

Enhancing Innovative Capabilities in Lagging Regions: An Extra-Regional Collaborative Approach to RIS3

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Abstract

Smart Specialisation (SS) is a place-based industrial strategy which 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 upon technological relatedness might be less effective, compared to 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.

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1. Introduction

Smart Specialisation (SS) has been the major component of the European Union's 2020 flagship 'Innovation Union' programme (known as RIS3). SS 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 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 (Barca et al., 2012). However, the inherent logic of SS 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 upon its application in more dynamic (exemplar) regional contexts. In contrast, in lagging/peripheral¹ 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).

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 EU's wider policy aims of building '*inclusive, innovative and reflective societies*' (European Commission, 2017) and EU 2014-2020 Cohesion policy. However, recently there has been more consideration as to how SS might be better tailored towards lagging regions and how they may fully participate in RIS3. In this regard, there has been a particular emphasis upon fostering *technological diversification*² and *technological upgrading* that can be enhanced through

¹ We acknowledge a difference between geographically peripheral and economically lagging regions exists in strict definitional terms, but given many geographically peripheral regions in the EU are also economically lagging, but not all lagging EU regions are necessarily geographically peripheral, for our purposes we use the term lagging regions throughout for consistency.

² Technological diversification refers to the branching into new industries using technologies related to their existing technological domain, discovered and adopted within extra-regional linkages (McCann and Ortega-Argilés, 2015: 1297). Different firms even in the same sector may find different branching opportunities. For instance, upgrading in

extra-regional collaborative linkages, especially between lagging and more knowledge intensive regions (McCann and Ortega-Argilés, 2015, Boschma, 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 obvious³. 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)⁴. Notwithstanding, there exists little empirical support for the importance of such linkages in the context of lagging regions.

In this paper, 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 1985-2010. 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. Secondly, we estimate panel regression models (namely, fixed-effects regression, multilevel maximum likelihood and system generalised method of moments models) to assess the impact of these collaborative linkages upon regional innovation within weaker regions. Finally, we then reconsider the current RIS3 framework and 'place based' industrial policy to deliver balanced inclusive regional growth.

The paper has three major results. First, extra-regional collaboration has a positive impact upon 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

the fashion sector in Italy has occurred using diverse technologies, from laser to nanotechnologies or ICTs. Hence the requirement of RIS3 to choose a limited number of technologies on which regional policy should focus may have limited effects in lagging regions.

³ Initiatives such as Vanguard may point to the contrary. Vanguard is an association of European regions, with the objective of fostering (research) collaboration between European businesses to enhance innovation in new technological domains (see <https://s3vanguardinitiative.eu/>). The initiative has tended to incentivise extra-collaboration between leading regions (see Bianchi and Labory, 2018).

⁴ 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/>

secondly, lagging regions are likely to find it difficult to attract collaboration from more advanced regions (De Noni et al., 2018). In contrast, for regions characterised by increasing levels of internal technological competencies, the benefits from extra-regional collaboration are less necessary. This asymmetric result may suggest that calls for lagging regions to set up partnerships with advanced regions (McCann and Ortega-Argilés, 2015, Foray, 2015, Boschma, 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 relatedness in extra-regional co-inventor collaboration 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 paper is set out as follows. In Section 2, we present a review of the existing literature on SS, extra-regional collaboration and lagging regions. Section 3 introduces the PATSTAT- CRIOS dataset and provides descriptive evidence on the evolution of extra-regional collaborations on innovation across Europe, before setting out our econometric specification. Section 4 presents and discusses the econometric results, while Section 5 provides some wider consideration of RIS3 policy and the role of extra-regional collaborations for the development of lagging regions. Finally, Section 6 concludes.

2. Literature Review

2.1. 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, with the potential for knowledge spill-overs, innovation, scale and agglomeration economies and market opportunities. The rationale is RIS3 policies should support these ‘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 SS would eliminate any

severe troughs 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 SS may be especially challenging for lagging regions. Indeed, lagging regions are typically deficient in entrepreneurial and innovation capabilities; the entrepreneurial discovery process which SS relies upon 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 SS within existing economic geography frameworks and recognising that future regional trajectories are largely conditioned upon their history (Morgan, 2013). McCann and Ortega-Argilés (2015), for instance, outline an integrative SS strategy for lagging regions, based upon 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 SS. 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 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)⁵. 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). Recent evidence suggests

⁵ 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' (Nooteboom, 2000, Boschma, 2005).

regional branching - where new industrial and technological paths emerge out of existing embedded industrial structures – has become a pattern in European regions (Kogler et al., 2017), and indeed, offers the promise of possibilities for regional growth (Boschma and Gianelle, 2014, Mameli et al., 2014, Neffke et al., 2011). However, there are also many instances of historical regions which followed trajectories founded in historical regional strengths which ultimately lead to ‘rigid specialisation’ and ‘lock-in’; the notion of ‘distance’ with respect to relatedness is still not clear within studies on related diversification, regional branching and consequently what is really meant by ‘smart’ and ‘specialisation’.

