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The impact of intra- and inter-regional knowledge collaboration and technological variety on the knowledge productivity of European regions

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ABSTRACT

Collaboration is the cornerstone of European innovation policy, because it stimulates the recombination of knowledge across technological, social, institutional and organizational boundaries and strengthens the knowledge productivity of regions. Despite this key role, little attention has been paid to collaboration as a specific set of organizational arrangements strengthening the knowledge productivity of regions. Therefore, this study focuses on collaboration and looks at the effect of intra- and inter-regional collaboration on the knowledge productivity of regions. Furthermore, it examines the interaction between collaboration and technological variety as complementary drivers of this productivity. The analysis uses a large dataset referring to 269 European regions. This study produces some major original contributions. First, we show that a balance between intra- and inter-regional collaboration is required to support regional knowledge performance. Second, we emphasize that the effect on knowledge productivity is stronger in regions with a diversified knowledge base. The implications of these findings in terms of policy design are then discussed extensively.

1. Introduction

Collaboration is the cornerstone of innovation policy for the European Union (EU) (Hoekman et al., 2009; Scherngell and Lata, 2013). The main idea underlying this policy is that the flow of knowledge between and within regions strengthens the innovative capacity of regions through the continuous recombination of pieces of knowledge embedded in different technological, organizational and institutional settings (Marrocu et al., 2013; Paci and Usai, 2009). The theoretical foundations of such an idea are to be found in the literature on spatial agglomeration and more specifically in the evolutionary view of regional innovation systems (Cooke et al., 1998). Central to this literature are the concepts of knowledge spillovers, which represent the unconscious exchange of knowledge between two or more actors sharing some degree of cognitive proximity (Boschma, 2005), and of technological variety, a characteristic that strengthens the capability of regions to produce new knowledge by means of knowledge spillovers across technological boundaries (Asheim et al., 2011; Frenken et al., 2007). However, the capability of a region to sustain the production of new knowledge is also associated with its capability to sustain the recombination of knowledge through collaboration within and between regions (Maggioni et al., 2007; Marrocu et al., 2013). Even if the contribution of collaboration to the knowledge productivity of regions is commonly recognized, few studies attempt to assess its specific effect (Lamin and Dunlap, 2011). This is because the focus of most studies is on the role of regions in innovation, rather than the role of actors, and the outcome of collaboration is often treated as similar to knowledge spillover itself (Sun and Cao, 2015); however, there is a significant difference between knowledge spillovers and collaboration. The first is a largely unconscious and often unwanted process, while the second implies intentionality; indeed, and the definition of a specific organizational arrangement of strength: the capability of actors to innovate through sharing and knowledge recombination (Boschma, 2005; Marrocu et al., 2013).

Therefore, in this paper, we focus on collaboration between inventors at the regional level as a specific organizational arrangement meant to stimulate innovation through the sharing and re-combination of knowledge across organizational and institutional settings. We distinguish between two forms of collaboration: intra- and inter-regional (Sun, 2016; Sun and Cao, 2015). Intra-regional collaboration supports the recombination and sharing of knowledge within and between actors in a regional system (Belussi et al., 2010; Broekel, 2012; Fitjar and Rodríguez-Pose, 2013; Sun, 2016), while inter-regional collaboration, by providing access to complementary and diversified sources of knowledge, is supposed to be a remedy to the problem of spatial lock-in generated by an excessive propensity to collaborate intra-regionally (Boschma, 2005; Sun and Cao, 2015). Since these two forms of collaboration are often portrayed as complementary in the virtuous development of a region (Asheim and Isaksen, 2002; Boschma, 2005; Broekel,

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2012; Tödtling et al., 2009; Sun and Cao, 2015), the role of a balanced ratio between these two forms of collaboration is specifically explored in this study.

Furthermore, since it has also been shown that organizational and collaborative 'thickness' influences a region's capability to absorb the potential of diversification embedded in external sources of knowledge (Asheim and Isaksen, 2002; Tödtling et al., 2009), the interactive effect of collaboration with technological variety must be further investigated.

Based on a longitudinal panel dataset involving 269 regions in 29 countries over a 7-year period (2002–2008), this study makes two major contributions to the existing literature. First, it shows that inter-regional collaborations have a negative effect on the knowledge productivity of regions. Second, the effect of collaboration becomes positive in regions where there is a balance between intra- and inter-regional collaborations, and is even stronger in regions where a diversified knowledge base already exists. This result has significant implications in terms of policy.

The next section of this paper discusses the background literature and frames the hypotheses of the study. In Section 3, we address the methodology and the main results are presented. Section 4 discusses those results. In the last section, the results and limitations of the study are summarised while directions for further research are addressed.

2. Theoretical background and building of hypotheses

Collaboration is becoming a critical competence to strengthen the capability of regions to innovate (Fitjar and Rodríguez-Pose, 2013). The number of collaborations has grown in recent decades, for several reasons. Innovation requires exploring and exploiting a wide array of highly specialized and spatially distributed bodies of knowledge and know-how[1] (Singh, 2008). Thus, collaboration enables actors to jointly lower the costs associated with gaining access to, mobilizing, and exploiting complementary sources of knowledge (Powell and Giannella, 2010; Singh and Fleming, 2010). This is common not only in industries where invention is modular, such as software and biotech, but also in industries where the underlying process of solving problems cannot be broken apart and addressed discretely, such as the pharmaceutical industry (Powell and Giannella, 2010). However, productivity and efficiency are not the only reasons why inventors collaborate. Improving the quality of their outputs, developing path breaking inventions, and supporting acceptance and adoption of innovations, are other reasons that motivate both inventors and companies to unite their efforts in a collaborative venture (Singh, 2008).

For a long time, collaboration has mainly been associated with geographical proximity (Sun and Cao, 2015). Geographical proximity contributes to interactive learning and innovating by supplying actors with a common base of collaborative relationships (Boschma, 2005). Local collaboration is expected to facilitate and strengthen network embeddedness and to thicken social capital, stimulating the formation and evolution of organizations and institutions, which may reduce the cost of opportunism associated with the transmission and sharing of tacit knowledge and untraded interdependencies (D'Este et al., 2013; Johnston and Huggins, in press). In other words, geographical proximity supplies local actors with a form of collective capital, strengthening their collective capability to exchange and combine (tacit) knowledge smoothly across organizational and technological boundaries. However, too much geographical proximity may hamper the capability of local actors to harness these dynamics (Boschma, 2005; Sun and Cao, 2015). There are two main reasons why this may happen. First, geographically-bounded knowledge externalities and local collaboration may lead to the standardization of know-how between firms and inventors (Belussi et al., 2010; Fitjar and Rodríguez-Pose, 2013; Sun, 2016). Therefore, extensive sharing of knowledge between local actors does not lead to any innovation capable of stimulating the development of the local knowledge base. Moreover, dismissing knowledge diversity reduces the possibility for communication and interaction between different kinds of skills, knowledge and competencies, thus reducing learning possibilities (Nooteboom, 2000; Sedita et al., 2016). Second, local interaction and collaboration between geographically close actors fuel their inability to interact and collaborate with actors located outside the geographical system (Boschma, 2005). This is because local collaboration promotes the internalization of common organizational routines, which increasingly prevents members from seeing potential in ideas far away from the set of core competencies and know-hows already shared within the network (Andersen, 2013). Even if these two factors are often strongly interlinked, the difficulties encountered in collaborating with external actors is often the main driver triggering local homogenization of knowledge between actors and heightening their inability to absorb external knowledge that is cognitively distant from what is available locally (Boschma, 2005). Therefore, intra-regional collaboration is expected to positively influence the knowledge productivity of regions, but this effect is in decline (Broekel, 2012). Therefore the following hypothesis should hold:

H1a. :The relationship between intra-regional collaboration and the knowledge productivity of regions takes an inverted U-shape.

