Journal of Economic Geography **0** (2018) pp. 1–28 doi:10.1093/jeg/lby058

Between spilling over and boiling down: network-mediated spillovers, local knowledge base and productivity in European regions

Nicola Cortinovis[†] *and Frank van Oort*

Department of Applied Economics, Erasmus Universiteit Rotterdam, Rotterdam, Zuid-Holland, The Netherlands
[†]Correspondence to: *email* <cortinovis@ese.eur.nl>

Abstract

Productivity across European regions is related to three types of networks that mediate R&D-related knowledge spillovers: trade, co-patenting and geographical 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. Both import and co-patenting relations affect local productivity directly, but spillovers from innovation-leading regions are effective only when they are import-mediated and when recipient regions have a solid knowledge base. From a policy perspective, this may frustrate recent European policy initiatives, such as Smart Specialization, which are designed to benefit all regions in Europe.

Keywords: Productivity, economic networks, trade, knowledge, regions
JEL classifications: R11, O32
Date submitted: 26 December 2017 **Editorial decision:** 24 October 2018 **Date accepted:** 21 November 2018

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. Economics and economic geography have increasingly focused on the role of spatial and network linkages and relate it to innovation and productivity performance.

Departing from the crucial role of knowledge in fostering innovation, productivity and development (Lucas, 1988; Romer, 1986), different scholars have investigated how spatial and network relations mediate and allow for the diffusion of ideas and technologies across space (Jones, 1995; Durlauf et al., 2001). Early contributions (Grossman and Helpman, 1991; Jaffe et al., 1993; Coe and Helpman, 1995; Jaffe and Trajtenberg, 1999) have focused on local spillover effects of patents and trade relations as channels for knowledge exchange. More recently, these contributions have been extended by a number of scholars looking at spatial, market, investment and technological relations as sources of productivity and innovation, both at country level (Keller, 2002; Lumenga-Neso et al., 2005; Fracasso and Vittucci Marzetti, 2015) and firm level (Keller and Yeaple, 2009; Bloom et al., 2013; Lychagin et al., 2016). While studies at country and firm level focus on specific channels, economists have provided less detailed evidence at regional level, with most of the literature merely referring to spatial spillovers (Bottazzi and Peri, 2002; Dall'Erba and Le Gallo, 2008).

Building on older contributions of industrial districts (Becattini et al., 2009), economic geography literature focused more closely on the regional effects of space and networks. Putting as theoretical cornerstones the concepts of proximity and relatedness, this stream of research investigates and, with varying success, empirically tests, what types of relatedness mold knowledge interaction, learning and innovation (Camagni, 1991; Ratti et al., 1997; Torre and Gilly, 1999; Boschma, 2005; Frenken et al., 2007). Whereas traditionally more interested in the role of local factors and conditions, the proximity-based literature has increasingly investigated the role of wider spatial relations and networks. Different contributions have considered the effects of spatial spillovers, co-patenting, industrial and technological similarity, and migration as channels for the diffusion of knowledge (Maggioni et al., 2007; Rosenthal and Strange, 2008; Paci et al., 2014; Caragliu and Nijkamp, 2015; Miguélez and Moreno, 2015). Apart from co-inventorship relations, these contributions (with the exception of Thissen et al., 2016) have paid less attention to the traditional factors—such as trade and investments—identified by growth literature.

This article links these two successful streams of literature by investigating the productivity effects of spatial and network relations for R&D at regional level in Europe. More specifically, this article is among the first to directly study the impact of import, co-patenting and spatial relations vis-à-vis each other. 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 (Miguélez 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 article is 3-fold. Firstly, we investigate in a spatial panel setting with region and year fixed effects whether and how network relations affect local productivity, once the spatial proximity dimension is controlled for. Second, we specifically model network relations with high knowledge-intensive and technologically advanced regions (Wintjes and Hollanders, 2011; Cortinovis and Van Oort, 2015) to study whether such linkages particularly provide directed spillover effects. Thirdly, we test whether the knowledge base (the stock of learning or internalizing capabilities of regions' population and firms, captured on an educational level) act as precondition for regions to benefit from network relations with most advanced regions (Cortinovis and Van Oort, 2015; Miguélez and Moreno, 2015). We check the validity of our potentially endogenous results with an instrumental variable (IV) strategy, in which illiteracy rates and gross reproduction rates (GRR) in European regions in the early 1930s are used as an instrument for current R&D expenditures.

Our empirical analysis puts forward a number of important results. Firstly, both our spatial panel and IV estimates highlight that, even controlling for spatial effects in R&D

1 In the article, we use the terms 'linking-in', 'connecting' and 'recipient' regions as synonyms. These 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.

spillovers and in the residuals, embeddedness in network relations affect regional productivity. In particular, cross-regional cooperation on patents is an important vector of technological diffusion, resulting in higher levels of productivity for regions. Similarly, trade relations (measured by import flows in intermediate goods) also have a direct effect on productivity, but only in the case of more technologically advanced imports. Second, the knowledge base of regions is of importance: trade relations with innovation-leading regions induce productivity effects to recipient regions, but only when conditions of local learning capabilities are met. When inter-regional network linkages and a strong knowledge base are lacking, spillovers do not occur and productivity advantages then boils 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 peripheral Eastern Europe and low growth rates in Southern Europe) by the introduction of a European Research Area (Frenken et al., 2007) and smart specialization strategies (Foray, 2015).

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

2. Theoretical framework: regional productivity, networked knowledge spillovers and the knowledge base of regions

To legibly combine the various strands of literature we refer to, we direct our discussion toward the relationships between (i) regional productivity and mechanisms of agglomeration economies, (ii) the strength and nature of network ties between (firms in) regions and (iii) the knowledge base of sender and recipient regions in such ties. Our central argument is that network positions of regions potentially facilitate spillovers when the knowledge base permits this. We elaborate on these aspects in this section, indicating the rationale of our research and formulating research questions and related hypotheses.

2.1. Regional productivity, agglomeration and localized knowledge spillovers

Regional productivity as a prime component of economic growth is built up by that of firms, entrepreneurs and employees, yet agglomeration economies have traditionally been argued to induce a place-based effect, independent and identifiable from sorting (Behrens and Robert-Nicoud, 2015; Belussi and Hervas-Oliver, 2018). Concentration usually brings about effects more than proportional to scale, both on the positive (reduced search costs for labor, local indivisibles) and negative side (congestion, pollution). Place-based policies aim at leveraging on mechanisms stimulating localized knowledge, productivity and economic growth to foster positive externalities and battle negative ones (Barca et al., 2012; Neumark and Simpson, 2015; Koster et al., 2018).

Yet, exactly these mechanisms are subject to much debate in recent research (Combes and Gobillon, 2015) as their identification proves problematic in many respects. The question of how firms and entrepreneurs learn of new, productive ideas outside their own organization is increasingly answered using network data (Huggins and Thompson, 2014). Regional externalities are arguably both determining and resulting from such networks.

The idea of spillovers has been widely studied by economists and geographers, especially in relation to agglomeration economies and knowledge flows across space. Regardless of whether externalities come from a firm in the same sector (localization economies) or emerge from knowledge recombination in a diversified urban environment (urbanization economies), these spillovers are considered as inherently localized, not spanning further than what face-to-face interactions allow (Breschi and Lissoni, 2001; Van Soest et al., 2006). Due to their localized nature, knowledge externalities are used to explain the emergence and persistence of spatial disparities (Capello, 2009; Lissoni and Miguelez, 2014; McCann and Ortega-Argiles, 2016).

It is thus not surprising that the spatial dimension of knowledge spillovers has received significant attention in economic and geographical research. Remarkably, empirical testing of this key hypothesis is predominantly done without (spatial) interaction data: partly because of a lack of such data (in the past), but also because of research traditions focusing on physical proximity (McCann and van Oort, 2018). Especially since the development of spatial econometric tools, different studies have shown that knowledge exchange patterns occur across the borders of cities, clusters and regions (Dall'Erba and Le Gallo, 2008; Arbia et al., 2010; Lissoni and Miguelez, 2014; Caragliu and Nijkamp, 2015). Empirical research has provided significant evidence in these respects, showing that, within Europe, knowledge externalities unfold within 200–300 km or comparable distance ranges (Bottazzi and Peri, 2002; Greunz, 2003; Moreno et al., 2005; Crescenzi and Rodríguez-Pose, 2011). This is a much larger distance than the face-to-face impact of localized externalities literature indicates, suggesting that other or additional mechanisms functioning on different scales are at play.

2.2. Network-mediated knowledge spillovers and regional productivity

The interpretation that geographical proximity—without any network relation linking two individuals or firms—leads to knowledge diffusion has however been criticized (Boschma, 2005; Torre and Rallet, 2005; Capello, 2009). The idea of socio-economic linkages as infrastructure for knowledge diffusion within localities, across space, among specific actors or in the broader community is not new (Granovetter, 1973; Akerlof, 1997; Camagni, 1991; Conley and Ligon, 2002; Bathelt et al., 2004; Morrison and Rabelotti, 2009). 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 facilitate knowledge spillovers. In this sense, connections with cognitively similar actors, even if located far away, can provide access to valuable information for firms and individuals (Nooteboom, 1992; Frenken et al., 2007). Building on endogenous growth and evolutionary arguments, Huggins et al. (2012) and Huggins and Thompson (2014, 2017) have developed the concept of 'network capital' that theorizes a tight conceptual link between local economic performance and the ability to access economically valuable knowledge through network linkages.

In this sense, while geographical distance makes it costlier and harder to diffuse ideas and technologies, network relations still make such exchanges possible. The literature has theoretically discussed and increasingly empirically investigated whether and how different linkages enable knowledge to diffuse.[2]

The mechanisms linking international trade, innovation and growth have been studied in a long tradition (Romer, 1986; Fagerberg, 1988). 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: since international trade is mostly in intermediate goods, imports can increase domestic production thanks to the technological progress and innovation from trading partners. Empirical evidence on these mechanisms has confirmed the beneficial effects of import-mediated foreign R&D across countries (Coe et al., 2009; Fracasso and Vittucci Marzetti, 2015), even though, at firm level, the impact of R&D spillovers appears to be weaker (Keller and Yeaple, 2009). In a regional perspective, the focus of this article, Thissen et al. (2016) have recently demonstrated the relevance of trade networks for European regions, showing that local positions in trade relations and value chains can contribute to sectoral growth in productivity across EU regions.