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 amongst those which are signalled by entrepreneurial activities. In regions reliant upon a single industry (e.g. steel) that is mature or even in the declining phase of its lifecycle (Todtling and Trippl, 2004, Virkkala, 2007, Isaksen, 2015, Isaksen and Trippl, 2016), *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, focusing 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. This, to our knowledge, has not yet been empirically tested. Moreover, on which basis the renewal or new path creation should be founded is still largely overlooked being merely weakly defined as ‘activities’ in the SS literature.

McCann and Ortega-Argiles (2015) suggest that 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 focused upon strengthening intra-regional networks to foster agglomeration and innovative milieus (Crevoisier, 2004). However, it is now acknowledged 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.

2.2. 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 both informal networks (Grillitsch and Nilsson, 2015) that foster the establishment of formal collaborations and can endure even after formal collaborations are over (Owen-Smith and Powell, 2004)⁶. Networks can be a substitute for agglomeration (Johansson and Quigley, 2004) hence, firms in lagging regions can use collaborations with distant partners as a tool to compensate a weaker supply of local knowledge spillovers (Grillitsch and Nilsson, 2015). Indeed, 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. Similarly, in regions with low absorptive capacities but strong a 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 of actors with the absorptive capacities to engage in interactive learning and knowledge transfer (Giuliani, 2006, Gilsing et al., 2007). 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 upon related

⁶ 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.

and complementary (rather than similar) technologies⁷. 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 upon 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 SS, 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 SS 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

⁷ It should also be recognized extra-regional linkages involving cross-sectoral collaborations based upon largely dissimilar knowledge bases (so called ‘unrelated’ variety) can and do prosper and may lead to more radical innovation. See, Grillitsch et al. (2018).

regions, extra-regional collaborations based upon technological relatedness might be less effective, compared to 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).

3. The Impact of Extra-Regional Collaboration on Innovation Across Europe

3.1 Data

The analysis utilises patent data from the PATSTAT-CRIOS database⁸. This contains harmonised data based on the European Patent Office (EPO) master database, offering information on priority date, International Patent Classification (IPC) classification, as well as 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 dataset, there are 29 countries, and just over 260 NUTS2 regions. For the variables including a measure of technological class of patents, a 5-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, Moreno et al., 2005, Miguelez and Moreno, 2018). 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 focus upon regional science and functional knowledge bases, in line with previous empirical evidence on

⁸ For more information on PATSTAT-CRIOS and patent data harmonisation, see Coffano and Tarasconi (2014).

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.

3.2 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 (Miguelez and Moreno, 2018; De Noni et al., 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. Secondly, 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:

$$PGROWTH_{rt} = \log(P_{rt+3}) - \log(P_{rt}) \quad (1)$$

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:

$$SHARE_COLL_{rt} = \frac{C_{rt}}{N_{rt}} \quad (2)$$

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 REL_COLL) of similarity between the knowledge in a region and the collaboration with inventors in other regions as follows:

$$REL_COLL_{rt} = \log \sum_i^I P_{rt,i} Col_{rt,i} \quad (3)$$

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 $Col_{rt,i}$ 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:

$$K_STOCK_{rt} = N_{rt} + (1 - \delta)K_stock_{rt} - 1 \quad (4)$$

where δ is a depreciation rate set, as customary, at 15%. Finally, our measure of technological diversification within a region, labelled $TECH_DIV$, is defined as an inverse Herfindhal index (Corradini and De Propris, 2015) weighted by relatedness across IPC classes as follows:

$$TECH_DIV_{rt} = \frac{N_{rt}}{N_{rt}-1} \left(1 - \sum_i^I p_{rt,i} \left(\frac{\sum_j^J S_{ij} p_{rt,j}}{N_{rt}} \right)^2 \right) \quad (5)$$

