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Abstract

A large academic consensus exists on the idea that successful innovative processes are geographically bounded within regions. Nevertheless, the ability of regions to capture and re-use external knowledge is also regarded as a fundamental element to sustain and refine the local profile of specialisation and competitiveness. The present article combines these views to investigate the sources of the regional innovation process, by analysing data on Italian regions over the period 2007-2012. We define regional external networks based on all the foreign subsidiaries of local multinational enterprises identifiable as global ultimate owners. Our main results suggest that both the internal specialisation and the outward networks can generate indigenous innovation, but the role of the networks varies substantially according to its density, its degree of complementarity with the specialisation profile, its geographical spread and the specific location of the foreign subsidiaries. Our results, then, support a view of the regional innovation as an interactive process whereby valuable knowledge resources are not only generated within the reach of the local economy, but they are also integrated with external inputs. This contrasts with recent anti-globalisation views according to which the increase in the foreign operations of national companies impoverishes the local economy.

Keywords: outward foreign direct investment, innovation, specialisation, networks, relatedness

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1. Introduction

A long-standing tradition of scholarly works in innovation economics and economic geography emphasises the path-dependent and spatially-bound nature of innovation (e.g. Jaffe et al., 1993; Audretsch and Feldman, 1996; Storper, 1997; Iammarino, 2005; Heimeriks and Boschma, 2013), while others highlight the complementary role of the external linkages that regions can establish in order to access new pools of knowledge (e.g. Bathelt et al., 2004; Turkina and van Assche, 2018). These linkages are often conceptualised in terms of the network of foreign subsidiaries that local companies are able to establish via outward foreign direct investment, as multinational enterprises (MNEs) are able to connect knowledge in diverse locations and subsequently exploit the benefits of their operations at home (Bathelt and Cohendet, 2014). While regional internal specialisation and the establishment of external linkages are theoretically considered as complementary elements for local innovativeness within the academic debate, the empirical evidence on their joint role and their interplay remains scant, as most academic contributions tend to focus on one or the other aspect only (Li et al., 2016; Balland and Rigby, 2017). More importantly, from the political standpoint there is a growing scepticism towards the internationalisation of local companies through outward investments, as opposed to their export activities, based on the belief that such investment will hinder local economic development through the offshoring of jobs, the loss of local activities and the transfer of resources to the benefit of foreign locations (Gagliardi et al. 2015; Iammarino, 2018). This type of considerations seems to dominate industrial and investment policy-making in recent years, with the surge of populist views in most developed countries about the negative effects of globalisation (Bathelt and Buchoz, 2019). As such, contrary to the scholarly view, this anti-globalisation perspective considers that the process of internal regional specialisation and the establishment of an external network of subsidiaries are not complementary forces supporting local innovative efforts. Rather, the establishment of activities in foreign markets is seen as diverting resources from the regional economy, thus substantially deteriorating its patterns of industrial specialisation, with a consequent loss of innovation potential.

Hence, this article offers an analysis of the regional innovation process resulting from the joint action of the internal specialisation of regions and their external global networks of subsidiaries, with the aim of clarifying whether these are complementary elements and under which circumstances external networks and local industrial specialisation produce the most favourable – or unfavourable – conditions for local innovative activities. We assemble an original dataset for Italian regional economies (NUTS-2) over the period 2007-2012, by considering EPO data on the specific IPC technology classes in which regional patents are filed. Furthermore, we connect these technology classes to both the manufacturing sectors in which regions are specialised, based on employment figures taken from Italian National Statistical Office (ISTAT), and to the sectors of the foreign subsidiaries of local parent companies, based on data from the Bureau van Dijk – Amadeus, as a direct measure of regional external network. Methodologically, we estimate panel fixed-effects models and we subsequently control for the endogeneity of the regional external network by means of an instrumental variable approach.

Our main results suggest that both the internal specialisation and the outward networks of Italian regional economies can generate indigenous innovation, but the role of the network varies substantially according to its geographical spread, the specific location of the foreign subsidiaries and the specialisation level of the regional economy. Importantly, the positive effect of the network of foreign subsidiaries in a certain industry tends to be concentrated on regions with a strong specialisation in that very same industry. Our findings, then, support a view of regional innovation as an interactive process whereby valuable knowledge resources are not only generated within the reach of the local economy, but they are also integrated with external inputs. Therefore, the establishment of an external network of subsidiaries can produce positive effects for the economic system in which parent companies are located. These firms play the role of knowledge gatekeepers: namely, actors with the ability to generate trans-local networks to tap into external knowledge pools that are locally unavailable or too costly to create. Therefore, one fundamental policy implication is that regional openness and the support of the internationalisation of local companies by means of foreign investments can be a catalyst of regional success in terms of innovativeness, especially for highly specialised regional economies. Not only does this contrast with recent anti-globalisation views according to which the increase in the foreign operations of national companies impoverishes the local economy, but it also suggests that discouraging this type of internationalisation of local firms can be particularly detrimental for the most advanced and specialised regions.

The article is organised as follows. The next section provides a literature background on the roles of internal and external forces in shaping local innovativeness. Subsequently, we present and describe our data. Next, we explain our methodological approach. Then, we discuss our results and, finally, we draw some conclusions and implications for industrial and regional policy-making.

2. Literature background

Since the work of Marshall (1890), the spatiality of new knowledge creation occupies centre stage in the academic debate on regional development and growth. A large consensus exists nowadays on the idea that successful innovative processes are geographically bounded within regions (Amin and Thrift, 1994; Audretsch and Feldman, 1996; Storper, 1997; Cooke et al., 1998; Balland and Rigby, 2017), where persistent and dense interactions between co-located organisations stimulate economic specialisation, learning and the development of new competences (Becattini, 1990; Boschma and Frenken, 2007). This systematic web of linkages ultimately supports the capacity of regional economies to produce new knowledge, thus constituting a regional system of innovation that is a spatially and institutionally distinctive knowledge-based structure within national boundaries (Howells, 1999; Lundvall, 1992). Hence, the region represents the locus within which firms accumulate competences and sustain processes of new knowledge creation with the aim of increasing their competitiveness (Oinas and Malecki, 2002; Iammarino, 2005). Furthermore, path-dependent localised capabilities such as regions' institutional setting, their infrastructural environment and human resources are functional to firm-level efforts in this sense, as they provide a historically-determined and spatially-defined configuration to feed, upgrade and renew local comparative advantages (Storper, 1997; Maskell and Malmberg, 1999), thus stimulating economic specialisation at the local level (Malmberg and Maskell, 1997).

