***Between spilling over and boiling down: regional absorptive conditions for productivity capture from networked R&D in Europe***

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*Abstract*
Productivity across European regions is related to three types of networks that mediate R&D-related knowledge spillovers: trade, co-patenting and physical proximity. Both our panel and instrumental variable estimations for European regions suggest that network relations are crucial sources of R&D spillovers, but with potentially different features. While copatenting relations appear to affect local productivity directly, regions that link up to innovative leader regions via imports gain in productivity only when they have relatively high levels of human capital and absorptive capacity. From a policy perspective, this may frustrate recent European policy initiatives, such as the Open Research Area and Smart Specialization, that are designed to benefit all regions in Europe.

## 1. Introduction

Linkages between different peoples and countries, through trade, capital and cultural ties, have had large economic effects since the beginning of human civilization. Over the past few decades, the opportunities for exchanging goods, services, technologies and knowledge have dramatically increased, bringing the concepts of networks, interaction, and diffusion to the forefront of academic and political debates. In the still burgeoning, geographically embedded proximities literature, there is large heterogeneity in conceptualized (and, with varying success, empirically tested) types of relatedness that mold knowledge interaction, learning and innovation (Torre et al. 1999, Boschma 2005). The proximities literature builds on older contributions of industrial districts (Becattini et al. 2009) that conceptualize lower transaction costs due to co-location of firms and the possibility to overcome the limits of firms' small size due to common social and cultural characteristics in a geographically bound and historically determined area. Other strands of research focusing on proximities are the innovative milieus and regions approach (Ratti et al. 1997, Camagni 1991), where value-chain relations profit from localization advantages and the key driver of interaction is relational proximity (Caragliu & Nijkamp 2015), the learning region approach, in which institutional proximity is central (Morgan 1997), and the spatial knowledge spillover and knowledge production function approaches (Jaffe 1986, Ertur and Koch 2007). More recently, the evolutionary economic geography approach has highlighted how cognitive proximity determines product and industrial relatedness and knowledge diffusion (Nooteboom 1992, Frenken et al. 2007). Cognitive and technological proximities also play a crucial role in the recent approach of geography of innovation (Scherngell 2013, Massard and Autant-Bernard 2015). Other contributions have focused on trade and FDI (Keller and Yeaple, 2009; Liang, 2017) and different measures of spatial, technological and product proximity (Keller, 2002; Bottazzi and Peri, 2002; Lychagin et al., 2016) providing evidence on the role of spillovers through network relations for local productivity. However, many of these forms of proximity interact conceptually and empirically with each other (Caragliu and Nijkamp 2015), which poses serious empirical problems with the identification and testing of these theories.

More surprisingly, the link of various proximities to regional economic growth appears not yet fully established. The number of empirical studies focused on comparing the relative importance of different types of network linkages for growth on the regional level is limited. However, there is a body of mature growth literature that conceptualizes research and development (R&D) and trade networks as mediating economic (productivity) growth (Jones 1995, Durlauf et al. 2001). Grossman and Helpman (1991), Coe and Helpman (1995) and Coe et al. (1997), among others, suggest that international trade may be considered a major diffusion vector of technological progress so that trade flows may proxy multi-country technological interactions. Indeed, as emphasized by Coe and Helpman (1995), the benefits from foreign R&D can be both direct and indirect. Direct benefits consist of learning about new technologies and materials, production processes, or organizational methods (Lychagin et al., 2016). Indirect benefits emanate from imports of goods and services that have been developed by trade partners (Ertur and Koch 2011). Although there is substantial evidence of this thesis on the country level, there is not much evidence on the regional level, often due to data restrictions on trade flow and R&D stocks. Notably, Thissen et al. (2016) present economic growth analyses based on European interregional trade patterns (at the NUTS 2 level in a selection of European regions). Capello and Lenzi (2015) investigate productivity gains across European regions; they omit trade relations as mediating networks but stress the role of interaction between knowledge intensities and absorptive capacities with the productivity of regional economies. Along with trade relations, co-inventorship and patent collaborations have been often used to investigate the dynamics of knowledge diffusion. Miguelez and Moreno (2015) show that external inflows of knowledge via copatenting and inventors' mobility are crucial for regional innovation performance, though their effects critically varies on the level of absorptive capacity. Ponds et al. (2007, 2010) and Hoekman et al. (2009) show that international knowledge relations may not be symmetrical in character. Less knowledge-endowed regions may profit from linking to better endowed regions (by cooperation, student exchange or subcontracting relations), while better endowed (also called elite regions) will benefit from linking with other elite regions for learning opportunities. Nonetheless, the consequences for productivity growth of all this suggested evidence on knowledge relations is not unambiguously clear.

Our research adds to the empirical literature on regional economic growth by combining several of these conceptualizations. This is the first paper to directly study the impact of trade, co-patenting and spatial relations vis-à-vis each other on regional productivity in Europe. Besides, given the unequal distribution of knowledge assets and innovating capabilities across regions, it can be expected that not all linkages are equally important for each and every region (Hoekman et al. 2009) and conditions for profiting from network relations may exist (Miguelez and Moreno, 2015). Based on these intuitions, we test whether linkages to most advanced regions provide a significant benefit for recipient[1] regions. The aim of this paper is three-fold. Firstly, we investigate in a spatial panel setting whether and how network relations affect local productivity, once the spatial dimension is accounted for. Secondly, we specifically model network relations with most knowledge and technologically advanced regions (Wintijes and Hoolanders, 2010; Cortinovis and Van Oort, 2015) to study whether such linkages provide stronger spillover effects. Thirdly, we test whether the stocks of absorptive capabilities of regions (on an educational level) act

[1] In the paper, we use the terms "linking-in", "connecting" and "recipient" regions as synonyms. These simply refer to regions which are "in touch", either via import or via co-patenting, with most innovative regions. These terms do not attribute any characteristic to the regions. For instance, a "recipient region" can be either a lagging region, an innovative follower or an innovation leader.

as preconditions for regions to profit (take in) from network relations with most advanced regions (Miguelez and Moreno, 2015; Cortinovis and Van Oort, 2015). Finally, we check validity of our potentially endogenous results within an instrumental variable framework, in which gross reproduction rate in European regions in 1930 and 1931 is used as an instrument for current R&D expenditures.

Interesting results emerge from our regional analysis. First, our results highlight that, even controlling for spatial effects in R&D spillovers and in the residuals, copatenting relations systematically affect local productivity directly. This suggests that international cooperation on patents may be considered an important diffusion vector of technological progress, resulting in higher levels of productivity. These conclusions are confirmed in our two-stage least squares (2SLS) regressions. Similarly, our instrumental variable regressions indicate a positive significant effect of trade relations on local productivity. Second, whereas the effects of copatenting-mediated R&D spillovers are not found to depend on local human capital, trade relations with most knowledge-endowed regions provide productivity advantages to recipient regions only when conditions of absorptive capacity are met. The analysis of local preconditions demonstrates that only regions with a significant amount of knowledge assets actually profit from relations with top innovators. At least with respect to trade relations, without interregional network linkages and strong absorptive capacity, spillovers will not occur. Instead, productivity advantages will boil down in only the most advanced and well-connected regions. This questions policy efforts to link catching-up European regions in terms of productivity (with currently low starting values in Eastern Europe and low growth rates in Southern Europe) by the introduction of smart specialization strategies (Foray 2015).

To reach these conclusions, we structure our paper as follows. The theoretical underpinnings of spatial and network spillovers are discussed and related to absorptive capacity and knowledge capabilities in advanced and linking regions in the second section of the paper. Based on the theoretical discussion, we pose two research questions and three testable hypotheses, followed by a discussion on the models, methods and data sources used in the empirical analysis in the third part of the paper. The results of our econometric exercises are reviewed and interpreted in the fourth section of the paper. The final section is devoted to the discussion of policy and research implications related to our findings.

## 2. Theoretical framework: knowledge spillovers, absorptive capacity and linkages to advanced regions

*Localized knowledge and spatial spillovers*

Since the emergence of endogenous growth theory (Romer 1986, Lucas 1988), the role of knowledge resources has been at the center of the process of economic growth. As noted by Grossman and Helpman (1994), the accumulation of both physical (technology and machinery) and human capital (knowledge and skills) by an individual contributes to improving the productivity of other individuals in the economy. In other words, investment and resources in part spill over to other actors.

The idea of spillovers has been widely studied by economists and geographers, especially in relation to agglomeration economies and knowledge flows across space. Since the work by Marshall (1920), it has been well accepted that firms benefit in different ways from being located close to other firms. Agglomeration economies literature usually considers Marshall-type knowledge spillovers as intra-sectoral — i.e. they can be exploited only by firms in the same industry—. Differently, Jane Jacobs (1969) suggests that knowledge externalities mostly emerge from the cross-fertilization of ideas and competences from different sectors. In her original work (1969), built on by Glaeser et al. (1992), a recombination of knowledge is the key behind the higher prosperity and faster growth of cities. Regardless of whether they come from a firm in the same sector or emerge from knowledge recombination in a diversified urban environment, these spillovers are inherently localized, not spanning further than what face-to-face interactions allow (Breschi and Lissoni 2001). Precisely because of their localized nature, knowledge externalities can explain the emergence and persistence of spatial disparities in development and economic performance (Capello 2009, Lissoni and Miguelez 2014).

It is thus not surprising that the spatial dimension of knowledge spillovers has received significant attention in economic geography and regional studies. In their seminal work, Jaffe et al. (1993) demonstrate the geographically bound character of knowledge, showing that patent citations occur more likely within the same state and metropolitan area of the original patent. However, especially since the development of spatial econometric tools, different studies have demonstrated that spillovers do not stop at the administrative borders of a country or region (Dall'Erba and Le Gallo 2008, Arbia et al. 2010, Caragliu and Nijkamp 2015). In this sense, knowledge exchanges occur across the borders of cities and clusters, even though they are facilitated by geographical proximity and subject to distance decay (Lissoni and Miguelez 2014). Empirical research has provided significant evidence in these respects, even estimating the range within which spillovers can be expected. Bottazzi and Peri (2002) show that within Europe, knowledge externalities have a significant impact within a range of 200-300 km, dying out once this distance threshold is crossed. Similarly, Crescenzi and Rodriguez-Pose (2011) find evidence of knowledge exchange within a range of a three-hour drive but not further than that. Works by Greunz (2003) and Moreno et al. (2005) find significant effects of knowledge spillover within comparable distance ranges.

Due to the lower costs and the greater probability of meeting and having face-to-face interactions, spatial proximity is generally considered a critical element in facilitating knowledge transmission. In spite of such solid evidence, the role of geographical proximity with respect to knowledge flows has also been subject to different critiques (Capello 2009, Boschma 2005).