While this hypothesis implies the existence of an optimal level of intra-regional collaboration, at the same time we suppose that this optimum changes according to the level of technological variety characterizing the regional knowledge base. This occurs because we expect knowledge homogenization to take place more slowly in regions with a more diversified base of technological knowledge. In fact, even though the literature on agglomeration economies has initially emphasized the benefits of Marshallian externalities and the advantages of a local base of specialized knowledge, more recently the focus has shifted to emphasize the role of Jacobs' externalities and the advantages of a more diversified local knowledge base (Asheim et al., 2011; Frenken et al., 2007). As suggested by Asheim et al. (2011), the more diversified the regional knowledge base the better, because diversity triggers new ideas, induces knowledge spillovers and provides valuable resources required for innovation. This is because of the higher number of knowledge recombination opportunities (Sun and Liu, 2016), novel linkages and associations (Phene et al., 2006), and collaboration opportunities. Therefore, intra-regional collaboration in technologically diversified regions strengthens the flow of knowledge within and across industries, stimulating the production of further diversified knowledge and in contrast with the homogenization of the knowledge base.[2] Therefore, the following hypothesis should also hold:

H1b. : The more diverse the regional knowledge base, the higher the contribution of intra-regional collaboration to a region's knowledge productivity.

Although geographical proximity is still an advantage in exchanging information and sharing (tacit) knowledge, it is not a prerequisite for interactive learning to take place (Boschma, 2005). Other forms of proximity have recently been asserted to stimulate interaction and collaboration more than the spatial form. Boschma (2005) and Paci et al. (2014) emphasize the role of cognitive, social, organizational and institutional proximity as drivers affecting interactive learning,

[1] Even if the availability of powerful digital infrastructures has reduced the geographical constraints linked to the exchange of knowledge, it still makes sense to talk about the geographical distribution of knowledge, particularly because knowledge is often tacit, embodied, and embedded into specific geographical systems and/or fields of specialization.

[2] The extent to which intra-regional collaboration in technologically diversified regions contrasts homogenization depends on the morphology of the collaboration network. Specifically, if this is clustered within industries, the opportunities for recombination and collaboration do not increase. However, if it spans across industries than the opportunities to produce diversified forms of knowledge either through spillovers or collaboration increases.

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opportunities for collaboration and the production of knowledge. In this light, increasing attention has recently been placed on inter-regional collaboration as a complementary driver supporting regional knowledge production (Sun and Cao, 2015). In these relationships, the exchange of knowledge requires actors to share some degree of cognitive (technical) proximity, while their collaboration may be the result of their being socially, institutionally or organizationally close to each other (Marrocu et al., 2013). These inter-regional collaborative relationships and networks may arise spontaneously, primarily through the mobility of persons, or may be institutionalized from the top down, through organizational arrangements within and between firms, or within and between regional and national institutions (Maggioni et al., 2007). For instance, collaborations may take place between two local branches of multinational companies, within a joint venture or strategic alliances between two independent companies, or between independent actors within an EU-funded project.[3] Non-local connections enable regionally embedded parties to gain access to complementary and diversified external sources of knowledge.[4] Therefore, inter-regional collaboration supports the knowledge productivity of regions through the absorption and embeddedness of new and diversified sources of knowledge (Boschma and Ter Wal, 2007; Gertler and Levitte, 2005; Sun, 2016).

H2a. : The higher the level of inter-regional collaboration, the higher the level of a region's knowledge productivity.

Even though inter-regional collaborations are often portrayed as a possible solution to spatial lock-in, the capacity of a region to exploit the innovative potential embedded in the knowledge absorbed through inter-regional linkages also depends on the interaction with the technological variety of the regional base of knowledge (Boschma, 2005; Sun and Cao, 2015). As we have suggested above, technological variety is the source of Jacobs' externalities and the extension of those externalities depends on the variety of the technological base of knowledge available within regions. Therefore, the higher the variety, the higher the extension of the Jacobs' externalities that the absorption of an additional source of external knowledge triggers. If a new patent is produced through inter-regional collaboration in regions patenting only in a single technological field, the number of innovative combinations triggered by the absorption of that piece of knowledge is very limited as there are only a few patents with which knowledge can combine. In contrast, if the same patent interacts with a diversified base of knowledge, the number of innovative recombinations grows exponentially as it may also trigger path breaking events in related and unrelated technological fields (Cattani, 2006; Levinthal, 1998). Therefore, the following hypothesis should also hold:

H2b. : The more diverse the regional knowledge base, the higher the contribution of inter-regional collaboration to a region's knowledge productivity.

Although the capability to exploit the knowledge absorbed through inter-regional network depends on the technological variety of the regional base of knowledge, a balance between intra- and inter-regional collaboration is also required to strengthen interactive learning and knowledge absorption between regions (Asheim and Isaksen, 2002; Boschma, 2005; Broekel, 2012; Tödtling et al., 2009; Sun and Cao, 2015). This is required for two reasons. The first reason is logistical. On the one hand, the capacity of a region to gain access to external sources of knowledge depends on the extent to which it is connected to other regions. On the other hand, knowledge absorbed through inter-regional collaboration spreads at a regional level, the extent to which inter-regional collaborations are socially embedded in the regional context. Given the fact that the capacity to establish and manage collaborative relationships is limited, there is a trade-off between geographical openness and regional embeddedness (Bathelt et al., 2004). Therefore, significant imbalances in the distribution of collaboration between intra- and inter-regional collaboration imply a limited capacity of the region to either gain access to external sources of knowledge or exploit the knowledge absorbed inter-regionally. The latter happens when universities attract the best scholars worldwide, but fail to embed themselves in the regional system of which scholars are a part. The second reason is cognitive. The kinds of language spoken in inter-regional and regional networks are different. In the former, technical languages prevail over practical and operative ones; the opposite is true for the latter, where knowledge creation and transmission are mainly contextualized and based on socialization and learning by doing. Thus, from a cognitive perspective, the balance between intra- and inter-regional collaboration is required in order to support a more organic translation of technical knowledge into contextual practice and vice versa (Asheim and Isaksen, 2002). Therefore, the following hypothesis should hold:

H3a. : The greater the extent of balanced collaboration in the regional base of knowledge, the higher its contribution to the region's knowledge productivity.

