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Enhancing innovative capabilities in lagging regions: an extra-regional collaborative approach to RIS3

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Smart Specialisation (S3) is a place-based industrial strategy that forms the major component of the European Union's 2020 Innovation policy (RIS3). Lagging regions, however, lack the technological capabilities and networks to fully participate and benefit from RIS3. Extra-regional collaboration offers lagging regions opportunities for technological upgrading to overcome this deficit. Using patent data for EU NUTS2 regions, we find extra-regional collaboration raises innovation in lagging regions, although collaborations based on technological relatedness might be less effective, compared with advanced regions. This has implications for the design of policies to engender extra-regional collaboration and their alignment with RIS3 initiatives.

Keywords: extra-regional collaborations, lagging regions, Smart Specialisation, RIS3, patents, Europe
JEL Classifications: N94, O25, R10

Introduction

Smart Specialisation Strategies (S3) have been the major component of the European Union's 2020 flagship 'Innovation Union' programme (known as RIS3). S3 advocates prioritising state support for 'activities' in particular technologies, fields or domains at the regional level, which have the potential for 'entrepreneurial discovery' and commercial exploitation (Foray, 2015). RIS3 seeks to achieve this by deliberately building upon a region's existing advantages and capabilities to stimulate knowledge and innovation opportunities. As such, it has been labelled as being 'place-based' and is a return to a non-neutral and more vertical (or selective) mode of industrial policy intervention. Consequently, much excitement surrounds the rhetoric about RIS3, especially its perceived potential to generate an industrial renaissance in mature industrial regions and breathe life into 'phoenix' industries[1] (Barca et al., 2012). However, the inherent logic of S3 may actually extenuate regional imbalances by unduly favouring leading and/or more dynamic regions, where greater entrepreneurial and technological capabilities and good networks already reside, and from which new opportunities are more likely to arise. Indeed, much of the empirical evaluation of RIS3 has so far tended to focus on its application in more dynamic (exemplary) regional contexts. In contrast, in lagging regions with 'hollowed out' manufacturing bases, these capabilities are much diminished, which weakens their ability to participate in and benefit from RIS3 initiatives (McCann and Ortega-Argilés, 2015).[2]

This represents a significant challenge to the legitimacy of RIS3, especially given the difficulties in reconciling the possible adverse impacts of its implementation (for regional balance) within the context of the EU's wider policy aims of building 'inclusive, innovative and reflective societies' (European Commission, 2017b) and the EU 2014–2020 Cohesion policy. Recently, there has been more consideration as to how S3 might be better tailored towards lagging regions and how they may fully participate in RIS3. In this regard, there has been a particular emphasis on fostering *technological diversification* and *technological upgrading* that can be enhanced through extra-regional collaborative linkages, especially between lagging and more knowledge-intensive regions (Boschma, 2015; McCann and Ortega-Argilés, 2015). However, the incentives for extra-regional collaboration may be asymmetric; while lagging regions' incentives to collaborate with advanced ones appear to be straightforward, the reverse might be not so obvious. Policy itself has, of course, sought to support extra-regional collaboration at various levels through, for instance, the EU's H2020 and Interreg programmes, and at national levels via initiatives such as the UK's Knowledge Transfer Network (KTN).[3] Notwithstanding, there exists little empirical support for the importance of such linkages in the context of lagging regions.

In this article, we seek to address this research gap by providing new empirical evidence on the potential benefits for lagging regions in establishing extra-regional collaborative linkages, within the context of RIS3. We first utilise data from the PATSTAT-CRIOS database to map changes in extra-regional collaborations (with regard to innovation) in EU NUTS2 (Nomenclature of Territorial Units for Statistics) regions between 1985 and 2010. This mapping exercise is useful not only in highlighting the evolving density of extra-regional collaboration, but also in identifying idiosyncrasies across regions and where policy support (for networks) might be better targeted. Second, we estimate panel regression models (namely, fixed-effects regression, multilevel maximum likelihood (ML) and system generalised method of moments models) to assess the impact of these collaborative linkages on regional innovation within weaker regions. Finally, we then re-consider the current RIS3 framework and the ability of 'place-based' industrial policy to deliver balanced inclusive regional growth.

The article has three major results. First, extra-regional collaboration has a positive impact on innovation in lagging regions, and as such, may compensate for limited knowledge bases and the lack of critical mass of research and productive capabilities in these regions. However, and second, lagging regions are likely to find it difficult to attract collaboration from more advanced regions (De Noni et al., 2018), as the returns from extra-regional collaboration for regions characterised by increasing levels of internal technological competencies are found to be lower than in lagging regions. This asymmetric result may suggest that calls for lagging regions to set up partnerships with advanced regions (Boschma, 2015; Foray, 2015; McCann and Ortega-Argilés, 2015) are unlikely to become concrete, unless policy incentives are provided to actors in advanced regions so they are also able to derive some gains from such collaborations, even if these are not knowledge related. Third, we observe a negative effect of technological similarity between the external knowledge accessed through collaborations and the existing knowledge base for lagging regions, suggesting that policy should not target-specific sectors and technologies in these regions but rather support the entrepreneurial discovery process across a wider set of opportunities.

The remainder of this article is set out as follows. First, we present a review of the existing literature on S3, extra-regional collaboration and lagging regions. Second, we introduce the PATSTAT-CRIOS data set which provides descriptive evidence on the evolution of extra-regional collaborations on innovation across Europe. Third, we set out our econometric specification, before presenting and discussing the econometric results. Fourth, we then offer some wider consideration of RIS3 policy and the role of extra-regional collaborations for the development of lagging regions. Finally, we conclude.

Literature review

Smart specialisation and lagging regions

Foray (2013) describes Smart Specialisation as one part of a broader regional and industrial policy within which 'entrepreneurial discovery' processes identify new *activities* in uncharted technological and/or sectoral domains, which have the potential for knowledge spillovers, innovation, scale and agglomeration economies and market opportunities. The notion of 'activities' is itself quite generic and not adequately defined in the literature. In S3, they commonly refer to a granular level set of explorative actions (undertaken by regional actors) which often (but not always) arise at the interstices of sectors—for example, an identified 'activity' might be to explore the processing and analysis of big data in relation to energy loss (which will have applications across multiple sectors). The rationale is RIS3 policies should support those most promising (and identified) 'activities' more extensively for an exploratory period, after which only those demonstrating 'potential' should be fostered by more traditional regional and industrial policies. In the meantime, RIS3 policies should start to identify and explore the next set of 'activities' signalled through entrepreneurial discovery processes. This suggests S3 would eliminate any severe troughs or downturns in a region's potential developmental pathway, as the region's trajectory becomes 'smoothed' by the multiple paths of potential growth across a range of activities that overlap over time.

The identification of 'new activities' advocated by S3 may be especially challenging for lagging regions. Indeed, lagging regions are typically deficient in entrepreneurial and innovation capabilities; the entrepreneurial discovery process which S3 relies on may be absent. Lagging regions also typically exhibit weak networks, which inhibit knowledge exchange, cross-fertilisation of ideas and the emergence of new areas of market opportunities (Capello and Kroll, 2016). Nevertheless, scholars have recently begun to theoretically outline ways in which lagging regions can potentially participate more fully in, and benefit from, RIS3 initiatives. For example, by formally integrating S3 within existing economic geography frameworks and recognising that future regional trajectories are largely conditioned by their history (Morgan, 2013). McCann and Ortega-Argilés (2015), for instance, outline an integrative S3 strategy for lagging regions, based on the concepts of *embeddedness*, *technological diversification* and *connectivity* and which is sensitive to existing industrial structures. They advocate strengthening regional *embeddedness*, by better aligning skills enhancement programmes to meet local sectoral needs so as to reduce regional skills mismatches that hamper the ability of local firms to fully engage in global value chains. Such programmes could be flexibly tailored to ensure the region retains its competences in the face of ongoing structural changes in labour, technology and product markets (see Bailey et al., 2018).

