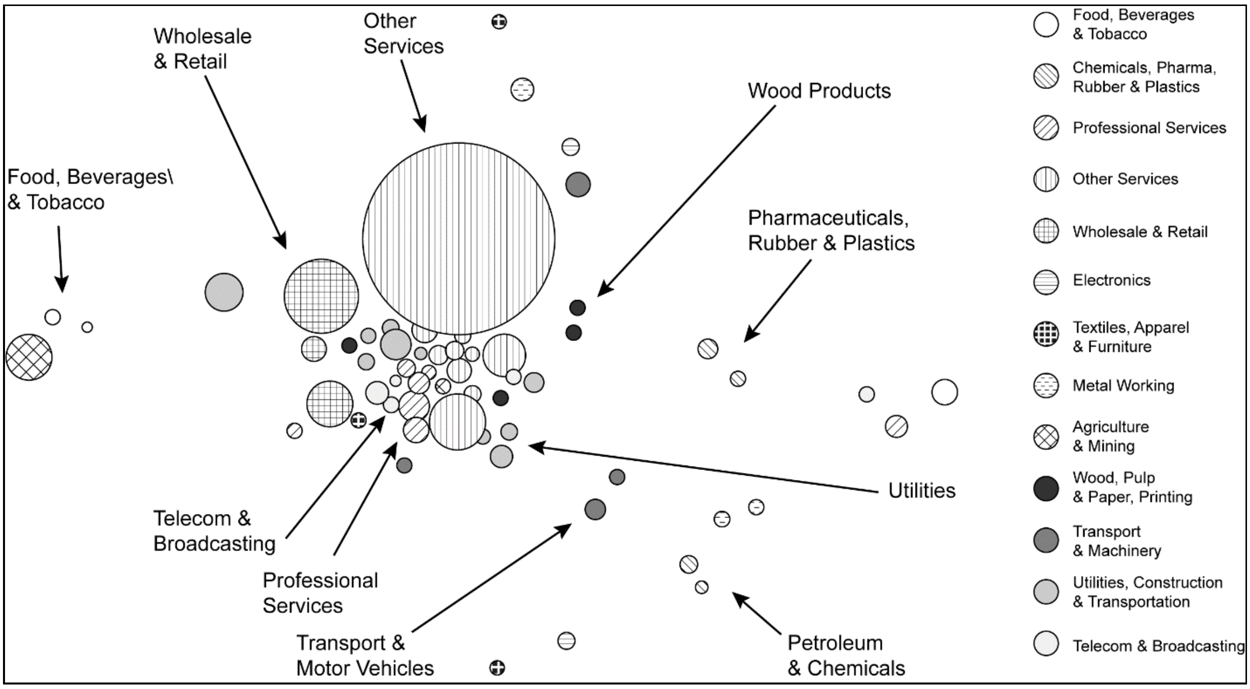
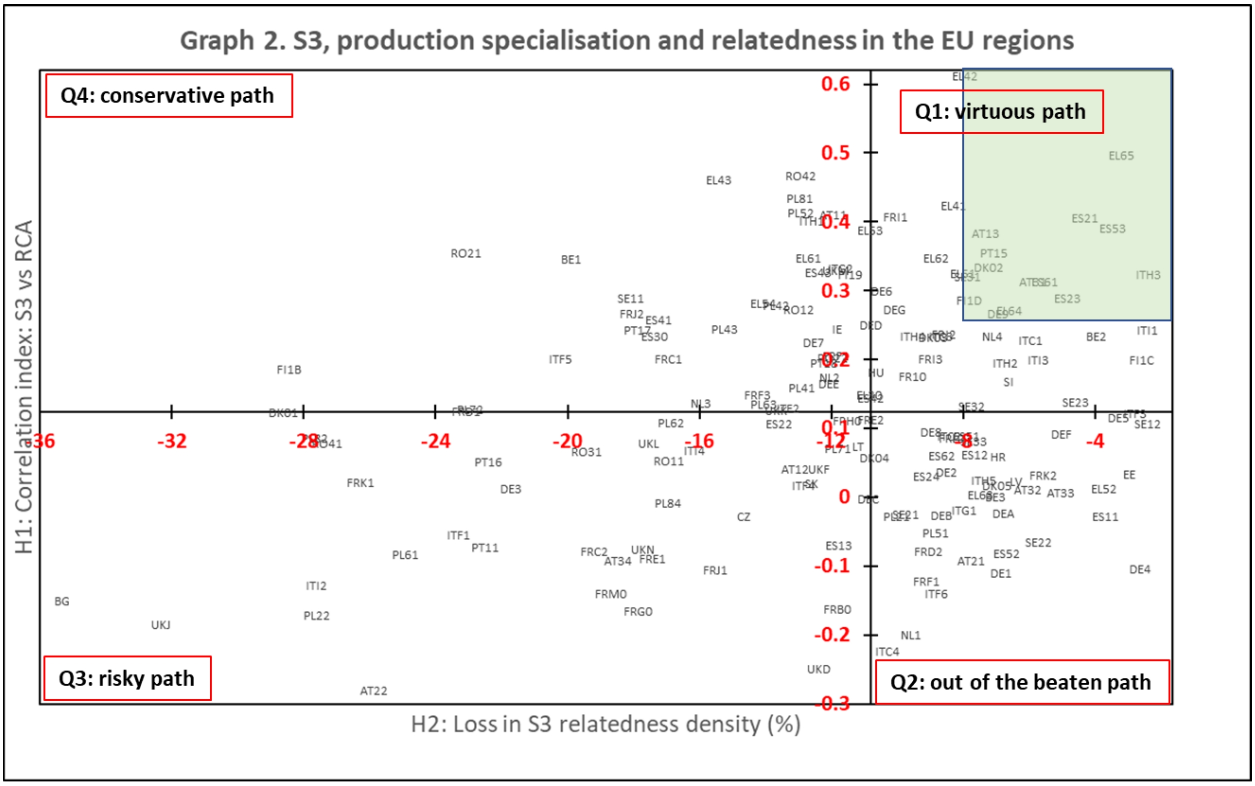
Graph 1. Production relatedness in Europe (64 sectors grouped in 13 macrosectors)