In fact, behind most academic contributions lies the common idea that successful regional economic performance mostly emerges as a result of an incremental and cumulative process of territorial specialisation in a number of activities or tasks. Accordingly, the notion of flexible specialisation dominates studies on Marshallian industrial districts (Bagnasco, 1977; Piore and Sabel, 1984; Becattini, 1987; Cucculelli and Storai, 2018), and the long-standing evidence in favour of inter-industry as well as intra-industry effects in agglomeration economies (Glaeser et al., 1992; Henderson et al., 1995) supports a similar view. Also, works in evolutionary economic geography suggest that regions specialising in related activities tend to be more innovative than those characterised by a number of unrelated industries (Frenken et al., 2007). Combined together, the relevance of the subnational geography of economic activity and the diverse patterns of industry specialisation across space provide an insightful interpretative key to understand the performance of modern economies: in fact, only a limited number of highly specialised spatial units within countries contribute to generating large shares of national output, export activity and innovation (Porter, 1990; Kemeny and Storper, 2015). This enduring and marked spatial unevenness in economic specialisation reflects the sticky nature of knowledge and the process of learning (Markusen, 1996), as well as the existence of serious barriers to knowledge diffusion and imitation (Kogut and Zander, 1992).

Nevertheless, the ability of regions to capture, understand, absorb and re-use external knowledge is also regarded by an increasing number of scholars as a fundamental element to sustain and refine the local profile of specialisation and competitiveness (Pyke et al., 1990; Ernst and Kim, 2002; Bathelt et al., 2004). In fact, trans-local networks can provide specific regions with diverse and related information sources and opportunities to develop novel trajectories of specialisation by combining internal and external knowledge resources (Owen-Smith and Powell, 2004; Boschma and Iammarino, 2009). Therefore, these extra-regional linkages are believed to play a crucial role in upgrading local competences, contributing to avoiding industrial and technological stagnation and lock-in that may result from a rigidly inward-looking regional system of local interactions and over-embeddedness (Uzzi, 1996; Visser and Boschma, 2004; Bathelt, 2007). As such, linking knowledge sources across multiple spatial scales challenges the exclusive and dominant role of the local dimension as a self-sufficient institutional and economic construct able to generate innovation as an isolated system (Gertler and Levitte, 2005; Gertler and Wolfe, 2006). In fact, by creating external connections with international nodes for the transmission and sharing of knowledge (Simmie, 2003) and distant knowledge communities (Coe and Bunnell, 2003), regions can integrate diverse and complementary technological contexts and improve the quality of local specialisation dynamics (Bathelt et al. 2004).

Nonetheless, regional economies cannot be considered as entities that *per se* establish linkages, access, learn and share external knowledge. Hence, a key element in the above discussion regards the specific actors and the mechanisms through which extra-regional connectivity generates new innovation opportunities at the local level. Knowledge gatekeepers are identified as those local actors with the ability to generate trans-local networks and tap into external knowledge pools that are locally unavailable or too costly to create (Morrison, 2008; Rychen and Zimmerman, 2008). Recent contributions on the relevance of external regional interactions for local economic growth (re)position this debate within the open and interdependent perspective of economic globalisation, thus identifying the multinational firm as a critical actor connecting knowledge resources at multiple geographical scales via its foreign direct investments (Iammarino and McCann, 2013; Iammarino, 2018). In this framework, the trans-local ownership network of a multinational company provides its region of origin with an international set of connections aimed at sourcing knowledge from spatially distant and complementary technological bases (Bathelt and Li, 2014; Turkina and van Assche, 2018). Consistent with this view, the accumulation and acquisition of capabilities as well as the generation of new competences within multinational organisations has gradually shifted towards foreign subsidiaries (Rugman and Verbeke, 2001; Cantwell and Mudambi, 2005; Ascani, 2018). Hence, this type of regional connectivity through local multinationals' subsidiaries abroad can shape the pre-existing profile of specialisation of origin regions, thus determining a co-evolution of regions' internal competitiveness and external corporate strategies (Cantwell and Iammarino, 2000).

The overview above provides the theoretical background to the idea that innovation activity is a complex process that combines the direct production of knowledge at local level with the knowledge produced outside and channelled into the local economies by knowledge gatekeepers, i.e. multinational corporations (in the context of this article). Therefore, by jointly considering these parallel strands of literature, we focus on the specific interactive dynamics between regions' internal specialisation and their external networks with the objective of clarifying under which circumstances regional specialisation and external networks generate favourable conditions for local innovativeness. Are external networks a valuable source of knowledge able to enhance local innovation? Can external networks substitute or complement internal sources of innovation? Are all local systems able to capture and re-use external knowledge to improve their innovation capacity? Existing empirical evidence on these issues remains rather scant, with only a limited number of recent studies focusing empirically on the innovation returns to technological linkages (Miguelez and Moreno, 2015; Capello and Caragliu, 2018) or on the channels of transmission of external knowledge (Marrocu et al., 2013; Miguelez and Moreno, 2018).

In the next sections, we examine empirically these issues, reaching interesting and original results. In particular, we focus on the nature of the interaction between internal and external sources of knowledge and on the characteristics of the networks more conducive to local innovation processes.

3. Data description

In the empirical analysis that follows we make use of a hand-collected and comprehensive dataset that develops along three dimensions: space, time and economic sector. More specifically, we focus on the innovative performance of the 21 Italian NUTS-2 regions, over the period 2007-2012 across nine manufacturing macro-sectors.[1] We restrict the analysis to the manufacturing sector since the literature has already acknowledge its pivotal role as source of innovation (Tether, 2005; Tiri et al., 2006; Evangelista, 2006; Morrar, 2014). The aggregation in nine manufacturing macro-sectors has been driven by the availability of data. Indeed, the Italian National Statistical Office (ISTAT) provides employment data at regional level only at this level of sectoral disaggregation. The choice of NUTS-2 regions, rather than NUTS-3, instead, has been dictated by the fact that NUTS-3 areas exhibit a large number of zeros when it comes to the number of local companies establishing foreign networks in each single manufacturing macro-sector considered. Overall, our dataset includes 1,134 observations, i.e. 21 regions, observed over 6 years across 9 different manufacturing macro-sectors.