The balance between intra- and inter-regional collaboration ensures greater efficiency and effectiveness of regions in exploring, disseminating and exploiting external knowledge. This greater efficiency has a larger effect in regions with a more diversified base of technological knowledge. Even though this type of region does not need to gain access to external knowledge because of the internal variety, the expected capability to better embed and exploit external knowledge either directly, through recombination, or indirectly, through disruption, makes external knowledge highly attractive (Boschma, 2005). Moreover, the large internal variety fosters access to a larger number of diversified external sources of knowledge, increases the collaboration opportunities and produces knowledge spillovers (Asheim et al., 2011). Therefore, the balance produces a virtuous circle between technological diversity and a balanced relationship between intra- and inter-regional collaboration, further feeding the knowledge productivity of regions. This is because the balance enables diversified regions to both recombine internal knowledge through intra-regional collaboration and to recombine the latter with the external knowledge the regions acquire through inter-regional collaborations. In contrast, since the regions with high levels of technological specialization are typically associated with high levels of intra-regional collaboration, the effect of balance is decreasing because the lack of inter-regional collaboration reduces the opportunities for increasing variety and leads to the homogenization of the internal knowledge base. Similarly, the regions with excessive levels of inter-regional collaboration are unable to embed the potential of the external knowledge they explore because of the lack of intra-regional collaboration. High levels of intra-regional collaboration are typical of manufacturing regions dominated by the presence of Marshallian industrial districts (De Marchi and Grandinetti, 2014). Furthermore, in these regions, collaboration is mainly clustered within rather than between industrial districts and even technological homogeneous geographical areas. High levels of inter-regional collaboration are typical of peripheral regions where the lack of variety and thinness of innovation structures negatively affects the capability of these regions to exploit external knowledge (Isaksen, 2014). Therefore, the following hypothesis should hold.

[3] Although the development of transportation and communication technologies has drastically reduced the costs of establishing, managing and maintaining those relationships, geographical proximity still plays a role in their development as many of these relationships are established with actors located in neighboring regions.

[4] The opportunity to establish external connections depends on the attractiveness of the knowledge base of a region. Therefore, in this perspective, regions with a diversified knowledge base enjoy a competitive advantage compare to those with a specialized one as they may establish collaborations with a larger number of partners in different regions, the quality of their knowledge base is higher, and they might have a consolidated base of inter-regional collaboration. However, regions with a specialized knowledge base may use financial resources, such as EU funding, to attract human capital from and establish collaboration with technologically diversified regions.

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H3b. : The higher the level of technological diversity in a region, the greater the balanced collaboration effect on the region's knowledge productivity.

3. Methodology

3.1. Setting and sample

The goal of this paper is to explore the role of collaboration and technological variety on the knowledge productivity of regions. The recent attention the European Commission (EC) has placed on collaboration across regions and the increasing number of programmes supporting the development of regional innovation systems make European regions a suitable and highly relevant population to analyse. For analysis purposes, the European regions are defined at the NUTS2[5] level. NUTS2 represents fundamental regions and is used by the EC for the application of regional policies supporting job creation, innovation, competitiveness, economic growth, improved quality of life and sustainable development. For this reason, and as also suggested by other contributors to the field of regional innovation systems (e.g. Bottazzi and Peri, 2003; Capello, 2009; Marrocu et al., 2013; Paci et al., 2014; Rodríguez-Pose and Crescenzi, 2008), the population of NUTS2 European regions is significant in order to analyse and discuss EU policies in the field of regional cooperation, innovation and knowledge production.

The data collection process merges data on patents and their inventors from the OECD (Organisation for Economic Co-operation and Development) RegPat database,[6] and demographic and economic data from Eurostat, over a 10-year window (from 2002 to 2011). Patent data include all patents granted by the European Patent Office (EPO).[7] Patents are assigned to regions based on the address of their inventors. Thus, EPO patents not involving European inventors are not considered. Similarly, patent data involving inventors from regions 'not classified' are also excluded. 'Priority year' is used to assign patents to each year. Finally, in case a patent has several inventors coming from more than one region, fractional counting is applied in order to calculate the inventor share (*Inv_share*). Regional share (*Reg_share*) also needs to be taken into account since, in a number of cases, an inventor's address could not be allocated to a unique NUTS2 region.[8] Hence, the weighted patent contributions per region *r* and per year *t* are counted as follows:

$$\text{Number of patents}_{r,t} = \sum_{r,t} \sum_{i} \text{Inv}_{share} * \text{Reg}_{share.}$$

where Inv_{share} is the share that inventor *i* is involved in, in the creation of the patent, and Reg_{share} is the regional share, if inventor *i* is registered in different regions. Moreover, the total sum of patent contributions does not correspond to the total number of EPO patents considered because shares pertaining to extra-EU inventors, or of inventors moving outside the EU, are not counted.

The initial sample consists of the 284 European regions defined within the 28 EU countries, plus Norway and Switzerland. Due to missing data related to control variables, we then exclude the seven regions of Switzerland, the four French regions of the *Départements d'outre-mer*, the German regions of Niederbayern and Oberpfalz, Kontinentalna Hrvatska in Croatia and South Finland. A final balanced panel dataset is built up, consisting of 269 European regions in 29 countries (EU28 plus Norway) over a 7-year period (2002–2008). The dependent variable has been operationalized as a shifted window over the subsequent three years with respect to exploratory and control variables and covers the period 2003–2011.

Finally, a fixed effect panel model is preferred to a random effect panel or pooled Ordinary Least Squares (OLS) model because of specific regional features, which may be latent or not included in the available set of variables. A spatial autoregressive (SAR) panel specification is further introduced because innovation is generally considered to be a spatially lagged, dependent phenomenon (Acs et al., 2002; Anselin, 2003; Castaldi et al., 2015; Marrocu et al., 2013; Millo and Piras, 2012; Paci et al., 2014). Several statistical tests are adopted to control these expectations in Section 3.3.

3.2. Variables

3.2.1. Dependent variables

3.2.1.1. Knowledge productivity (KNW·PRD). Since knowledge is typically considered to be a cumulative process, based on Charlot et al. (2014) and Tavassoli and Carbonara (2014), regional knowledge productivity is measured as the logarithmic transformation of the weighted regional patent contributions[9] per million inhabitants over a shifted window over the subsequent three years. Patents have been found to be a good proxy for innovation at a regional level (Acs et al., 2002), and a 3-year lag window is convenient for measuring the lagged effect of the invention process (Crescenzi et al., 2012; Paci and Usai, 2009; Ponds et al., 2010). A 3-year lag window smooths away undue cycle effects, while the lag permits a consistent response time for innovation to vary in response to input factors while avoiding potential endogeneity problems (Marrocu et al., 2013; Paci et al., 2014). For instance, the set of independent and control variables measured in 2007 is expected to produce effects on regional innovation performance (*KNW·PRD*) in the subsequent lagged time, from 2008 to 2010, while in 2008 the same set of variables is expected to generate effects on the same variable from 2009 to 2011.