*Network-mediated knowledge spillovers*

Even if the process of knowledge diffusion across space is negatively affected by geography (distance decay), it is still possible to exchange knowledge assets across longer distances. In these respects, different studies have highlighted how trade (Hausman et al. 2007, Coe and Helpman 1995, 2009), investment flows (Iammarino and McCann 2013; Keller and Yeaple, 2009), co-patenting (Maggioni et al. 2007, Breschi and Lissoni 2009; Lychagin et al., 2016) and migration (Lissoni 2016; Hornung, 2010) networks work as channels for knowledge diffusion. Contrary to what traditional agglomeration theories suggest, knowledge can travel longer—at least when embodied in flows of people, capital or objects within certain networks.

The idea of socio-economic linkages as infrastructure allowing knowledge diffusion within localities, across space, among specific actors or in the broader community is certainly not new (Granovetter 1973, Conly et al. 2002, Akerlof 1997, Camagni, 1991, Morrison and Rabelotti 2009, Bathelt et al. 2004). Within an evolutionary economic geography framework, Boschma (2005) offers a general critique of the role of spatial proximity as the major catalyst for knowledge spillovers, suggesting that along with spatial closeness, other forms of proximity may facilitate knowledge spillovers. In this sense, cognitive, social, organizational and institutional proximity strongly affect the possibility to learn, absorb and make use of external knowledge assets. Connections with cognitively similar actors, even if located far away, can provide access to valuable information (Nooteboom 1992, Frenken et al. 2007).

Similarly, Bathelt et al. (2004) suggest the existence of global pipelines through which knowledge can flow from one place to the other. Combining a good quality of local "buzz" with many outward directed pipelines, some firms and clusters may acquire important resources and advantages over competitors. More recently, Huggins et al. (2012) and Huggins and Thompson (2014) have developed the concept of "network capital" to account for the effect of inter-organizational relations within an endogenous growth framework. The concept of network capital then establishes a tight conceptual link between local economic performance and the ability to access economically valuable knowledge through network relations. While conceptualizing the potential impact of networks in terms of growth, these contributions are agnostic with respect to what type of relations network capital can be built on. However, empirical research has already highlighted potential channels for network-mediated spillovers.

The links among international trade, innovation and growth have long been studied (Fagerberg 1988, Romer 1986). While technological and knowledge transfers are not automatic in trade relations, international economists have realized how trade connections can give access to relevant cognitive resources (Grossman and Helpman 1994). Coe and Helpman (1995) provide theoretical arguments establishing the link between international trade and R&D spillovers. Based on the idea that most international trade is in intermediate goods, the importing economy can increase its production thanks to the technological progress and innovation from trading partners.

As foreign R&D is incorporated into foreign goods, imports can complement local R&D expenditures, so local productivity is positively affected by foreign R&D. Empirical evidence on these mechanisms has confirmed the beneficial effect of import-mediated foreign R&D across countries (Coe and Helpman 1995, Coe et al. 2009, Fracasso and Vitucci Marzetti 2015): expenditures in research and development by trading partners contribute to local productivity. Within a regional perspective, Thissen et al. (2016) have recently demonstrated the relevance of trade networks for European regions, showing that trade relations can explain sectoral growth in productivity across EU regions.

Following Boschma (2005), different empirical studies have investigated the role of knowledge diffusion of different proximities. While geographical closeness facilitates the acquisition of new knowledge, other forms of proximity seem to act as conditioning factors (Caragliu and Nijkamp 2015, Paci et al. 2014, Morrison and Rabellotti 2009). Among the different sources of proximity, co-patenting and collaborative relations among inventors—used as a proxy for relational closeness—are of large hypothesized importance (Maggioni et al. 2007, Maggioni and Uberti 2009; Miguelez and Moreno, 2015). The conceptual link between co-patenting networks and knowledge spillovers is rather straightforward. Co-patenting is a process that involves a substantial and successful exchange of knowledge between individuals, which leads to the acquisition of a patent. By taking part in processes of collective learning based on knowledge sharing, local actors have the opportunity to acquire fresh knowledge that has originated elsewhere and bring it to the local context. While this has a direct effect on the local performance through innovation and eventually growth (Caragliu and Nijkamp 2015), connections to external sources of knowledge might increase the quality and value of the "local buzz" (Bathelt et al. 2004). However, the importance of being part of a collaboration network has mostly been assessed with respect to local innovation performance. Maggioni et al. (2007), Ponds et al. (2010) and Hoekman et al. (2009) indicate that while social network relations in terms of scientific collaborations matter, they might have a smaller effect than spatial proximity. Basile et al. (2012) reach similar conclusions, demonstrating the synergic effects between spatial and relational/social proximities. Generally speaking, empirical evidence shows that firms and regions engaging in cooperation are usually better able to access and benefit from new sources of knowledge, thus becoming more innovative and competitive (Ozman 2009, Hoekman et al. 2009).

In this short discussion of the literature on spillovers, three main channels for the transmission of knowledge have been identified. The literature on agglomeration economies strongly focuses on the spatial dimension of knowledge spillovers, stressing their localized nature (Lissoni and Miguelez 2014; Bottazzi and Peri, 2002; Keller, 2002). Alternatively, studies on growth and international trade suggest that through imports, local actors can acquire and capitalize on knowledge that has originated elsewhere (Coe and Helpman 1995; Keller and Yeaple, 2009). Finally, scientists in the field of geography of innovation claim coinventorship and copatenting relations, as a form of relational proximity (Boschma, 2005), affect local economic performance. Supportive, but sometimes suggestive, empirical evidence has been produced for each of these channels individually. However, only a few attempts have been made to analyze these contributions vis-à-vis one another. As the influence of space and network affect the regional economy concurrently, we formulate the first research question that we will address in this paper:

RQ 1: *Once spatial proximity is controlled for, do networked trade and networked co-patenting relations affect regional productivity and is any of these two channels more relevant than the other?*

<u>*Origin of knowledge and absorptive capacity of the recipient*</u>

While significant attention has been devoted to understanding whether knowledge externalities really exist, less attention has been paid to the characteristics of the parties involved in the knowledge exchange and especially to the features of organization or the place from which the knowledge originates. Most country-level (Grossman and Helpman 1990, Coe and Helpman 1995, 2009) and regional studies (Caragliu and Nijkamp 2015, Basile et al. 2012, Paci et al. 2014, Greunz 2003) assume that regardless of whether knowledge spillovers originate from a highly advanced economy or a more backward one, the inflow of knowledge outside-in will be equally beneficial. A potential reason for this is the focus on redundancy of information. Because knowledge is, at least to a certain extent, spatially bound, knowledge that has originated elsewhere is by definition not redundant and thus is new and potentially useful for local actors. However, while some studies highlight the tradeoff between redundancy and cognitive distance (Frenken et al., 2007; Hidalgo et al., 2007), it is still unclear whether connections to actors and organizations at the technological frontier are more beneficial than relations with technological followers or laggards.

This concern is partially addressed by the concept of network capital, which is directly linked to the ability to "access and subsequently utilize appropriate economically beneficial knowledge" (Huggings and Thompson, 2014, p. 532). The links among economically valuable knowledge, network relations and local performance suggest that linkages to most advanced economies, which embody most valuable knowledge, should provide access to potentially groundbreaking know-how and thus imply particular benefits for linking (firms and sectors in) regions. The international business literature has also addressed this issue, showing that whereas spillovers to domestic firms are influenced by certain factors on the "input" side (origin of the multinational, type of industry, mode and reason for entry), the positive, neutral or negative nature of the externalities largely depends on local conditions, especially absorptive capacity (Crespo and Fontoura 2007, Fu et al. 2011, Morrison et al. 2013). Keller (2002) also investigates this issue at country level, finding a positive relation between productivity in the other OECD and spatial R&D spillovers from five innovation leaders: Japan, USA, UK, France and Germany.

Unlike the discussion of the source of knowledge, different contributions have shown that some preconditions are necessary for the recipient to benefit from knowledge externalities (Abreu et al. 2004). In their seminal paper, Cohen and Levinthal (1990) introduce the concept of the absorptive capacity of firms. The main intuition behind this concept is that to make use and take advantage of new knowledge, firms must have the ability to access, evaluate and assimilate it. This ability, in turn, mostly depends on the amount of prior related knowledge that the firm has (Cohen and Levinthal 1990). In other words, only firms with a high stock of knowledge, cognitively similar to the content of the spillovers, are able to internalize and take advantage of such externalities (Knoben et al. 2016). Similar to firms, for regions and countries, preconditions determine whether knowledge spillovers can translate into innovation and growth (Benhabib and Spiegel 2005, Nelson and Phelps 2006, Caragliu and Nijkamp, 2008). If larger stocks of knowledge and human capital improve the possibility to learn and absorb new information, a good endowment of these resources is necessary to profit from spillovers. While this is the case for agglomeration externalities within the boundaries of the local economy (Cortinovis and Van Oort, 2015), similar arguments also hold for cross-border spillovers and knowledge exchanges (Caragliu and Nijkamp 2008, Beugelsdijk et al. 2008). In particular, Miguelez and Moreno (2015) show how higher levels of absorptive capacity (proxied by R&D expenditure) enhance the effect of inward inventors' relations and movements on the innovative performance of regions.

Bringing together the issues concerning the characteristics of the source of knowledge spillovers and the absorptive capacity of the potential recipient, it can be argued that different knowledge sources produce knowledge spillovers of different qualities. Assuming that most valuable knowledge is present in most advanced regions, connections to most knowledge-endowed places may provide substantial advantages to regions vis-à-vis their competitors. At the same time, as most advanced knowledge may be particularly complex and require specific skills and competences (Balland and Rigby, 2015; Miguelez and Moreno, 2015), a larger absorptive capacity is needed to assimilate knowledge spillovers. On these bases, we put forward our second research question:

RQ 2: *Do relations to most advanced regions provide a particular advantage for in-linking regions for regional productivity, and are absorptive capacities necessary to substantiate these benefits?*

Research hypotheses

The relationship between knowledge spillovers and economic performance has been studied in different streams of economic research. Analyses in regional economics have the merit of highlighting the importance of spatial proximity (Gleaser et al. 1992, Henderson 1995, Frenken et al. 2007) and, more recently, of assessing the role of various other forms of proximity (Greunz 2003, Paci et al. 2014, Caragliu and Nijkamp 2015). However, these studies have largely overlooked the role of trade linkages as channels for knowledge spillovers, with the notable exceptions of Boschma and Iammarino (2009) and Thissen et al. (2016). On the other side, studies in the international R&D spillover literature ignore the sub-national territorial dimension and almost exclusively focus on spillovers mediated by trade (Coe and Helpman 1995, Coe et al. 2009, Fracasso and Vitucci Marzetti 2015) and FDI relations (Cipollina et al. 2012, Beugelsdijk et al. 2008, Gorodnichenko et al. 2014; Keller and Yeaple, 2009). In addition, while different studies discuss the importance of absorptive capacity for an economy to benefit from knowledge spillovers, the effect of spillovers from particularly advanced regions to recipient regions has received little attention.