3.1 Dependent variable

As a proxy of regions' innovative activity, we use the number of patent applications to the European Patent Office (EPO) based on the inventor's place of residence (Marrocu et al., 2013; Balland et al., 2019; Miguelez and Moreno, 2015). Specifically, we analyse 98,881 patent applications in 577 manufacturing IPC technological classes, and we connect them to the corresponding NACE 2-digit categories by means of the Eurostat concordance tables (Van Looy et al., 2014). Then, we aggregate patents according to the inventors' regions and the above-mentioned manufacturing macro-sectors. Furthermore, since Italian regions are quite different in size, we consider the number of patent applications per million inhabitants in each manufacturing macro-sector and year.[2]

The summary statistics reported in Table 1 show substantial differences in patenting activity across Italian regions over the sample period, ranging, in absolute value, from an average of about 15.5 patents in Aosta Valley to an average of 5084.8 patents in Lombardy. On a sectoral basis, patents

[1] See Table A1 in the Statistical Appendix for more details on the aggregation strategy.

[2] Each patent has been assigned to a region according to the registered residence of the inventors who participated in the patenting activity. This implies that the same patent can be allocated to more than one region at the same time. We also consider an alternative dependent variable, where patent applications have been attributed to one region only, according to the residence of the principal inventor. Results – not reported here for sake of brevity but available upon request – remain qualitatively unchanged.

concentrate mainly in two sectors (Table 2) that jointly account for 71.6% of total patents in Italy: Computer (44.2%) and Chemical (27.4%). All other sectors exhibit one-digit share of patenting activity.

[Tables 1 and 2 here]

3.2 Network variables

Since the main emphasis of the paper is on the effects of regional external connections as potential sources of external knowledge, we take a closer look at the network of foreign subsidiaries established by regional companies. As explained in Section 2, regional economies cannot be considered as entities that *per se* establish economic ties. Indeed, the latter result from the activity of what the literature has identified as key actors in connecting regions and cities into the global production system, i.e. MNEs and their subsidiaries (Rychen and Zimmerman, 2008; Todeva and Rakhmatullin, 2016). In order to operationalise this concept, we collect data on all firms headquartered in the Italian region *i*, manufacturing macro-sector *s*, at time *t*, which own at least one subsidiary located in the EU-28, except Italy.[3] To clearly identify ownership ties, as well as the nationality of firms, we follow the standard definition of Global Ultimate Owner (GUO) provided by Amadeus, i.e. the highest company at the top of the corporate ownership structure.[4] We limit the analysis to EU-28 countries, for two main reasons. First, data on firms' linkages within Europe are much more precise, extensive and reliable. Second, previous evidence demonstrates that over 80% of Italian foreign investments are established within Europe (Bettarelli and Resmini, 2018). We capture these regions' external connections at three different points in time, i.e. 2007, 2009 and 2011. The number of foreign subsidiaries in our data, indeed, is quite stable over time, especially when measured at the regional level; therefore, year-by-year variation would not be very relevant. Lastly, it is worth mentioning that our definition of regions' external network includes vertical ties, i.e. direct or indirect linkages between each Italian GUO and its foreign subsidiaries, but not horizontal linkages, i.e. direct or indirect ties between subsidiaries themselves. This reflects the fact that global production networks organised by MNEs are vertical in nature, being the GUO that decides not only where to locate foreign affiliates, but also what functions and tasks within the group foreign affiliates should perform. However, this conservative strategy may yield at most an underestimation of the impact of network externalities.[5]

We measure external networks along three different dimensions: intensity, sectoral composition and geographical dispersion.

Intensity. Network intensity reflects the idea that the benefits accruing to members of networks increase with the number of participants (Katz and Shapiro, 1985). Accordingly, we operationalize the concept of network intensity as the total number of firms participating in it. This implies to consider both firms that create the network, i.e. Italian GUOs headquartered in region *i*, manufacturing macro-sector *s*, at time *t*, and their foreign subsidiaries:

[3] These data come from the Amadeus dataset, issued by Bureau van Dijk. Amadeus stores financial and business information about over 20 million companies across Europe; moreover, it reports firms' location, sector of activity and ownership data with up to twenty years archive. This allows us to trace accurately the ownership linkages across firms and over time.
[4] The minimum ownership percentage we use to draw the path from a subject company up to its Global Ultimate Owner is 25.01%.
[5] We intentionally do not consider national networks, i.e. ownership linkages between Italian firms located in different regions. Indeed, this paper focuses on the importance of international networks compared to internal knowledge sources, rather than on the importance of networks broadly defined on regional patenting activity. We let the comparative analysis of the role played by national and international networks on regional innovation performance to future researches.

$$IntensityTOT_{ist} = \sum_{ist} (GUO_{ist} + SUB_{ist}) \quad (1)$$

Then, we split total intensity into inside and outside intensity: the former counts the number of GUOs (*IntensityGUO*), while the latter the number of foreign subsidiaries (*InstensitySUB*), both of them computed by region *i*, manufacturing macro-sector *s* and year *t*. In so doing, we can distinguish benefits accruing to regions because of the presence of local MNEs from externalities generated by their subsidiaries abroad, thus differentiating our approach from that of recent works on outward foreign investments (e.g. Bathelt and Buchoz, 2019).

Over the considered period, we count a total of 9,698 Italian GUOs and foreign subsidiaries combined. As shown by Table 3, external connections are particularly intense in Lombardy (3,724 networked firms, about 38% of total connected firms in Italy), followed by Emilia-Romagna (1,584), Veneto (1,218) and Piedmont (1,116). Unpacking these figures by a number of GUOs and subsidiaries confirms the leadership of these four regions. In fact, with a combined total of 1,206 GUOs and 6,436 subsidiaries abroad these regions host about 77% of Italian parent companies and own about 79% of affiliates located in the EU-28 countries. From a sectoral perspective, Computer is the sector whose firms establish the majority of external connections, while Food is the least internationally connected one (see Table 4). These sectoral differences persist when we separately consider GUOs and subsidiaries.