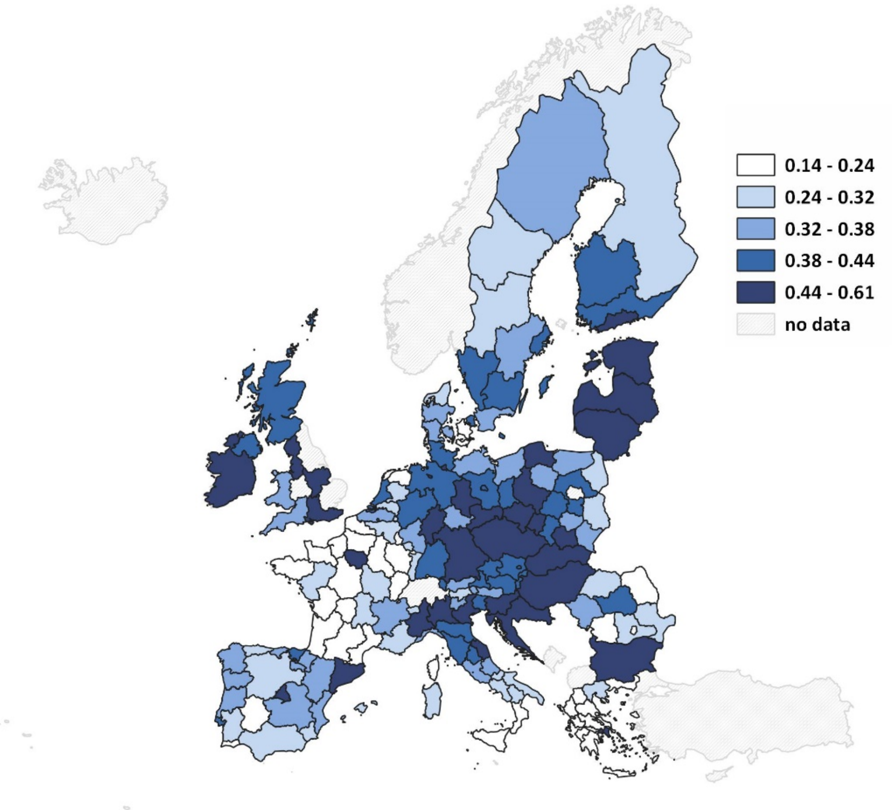




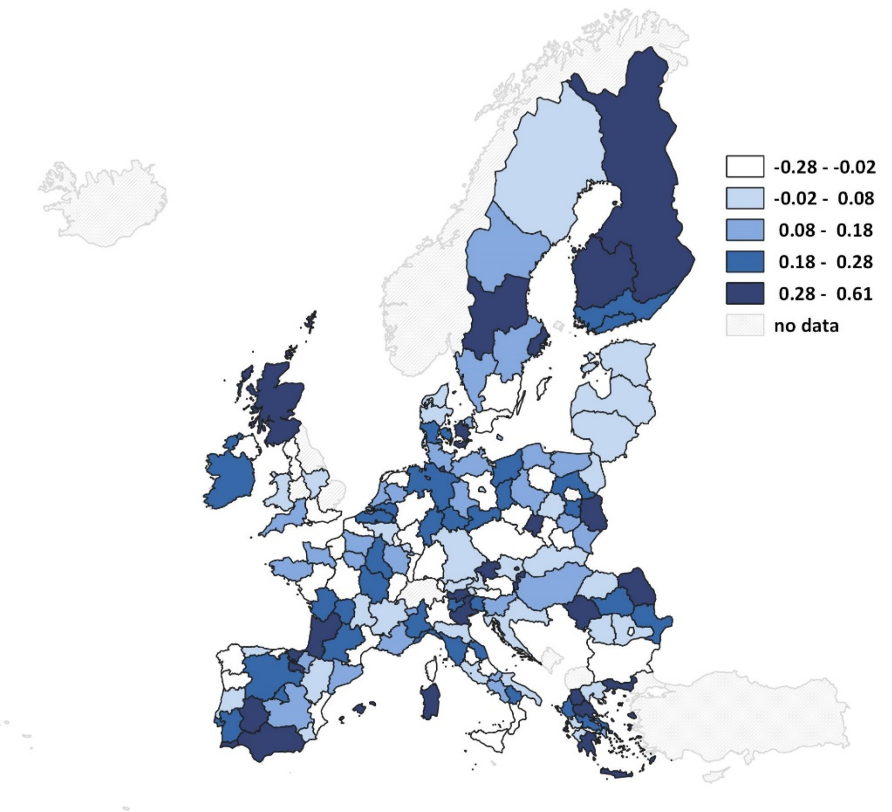
Graph 2. S3, production specialisation and relatedness in the EU regions