Based on the two research questions presented above, we put forward the following three hypotheses. First, as discussed in the theoretical section, spatial proximity might not be the only relevant dimension through which knowledge spillovers may occur. Generally speaking, our hypotheses suggest a positive relation between network-mediated R&D spillovers and local productivity. Following Coe and Helpman (1995, 2009), we theorize that regions can access new knowledge assets through trade relations, especially via the import of goods. Similarly, in light of the debate on different sources of proximity (Boschma 2005, Breschi and Lissoni 2009, Maggioni and Uberti 2009, Maggioni et al. 2007), we expect that intense co-patenting cooperation, as a proxy for relational proximity, will lead to substantial knowledge spillovers, thus having a positive effect on regional productivity.

<u>Hypothesis 1a</u>: *The level of productivity in region* R *is positively related to the level of R&D in regions from which R imports.*

<u>Hypothesis 1b</u>: *The level of productivity in region* R *is positively related to the level of R&D in regions which R patents with.*

To address our second research question, a third set of hypotheses specifically takes into account the relations with regions that are at the forefront in terms of innovation. Given the great amount of knowledge resources that most advanced regions are bound to have, being connected via import or co-patenting relations with top innovators may provide privileged access to highly valuable knowledge regardless of the type of connecting regions (innovation laggard, follower or leader).

Hypothesis 2a: *The positive relation between the level of productivity in region* R *and the level of R&D in regions which R import from is stronger, if the trade partner regions are innovation leaders.*

Hypothesis 2b: *The positive relation between the level of productivity in region* R *and the level of R&D in regions which R patents with is stronger, if the copatenting partner regions are innovation leaders.*

Finally, given the potential conditioning role of absorptive capacity (Cohen and Levinthal, 1990), we expect that regions with higher levels of human capital will be better able to profit from highly advanced knowledge spilling over through trade and co-patenting networks.

Hypothesis 3: *The positive relation between the level of productivity in region* R *and the R&D spillovers from trade and copatenting with highly advanced partners is conditional on higher level of absorptive capacity.*

## 3. Modeling, methodology and data sources

We model the level of productivity[2] in region *r* as a function of its own R&D expenses and the R&D of its neighbors and partners, weighted by import and co-patenting intensity. Unlike in previous studies (Coe and Helpman 1995, 2009, Maggioni et al. 2007), we study the effects of spillovers deriving from two different network channels simultaneously and extensively controlling for spatial effects. To test the three hypotheses put forward in the previous section, the relation between the dependent variable and our variables of interest is expressed through three panel data model specifications.

[2] The choice of studying regional productivity levels rather than growth is made in consideration of the economic recession characterizing the period of analysis and the limited number of years available in our sample. This choice is not uncommon in the literature, as in the case of Coe and Helpman (1995), Coe et al. (2009), and Fracasso and Vitucci-Marzetti (2015).

The baseline model, reported in Equation 1, is used to estimate the impact of spatial spillovers on the level of regional productivity (Hypothesis 1a and 1b):

$$log\_TFP_{r,t} = \alpha_r + \tau_t + \beta logR\&D_{r,t-1} + \delta \boldsymbol{W} logR\&D_{r,t-1} + \delta \boldsymbol{T} logR\&D_{r,t-1} + \delta \boldsymbol{P} logR\&D_{r,t-1} + \gamma Controls_{r,t-1} + \lambda\, \boldsymbol{W} \varepsilon_{r,t} + u_{r,t}, \quad (1)$$

where $log\_TFP_{r,t}$ represents the level of total factor productivity in region *r* at time *t* (in logs) and $\boldsymbol{W}logR\&D_{r,t-1}$ is the distance-weighted per capita R&D, $\boldsymbol{T}logR\&D_{r,t-1}$ captures the import-mediated spillovers, and $\boldsymbol{P}logR\&D_{r,t-1}$refers to copatenting-mediated effects. In order to fully control for spatial dependence, the error terms is split in a spatially lagged term ($\lambda\, \boldsymbol{W}\varepsilon_{r,t}$) and in the residuals ($u_{r,t}$). Finally, $\alpha_r$ and $\tau_t$ represent the cross-sectional and time fixed effects.

Hypotheses 2a and 2b consider the heterogeneity in the effects due to relations with most knowledge-endowed regions. To capture the potential spillovers deriving from network relations with technological leaders, we compute two new variables, $\boldsymbol{TE}logR\&D_{r,t}$ and $\boldsymbol{PE}logR\&D_{r,t}$, which account for only the directional trade and co-patenting linkages from the most advanced regions to linking-in regions[3]. To guarantee some degree of heterogeneity, we decide not to apply the same transformation to $\boldsymbol{W}logR\&D_{r,t}$ . In Equation 3, the terms $\boldsymbol{T}logR\&D_{r,t}$ and $\boldsymbol{P}logR\&D_{r,t}$ are substituted by the newly computed variables ($\boldsymbol{TE}logR\&D_{r,t}$ and $\boldsymbol{PE}logR\&D_{r,t}$).

$$log\_TFP_{r,t} = \alpha_r + \tau_t + \beta logR\&D_{r,t-1} + \delta \boldsymbol{W} logR\&D_{r,t-1} + \delta \boldsymbol{TE} logR\&D_{r,t-1} + \delta \boldsymbol{PE} logR\&D_{r,t-1} + \gamma Controls_{r,t-1} + \lambda\, \boldsymbol{W} \varepsilon_{r,t} + u_{r,t}, \quad (2)$$

In the last specification, we introduce a term interacting the import-weighted (or co-patenting-weighted[4]) level of R&D from most advanced regions, with the level of human capital in the region $Ter\_HK_{r,t}$. In this way, we can consider whether stronger capabilities are required to profit from relations to most technological leaders, as we

[3] As mentioned above, linking-in regions may of any type, i.e., other advanced regions, innovation followers, or less developed areas.
[4] For sake of brevity, only the model referring to import relations is reported in Equation 4.

theorize in Hypothesis 3. However, the concurrent presence of the two interaction terms and of their components ( $\boldsymbol{PE}logR\&D_{r,t}$ , $\boldsymbol{TE}logR\&D_{r,t}$ and $Ter\_HK_{r,t}$ ) suggests caution in proceeding with a joint estimation due to collinearity issues. We therefore decide to estimate the models for import-mediated and co-patenting-mediated externalities individually.

$$log\_TFP_{r,t} = \alpha_r + \tau_t + \beta logR\&D_{r,t-1} + \delta \boldsymbol{W} logR\&D_{r,t-1} + \delta \boldsymbol{TE} logR\&D_{r,t-1} + \delta \boldsymbol{PE} logR\&D_{r,t-1} + \varphi \boldsymbol{TE} logR\&D_{r,t-1} * Ter\_HK_{r,t-1} + \gamma Controls_{r,t-1} + \lambda \, \boldsymbol{W} \varepsilon_{r,t} + u_{r,t}, \tag{3}$$

<u>*Construction of the weight matrices*</u>

To perform our analysis, the crucial step is to construct the weight matrices to track the intensity of the relations between regional economies. Based on the review of the literature, we identify two main channels of interest, namely, trade and co-patentingm and one channels for which would be necessary to control for (i.e., space). As Ertur and Koch (2011, p.236) state, "various weights matrices based on geographical space have thus been used in the spatial econometric literature, such as contiguity, nearest neighbors and geographical distance-based matrices. However the definition is in fact much broader and can be generalized to any network structure to reflect any kind of interactions between observations".

Starting from geographical relations, the literature on spatial knowledge spillovers suggests that knowledge exchanges usually take place within boundaries of 200-300 km (Bottazzi and Peri 2002, Crescenzi and Rodriguez-Pose 2011). To ensure the capture of most knowledge flows across space, we follow the spatial econometrics literature (Elhorst 2014, LeSage 2014) and construct spatial matrix **W**, using Eurostat geographical data, on the basis of the following rule:

$$\boldsymbol{W}_{i,j} = \begin{cases} d_{ij}^{-1}, if \ 0 < d_{ij} \leq d \\ 0, otherwise \end{cases} \tag{4}$$

In Equation 4, $d_{ij}$ represents the distance between the centroids of regions $i$ and $j$, while $d$ represents the threshold of maximum distance we allow for. In other words, for every region, we define as spatially related and thus potentially as source of knowledge spillovers regions located within a 300 km radius. Additionally, to account for the fact that greater distances reduce knowledge exchanges, the entries in the spatial matrix will take the value of the inverse of the distance between the neighboring regional centroids (Elhorst, 2014). Finally, as is customary in spatial econometrics (LeSage and Pace 2009), the spatial matrix is row-standardized.

While a significant amount of work has been performed using spatial weight matrices, a number of concerns emerge when addressing a-spatial relational matrices, despite the citation of Ertur and Koch (2011). First, while spatial distances are fixed in time and clearly exogenous with respect to economic dynamics, non-spatial relations based on trade and co-patenting are not. It can be argued, for instance, that two well-performing economies are able to engage and cooperate more in trade and patenting so that an increasing intensity of network relations is brought about by better economic performance, rather than the other way around. In other words, there is a significant risk of running into reverse causality and endogeneity problems. Second, one of the main reasons why geographical distance has been successfully used in the literature is that greater distances are associated with higher costs. For this reason, trade, co-patenting and virtually all types of human interactions are to some extent subject to distance decay, so it can be expected that geographically proximate regions will also trade and co-patent more with one another (Abreu et al. 2004). We construct our import and co-patenting matrices bearing in mind these two concerns.