3.2.2. Exploratory variables

3.2.2.1. Collaboration (INTRA.CLL, INTER.CLL and CLL.BLC). The regional collaboration preference is measured by distinguishing a) *intra-regional collaboration* (*INTRA.CLL*) when the patent involves more inventors within the same European region, b) *inter-regional collaboration* (*INTER.CLL*) when the patent involves more inventors belonging to different European regions and c) *intra/inter-collaboration balance* (*CLL.BLC*) as the interaction between *intra- and inter-regional collaboration*. *INTRA.CLL* is measured as a share of intra-regional collaborative patents over the total regional co-patents. *INTER.CLL* is defined as a share of inter-regional collaborative patents over the total regional co-patents. The *CLL.BLC* index is operationalized as the reverse of the

[5] The Nomenclature of territorial units for statistics (NUTS) classification is a hierarchical system for dividing up the economic territory of the EU for the purposes of a) the collection, development and harmonization of European regional statistics, b) socio-economic analyses of the regions and c) framing of EU regional policies. Data collected from OECD RegPat database (February 2015 edition) and Eurostat are updated to the NUTS2 2010 version.

[6] We use the OECD RegPat database edition released in February 2015, which contains regionalized data on all patent applications filed at the EPO from 1977 to 2014. However, the data from 2012 to 2014 are excluded from the analysis because of their incompleteness. Due to the time lag between patent filing, the disclosure of filing information by the patent office, and data processing by the database provider (i.e. OECD), 2011 is the most recent year that is currently available.

[7] This choice is justified by a) the quality of the basic data (clean and complete addresses are not easily accessible from most other patent offices) and b) the international character of EPO patents, which makes the resulting data more comparable across countries.

[8] *Reg_share* and *Inv_share* are directly provided by the RegPat database. *Inv_share* is 1 if the patent has a unique inventor, while it is <1 when the patent is co-invented. Thus, if a patent has more than one inventor, each is weighted equally based on the number of inventors. *Reg_share* is <1 if the inventor has multiple address registrations due to the regionalization procedure applied in RegPat, which could be based on postal code, town name or mixed methods. When unique assignment is not possible, the same inventor is allocated to different regions, each having a regional share (where the sum is 1).

[9] See Section 3.1

squared collaboration ratio (*CLLratio*):

$$\mathrm{CLL.BLC} = 1 - [\mathrm{CLLratio}]^2$$

$$\mathrm{CLLratio} = \frac{(\mathrm{INTRA.CNN} - \mathrm{INTER.CNN})}{(\mathrm{INTRA.CNN} + \mathrm{INTER.CNN})}$$

where *CLLratio* represents a value between -1 and $+1$. Values close to $+1$ indicate a regional tendency towards *intra-regional collaboration*, values close to -1 imply a regional tendency towards *inter-regional collaboration*, while values close to 0 suggest a balance between *intra-* and *inter-collaboration* (see Fig. 2). If we square this term and subtract 1, we obtain an indicator varying between 0 and 1, where 1 indicates a perfect balance, whilst 0 suggests the prevalence of *intra-* or *inter-regional collaboration*.

3.2.2.2. Technological diversification (TCN.DIV). Technological diversification is adopted as a proxy for regional knowledge variety (Boschma et al., 2012; Frenken, 2007; Quatraro, 2010; Tavassoli and Carbonara, 2014). It measures the distribution of regional patents across technological classes using the International Patent Classification (IPC) and is operationalized by using the entropy index at the 4-digit IPC level, based on Castaldi et al. (2015), according to the following formula:

$$\mathrm{TCN.DIV}_r = -\sum_{j=1}^{n} p_j \ \ln\left(p_j\right)$$

where $p_j = E_{j,s}/E_r$. The number of patents guaranteed in each IPC class within a region r ($E_{j,r}$) is related to the overall number of patents guaranteed in the same region r (E_r). Patents relying on multiple IPC classes are homogeneously weighted for the number of classes they are in. The higher the index, the more diversified the regional patent distribution across the IPC classes. Conversely, specialized innovation regional systems should show lower index values.

3.2.3. Control variables

3.2.3.1. R&D expenditures (RD.EXP. Gross domestic expenditure on Research & Development (R&D) as a percentage of gross domestic product (GDP) is an indicator of high political importance at the EU, national and regional levels. R&D intensity is expected to have a positive impact on innovation, as long as a positive correlation exists between technological input and output (Gilsing et al., 2008; Maurseth and Verspagen, 2002). R&D represents the basic measure of economic input employed to generate innovation in each region (Crescenzi and Rodríguez-Pose, 2013; Jiao et al., forthcoming).

3.2.3.2. Human capital (HUM.CAP). Human capital supports and enhances the innovative processes because highly specific skills are necessary to produce new ideas, and also impact on the capability to absorb external knowledge (Ponds et al., 2010). Thus, the propensity of a region to innovate depends on the average level of human capital within the local economy (Lee et al., 2010); tertiary educational attainment is used here as a proxy for human capital; the higher the overall educational level, the higher the potential number of inventors. This variable is defined as the percentage of the population aged 25–64 who have successfully completed tertiary studies (e.g. university, higher technical institution, etc.) (Charlot et al., 2014; Hervas-Oliver et al., 2011; Marrocu et al., 2013; Paci et al., 2014). The indicator is provided by Eurostat and is calculated based on the EU Labour Force Survey. Specifically, for data up to 2013, educational attainment refers to ISCED (International Standard Classification of Education) 1997, levels 5–6.

3.2.3.3. Manufacturing specialization (MAN·SPC). Since sectors have different technology and innovation opportunities, and manufacturing is typically more inclined towards innovation than services (Hipp and Grupp, 2005), the location of manufacturing activity is one of the most significant drivers of the spatial distribution of innovation (Audretsch and Feldman, 1996). Therefore, manufacturing specialization is introduced as a control variable: the manufacturing concentration index is operationalized as the share of regional employees operating in manufacturing with respect to the total number of regional employees.

3.2.3.4. Inventor productivity (INV·PRD). Despite the potential established through human capital, the regional capability to innovate also depends on individual inventors, in particular their areas of competence and their creativity (Zhang et al., 2014). The productivity of inventors is measured as the effective yearly number of individual and co-invented EPO patents; an average value is calculated at the regional level for each year.

3.2.3.5. Population density (POP.DEN). The population per square kilometre in each region for each year is applied as a proxy for externalities related to urbanization. The urbanization process is expected to be positively associated with the presence of universities, industry research laboratories, trade associations and other knowledge generating organizations (Frenken et al., 2007, Marrocu et al., 2013; *Pac*i et al., 2014). Thus, urbanization economies may strengthen regional innovation performance.