[Tables 3 and 4 here]

Sectoral composition. In order to understand and transform external knowledge flows into local innovative capacity, a homogeneous cognitive base with respect to the original knowledge is needed (Cohen and Levinthal, 1990; Boschma and Iammarino, 2009; Marrocu et al., 2013; Miguelez and Moreno, 2015). This implies that only networked firms that carry out production activities in similar fields are able to absorb and re-use knowledge flowing within the network effectively, with positive effects on regional patenting activity. Of course, similarity does not mean that all firms participating in the network operate in the *same* manufacturing sector, but in complementary ones, in terms of shared competences. In order to measure the degree of relatedness of the technological competences of networked firms, we make use of entropy measures and the associated concepts of related and unrelated variety (Frenken et al., 2007). In details, we use the NACE-classification in which GUOs and subsidiaries operate, by region *i*, manufacturing macro-sector *s*, and time *t*, to establish the degree of unrelated variety that characterises the network at 2-digit NACE level as follows:

$$SectUnrelVar_{ist} = \sum_{g=1}^{G} \mathrm{P_g} \ln\left(\frac{1}{\mathrm{P_g}}\right) \quad (2)$$

where P_g represents the share of GUOs and subsidiaries which operate in the 2-digit class g, over the total number of firms that contribute to form the regional network.[6]

The degree of related variety, instead, is computed within each NACE 2-digit class as follows:

$$SectRelVar_{\mathrm{ist}} = \sum_{g=1}^{G} \mathrm{P_g H_g} \quad (3)$$

where:

[6] Shares are computed using the number of firms (GUOs and subsidiaries).

$$H_g = \sum_{i \in S_g} \frac{p_i}{P_g} \ln\left(\frac{1}{p_i/P_g}\right) \qquad (4)$$

where S_g is a 2-digit class, P_g is a 2-digit class share over the entire set of 2-digit classes (the number of which is *G*), and p_i is the 4-digit share. Given the properties of the entropy index, total sectoral variety (*SectTotVar*) is simply the sum of the degrees of related and unrelated variety that characterise the network.

Since the innovation capacity is the dependent variable, we expect that networks composed of firms that operate in related economic sectors may offer a positive contribution to innovation output, while networks composed of unrelated sectors do not. In fact, related variety ensures cognitive proximity, which fosters interactive learning and makes the exchanges of information easier and less costly (Boschma, 2005).

Geographical dispersion. MNEs fragment the production process across countries to exploit competitive advantages embedded into different locations (Qian et al., 2010; Coe et al., 2004, 2008). As a result, the geographical dispersion of the network reflects, on the one hand, how MNEs internationalise and, on the other hand, what types of benefits accrue to networked regions (Hitt et al., 1997; Rugman and Verbeke, 2004; Peng et al., 2010). In order to control for the geographical fragmentation of the network we employ an entropy index (*GeoDisp*) based on the geographical distribution of the foreign subsidiaries, by region *i*, manufacturing sector *s* and year *t*:

$$GeoDisp_{ist} = \sum_{r=1}^{m} P_i^r \ln\left(\frac{1}{P_i^r}\right) \qquad (5)$$

where *r* refers to EU-countries, except Italy, and *m* is the total number of foreign countries, i.e. EU-28 minus Italy. P_i^r is the proportion of subsidiaries operating in the *r-th* country to the total number of foreign subsidiaries in the EU.

Of course, the higher the index, the larger the number of countries involved in the network, the most diversified are the external sources of knowledge. Therefore, we expect that regions with geographically dispersed networks gain more than regions with highly concentrated networks in terms of patenting activity.

3.3 Other controls

Consistently with the theoretical framework discussed in Section 2 and with the objectives of the paper, we place specific emphasis on the role of regional sector specialisation (*SPEC*) as a key element conducive of innovation. This is measured as the total number of employees in a specific manufacturing macro-sector, following the argument that the size of an activity matters for local performance (Kemeny and Storper, 2015)[7]. In fact, dense interactions between co-located organisations operating within an industry can stimulate learning and the development of new competences (Becattini, 1990; Boschma and Frenken, 2007). Similarly, the existence of agglomeration externalities can expedite the creation of new knowledge within regions where different types of actors

[7] We also consider two alternative measures of (relative) specialisation, i.e. the share of each manufacturing macro-sectors in total employment at regional level, and the traditional location quotients. Results do not change and are available upon request.

operating in the same sector of economic activity facilitate knowledge diffusion through well-known mechanisms such as shared suppliers, labour pooling and technological spillovers (Duranton and Puga, 2004; Rosenthal and Strange, 2004).

Furthermore, our analysis also encompasses the role of the traditional inputs for local knowledge output, such as regional R&D expenditures over GDP (*R&D*), which represents the main capital input for the creation of new technologies (Keller, 2004), and the regional endowments of human capital (*HumCap*), as a proxy for the ability of local workers to innovate (e.g. Faggian and McCann, 2008; D'Este et al., 2014). This is captured by means of a Principal Component Analysis, on the basis of three indicators (EC, 2018): percentage of people with tertiary education; attractiveness of the university system, proxied with the students' net immigration rate, and lifelong learning, measured as the percentage of adults 25-64 who attend educational and/or professional courses over total population 25-64.[8]

We also account for other covariates in order to control for the spatial differences in regional structures that may affect innovation. More specifically, we include the proportion of urban waste over total waste production as proxy for the role of urbanisation economies (*URB*) (e.g. Cooke and De Propris, 2011), and the long-term unemployment rate (*LUR*) to reflect the dynamism of the local economic system. A higher level of long-term unemployment, indeed, indicates a stagnating economy with low investment capacity, slow skill formation rate, and consequently, low knowledge production capacity (Gordon, 2001).

As far as the sources of knowledge *external* to the regional economy are concerned, we control for two alternative measures of regions' degree of openness. The first refers to trade openness (*Trade*), computed as the sum of import and export over GDP, and the second relates to inward FDI (*InFDI*), proxied by the number of employees in foreign-owned companies. Both variables may exert an ambiguous effect on regional patenting activity. Indeed, while the impact of trade strongly depends on the technological content of the traded goods (Bloom et al., 2016; Coe and Helpmann, 1995; Coe et al., 2009; Keller, 2009), inward FDI may brought into the region new knowledge and technology which may positively stimulate local innovation capacity (Antonietti et al., 2015; Ascani et al., 2019). However, the increased competition from high-performing foreign entrants may relegate local firms to operate in less innovative markets, thus reducing the innovation capacity of the local system (Garcia et al., 2013).[9]

Tables A4 and A5, in the Statistical Appendix, report summary statistics and the correlation matrix for all the variables, respectively. It is worth noticing that variables measuring network's characteristics sometimes overlap, as indicated by the large correlation rates reported in Table A5. This is mainly due to computational criteria. Indeed, most of these variables have been computed using the same unit of observation, i.e. the number of firms involved in the network and refer to complementary phenomena. Indeed, *IntensityTOT* is the sum of *IntensitySUB* and *IntensityGUO*; therefore we are not surprised to observe high correlation rates between the first and its two components (.996 and .844, respectively). Similarly, *SectTotVar* is highly correlated with its sub-components, i.e. *SectRelVar* and *SectUnrelVar* (.851 and .972, respectively). Therefore, we never consider the above variables simultaneously in our estimations. As for the other explanatory variables, some of them appear to be correlated, since they reflect similar or complementary phenomena. In order to verify whether and to what extent multicollinearity may affect the findings, we compute the Variance Inflation Factor (VIF) test on

[8] Table A2 in the Statistical Annex shows the results of the Principal Component Analysis. We consider the first component, which shows an Eigenvalue of 2.14 and explains about 71% of the total variation in the data.