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 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 by in Hall (2005) for small sample bias (i.e. $N_{rt}/(N_{rt}-1)$). Finally, we include controls on per capita GDP levels, population density (PDENS) and education (EDUC) from 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:

$$Y_{rt} = \beta_0 + \beta_1 Kstock_{rt-1} + \beta_2 ShareColl_{rt-1} + \beta_{12} Kstock_{rt-1} ShareColl_{tr-1} + \beta_3 RelColl_{rt-1} + \beta_{13} Kstock_{rt-1} RelColl_{tr-1} + Z_{rt-1} + \delta_r + \delta_t + \epsilon_{rt} \quad (6)$$

To test the differential effect of $SHARE_COLL$ and REL_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 dataset.

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. Secondly, we run a multilevel maximum likelihood (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.

3.3 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 characterise 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 stronger regions may be less reliant upon external knowledge for innovation. Conversely, in line with the concept of SS and the findings by Kogler et al. (2017), technological diversification (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 relatedness in external collaborations (REL_COLL), which points to increasing specialisation as regions develop. As expected, looking at the correlaton 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.

[Insert Table 1 HERE]

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 focusing upon 2005-2010, we also note significant differences in various countries. In particular, Figure 1b 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 are recorded in the weaker regions of the UK and (East) Germany as well as some of the transition economies.

[Insert Figure 1a and b here]

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 5).

4. Econometric Results

Results for the regression analysis are reported in Table 2. In columns 1 to 3, we report results for patent intensity (PINT), with column 1 showing fixed-effects panel estimations, column 2 the maximum-likelihood results, while 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 PGROWTH⁹. This indicates the extent of 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

⁹ 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.

SHARE_COLL reduces progressively. This indicates regions with weaker knowledge capabilities may benefit more from external knowledge inputs than regions with strong knowledge capabilities (Boschma, 2015, De Noni et al., 2018). Indeed, extra-regional collaboration even has a negative impact for the strongest quartile of regions, perhaps suggesting the relative importance of more localised connections and a lower reliance on external competencies for innovation for regions at the technological frontier ¹⁰.

Looking at technological relatedness in extra-regional collaborations, REL_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 (e.g. Capello and Kroll, 2016) and reduced combinatorial opportunities. However, this is once again dependent upon the level of regional internal knowledge stock, as evidenced by the significant positive interaction term between REL_COLL and K_STOCK. Once again, we can test the differential impact of collaboration for lagging regions exploring the impact of REL_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 relatedness in extra-regional co-inventor collaboration for lagging regions in the lower quartile of the K_STOCK distribution, whilst 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 focused on a particular subset of technologies (i.e. 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 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

¹⁰ Results are fully robust to the use of GDP values as threshold to identify lagging regions.

intra-regional diversification, we find an inverted U relationship (as shown by the quadratic term for TECH_DIV). This suggests that, while a certain amount of technological diversification may allow for more recombination opportunities, there are diminishing returns to this effect in line with theoretical insights on regional cognitive proximity (Boschma, 2005).

Overall, our results are robust to the models based on both patent levels (PINT) and patent growth (PGROWTH), for both FE and ML specifications. 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 relatedness no longer hold. 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).

[Insert Table 2 and Figure 2 here]

5. Policy Challenges 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 Section (2.1), 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 by lagging regions. 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 SS. 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 upon specialisation but instead seek to diversify their technological base through 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 (e.g. 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 lagging regions benefit from such extra-regional collaborations, advanced regions benefit less so. In terms of policy implication, this result seems to suggest policymakers should provide incentives to actors in advanced regions to collaborate with actors in lagging ones. One possibility is by 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 SS. 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 financial incentives for the collaboration of advanced and lagging regions. In this regard, the EU's formal programmes - such as H2020 and Interreg - 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 to meet societal challenges and facilitate industrial leadership, a key element of H2020 is to foster international (and by implication, extra-regional) collaboration through vehicles such as Marie Skłodowska-Curie Actions (MCAs) and Joint Technology

Initiatives (JTIs) (European Commission, 2013). For instance, ¡VAMOS!¹¹ 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 minerals¹². It involves 17 industrial and academic partners from 9 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 offers 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 EU's Structural and Investment Funds, especially both the European Regional Development Fund and Cohesion Fund, have been 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 operates in three separate categories of co-operation; cross border, transnational and extra-regional, with a budget (for 2014-2020) of €10.1 billion and currently supports over 100 co-operation projects between EU regions. These projects seek to foster synergies between RIS3, clusters and network collaboration, and industrial and social innovation (Council of European Union, 2015). The programme is designed to be inclusive, and geared towards addressing common challenges through collaborative, shared solutions in a diverse range of fields from sustainable energy, health to transport. As an example, the V-B Adriatic-Ionian (ADRION) Interreg programme between 8 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 (e.g. Puglia). ADRION primarily aims at providing framework conditions for the development and integration of the concerned areas, focusing 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

¹¹ Further information can be found at: <http://vamos-project.eu/>.