Following Coe and Helpman (1995), we want to use the intensity of import relations between each pair of European regions to account for import-related knowledge spillovers. To this aim, we use the data provided by Planbureau voor de Leefomgeving (PBL) and used by Thissen et al. (2016). This dataset provides information on the trade flows in intermediate goods between most European regions in the 2000-2010 period for six main sectors (for a technical description, see Thissen et al. 2014a, 2014b). When building our import intensity matrix, we limit the concerns for potential endogeneity between trade intensity and economic performance in the following ways. First, we consider only import data on years that are antecedent to the period considered in our study to ensure that the intensity in trade is not driven by regional performance. Second, as single-year trade flows may not offer an accurate picture as for import intensity, we approximate a measure of import stock by summing different yearly import flows. The import matrix used in our analysis is thus based on the pairwise sum of imports in intermediate goods for the 2000-2003 period.

$$\boldsymbol{T}_{i,j} = \frac{I\_2000\_2003_{ij}}{\sum_r I\_2000\_2003_{ij}} \tag{5}$$

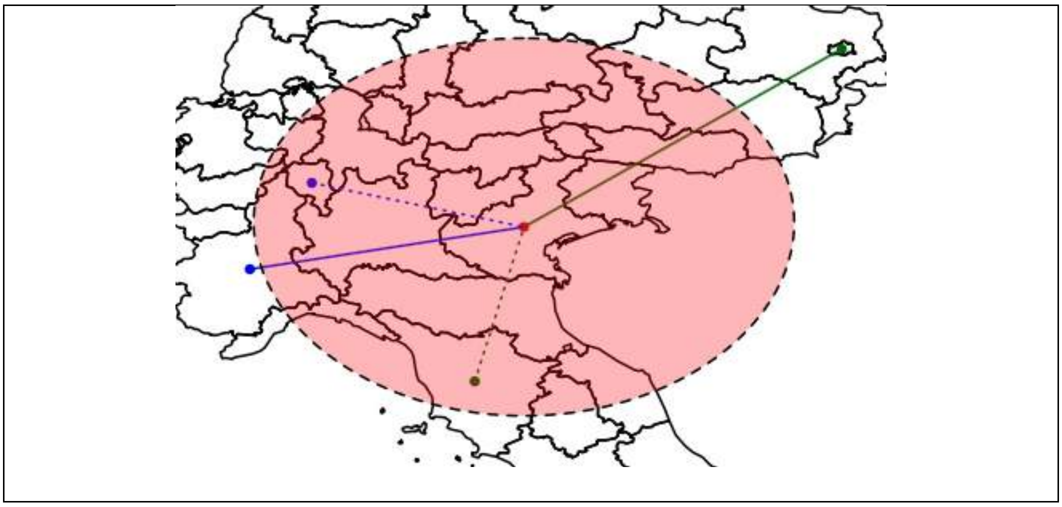
In Equation 5, $I\_2000\_2003_{i,j}$ is the value at constant prices of imports in intermediate goods that region *i* imported from region *j* between 2000 and 2003. In order to exploit the broad sectoral categories offered by the data, the same equation is applied to intermediate goods in more advanced sectors (matrix **A** below) encompassing chemicals, petroleum, electronics, etc., and less advanced ones (matrix **L** below), which refers to imports of intermediate goods in agriculture, leather, food and beverages industries. As for the **W** matrix, we row-standardize the trade matrix.

Following a significant amount of literature in the field, we use patent collaboration as a way to track relational proximity across regions. The matrix **P** is constructed using the OECD REGPAT database, which contains detailed information on patent cooperation between inventors residing in different regions. From the raw data, only information on copatenting relations involving more than one European region between 1988 and 2003 is used. An equal share of each of these patents is allocated across the different inventors, before aggregating such information from inventor-level to regional level. Regionalized information on co-patents is then used to compute a weight matrix as shown in Equation 6.

$$\boldsymbol{P}_{i,j} = \frac{share\_pat\_1988\_2003_{ij}}{\sum_r share\_pat\_1988\_2003_{ij}} \tag{6}$$

As in the case of trade, we use information on the years before 2004 to reduce the concern regarding reverse causality. It should be noted that given the focus on inventors' collaboration, unlike the import matrix, our co-patenting matrix is symmetric. Finally, as for the spatial and import matrices, the co-patenting matrix is row-standardized.

Figure 1: Spatial and network relations in region **R**



In addition to concerns regarding endogeneity, a second issue we consider is the overlap between spatial proximity and other channels of knowledge transmission, due to the fact that trade and co-patenting relations are facilitated when actors are located physically close to one another (Caragliu and Nijkamp 2015). Figure 1 (below) provides a graphical representation of the problem at stake. In the hypothetical example of Veneto region (**R**) in Italy, the spatial matrix captures the regions falling within a 300-km threshold (shaded in red). At the same time, some of the regions are also linked to **R** through networks (e.g., the green and the blue links). Such overlap between the different matrices creates two main problems: (i) including spatially proximate regions in the a-spatial matrices would not reflect the "pure" effects of R&D spillovers, and (ii) the spatial and a-spatial matrices would then be correlated, potentially making the simultaneous inclusion of spatially and network-weighted variables problematic from a statistical point of view.

The previous literature has dealt with this issue in different ways, for instance combining the different matrices in one (Hazir et al. 2014) or setting to zero the entries for the cells in the network matrices that have non-zero values in the spatial matrix (Maggioni et al., 2007). A closer inspection to our data however provide reassuring evidence. As reported in Table 1, the highest average row-wise correlation (49%) between the weight matrices is found between the spatial matrix **W** and the copatenting matrix **P**. Even in this case, however, the correlation does not appear to be particularly worrisome.

| Table 1: Row-wise correlation among weight matrices | | | | | | | |
|---|---|---|---|---|---|---|---|
| | W-T | W-A | W-L | W-P | T-P | A-P | L-P |
| **Min.** | -0.06183 | -0.11556 | -0.02039 | -0.04347 | -0.0217 | -0.04258 | -0.02246 |
| **1st Quart.** | 0.08422 | -0.01285 | 0.26642 | 0.34333 | 0.1279 | 0.0346 | 0.26364 |
| **Median** | 0.19771 | 0.07265 | 0.41972 | 0.52198 | 0.2326 | 0.1314 | 0.41942 |
| **Mean** | 0.23825 | 0.11435 | 0.41659 | 0.48778 | 0.2815 | 0.17641 | 0.42233 |
| **3rd Quart.** | 0.37167 | 0.20059 | 0.58147 | 0.66504 | 0.4114 | 0.27169 | 0.58681 |
| **Max** | 0.80552 | 0.68881 | 0.91811 | 0.98005 | 0.9222 | 0.9253 | 0.99516 |

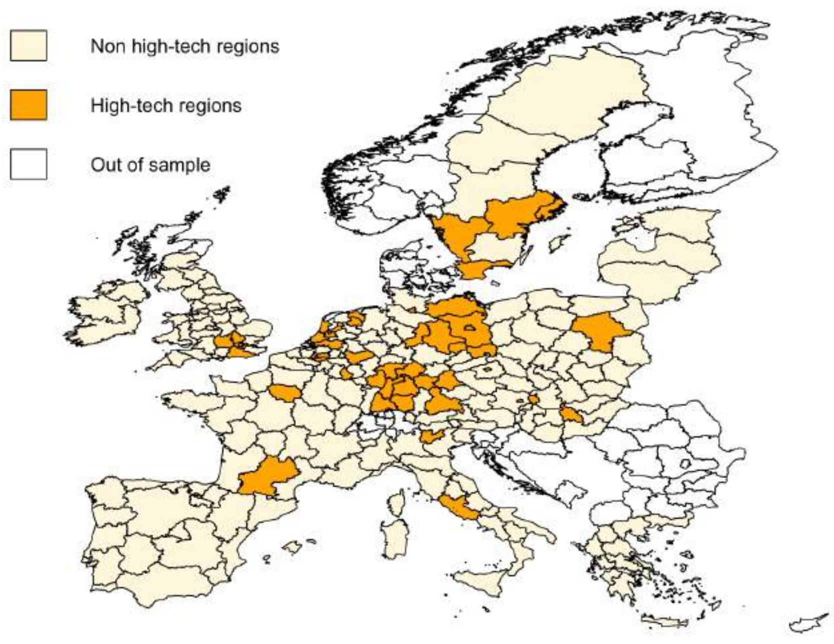
Finally, our last two sets of hypotheses consider the case of relations with top regions, from which we hypothesize a greater quantity and better quality of spillovers can be obtained. Cortinovis and Van Oort (2015) divided regions in three technological regimes (Table 2) on the basis of a previous classification by Wintijes and Hollanders

| Table 2: Technological regimes and types of regions (Cortinovis and Van Oort, 2015) | | |
|---|---|---|
| *Technological Regimes* | *Type of Region* | *Features* |
| High technological regime | Metropolitan knowledge-intensive services regions | High absorption capacity |
| | Public knowledge centers | High accessibility |
| | High-tech regions | High diffusion, accessibility and absorption capacity |
| Medium technological regime | Knowledge-absorbing regions<br>Skilled technology regions | Average performance in diffusion, accessibility and absorption capacity |
| Low technological regime | Traditional Southern regions | Below average in diffusion, accessibility and absorption capacity |
| | Skilled industrial Eastern EU regions | Below average in diffusion and absorption capacity |

(2011). We follow the same approach to identify the regions with higher knowledge and technological endowment, by considering regions in our sample belonging to the "high technological regime" as areas particularly rich in knowledge and technologies.

Figure 2 represents the geographical distribution of regions categorized as "high technological regime" (orange). Most of advanced regions are located in the core of Europe, between Southeast England and German Bayern, the Netherlands and in Scandinavian countries. Nonetheless, regions from Eastern (Warsaw, Budapest, Prague) and Southern Europe (Rome and Lisbon) are also part of the advanced regime, especially for their high score in knowledge accessibility (Wintijes and Hollanders, 2011).

Figure 2: Classification of EU regions in terms of innovation performance




*Data and sources*

In addition to the data provided Eurostat for the spatial matrix and PBL for trade flows and the OECD REGPAT for the co-patenting matrix, we construct our database using information from Cambridge Econometrics (CE) and Eurostat. More precisely, we estimate our dependent variable - the regional level of Total Factor Productivity (TFP - *tfp (log)*) - by taking the residuals from the following model:

$$log\_GVApc_{r,t} = \alpha_r + \tau_t + \beta * worked\_hours_{r,t} + \gamma * K\_investment_{r,t} + \varepsilon_{r,t}. \quad (7)$$

In the model above, the number of hours worked per capita ($worked\_hours_{r,t}$) captures the amount of labour employed in region $r$ at time $t$. Besides, following Beugelsdijk et al. (2015), we estimate the stock of capital ($K\_investment_{r,t}$), starting from gross fixed capital formation and applying the permanent inventory method. As shown in Equations 1 to 3, the lagged value of *tfp (log)* enters as regressor in the model.

Our main variables of interest are the level of R&D of each region as well as the spatially and network-weighted levels of R&D. As for the former, Eurostat provides information the level of R&D in each region. We therefore use the log of R&D per capita in PPS (*R&D pc (log)*) to construct our other main explanatory variables. More precisely, as spatially and network-weighted measures of R&D, which we use as a proxy for knowledge spillovers, we interact the row-standardized weight matrices with the vector of *R&D pc (log)*. Equation 8 shows the formula for the spatially weighted R&D level, and we apply the same procedure for matrices **T**, **P**, **TE** and **PE**.

$$\boldsymbol{W} logR\&D_{r,t} = \boldsymbol{W}* \ logR\&D_{r,t}. \tag{8}$$

In addition to these explanatory variables, we include different control variables ($Controls_{r,t}$ in Equations 1-3). Based on data from Eurostat, *US HK* and *Te HK* measure the share of the workforce with upper-secondary and tertiary education to control for the levels and quality of human capital endowment within each region. Additionally, when testing Hypothesis 3, *Te HK* interacts with ***TE**logR&D* and ***PE**logR&D*[5]. We include in all specifications three more control variables computed from the CE database. As is customary in the literature on agglomeration economies, we include a measure of population density (*Popd (log)*) to control for the heterogeneity between highly urbanized and rural areas. We also include a variable approximating[6] the stock of foreign population in the region (*Migr (log)*), in order to partially control for migration, another important channel of knowledge diffusion (Breschi and Lissoni, 2009; Miguelez and Moreno, 2015; Hornung, 2010).