[9] See Table A3 in the Statistical Annex for further information on the above mentioned variables.

pooled OLS regressions. The results never overcome the critical level of five, keeping constant across different specifications around a value of 3.[10] Hence, we can conclude that multicollinearity is not a serious concern in our setting.

4. Methodology

4.1 The baseline model

In order to achieve our research objectives, we assume a traditional regional Knowledge Production Function (KPF) framework:

$$Y_{ist} = \alpha + NET_{ist}\beta + X_{it}\gamma + \delta_i + \delta_s + \delta_t + \delta_{st} + \varepsilon_{ist} \qquad (6)$$

where subscripts *i, s* and *t* indicate region, manufacturing macro-sector and year, respectively. The dependent variable *Y* is the number of patent applications per million inhabitants. *NET* is a vector that includes the different dimensions of the external networks previously discussed; *X* represents a vector of covariates controlling for the many factors that can influence local innovation, both internal and external to the regional economy, as described in the data section. We exploit the panel nature of our dataset by estimating equation (6) by means of a region fixed-effect model to account for unobserved local time-invariant determinants of innovation output, such as institutional characteristics, technology-oriented regional policies, etc. In addition, we also consider sector-, year- and sector-year dummies to control for temporal heterogeneity influencing all regions and sectors simultaneously, as well as industry-specific shocks that may have occurred at a certain point in time.

Note that all explanatory variables included in the model have been standardized using the z-score, i.e. mean equal to zero and standard deviation equal to one. Standardizing makes the comparison between coefficients measured on different scale easier; therefore, we can immediately understand the relative importance of the various sources of knowledge as drivers for local innovation capacity.

While estimating equation (6) produces a baseline snapshot for the relationship under consideration, we are interested in exploring the dynamics between internal specialisation and external networks. Hence, given this goal, we extend our investigation to explore the potential interplay between these elements by augmenting equation (6) with an interaction term, which involves local specialisation (*SPEC*) and network external intensity (*IntTOT*). This allows us to clarify whether and to what extent specialised sectors within a region benefit from the establishment of a network of foreign subsidiaries or, alternatively, whether external networks can compensate for a lack of local specialisation.

4.2 Tackling the endogeneity of the external network

While the panel fixed effects approach exemplified by equation (6) can provide a rather clean picture of the relationship between regional innovation and outward networks, by eliminating regional unobserved time-invariant attributes and also controlling for industry and time shocks, it is still possible that our estimated coefficients are biased. Time-varying regional omitted variables can, for instance, be correlated with the propensity of local firms to internationalise or innovate. Furthermore, whilst we consider that causality is running from the regional outward network to innovation, there is also the possibility that regional innovativeness makes local companies more prone to explore foreign locations through the establishment of a network of subsidiaries. The latter can be a serious concern

[10] Results are available upon request.

especially considering that existing scientific evidence suggests that more productive companies tend to self-select into FDI (Helpman et al., 2004).

Hence, we adopt an instrumental variables (IV) strategy in order to cope with these econometric issues. To identify exogenous shifts in the intensity of the outward network of regions, we adopt as an instrument the weighted average of the dependence on external finance by the manufacturing industry, with regional weights consisting of the local availability of expansion venture capital.

We formally define the instrument as follows:

$$Z_{ist} = \sum_{s} EFD_{st} \times (-VC_{iT}) \quad (7)$$

where *EFD* stands for the external finance dependence of sector *s* at time *t*, and *VC* is the share on GDP of venture capital for expansion and replacement in region *i*. Sector EFD is calculated on Compustat data on US firms, following the seminal contribution of Rajan and Zingales (1998) and subsequent works (e.g. Bellon et al. 2016) as the difference between firm capital expenditure and cash flow from operations divided by capital expenditure. This measure captures the investment that firms cannot finance through the internal cash flow produced with their business activities, thus indicating the amount of resources that firms need to access externally, i.e. their demand for capital. To aggregate these ratios across firms we use the sector median in order to reduce the impact of outlier companies. We aggregate firm-level EFD by NAICS sector, as provided by Compustat, and we then translate it into the ISIC classification and subsequently into NACE codes via dedicated correspondence tables produced by the Reference And Management Of Nomenclatures (RAMON) service of Eurostat.

Regional VC is based instead on ISTAT data and it captures the regional access to capital sources aimed at business expansion, thus being particularly appropriate for the case of firm internationalisation.[11] In fact, recent evidence suggests that financial tightness may constrain firms' decisions to establish foreign networks (Buch et al., 2014). We adopt two different timing strategies for regional VC. First, we consider *T* as a lag. Considering that the first available year for VC is 1999, we construct the longest time lag possible, equal to 8 years. Second, we consider *T* as a fixed time period and hence we take the value of VC in 1999 by constructing start-of-the-period regional weights for our instrument. We also decide to take the additive inverse of VC for interpretative reasons. In fact, on the one hand, higher values of EFD imply that financing foreign investments is more dependent on external sources of capital, rather than internal, thus suggesting that internationalisation can be financially more difficult. On the other hand, higher values of VC indicate that a specific location offers larger opportunities for financing foreign activities. By taking the additive inverse of VC, instead, we can expect that higher absolute values of VC make financing further investment more difficult. Consider, for instance, one specific sector located into different regions. If the absolute value of VC in a region increases (decreases) with respect to the other region, that sector will have less (more) opportunities to access local venture capital and, therefore, to finance more foreign investment activities.