The axes intercepts are set at the variables median

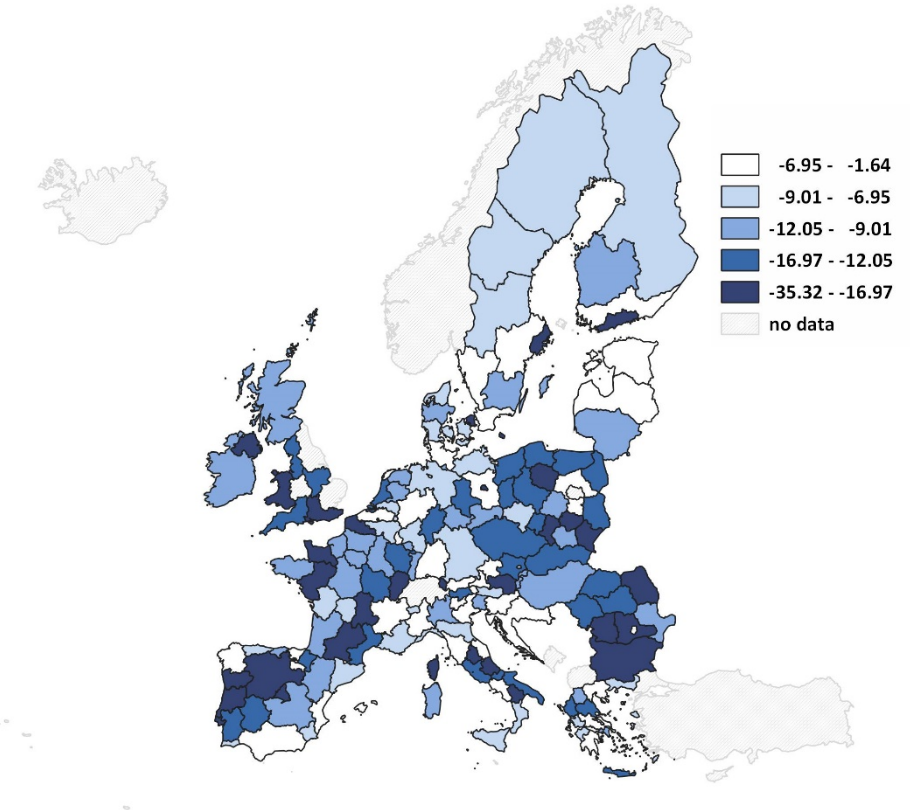
Map 1. All sectors' relatedness density



Map 2. Correlation coefficient between S3 and RCA



Map 3. Loss of S3 relatedness density



Map 4. The four scenarios implied by S3

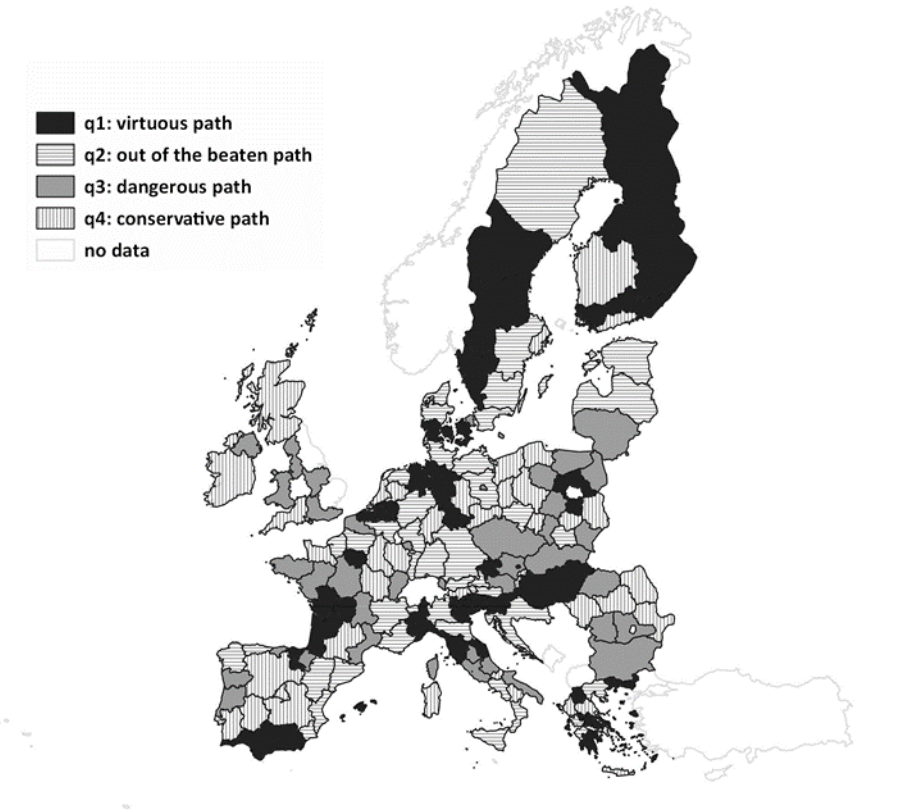


Table 1. S3 choices and regional characteristics

Dependent variable	*Coherence index*			*H1 index*			*H2 index*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
S3 drivers									
Quality of Government	0.0025 **	0.0031 ***		0.0029 **	0.0033 **		0.0025	0.0029 *	
	(0.0013)	*(0.0011)*		*(0.0015)*	*(0.0014)*		*(0.0017)*	*(0.0016)*	
GDP per capita	0.0947		0.1419 **	0.0752		0.1290	0.0756		0.1212
	(0.0702)		*(0.0633)*	*(0.0957)*		*(0.0904)*	*(0.0895)*		*(0.0844)*
Other variables									
Human capital	-0.0001	-0.0002	0.0012	0.0015	0.0014	0.0030	-0.0032	-0.0033	-0.0019
	(0.0018)	*(0.0018)*	*(0.0017)*	*(0.0024)*	*(0.0024)*	*(0.0023)*	*(0.0024)*	*(0.0024)*	*(0.0023)*
Technological capital	-0.0371	-0.0185	-0.0370	-0.0619 **	-0.0472 **	-0.0618 **	0.0220	0.0368 *	0.0221
	(0.0246)	*(0.0190)*	*(0.0249)*	*(0.0309)*	*(0.0237)*	*(0.0314)*	*(0.0289)*	*(0.0221)*	*(0.0287)*