In conclusion, our dataset contains information on 233 European regions at the NUTS 2 level, for a period of 9 years (2004-2012). Because our dataset has been built using different data sources, some regions and countries cannot be included in the analysis. While most of EU-27 regions regions are included, a lack of data on trade flows and co-patenting forces us to exclude Danish, Finnish, Bulgarian and Romanian regions.

[5]Both *Ter HK* and the weighted measures of R&D are mean-centered before estimating Equation 4.
[6] Eurostat does not provide information on foreign population at regional level. In order to overcome this issue we took the foreign population at country level and redistribute it according to the share of national population accruing to each region.

Additionally, because network data are not regionalized for Slovenia, we must use information on the whole country.

Tables 3 and 4 report the summary statistics and the correlation across the variable included in the models. While most of the cells in Table 2 have the expected magnitude and size, some of the correlation scores are especially interesting. In particular, the correlation between the levels of R&D at local, space-mediated and network-mediated levels are relatively strong. This suggests that regions investing in research and development tend to be proximate, in a geographical and network sense, with other innovation-oriented regions. The exception in these respects is represented by TI-R&D, which is uncorrelated with the local level of R&D expenditures; this suggests that not only advanced regions but also less developed areas are connected via trade to top innovators, allowing the acquisition of top-notch knowledge.

Table 3: Descriptives statistics

| VARIABLES | N | mean | sd | min | max |
|---|---|---|---|---|---|
| tfp (log) (*) | 1,864 | -0.0473 | 0.979 | -2.857 | 2.012 |
| migr (log)(*) | 1,864 | -0.00379 | 1.012 | -3.519 | 1.911 |
| pop_density (log) (*) | 1,864 | 0.0517 | 0.95 | -3.269 | 3.469 |
| US_HK(*) | 1,864 | 0.0069 | 1.012 | -2.686 | 2.558 |
| Te_HK(*) | 1,864 | -0.0682 | 0.979 | -2.147 | 5.084 |
| R&D pc (log) | 1,864 | -0.0346 | 1.01 | -3.591 | 2.2 |
| W-R&D pc (log) | 1,864 | 0.00953 | 0.684 | -2.234 | 1.445 |
| T-R&D pc (log) | 1,864 | 0.632 | 0.268 | -0.575 | 1.093 |
| P-R&D pc (log) | 1,864 | 0.643 | 0.409 | -1.011 | 1.561 |
| L-R&D pc (log) | 1,864 | 0.323 | 0.424 | -1.032 | 1.105 |
| A-R&D pc (log) | 1,864 | 0.708 | 0.22 | -0.108 | 1.187 |
| TI-R&D pc (log) | 1,864 | 1.045 | 0.108 | 0.707 | 1.385 |
| PI-R&D pc (log) | 1,864 | 1.108 | 0.311 | 0 | 1.781 |
| LI-R&D pc (log) | 1,864 | 0.962 | 0.14 | 0.296 | 1.299 |
| AI-R&D pc (log) | 1,864 | 1.069 | 0.112 | 0.727 | 1.494 |
| TE-R&D pc (log) | 1,864 | 1.321 | 0.0995 | 0.908 | 1.58 |
| PE-R&D pc (log) | 1,864 | 1.136 | 0.376 | -0.24 | 1.797 |
| LE-R&D pc (log) | 1,864 | 1.178 | 0.168 | 0.455 | 1.554 |
| AE-R&D pc (log) | 1,864 | 1.341 | 0.11 | 0.858 | 1.655 |

| | | | | | |
|---|---|---|---|---|---|
| Number of regions | 233 | 233 | 233 | 233 | 233 |

Data refer to already lagged variables. (*) refers to standardize variables.

able 4: Correlation matrix

| | | a | b | c | d | e | f | g | h | i | j | k | l | m | n | o | p | q | r |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| p (log) | **a** | 1 | | | | | | | | | | | | | | | | | |
| op_density | **b** | 0.32 | 1 | | | | | | | | | | | | | | | | |
| 'S_HK | **c** | -0.34 | -0.04 | 1 | | | | | | | | | | | | | | | |
| e_HK | **d** | 0.45 | 0.37 | -0.3 | 1 | | | | | | | | | | | | | | |
| ıigr (log) | **e** | 0.5 | 0.46 | -0.04 | 0.38 | 1 | | | | | | | | | | | | | |
| &D pc (log) | **f** | 0.7 | 0.4 | -0.09 | 0.5 | 0.56 | 1 | | | | | | | | | | | | |
| /-R&D pc (log) | **g** | 0.74 | 0.2 | -0.01 | 0.31 | 0.4 | 0.63 | 1 | | | | | | | | | | | |
| -R&D pc (log) | **h** | 0.48 | 0.24 | 0.18 | 0.4 | 0.44 | 0.54 | 0.67 | 1 | | | | | | | | | | |
| .-R&D pc (log) | **i** | 0.51 | 0.15 | -0.01 | 0.38 | 0.28 | 0.49 | 0.62 | 0.84 | 1 | | | | | | | | | |
| -R&D pc (log) | **j** | 0.56 | 0.29 | 0.2 | 0.42 | 0.43 | 0.58 | 0.72 | 0.86 | 0.65 | 1 | | | | | | | | |
| I-R&D pc (log) | **k** | -0.19 | -0.12 | -0.12 | 0.2 | -0.01 | 0.03 | -0.06 | 0.16 | 0.18 | 0 | 1 | | | | | | | |
| .I-R&D pc (log) | **l** | -0.2 | -0.14 | -0.15 | 0.17 | 0.02 | 0 | -0.09 | 0.12 | 0.12 | -0.02 | 0.94 | 1 | | | | | | |
| I-R&D pc (log) | **m** | -0.09 | -0.25 | -0.22 | 0.13 | -0.16 | -0.12 | -0.12 | 0.04 | 0.15 | -0.07 | 0.55 | 0.45 | 1 | | | | | |
| E-R&D pc (log) | **n** | 0.24 | 0.02 | -0.24 | 0.32 | 0.14 | 0.27 | 0.31 | 0.49 | 0.62 | 0.29 | 0.65 | 0.6 | 0.33 | 1 | | | | |
| .E-R&D pc (log) | **o** | 0.34 | 0.01 | -0.36 | 0.32 | 0.18 | 0.31 | 0.34 | 0.43 | 0.69 | 0.26 | 0.53 | 0.52 | 0.33 | 0.87 | 1 | | | |
| E-R&D pc (log) | **p** | 0.38 | -0.06 | -0.28 | 0.27 | -0.04 | 0.25 | 0.31 | 0.32 | 0.46 | 0.3 | 0.26 | 0.2 | 0.57 | 0.57 | 0.52 | 1 | | |
| -R&D pc (log) | **q** | 0.51 | -0.02 | -0.05 | 0.24 | 0.25 | 0.48 | 0.64 | 0.5 | 0.49 | 0.56 | 0.13 | 0.1 | -0.03 | 0.35 | 0.38 | 0.31 | 1 | |
| I-R&D pc (log) | **r** | 0.05 | -0.17 | 0.1 | 0 | 0.1 | 0.14 | 0.12 | 0.17 | 0.12 | 0.13 | 0.21 | 0.18 | 0.3 | 0.1 | 0.12 | 0.23 | 0.35 | 1 |
| E-R&D pc (log) | **s** | 0.39 | -0.06 | -0.01 | 0.15 | 0.24 | 0.45 | 0.46 | 0.35 | 0.32 | 0.37 | 0.14 | 0.13 | 0.03 | 0.28 | 0.27 | 0.38 | 0.59 | 0.6 |

## 4. Econometric analysis

Table 4: Spatial, trade and copatenting relations

| VARIABLES | Space | Total Trade | Advanced Trade | Low-tech Trade | Co-patenting | All Net | All Net |
|---|---|---|---|---|---|---|---|
| L.pop_density | 0.0322 | 0.125 | 0.117 | 0.182 | 0.112 | 0.187 | 0.192 |
| | (0.652) | (0.671) | (0.674) | (0.695) | (0.639) | (0.655) | (0.661) |
| L.US_HK | 0.0287 | 0.0299 | 0.0302* | 0.0277 | 0.0270 | 0.0280 | 0.0285 |
| | (0.0185) | (0.0184) | (0.0183) | (0.0183) | (0.0181) | (0.0180) | (0.0179) |
| L.Te_HK | 0.0168 | 0.0174 | 0.0177 | 0.0161 | 0.0163 | 0.0168 | 0.0172 |
| | (0.0126) | (0.0128) | (0.0127) | (0.0125) | (0.0124) | (0.0125) | (0.0124) |
| L.migr (log) | 0.0425 | -0.0517 | -0.0407 | -0.105 | -0.0245 | -0.101 | -0.103 |
| | (0.568) | (0.582) | (0.583) | (0.606) | (0.550) | (0.563) | (0.565) |
| L.R&D pc (log) | 0.0227 | 0.0218 | 0.0230 | 0.0200 | 0.0164 | 0.0158 | 0.0168 |
| | (0.0147) | (0.0145) | (0.0145) | (0.0150) | (0.0144) | (0.0143) | (0.0142) |
| L.W-R&D pc (log) | 0.126*** | 0.111** | 0.114** | 0.109** | 0.0599 | 0.0482 | 0.0489 |
| | (0.0479) | (0.0487) | (0.0477) | (0.0490) | (0.0500) | (0.0506) | (0.0498) |
| L.T-R&D pc (log) | | 0.204 | | | | 0.170 | |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | (0.190) | | | | (0.178) | |
| L.A-R&D pc (log) | | | 0.285* | | | | 0.275 |
| | | | (0.171) | | | | (0.170) |
| L.L-R&D pc (log) | | | | 0.103 | | | |
| | | | | (0.0901) | | | |
| L.P-R&D pc (log) | | | | | 0.200*** | 0.195*** | 0.198*** |
| | | | | | (0.0677) | (0.0692) | (0.0686) |
| lambda | 0.672*** | 0.673*** | 0.674*** | 0.670*** | 0.664*** | 0.666*** | 0.667*** |
| | (0.0443) | (0.0430) | (0.0426) | (0.0441) | (0.0457) | (0.0444) | (0.0440) |
| Observations | 1,864 | 1,864 | 1,864 | 1,864 | 1,864 | 1,864 | 1,864 |
| R-squared | 0.531 | 0.331 | 0.392 | 0.202 | 0.389 | 0.228 | 0.252 |
| Number of reg1 | 233 | 233 | 233 | 233 | 233 | 233 | 233 |
| Region FE | YES | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES | YES |
| R-Squared (w) | 0.0844 | 0.0456 | 0.0371 | 0.0657 | 0.0806 | 0.0520 | 0.0413 |
| Log-likelihood | 3089 | 3092 | 3094 | 3091 | 3105 | 3106 | 3110 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Tables 4, 5 and 6 report the estimated coefficients for our models. Each column of each table refers to a different specification, for which the weight matrix used is indicated in the header of the column.