3.3. Model

Spatial panel data models capture spatial interactions across spatial units and over time (Millo and Piras, 2012). Our research strategy highlights that a spatial SAR panel specification is adequate to model the regional collaboration pattern, which allows the exchange of innovation across neighboring territories (Paci et al., 2014). According to Anselin (2003), because of the spatial lag of the dependent variable, the SAR model yields global spillovers. The related structural model indicates that the result of a given dependent variable is the effect of all the interactions among units (in our case regions) that have taken place across space and over time. Spatial lag models therefore imply possible diffusion processes of knowledge creation (Acs et al., 2002; Anselin, 2003; Paci et al., 2014), because spatial dimensions of social interactions and collaboration processes are typically considered an important aspect of innovation and knowledge spillovers (Bathelt et al., 2004; Breschi and Lissoni, 2001; Malmberg and Maskell, 2002, 2006; Ponds et al., 2010; Tödtling et al., 2009). Moreover, since we expect our data to be characterized by spatial dependence, some tests are implemented to verify the conditions of application for the SAR panel model.

The first step in this modelling technique is to compare the goodness of fit for the panel models with the common OLS model. Here, we report only the results concerning the base model (Model 1 in Table 2), but all the models show the same significance and behaviour. An F-test ($F = 197.45$ and $p < 0.001$ in Model 1), as measured by the *pFtest* function of R's *plm* package,[10] confirms that both fixed effect and random effect panel models are a better fit than OLS.

In the second step, the fixed effect was expected to fit better than the random effect because the innovation diffusion in the European regions is not likely to be randomized but rather is influenced by observed and latent time-invariant territorial features; the Hausman test on the full model ($\chi^2 = 452.76$, and $p < 0.001$ in model 1, measured by the *phtest* function of R's *plm* package) confirms this expectation.

Third, since we expect a 'time effect' due to the financial crisis in 2007/2008, an F-test is used to assess whether the time effect needs to be considered further. The result on the baseline model suggests that a time effect must be included (time effect is preferred since $F = 2.507$ and $p < 0.05$).

[10] R is an open source software environment for statistical computing and graphics.

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Next we use the Breusch-Pagan test to evaluate the presence of heteroscedasticity in the models. The low probabilities calculated for this test in the full model highlight the existence of heteroscedasticity ($BP = 290.56$ and $p < 0.001$). This is not necessarily a surprise because the variance could well be affected by the spatial dependence in the data (see Moran I test).

Finally, we run Moran I and Lagrange multiplier (*LM*) tests to assess the spatial dependence of models implemented in the R package *spdep* (spatial dependence). The Moran I test score of 18.069 in model 1 is highly significant ($p < 0.001$), indicating strong spatial autocorrelation of the residuals.

The *LM* statistics are the simple *LM* test for a missing spatially lagged dependent variable (*LM-lag*), the simple *LM* test for error dependence (*LM-err*) and the robust variants of these two tests (*RLM-lag* and *RLM-err*) (Anselin, 1988a, 1988b).

Simple tests of both lag (*LM-lag* = 251.95 and $p < 0.001$) and error (*LM-err* = 204.15 and $p < 0.001$) are significant, indicating the presence of spatial dependence. The robust variant of these tests allows us to understand what type of spatial dependence may be at work in our data. The robust measure for the lag test is still significant (*RLM-lag* = 51.19 and $p < 0.001$), but the robust error test becomes insignificant (*RLM-err* = 3.39 and $p > 0.05$), which means that apparent spatial dependence in the error terms is not an issue in modelling the level of regional knowledge productivity; therefore, the spatial error model is not the most appropriate choice for model specification.

After identifying the presence of spatial dependence utilizing the Moran I test and *LM* tests, we use the R package *splm* (spatial panel linear model) to re-estimate the regression models with a maximum likelihood approach, while controlling for both spatial dependences (spatial lag and spatial error). In Table 2 we present only the results of the spatial lag panel model, which are more useful to capture the effects of spatial spillovers on knowledge production (Anselin, 2003) than the spatial error models. Moreover, the results obtained by the two specifications are quite similar, except that the spatial lag model results seem to be more robust than the spatial error panel model.[11] Thus, following Millo and Piras (2012), the expression of the spatial lag panel model is defined as

$$Y = \lambda(I_T \otimes W_N)y + (\iota_T \otimes I_N)\mu + X\beta + \varepsilon$$

where Y is a vector of the dependent variables, X is a matrix of the explanatory and control variables, β represents the vector of the coefficients, ε is the vector of the residuals, ι_T a column vector of ones of dimension T, I_N an $N \times N$ identity matrix, μ is the vector of cross-sectional specific effects, λ is the SAR coefficient and W_N is the spatial weight matrix, which shows the strength of the interaction between two regions. A weights matrix is used to impose a neighbourhood structure on the data to assess the extent of similarity between locations and values (spatial dependence). In this analysis, we use a contiguity-based weights matrix where regions are neighbours if they share either a border or point (the queen criterion).

4. Results

The map in Fig. 1 shows the more innovative European regions (on the left) which are mainly in Germany, Scandinavia, northern Italy, Austria and England, alongside a map showing the regions with more balanced levels of intra- and inter-collaboration (on the right). The map in Fig. 2 highlights the regions that are inclined to develop high intra-regional collaboration (Spain, southern France, Italy, Greece, Bulgaria, Scandinavia and the Baltic countries) and regions showing high inter-regional collaboration (the Benelux countries, Germany, and most of Central and Eastern Europe).[12]

Table 1 presents the descriptive statistics and the correlation values for all variables. The correlation values among explanatory and control variables are relatively low, i.e. below the cut-off point of 0.50 (Hair et al., 2010, p. 189), except for two bivariate correlations *HUM.CAP*/*R&D.EXP* and *R&D.EXP*/*TCN.DIV* that are above the suggested cut-off point. Therefore, we eliminated the *R&D.EXP* variable from the spatial regression analysis to avoid collinearity issues. We also checked for the existence of multicollinearity by measuring the variance inflation factors (*VIFs*) (see Table 2) which are lower than the threshold of 4 suggested by O'Brien (2007), and found multicollinearity not to be a problem. Furthermore, we entered interaction terms in the analyses because our hypotheses expect *intra-regional collaboration*, *inter-regional collaboration*, *intra/inter collaboration balance* and *technological diversification* to interact. In addition, we standardize these variables prior to calculating their interaction terms, in order to avoid unnecessary multicollinearity, as well as the quadratic terms (Aiken et al., 1991; Gilsing et al., 2008; Rothaermel and Deeds, 2004).

Table 2 presents the spatial panel fixed effect estimates with spatial lag to explain the *knowledge productivity* of the European regions in our sample.

We operationalized the *adjusted R squared* and the *Generalised Least Squares* (GLS) residual variance to evaluate the goodness of fit of the models. As a base model, we first present the outcome using only the control variables. Model 1 represents the effect of control variables on the dependent variable *knowledge productivity*. Model 2 introduces *intra-regional collaboration*, *technological diversification*, their pairwise interaction term and the quadratic form of *intra-regional collaboration* (*INTRA.CLL^2*) to test our first two hypotheses (H1a and H1b). In model 3, the linear effect on the *knowledge productivity* of each European region of *inter-regional collaboration* and its interaction with *technological diversification* are also verified (H2a and H2b). Finally, model 4 presents the results of the impact of *collaboration balance* and its interaction with *technological diversification* on *knowledge productivity* (H3a and H3b).