Population density	0.0000	0.0000	0.0000	0.0000 **	0.0001	0.0000 **	0.0000	0.0000	0.0000
	(0.00002)	*(0.00001)*	*(0.00001)*	*(0.00002)*	*(0.00001)*	*(0.00001)*	*(0.00002)*	*(0.00002)*	*(0.00002)*
Knowledge intensive services (RCA index)	-0.1811	-0.1794	-0.1806	-0.2377 *	-0.2363 *	-0.2371 *	-0.1404	-0.1390	-0.1399
	(0.1126)	*(0.1107)*	*(0.1142)*	*(0.1449)*	*(0.1426)*	*(0.1460)*	*(0.1370)*	*(0.1369)*	*(0.1380)*
Low tech manufacturing (RCA index)	-0.0483	-0.0492	-0.0405	-0.0661 *	-0.0668 *	-0.0572	-0.0354	-0.0361	-0.0279
	(0.0383)	*(0.0400)*	*(0.0370)*	*(0.0388)*	*(0.0398)*	*(0.0374)*	*(0.0489)*	*(0.0503)*	*(0.0479)*
Dummy New accession regions (11 countries)	-0.0235	-0.0136	-0.0743	-0.0072	0.0007	-0.0651	0.0233	0.0312	-0.0258
	(0.0596)	*(0.0571)*	*(0.0546)*	*(0.0716)*	*(0.0703)*	*(0.0655)*	*(0.0835)*	*(0.0822)*	*(0.0779)*
Dummy Southern regions (IT, GR, ES, PT)	0.0824 **	0.0953 ***	0.0357	0.0833 *	0.0935 *	0.0300	0.0935 *	0.1039 **	0.0484
	(0.0391)	*(0.0368)*	*(0.0324)*	*(0.0511)*	*(0.0494)*	*(0.0426)*	*(0.0501)*	*(0.0491)*	*(0.0433)*
R^2-adj	0.131	0.122	0.111	0.134	0.131	0.118	0.108	0.105	0.097