The first column of Table 4 shows the baseline mode which only includes the spatially weighted measure of R&D and spatially lagged error term. This latter coefficient is strongly positive and significant, suggesting that a substantial portion of spatial dependence is captured by the spatially lagged error term. With respect to the control variables we notice most of them, throughout the specifications, do not appear to significantly impact on regional TFP. Whereas this may be surprising, we suspect that the reason is the inclusion of the fixed effects and limited overtime variation that characterizes these variables. With respect to the spatially lagged level of R&D, in line with the previous studies, the R&D expenditures in neighboring regions have a strong and significant effect on regional productivity. An increase by 1 percent increase in *W-R&D pc* increases the level of productivity by around 0.13 percent. Looking at the effects of trade-weighted R&D spillovers (columns 2 to 4), only R&D spillovers deriving from trade in more advanced goods (*A-R&D pc*) have an impact on local TFP, while the coefficients for *T-R&D pc* and *L-R&D pc* are not different from zero. In terms of magnitudes of the coefficients, the effect of *A-R&D pc* seems substantial: a 1 percent increase in *A-R&D pc* would lead to an increase in TFP of 0.28 percent. Besides, it is interesting to notice that in column 3, the spatially-weighted R&D term is still positive significant, though slightly smaller than in column 1. The inclusion of slightly change the pictured presented so far by Table 4. Similar to the case of trade, the estimated coefficient for *P-R&D pc* appears to be substantial, with a 1 percent increase in copatenting spillovers leading to an increase in TFP of 0.19 percent. Besides, once the spillovers from co-patenting relations are accounted for (columns 5, 6 and 7), the *P-R&D pc* term makes *W-R&D pc* insignificant. This would suggest that a substantial portion of what the spatially-weighted R&D term actually captures co-patenting relationships, as also indicated by other literature (Miguelez and Moreno, 2015). Whereas also *A-R&D pc* becomes insignificant once *P-R&D pc* is included in the model, it is important to notice that the magnitude of its coefficient is only slightly reduced and the coefficient is only marginally insignificant. In this sense, if *W-R&D pc* seems to capture most of the effect of *P-R&D pc*, the insignificant effect of *A-R&D pc* in the last column of Table 4 may be explained by some collinearity between *P-R&D pc* and *A-R&D pc.*

In Table 5, we address our second research question, looking exclusively at network relations with most advanced regions in terms of technology and innovation. Our hypotheses are that connections to these regions can be particularly beneficial due to the high quality and quantity of knowledge resources they have accumulated. The first three columns of Table 5 relate to trade relations, the fourth column to copatenting relations and the fifth and sixth one look at spatial, trade and copatenting relations jointly. When we include only observations from most innovative regions, no significant effect is found for any kind of trade-mediated R&D. However, a positive effect, slightly smaller than those reported in Table 4, is found for *PE-R&D pc*. These results, while not in line with hypotheses 2, suggest that by relations to most advanced regions do not necessarily imply any stronger effect in terms of R&D spillovers on local productivity.

Table 5: Spatial, trade and copatenting relations to regions in top technological regimes

| VARIABLES | Total Trade - TE | Advanced Trade - TE | Low-tech Trade - TE | Copatenting - TE | All Net - TE | All Net - TE |
|---|---|---|---|---|---|---|
| L.pop_density | 0.0611 | 0.0336 | 0.0294 | 0.144 | 0.165 | 0.145 |
| | (0.668) | (0.665) | (0.663) | (0.679) | (0.694) | (0.693) |
| L.US_HK | 0.0283 | 0.0286 | 0.0287 | 0.0276 | 0.0273 | 0.0276 |
| | (0.0183) | (0.0183) | (0.0185) | (0.0185) | (0.0183) | (0.0183) |
| L.Te_HK | 0.0166 | 0.0172 | 0.0168 | 0.0168 | 0.0167 | 0.0173 |
| | (0.0126) | (0.0127) | (0.0126) | (0.0130) | (0.0129) | (0.0131) |
| L.migr (log) | 0.0276 | 0.0410 | 0.0451 | -0.0739 | -0.0831 | -0.0744 |
| | (0.578) | (0.578) | (0.577) | (0.591) | (0.600) | (0.602) |

| | | | | | | |
|---|---|---|---|---|---|---|
| L.R&D pc (log) | 0.0228 | 0.0231 | 0.0227 | 0.0200 | 0.0202 | 0.0205 |
| | (0.0147) | (0.0146) | (0.0148) | (0.0140) | (0.0140) | (0.0140) |
| L.W-R&D pc (log) | 0.122** | 0.124** | 0.127*** | 0.0959* | 0.0928* | 0.0940* |
| | (0.0482) | (0.0485) | (0.0478) | (0.0510) | (0.0512) | (0.0518) |
| L.TE-R&D pc (log) | 0.181 | | | | 0.149 | |
| | (0.255) | | | | (0.253) | |
| L.AE-R&D pc (log) | | 0.181 | | | | 0.175 |
| | | (0.213) | | | | (0.214) |
| L.LE-R&D pc (log) | | | -0.00466 | | | |
| | | | (0.111) | | | |
| L.PE-R&D pc (log) | | | | 0.132* | 0.129* | 0.131* |
| | | | | (0.0768) | (0.0767) | (0.0767) |
| lambda | 0.676*** | 0.676*** | 0.672*** | 0.664*** | 0.667*** | 0.668*** |
| | (0.0436) | (0.0434) | (0.0443) | (0.0464) | (0.0459) | (0.0455) |
| Observations | 1,864 | 1,864 | 1,864 | 1,864 | 1,864 | 1,864 |
| R-squared | 0.505 | 0.549 | 0.530 | 0.271 | 0.247 | 0.295 |
| Number of reg1 | 233 | 233 | 233 | 233 | 233 | 233 |
| Region FE | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES |
| R-Squared (w) | 0.0456 | 0.0461 | 0.0857 | 0.0776 | 0.0486 | 0.0456 |
| Log-likelihood | 3090 | 3090 | 3089 | 3096 | 3097 | 3097 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

However, as discussed in the theoretical framework, the effect of spillovers from advanced regions may be present, but only for regions which are best equipped in term of capacity to absorb knowledge spillovers. For this reason, we re-estimate our models on network spillovers and network spillovers from technologically advanced regions now including an interaction term between local human capital and network spillovers. The results are presented in Table 6. The results from Table 4 are mostly confirmed in Table 6 (columns 1, 3, 5 and 7), with only *A-R&D pc* and *P-R&D pc* having a positive significant effect on local TFP and no interaction effect being significantly different from zero (see Wald test at the bottom of the table). Unlike, looking at column 2, it is interesting to notice that the interaction term *L.TE-R&D pc (log) X L.Te_HK* has a positive significant coefficient. This suggest that, unlike the case of *T-R&D pc*, regions with high absorptive capacity benefit from spillovers derived from intermediate inputs bought from more technologically advanced regions.

Table 6: Spatial, trade and copatenting relations to top-innovators with interactions

| VARIABLES | All Net – All reg. | All Net - TE | All Net - All reg. | All Net - TE | All Net - All reg. | All Net - TE | All Net - All reg. | All Net - TE |
|---|---|---|---|---|---|---|---|---|
| L.Te_HK | 0.0148 | 0.0129 | 0.0163 | 0.0143 | 0.0186 | 0.0162 | 0.0193 | 0.0168 |
| | (0.0128) | (0.0129) | (0.0126) | (0.0132) | (0.0121) | (0.0131) | (0.0121) | (0.0132) |
| L.R&D pc (log) | 0.0181 | 0.0266* | 0.0182 | 0.0251* | 0.0181 | 0.0179 | 0.0196 | 0.0181 |
| | (0.0141) | (0.0141) | (0.0143) | (0.0142) | (0.0148) | (0.0145) | (0.0147) | (0.0144) |
| L.W-R&D pc (log) | 0.0546 | 0.104** | 0.0526 | 0.104** | 0.0432 | 0.0959* | 0.0443 | 0.0973* |