McCann and Ortega-Argiles (2015) also point out the critical role of *technological* *diversification* and *relatedness* within the context of S3. These concepts highlight potential complementarities and synergies, which may arise as regions diversify into technologies adjacent to their extant technological domain. This is possible where the cognitive distance between related technological fields is sufficient to allow firms to communicate with each other more effectively, and absorb and apply new knowledge in different ways (Boschma and Frenken, 2011).[4] The fusion of related technologies, capabilities and expertise and the combining of knowledge can thus spur innovation and therefore the 'entrepreneurial discovery' process (Foray, 2015). Balland et al. (2018), for instance, find at the NUTS2 level and across the EU, 'relatedness' is positively associated with technological diversification, that is, regions are most likely to develop new technological specialisations that are related to their knowledge base. This can give rise to regional branching—where new industrial and technological paths emerge out of existing embedded industrial structures—and which has become a pattern in European regions (Kogler et al., 2017), offering the promise of possibilities for regional growth (Boschma and Gianelle, 2014; Mameli et al., 2014; Neffke et al., 2011). Dynamic growth, however, depends largely on the complexity of a region's knowledge base. More complex knowledge bases (and complex technologies) are difficult to imitate and/or dislodge (in spatial terms), and hence are more valuable in they offer potentially unique opportunities for regions to carve out new competitive advantages (Bailey et al., 2018, 2019; Balland et al., 2018). Yet lagging regions are typically characterised by low levels of knowledge complexity and they also lack the diverse set of capabilities from which to derive their own complex technologies (Balland and Rigby, 2017). Moreover, while 'relatedness' may offer a potential route forward, there are also many instances of regions following trajectories founded in historical regional strengths which ultimately lead to 'rigid specialisation' and 'lock-in'.

The cases which support lagging regions finding a new lease of life by branching into new industries while applying their underlying historical knowledge in new directions benefit from *ex post* rationalisation. However, the *ex ante* selection of 'priority areas' for policy support is difficult, even among those which are signalled by entrepreneurial activities. In regions reliant on a single industry (for example, steel) that is mature or even in the declining phase of its lifecycle (Isaksen, 2015; Isaksen and Trippl, 2017; Tödtling and Trippl, 2004; Virkkala, 2007), *ex ante* selection is difficult for two main reasons: (i) there is insufficient technological diversity to select from within the region, or (ii) the region's historical comparative advantage has eroded and does not offer long-term potential for economic growth given wider industry dynamics and globalisation (Foray, 2013). For regions founded on traditional industries, focussing on their *current industrial* strengths may lead them to enter the 'trap of rigid specialisation' (Grabher, 1993). Indeed, lagging regions may need to establish paths of renewal or create entirely new paths to avoid this. On this point, the S3 literature is at a tentative stage. Balland et al. (2018) have recently set out an S3 framework based on mapping 'relatedness' and 'knowledge complexity' within regions (and targeting policy appropriately). However, on which basis regional renewal or new path creation should be founded remains largely overlooked, being merely weakly defined as 'activities' within the S3 terminology.

Finally, McCann and Ortega-Argiles (2015) also suggest enhanced regional embeddedness and technological diversification should be complemented by measures to improve *connectivity* between actors so as to foster stronger knowledge linkages and learning. Traditionally, regional policies have focussed on strengthening intra-regional networks to foster agglomeration and innovative milieus

(Crevoisier, 2004). However, it is now acknowledged that knowledge networks are often delineated non-territorially, and that extra-regional links are increasingly important for widening a region's knowledge pool and in stimulating learning (Bathelt et al., 2004; Boschma and Ter Wal, 2007; Rychen and Zimmermann, 2008). Indeed, when combined with local knowledge bases, external knowledge inflows can re-energise local industrial clusters and revitalise regional growth paths (Maskell et al., 2006). We consider this further in the following section.

Extra-regional linkages and lagging regions

Collaborations facilitate the highest degree of interactive learning and knowledge transfer (Tödtling et al., 2006; Trippl et al., 2009). They represent informal networks that foster the establishment of formal collaborations and can endure even after formal collaborations are over (Owen-Smith and Powell, 2004).[5] Networks can be a substitute for the benefits typically associated with regional agglomeration (Johansson and Quigley, 2004), and firms located in lagging regions may exploit collaborations with distant partners as a means to compensate for weak local linkages and a lack of local knowledge spillovers. Indeed, Grillitsch and Nilsson (2015) find in a study of Swedish firms that this is especially the case for large and high technological intensity firms located in lagging regions, who are far more likely than their counterparts in leading regions to engage in extra-regional collaborations to access external knowledge. Moreover, firms may establish research collaborations with universities located in other regions for various reasons, for example due to a lack of adequate scientific competencies in their local universities, or a lack of willingness (from their local universities) to collaborate. Again, Tödtling et al.'s (2012) study of the Austrian ICT sector suggests firms located in weak regional innovation systems are more likely (compared to firms based in stronger regional innovation systems) to engage in international (and by implication, extra-regional) R&D collaborations to compensate for weak local knowledge exchange. Finally, in regions with low absorptive capacities but with a strong science base, researchers within universities may seek to collaborate with both other universities or industrial partners located outside their own region (Azagra-Caro, 2007).

From a RIS3 perspective, there is a strong case to support the development of extra-regional linkages more broadly. Knowledge networks are highly selective and largely comprise actors with the absorptive capacities to engage in interactive learning and knowledge transfer (Gilsing et al., 2007; Giuliani, 2006). Consequently, extra-regional linkages are easier to establish, and more likely to succeed when connections are made between spatially distant actors in similar technological domains (Boschma and Iammarino, 2009). Miguelez and Moreno's (2018) study of 255 NUTS2 European regions refines this further, finding that when regional knowledge bases are similar, extra-regional knowledge inflows significantly enhance incremental innovation, yet more radical innovations largely arise through extra-regional knowledge linkages based on related and complementary (rather than similar) technologies.[6] However, these studies do not explicitly consider the case of lagging regions.

For lagging regions, establishing and supporting extra-regional linkages with more knowledge-intensive regions can support technological upgrading and enhance the 'entrepreneurial discovery' process. Lagging regions are often dominated by low to medium tech sectors. These sectors largely rely on practice-based innovation facilitated by learning by doing and local inter-firm collaboration, yet the regional capacity to generate and sustain local knowledge spillovers can be weak (Asheim, 2012). In their industrial upgrading efforts, extra-regional linkages could facilitate quicker access to new technologies, foster more significant skills enhancement and open up new possibilities for knowledge transfer (Asheim et al., 2011). By engaging in collaborative networks with external actors based in more knowledge-rich regions (that may include other firms and/or universities or RTOs), firms located in lagging regions may not only augment their own innovative capabilities, but also the innovation capacity of their region. Indeed, there is emerging evidence that the (positive) impact on innovation in lagging regions appears to be more pronounced when firms are engaged in collaborative extra-regional networks with (more prolific) inventors from knowledge-intensive regions (De Noni et al., 2018).

Critically, within the theoretical framework of S3, the quality of extra-regional links is also crucial. For lagging regions specifically, perhaps the foci of the diversification should not be drawn too narrowly. In other words, their interpretation of 'smart specialisation' should not lead them to focus on diversifying into those technologies which are similar to what they already possess. This strategy is likely to lead only to incremental changes and be insufficient to contribute to their industrial upgrading. Accordingly, Foray (2015) suggests the S3 process may start when regions have sufficiently developed technological specialisations. Instead, when the historically founded local technological base is narrow and offers few new opportunities for growth, regional businesses may find greater benefit from engaging in building new complementarities and synergies with different types of technologies engaging in a process of explorative technological search that may lead to new trajectories (Castaldi et al., 2015). For these reasons, in lagging regions, extra-regional collaborations based on technological relatedness might be less effective, compared with advanced regions. Building on these issues, we now turn to our formal analysis of the impact of extra-regional linkages in different technological domains across the EU at NUTS2 level on regional innovative performance (with a particular focus on lagging regions).

The impact of extra-regional collaboration on innovation across Europe

Data

The analysis utilises patent data from the PATSTAT-CRIOS database.[7] This contains harmonised data based on the European Patent Office (EPO) master database, offering information on priority date and International Patent Classification (IPC) classification, as well as the NUTS2 location of inventors for all patent applications at the EPO. For this study, we refer to the priority date of patents to identify time, as this is closest to the date of invention (Hinze and Schmoch, 2004), and use the fractional count of inventors to determine location at the NUTS2 regional level, for the period 2000–2014. In the full data set, there are 29 countries, and just over 260 NUTS2 regions. For the variables, including a measure of technological class of patents, a five-digit IPC classification, which corresponds to 635 distinct IPC classes, is used. Additional regional socio-economic indicators are taken from Eurostat.