Notes

H1: actual specialization (correlation index between RCA and S3, standardized)

H2: potential related diversification (loss of potential relatedness, standardized)

Coherence index: average of H1 and H2 indeces

Number of observations 166

LS estimation method; robust standard errors in parentheses.

*** indicates significance at the 1% level, ** at the 5% level and * at the 10% level.

GDP per capita and Technological capital (R&D per capita) are log-transformed

All models include a constant

See Table A3 for variables' definition

Appendix

Online supplemental material

Evaluating the Implementation of Smart Specialization Policy

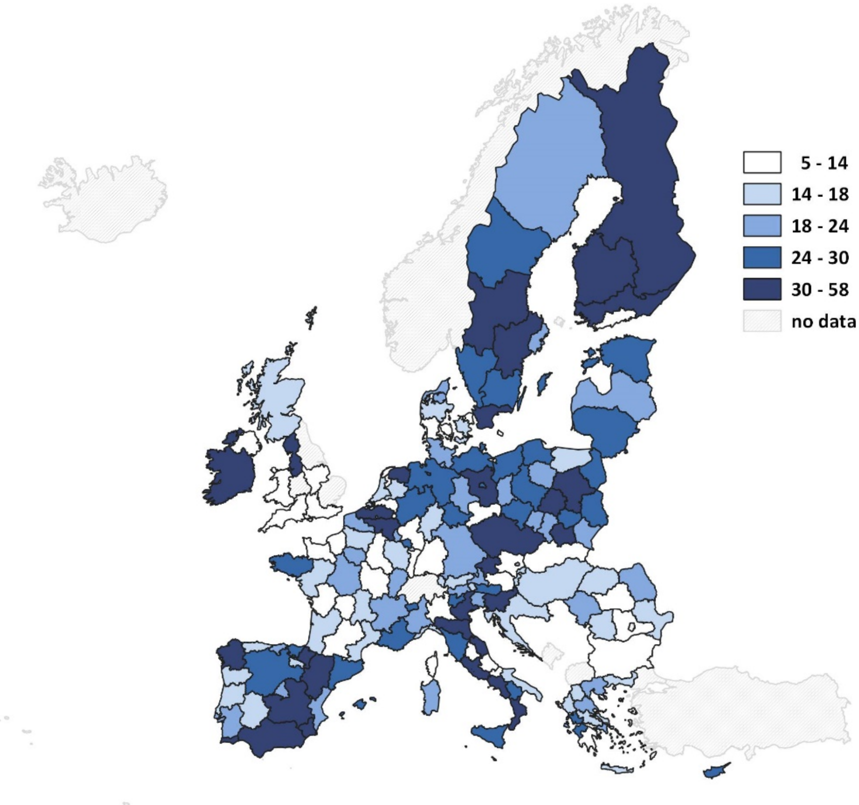
Descriptive analysis

S3 Priorities. The average number of selected priorities is 6, with a minimum of 2 in three small regions in Greece, Finland and Sweden and a maximum of 15 in Galicia. The thematic nature of the selected priorities is extremely differentiated. Some of them are labelled in a very general way: *Bio-Economy and Sustainability*; *Humans and Technology*; *Energy*; *ICT*. In other cases, S3 priorities have been defined more narrowly: *Construction based on wood material*; *Surface coating technologies*; *Wind energy*; *3d printing and friction welding*. If a priority intends to identify a region's competitive advantage then the narrow definition seems easier to defend. Indeed, it is hard to conceive that a region may have a comparative advantage (or disadvantage) in a very general field like *Humans and technology*.

S3 Sectors. The average number of sectors classified in each priority is 3.6, though this average varies considerably across regions. The maximum number of sectors per priority, around 10, is found in the Polish regions of Mazowieckie, in the Italian region of Tuscany and in the Northern Netherlands. At the other extreme, the Italian region of Lombardy, the French region of Poitou-Charentes and Northern Ireland have only one sector on average per priority. In the former regions, priorities are very general and involve many economic activities. At the other extreme, priorities are rather specific and, therefore, associated with only one economic sector. Looking at the geographical areas, Northern and Central regions have behaved similarly to Southern regions with an average of 3.5 sectors per priority, Eastern regions have chosen wide-ranging priorities including on average 4.4 economic sectors.