Following Boschma (2005), various empirical studies have investigated the role of different forms of proximity in the diffusion of knowledge. Proximity—in forms other than the spatial one—seems to act as conditioning factor (Morrison and Rabellotti, 2009; Paci et al., 2014; Caragliu and Nijkamp, 2015). In these studies, 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; Miguélez 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. While this has a direct effect on the local performance through innovation and eventually growth (Caragliu and Nijkamp, 2015), the effects of collaborative relations have mostly been assessed with respect to local innovation performance only (Maggioni et al., 2007; Hoekman et al., 2009; Ponds et al., 2010; Paci et al., 2014), with the exception of Basile et al. (2012).

2.3. The knowledge base of origin and recipient regions in network ties

While significant attention has been devoted in understanding whether knowledge externalities exist, less attention has been paid to the characteristics of the parties involved in the knowledge exchange. Most country-level studies (Coe and Helpman, 1995; Grossman and Helpman, 1991; Coe et al., 2009) and regional studies (Greunz, 2003; Basile et al., 2012; Paci et al., 2014; Caragliu and Nijkamp, 2015) assume the inflow of knowledge outside–in will be equally beneficial, whether it comes from an innovation-leading region or a more backwashed one. A relevant exception in this case

2 In addition to trade and various forms of proximity, different studies have highlighted how investment flows (Keller and Yeaple, 2009; Iammarino and McCann, 2013), migration networks (Hornung, 2014; Lissoni, 2016) and global value chains (Morrison et al., 2008, 2013) work as channels for knowledge diffusion. For sake of brevity, we do not discuss these in this article.

is Mancusi (2008), who looks at patents and patent citations and finds that technologically leading countries act as spillovers sources rather than recipients. Conceptually, the issue of the source of knowledge spillovers is partially addressed by the idea of network capital (Huggins et al., 2012; Huggins and Thompson, 2014, 2017),[3] in which the relation between economically valuable knowledge, networks and local performance suggests that linkages to most advanced economies should provide access to potentially groundbreaking know-how. The international business literature has also reached similar conclusions, showing that spillovers to domestic firms are influenced by factors on the 'input' side, such as the origin of the multinational, the type of industry and the mode and reason for entry (Crespo and Fontoura, 2007; Fu et al., 2011).

Unlike the issue of the source of knowledge, different contributions have shown that some preconditions are necessary for a recipient (firm, country or region) to benefit from knowledge externalities (Abreu et al., 2008). As for firm absorptive capacity, which depends on the amount of prior related knowledge that the firm has (Cohen and Levinthal, 1990; Knoben et al., 2016), regions and countries may face preconditions for translating knowledge spillovers into innovation and growth (Benhabib and Spiegel, 2005; Nelson and Phelps, 1966; Caragliu and Nijkamp, 2008). While this has been shown to be the case for agglomeration externalities within the boundaries of the local economy (Cortinovis and Van Oort, 2015), similar arguments hold for cross-border spillovers and knowledge exchanges (Beugelsdijk et al., 2008; Caragliu and Nijkamp, 2008; Miguélez and Moreno, 2015). In our regional analysis and interpretation though, we refrain from using the term absorptive capacity, in consideration of the scale of analysis.[4] We therefore refer more generally to learning capabilities and the knowledge base of regions.

2.4. Rationale, research questions and hypotheses

From the discussion of the literature on agglomeration, spillovers and network positions of regions, three main channels for the transmission of knowledge surface. Firstly, the literature on agglomeration economies strongly focuses on the spatial, place-based dimension of knowledge spillovers, stressing their localized nature (Van Soest et al., 2006; Lissoni and Miguelez, 2014). Second, studies on growth and international trade suggest that through imports, local actors can acquire and capitalize on knowledge that has originated elsewhere, by value chains even at far distance (Lumenga-Neso et al., 2005; Keller and Yeaple, 2009). Third, studies in the field of geography of innovation claim co-inventorship and co-patenting relations, as a form of relational proximity (Boschma, 2005), affect local economic performance (Basile et al.,

3 With their network capital, regions acquire the ability to 'access and subsequently utilize appropriate economically beneficial knowledge' (Huggins and Thompson, 2014, 532).

4 In the literature, accumulated prior and dedicated knowledge a usually conceptualized as the absorptive capacity of firms (Cohen and Levinthal, 1990). In a recent comprehensive overview, Apriliyanti and Alon (2017) show that firms endowed with high levels of such absorptive capacity can efficiently use external knowledge and gain competitive advantages in the forms of innovation, profitability and growth. The literature distinguishes many additive indicators of firm-level absorptive capacity, ranging from the educational level of employees, management capacities, innovation focused R&D facilities, and marketing and customer focused specializations (Flatten et al., 2011). Although, following Caragliu and Nijkamp (2015) and Qian and Acs (2013), the term regional absorptive capacity could be adopted in our research while using aggregated regional data on human capital and R&D, we technically lack indicators for accumulated and dedicated (industry-specific) knowledge.

2012). Supportive, but sometimes suggestive, empirical evidence has been produced for each of these channels. However, only a few attempts have been made to analyze these contributions in a single framework, simultaneously and vis-à-vis one another. As the influence of space and networks affects the regional economy concurrently, we formulate the first research question that we will address in this article, followed by a first set of accompanying hypotheses that we want to test empirically:

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

The discussion in the theoretical section suggests a positive relation between network-mediated R&D spillovers and local productivity. Following the debate on trade spillovers and on different sources of proximity (Coe and Helpman, 1995; Boschma, 2005; Maggioni and Uberti, 2009), we therefore formulate the following hypotheses with RQ 1:

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

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

Based on the discussion of the sources of knowledge and recipient's regional knowledge base, we further theorize that (firms and employees in) different regions produce knowledge spillovers of different qualities according to their average regional level of technological progress. Connections to more advanced places may then provide access to particularly valuable spillovers, generated from state of art knowledge. At the same time, as advanced knowledge tends to be particularly complex and requires specific skills and competences (Balland and Rigby, 2015; Miguélez and Moreno, 2015), larger learning capabilities as knowledge base may be needed for regions to fruitfully assimilate those spillovers. On these bases, we put forward our second research question, accompanied by further testable hypotheses:

RQ 2: *Do relations to more advanced regions provide a particular advantage for in-linking (recipient) regions for regional productivity, and is a more advanced knowledge base necessary to substantiate these benefits?*

To address our second research question, a second set of hypotheses specifically considers the relations with regions that are at the forefront in terms of innovative and technological capabilities. Assuming increasing returns in knowledge generation and transmission mechanisms, leading top patenting regions will spill over more knowledge to other regions than areas with less knowledge generation performance. This insight is incorporated in the following two hypotheses:

Hypothesis 2a: *The positive relation between the level of productivity in recipient 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 recipient region r and the level of R&D in regions which r patents with is stronger, if the co-patenting partner regions are innovation leaders.*

Finally, given the potential conditioning role of learning capabilities in the regional knowledge base, 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 recipient region r and the R&D spillovers from trade and co-patenting with highly advanced partners is conditional on a higher regional knowledge base in r.*

3. Modeling, methodology and data sources

In this section, we introduce and discuss (i) the basic modeling framework of our analyses, (ii) the construction of the weight matrices used, (iii) the data and sources for our variables and (iv) descriptive statistics of the variables used, with emphasis on the explained and explanatory variables of our interest (productivity, networks and R&D intensity).

3.1. Basic modeling framework of our analysis

Staying close to previous work, we model the level of productivity[5] 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 contributions (Coe and Helpman, 1995; Coe et al., 2009; Maggioni et al., 2007), we study the effects of spillovers deriving from two different network channels simultaneously while controlling for spatial effects. We test the three hypotheses put forward in the previous section resorting to three panel data models for the years 2004–2012.[6] Control variables and constructed weight matrices reflect as much as possible begin of period (year) circumstances, yet this is limited to the availability of often complex and unique data. We will discuss this when appropriate in this section.

To combine the spatial and network dimensions of spillovers in our article, we resort to a spatial Durbin error model. In such specification, the spatial- and network-lagged R&D per capita allow us to capture the spillover effects related to different channels and to control for spatial correlation of the residuals. This choice is motivated both by conceptual and methodological reasons.[7]

5 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 Vittucci Marzetti (2015).

6 Whereas the data cover a period of 9 years, introducing the covariates with 1-year lag reduced to 8 the years actually used.

7 As for the conceptual reasons, whereas the existence of spatial spillovers is well established in the literature, we are mostly interested in controlling for it rather than specifically modeling its source, other than from spatially lagged R&D per capita. The SDEM specification is in this sense more flexible, as it does not constrain the spatial effect to follow the spatial lag of the dependent variable. Besides, the main difference between spatial Durbin model (SDM) and SDEM lays in the fact that the former captures so-called 'global' spillovers (in which there is a spatial feedback from region *r* to the dependent variable of its neighboring regions, neighbors of neighboring regions etc.), whereas the latter captures 'local' spillovers (the neighbors of *r* affects *r*'s dependent variable, but the effect does not feedback and propagate). Considering that our dependent variable is TFP, whose change over time is rather limited, 'global' spillovers are unlikely to propagate—from 1 year to the other—from region *r* to all the other regions of

The baseline model, reported in Equation 3.1, is used to estimate the impact of network spillovers on the level of regional productivity while controlling for spatial relations (Hypotheses 1a and b):

$$\log\_\mathrm{TFP}_{r,t} = \alpha_r + \tau_t + \beta * \log\mathrm{R\&D}_{r,t-1} + \delta * W\log\mathrm{R\&D}_{r,t-1} + \vartheta * T\log\mathrm{R\&D}_{r,t-1} + \theta * P\log\mathrm{R\&D}_{r,t-1} + \gamma * \mathrm{Controls}_{r,t-1} + \lambda * W\varepsilon_{r,t} + u_{r,t} \quad (3.1)$$

where $\log\_\mathrm{TFP}_{r,t}$ represents the level of total factor productivity (TFP) in region r at time t (in logs) and $W\log R\&D_{r,t-1}$ is the distance-weighted per capita R&D, $T\log R\&D_{r,t-1}$ captures the import-mediated spillovers and $P\log R\&D_{r,t-1}$ refers to co-patenting-mediated effects. In order to fully control for spatial dependence, the error term is split in a spatially lagged component ($W\varepsilon_{r,t}$) and in the residuals ($u_{r,t}$). Finally, α_r and τ_t represent the cross-sectional and time fixed effects.