With respect to the exogeneity of this instrument, the EFD component is constructed based on data on US firms by sector, thus reassuring us on the fact that it can be considered as exogenous to the context of Italian manufacturing sectors and their specific demand for capital. Importantly, previous works suggest that the use of external finance demanded by US firms can be a very reliable measure of demand for capital also in the context of other countries, due to the very low frictions in the US capital

[11] Importantly, this measure excludes early stage venture capital sources, which are usually associated with the activities of start-up companies.

market (Rajan and Zingales, 1998). Regarding the VC component, the exogeneity of the regional weights should derive from the long time-lags adopted. Furthermore, the fact that our sample period is mostly post-financial crisis, while the VC weights largely refer to the pre-crisis time period should alleviate concerns of serial autocorrelation across time in this measure. In this respect, several studies have already suggested how the financial crisis has generated or aggravated liquidity and credit crunches disrupting most pre-crisis financial links and behaviours (Campello et al., 2010; Bricongne et al., 2012; Iyer et al., 2014).

5. Results

5.1 The baseline model

Table 5 reports the results of our benchmark regression analysis, i.e. traditional innovation determinants with a full set of fixed-effects. The basic region-level variables perform largely as expected. Among them, regions' specialisation (*SPEC*) emerges as a crucial driver for innovation. Indeed, according to our estimates, *SPEC* is positive and significant at the conventional levels in all specifications. This implies that the larger the localized activities the higher the innovativeness within sectors, because of the multiple effects that localized externalities exert on performance, well-acknowledged by the theoretical literature (Kemeny and Storper, 2015). The magnitude of these effects is not only considerable but also stable across specifications;[12] indeed, a one standard deviation increase in *SPEC* leads to a variation in the patenting activity in the range of 26.99.-26.93. No other explanatory variable is able to exert an impact on regional innovation output as strong as that exerted by internal specialisation. In particular, our findings suggest that there is a positive and significant association between the number of patent applications per million inhabitants and human capital, R&D activity and urbanisation externalities. The long-term unemployment parameter, instead, is never significant, as well as trade openness and inward FDI, whose poor performance as predictors of innovation performance has already been acknowledged in the literature (Ganotakis and Love, 2011; Harris and Li, 2008; Aghion et al., 2009). Overall, these baseline findings – which remain constant throughout the paper – support the strand of the literature that considers local sources of knowledge as crucial determinants of the innovation capacity of Italian regions.

When network variables are included in the regression equation, several interesting facts emerge, as indicated by Table 6. In particular, we find that the larger the network the higher the regional innovation output (column 1). A one standard deviation increases in the intensity of the network, measured as the total number of firms – both local and foreign – participating in the network leads to an increase in the innovation output of about 13 patent applications per capita. This effect, implying that large networks facilitate knowledge sharing and diffusion (Spencer, 2003; Roper et al., 2017), though consistent, is, however, less than the impact of the two main sources of internal knowledge, i.e. absolute specialisation and R&D.

[Table 5 here]

The positive impact of the network intensity on the innovation output depends on both the components of the network, i.e. the external subsidiaries controlled for by local firms operating in a specific sector, as well as local multinationals headquartered in each sector/region (column 2). The impact of the latter is relatively more important than that of the former. Firms investing abroad are presumably more disposed to innovate than local firms, and, thus, an increase in the number of firms investing abroad

[12] This is a clear indication that multicollinearity does not represent a serious issue in this setting.

leads to an increase in innovation output at sector and region level. The impact of subsidiaries abroad is smaller but still appreciable and highly significant, supporting the idea that investing abroad gives access to external sources of knowledge that complement and enlarge the local ones. The small coefficient of external subsidiaries suggests that not all outward investments have the same beneficial effects on local innovation performance, because they may be knowledge-exploiting rather than knowledge-seeking (Iammarino and McCann, 2013). Further analysis is therefore needed in order to differentiate between the effects of alternative foreign investments.

With regard to the effect of the sectoral composition of the network, Table 6 (column 3) shows that it is not significant, the main reason being that its two components have opposite behaviours. Indeed, networks made of sectors sharing complementarity in competences stimulate regional innovation capacity, while networks composed by sectors completely unrelated (column 4) reduce regional innovation potential. Relatedness, in fact, is more likely to induce effective learning and innovation than unrelatedness, which, instead, precludes the efficient deployment of complementary competences in the production of goods and services (Boschma, 2005). Therefore, we can conclude that while external knowledge is crucial in order to improve existing knowledge base (Boschma and Iammarino, 2009; Camagni, 1991), networks should bring new knowledge from different but cognitively proximate sectors.

Lastly, our findings show that geographical dispersion has the expected sign but it is not able to exert a significant impact on regional patenting activities (column 5). Therefore, spreading investments across different EU countries does not help in improving patenting activities. We can offer two alternative but not mutually exclusive explanations of this surprising result. First, EU countries, being quite similar, do not ensure access to variegated sources of external knowledge. Secondly, the impact of geographical dispersion is already captured by sectoral dispersion, as the strengthening of the estimated coefficient of *SectUnrelVar* variable seems to suggest. Section 5.3 below will help in disentangling this issue.

[Table 6 here]

5.2 The interplay between internal and external knowledge sources

In this subsection we investigate whether synergies do exist between local and external sources of knowledge. We explore this issue by interacting the main variables of interest, namely regional absolute specialisation (*SPEC*) and the intensity of the external network (*IntTot*).

In order to make the interpretation of the coefficients easy, we re-parameterize the interaction term by “centering” *SPEC* before multiplying it with *IntTot.* In other words, we subtract specific values of interest from the variable *SPEC* itself before interacting it, the values of interest being the 10^{th}, 25^{th}, 50^{th}, 75^{th} and 90^{th} percentile along the *SPEC* distribution. This transformation of the interaction term allows us to interpret the coefficient on *IntTot* as the partial effect of the regional external network on regional innovation for specific levels of regional specialisation by sector, ranging from regions not specialised in a certain sector (10^{th} percentile) to regions that are highly specialised in a sector (90^{th} percentile). A key advantage of this re-parametrization is that we immediately obtain the standard errors of the partial effects with the estimates (Wooldridge, 2009). Therefore, we can interpret the coefficient as the effect of *IntTot* on regional patenting activities, conditional to regional specialisation being equal to one of the percentiles specified above along the distribution of the *SPEC*.