For operational purposes, we compute for each region the entire set of S3 targeted sectors, regardless of the original priorities, including all the NACE sectors selected at least once in the original priorities. The average number of S3 target sectors is 22 (out of 82 total NACE sectors) with a high variation across regions, ranging from a maximum of 58 in Etelä-Suomi (Finland) to a minimum of 5 sectors in the East Midlands (UK). The regions with the highest number of sectors are in Finland and Sweden where we have aggregated the S3 defined at the NUTS3 level to the corresponding NUTS2 regions. Interestingly, a high number of sectors (48) are targeted in the S3 of both Calabria in Southern Italy and the Northern Netherlands, two completely different regions in terms of institutional and economic context. Looking at the entire distribution (see Map A1), a clear geographic pattern does not emerge (i.e. north vs south, east vs west, country specific), that might have helped in explaining the choice to restrict or widen the set of S3 sectors. It is also interesting to observe which economic sectors have been selected more frequently in the regional S3. The most targeted sector (chosen by 134 regions out of 169) is Human health activities; other service activities like Information service, Computer programming, and Scientific R&D are very popular, too. The highest ranked manufacturing sectors targeted are Food products (6th) and Machinery and equipment (8th). Interestingly, 84 regions have selected the Creative, arts and entertainment activities (11th), which are, thus, considered a key driver of local development.

Map A1. Number of sectors included in S3 in the EU regions



Revealed Comparative Advantages. We compute the RCA index for 166 regions and 64 economic sectors using employment data. Some important differences across regions and sectors emerge. The five territorial units with the widest sectoral specialisation are, as expected, countries, namely Hungary with 38 sectors (out of 64) with RCA>1, followed by Czech Republic, Slovenia and Slovakia with 36 and Croatia with 35. At the other end of the distribution, we find small regions with a production structure highly specialised in only a few sectors (9): two Greek regions mainly devoted to tourism and related activities (Notio Aigaio and Ionia Nisia), the French Languedoc-Roussillon and Nord-Est in Romania. We also look at the pattern of specialisation of sectors across regions, what is often termed the ubiquity of a sector. The most ubiquitous activities are *Manufacture of food products* (98 out of 166 regions have RCA>1 in this sector) followed by two construction related activities, *Construction of buildings* (95) and *Specialised construction activities* (83). Other ubiquitous activities are *Restaurant and bar services* (85) and the macro area of *Public Administration, education and health* (86). The least ubiquitous activities, those concentrated in few specific areas, are *Air transport* (RCA>1 in only 24 regions), *Motion picture, TV production, music* (27) *Telecommunications* (32) and *Postal and courier activities* (32).

The European production space. The production space matrix (64*64 sectors) based on employment provides a measure of co-specialisation of any two economic sectors. In Europe the highest value (0.74) of co-specialisation is found for the couple S15 *Man. of rubber and plastic products* and S18 *Man. of fabricated metal products*. Also, the pair S34 *Retail Trade* and S40 *Accommodation* has a high proximity (0.71). Interestingly, among the total of 2016 pairs, we have only one case of disconnected pair of sectors – S1 (Agriculture) and S51 (Activities of head offices) – with a zero-proximity value. Only 155 pairs (7.6% of total cases) show a relatedness higher than 0.5, while 445 pairs (22%) are below the 0.2 probability of co-specialisation.

It is also interesting to compute for each of our 64 sectors its average value of proximity with respect to all other sectors (the row average of the matrix). Notably, the sector S19 *Manufacture of computer and electronic products* shows the highest value of average relatedness (0.37), followed by five service sectors. At the other extreme, the most isolated sector in the European production space is S42 *Publishing activities* with an average relatedness of 0.17.