Hypotheses 2a and b consider the heterogeneity in the effects due to relations with more knowledge-endowed regions. To capture the potential spillovers deriving from network relations with technological leaders, we compute two new variables, $TE\log\mathrm{R\&D}_{r,t}$ and, $PE\log R\&D_{r,t}$which, respectively, capture the intensity of trade and co-patenting linkages between the most advanced regions ('elite') and linking-in regions.[8] Since spatial relations are less prone to be molded by policy and to guarantee some heterogeneity, we decided not to apply the same transformation to $W\log R\&D_{r,t}$. In Equation 3.2, the terms $T\log R\&D_{r,t}$ and $P\log\mathrm{R\&D}_{r,t}$ are substituted by the newly computed variables ($TE\log R\&D_{r,t}$ and $PE\log R\&D_{r,t}$).

$$\log\_\mathrm{TFP}_{r,t} = \alpha_r + \tau_t + \beta * \log\mathrm{R\&D}_{r,t-1} + \delta * W\log\mathrm{R\&D}_{r,t-1} + \vartheta * TE\log\mathrm{R\&D}_{r,t-1} + \theta * PE\log\mathrm{R\&D}_{r,t-1} + \gamma * \mathrm{Controls}_{r,t-1} + \lambda * W\varepsilon_{r,t} + u_{r,t} \quad (3.2)$$

In the last specification, we introduce a term interacting the import-weighted (or co-patenting-weighted[9]) level of R&D with the level of human capital in the region $Ter\_HK_{r,t}$ as indicators of (learning capabilities in) the regional knowledge base. We do this both for the variables capturing the general trade and co-patenting relations (Equation 3.3) and for those proxying the relations with most advanced regions. In this way, we can consider whether stronger capabilities are required to profit from relations to more technological leaders, as we theorize in Hypothesis 3.[10]

the sample. Besides, for methodological reasons, the SDM specification is rather difficult to apply in panel settings, in which contemporaneous relations (between the dependent variable and the spatially lagged dependent variable) shall be avoided for endogeneity reasons.

8 Linking-in regions may of any type, that is, other advanced regions, innovation followers or less developed areas.

9 For sake of brevity, only the model referring to import relations is reported in Equations (3.3) and (3.4).

10 Because of potential collinearity issues, we do not include both interaction terms at the same time in our models.

$$\log\_TFP_{r,t} = \alpha_r + \tau_t + \beta * \log R\&D_{r,t-1} + \delta * W\log R\&D_{r,t-1} + \vartheta * T\log R\&D_{r,t-1} + \theta * P\log R\&D_{r,t-1} + \varphi * (T\log R\&D_{r,t-1} * Ter\_HK_{r,t-1}) + \gamma * Controls_{r,t-1} + \lambda * W\varepsilon_{r,t} + u_{r,t} \tag{3.3}$$

$$\log\_TFP_{r,t} = \alpha_r + \tau_t + \beta * \log R\&D_{r,t-1} + \delta * W\log R\&D_{r,t-1} + \vartheta * TE\log R\&D_{r,t-1} + \theta * PE\log R\&D_{r,t-1} + \varphi * (TE\log R\&D_{r,t-1} * Ter\_HK_{r,t-1}) + \gamma * Controls_{r,t-1} + \lambda * W\varepsilon_{r,t} + u_{r,t} \tag{3.4}$$

3.2. Construction of the weight matrices

A crucial step in our analysis is to construct the weight matrices to track the intensity of the spatial and network relations between regional economies. Unlike other contributions (Jaffe et al., 1993; Bloom et al., 2013; Lychagin et al., 2016), we follow the spatial econometric literature in computing our weight matrices (Ertur and Koch, 2007, 2011).

Starting from geographical relations, the literature on spatial knowledge spillovers suggests that knowledge exchange in Europe usually takes place within boundaries of 200–300 km (Bottazzi and Peri, 2002; Crescenzi and Rodríguez-Pose, 2011). To ensure the capture of most knowledge flows across space, we construct the spatial matrix **W**, using Eurostat geographical data, on the basis of the following definition:

$$\boldsymbol{W}_{i,j} = \begin{cases} d_{ij}^{-1}, & \text{if } 0 < d_{ij} \leq d \\ 0, & \text{otherwise} \end{cases} \tag{3.5}$$

where d_{ij} represents the distance between the centroids of regions i and j, while d represents the threshold of maximum distance we allow for (300 km).[11] As is customary in spatial econometrics (LeSage, 2014; LeSage and Pace, 2009), the spatial matrix is row-standardized.

To capture the strength of trade relations, we use the intensity of import for intermediate goods between each pair of European regions. The Netherlands Environmental Assessment Agency (PBL) has computed the yearly trade flows among EU regions for six main sectors, for the period 2000–2010 (Thissen et al., 2016; for a technical description, see Thissen et al., 2013).[12] In order to exploit the broad sectoral categories offered by the data, we construct three import weight matrices, one for all sectors (matrix **T** below) and one for trade in more advanced sectors (matrix **A**)

11 In other words, for every region, we define as spatially related two region located within a 300 km radius. Additionally, to account for the fact that larger 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).

12 Following the suggestion of an anonymous reviewer, we tried estimating the trade flows using data on the quality of institutions. The reduced variation owing to the use of country-level information (rather the regional one, at it is not available for years before 2010) does not allow for a precise prediction of the trade relations.

such as chemicals, petroleum and electronics. The import matrices used in our analysis are computed as follows:

$$\boldsymbol{T}_{i,j} = \frac{I\_2000\_2003_{ij}}{\sum_r I\_2000\_2003_{ij}} \tag{3.6}$$

where $I\_2000\_2003_{i,j}$ is the value at constant prices of imports in intermediate goods that region i imported from region j between 2000 and 2003. When building our import intensity matrices, we try to limit concerns for potential endogeneity between trade intensity and economic performance in the following ways. Firstly, as clearly shown in Equation (3.6), we consider only import data on years that are antecedent to the period considered in our study, so 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. Finally, as for the **W** matrix, we row-standardize the trade matrix (Lumenga-Neso et al., 2005).

The matrix **P**, capturing cross-regional patent collaboration, 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 co-patenting relations involving more than one European region between 1988 and 2003 is used.[13] An equal share of each of these patents is allocated across the different inventors [share_pat_1988_2003 in Equation (3.7)], before aggregating the patent counts to regional level. Regionalized information on co-patents is then used to compute the weight matrix as shown in Equation (3.7).

$$\boldsymbol{P}_{i,j} = \frac{\text{share\_pat\_1988\_2003}_{ij}}{\sum_r \text{share\_pat\_1988\_2003}_{ij}} \tag{3.7}$$

As in the case of trade, we use information on the years before 2004 to reduce the concern for endogeneity. As for the spatial and import matrices, the co-patenting matrix is row-standardized.

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). The previous literature has dealt with this issue in differrent ways, for instance, combining the different matrices in one (Hazir et al., 2018) 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, provides 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 co-patenting matrix **P**. Even in this case, however, the correlation does not appear to be particularly high.

13 Both our trade and co-patenting matrices aim at capturing the structure of respective inter-regional networks, in a way that allows us to approximate current relations across regions but that is not prone to endogeneity. In this sense, it is important to stress that all these network matrices are time-invariant: this is motivated by our interest in capturing the change over time in network-mediated R&D spillovers (and their effects on local productivity). If we would use time-varying matrices, then it would be impossible to disentangle how much of the effect is due to changes in R&D spillovers and how much to the change in the network structure.

Table 1. Row-wise correlation among weight matrices

	W-T	W-A	W-P	T-P	A-P
Minimum	−0.06183	−0.11556	−0.04347	−0.0217	−0.04258
First quarter	0.08422	−0.01285	0.34333	0.1279	0.0346
Median	0.19771	0.07265	0.52198	0.2326	0.1314
Mean	0.23825*	0.11435*	0.48778*	0.2815*	0.17641*
Third quarter	0.37167	0.20059	0.66504	0.4114	0.27169
Maximum	0.80552	0.68881	0.98005	0.9222	0.9253

Notes: W, space; T, total trade; A, trade advanced sectors; P, co-patenting.
*$p < 0.05$.

Finally, our last two sets of hypotheses consider the case of relations with innovation leading or 'elite' regions (Hoekman et al., 2009), which we hypothesize to generate spillovers in greater quantity and of better quality of spillovers. To this aim, we consider the position of regions in the per capita distribution of patents for the period 1988–2003, and define as innovation leaders those regions in the top quartile of the distribution.[14] Linkages to innovation-leading elite regions are marked as TE, AE and PE for total trade, trade in advanced (high-tech) products and co-patenting, respectively.

Figure 1 represents the geographical distribution of regions categorized as 'Innovation Leaders' (darker shade). Most of advanced regions are located in the core of Europe, between Southeast England and the North of Italy, with the largest concentration in Germany and in Sweden.

3.3. 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 and Eurostat. Our dependent variable is estimated taking the residual components of a regional production function, as discussed in the Supplementary Appendix.

Our main variables of interest are the level of R&D of each region as well as the network-weighted levels of R&D. As for the former, Eurostat provides information on the level of R&D in each region. We therefore use the log of R&D per capita in PPS (R&D) to construct our other main explanatory variables. 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. Equation (3.8) shows the formula for the spatially weighted R&D level, and ≠we apply the same procedure for matrices **T**, **A**, **P**, **TE**, **AE** and **PE**.

$$W\mathrm{logR\&D}_{r,t} = \sum\nolimits_{s \neq r}^{N} \boldsymbol{W}_{r,s} * \mathrm{logR\&D}_{r,t} \tag{3.8}$$

14 Cortinovis and Van Oort (2015) divided regions in three technological regimes on the basis of a previous classification by Wintjes and Hollanders (2011). Using 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, leads to comparable results. In the online appendix we report a table with the list of 'lite' regions.