The use of patent data for the analysis of knowledge diffusion and technological development presents some well-known advantages and disadvantages. Notably, patents record the presence of a significant inventive step, as well as longitudinal information on inventors and characteristics of the invention. The major caveat is patents typically capture one specific type of knowledge base and, as such, they may not fully represent all innovative activities. This may especially be the case in lagging regions. Nevertheless, they are widely considered an effective proxy for regional innovative activities (Acs et al., 2002; Ronde and Hussler, 2005) and have been used to explore the importance of extra-regional knowledge sources (Bottazzi and Peri, 2003;

Miguelez and Moreno, 2018; Moreno et al., 2005). In addition, they have been recently utilised to examine the differential impact of extra-regional linkages for different levels of regional economic development (De Noni et al., 2018). Thus, the use of patent metrics allows us to explore processes of learning and knowledge exchange in regional scientific and analytical knowledge bases, in line with previous empirical evidence on technological relatedness (Kogler et al., 2017), and to empirically explore the impact of extra-regional collaborative linkages for technological innovation in lagging regions. In doing so, we acknowledge the need to explore other types of knowledge bases (Asheim et al., 2011) and innovation to fully understand these dynamics across the broader spectrum of other skills and capabilities across regions.

Variables and empirical model

To measure regional innovation performance, we follow two perspectives. The first reflects a common approach in measuring new knowledge creation, based on the relative number of new patents normalised by regional population (De Noni et al., 2018; Miguelez and Moreno, 2018). In this analysis, this measure of patent intensity (PINT) is defined as the number of patents (P) per 100,000 population. For this measure, all covariates are lagged one period to reduce endogeneity and simultaneity concerns. Second, we explore patent growth alongside patent levels, since this allows for a more effective comparison across regions with very heterogeneous innovation activities. Also, growth may be of greater interest for lagging regions (Porter et al., 2004). This second measure, labelled PGROWTH, is defined as growth in patents over a three-year period, as follows:

$$\mathrm{PGROWTH}_{rt} = \log(P_{rt\,+\,3}) - \log(P_{rt}) \quad (1)$$

which represents the continuously compounded growth rate for region r over the following three years from time t. The three-year lag for growth is used to reflect lagged effects in innovation processes, as well as to smooth out volatile year-to-year variation along growth trajectories (Coad et al., 2014). This also reduces potential bias for regions with a low patent output.

We use two variables to explore the role of collaboration in the analysis. To capture the extent of extra-regional collaboration, labelled SHARE_COLL, we define the following measure:

$$\mathrm{SHARE\_COLL}_{rt} = \frac{C_{rt}}{N_{rt}} \quad (2)$$

where C_{rt} is the fractional count of inventors from other regions, and N_{rt} is the total number of patents in region r in time t. Following Boschma and Iammarino (2009) and Miguelez and Moreno (2018), we also define a measure (labelled SIM_COLL) of similarity between the knowledge in a region and the collaboration with inventors in other regions as follows:

$$\mathrm{SIM\_COLL}_{rt} = \log \sum_{i}^{I} P_{rt,i} \mathrm{Col}_{rt,i} \quad (3)$$

where $P_{rt,i}$ is the absolute number of patents in patent class i in region r in time t, reflecting the regional knowledge stock in that class, and $\mathrm{Col}_{rt,i}$ is the number of patents involving collaborating inventors from other regions in that patent class.

We also add a control for knowledge stock (K_STOCK) to proxy technological absorptive capacities and capabilities and account for the initial patent levels of regions. This is defined in line with the literature as follows:

$$\mathrm{K\_STOCK}_{rt} = N_{rt} + (1-\delta)\mathrm{K\_stock}_{rt} - 1 \quad (4)$$

where δ is a depreciation rate set, as customary, at 15%. Finally, our measure of technological diversity within a region, labelled TECH_DIV, is defined as an inverse Herfindahl index

(Corradini and De Propris, 2015), weighted by relatedness across IPC classes as follows:

$$\text{TECH\_DIV}_{rt} = \frac{N_{rt}}{N_{rt}-1}\left(1-\sum_{I}^{I} p_{rt,i}\left(\frac{\sum_j^J S_{ij}p_{rt,j}}{N_{rt}}\right)^2\right) \quad (5)$$

where N_{rt} is the total number of patents in region r at time t, p_{rt} represents the share of patents in the region in classes i or j, while S_{ij} is a measure of technological relatedness reflecting co-occurrence among IPC classes defined following Kogler et al. (2017). With respect to previous measures of relatedness, this index allows us to account for the bias introduced when a region has a limited number of patents, through the correction suggested in Hall (2005) for small sample bias (that is, $N_{rt}/(N_{rt} - 1)$). Finally, we include controls on per capita GDP levels, population density (PDENS) and education (EDUC) form Eurostat, together with time fixed effects across the panel.

To assess how extra-regional collaboration and relatedness in external collaboration affect regional innovation performance (Y_{rt}), we define:

$$\begin{aligned} Y_{rt} = {} & \beta_0 + \beta_1 \text{Kstock}_{rt-1} + \beta_2 \text{ShareColl}_{rt-1} \\ & + \beta_{12}\text{Kstock}_{rt-1}\text{ShareColl}_{tr-1} \\ & + \beta_3 \text{SimColl}_{rt-1} + \beta_{13}\text{Kstock}_{rt-1}\text{SimColl}_{tr-1} \\ & + Z_{rt-1} + \delta_r + \delta_t + \epsilon_{rt} \end{aligned} \quad (6)$$

To test the differential effect of SHARE_COLL and SIM_COLL for lagging regions, the above equation includes interaction terms for both variables with K_STOCK, allowing us to explore their impact across the distribution of knowledge capabilities of the regions in the data set. We use regional patent stock to identify lagging regions in the analysis as this measure presents a strong correlation with GDP, while also capturing specific technological capabilities. Results are fully robust to the use of GDP values as threshold to identify lagging regions.

For the estimation, we follow three different approaches. We first estimate our model using fixed-effects regression (FE) with cluster robust standard errors and the full set of NUTS2 regional fixed-effects to capture any time-invariant unobserved heterogeneity. Second, we run a multilevel ML model with country dummies to exploit between-variation in the panel structure. Finally, we also report results from the System Generalised Method of Moments (Sys-GMM) two-step estimator, with finite-sample correction to the two-step covariance matrix derived by Windmeijer (2005). This allows us to control for any potential dynamic effect in the model in line with an evolutionary economics perspective.

Descriptive statistics and patterns of extra-regional collaboration

Descriptive statistics and correlations for all variables are reported in Table 1. These show the well-known heterogeneity that characterises European regions across the various dimensions measured, as well as the strong correlation between GDP and regional knowledge stock (K-STOCK). We also find a moderate negative correlation between K_STOCK and extra-regional collaboration (SHARE_COLL), suggesting actors in stronger regions may be less reliant on external knowledge for innovation. Conversely, in line with the concept of S3 and the findings by Kogler et al. (2017), technological diversity (TECH_DIV) within regions is negatively correlated with both GDP as well as K_STOCK. Furthermore, this relationship is re-enforced by a relatively strong correlation between the knowledge stock of a region (K_STOCK) and the similarity in external collaborations (SIM_COLL), which points to increasing specialisation as regions develop. As expected, looking at the correlation with K_STOCK, the measure for regional patent intensity (PINT) shows a moderate bias towards stronger regions, while patent growth (PGROWTH) only presents a very marginal link to less developed regions.