Table A1. List of the 166 territorial units considered

Nuts	Nuts level	Region/Country Name
AT11	2	Burgenland (AT)
AT12	2	Niederösterreich
AT13	2	Wien
AT21	2	Kärnten
AT22	2	Steiermark
AT31	2	Oberösterreich
AT32	2	Salzburg
AT33	2	Tirol
AT34	2	Vorarlberg
BE1	1	Brussels-Capital Region
BE2	1	Flemish Region
BE3	1	Région Wallonne
BG	0	Bulgaria
CZ	0	Czech Republic
DE1	1	Baden-Württemberg
DE2	1	Bayern
DE3	1	Berlin
DE4	1	Brandenburg
DE5	1	Bremen
DE6	1	Hamburg
DE7	1	Hessen
DE8	1	Mecklenburg-Vorpommern
DE9	1	Niedersachsen
DEA	1	Nordrhein-Westfalen
DEB	1	Rheinland-Pfalz
DEC	1	Saarland
DED	1	Sachsen
DEE	1	Sachsen-Anhalt
DEF	1	Schleswig-Holstein
DEG	1	Thüringen
DK01	2	Hovedstaden
DK02	2	Sjælland
DK03	2	Syddanmark
DK04	2	Midtjylland
DK05	2	Nordjylland
EE	0	Estonia
EL30	2	Attiki
EL41	2	Voreio Aigaio
EL42	2	Notio Aigaio
EL43	2	Kriti
EL51	2	Anatoliki Makedonia, Thraki
EL52	2	Kentriki Makedonia
EL53	2	Dytiki Makedonia
EL54	2	Ipeiros
EL61	2	Thessalia
EL62	2	Ionia Nisia
EL63	2	Dytiki Ellada
EL64	2	Sterea Ellada
EL65	2	Peloponnisos
ES11	2	Galicia
ES12	2	Principado de Asturias
ES13	2	Cantabria
ES21	2	País Vasco
ES22	2	Comunidad Foral de Navarra
ES23	2	La Rioja
ES24	2	Aragón
ES30	2	Comunidad de Madrid
ES41	2	Castilla y León
ES42	2	Castilla-La Mancha
ES43	2	Extremadura
ES51	2	Cataluña
ES52	2	Comunidad Valenciana
ES53	2	Illes Balears
ES61	2	Andalucía
ES62	2	Región de Murcia
FI19	2	Länsi-Suomi
FI1B	2	Helsinki-Uusimaa
FI1C	2	Etelä-Suomi
FI1D	2	Pohjois- ja Itä-Suomi
FR10	2	Île de France
FRB0	2	Centre
FRC1	2	Bourgogne
FRC2	2	Franche-Comté
FRD1	2	Basse-Normandie
FRD2	2	Haute-Normandie
FRE1	2	Nord - Pas-de-Calais
FRE2	2	Picardie
FRF1	2	Alsace
FRF2	2	Champagne-Ardenne
FRF3	2	Lorraine
FRG0	2	Pays de la Loire
FRH0	2	Bretagne
FRI1	2	Aquitaine
FRI2	2	Limousin
FRI3	2	Poitou-Charentes
FRJ1	2	Languedoc-Roussillon
FRJ2	2	Midi-Pyrénées
FRK1	2	Auvergne
FRK2	2	Rhône-Alpes
FRL0	2	Provence-Alpes-Côte d'Azur
FRM0	2	Corse
HR	0	Croatia
HU	0	Hungary
IE	0	Ireland
ITC1	2	Piemonte
ITC2	2	Valle d'Aosta/Vallée d'Aoste
ITC3	2	Liguria
ITC4	2	Lombardia
ITF1	2	Abruzzo
ITF2	2	Molise
ITF3	2	Campania
ITF4	2	Puglia
ITF5	2	Basilicata
ITF6	2	Calabria
ITG1	2	Sicilia
ITG2	2	Sardegna
ITH1	2	Provincia Autonoma di Bolzano/Bozen
ITH2	2	Provincia Autonoma di Trento
ITH3	2	Veneto
ITH4	2	Friuli-Venezia Giulia
ITH5	2	Emilia-Romagna
ITI1	2	Toscana
ITI2	2	Umbria
ITI3	2	Marche
ITI4	2	Lazio
LT	0	Lithuania
LV	0	Latvia
NL1	1	Northern Netherlands
NL2	1	Eastern Netherlands
NL3	1	Western Netherlands
NL4	1	Southern Netherlands
PL21	2	Malopolskie
PL22	2	Slaskie
PL41	2	Wielkopolskie
PL42	2	Zachodniopomorskie
PL43	2	Lubuskie
PL51	2	Dolnoslaskie
PL52	2	Opolskie
PL61	2	Kujawsko-Pomorskie
PL62	2	Warminsko-Mazurskie
PL63	2	Pomorskie
PL71	2	Lódzkie
PL72	2	Swietokrzyskie
PL81	2	Lubelskie
PL82	2	Podkarpackie
PL84	2	Podlaskie
PL92	2	Mazowieckie
PT11	2	Norte
PT15	2	Algarve
PT16	2	Centro (PT)
PT17	2	Lisboa
PT18	2	Alentejo
RO11	2	Nord-Vest
RO12	2	Centru
RO21	2	Nord-Est
RO22	2	Sud-Est
RO31	2	Sud - Muntenia
RO41	2	Sud-Vest Oltenia
RO42	2	Vest
SE11	2	Stockholm
SE12	2	Östra Mellansverige
SE21	2	Småland med öarna
SE22	2	Sydsverige
SE23	2	Västsverige
SE31	2	Norra Mellansverige
SE32	2	Mellersta Norrland
SE33	2	Övre Norrland
SI	0	Slovenia
SK	0	Slovakia
UKD	1	North West (UK)
UKF	1	East Midlands (UK)
UKJ	1	South East (UK)
UKK	1	South West (UK)
UKL	1	Wales
UKM	1	Scotland
UKN	1	Northern Ireland