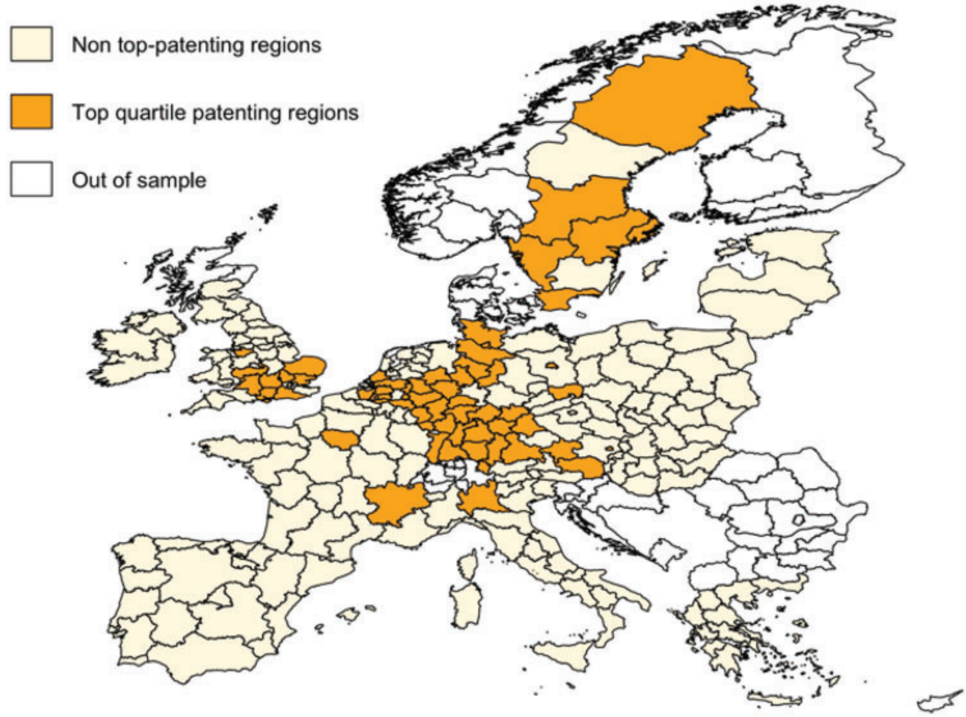

Figure 1. Classification of EU regions in terms of innovation performance.

In addition to these explanatory variables, we include different control variables [Controls$_{r,t}$ in Equations (3.1–3.3). Based on the data from *Eurostat, Sec. HK and Ter. 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, Ter. HK interacts with network-weighted R&D measures.[15] We include in all specifications four more control variables computed from the Cambridge Econometrics database. As is customary in the literature on agglomeration economies, we include a measure of population density (Pop. Density) to control for the heterogeneity between highly urbanized and rural areas. We also include a variable approximating[16] the stock of foreign population in the region (For. Pop.), in order to partially control for migration, another important channel of knowledge diffusion (Breschi and Lissoni, 2009; Hornung, 2014; Miguélez and Moreno, 2015). Finally, to partially control for the economic structure of regions, we include the variables Share Agr and Share Manuf capturing the share of worked hours in manufacturing over the total number of hours worked.

15 Both Ter HK and the weighted measures of R&D are mean-centred before estimating Equations (4.3) and (4.4).

16 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.

In conclusion, our dataset contains information on 233 European regions at the NUTS 2 level, for a period of 9 years (2004–2012).[17] 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 are included, a lack of data on trade flows and co-patenting forces us to exclude Danish, Finnish, Bulgarian and Romanian regions. Additionally, because network data are not regionalized for Slovenia, we must use information on the country as a whole.

3.4. Descriptive statistics

Table 2 report the summary statistics and the correlation across the variable included in the models. More detailed information concerning the data, correlation scores and variance inflation factors is reported in online appendix.

4. Econometric analysis

This section presents our econometric results in Tables 3–5, reporting the estimated coefficients in such a way that each column refers to a different specification for which the weight matrix used is indicated in the header of the column.

The first column of Table 3 shows a simple panel data mode with no spatial effect, in which R&D investments are strongly and significantly related to TFP. The model in the second only includes, along with the spatial error term, a spatially weighted measure of R&D. This latter coefficient is strongly positive and significant, suggesting that an increase in the R&D expenditures in geographically proximate regions of 1% has a positive impact on future TFP in the focal region of 0.06%. With respect to the control variables, we notice that most of them, throughout the specifications, do not appear to significantly relate with regional TFP, with as exception of the share of manufacturing and the share of population with upper secondary education. The period of economic crisis that our analysis covers may contribute to the unexpected negative impact of the share of manufacturing in region's economic composition. The exact nature and embedding of manufacturing may matter as well, with low-productive specializations in, for instance, peripheral Eastern-European regions (Dogaru et al., 2016). The insignificance of other variables may be due to the inclusion of the fixed effects and limited variation over time that characterises these variables.

Looking at the effects of trade-weighted R&D spillovers (Columns 3 and 4), only R&D spillovers deriving from trade in more advanced goods (*A-R&D*) have an impact on local TFP, while the coefficients for total trade (T-R&D) are not different from zero. In terms of magnitudes of the coefficients, the effect of advanced trade-weighted R&D is stronger than the coefficient of space-weighted R&D: a 1% increase in R&D spillovers mediated through advanced trade would lead to an increase in TFP of 0.15%. Besides, it is interesting to notice that in Column 4, the spatially weighted R&D term is

17 The period considered in analysis covers both the financial crisis started in 2008 as well as part of the sovereign debt crisis started in 2009. We account for such macro-economic turbulence by including year fixed effects both in our estimation of TFP and in all our models. An unreported (but available on request) robustness check tries to estimate the same models for the period before (2004–2007) and after (2009–2012) the crisis. The limited variation of TFP in a 4-year period makes it hard for our models to find a significant effect.

Table 2. Descriptive statistics

Variables	Description	Source	*N*	Mean	S.D.	Min	Max
TFP	TFP	Own calc.	1864	−0.0238	0.503	−1.474	1.022
Pop. density	Population density	EUROSTAT	1864	5.087	1.132	1.129	9.159
For. pop.	Foreign population (log)	EUROSTAT	1864	8.861	0.998	5.394	10.75
Share agr.	Agriculture employment (share)	CE	1864	0.0627	0.0575	0.000193	0.401
Share manuf.	Manufacturing employment (share)	CE	1864	0.184	0.0694	0.0364	0.499
Sec. HK	Population with upper-secondary education (share)	EUROSTAT	1864	0.443	0.132	0.0924	0.775
Ter. HK	Population with tertiary education (share)	EUROSTAT	1864	0.233	0.0784	0.0668	0.646
R&D	Per capita R&D expenditure in PPS (log)	EUROSTAT	1864	5.519	1.036	1.872	7.812
W-R&D pc	Spatially weighted R&D	EUROSTAT	1864	5.493	0.941	0	7.037
T-R&D	R&D weighted by total trade	EUROSTAT	1864	6.203	0.275	4.965	6.676
A-R&D	R&D weighted by trade in advanced goods	EUROSTAT	1864	6.281	0.225	5.444	6.772
P-R&D	R&D weighted by co-patenting	EUROSTAT	1864	6.143	0.814	0	7.156
TE-R&D	R&D weighted by total trade with 'elite' regions	EUROSTAT	1864	6.635	0.116	6.307	6.989
AE-R&D	R&D weighted by trade in advanced goods with 'elite' regions	EUROSTAT	1864	6.672	0.12	6.352	7.103
PE-R&D	R&D weighted by co-patenting with 'elite' regions	EUROSTAT	1864	6.525	1.177	0	7.427
Num. of regions			233				
Years			8 (2004–2012)				

Table 3. Spatial, trade and co-patenting relations

Variables	(1) Standard panel	(2) Space	(3) Total Trade (T)	(4) Advanced Trade (A)	(5) Co-patenting (P)	(6) All Net (TP)	(7) All Net (AP)
Pop. density	−0.0823	−0.022	0.0211	0.0146	0.0128	0.0482	0.0474
	(0.209)	(0.280)	(0.289)	(0.291)	(0.275)	(0.283)	(0.285)
For. pop.	0.0946	0.0379	−0.0171	−0.0076	0.00211	−0.0435	−0.0411
	(0.259)	(0.295)	(0.304)	(0.304)	(0.286)	(0.295)	(0.295)
Share agr.	−0.593***	−0.0853	−0.0734	−0.0742	−0.0756	−0.0651	−0.0644
	(0.184)	(0.137)	(0.139)	(0.139)	(0.123)	(0.124)	(0.124)
Share manuf.	−0.492***	−0.246*	−0.264*	−0.263*	−0.253*	−0.268**	−0.269**
	(0.181)	(0.138)	(0.138)	(0.138)	(0.134)	(0.135)	(0.134)
Sec. HK	0.231***	0.123*	0.130*	0.131*	0.117	0.123*	0.125*
	(0.0806)	(0.0743)	(0.0738)	(0.0735)	(0.0726)	(0.0725)	(0.0720)
Ter. HK	0.175	0.094	0.0988	0.101	0.0915	0.0956	0.098
	(0.111)	(0.0827)	(0.0836)	(0.0831)	(0.0810)	(0.0819)	(0.0812)
R&D	0.0361***	0.011	0.0105	0.0112	0.00785	0.00746	0.00801
	(0.00866)	(0.00726)	(0.00718)	(0.00715)	(0.00715)	(0.00710)	(0.00704)
W-R&D		0.0633***	0.0544**	0.0569**	0.0297	0.0229	0.0238
		(0.0237)	(0.0243)	(0.0236)	(0.0248)	(0.0253)	(0.0248)
T-R&D			0.116			0.0991	
			(0.0958)			(0.0901)	
A-R&D				0.152*			0.148*
				(0.0855)			(0.0851)
P-R&D					0.102***	0.0988***	0.100***
					(0.0337)	(0.0345)	(0.0341)
lambda		0.667***	0.669***	0.670***	0.659***	0.661***	0.662***
		(0.0442)	(0.0425)	(0.0422)	(0.0459)	(0.0442)	(0.0438)
Observations	1864	1864	1864	1864	1864	1864	1864
R-squared	0.119	0.463	0.397	0.462	0.289	0.23	0.273
Number of reg	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^2 (w)	0.119	0.0829	0.0435	0.0366	0.0792	0.0491	0.0404
Log-likelihood	4002	4328	4331	4334	4344	4346	4349

Notes: Robust standard errors in parentheses.
***$p<0.01$, **$p<0.05$, *$p<0.1$.

still positive significant even when the advanced trade-weighted R&D term is included. The inclusion of co-patenting-mediated R&D alters the findings presented so far. Similar to the case of trade, the estimated coefficient for co-patenting-mediated R&D spillovers appears to be substantial, with a 1% increase in co-patenting spillovers (P-R&D, Column 5) leading to an increase in TFP of 0.1%. Besides, once the spillovers from co-patenting relations are accounted for (Columns 5–7), the coefficient of spatially mediated R&D spillovers becomes insignificant, while the spatial error term reduces in size. This suggests that a substantial portion of what the spatially weighted R&D term actually captures is co-patenting relationships, as also indicated by other literature (Miguélez and Moreno, 2015). The last Column (7) of Table 3 shows that the effect of advanced trade-mediated R&D spillovers is robust to the inclusion of patent-mediated spillovers as that leaves the coefficient virtually unchanged.