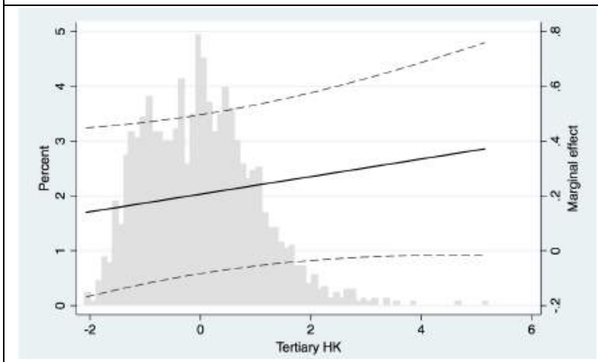
| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (0.0505) | (0.0520) | (0.0496) | (0.0523) | (0.0520) | (0.0514) | (0.0512) | (0.0519) |
| L.T-R&D pc (log) | 0.206 | | | | 0.202 | 0.161 | | |
| | (0.176) | | | | (0.178) | (0.253) | | |
| L.TE-R&D pc (log) | | 0.244 | | | | | | |
| | | (0.249) | | | | | | |
| L.A-R&D pc (log) | | | 0.286* | | | | 0.318* | |
| | | | (0.169) | | | | (0.170) | |
| L.AE-R&D pc (log) | | | | 0.210 | | | | 0.185 |
| | | | | (0.212) | | | | (0.215) |
| L.P-R&D pc (log) | 0.197*** | | 0.202*** | | 0.221*** | | 0.227*** | |
| | (0.0697) | | (0.0691) | | (0.0699) | | (0.0696) | |
| L.PE-R&D pc (log) | | 0.123 | | 0.130* | | 0.122* | | 0.125* |
| | | (0.0768) | | (0.0766) | | (0.0739) | | (0.0739) |
| L.T-R&D pc (log) X L.Te_HK | 0.0321 | | | | | | | |
| | (0.0305) | | | | | | | |
| L.TE-R&D pc (log) X L.Te_HK | | 0.110** | | | | | | |
| | | (0.0442) | | | | | | |
| L.A-R&D pc (log) X L.Te_HK | | | 0.0189 | | | | | |
| | | | (0.0328) | | | | | |
| L.AE-R&D pc (log) X L.Te_HK | | | | 0.0824* | | | | |
| | | | | (0.0440) | | | | |
| L.P-R&D pc (log) X L.Te_HK | | | | | 0.0249 | | 0.0282 | |
| | | | | | (0.0224) | | (0.0224) | |
| L.PE-R&D pc (log) X L.Te_HK | | | | | | -0.0118 | | -0.0120 |
| | | | | | | (0.0211) | | (0.0213) |
| lambda | 0.663*** | 0.665*** | 0.666*** | 0.669*** | 0.669*** | 0.667*** | 0.669*** | 0.668*** |
| | (0.0440) | (0.0445) | (0.0437) | (0.0443) | (0.0437) | (0.0459) | (0.0432) | (0.0455) |
| Observations | 1,864 | 1,864 | 1,864 | 1,864 | 1,864 | 1,864 | 1,864 | 1,864 |
| R-squared | 0.250 | 0.185 | 0.282 | 0.338 | 0.127 | 0.228 | 0.142 | 0.275 |
| Number of reg1 | 233 | 233 | 233 | 233 | 233 | 233 | 233 | 233 |
| Control variables | YES | YES | YES | YES | YES | YES | YES | YES |
| Region FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES | YES | YES |
| R-Squared (w) | 0.0500 | 0.0453 | 0.0407 | 0.0449 | 0.0454 | 0.0479 | 0.0358 | 0.0452 |
| Log-likelihood | 3108 | 3109 | 3110 | 3105 | 3109 | 3098 | 3113 | 3098 |
| Wald Test | 2.780 | 6.728 | 2.108 | 4.634 | 3.625 | 3.142 | 4.102 | 3.263 |
| Wald p-value | 0.249 | 0.0346** | 0.348 | 0.0986* | 0.163 | 0.208 | 0.129 | 0.196 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

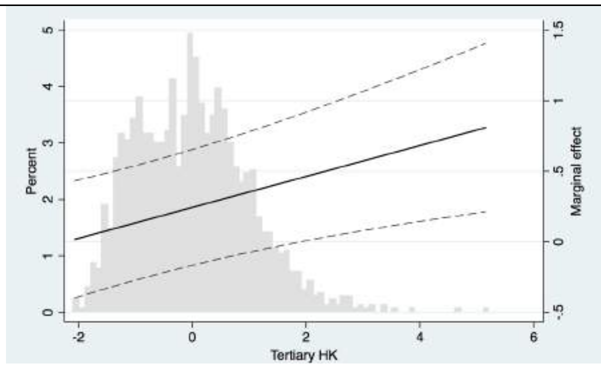
This is made more evident by comparing the graph reported in Panels A and B of Figure 3. As the left-hand graph show, the effect of *T-R&D pc* on TFP is never different from zero (right-hand side vertical axis), regardless of the level of human capital (horizontal axis). However, in Panel B, regions with a level of human capital around two standard deviations above the mean do experience a positive effect of *TE-R&D pc* on local productivity. A similarly reasoning applies to the case of *A-R&D pc* and *AE-R&D pc*, whose results are reported in columns 3 and 4 of Table 6 and graphically shown in Panels C and D. Comparing the effect of *A-R&D pc* with *AE-R&D pc* for regions with a level of human capital around 2 standard deviations above the mean suggest that, R&D spillovers from the advanced intermediate inputs sourced from advanced regions have a stronger impact than those sourced from elsewhere (0.45 against 0.35).

Figure 3: Marginal Effects (the dashed lines indicates 10% confidence interval)

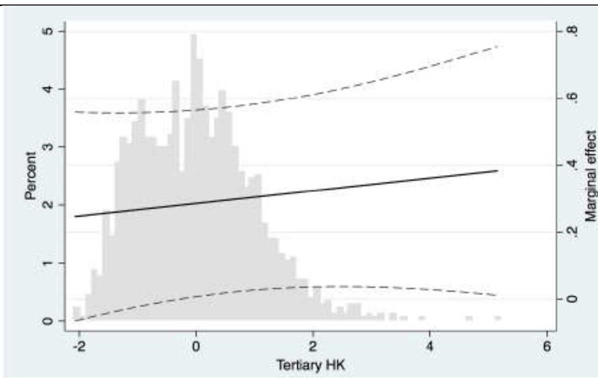
**Panel A: Marginal Effect of** *T-R&D pc*



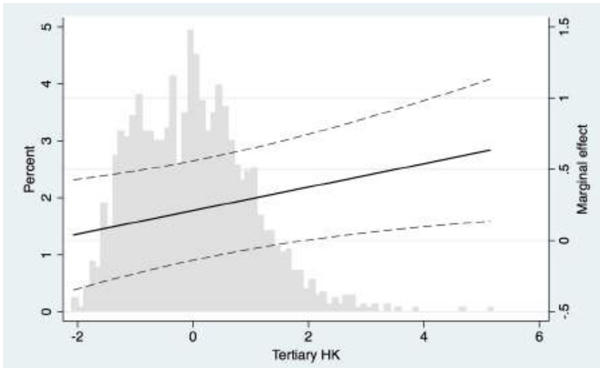

**Panel B: Marginal Effect of** *TE-R&D pc*




**Panel C: Marginal Effect of** *A-R&D pc*




**Panel D: Marginal Effect of** *AE-R&D pc*




Interestingly enough, columns 4 to 8 in Table 6 suggest that copatenting-mediated R&D spillovers present some differences with respect to trade. The Wald tests for each of these models indicate that no significant interaction is present between the variables of interests and local absorptive capacity. This would imply that, the effects of *P-R&D pc* and *PE-R&D pc* are not conditional on the level of human capital in the region. In other words, the effect on the local level of TFP of engaging in copateting relations with regions in the advanced technological regime appears to be positive regardless of the local ability to absorb knowledge[7]. In terms of robustness of the previous results, it should be noticed that, while the effect of *A-R&D pc* are robust to

[7] This result is surprising, especially considering the usual findings in the literature. However, a difference between our paper and the previous one is the proxy used for local absorptive capacity, which in our case is the share of employed personnel with tertiary education, while most of the literature in the field use R&D expenditures. This consideration may potentially explain the difference between our results and the previous literature.

the inclusion of *P-R&D pc*, the same is not true for *AE-R&D pc* which is no longer significant in the last column of Table 6.

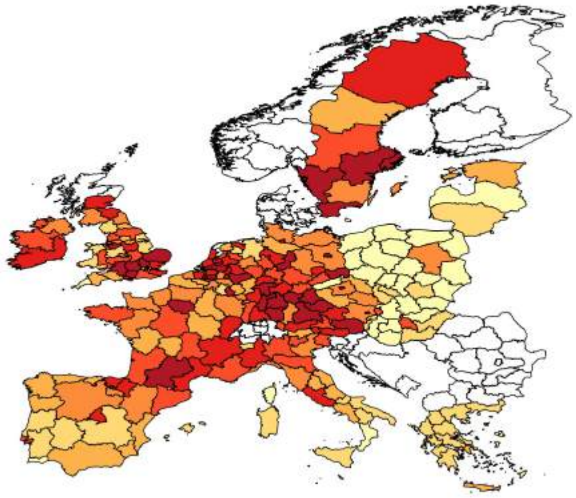
## 5. Robustness checks on causality

Endogeneity is an obvious concern when studying the relation between R&D spillovers and local productivity. Whereas the use of panel settings allow us to control for the potential bias of time-invariant omitted variables and the inclusion of lagged regressors somewhat reduce the problem of reverse causality, the coefficients discussed in the previous may still be affected by endogeneity. As a robustness check we adopted an instrumental variable strategy to check for the risk of having captured spurious relations.

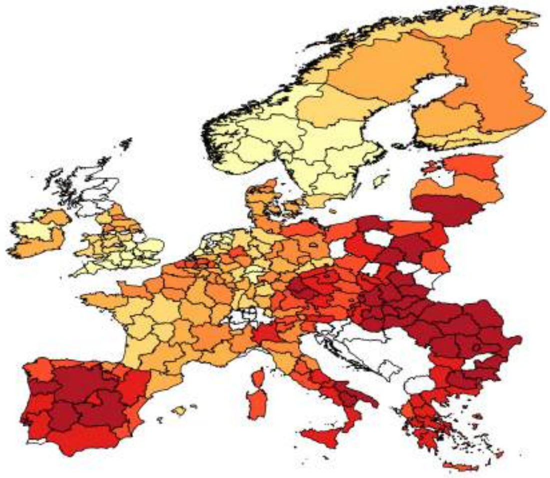
In order to correctly identify the effects of R&D on local productivity, the instrument should be correlated to current R&D expenditure but not with current productivity. For doing this, we exploit historical data on regional illiteracy rates and infant mortality rates in the 1930s (Kirk, 1946). The level of literacy has been used in the past as a proxy for current quality of regional government (Tabellini, 2010). In our case, it can argued that the level of illiteracy may capture the (lack of) propensity of territories to invest in knowledge resources and innovate. Similarly, the level of infant mortality capture more broadly the level of socio-economic development of the region in the early 1930s. In particular, as argued by Kirk (1946, p. 174) "the evaluation placed on the individual human life, the knowledge and education of parents, the quality of physical environment enjoyed by the population, the effectiveness of public health and social legislation – these are all collectively and sensitively measured by the level of infant mortality". Whereas attitude towards R&D and innovation is not directly captured by infant mortality, important determinants of these, such as the level of knowledge and education and the living conditions of the population or the public policy effectiveness, are indeed related to past levels of infant mortality. This intuition is confirmed by looking at the geographical distribution of current R&D expenditures and illiteracy rates and infant mortality rates in the 1930s. Generally speaking, regions investing more in R&D (darker shades in the map in Panel A of Figure 4) appear to be closely matched by lower levels of illiteracy and infant mortality (lighter shades in the maps in Panels B and C).