¹² 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 500-1,000 metres 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/>).

between European clusters and SMEs (particularly promoting innovation agents such as fablabs, co-working spaces and innovation hubs)¹³. This is particularly important for a lagging region, such as Puglia which is beginning to see benefits of its involvement in the Blue-Boost project (€1.5 million for 2 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 region¹⁴.

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.

6. Conclusions

This paper 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 paper has outlined some important differences across places that should be taken into account in the definition and implementation of SS strategies.

Our analysis highlights that whilst extra-regional collaboration assists the technological development of lagging regions in broad terms, those collaborative relationships based upon technological relatedness – 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

¹³ 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-ionic-regions

¹⁴ For more information, see www.adriinterreg.eu

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 more a flexible way¹⁵.

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 SS strategies, based upon 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 (Rodríguez-Pose and Di Cataldo, 2014, Aranguren et al., 2018). 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 focused skills programmes are one such vehicle, especially if they are designed not only to meet existing sectoral

¹⁵ 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 (i.e. Interreg and RIS3), to engage in extra-regional collaboration across a range of dissimilar technologies (e.g. marine, solar, biotech, smart-grids) and develop new territorial specialisms in renewable and sustainable energy sources.

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. 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 in lagging regions. At the same time, future work may also explore the role of universities and research institutions in exerting a brokering effect in connecting lagging to advanced regions as well as to explore the potential impact of imbalances between knowledge capabilities among collaborating regions.