Table 4. Spatial, trade and co-patenting relations with innovation leaders (E)

Variables	(1) Total trade (TE)	(2) Advanced trade (AE)	(3) Co-patenting (PE)	(4) All net (TEPE)	(5) All net (AEPE)
Pop. density	−0.00512	0.0409	−0.0186	−0.00269	0.0414
	(0.288)	(0.319)	(0.286)	(0.294)	(0.318)
For. pop.	0.0274	−0.0283	0.0329	0.0236	−0.0281
	(0.302)	(0.331)	(0.301)	(0.308)	(0.331)
Share agr.	−0.0846	−0.0878	−0.0888	−0.0873	−0.0861
	(0.137)	(0.138)	(0.137)	(0.137)	(0.137)
Share manuf.	−0.264*	−0.250*	−0.246*	−0.263*	−0.251*
	(0.140)	(0.138)	(0.138)	(0.140)	(0.138)
Sec. HK	0.120	0.114	0.122	0.118	0.115
	(0.0738)	(0.0733)	(0.0764)	(0.0759)	(0.0750)
Ter. HK	0.0934	0.0934	0.0929	0.0926	0.0939
	(0.0825)	(0.0836)	(0.0824)	(0.0822)	(0.0834)
R&D	0.0110	0.0105	0.0110	0.0110	0.0105
	(0.00722)	(0.00731)	(0.00725)	(0.00720)	(0.00730)
W-R&D	0.0624***	0.0612***	0.0626***	0.0619**	0.0615**
	(0.0240)	(0.0237)	(0.0240)	(0.0244)	(0.0239)
TE-R&D	0.133			0.132	
	(0.144)			(0.142)	
AE-R&D		0.107			0.111
		(0.127)			(0.131)
PE-R&D			0.00799	0.00608	−0.00409
			(0.0475)	(0.0471)	(0.0489)
Lambda	0.671***	0.668***	0.667***	0.671***	0.667***
	(0.0435)	(0.0441)	(0.0441)	(0.0435)	(0.0443)
Observations	1864	1864	1864	1864	1864
R^2	0.453	0.290	0.459	0.446	0.288
Number of reg	233	233	233	233	233
Region FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
R^2 (w)	0.0368	0.0437	0.0800	0.0364	0.0435
Log-likelihood	4329	4329	4328	4329	4329

Notes: Robust standard errors in parentheses
***$p<0.01$, **$p<0.05$, *$p<0.1$.

In Table 4, we present the results addressing our second research question, which looks exclusively at network relations with most advanced ('elite') 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 two columns of Table 4 consider to trade relations, the third column to co-patenting relations and the fourth and fifth columns look at spatial, trade and co-patenting relations jointly. Again, the share of manufacturing in the regional economy is negatively related to productivity. Concerning our main variables of interest, unlike in Table 3, the coefficient of the spatial-mediated spillovers is positive significant in all the specifications of Table 4. Focusing on the network relations to innovation leaders only that no significant effect is found for any kind of trade-mediated R&D externality. The same is true for co-patenting relations: Table 4

Table 5. Spatial, trade and co-patenting relations with interaction terms

Variables	(1) Total trade (TP)	(2) Total trade (TEPE)	(3) Advanced trade (AP)	(4) Advanced trade (AEPE)	(5) Co-patenting (PT)	(6) Co-patenting (PETE)	(7) Co-patenting (PA)	(8) Co-patenting (PEAE)
Ter. HK	0.0782	0.0376	0.0890	0.0264	0.100	0.105	0.110	0.1000
	(0.0842)	(0.0794)	(0.0823)	(0.0817)	(0.0806)	(0.0800)	(0.0779)	(0.0831)
R&D	0.00875	0.0140**	0.00888	0.0131*	0.00805	0.00933	0.00886	0.00909
	(0.00698)	(0.00707)	(0.00705)	(0.00714)	(0.00718)	(0.00779)	(0.00717)	(0.00783)
W-R&D	0.0265	0.0674***	0.0261	0.0729***	0.0215	0.0609**	0.0228	0.0604**
	(0.0254)	(0.0244)	(0.0248)	(0.0238)	(0.0256)	(0.0246)	(0.0250)	(0.0241)
T-R&D	0.119				0.107			
	(0.0893)				(0.0893)			
TE-R&D		0.203				0.134		
		(0.141)				(0.141)		
A-R&D			0.154*				0.162*	
			(0.0855)				(0.0844)	
AE-R&D				0.129				0.104
				(0.133)				(0.131)
P-R&D	0.0997***		0.103***		0.105***		0.108***	
	(0.0348)		(0.0345)		(0.0339)		(0.0337)	
PE-R&D		0.0132		0.00102		0.00776		−3.86e-05
		(0.0471)		(0.0491)		(0.0473)		(0.0492)
T-R&D*Ter. HK	0.231							
	(0.191)							
TE-R&D*Ter. HK		0.935***						
		(0.261)						
A-R&D*Ter. HK			0.152					
			(0.203)					
AE-R&D*Ter. HK				0.821***				
				(0.228)				
P-R&D*Ter. HK					0.0888		0.0972	
					(0.0776)		(0.0790)	
PE-R&D*Ter. HK						−0.0452		−0.0368
						(0.0493)		(0.0504)
Lambda	0.657***	0.666***	0.660***	0.654***	0.662***	0.676***	0.666***	0.669***
	(0.0436)	(0.0419)	(0.0434)	(0.0442)	(0.0435)	(0.0433)	(0.0429)	(0.0443)
Observations	1864	1864	1864	1864	1864	1864	1864	1864
R^2	0.230	0.102	0.283	0.210	0.204	0.413	0.222	0.325
Number of reg	233	233	233	233	233	233	233	233
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	YES	YES
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	YES	YES
R^2 (w)	0.0479	0.0378	0.0400	0.0595	0.0463	0.0343	0.0362	0.0444
Log-likelihood	4348	4352	4350	4350	4348	4330	4351	4330

Notes: Robust standard errors in parentheses.
***$p<0.01$, **$p<0.05$, *$p<0.1$.

(Columns 3–5) shows no significant relation between co-patenting-mediated R&D spillovers from innovation leaders and local productivity. Overall, the results in Table 4 are not in line with hypotheses 2a and 2 b as relations to most advanced regions do not appear to have any effect of local productivity.

As discussed in the theoretical framework, spillovers from advanced or elite regions may require a stronger knowledge base in recipient regions. We test this hypothesis through our models whose estimates are reported in Table 5. New relevant insights are provided here, in particular with respect to the role of trade.

Like in the previous estimates, the direct effects of total trade R&D spillovers are insignificant. However, the interaction term of total trade-mediated R&D from elite regions with tertiary education levels (TE-R&D * Ter. HK) is now positive significant, suggesting that the effect of trade from most technologically advanced regions varies positively with higher levels of human capital. The same holds true for the interaction between advanced trade from elite regions and tertiary education.[18] Unlike for elite trade network relations, in Table 5, no significant interaction effect is found for co-patenting relations with innovation-leading regions. However, the effects of R&D spillovers from trade in advanced inputs (A-R&D) and co-patenting relations (P-R&D) remain comparable to those reported in Table 3.

5. Robustness analysis on causality

Endogeneity is an obvious concern when studying the relation between R&D spillovers and local productivity. Whereas the use of panel settings allows 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. We address this problem by adopting an IV strategy.

To correctly identify the effects of R&D on local productivity, an instrument should be correlated to current R&D expenditure but not with current productivity. We exploit historical data on regional illiteracy rates (ILLIT) and GRR in the early 1930s (Kirk, 1946), which are likely to meet both those conditions. Although literacy rates have been used to proxy current quality of local institutions (Tabellini, 2010), the level of illiteracy is likely even better capture the (lack of) propensity to invest in knowledge. Similarly, GRR, a measure of replacement fertility capturing the average number of female newborns per fertile woman, relates to the local ability to invest in human capital. Based on these arguments, we expect both the illiteracy rate and GRR to be negatively related to the current level of regional R&D.

In order for the instruments to be valid, they should not be correlated with current level of productivity. Current productivity dynamics are likely to be influenced by many factors, some of which are only slowly changing over time (Tabellini, 2010). In these respects, the main intuition behind the choice of our instruments is to capture some of the historical conditions which made some regions better positioned to absorb knowledge and innovate. Even though the slowly changing nature of some of these factors makes it difficult to assume our instruments are the only channels linking R&D per capita and TFP, we argue that the profound economic, technological and political transformations undergone by European societies since the early 1930s make our instrument exogenous. In particular, we suggest—from a conceptual point of view—that two historical sets of factors contribute to make our instruments exogenous to the current level of productivity: (i) the Second World War and the Cold War and (ii) the rapid technological change that occurred in the last decades. Since our 2SLS models are overidentified, we can statistically

18 Part 3 of the Supplementary Appendix further discuss the marginal effects also with the help of on some graphs.

test the exogeneity of our instruments. Part 4 of the Supplementary Appendix is dedicated to a more thorough discussion of our identification strategy.