Table 1. *Descriptive statistics and correlation matrix.*

	Mean	SD	1	2	3	4	5	6	7	8
PINT (1)	10.53	13.43	1							
PGROWTH (2)	–0.11	0.75	0.02	1						
K_STOCK (3)	998.62	1908.95	0.70	–0.06	1					
SHARE_COLL (4)	0.30	0.14	–0.11	0.05	–0.15	1				
SIM_COLL (5)	3.57	2.95	0.74	–0.12	0.64	–0.07	1			
TECH_DIV (6)	0.08	0.19	–0.30	0.16	–0.20	0.24	–0.55	1		
GDP (7)	46 027	52 914	0.33	–0.06	0.74	–0.28	0.57	–0.26	1	
EDUC (8)	24.18	8.99	0.28	–0.33	0.25	–0.08	0.43	–0.32	0.25	1
PDENS (9)	350.13	843.77	0.06	–0.09	0.09	0.09	0.19	–0.11	0.21	0.30

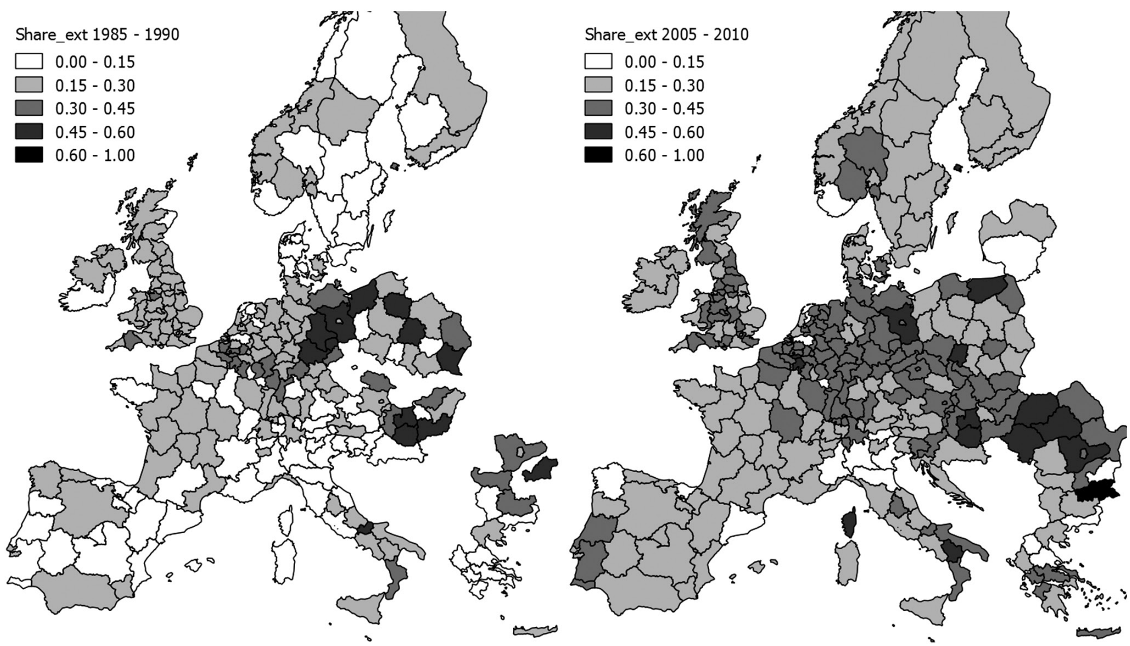

Figure 1. *Share of extra-regional collaboration (SHARE_COLL) for periods 1985–1990 and 2005–2010.*

In Figure 1, we can see the evolution of extra-regional collaboration across Europe, for the periods 1985–1990 and 2005–2010. We first observe an overall increase in collaboration across regions. Second, and focussing on 2005–2010, we also note significant differences in various countries. In particular, the data map for 2005–2010 highlights that several highly innovative regions such as those in northern Italy and Catalonia exhibit relatively low levels of extra-regional collaboration. Greater use of extra-regional collaboration is recorded in the weaker regions of the UK and (East) Germany as well as some of the transition economies.

These trends potentially reflect two phenomena. The first is the growth in global value chains, and especially their extension into Eastern Europe, with the opening up of the transition economies in the 1990s and their subsequent entry into the Single European Market (established in 1993). While this has led to a greater outsourcing of production and integration of these economies into European production chains (Dicken, 2015), it also provides the opportunity for technological upgrading of these lagging regions and, potentially, even their innovative output (as reflected by patenting activity). The second phenomenon may reflect the growth of EU programmes promoting extra-regional collaboration for innovation (see Section on Policy Issues for RIS3).

Econometric results

Results for the regression analysis are reported in Table 2. In columns 1–3, we report results for patent intensity (PINT), with column 1 showing fixed-effects panel estimations, column 2 the ML results, and column 3 Sys-GMM results. In columns 4–6, we present the results for regional patent growth (PGROWTH). As expected, K_STOCK is positive and significant across all model specifications, confirming the importance of accumulated regional technological capabilities for innovation. The key variable of interest, SHARE_COLL, is also positively associated both in models based on PINT and PGROWTH.[8] This indicates the extent to which extra-regional collaboration may be important in allowing for a stronger development of new technologies, reflecting the growing trend of extra-regional collaboration observed across time.

In order to ascertain the differential impact of extra-regional collaboration for lagging regions, we explore the relationship between the strength of the regional knowledge base and external collaboration by looking at the interaction term between K_STOCK and SHARE_COLL. The coefficient of the interaction term shows there is a significant and negative moderating effect of K_STOCK on SHARE_COLL in all models. This indicates the positive impact of any extra-regional collaboration falls as regions are increasingly characterised by a stronger internal knowledge base. We can examine this further by considering the marginal effects for this interaction term in Figure 2a, which shows the impact of extra-regional collaboration at different levels of regions' knowledge stock. As we move from lagging regions in the lower quartile of the K_STOCK distribution to regions with a higher level of knowledge stock, marginal effects for SHARE_COLL reduce progressively. This indicates regions with weaker knowledge capabilities may benefit more from extra-regional knowledge inputs than regions with strong knowledge capabilities (Boschma, 2015; De Noni et al., 2018), while extra-regional collaboration even has a negative impact for the strongest quartile of regions. These results are consistent with Grillitsch and Nilsson (2015) and suggest actors in lagging regions may compensate for weak local networks through extra-regional collaboration, whereas firms based in regions at the technological frontier are more likely to rely on localised knowledge bases in order to access external knowledge.

Looking at technological similarity in extra-regional collaborations, SIM_COLL is both significant and negative in all models, except in column 3. This may indicate that collaborations with other regions, in technological classes in which a region is already quite active, may actually hamper patent growth, perhaps due to lock-in effects (for example, Capello and Kroll, 2016) and reduced combinatorial opportunities. However, this is once again dependent on the level of regional internal knowledge stock, as evidenced by the significant positive interaction term between SIM_COLL and K_STOCK. Once again, we can test the differential impact of collaboration for lagging regions exploring the impact of SIM_COLL across the distribution of regional knowledge stock by looking at the average marginal effects for the interaction term between these two variables, shown in Figure 2b. In particular, we observe a negative effect of

Table 2. *FE regression, ML and Sys-GMM estimates.*

	Regional PINT			Regional PGROWTH		
	FE	ML	Sys-GMM	FE	ML	Sys-GMM
	(1)	(2)	(3)	(4)	(5)	(6)
L.DEPVAR			1.146***			−0.173**
			(0.114)			(0.075)
K_STOCK	7.253***	7.303***	17.026***	0.337***	0.264***	1.820***
	(1.019)	(0.406)	(3.498)	(0.124)	(0.045)	(0.509)
SHARE_COLL	15.920***	14.003***	132.926***	4.417***	3.269***	7.157***
	(2.735)	(1.931)	(45.576)	(0.471)	(0.247)	(1.810)
K_STOCK X SHARE_COLL	−4.012***	−3.589***	−12.016*	−0.672***	−0.465***	−1.023**
	(0.776)	(0.455)	(6.717)	(0.100)	(0.057)	(0.520)
SIM_COLL	−0.778***	−0.954***	1.240	−0.331***	−0.128***	−0.753***
	(0.277)	(0.190)	(1.858)	(0.052)	(0.022)	(0.245)
K_STOCK X SIM_COLL	0.207***	0.270***	−1.082***	0.040***	0.007**	0.078*
	(0.060)	(0.030)	(0.228)	(0.008)	(0.003)	(0.045)
TECH_DIV	20.315***	20.455***	−23.878	1.918***	0.968***	4.888**
	(3.254)	(2.326)	(59.488)	(0.491)	(0.309)	(2.199)
TECHDIV X TECHDIV	−15.355***	−15.379***	61.744	−1.136***	−0.409*	−3.123
	(2.653)	(2.095)	(64.477)	(0.439)	(0.279)	(2.216)
ln(GDP)	−1.318	−4.671***	3.618	1.351***	0.217***	−0.752
	(1.060)	(0.566)	(5.243)	(0.203)	(0.047)	(0.945)
EDUC	−0.073	−0.071**	−0.421**	−0.021**	−0.015***	−0.225***
	(0.059)	(0.032)	(0.203)	(0.009)	(0.003)	(0.057)
ln(PDENS)	−10.500**	−0.767**	−4.313*	−2.245***	−0.082***	0.241
	(4.505)	(0.344)	(2.343)	(0.685)	(0.023)	(0.604)
_cons	42.356*	26.367***	−93.698**	−3.588	−2.750***	2.242
	(23.636)	(4.675)	(45.223)	(3.826)	(0.407)	(7.103)
N	3107	3107	3092	2608	2608	2584
N groups	264	264	263	260	260	258
Hansen test X^2, Prob > X^2			119.23 (0.14)			86.91 (0.12)
AR1 test, Prob > *z*			−3.39 (0.00)			−4.39 (0.00)
AR2 test, Prob > *z*			0.84 (0.39)			−0.52 (0.61)

Robust standard errors in parentheses.
$^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

similarity in extra-regional co-inventor collaboration for lagging regions in the lower quartile of the K_STOCK distribution, while an increasingly positive effect—significant above the median value of K_STOCK—is present for regions that are characterised by a progressively higher stock of accumulated technological capabilities, in line with previous findings on extra-regional knowledge inflows (Miguelez and Moreno, 2018). This again highlights the need for a more subtle application of policies associated with RIS3.