The overall fit of the models increases compared to the baseline, as Models 2, 3 and 4 fit our data better and have more explanatory power than Model 1. Moreover, the coefficients and signs of the control variables remain stable along the different models, showing robust results and that multi-collinearity is not a particular problem in these regressions.

Model 1 presents estimates of the coefficients of the control variables. As expected, the regional stock of *human capital* is positive and significant ($p < 0.001$). To check for sectoral effects, we introduce the variable *manufacturing specialization*. The *manufacturing specialization* (*MAN·SPC*) of regions also has a significant ($p < 0.001$) and positive effect on *knowledge productivity*. The same is true in the case of *inventor productivity* ($p < 0.001$). In contrast, the *population density* is positive but not significant in any of the five models.

Model 2 provides support for the inverted U-shape relationship between the *intra-regional collaboration* and regional *knowledge productivity* (H1a). As we expect, a certain level of *intra-regional collaboration* supports the exploitation of the regional knowledge base, but we also expect high values of *intra-regional collaboration* to lead to diminishing returns on *knowledge productivity*, since the linear term of *intra-regional collaboration* is positive and significant ($p < 0.001$), while the squared term is negative and significant ($p < 0.1$). Moreover, the coefficient of *technological diversification* ($p < 0.001$) is positive and statistically significant. As the first hypothesis (H1b) suggests, *intra-regional collaboration* and *technological diversification* as well as their interaction (*INTRA.CLL*TCN.DIV*) yield a positive effect on the dependent variable; in fact, the interaction effect is also significant ($p < 0.001$). Hence, our hypothesis 1b is confirmed. The diversity of the knowledge base of regions mediates the effect of collaboration on the *knowledge productivity* of regions.

Model 3 points out a negative and statistically significant direct effect of *inter-regional collaboration* ($p < 0.001$) and a positive and

[11] We also ran a SARMA model with both spatial lag and spatial error, but obtained similar coefficients to those in the spatial lag model.

[12] The indices shown in Figs. 1 and 2 are average values for the period analyzed. Thus, some differences with respect to the panel regression analyses results are expected. The legend clusters and colours are based on quartile distribution.

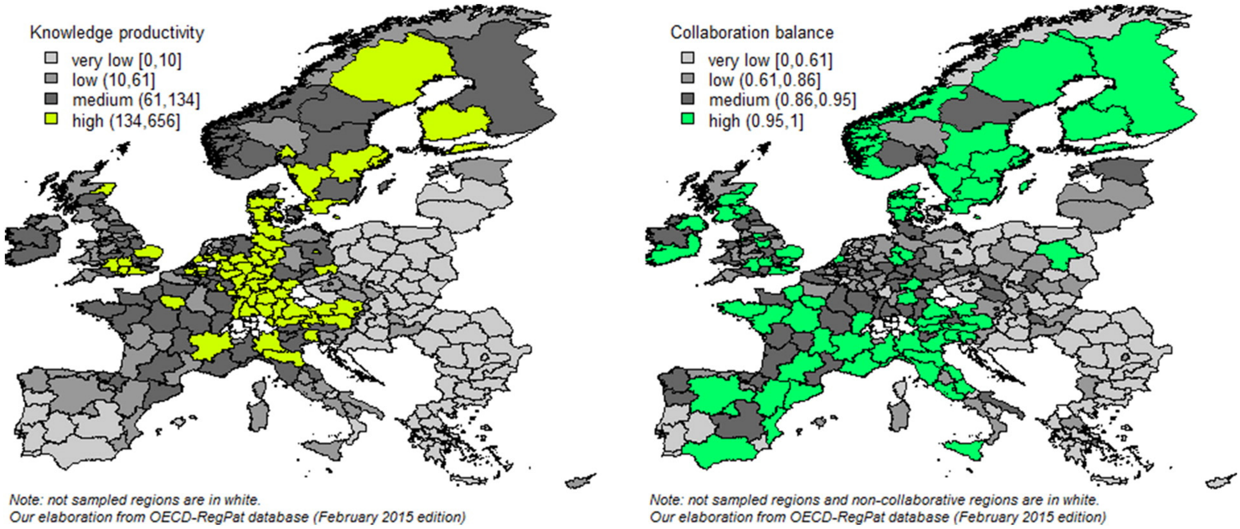

Fig. 1. – Knowledge productivity (left) and collaboration balance (right) of European regions.

significant direct effect of *technological diversification* ($p < 0.001$). Hence, our hypothesis 2a is not confirmed. A positive but not significant impact of the interaction between these variables (*INTER.CLL*TCN.DIV*) would seem to suggest that technological variety may mitigate the impact of *inter-regional collaboration*, but we cannot confirm our hypothesis 2b statistically.

The results of Model 4 provide support for hypothesis 3a. Model 4 shows a positive and significant direct impact ($p < 0.001$) of *collaboration balance* and *technological diversification* ($p < 0.001$). Thus, regions with a good balance between intra- and inter-regional collaboration propensity and also those featuring a higher degree of technological variety see enhanced innovation. The pairwise interaction of these two variables (*CLL.BLC*TCN.DIV*) is also positive and significant ($p < 0.05$) confirming hypothesis 3b. As we expect, there is an optimal level of *collaboration balance*, which maximizes the *knowledge productivity* of regions; meanwhile, the higher the level of technological diversity in a region, the higher the effect of a *balanced collaboration mix* on its *knowledge productivity*.

Finally, all models confirm the important spatial dependence on the knowledge performance of European regions, as has been strongly argued in regional studies that rely on notions of spatial interaction and diffusion effects, hierarchies of place and spatial spillovers (Basile et al., 2012; Capello, 2009; Ponds et al., 2010). The positive and significant lamba-coefficient (spatial lag dependence) means that being part of a highly innovative geographical context supports the *knowledge productivity* of regions.

5. Discussion

The objective of this paper is to investigate the interactive effect of collaboration and technological variety at a regional level by distinguishing between intra- and inter-regional collaboration. Several studies have recently looked at the roles of collaboration and variety on regional performance (Basile et al., 2012; Boschma, 2005; Bottazzi and Peri, 2003; Broekel, 2012), but none has explored the effect of the interplay between them (Sun and Cao, 2015).