Whereas our illiteracy rates and GRR appear to be promising instruments, we observe them only at one point in time. IV estimation in a panel model with fixed effects instead would require an instrument whose overtime variation closely mimic the one of the endogenous variables. As such variable is probably impossible to find, we choose to move from panel to cross-sectional settings to identify the exogenous effects of network-mediated R&D spillovers. Since we then can no longer rely on regional fixed effects for capturing time-invariant factors affecting regional productivity, we slightly modified the model reported in Equation (5.1). Firstly, we select as dependent variable the level of regional TFP in 2012. Second, we include the 2004 value of the control variables and the network-related R&D spillovers used in the previous estimations. To the existing control variables, we add the 2004 level of TFP in order to control for the historical productivity conditions of the regions. Third, given the high collinearity of R&D and W-R&D and their instruments, we sum the two terms and enter them as a single variable.[19] As the spatial weight matrix has all 0 s in the diagonal, the new variable captures the total effect of R&D expenditures in the region and in neighboring areas. Fourthly, we include macro-regional dummies (at NUTS1 level) to capture the residual spatial relations of regions, as we cannot include a spatial error term.[20] Finally, we follow Bloom et al. (2013) and we build the instruments for the space- and network-weighted variables interacting the respective matrix with ILLIT and GRR. In mathematical notation, our 2SLS model can be represented as follows:

$$\begin{aligned}\text{log\_TFP}_{r,2012} &= \pi * \text{log\_TFP}_{r,2004} + \alpha * \text{log\_tot\_locR\&D}_{r,2004} + \vartheta * T\text{logR\&D}_{r,2004} \\ &\quad + \theta * P\text{logR\&D}_{r,2004} + \gamma * \text{Controls}_{r,2004} + \varphi * \text{NUTS1}_r + u_r \end{aligned} \tag{5.1}$$

The second stage results of our IV regressions are reported in Table 6, along with the standard tests for relevance and exogeneity of the instruments. Starting from the bottom part of the table, throughout the five specifications, both the tests on the relevance of the excluded instruments and the tests on over-identification provide convincing evidence on the validity of our IV strategy. The only exception is the significant Hansen J test in the fifth column of the table. 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 considering the size and significant coefficients of the IV estimations, we find substantial confirmation of the results reported in Table 3. In particular, along with significant local-spatial R&D spillovers, the effects of R&D externalities from network relations are found for both imports of advanced intermediate goods (Column 3 in Table 6) and co-patenting relations (Column 4 in Table 6). It is interesting to notice that the sizes of the coefficients in these 2SLS regressions are smaller but comparable to those reported in Tables 3 and 5. According to our IV estimates, a 1% increase in R&D expenditures in regions from which an average region buys advanced intermediate

19 In more formal terms: $\text{log\_tot\_locR\&D}_{\text{r},2004} = \log(\text{R\&D}_{\text{r},2004} + W\text{R\&D}_{\text{r},2004})$.

20 Whereas Strata allows to estimate spatial error IV regressions using—spivreg—, such command does not allow for thorough testing of the validity of the instruments 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.

Table 6. IV estimation using historical data

Variables	(1) RD + W ILL GRR	(2) T − ILL GRR	(3) A − ILL GRR	(4) P − ILL GRR	(5) T P − ILL GRR	(6) A P − ILL GRR
TFP 2004	0.971***	0.971***	0.977***	0.995***	0.988***	0.997***
	(0.0702)	(0.0707)	(0.0687)	(0.0732)	(0.0737)	(0.0707)
Pop. Density	0.0108	0.00984	0.0111	0.0122	0.0116	0.0122
	(0.00859)	(0.00851)	(0.00834)	(0.00819)	(0.00825)	(0.00814)
For. pop.	−0.0128**	−0.0138**	−0.0141***	−0.0114**	−0.0114**	−0.0121**
	(0.00549)	(0.00566)	(0.00534)	(0.00525)	(0.00532)	(0.00512)
Share agr.	0.0337	0.00766	0.0631	0.166	0.159	0.172
	(0.141)	(0.148)	(0.135)	(0.115)	(0.111)	(0.113)
Share manuf.	−0.0215	−0.036	−0.013	0.0198	0.0195	0.0219
	(0.0923)	(0.0929)	(0.0896)	(0.0816)	(0.0828)	(0.0810)
Ter. HK	−0.259	−0.266*	−0.266	−0.187	−0.204	−0.194
	(0.164)	(0.160)	(0.164)	(0.149)	(0.150)	(0.153)
Sec. HK	−0.176**	−0.197**	−0.210**	−0.199**	−0.202**	−0.216**
	(0.0884)	(0.0918)	(0.0912)	(0.0878)	(0.0882)	(0.0889)
Tot. Loc. R&D	0.0415*	0.0421*	0.0434*	0.0397*	0.0451*	0.0404*
	(0.0247)	(0.0246)	(0.0241)	(0.0235)	(0.0240)	(0.0229)
T-R&D		0.0371			−0.00326	
		(0.0417)			(0.0345)	
A-R&D			0.0768*			0.0413
			(0.0418)			(0.0360)
P-R&D				0.0472*	0.0451	0.0422*
				(0.0274)	(0.0274)	(0.0251)
Observations	192	192	192	190	190	190
R^2	0.881	0.881	0.885	0.888	0.887	0.89
NUTS1 FE	Yes	Yes	Yes	Yes	Yes	Yes
K-P LM	28.97***	29.64***	30.06***	29.02***	30.67***	28.64***
LM P-val	5.11E-07	1.64E-06	1.34E-06	2.22E-06	3.58E-06	9.24E-06
S-W F Loc	9.263***	6.667***	6.088***	6.269***	5.155	4.832***
S-W F P-val Loc	0.000185	0.000346	0.000702	0.000565	0.000757	0.00125
S-W F N1		40.27***	46.78***	29.6***	32.57***	34.28***
S-W F P-val N1		0	0	0	0	0
S-W F N2					23.26***	24.15***
S-W F P-val N2					0	0
Hansen J	0.816	2.922	3.384	1.751	6.015	2.773
J P-val	0.366	0.232	0.184	0.417	0.111	0.428

Notes: Robust standard errors in parentheses.
***$p<0.01$, **$p<0.05$, *$p<0.1$.

goods induces an increase in the local productivity of 0.08%. Similarly, incrementing R&D expenditures in co-patenting partners by 1% increases local productivity by 0.04%. As in the previous results, advanced trade R&D spillovers have a stronger effect than co-patenting R&D spillovers. The last two columns of Table 6 do not report any significant coefficient for the network-mediated R&D apart from the coefficient for total local R&D per capita which is positive significant. These imprecise estimates are likely to be due to the high correlation scores among the instruments (see Supplementary Table A.2 in part 5) and limited variation in our cross-sectional data.

6. Conclusions and discussion

This article contributes to the debate on knowledge spillovers showing that local productivity is affected not only by localized externalities, but also—and to a greater extent—by network-mediated spillovers due to interregional trade and co-patenting relations. We find evidence that such knowledge intensive network linkages are directional, with less technologically advanced (firms in) regions learning from R&D investments in more advanced regions. We also find that in order to gain from trade and co-patenting network relations, recipient regions need sufficient internalizing and learning capabilities. Expertise, skills and human capital contribute to build up the necessary knowledge base, without which R&D spillovers do not significantly impact on local productivity. Whereas R&D externalities are in theory free to spill over from any (advanced) region through transfer mechanisms like trade and co-patent connectedness, it takes a critical mass of relevant existing knowledge to actually capture them in recipient regions.

These findings are reached by applying econometric models on TFP and detailed network data for EU regions in the period 2004–1012. This modeling approach has several advantages over previous research. Firstly, the use of TFP ensures a better interpretation of regional economic performance, compared to employment or labor productivity data predominantly used in the economic–geographical literature before. Second, we simultaneously introduce two forms of network linkages, namely trade (import) and technological cooperation (co-patenting), which work as transfer mechanisms. Third, we are able to control for unobserved heterogeneity that is constant over time in EU regions using of a panel data setting. This also allows us to time-lag the explanatory variables, which reduces the possibility of capturing spurious relations. Finally, as endogeneity can still be present, our fourth modeling improvement over previous contributions is the use of an IV (2SLS) strategy. Our results are robust also using this approach.

We applied our methodology on EU data to test three sets of hypotheses. Firstly, based on the empirical research on agglomeration economies, we expected R&D spillovers deriving from network relations to have a strong impact on local productivity (Hypotheses 1a and b). Our estimates consistently confirm these hypotheses for spillovers from technologically advanced imports and spillovers from co-patenting relations. Both these effects find confirmation in our 2SLS estimations. Our expectations on the role of R&D spillovers from innovation leaders, expressed in Hypotheses 2a and b are instead not confirmed. According to our estimates, the superior knowledge endowment of top innovating regions does not necessarily spill over and translate into higher productivity for trade partners and co-inventors. A potential explanation for this, conceptualized in Hypothesis 3, refers to the lack of a sufficient knowledge base in recipient regions. Including an interaction between network-mediated spillovers and human capital endowments, our analysis suggests that preconditions exist for regions to profit from connections with innovation-leading areas. Interestingly, knowledge embodied in goods and technologies and diffused via trade seems to be relatively hard to assimilate by recipients, whereas co-patenting spillovers are much less influenced by local knowledge base conditions. Because the impact of different forms of networks have not simultaneously been analyzed before, this finding adds value to policy debates, to which we turn later on in this section.

Our research bridges different theoretical sub-disciplines in economics and economic geography, that together point at contrasting conclusions: local knowledge spillovers are only perceived through face-to-face and around the corner (economic geographical literature), but also (in a European setting) within a distance range of 250 km (spatial econometrics literature). The simultaneous inclusion of various forms of proximity helps explaining this contradiction. This is not the only conceptual contribution our article offers. Economic studies in the growth and cross-border R&D spillover literature tend to ignore the sub-national territorial dimension and almost exclusively focus on spillovers mediated by trade and foreign direct investments (FDI) relations. On the other hand, regional level studies have largely overlooked the role of trade linkages as channels for knowledge spillovers, focusing more explicitly on spatial patterns interpreted as relations and, more recently, on assessing the role of various other forms of proximity. By jointly looking at spatial and network effects, our artilce is the first that is able to offer a more comprehensive and causal perspective on the productivity effects of spatial and network relations.