While stronger knowledge-based regions focussed on a particular subset of technologies (that is, those which are "smartly" specialised) will benefit from extra-regional collaborations with other regions also specialised in related technological areas, this does not hold true for lagging regions. Our findings suggest that lagging regions might benefit more by developing extra-regional collaborations with regions whose technological specialisms differ to their own, so that their own entrepreneurial discovery processes foster connections across a

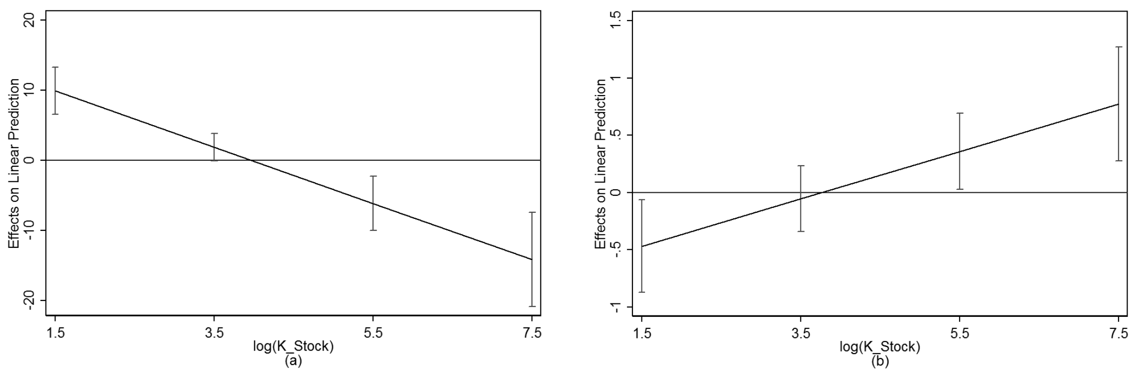

Figure 2. *Average marginal effects for SHARE_COLL (a) and SIM_COLL (b) across quantiles of K_STOCK.*

diverse set of opportunities—any one of which may become the basis for 'smart specialisation' of the region in the future. Finally, with respect to intra-regional diversity, we find an inverted 'U' relationship (as shown by the quadratic term for TECH_DIV). This suggests that, while a certain amount of technological diversity may allow for more recombination opportunities, there are diminishing returns to this effect, in line with theoretical insights on regional cognitive proximity (Boschma, 2005). While engaging in diversification would allow lagging regions to explore possible alternative directions of development as well as reducing lock-in effects, a high level of diversification may be detrimental for them. Indeed, the cognitive distance across technologies present in these regions would become too wide to be effectively recombined (as indicated by the quadratic term result underlining the presence of decreasing returns to this effect). This provides a complementary—but consistent—view to previous studies on RIS3 (for example, Balland et al., 2018; Kogler et al., 2017).

Overall, our results are robust to the models based on both patent levels (PINT) and patent growth (PGROWTH), for both FE and ML specifications.[9] Moving to dynamic models, in columns 3 and 6, the Hansen tests for over-identifying restrictions are insignificant, confirming the validity of the instruments in our estimations. Similarly, Arellano–Bond tests for serial correlation are as expected, with negative first-order and not significant second-order serial correlations. Results are quite robust in the model for patent growth (column 6), while looking at patent intensity (column 3), we note our earlier results for technological similarity no longer hold. This seems to be due to this variable being affected by changes in the lag structure, suggesting its GMM estimate may be unstable. Interestingly, we observe a positive dynamic coefficient for patent intensity, suggesting the presence of dynamic increasing returns in innovation as suggested by evolutionary perspectives (Breschi, 1999; Martin and Sunley, 2006), while a negative coefficient for patent growth points to a random walk in regional patent growth similar to those identified in the research on firm growth (Coad, 2009; Coad et al., 2014).

Policy issues for RIS3: enhancing extra-regional collaboration for lagging regions

Our empirical analysis provides evidence on the importance of extra-regional collaboration in innovation for lagging regions, with important policy implications related to the specific characteristics of their knowledge base. First, as noted in our literature review, industrial sectors based in lagging regions may lack the scale to reach or attain a critical mass of knowledge and/or the absorptive capacity to take advantage of new technologies. In both cases, extra-regional collaboration may help bridge these gaps. Morrison et al. (2013), for instance, have demonstrated the importance of establishing such linkages for weaker regions to widen their knowledge base and improve their performance. Moreover, from a RIS3 perspective, establishing extra-regional linkages between leading and lagging regions can foster a quicker adoption of new technologies in the latter. In turn, these technologies can open up opportunities for further cross-sectoral collaborations, entrepreneurial discoveries, opportunities and the emergence of new regional competences and specialisms which, in due course, may facilitate S3. As such, widening the take-up of new technologies has become an important component of RIS3 (Evangelista et al., 2015).

A second implication regards technological specialisation in collaboration. Lagging regions, typically with weaker knowledge bases, should not focus on specialisation but instead seek to diversify their technological base through encouraging their resident actors to engage in external collaborations. Opportunities for upgrading or branching into new activities by using different technologies may not be obvious *ex ante*, and a period of experimentation with a wider range of technologies may be required before a potentially fruitful path for future specialisation emerges (for example, the adoption of nano-technologies and advanced materials in the traditional textile and clothing sectors, and ICTs in tourism—see Grillitsch et al., 2018).

However, our findings also indicate that incentives to collaborate differ between more advanced and lagging regions. While actors located in lagging regions benefit from such extra-regional collaborations, those in advanced regions benefit less so. This reflects in part the role of actors in lagging regions utilising extra-regional collaboration—through global value chains and/or linkages with research institutions elsewhere—to offset the weaknesses of their local knowledge base. In advanced regions, local actors benefit from stronger regional innovation systems and knowledge infrastructures, enabling them to exploit local knowledge spillovers, which may mean extra-regional links are less important (Grillitsch and Nilsson, 2015; Tödtling et al., 2012). Indeed, as both Fritsch (2004) and Fritsch and Franke (2004) show, the more complex knowledge interactions and learning processes—that largely arise in leading regions—tend to be located in close geographic proximity (namely, local and regional).

Of course, firms in advanced regions do engage in extra-regional collaborations. With regard to advanced technological collaboration, these firms are more inclined to collaborate with like-minded actors in other advanced regions since mutually strong knowledge bases facilitate knowledge creation, exploitation and make innovation (and patenting) more likely (Bianchi and Labory, 2018). In contrast, for firms in advanced regions, the incentives to engage in extra-regional collaboration with actors in lagging regions largely revolve around the commercialisation (via licensing or direct technology sales) of their own technologies/technological competences. Firms in lagging regions can benefit from technological adoption and hitherto gain efficiencies in their existing production operations. However, the potential adaptation of these technologies—by actors in lagging regions—can also support technological diversification and the emergence of new specialisations and market opportunities from the existing industrial base (Kogler et al., 2017). In turn, this process may enhance knowledge and technological complexity (and uniqueness) within lagging regions, on which to acquire a new competitive advantage (Balland et al., 2018).[10]

In terms of policy implications, our results point to an intra-marginal Coasian-type solution, whereby policymakers provide incentives to actors in advanced regions to collaborate with actors in lagging ones.[11] Given the heterogeneity of lagging regions, there is no unique formula. One possibility, which has been stressed and implemented for many years, is fostering the development of the knowledge base of lagging regions, in order to raise interest in actors located in advanced regions to establishing an extra-regional collaboration. Thus, where firms are engaged in extra-regional collaboration on training and skills programmes and/or extra-regional temporary work teams (Grillitsch and Nilsson, 2015), the lagging region may benefit from human capital enhancement, again raising its capability to participate in S3. This point needs, of course, to be tempered with the caveat that enhancing human capital has a tendency to raise labour mobility, and while this itself is a source of knowledge spillovers (Breschi and Lissoni, 2009), it can lead to outward-migration of knowledge and skills from the lagging region (McCann and Ortega-Argilés, 2015) and extenuate regional imbalances.