The results of our spatial model highlight these findings:

- Intra-regional collaboration enhances the knowledge productivity of regions; however, the effect tends to flatten for high levels of intra-regional collaboration.
- Contrary to what we expected, a high propensity towards inter-regional collaboration negatively affects the knowledge productivity of regions. Thus, a disproportionate emphasis on inter-regional

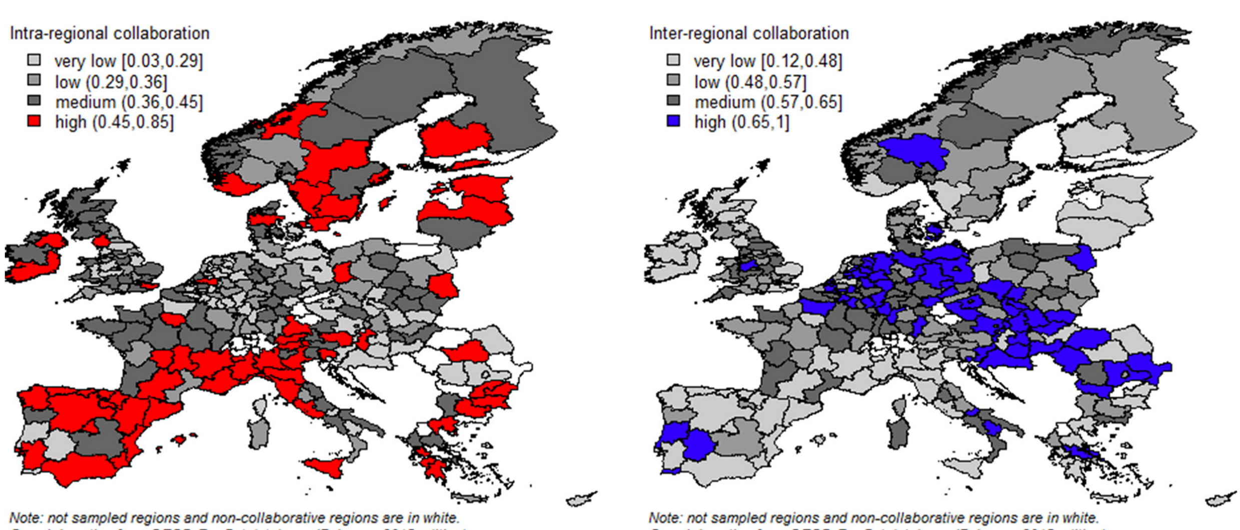

Fig. 2. – Intra-regional (left) and inter-regional (right) collaboration attitude of European regions.

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Table 1
– Descriptive statistics and correlation matrix.

	Variables	Mean	St.dev.	1	2	3	4	5	6	7	8	9	10
1	KNW·PRD	7.668	0.781	1									
2	INTRA.CLL	0.320	0.201	0.37***	1								
3	INTER.CLL	0.557	0.231	0.13***	−0.43***	1							
4	CLL.BLC	0.223	0.322	0.41***	0.52***	−0.56***	1						
5	TCN.DIV	3.403	1.333	0.87***	0.41***	0.19***	0.43***	1					
6	R&D.EXP	1.423	1.285	0.62***	0.23***	0.02	0.29***	0.52***	1				
7	HUM.CAP	22.960	8.387	0.54***	0.22***	0.00	0.25***	0.46***	0.52***	1			
8	MAN·SPC	18.021	6.792	0.04†	0.05*	0.12***	−0.03	0.11***	−0.04	−0.35***	1		
9	INV·PRD	0.499	0.171	0.21***	0.09***	0.06**	−0.02	0.19***	0.00	0.01	0.07**	1	
10	POP.DEN	344.585	848.485	0.15***	−0.03	0.06**	0.04†	0.18***	0.10***	0.29***	−0.22***	−0.02	1

Notes: Significant levels are $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}p < 0.10$. The average value of *KNW·PRD* and *HUM.CAP* are not in logarithmic form for easier reading.

collaboration reduces the capacity of a region to produce new knowledge.

- Technological variety is confirmed to be a fundamental determinant of regional knowledge productivity. It moderates the decreasing effects of intra-regional collaboration and reduces the risk of lock-in due to knowledge homogenization. Furthermore, the technological variety of a region not only moderates the negative effect of excessive inter-regional collaboration, but even changes the sign of this relationship. Thus, in regions with a diversified knowledge base, an emphasis on inter-regional collaboration supports knowledge productivity.

Table 2
– Spatial fixed effects lag regression results.

Dependent variable - KNW·PRD	Spatial panel fixed effects lag models			
	Model 1	Model 2	Model 3	Model 4
Lambda (spatial lag)	0.748(0.012)***	0.509 (0.013)***	0.508 (0.013)***	0.507 (0.013)***
Explanatory variables				
INTRA.CLL		0.253 (0.042)***		
INTRA.CLL^2		−0.009 (0.006)†		
INTER.CLL			−0.140 (0.041)***	
INTER.CLL^2				
CLL.BLC				0.165 (0.030)***
TCN.DIV		0.240 (0.009)***	0.258 (0.007)***	0.239 (0.008)***
INTRA.CLL*TCN.DIV		0.022 (0.006)***		
INTER.CLL*TCN.DIV			0.001 (0.006)	
CLL.BLC*TCN.DIV				0.014 (0.007)*
Control variables				
HUM.CAP	0.525 (0.025)***	0.289 (0.020)***	0.278 (0.020)***	0.279 (0.020)***
MAN.SPC	0.014 (0.001)***	0.003 (0.001)**	0.004 (0.001)***	0.004 (0.001)***
INV.PRD	0.184 (0.044)***	0.094 (0.036)**	0.079 (0.036)*	0.096 (0.036)**
POP.DEN	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
No. of observations	1883	1883	1883	1883
EU NUTS2 regions	269	269	269	269
No. of years	7	7	7	7
R squared	0.828	0.885	0.884	0.885
GLS residual variance	0.0865	0.0590	0.0593	0.0590
Max VIF	1.554	3.348	2.538	2.617
Mean VIF	1.237	1.826	1.718	1.725

Notes: Standard errors are in parentheses. Significant levels are $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}p < 0.10$.

- Finally, the significant effect of the mix of intra- and inter-regional collaboration suggests that an optimal balance between the two maximizes knowledge productivity at a regional level. Furthermore, this optimal mix enables regions to boost the effect of technological variety.

Theory has suggested that co-location supports knowledge flows between inventors because of spatial and cultural proximity, which increases interaction opportunities and facilitates collaboration. However, the significant negative coefficient of the squared value of intra-collaboration in Model 2 suggests that an excess of local collaboration may produce homogenization and flattening of shared knowledge, and lead to lock-in situations (Nooteboom, 2000). However, the significant interaction between intra-regional collaboration and variety suggests that increased variety may reduce the decreasing returns to intra-regional collaboration in the long run. In other words, the strength of local collaboration is crucial to foster regional knowledge flows and to increase the knowledge creation and recombination opportunities, but it may require that the stock of knowledge internal to the region be sustained by external knowledge flows. In this context, the development of inter-regional relationships and collaborations, as a means of access to external knowledge and to balance the specialization of locally embedded innovation networks, is to be encouraged and supported by regional policies.

Analysis of the relationships between intra- and inter-regional collaboration balance and knowledge productivity suggests that a degree of balance is required to optimize access to and utilization of knowledge. A high level of intra-regional collaboration suggests that the region has developed locally embedded innovation networks to support knowledge production and recombination, but that increased inter-regional openness is required in order to foster access to new and diversified sources of knowledge. In contrast, a high level of inter-regional collaboration suggests that the region needs external collaborative relationships to innovate, but that internal research structures and services must develop in order to assimilate and exploit external knowledge, foster the diffusion of external knowledge within the regional system and enhance innovation performance.