Our approach also has various limitations, which could should be tackled by future research. It became clear that our focus on NUTS-2 regions in Europe also hides some of the network dynamics. Especially co-patenting relations to a large extent stay within the 50–70 km radius, which explain why co-patenting and geographical proximity variables turned out to be mutually exclusive in our models. A solution could be to analyze more fine-grained spatial detail, yet this is not available for the trade data. Another restriction concerns the years analyzed (2004–2012): even if we control for time-specific effects, economic growth was rather weak in many parts of Europe over these years. The negative impact of our control variable of manufacturing as share in the regional economies may be related to this. More research into sub-periods may offer interesting insights on the intensity and role of network spillovers in different phases of the macro-economic cycle. Furthermore, more and varying definitions of innovation leading or elite regions may be applied, also in a more tailored or industrially characterized fashion. Our focus on manufacturing industries is well served by our approach, but patent-intensity may not be the best or only indicator for identifying advanced regions, especially when a burgeoning services industry prospers in many regions. Our analyses may also be subject to sensitivity because of network change—especially in trade relations that can be hit by policy shocks unexpectedly. Co-patenting networks are more stable over time, yet sometimes are tied to large companies or research organizations (Hoekman et al., 2009; Ponds et al., 2010). Outsourcing or replacement of R&D-facilities may induce changes in the network of co-patenting relations over time.

Our research clearly has policy implications on various spatial scales, showing that network relations do complement localized knowledge endowments of regions and contribute to higher levels of productivity. This has already fueled for long time the idea that networks, complementary to places, can be subject to subsidies, like Framework programs and the European Research Area (Frenken et al., 2007). Trade linkages can be subject to subsidies as well as to positive or negative shocks due to changes in institutionalized trade relations. With trade disputes on the rise, the policy relevance of our contribution is clearer than ever. Relevant political decision power is at EU and national state levels, but increasingly also at regional levels within countries. Whereas these latter regions cannot influence the whole network of linkages fully, they can invest in the local knowledge base and in gaining a hub position to link into these networks optimally. The network formation as a whole is predominantly market driven in both trade and knowledge, yet institutional and facilitating conditions are crucial. Restrictions on trade and on the freedom of movements for instance, may jeopardize knowledge exchange and collaborations with negative consequences on local productivity.

Our results also suggest that preconditions are important for network effects to materialize. In particular, the strongest impact of trade-mediated knowledge spillovers occurs when the receiving region has abundant human capital and knowledge assets. From the one hand, this result indicates the crucial importance of investments in local knowledge capacity. From the other hand, our results question the applicability of recent European policy initiatives, such as smart specialization opportunities for all regions in Europe. Currently lagging regions in Europe may not fully benefit from trade relations, as they may lack the necessary and dedicated skills and human capital to absorb and internalize the knowledge embedded in the networks and put it to use locally. With regions lacking of suitable knowledge bases—such as in peripheral Eastern Europe or Southern Europe—relations to innovation leaders become self-sustaining (Desdoigts, 1999; Hoekman et al., 2009). This may well explain the change in the European economic landscape, from one characterized by convergence (until the 1980s) to the present one showing ‘islands of prosperity in a sea of stagnation’ (Roses and Wolf, 2018). Trade and FDI have since the opening up of the Iron Wall in 1990 been regarded as main sources of local productivity and employment in less advanced Central and Eastern European recipient countries and regions (Tondel, 2001; Deichman et al., 2003), yet our research shows that lacking learning capabilities and a knowledge base may hamper spillovers and integration. Without simultaneously developed local, endogenous sources of knowledge, network relations may be predominantly profitable for first-tier source regions (Dogaru et al., 2015). This suggests that place-based development policies in Europe should incorporate and develop policies on network-based dependencies and vice versa (Barca et al., 2012; Thissen et al., 2013).

In order to help assess such policy-based initiatives, our work points at further conceptual and theoretical challenges. The agglomeration literature increasingly incorporates network, proximities or relatedness indicators into its analyses (Boschma, 2005; Frenken et al., 2007), yet not always is the exact network nature of such concepts and data clear. Studies in many cases only consider static relatedness rather than a network interpretation of inter-regional linkages, resulting in over-emphasizing the impact of place-based development and subsequent policy orientations (Thissen et al., 2013). More research on measurable inter-regional flows and relations and their impacts is therefore needed, also for policy advice. Regions underperforming in terms of income (Eastern Europe) or economic growth (Southern Europe) should pay explicit attention to these, as barriers to trade and knowledge exchange may as well be related to persistent institutional differences (like quality of governance and informal institutions) which have been shown to importantly determine the development trajectory of regions (Cortinovis et al., 2017; Ketterer and Rodríguez-Pose, 2018).

Supplementary material

Supplementary data for this paper are available at *Journal of Economic Geography* online.

References

Abreu, M., Grinevich, V., Kitson, M., Savona, M. (2008) *Absorptive Capacity and Regional Patterns of Education. DIUS Research Report 08 11,* Center for Business Research. University of Cambridge.

Akerlof, G. A. (1997) Social distance and social decision. *Econometrica*, 65: 1005–1027.

Apriliyanti, I. D., Alon, I. (2017) Bibliometric analysis of absorptive capacity. *International Business Review*, 26: 896–907.

Arbia, G., Battisti, M., Di Vaio, G. (2010) Institutions and geography: empirical test of spatial growth models for European regions. *Economic Modelling*, 27: 12–21.

Balland, P. A., Rigby, D. (2015) The geography and evolution of complex knowledge. *Economic Geography*, 93: 1–23.

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

Basile, R., Capello, R., Caragliu, A. (2012) Technological interdependence and regional growth in Europe: proximity and synergy in knowledge spillovers. *Papers in Regional Science*, 91: 697–722.

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

Becattini, G., Bellandi, M., De Propris, L. (eds) (2009) *A Handbook of Industrial Districts*. Cheltenham: Edward Elgar.

Benhabib, J., Spiegel, M. M. (2005) Human capital and technology diffusion. In P. Aghion and S. Durlauf (eds) *Handbook of Economic Growth*. North-Holland: Elsevier.

Behrens, K., Robert-Nicoud, F. (2015) Agglomeration theory with heterogeneous agents. In G. Duranton, J. V. Henderson and W. Strange (eds) *Handbook of Regional and Urban Economics 5A*, pp. 171–246.

Belussi, F., Hervas-Oliver, J. L. (2018) *Agglomeration and Firm Performance*. Berlin: Springer.

Beugelsdijk, S., Smeets, R., Zwinkels, R. (2008) The impact of horizontal and vertical FDI on host's country economic growth. *International Business Review*, 17: 452–472.

Bloom, N., Schankerman, M., van Reenen, J. (2013) Identifying technology spillovers and product market rivalry. *Econometrica*, 81: 1347–1393.

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

Bottazzi, L., Peri, G. (2002) Innovation and spillovers in regions: evidence from European Patent Data. IGIER Working Paper Series No. 215, Bocconi University.

Breschi, S., Lissoni, F. (2001) Knowledge spillovers and local innovation systems: a critical survey. *Industrial and Corporate Change*, 10: 975–1005.

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

Camagni R. (1991) Local milieu, uncertainty and innovation networks: towards a dynamic theory of economic space. In R. Camagni (ed) *Innovation Networks: Spatial Perspectives*. London: Belhaven-Pinter, 121–144.

Capello, R. (2009) Spatial spillovers and regional growth. *European Planning Studies*, 17: 639–658.

Capello, R. (2009) Indivisibilities, synergy and proximity: the need for an integrated approach to agglomeration economies. *Tijdschrift voor Economische en Sociale Geografie*, 100: 145–159.

Caragliu, A., Nijkamp, P. (2008) The impact of regional absorptive capacity on spatial knowledge spillovers. Tinbergen Institute Discussion Papers 08-119/3, Tinbergen Institute.

Caragliu, A., Nijkamp, P. (2015) Space and knowledge spillovers in European regions: the impact of different forms of proximity on spatial knowledge diffusion. *Journal of Economic Geography*, 16:749–774.

Coe, D., Helpman, E. (1995) International R&D spillovers. *European Economic Review*, 39: 859–887.

Coe, D., Helpman, E., Hoffmaister, A. (2009) International R&D spillovers and institutions. *European Economic Review*, 53: 723–741.

Cohen, W. M., Levinthal, D. A. (1990) Absorptive capacity: a new perspective on learning and innovation. *Administrative Science Quarterly*, 35: 128–152.