Another way is to provide an institutional framework for collaboration between advanced and lagging regions. In this regard, the EU's formal programmes—such as H2020 and Interreg[12]—are useful and deliberate mechanisms to encourage the participation of actors from both leader and lagging regions to work together on projects. While these programmes aim to develop a world-class European research base, a key element of H2020 is to foster international (and by implication, extra-regional) collaboration (European Commission, 2013). For instance, ¡VAMOS![12] is a 42-month H2020 project aimed at developing an underwater, remotely controlled, environmentally viable mining system to enable the exploitation and rehabilitation of underexploited (and abandoned) European deposits of high-grade minerals.[13] It involves 17 industrial and academic partners from nine EU countries, several of whom are based in lagging regions, and fuses expertise from diverse fields including geology, robotics and mining. For partners based in a lagging region such as Cornwall, UK, the project has begun to open up the possibility of developing new specialisms in environmental marine mining techniques (with potential global application) that could in turn attract new investment and jobs.

Similarly, the European Regional Development and Cohesion Funds have aimed at fostering stronger European extra-regional collaboration to reduce regional disparities and enhance the integration of lagging regions. In this regard, the European Territorial Cooperation (ETC) programme, better known as 'Interreg' has—since 1990—been a significant vehicle (Reitel et al., 2018). Interreg projects have sought to foster synergies between RIS3, clusters and network collaboration, and industrial and social innovation (Council of European Union, 2015). For example, the V-B Adriatic-Ionian (ADRION) Interreg programme between eight partner states of the Adriatic—Ionian area, involves collaboration between advanced (Lombardy, Emilia Romagna in Italy, as well as regions in Slovenia) and lagging regions (for example, Puglia). ADRION primarily aims at providing framework conditions for the development and integration of the concerned areas, focussing on building networking structures, strategy and pilot actions, as well as institutional capacity. The focus is on creating related variety (cross-fertilisations) by favouring networking between European clusters and SMEs (particularly promoting innovation agents such as fablabs, co-working spaces and innovation hubs).[14] This is particularly important for a lagging region such as Puglia, which is beginning to see the benefits of its involvement in the Blue-Boost project (€1.5 million for two years), aimed at promoting innovation and cross-fertilisations in maritime sectors (fisheries, shipbuilding, blue technologies such as green shipbuilding, robotics and new materials). Participation in such programmes is already enabling Puglia's constituent firms to develop fruitful links with technological leaders elsewhere, and it is beginning to foster a more collaborative culture (for innovation), while raising administrative capacity (to lead and manage such projects) within its own region.[15]

In short, these types of framework can help to facilitate a broad spectrum of extra-regional collaborations, including linkages between medium- and low-tech regions, where the lower technological gap might deliver more fruitful synergies and innovation. Moreover, such networks and collaborations may endure (and deliver mutual benefits) beyond their funding cycles.

Conclusions

This article has examined the nature of extra-regional linkages for innovation, with a particular focus on lagging regions within the context of RIS3. While the academic and policy literatures have outlined the importance of extra-regional linkages for successful regional development, these claims are largely conjectural and pay insufficient attention as to whether 'one-size fit all' or whether asymmetries between lagging and advanced regions exist in the ability and incentives to engage in extra-regional collaboration; little systematic evidence exists on the type of collaborations most favourable to lagging regions. This article has outlined some important differences across places which should be taken into account in the definition and implementation of S3. In particular, it highlights the asymmetry in incentives (and benefits) from extra-regional collaboration across lagging and advanced regions, suggesting that there might not be circular benefits for all parties involved in the process of collaboration.

Our analysis shows that while extra-regional collaboration assists the technological development of lagging regions in broad terms, those collaborative relationships based on technological similarity—in contrast to those for leading regions—may be less useful. Lagging regions require a degree of diversity to explore, experiment and discover their own new specialisation. In this regard, lagging regions should perhaps favour low and medium sectors to search for new technological specialisms for their upgrading or their branching into more value-adding activities. Traditionally low- or medium-tech sectors, based in lagging regions, may exploit opportunities for industrial upgrading through different (unrelated) technologies (Grillitsch et al., 2018). As noted, this may run counter to the existing RIS3 discourse, which argues for a concentration of funding in specific technological domains (McCann and Ortega-Argilés, 2015). Industrial and regional policies need to be sufficiently flexible to accommodate a range of possibilities. In this regard, there is further scope for aligning existing EU extra-regional collaborative frameworks more closely with specific (regional) RIS3 objectives and to do so in a more flexible way.[16]

One important consequence of our analysis is that place-based innovation and industrial policies are essential: regions are highly heterogeneous, and policy actions have to be tailored to regional specificities. RIS3 has stressed the importance for regions to define specific S3 strategies, based on analyses of regions' strengths and weaknesses. It is, of course, important to note that neither EU-funded extra-regional collaborative projects nor those instigated through global value chains are sufficient to raise the innovative capacity of lagging regions. A critical adjunct for policy is to concomitantly tackle the inherent deficiencies (such as weak labour markets, or sparse local entrepreneurial networks) residing within lagging regions that inhibit innovation (Capello and Kroll, 2016). These deficiencies are not easy to address since they require a concerted effort to reverse path-dependent institutional failures such as poor governance and corruption (Aranguren et al., 2019; Rodríguez-Pose and Di Cataldo, 2014). For instance, in Eastern

Europe, weak local networks are an artefact of former Communist regimes, with efforts to build co-operative networks sometimes being viewed with suspicion (Spiesberger et al., 2018). A way forward is to enhance the participation of local actors in their regional innovation systems. Territorial-focussed skills programmes are one such vehicle, especially if they are designed not only to meet existing sectoral needs, but also to enhance transferable skills in the local labour market (such as those linked to key enabling technologies). Such a policy can enhance a region's absorptive capacity, so as to attract new foreign investment and simultaneously foster the possibility of engagement in extra-regional collaboration.

Finally, the results presented on extra-regional linkages should be considered with the usual caveats applying to the use of patent data, which mostly reflect scientific and analytical knowledge. Particularly, in the context of lagging regions, it is important to note further evidence reflecting other types of knowledge bases, including medium- and low-tech capabilities and other forms of design and creativity, is required to present a more comprehensive picture of innovation. Moreover, there might be further dynamics defined by imbalances between economic development in advanced and lagging regions, and future work should also explore the role of universities and research institutions in exerting a brokering effect in connecting lagging to advanced regions, as well as analyse in more detail the potential impact of imbalances between knowledge capabilities among collaborating regions. Finally, exploring the importance of extra-regional collaborations for the development of new specialisations in the context of lagging regions may also provide important complementary insights.

Endnotes

[1] Phoenix industries are clusters of businesses—with broadly similar technologies—that arise in former industrial areas (Amison and Bailey, 2014).

[2] The current European Commission (EC, 2017a) definition of lagging regions categorises them as either (i) low growth regions *(that is, NUTS2 regions which have not converged with the EU average GDP per capita (in Purchasing Power Standard—PPS) between 2000 and 2013)* or (ii) low-income regions *(that is, NUTS2 regions with a GDP per capita in PPS bellow 50% of the EU average in 2013)*. Lagging regions typically have low innovative capacity.

[3] For Interreg, see https://www.interregeurope.eu/; for H2020, see https://ec.europa.eu/programmes/horizon2020/; and for the KTN, see https://ktn-uk.co.uk/.

[4] Technically, cognitive distance between actors should not be too wide to preclude any form of collaboration nor too close, which could lead to 'cognitive lock-in' (Boschma, 2005; Nooteboom, 2000).