Table A2. List of the 64 sectors considered

ID	NACE_R2	Description
S1	A	Agriculture
S2	B	Mining
S3	C10	Manufacture of food products
S4	C11	Manufacture of beverages
S5	C12	Manufacture of tobacco products
S6	C13	Manufacture of textiles
S7	C14	Manufacture of wearing apparel
S8	C15	Manufacture of leather and related products
S9	C16	Manufacture of wood and of products of wood and cork, except furniture; manufacture
S10	C17	Manufacture of paper and paper products
S11	C18	Printing and reproduction of recorded media
S12	C19	Manufacture of coke and refined petroleum products
S13	C20	Manufacture of chemicals and chemical products
S14	C21	Manufacture of basic pharmaceutical products and pharmaceutical preparations
S15	C22	Manufacture of rubber and plastic products
S16	C23	Manufacture of other non-metallic mineral products
S17	C24	Manufacture of basic metals
S18	C25	Manufacture of fabricated metal products, except machinery and equipment
S19	C26	Manufacture of computer, electronic and optical products
S20	C27	Manufacture of electrical equipment
S21	C28	Manufacture of machinery and equipment n.e.c.
S22	C29	Manufacture of motor vehicles, trailers and semi-trailers
S23	C30	Manufacture of other transport equipment
S24	C31	Manufacture of furniture
S25	C32	Other manufacturing
S26	C33	Repair and installation of machinery and equipment
S27	D	Electricity, gas, steam and air conditioning supply
S28	E	Water, sewerage, waste
S29	F41	Construction of buildings
S30	F42	Civil engineering
S31	F43	Specialised construction activities
S32	G45	Wholesale and retail trade and repair of motor vehicles and motorcycles
S33	G46	Wholesale trade, except of motor vehicles and motorcycles
S34	G47	Retail trade, except of motor vehicles and motorcycles
S35	H49	Land transport and transport via pipelines
S36	H50	Water transport
S37	H51	Air transport
S38	H52	Warehousing and support activities for transportation
S39	H53	Postal and courier activities
S40	I55	Accommodation
S41	I56	Food and beverage service activities
S42	J58	Publishing activities
S43	J59	Motion picture, video and television programme production, sound recording and
S44	J60	Programming and broadcasting activities
S45	J61	Telecommunications
S46	J62	Computer programming, consultancy and related activities
S47	J63	Information service activities
S48	K	Financial, insurance services
S49	L	Real estate activities
S50	M69	Legal and accounting activities
S51	M70	Activities of head offices; management consultancy activities
S52	M71	Architectural and engineering activities; technical testing and analysis
S53	M72	Scientific research and development
S54	M73	Advertising and market research
S55	M74	Other professional, scientific and technical activities
S56	M75	Veterinary activities
S57	N77	Rental and leasing activities
S58	N78	Employment activities
S59	N79	Travel agency, tour operator and other reservation service and related activities
S60	N80	Security and investigation activities
S61	N81	Services to buildings and landscape activities
S62	N82	Office administrative, office support and other business support activities
S63	OPQ	Public administration, education, health
S64	RST	Arts, entertainment and recreation

Table A3. Variables definition and sources

Variable	Definition	Year	Source
H1 indicator	Correlation index RCA vs S3, min-max standard.		Own calculation, see text
H2 indicator	Loss of potential relatedness, min-max standard.		Own calculation, see text
Coherence indicator	Composite indicator of S3 coherence, average H1 and H2		Own calculation, see text
Institutional capital	European Quality of Government Index, 2017 edition	2013	Gothenburg University
GDP	GDP per capita, PPS	2015	Eurostat
Human capital	Population aged 25-64 by educational attainment level ISCEED 5-8, %	2015	Eurostat
Technological capital, R&D	R&D expenditure, Euro per inhabitant	2015	Eurostat
Technological capital, patent	Patent applications to EPO by priority year, per million inhabitants	2012	Eurostat
Population density	Persons per square kilometre	2015	Eurostat
Production structure, LTM	RCA in Low-technology manufacturing	2015	Eurostat
Production structure, KIS	RCA in Knowledge-intensive services	2015	Eurostat
Dummy New	Dummy for 11 New accession countries, 32 regions		
Dummy South	Dummy for Southern countries (EL, IT, ES, PT), 55 regions		