References

- Acs, Z. J., Anselin, L. & Varga, A. 2002. Patents and innovation counts as measures of regional production of new knowledge. *Research policy*, 31, 1069-1085.
- Aranguren, M. J., Magro, E., Navarro, M. & Wilson, J. R. 2018. Governance of the territorial entrepreneurial discovery process: looking under the bonnet of RIS3. *Regional Studies*, 1-11.
- 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. & 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. & Tomlinson, P. R. 2018. A place-based developmental regional industrial strategy for sustainable capture of co-created value. *Cambridge Journal of Economics*.
- Barca, F., McCann, P. & 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. & 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. & Labory, S. 2018. What policies, initiatives or programmes can support attracting, embedding and reshaping GVCs in regions? In: PROJECT, O. A. E. C. (ed.) *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: ANTONIETTI, R., CORÒ, G. & GAMBAROTTO, F. (eds.) *Uscire dalla crisi. Città, comunità, specializzazioni intelligenti*. Milan: Franco Angeli.
- Boschma, R. & Frenken, K. 2011. Technological relatedness, related variety and economic geography. In: COOKE, P., ASHEIM, B., BOSCHMA, R., MARTIN, R., SCHWARTZ, D. & TODTLING, F. (eds.) *The Handbook of Regional Innovation and Growth*. Cheltenham: Edward Elgar Publishing.
- Boschma, R. & 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*.
- Boschma, R. & Iammarino, S. 2009. Related variety, trade linkages, and regional growth in Italy. *Economic geography*, 85, 289-311.
- Boschma, R. A. & 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. & 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. *The organization of economic innovation in Europe*, 1999, 71-102.
- Breschi, S. & 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. & 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. & 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*, Edward Elgar Publishing.
- Coad, A., Daunfeldt, S.-O., Johansson, D. & Wennberg, K. 2014. Whom do high-growth firms hire? *Industrial and Corporate Change*, 23, 293-327.
- Coffano, M. & Tarasconi, G. 2014. CRIOS – Patstat Database: Sources, Contents and Access Rules. Center for Research on Innovation, Organization and Strategy. In: CRIOS (ed.) *Working Paper n.1*.
- Corradini, C. & De Propriis, 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.
- Crevoisier, O. 2004. The innovative milieus approach: toward a territorialized understanding of the economy? *Economic geography*, 80, 367-379.
- De Noni, I., Orsi, L. & 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. In: COMMISSION, E. (ed.). Brussels.
- European Commission 2017. Europe in a Changing World – Inclusive, innovative and reflective societies,. In: HORIZON 2020, W. P.-. (ed.). Brussels.
- Evangelista, R., Meliciani, V. & Vezzani, A. 2015. The Specialisation of EU Regions in Fast Growing and Key Enabling Technologies. Joint Research Centre (Seville site).
- 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*, Routledge.
- Gilsing, V. A., Lemmens, C. E. & 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. *The embedded firm: On the socioeconomics of industrial networks*. London & New York: Routledge.
- Grillitsch, M., Asheim, B. & 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. & 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. & Schmoch, U. 2004. Opening the black box. *Handbook of quantitative science and technology research*. Springer.
- Isaksen, A. 2015. Industrial development in thin regions: trapped in path extension? *Journal of economic geography*, 15, 585-600.
- Isaksen, A. & Trippel, M. 2016. Exogenously Led and Policy-Supported New Path Development in Peripheral Regions: Analytical and Synthetic Routes. *Economic Geography*, 1-22.
- Johansson, B. & Quigley, J. M. 2004. Agglomeration and networks in spatial economics. *Papers in Regional Science*, 83, 165-176.
- Kogler, D. F., Essletzbichler, J. & Rigby, D. L. 2017. The evolution of specialization in the EU15 knowledge space. *Journal of Economic Geography*, 17, 345-373.
- Mameli, F., Faggian, A. & Mccann, P. 2014. Estimation of local employment growth: Do sectoral aggregation and industry definition matter? *Regional Studies*, 48, 1813-1828.
- Martin, R. & Sunley, P. 2006. Path dependence and regional economic evolution. *Journal of economic geography*, 6, 395-437.
- Maskell, P., Bathelt, H. & Malmberg, A. 2006. Building global knowledge pipelines: the role of temporary clusters. *European planning studies*, 14, 997-1013.
- McCann, P. & Ortega-Argilés, R. 2015. Smart specialization, regional growth and applications to European Union cohesion policy. *Regional Studies*, 49, 1291-1302.
- Miguelé, E. & Moreno, R. 2018. Relatedness, external linkages and regional innovation in Europe. *Regional Studies*, 52, 688-701.
- Moreno, R., Paci, R. & 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. & 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. & 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. & Powell, W. W. 2004. Knowledge networks as channels and conduits: The effects of spillovers in the Boston biotechnology community. *Organization science*, 15, 5-21.
- Porter, M. E., Ketels, C. H., Miller, K. & 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. & 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. & Peyrony, J. 2018. The INTERREG Experience in Bridging European Territories. A 30-Year Summary. *European Territorial Cooperation*. Springer.

- Rodríguez-Pose, A. & Di Cataldo, M. 2014. Quality of government and innovative performance in the regions of Europe. *Journal of Economic Geography*, 15, 673-706.
- Ronde, P. & Hussler, C. 2005. Innovation in regions: What does really matter? *Research Policy*, 34, 1150-1172.
- Rychen, F. & 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. & Seigneur, I. 2018. Smart specialisation and social innovation: from policy relations to opportunities and challenges. Joint Research Centre (Seville site).
- Tödtling, F., Lehner, P. & Tripl, M. 2006. Innovation in knowledge intensive industries: The nature and geography of knowledge links. *European planning studies*, 14, 1035-1058.
- Tödtling, F. & Tripl, M. 2004. Like phoenix from the ashes? The renewal of clusters in old industrial areas. *Urban studies*, 41, 1175-1195.
- Tripl, M., Tödtling, F. & 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.