[5] For instance, collaborations originated within H2020 framework create links between actors taking part in the project. Such links usually outlive the formal H2020 collaboration and they can potentially be re-activated for future joint projects.

[6] It should also be recognised extra-regional linkages involving cross-sectoral collaborations based on largely dissimilar knowledge bases (so-called 'unrelated' variety) can and do prosper and may lead to more radical innovation. See Grillitsch et al. (2018).

[7] For more information on PATSTAT-CRIOS and patent data harmonisation, see Coffano and Tarasconi (2014).

[8] Results are also robust when removing regions in the upper and lower decile of K_STOCK distribution, suggesting outliers are not a significant concern in the analysis. These robustness checks are available on request.

[9] Results are robust to splitting the sample before and after the crisis of 2008, as well as considering only regions with a patent stock lower than the median EU value. Again, these results are available on request.

[10] There are similarities here with the post-World War II industrial policies of Japan, which deliberately licensed US technologies, and 'adapted' them in new ways to become technological leaders in their own right (Ozawa, 1974, 2007).

[11] This is feasible where the marginal gain for the lagging region (with respect to the baseline of no

extra-regional collaboration with stronger regions) is greater than (any) marginal loss for the stronger region. We are grateful to an anonymous referee for this point.

[12]In particular, the stable institutional framework offered by Interreg helps to overcome institutional failures of lagging regions (especially in the South of Italy). Further information can be found at: http://vamos-project.eu/.

[13]The EU is a heavy user of minerals, consuming 25–30% of the world's metal production, yet it only accounts for 3% of global ore production. However, it is estimated the value of unexploited EU mineral resources at a depth of 500–1000 m is approximately €100 billion. The project seeks to contribute to ensuring the EU has a sustainable supply of raw materials, while developing innovations in alternative mining techniques (see http://vamos-project.eu/partners/).

[14]For further details, see http://ec.europa.eu/regional_policy/en/newsroom/news/2018/05/17-05-2018-boosting-blue-growth-for-smes-in-the-adriatic-and-ionian-regions.

[15]For more information, see www.adrioninterreg.eu.

[16]For example, Prieto et al. (2017) document the potential synergies arising from existing Interreg programmes and the EU's new Smart Specialisation Platform on Energy (S3PEnergy), which is a strategic priority across the EU. In this particular case, there are opportunities for regions—especially lagging regions—to access a combination of EU Cohesion policy funding streams (that is, Interreg and RIS3), to engage in extra-regional collaboration across a range of dissimilar technologies (for example, marine, solar, biotech, smart-grids) and develop new territorial specialisms in renewable and sustainable energy sources.

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References

Acs, Z. J., Anselin, L. and Varga, A. (2002) Patents and innovation counts as measures of regional production of new knowledge, *Research Policy*, **31**: 1069–1085.

Amison, P. and Bailey, D. (2014) Phoenix industries and open innovation? The Midlands advanced automotive manufacturing and engineering industry, *Cambridge Journal of Regions, Economy and Society*, **7**: 397–411.

Aranguren, M. J., Magro, E., Navarro, M. and Wilson, J. R. (2019) Governance of the territorial entrepreneurial discovery process: looking under the bonnet of RIS3. *Regional Studies*, **53**: 451–461.

Asheim, B. (2012) The changing role of learning regions in the globalizing knowledge economy: a theoretical re-examination, *Regional Studies*, **46**: 993–1004.

Asheim, B. T., Boschma, R. and Cooke, P. (2011) Constructing regional advantage: platform policies based on related variety and differentiated knowledge bases, *Regional Studies*, **45**: 893–904.

Azagra-Caro, J. M. (2007) What type of faculty member interacts with what type of firm? Some reasons for the delocalisation of university–industry interaction, *Technovation*, **27**: 704–715.

Bailey, D., Pitelis, C. and Tomlinson, P. R. (2018) A place-based developmental regional industrial strategy for sustainable capture of co-created value, *Cambridge Journal of Economics*, **42**: 1521–1542.

Bailey, D., Pitelis, C. and Tomlinson, P. R. (2019) Strategic management and regional industrial strategy: cross fertilisation to mutual advantage, mimeographed, University of Bath.

Balland, P. A., Boschma, R., Crespo, J. and Rigby, D. L. (2018) Smart Specialisation policy in the European Union: relatedness, knowledge complexity and regional diversification, *Regional Studies*. doi:10.1080/00343404.2018.1437900.

Balland, P. A. and Rigby, D. L. (2017) The geography of complex knowledge, *Economic Geography*, **93**: 1–23.

Barca, F., McCann, P. and Rodríguez-Pose, A. (2012) The case for regional development intervention: place-based versus place-neutral approaches, *Journal of Regional Science*, **52**: 134–152.

Bathelt, H., Malmberg, A. and Maskell, P. (2004) Clusters and knowledge: local buzz, global pipelines and the process of knowledge creation, *Progress in Human Geography*, **28**: 31–56.

Bianchi, P. and Labory, S. (2018) *What Policies, Initiatives or Programmes can Support Attracting, Embedding and Reshaping GVCs in Regions?* OECD Broadening Innovation Policy: New Insights for Regions and Cities, Topic 2: Building, Embedding and Reshaping Global Value Chains. Paris: OECD.

Boschma, R. (2005) Proximity and innovation: a critical assessment, *Regional Studies*, **39**: 61–74.

Boschma, R. (2015) Smart specialization and regional innovation policy. In R. Antonietti, G. Corò and F. Gambarotto (eds) *Uscire Dalla Crisi. Città, Comunità, Specializzazioni Intelligenti*. Milan: Franco Angeli.

Boschma, R. and Frenken, K. (2011) Technological relatedness, related variety and economic geography. In P. Cooke, B. Asheim, R. Boschma, R. Martin, D. Schwartz and F. Todtling (eds) *The Handbook of Regional Innovation and Growth*. Cheltenham: Edward Elgar Publishing.

Boschma, R. and Gianelle, C. (2014) *Regional Branching and Smart Specialisation Policy*. S3 Policy Brief Series No. 06/2014. Institute for Prospective and Technological Studies, Joint Research Centre, Seville.

Boschma, R. and Iammarino, S. (2009) Related variety, trade linkages, and regional growth in Italy, *Economic Geography*, **85**: 289–311.

Boschma, R. A. and Ter Wal, A. L. (2007) Knowledge networks and innovative performance in an industrial district: the case of a footwear district in the South of Italy, *Industry and Innovation*, **14**: 177–199.

Bottazzi, L. and Peri, G. (2003) Innovation and spillovers in regions: evidence from European patent data, *European Economic Review*, **47**: 687–710.

Breschi, S. (1999) Spatial patterns of innovation: evidence from patent data. In A. Gambardella and F. Malerba (eds) *The Organization of Economic Innovation in Europe*, pp. 71–102. Cambridge: Cambridge University Press.

Breschi, S. and Lissoni, F. (2009) Mobility of skilled workers and co-invention networks: an anatomy of localized knowledge flows, *Journal of Economic Geography*, **9**: 439–468.

Capello, R. and Kroll, H. (2016) From theory to practice in smart specialization strategy: emerging limits and possible future trajectories, *European Planning Studies*, **24**: 1393–1406.

Castaldi, C., Frenken, K. and Los, B. (2015) Related variety, unrelated variety and technological breakthroughs: an analysis of US state-level patenting, *Regional Studies*, **49**: 767–781.

Coad, A. (2009) *The Growth of Firms: A Survey of Theories and Empirical Evidence*. Cheltenham: Edward Elgar Publishing.

Coad, A., Daunfeldt, S. O., Johansson, D. and Wennberg, K. (2014) Whom do high-growth firms hire?, *Industrial and Corporate Change*, **23**: 293–327.

Coffano, M. and Tarasconi, G. (2014) *CRIOS – Patstat Database: Sources, Contents and Access Rules*. CRIOS Working Paper n.1. Center for Research on Innovation, Organization and Strategy, Bocconi.

Corradini, C. and De Propris, L. (2015) Technological diversification and new innovators in European regions: evidence from patent data, *Environment and Planning A*, **47**: 2170–2186.

Council of European Union (2015) *Outcome of Proceedings: 25 Years of Interreg: its Contribution to the Cohesion Policy Goals*. Brussels: European Commission.

Crevoisier, O. (2004) The innovative milieus approach: toward a territorialized understanding of the economy?, *Economic Geography*, **80**: 367–379.