Fig. 2 in Section 4 shows that regions with high levels of intra-regional collaboration, outside of Scandinavia, are mainly Latin regions, which historically have a low degree of openness (Fukuyama, 1996) and are inclined to individually develop internal resources and structures. In contrast, high levels of inter-regional collaboration involve two contrasting types of regions: innovative regions of Germany and the Benelux countries, where inter-regional, compared to intra-regional, cooperation is prevalent, and those regions of Central and Eastern Europe which are typically less structured for innovation and collaborate with knowledge intensive regions because they lack internal resources and competencies (Hajek et al., 2014). In the latter case, the attitude to inter-regional collaboration in these regions is often the result of European projects which required them to collaborate to gain access to European funds.

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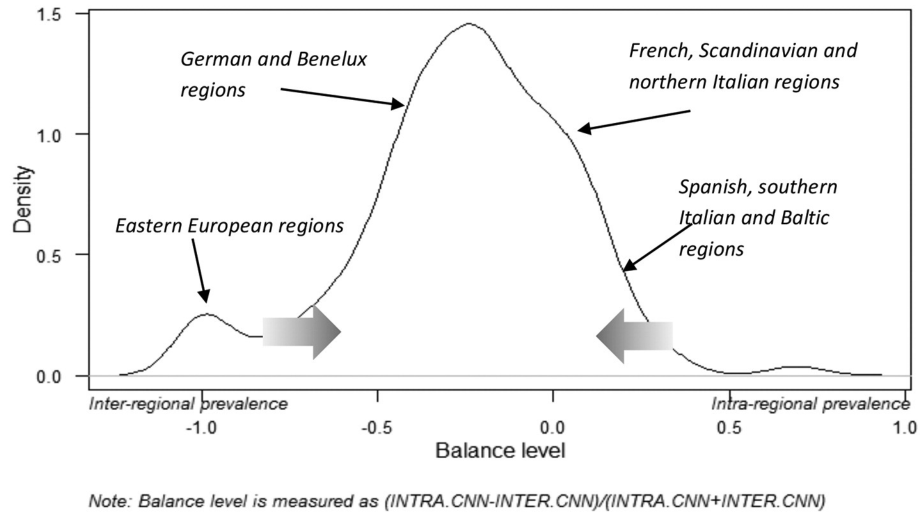

Fig. 3. – The intra- and inter-regional balance across European regions.

Furthermore, the map in Fig. 1 suggests that the most innovative regions match those of a medium-high and high balance between internal and external collaboration. However, different equilibrium levels are potentially conceivable. If we plot the density of the collaboration ratio[13] (Fig. 3), we can observe the average inclination of regions to balance or to specialize in the intra- or inter-regional collaboration approach. Looking at Fig. 3, on the one hand, French regions are more inclined towards a balance on the side of intra-regional connectivity, which encourages the development of local networks, while German regions have a larger inclination to inter-regional collaboration. However, the significance of spatial lag may suggest that the inter-regional aptitude of German regions does not mean a greater openness than other regions but it is likely to be due to a strong collaboration with spatially closed regions. Similarly, the inability of regions of Spain to exploit their balance between intra- and inter-regional collaborations may be due to an inter-regional collaboration system that is limited to other regions of Spain, rather than extended to more diverse European regions. As highlighted in the following section, this study is limited, as it does not distinguish between collaboration across regions of the same country and with regions of other countries.

Finally, in recent decades, the increasing commitment of EU to policies sustaining the innovation performance of both core and peripheral regions has led to contradictory results, as suggested by the so-called European paradox on innovation. The establishment of the European Research Area (ERA) in 2000 has facilitated and encouraged inter-regional collaboration as a means to promote knowledge diffusion across regions. However, this study highlights that fragmentation and heterogeneity in regional innovation capacity needs to evolve towards structure and balance in order to make inter-regional collaboration more effective. Development strategies promoting inter-regional collaboration are effective mainly in the core regions, where the level of social, organizational, institutional and technological 'thickness' and diversity is already high.

Therefore, European research and innovation policies should support regional innovation by distinguishing local innovation systems according to their breadth and complexity. On the one hand, core regions characterized by structured internal innovation systems based intra-regional collaboration should be encouraged and supported to extend their inter-regional networks in order to improve their access to external knowledge and foster the diversity of knowledge available and its potential utilization. On the other hand, interventions meant to strengthen the knowledge productivity of more peripheral regions through inter-regional collaboration should be complemented by others to strengthen the social, organizational and institutional capacities of the region. In other words, peripheral regions focusing on high inter-regional collaboration should be encouraged and supported in improving their internal collaborative configuration by developing synergies among regional governments, research institutions, universities and private firms (Zhao et al., 2015).

6. Concluding remarks, limitations of this study and directions for future research

In this paper, we focus mainly on the interaction between technological variety and intra- and inter-regional collaboration in order to understand how these factors support regional knowledge productivity, as measured by patent performance.

Our main findings suggest, first, that local collaboration has a curvilinear effect on the knowledge productivity of regions and that there is an optimal level of intra-regional collaboration. Secondly, inter-regional collaborations positively affect the innovation performance of regions only if balanced with intra-regional collaboration (as a proxy of a good organizational, social and institutional density). Finally, regional technological variety positively moderates the decreasing effect of high intra-regional collaboration in the long-run, counters the negative effect of inter-regional collaboration in the absence of organizational and institutional thickness, and increases the effect of the collaboration mix on knowledge productivity.

This study has several limitations. First, a more comprehensive evaluation of the impact of intra- and inter-regional collaboration on the level of knowledge productivity should not rely only on patent measurements, but also measure innovative or improved products and processes. The availability of more comprehensive datasets providing further information on regional knowledge productivity and R&D outcomes would allow future research results to be extended and improved. Furthermore, a more realistic representation of the interactive dynamics linking regional and inter-regional levels is also required. In our perspective, we already emphasize the need to understand the way collaboration spans industries and consider cognitive distance as a driver of path breaking events. However, the morphology of the network between institutionally different actors should have a significant effect on the way absorbed knowledge is diffused in the regional system and indeed on the knowledge productivity of regions. Second, we are aware that some particular forms of knowledge spillover might not be properly captured by using only physical distance (contiguity-based weights matrix) without considering other forms of distance (e.g. cognitive). Third, the IPC, although acceptable and sufficiently clear for

[13] See the formula of *CLLratio* in Section 3.2

our purpose, has been developed for reasons other than providing scholars with a complete picture of the knowledge bases and variety of organizations and regions. Fourth, we have not distinguished between inter-regional collaborations within a country and those across countries; this could also be of analytical and policy interest.

Future research could examine the dynamics of knowledge productivity among European regions using not only intra- and inter-EU regional collaboration, but also including the interactions with countries outside the EU, such as with regions of North America, Eurasia or in developing countries.

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