FIGURES

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

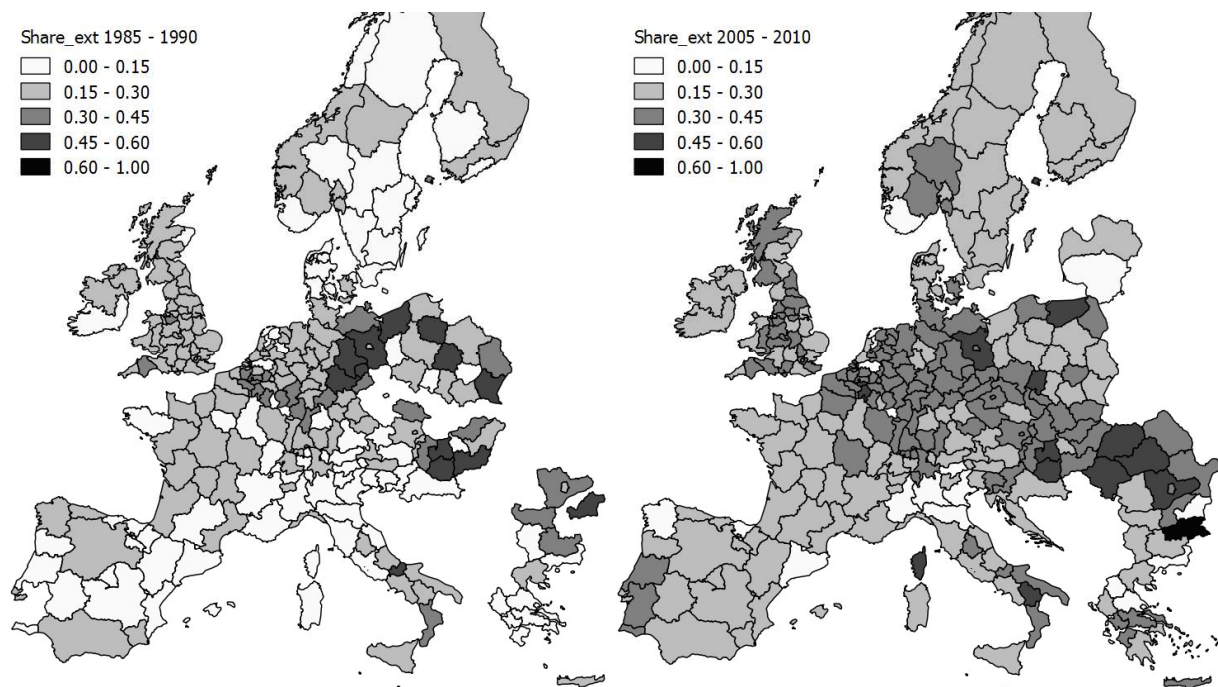
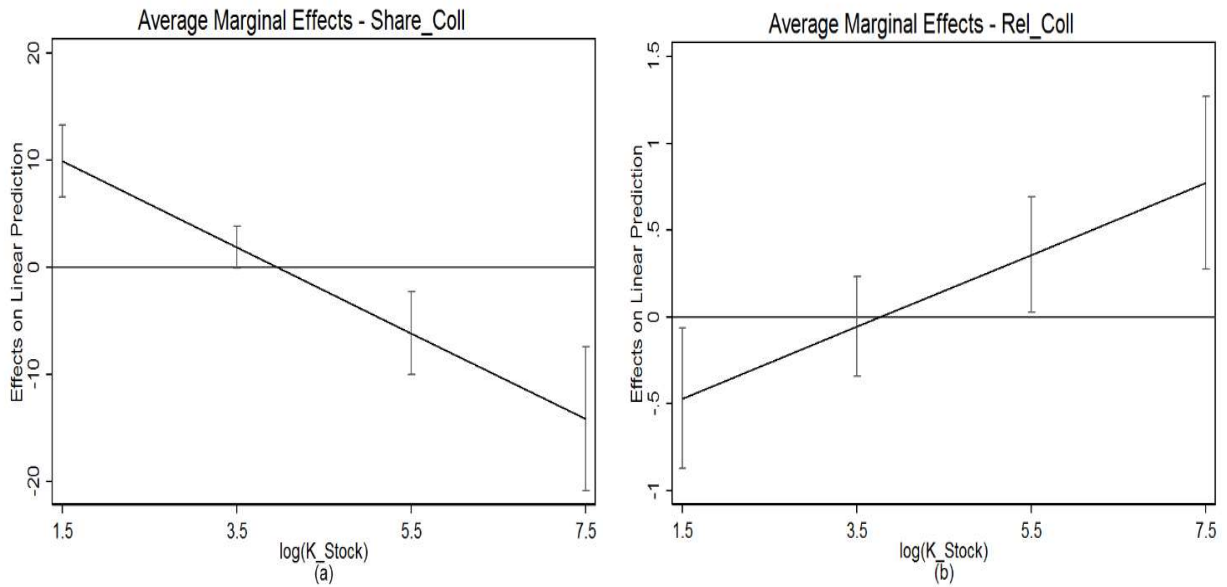


Figure 2: Average Marginal Effects for SHARE_COLL (a) and REL_COLL (b) across quantiles of K_STOCK



TABLES

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				
REL_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)	46027	52914	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

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