Figure 4: R&D per capita expenditure and IVs

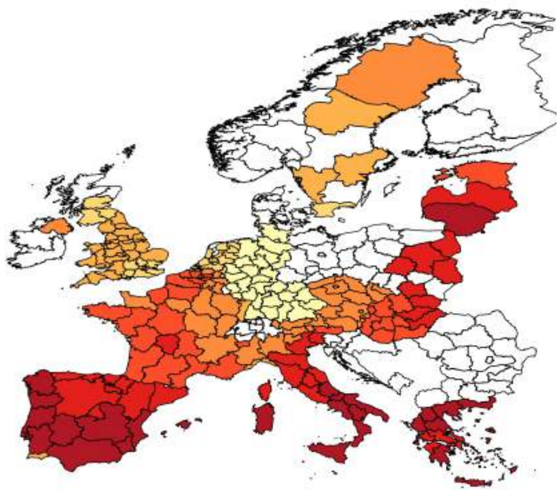
**Panel A: Average R&D exp. pc (2004-2012)**



**Panel B: Infant mortality rate (1930-1931)**



**Panel C: Illiteracy rates (1930-1931)**



In order for the instruments to be valid, they should not be correlated with current level of productivity. In these respects, current productivity dynamics are likely to be influenced by many factors, some of which only slowly changing over time (Tabellini, 2010). However, it is probably safe to assume that our instrument to be exogenous from current productivity dynamics, especially considering the profound economic, cultural, social and political transformation undergone by European societies since the early 1930s.

Whereas our illiteracy rates and infant mortality appear to be promising instruments, we observe them only at one point in time. Instrumental variable estimation in a panel model with fixed effects instead would require an instrument whose overtime variation closely mimick the one of the endogenous variable. As such variable is probably impossible to find, we choose to move from panel to cross-sectional settings and identify the effects of network-mediated R&D spillovers by looking at cross-sectional variation. Since we can no longer rely on regional fixed effects for capturing time invariant factors affecting regional productivity, we slightly modified the model reported in Equation 1. Firstly, we select as dependent variable the level of regional TFP in 2012. Secondly, we include the 2004 value of the control varialbes and the network-related R&D spillovers, used in the previous estimations. Thirdly, given the high number of endogenous variables that should be instrumented for, in the IV regressions we substitute the local and the spatially-lagged level of R&D (*R&D pc* and *W-R&D pc*) with macro-regional dummies (at NUTS1 level) capturing the spatial relations of regions. Besides, we further control for local economic conditions by adding the regional level of TFP in 2004 as control variable. Finally, we abandon the spatial econometric framework and drop from our model the spatially lagged-error term[8]. In mathematical notation, our 2SLS model can be represented as follows:

$$log\_TFP_{r,2012} = log\_TFP_{r,2004} + \delta \boldsymbol{T} logR\&D_{r,2004} + \delta \boldsymbol{P} logR\&D_{r,2004} + \gamma Controls_{r,2004} + \varphi NUTS1_R + u_r. \quad (4)$$

Table 7: Instrumental variable estimation (IV= Gross reproduction rate)

| VARIABLES | (1) IV – Total trade | (2) IV – Adv. trade | (3) IV – Copatenting | (4) IV – Total trade and copatenting | (5) IV – Adv. trade and copatenting |
|---|---|---|---|---|---|
| L.tfp (log) | 1.034*** | 1.038*** | 1.025*** | 1.025*** | 1.027*** |
| | (0.0597) | (0.0568) | (0.0615) | (0.0616) | (0.0596) |
| L.pop_density | 0.0267 | 0.0248 | 0.0251 | 0.0256* | 0.0246 |
| | (0.0175) | (0.0162) | (0.0153) | (0.0154) | (0.0154) |
| L.US_HK | -0.0388 | -0.0435* | -0.0426* | -0.0408* | -0.0492** |
| | (0.0239) | (0.0244) | (0.0221) | (0.0224) | (0.0232) |
| L.Te_HK | -0.0241 | -0.0252 | -0.00859 | -0.00854 | -0.00976 |

[8] Whereas Stata allows to estimate spatial error IV regressions using – spivreg – such command does not allow for thorough testing of the validity of the instrument and does not make available the first stage results of the regression. This motivated our decision to drop the spatial error term from the model.

| | | | | | |
|---|---|---|---|---|---|
| | (0.0207) | (0.0209) | (0.0193) | (0.0193) | (0.0196) |
| L.migr (log) | -0.0282** | -0.0254** | -0.0226** | -0.0220** | -0.0239** |
| | (0.0112) | (0.0104) | (0.00988) | (0.0102) | (0.00969) |
| L.T-R&D pc (log) | 0.141* | | | -0.0262 | |
| | (0.0809) | | | (0.0609) | |
| L.A-R&D pc (log) | | 0.259*** | | | 0.119* |
| | | (0.0986) | | | (0.0702) |
| L.L-R&D pc (log) | | | 0.130** | 0.137** | 0.120** |
| | | | (0.0533) | (0.0557) | (0.0506) |
| | | | | | |
| Observations | 195 | 195 | 192 | 192 | 192 |
| NUTS1 FE | YES | YES | YES | YES | YES |
| R-squared | 0.887 | 0.887 | 0.892 | 0.891 | 0.894 |
| | | Relevance of excluded instruments | | | |
| F | 78.05*** | 99.12*** | 29.20*** | 19.67*** | 16.16*** |
| F P-val | 0 | 0 | 5.15e-11 | 0 | 1.57e-10 |
| K-P LM | 13.24*** | 26.85*** | 15.46*** | 18.47*** | 13.85*** |
| LM P-val | 0.00133 | 1.48e-06 | 0.000440 | 0.000352 | 0.00311 |
| A-P F | 78.05*** | 99.12*** | 29.20*** | 25.10*** | 21.22*** |
| A-P F P-val | 0 | 0 | 5.15e-11 | 0 | 5.20e-11 |
| S-W F | 78.05*** | 99.12*** | 29.20*** | 25.39*** | 20.90*** |
| S-W F P-val | 0 | 0 | 5.15e-11 | 0 | 7.09e-11 |
| | | Weak identification | | | |
| A-R F | 1.237 | 2.207 | 2.848* | 1.438 | 1.687 |
| A-R F P-val | 0.294 | 0.115 | 0.0620 | 0.226 | 0.158 |
| A-R Chi | 4.019 | 7.172** | 9.349*** | 9.605** | 11.27** |
| A-R Chi P-val | 0.134 | 0.0277 | 0.00933 | 0.0476 | 0.0237 |
| S | 3.159 | 7.796** | 4.206 | 5.110 | 5.657 |
| S P-val | 0.206 | 0.0203 | 0.122 | 0.276 | 0.226 |
| K-P F | 78.05 | 99.12 | 29.20 | 19.09 | 14.86 |
| | | Over-identification | | | |
| Hansen J test | 1.976 | 1.260 | 0.493 | 2.456 | 2.083 |
| J test P-val | 0.160 | 0.262 | 0.483 | 0.293 | 0.353 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The second stage results of our regressions are reported in Table 7, above. Starting from the bottom part of the table, throughout the 5 specifications, both the tests on the relevance of the excluded instruments and the tests on overidentification provide convincing evidence on the validity of our IV strategy. The tests however detect in some cases (most relevantly in column 1 of Table 7), that our instruments only weakly relate to the endogenous regressors. Also, it should be noticed that, of the 233 regions which were included in our panel, around 40 have dropped out from the 2SLS regression due to missing values for the instruments.

When looking at the coefficients of the instrumented variables, we see that they all are positive significant throughout the specifications, thus suggesting that R&D spillovers via copatenting and trade do affect local productivity. In particular, R&D spillovers effects from network relations are consistently found from imports of advanced intermediate goods (columns 2 and 5 of Table 7) and copatenting relations (columns 3, 4 and 5). Besides, it is interesting to notice that the size of the coefficients in the 2SLS regression is comparable to those reported in Tables 4-6. According to our IV estimates, a 1 percent increase in R&D expenditures in regions from which an average region buys advanced intermediate goods induces an increase in productivity between 0.12 and 0.26 percent. Similarly, incrementing R&D expenditures in copatenting partners by 1 percent increases local productivity by 0.13 percent.

## 6. Conclusions

The aim of this paper is to contribute to the debate on knowledge spillover, which involves different sub-disciplines of economics and geography. In doing this, we adopt a regional perspective, and we assess how the regional level of productivity is affected by R&D externalities deriving from trade and co-patenting relations with other regions on a European regional scale. The attention devoted to import-mediated R&D spillover is particularly innovative for the regional economic literature, as a comparison of this trade network vis-à-vis other networks (spatial and co-inventorship) has not been previously examined, mainly because of lack of interregional trade data at the EU level. A second, more qualitative contribution of this work relates to the study of the direction of network relations, i.e., import- and co-patenting-mediated relations to regions that are innovation leaders. A third substantial innovation is represented by the instrumental variable strategy, which provides robust evidence on the causal effects linking network-related R&D spillovers and local productivity.

After a short review of the extensive literature on knowledge spillovers, we put forward our research questions and hypotheses. First, based on the empirical research on agglomeration economies, we expect R&D spillovers deriving from network relations to have a strong impact on local productivity (Hypothesis 1a and 1b). Our estimates consistently confirm these hypotheses, especially for what concerns spillovers from advanced imports and spillovers from copatenting relations. Both these effects have been confirmed by our 2SLS estimations. Similarly, our expectations on the role of R&D spillovers from innovation leaders, expressed in Hypotheses 2a for import-related networks and 2b for co-patenting related networks, are not confirmed. According to our estimates, the superior knowledge endowment that top innovating regions have does not automatically spill over to trade partners and co-inventors. A potential explanation for this, generally conceptualized in Hypothesis 3, is related to a possible lack of absorptive capacity in recipient regions. After including a term interacting the network-mediated spillovers with human capital endowments of recipient regions, our analysis indeed suggests that preconditions have to be met for regions to profit from connections with most advanced areas. Interestingly, knowledge embodied in goods and technologies and diffused via trade seems to be harder to assimilate by recipients, whereas spillovers related to co-patenting appear not to be influenced by local conditions in terms of absorptive capacity.

Different insights in terms of policy implications can be drawn from the results of our analysis. Our results show that network relations do complement localized knowledge endowments of regions and contribute to a higher level of prosperity. These results should be found informative, in particular with reference to the recent debates concerning restrictions on trade and political decisions on freedom of movements, potentially jeopardizing knowledge collaboration. However, our results also suggest that some conditions may exist for network effects to materialize. In particular, the strongest effects of knowledge spillovers through trade appear when the receiving region is well endowed with human capital and knowledge assets. From the one hand, this indicates policy makes the crucial importance of investments in human capital and absorptive capacity. From the other hand, this result questions the applicability of recent European policy initiatives, such as smart specialization opportunities for all regions in Europe, and the creation of an open Research Area in which all regions can participate. In other words, lagging regions (Eastern Europe, with low income, and Southern Europe, with low growth in the last decade) may have substantial difficulties in linking-in in both processes, as they lack the necessary and dedicated skills and human capital to absorb the knowledge embedded in the networks and put it to use in local productive economies. Instead of regionally spilling over in the networks, valuable knowledge may boil down in some (i.e., elite) regions in a closed "old boys" network (Desdoigts 1999, Hoekman et al. 2009).

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