Table 7 reports the results of this exercise. Each column shows the impact of the intensity of the network created by local firms via outward foreign investment on regional innovation capacity for different values of regions' specialisation. The findings suggest that for low levels of specialisation, the effect of the network is negative and not significant. However, when specialisation increases, it turns positive, increases in magnitude, becoming significant for high levels of specialisation (50th percentile and above). This implies that engaging in external networks does not suffice to improve innovation output: a certain degree of internal knowledge is required to absorb external knowledge and transform it in competences conducive for innovation. Thus, external sources of knowledge may complement rather than substitute for internal sources of knowledge.[13]

[Table 7 here]

5.3 Geographical dispersion: further results

This final subsection aims at verifying whether geographical dispersion may become relevant should specific contextual characteristics emerge. As discussed above, EU countries may differ in terms of several aspects, the most relevant of which, given the objective of this paper, is the diverging effectiveness of their national innovation systems (EC, 2018). This implies that the potential benefits geographical dispersion may exert on regional innovation capacity are strongly related to the technological profile of foreign destinations. Thus, what may matter is not geographical dispersion *per se*, but geographical dispersion across technologically advanced countries endowed with different technological competencies. In other words, we argue that investing in a large number of countries with a poor innovation performance does not help in improving local innovation activity, while investing in a large number of countries with good innovation performance does it, since this allows bringing into Italian regions knowledge flows able to enrich and enlarge their local innovation base.

In order to investigate this issue, we interact the geographical dispersion index with a new variable (*AdvTec*) measuring the proportion of foreign subsidiaries located in technologically advanced EU countries over the total number of subsidiaries.[14] Table 8 shows the results, which can be interpreted according to the same logic we used to analyse the potential interplay between internal and external sources of knowledge (i.e. by re-parametrizing the interaction term). As expected, the impact of geographical dispersion is positive in all specification. Its magnitude increases with the level of technological development of the host locations and turns statistically significant only if it concerns foreign locations with a very high level of technological competencies (75th percentile and above). Therefore, we can conclude that in order to improve Italian regions' innovation performance external networks have to widespread over a large number of countries with high technological competencies.

[Table 8 here]

5.4 IV estimations

In this section we check for the robustness of our panel fixed effects estimates by considering the 2SLS strategy explained in Section 4.1. As described, we construct two instruments based on a different treatment of the time dimension in the regional weights. The first version of the instrument

[13] As robustness check, we estimated the same regression splitting the network intensity into its two subcomponents, i.e. *IntensitySub* and *IntensityGUO*. Conclusions on the complementarity nature of the interplay between internal and external sources of knowledge remain unchanged. Results can be provided upon request.

[14] According to our definition, a country is technologically advanced if its score in the European Innovation Scoreboard classification is above the 75th percentile of the distribution (EC, 2018).

incorporates an eight-year lag in the regional weights, while the second version of the instrument considers start-of-the-period regional weights.

In implementing our 2SLS estimation strategy, we first replicate the specification reported in column 1 of Table 6, by instrumenting the total intensity of the outward network. Second, because we aggregated firm level EFD to manufacturing macro-sectors, we also consider that across narrowly defined industries there might be systematic differences in EFD, thus introducing a potential measurement issue in our instrument. Therefore, we augment the 2SLS regressions by including the standard deviation of EFD (*SD EFD*) to control for the dispersion of this measure within our macro sectors. Third, given that access to expansion venture capital can be correlated with the regional endowment of specialised companies in these activities, we further extend our 2SLS model by entering a standardized control for regional employment in business services, as a proxy for the relevance of regional venture capital providers.[15] Therefore, for each version of the instrument we estimate three separate regressions.

Before delving into the second-stage regression results, we present the first-stage diagnostics on the appropriateness of our strategy and the associated first-stage estimates. Table 9 (bottom panel) reports a set of statistics for the under-identification and the weak identification tests. The former is aimed at assuring that the excluded instrument is relevant, i.e., that it is correlated with the endogenous variable. The latter is aimed at testing the strength of the correlation between the instrument and the endogenous regressor, i.e. whether the IV estimator performs poorly. Considering that our estimation accounts for clustered standard errors for regions, the i.i.d assumption is no longer valid and we consequently report the appropriate statistics for such cases, namely the LM and Wald versions of the Kleibergen and Paap (2006) rk statistics. Regarding the LM statistics, the associated p-values indicate that we cannot reject the null hypothesis that the equation is under-identified in the case of an instrument with lagged regional weights (columns 1 to 3 of Table 9). Hence, this result suggests that this version of the instrument may not be relevant. Nonetheless, we largely reject the null in the case of the instrument with start-of-the-period regional weights (columns 4 to 6), for which the equation is therefore identified. For the detection of weak instruments we adopt Stock and Yogo (2005)'s size method. The Kleibergen-Paap rk Wald F statistics appear sufficiently large as compared to the Stock-Yogo critical values for maximal IV size in the case of one instrument and one endogenous regressor for a Wald test with a 5% significant level. Specifically, the F-statistics exceed the critical values for the desired maximal size distortion of 10% in columns 1 to 3 and 15% in columns 4 to 6. These results, hence, suggest that our instruments perform fairly well, although the version with lagged regional weights could be under-identified. Table 9 also reports the estimated coefficients for the first-stage regressions. Unsurprisingly, our instruments exhibit a statistically strong and negative correlation with the regional outward networks, indicating that higher industry dependence on external sources of capital as well as a tighter regional access to venture capital may inhibit the internationalisation of local firms.

[Table 9 here]

Lastly, the top panel of Table 9 presents the second-stage regression coefficients. Qualitatively, these results are in line with the baseline fixed effects estimates, thus supporting our previous findings. Specifically, regions with industries that establish foreign networks of subsidiaries become more innovative in technological classes that are connected to those industries. Quantitatively, the

[15] Given the lack of official data for the whole period taken in consideration, we proxy this variable using *Amadeus* dataset. More specifically, we summed up the employees of each firm in region *i* and year *t* active in the NACE Rev. 2 categories 82.9, i.e. business support service activities.

magnitude of the coefficients on the outward network remains slightly lower as compared to the panel fixed effects regressions, as far as the case of the instrument with lagged regional weights is concerned (columns 1 to 3). Instead, in the regressions with the instrument with start-of-the-period regional weights (columns 4 to 6), the point estimates are very similar to those in Table 6. This version of the instrument provides our preferred results, in consideration of the good diagnostics in the first-stage (as opposed to the under-identification issue detected with the other version of the instrument) and also because the start-of-the-period regional weights reassure us more on the exogeneity of the instrument, as compared to the 8 years lag version. In fact, it is more plausible that access to venture capital in 1999 is exogeneous to the status of firm internationalisation and innovativeness during our sample period, especially in the light of the deep disruption of financial linkages and dynamics caused by the crisis (Campello et al., 2010; Bricongne et al., 2012; Iyer et al., 2014). Interestingly, neither the inclusion of the EFD dispersion variable (*SD EFD*) nor the presence of the regional endowment of business services affects our coefficients of interest, thus indicating that our estimates are also very stable to the inclusion of further regressors. Overall, we consider the evidence emerging from the 2SLS estimation as an important check for the robustness of our empirical framework to endogeneity concerns.