De Noni, I., Orsi, L. and Belussi, F. (2018) The role of collaborative networks in supporting the innovation performances of lagging-behind European regions, *Research Policy*, **47**: 1–13.

Dicken, P. (2015) *Global Shift, Mapping the Contours of the World Economy*. New York: Guilford Publications.

European Commission (2013) *Fact Sheet: International Participation in Horizon 2020*. Brussels: European Commission.

European Commission (2017a) *Economic Challenges of Lagging Regions*. Final Report. Brussels: European Commission.

European Commission (2017b) *Europe in a Changing World – Inclusive, Innovative and Reflective Societies. HORIZON 2020*. Brussels: European Commission.

Evangelista, R., Meliciani, V. and Vezzani, A. (2015) *The Specialisation of EU Regions in Fast Growing and Key Enabling Technologies*. JRC Technical Report. Seville site: Joint Research Centre. EUR 27524 EN; doi:10.2791/844794

Foray, D. (2013) The economic fundamentals of smart specialisation, *Ekonomiaz*, **83**: 55–82.

Foray, D. (2015) *Smart Specialisation: Opportunities and Challenges for Regional Innovation Policy*. London: Routledge.

Fritsch, M. (2004) Cooperation and the efficiency of regional R&D activities, *Cambridge Journal of Economics*, **28**: 829–846.

Fritsch, M. and Franke, G. (2004) Innovation, regional knowledge spillovers and R&D cooperation, *Research Policy*, **33**: 245–255.

Gilsing, V. A., Lemmens, C. E. and Duysters, G. (2007) Strategic alliance networks and innovation: a deterministic and voluntaristic view combined, *Technology Analysis & Strategic Management*, **19**: 227–249.

Giuliani, E. (2006) The selective nature of knowledge networks in clusters: evidence from the wine industry, *Journal of Economic Geography*, **7**: 139–168.

Grabher, G. (1993) The weakness of strong ties; the lock-in of regional development in the Ruhr Area. In G. Grabher (ed.) *The Embedded Firm: On the Socioeconomics of Industrial Networks*, pp. 255–277. London and New York: Routledge.

Grillitsch, M., Asheim, B. and Trippl, M. (2018) Unrelated knowledge combinations: the unexplored potential for regional industrial path development, *Cambridge Journal of Regions, Economy and Society*, **11**: 257–274.

Grillitsch, M. and Nilsson, M. (2015) Innovation in peripheral regions: do collaborations compensate for a lack of local knowledge spillovers?, *The Annals of Regional Science*, **54**: 299–321.

Hall, B. H. (2005) A note on the bias in Herfindahl-type measures based on count data, *Revue d'Economie Industrielle*, **110**: 149–156.

Hinze, S. and Schmoch, U. (2004) Opening the black box. In H. F. Moed, W. Glänzel and U. Schmoch (eds) *Handbook of Quantitative Science and Technology Research*, pp. 215–235. Dordrecht: Springer.

Isaksen, A. (2015) Industrial development in thin regions: trapped in path extension?, *Journal of Economic Geography*, **15**: 585–600.

Isaksen, A. and Trippl, M. (2017) Exogenously led and policy-supported new path development in peripheral regions: analytical and synthetic routes, *Economic Geography*, **93**: 436–457.

Johansson, B. and Quigley, J. M. (2004) Agglomeration and networks in spatial economics, *Papers in Regional Science*, **83**: 165–176.

Kogler, D. F., Essletzbichler, J. and Rigby, D. L. (2017) The evolution of specialization in the EU15 knowledge space, *Journal of Economic Geography*, **17**: 345–373.

Mameli, F., Faggian, A. and Mccann, P. (2014) Estimation of local employment growth: do sectoral aggregation and industry definition matter?, *Regional Studies*, **48**: 1813–1828.

Martin, R. and Sunley, P. (2006) Path dependence and regional economic evolution, *Journal of Economic Geography*, **6**: 395–437.

Maskell, P., Bathelt, H. and Malmberg, A. (2006) Building global knowledge pipelines: the role of temporary clusters, *European Planning Studies*, **14**: 997–1013.

McCann, P. and Ortega-Argilés, R. (2015) Smart specialization, regional growth and applications to European Union cohesion policy, *Regional Studies*, **49**: 1291–1302.

Miguelez, E. and Moreno, R. (2018) Relatedness, external linkages and regional innovation in Europe, *Regional Studies*, **52**: 688–701.

Moreno, R., Paci, R. and Usai, S. (2005) Spatial spillovers and innovation activity in European regions, *Environment and Planning A*, **37**: 1793–1812.

Morgan, K. (2013) The regional state in the era of smart specialisation, *Ekonomiaz – Revista vasca de Economía*, **83**: 103–126.

Morrison, A., Rabellotti, R. and Zirulia, L. (2013) When do global pipelines enhance the diffusion of knowledge in clusters?, *Economic Geography*, **89**: 77–96.

Neffke, F., Henning, M., Boschma, R., Lundquist, K. J. and Olander, L. O. (2011) The dynamics of agglomeration externalities along the life cycle of industries, *Regional Studies*, **45**: 49–65.

Nooteboom, B. (2000) *Learning and Innovation in Organisations and Economies*. Oxford: Oxford University Press.

Owen-Smith, J. and Powell, W. W. (2004) Knowledge networks as channels and conduits: the effects of spillovers in the Boston biotechnology community, *Organization Science*, **15**: 5–21.

Ozawa, T. (1974) *Japan's Technological Challenge to the West, 1950–1974, Motivation and Accomplishment*. Cambridge, MA: MIT Press.

Ozawa, T. (2007) Institutionally driven growth and stagnation – and struggle for reform. In D. Bailey, D. Coffey and P. R. Tomlinson (eds) *Crisis or Recovery in Japan: State and Industrial Economy*, pp. 106–132. Cheltenham: Edward Elgar.

Porter, M. E., Ketels, C. H., Miller, K. and Bryden, R. (2004) *Competitiveness in Rural US Regions: Learning and Research Agenda*. Washington, DC: US Economic Development Administration (EDA).

Prieto, J. G., Perianez-Forte, I. and Palazuelos-Martinez, M. (2017) *Capitalising on Smart Specialisation and Interreg, the Case of Energy*.

Joint Research Centre (JRC) Technical Reports. Brussels: EU Commission.

Reitel, B., Wassenberg, B. and Peyrony, J. (2018) The INTERREG experience in bridging European territories. A 30-year summary. In E. Medeiros (ed.) *European Territorial Cooperation. The Urban Book Series*. Cham: Springer.

Rodríguez-Pose, A. and Di Cataldo, M. (2014) Quality of government and innovative performance in the regions of Europe, *Journal of Economic Geography*, **15**: 673–706.

Ronde, P. and Hussler, C. (2005) Innovation in regions: what does really matter?, *Research Policy*, **34**: 1150–1172.

Rychen, F. and Zimmermann, J. B. (2008) Clusters in the global knowledge-based economy: knowledge gatekeepers and temporary proximity, *Regional Studies*, **42**: 767–776.

Spiesberger, M., Prieto, J. G. and Seigneur, I. (2018) *Smart Specialisation and Social Innovation: From Policy Relations to Opportunities and Challenges*. JRC Working Papers JRC111371. Seville site: Joint Research Centre.

Tödtling, F., Grillitsch, M. and Hoglinger, C. (2012) Knowledge sourcing and innovation in Austrian ICT companies – how does geography matter?, *Industry and Innovation*, **19**: 327–348.

Tödtling, F., Lehner, P. and Trippl, M. (2006) Innovation in knowledge intensive industries: the nature and geography of knowledge links, *European Planning Studies*, **14**: 1035–1058.

Tödtling, F. and Trippl, M. (2004) Like phoenix from the ashes? The renewal of clusters in old industrial areas, *Urban Studies*, **41**: 1175–1195.

Trippl, M., Tödtling, F. and Lengauer, L. (2009) Knowledge sourcing beyond buzz and pipelines: evidence from the Vienna software sector, *Economic Geography*, **85**: 443–462.

Virkkala, S. (2007) Innovation and networking in peripheral areas. A case study of emergence and change in rural manufacturing, *European Planning Studies*, **15**: 511–529.

Windmeijer, F. (2005) A finite sample correction for the variance of linear efficient two-step GMM estimators, *Journal of Econometrics*, **126**: 25–51.