Combes, P. P., Gobillon, L. (2015) The empirics of agglomeration economies. In G. Duranton, J. V. Henderson and W. Strange (eds) *Handbook of Regional and Urban Economics 5A*. North-Holland: Elsevier. pp. 247–348.
Conley, T. G., Ligon, E. (2002) Economic distance and cross-country spillovers. *Journal of Economic Growth*, 7: 157–187.
Cortinovis, N., Van Oort, F. (2015) Variety, economic growth and knowledge-intensity of european regions: a spatial panel analysis. *Annals of Regional Science*, 55: 7–32.
Cortinovis, N., Xiao J., Boschma, R., Van Oort, F. (2017) Quality of government and social capital as drivers of regional diversification in Europe. *Journal of Economic Geography*, 17: 1179–1208.
Crescenzi, R., Rodríguez-Pose, A. (2011) *Innovation and Regional Growth in the European Union*. Berlin, Germany: Springer.
Crespo, N., Fontoura, M. P. (2007) Determinant factors of FDI spillovers—what do we really know? *World Development*, 35: 410–425.
Dall'Erba, S., Le Gallo, J. (2008) Regional convergence and the impact of European Structural Funds over 1989-1999: a spatial econometric analysis, *Papers in Regional Science*, 87: 219–242.
Desdoigts, A. (1999) Patterns of economic development and the formation of clubs. *Journal of Economic Growth*, 4: 305–330.
Deichman, J., Eshghi, A., Haughton, D., Ayek, S., Teebagy, N. (2003) Foreign direct investment in the Eurasian transition states. *Eastern European Economics*, 41: 5–34.
Dogaru, T., Burger, M., Karreman, B., van Oort, F. (2015) Division of labour and FDI in CEE countries. *Tijdschrijft voor Econische en Sociale Geografie*, 106: 120–129.
Dogaru, T., van Oort F., Cortinovis, N. (2016) Smart Specialisation and Local Economic Development in Eastern Europe. In P. McCann (ed) *The Empirical and Institutional Dimensions of Smart Specialisation*. London: Routledge.
Durlauf, S. N., Kourtellos, A., Minkin, A. (2001) The local Solow growth model. *European Economic Review*, 45: 928–940.
Elhorst, J. P. (2014) *Spatial Econometrics: From Cross-Sectional Data to Spatial Panels*. Berlin, New York, Dordrecht, London: Springer.
Ertur, C., Koch, W. (2007) Growth, technological interdependencies and spatial externalities: theory and evidence. *Journal of Applied Econometrics*, 22: 1033–1062.
Ertur, C., Koch, W. (2011) A contribution to the theory and empirics of Schumpetrian growth with worldwide interactions. *Journal of Economic Growth*, 16: 215–255.
Fagerberg, J. (1988) International competitiveness. *Economic Journal*, 98: 355–374.
Flatten, T. C., Greve, G. I., Brettel, M. (2011), Absorptive capacity and firm performance in SMEs: the mediating influence of strategic alliances. *European Management Review*, 8: 137–152.
Foray, D. (2015) *Smart Specialisation - Opportunities and Challenges for Regional Innovation Policy*. London: Routledge.
Fracasso, A., Vittucci Marzetti, G. (2015) International trade and R&D spillovers. *Journal of International Economics*, 96: 138–149
Frenken, K., Van Oort, F., Verburg, T. (2007) Related variety, unrelated variety and regional economic growth. *Regional Studies*, 41: 685–697.
Frenken, K., Hoekman, J., van Oort, F. (2007) *Towards a European Research Area*. Rotterdam: Nai Uitgevers & Ruimtelijk Planbureau.
Fu, X., Pietrobelli, C., Soete, L. (2011) The role of foreign technology and indigenous innovation in the emerging economies: technological change and catching-up, *World Development*, 39: 1204–1212.
Granovetter, M. (1973) The strength of weak ties. *American Journal of Sociology*, 78: 1360–1380.
Greunz, L. (2003) Geographically and technologically mediated knowledge spillovers between European regions. *Annals of Regional Science*, 37: 657–680.
Grossman, G. M., Helpman, E. (1991). *Innovation and Growth in the Global Economy*. Cambridge, MA: MIT Press.
Grossman, G., Helpman, E. (1994) Endogenous innovation in the theory of growth. *The Journal of Economic Perspectives*, 8: 23–44.
Hazir, C. S., LeSage, J. P., Autant-Bernard, C. (2018) The role of R&D collaboration networks on regional innovation performance. *Papers in Regional Science*, 97: 549–567.

Hoekman, J., Frenken, K., van Oort, F. G. (2009) The geography of collaborative knowledge production in Europe. *The Annals of Regional Science*, 43: 721–738.

Hornung, E. (2014) Immigration and the diffusion of technology: the Huguenot diaspora in Prussia. *American Economic Review*, 104: 84–122.

Huggins, R., Thompson, P. (2014) A network-based view of regional growth. *Journal of Economic Geography*, 14: 511–545.

Huggins, R., Thompson, P. (2017) Networks and regional economic growth: a spatial analysis of knowledge ties. *Environment and Planning A*, 49: 1247–1265.

Huggins, R., Johnston, A., Thompson, P. (2012) Network capital, social capital and knowledge flow: how the nature of inter-organizational networks impacts on innovation. *Industry and Innovation*, 19: 203–232.

Iammarino, S., McCann, P. (2013) *Multinationals and Economic Geography: Location and Technology, Innovation*. Cheltenham, UK: Edward Elgar.

Jaffe, A., Trajtenberg, M. (1999) International knowledge flows: evidence from patent citations. *Economics of Innovation and New Technology*, 8: 105–136.

Jaffe, A., Trajtenberg, M., Henderson, R. (1993) Geographic localization of knowledge spillovers as evidenced by patent citations. *The Quarterly Journal of Economics*, 108: 577–598.

Jones, C. I. (1995) R&D-based models of economic growth. *Journal of Political Economy*, 103: 759–784.

Keller, W. (2002) Geographic localization of international technology diffusion. *American Economic Review*, 92: 120–142.

Keller, W., Yeaple, S. R. (2009) Multinational enterprises, international trade, and productivity growth: firm-level evidence from the United States. *The Review of Economics and Statistics*, 91: 821–831.

Ketterer, T. D., Rodríguez-Pose, A. (2018) Institutions vs. 'first-nature' geography: what drives economic growth in Europe's regions? *Papers in Regional Science*, 97: S25–S62.

Kirk, D. (1946) *Europe's Population in the Interwar Years*. Geneva: League of Nations.

Knoben, K, Andac, A., van Oort, F., Raspe, O. (2016) Agglomeration and firm performance: one firm's medicine is another firm's poison. *Environment & Planning A*, 48: 132–153

Koster, H., Cheng, F., Gerritse M., van Oort, F. (2018) Place-based policies, firm productivity and displacement effects: evidence from Shenzhen, China. *Journal of Regional Science* (forthcoming).

Lissoni, F. (2016) Migration and innovation diffusion: an eclectic survey. *Cahier du GREThA 2016-11*, Université de Bordeaux.

Lissoni, F., Miguelez, E. (2014) Patents, innovation and economic geography. Chaiers du GREThA 2014-16, Groupe de Recherche en Economie Théorique et Appliquée.

LeSage, J. P., Pace, R. K. (2009) *Introduction to Spatial Econometrics*. Boca Raton: Taylor & Francis.

LeSage, J. P. (2014) What regional scientists need to know about spatial econometrics. *The Review of Regional Studies*, 44: 13–32.

Lychagin, S., Pinkse, J., Slade, M. E., van Reenen, J. (2016) Spillovers in space: does geography matter? *The Journal of Industrial Economics*, 64: 295–335.

Lucas, R. (1988) On the mechanics of economic development. *Journal of Monetary Economics*, 22: 3–42.

Lumenga-Neso, O., Olarreaga, M., Schiff, M. (2005) On 'indirect' trade-related R&D spillovers. *European Economic Review*, 49: 1785–1798.

Maggioni, M., Nosvelli, M., Uberti, E. (2007) Space versus networks in the geography of innovation: a European analysis. *Papers in Regional Science*, 86: 471–493.

Maggioni, M., Uberti, E. (2009) Knowledge networks across Europe: which distance matters? *Annals of Regional Science*, 43: 691–720.

Mancusi, M. L. (2008) International spillovers and absorptive capacity: a cross-country cross-sector analysis based on patents and citations. *Journal of International Economics*, 76: 155–165.

McCann, P., van Oort, F. (2018) Theories of agglomeration and regional economic growth: a historical review. In R. Capello and P. Nijkamp (eds) *Handbook of Regional Growth and Development Theories*, 2nd edn (forthcoming).

McCann, P., Ortega-Argiles, R. (2016) Regional innovation, R&D and knowledge spillovers: the role played by geographical and non-geographical factors. In R. Shearmur, C. Carrincazeaux and D. Doloreux (eds) *Handbook on the Geography of Innovation*. Cheltenham: Edward Elagar, pp. 22–44.

Miguélez, E., Moreno, R. (2015) Knowledge flows and the absorptive capacity of regions. *Research Policy*, 44: 833–848.

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

Morrison, A., Rabellotti, R. (2009) Knowledge and information networks in an Italian wine cluster, *European and Planning Studies*, 17: 983–1006.

Morrison, A., Pietrobelli, C., Rabellotti, R. (2008) Global value chains and technological capabilities: a framework to study learning and innovation in developing countries. *Oxford Development Studies*, 36: 39–58.

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

Nelson, R. R., Phelps, E. S. (1966) Investment in humans, technological diffusion, and economic growth. *American Economic Review*, 56: 69–75.

Neumark, D., Simpson, H. (2015) Place-based policies. In G. Duranton, J. V. Henderson and W. Strange (eds) *Handbook of Regional and Urban Economics*. Amsterdam: Elsevier.

Nooteboom, B. (1992) Towards a dynamic theory of transactions. *Journal of Evolutionary Economics*, 2: 281–299.

Paci, R., Marrocu, E., Usai, S. (2014) The complementary effects of proximity dimensions on knowledge spillovers. *Spatial Economic Analysis*, 9: 9–30.

Qian, H., Acs, Z. (2013) An absorptive capacity theory of knowledge spillover entrepreneurship. *Small Business Economics*, 40: 185–197.

Ponds, R., van Oort, F., Frenken, K. (2010) Innovation, spillovers, and university-industry collaboration: an extended knowledge production function approach. *Journal of Economic Geography*, 10: 231–255.

Ratti, R., Bramanti, A., Richard, G. (eds) (1997) *The Dynamics of Innovative Regions. The GREMI Approach*. Alderhot: Ashgate.

Romer, P. M. (1986) Increasing returns and long-run growth. *Journal of Political Economy*, 94: 1002–1037.

Rosenthal, S. S., Strange, W. C. (2008) The attenuation of human capital spillovers. *Journal of Urban Economics*, 64: 373–389.

Roses, J., Wolf, N. (2018) *Regional Economic Development in Europe, 1900-2010: A Description of the Patterns*. London: Centre for Economic Policy Research.

Thissen, M., Diodato, D., van Oort, F. (2013a) *Integrated Regional Europe: European Regional Trade Flows in 2000*. The Hague: Netherlands Environmental Assessment Agency (PBL).

Thissen, M., Diodato, D., van Oort, F. (2013b) *Integration and Convergence in Regional Europe: European Regional Trade Flows from 2000 to 2010*. The Hague: Netherlands Environmental Assessment Agency (PBL).

Thissen, M., de Graaff, T., van Oort, F. (2016) Competitive network positions in trade and structural economic growth: a geographically weighted regression analysis for European regions. *Papers in Regional Science*, 95: 159–180.

Tondel, L. (2001) Foreign direct investment during transition. Determinants and patterns in Central and Eastern Europe and the former Soviet Union. CMI Working Paper.

Torre, A., Gilly, J. P. (1999) On the analytical dimension of proximity dynamics. *Regional Studies*, 34: 169–180.

Torre, A., Rallet, A. (2005) Proximity and localization. *Regional Studies*, 39: 47–59.

Van Soest, D., Gerking, S., van Oort, F. (2006) Spatial impacts of agglomeration externalities. *Journal of Regional Science*, 46: 881–899.

Wintjes, R., Hollanders, H. (2011) Innovation pathways and policy challenges at the regional level: smart specialization. Working paper, United Nations University Maastricht.