6. Conclusions

This article offered an investigation of regional innovation processes resulting from the joint action of the internal sectoral specialisation of regions and the external global networks established by local firms via foreign direct investments. In this sense, our work contributes to the ongoing and revamped debate in innovation economics and economic geography on the role and the interlinkages between internal and external sources of regional innovativeness (Bathelt et al., 2004; Iammarino, 2018). We have exemplified external networks by considering the foreign subsidiaries of local parent companies, thus identifying the latter as the regional knowledge gatekeepers that can actively channel external knowledge inputs into the regional economy. This perspective also connects this article with the recent surge of anti-globalisation discourses, especially with respect to the view that outward foreign investments may impoverish local economies by offshoring resources and competences abroad. Contrary to these propositions, our results for a panel of Italian NUTS-2 regional economies over the period 2007-2012 support the notion that the role of regional internal industry specialisation and the role of external networks established by local firms are complementary, rather than substitute. In other words, we offer a view of regional innovation as an interactive process whereby valuable knowledge resources are not only generated within the reach of the local economy, but they are also integrated with external inputs. More specifically, regional economies first and foremost innovate based on internal factors associated with industry specialisation, thus corroborating the conventional wisdom that the engine of innovation is highly localised (e.g. Storper, 1997). At the same time, we find evidence that the external network provides regions with complementary knowledge resources that are conducive of innovation. Hence, based on these findings, this article rejects the notion that outward foreign direct investments deteriorate the competitive advantage of local economies. Importantly, this applies to the analysis of regional innovativeness, while we cannot exclude that other negative effects may be present.

Our results interestingly suggest that the external network of foreign subsidiaries in a given industry can foster patenting activity within regions that are highly specialised in that industry. This evidence highlights the synergic nature of the interaction between internal and external sources of knowledge in supporting local innovation. Also, it suggests that the anti-globalisation narrative on the detrimental role of outward foreign investments may negatively affect highly specialised regions that benefit the most from accessing external knowledge pools via the foreign operations of local companies. Importantly, the most relevant typology of external network for the sake of regional innovativeness resides in foreign locations that can realistically offer (relatively) advanced knowledge resources to local gatekeepers. In fact, on the one hand, our results suggest that networks spreading over a wide number of foreign locations with a weak innovation performance do not constitute a strengthening factor in terms of local innovativeness. On the other hand, possessing foreign subsidiaries in several locations exhibiting a (relatively) strong innovation performance may channel into Italian regions a set of knowledge resources to reinforce and sustain the local innovation base. Future research avenues include, on the one hand, a full exploration of industry heterogeneity, in order to clarify whether specific industries experience similar or diverse patterns in terms of the role of internal and external knowledge inputs. On the other hand, a deeper investigation of the motivations at the base of the creation of external networks by local enterprises is needed to understand the extent to which the different functions assigned to foreign subsidiaries by parent firms affect the nature and the magnitude of knowledge flows channelled into the region of origin. Furthermore, future research can also be dedicated to dissecting the composition of the effect between the innovativeness of the local parent company vs. the innovativeness of other actors within the regional economy.

These results can have important implications in terms of policy, both at the regional and the national level. Measures to support regional innovation efforts should primarily consider the local profile of industry specialisation, which can differ from region to region, and target activities that are at the core of each specific regional economy. Second, the internationalisation of local firms via foreign investments should be supported in those cases where the local parent company is a core actor within the regional industry specialisation and the foreign subsidiaries constitute a bridge between the regional economy and a foreign advanced location in terms of innovation potential. Therefore, the present article offers results that can also be linked to the debate around smart specialisation strategies for local economic development, as the role of non-local linkages in generating new and complementary capabilities is yet to be fully integrated in such a policy framework (Balland et al., 2019). In this sense, our results suggest that regional development possibilities can also plausibly revolve around place-based organisations with the capacity to connect the local knowledge base at multiple geographical scales, thus potentially sustaining new trajectories of regional competitive advantage with external knowledge inputs.

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Table 1: Number of patents – Summary statistics by region/year

Region	N	mean	sd	min	max
Abruzzo	54	206.667	32.43	165	258
Basilicata	54	35.167	10.033	21	46
Bolzano	54	158.333	29.34	120	202
Calabria	54	64.833	22.202	43	105
Campania	54	369.667	50.559	290	446
Emilia-Romagna	54	2633.667	251.113	2254	2924
Friuli-Venezia Giulia	54	611.5	79.104	488	746
Latium	54	821.667	74.263	681	907
Liguria	54	400.167	42.918	335	465
Lombardy	54	5084.833	228.498	4796	5358
Marche	54	445	29.59	403	483
Molise	54	11.333	13.208	2	40
Piedmont	54	1720.667	165.992	1398	1908
Apulia	54	256.5	48.994	210	355
Sardinia	54	83.833	26.453	38	115
Sicily	54	177.5	29.398	120	205
Tuscany	54	1215.833	118.611	1027	1376
Trento	54	118.833	26.632	85	166
Umbria	54	158	22.336	134	190
Aosta Valley	54	15.5	6.963	3	25
Veneto	54	1890.667	73.77	1796	2029

Note: *N* indicates the number of observations per region, i.e. 54, that is, 9 manufacturing macro-sectors over 6 years.

Table 2: Number of patents by manufacturing sector

Sector	N	Percent	Cum.
Chemical	27,110	27.4	27.4
Computer	43,703	44.2	71.6
Paper	570	.6	72.2
Food	1,538	1.6	73.8
Furniture	7,632	7.7	81.5
Metal	4,043	4.1	85.6
Plastic	6,768	6.8	92.4
Textile	1,308	1.3	93.7
Transport	6,209	6.3	100
Total	98,881		

Note: *N* indicates total number, which is computed on the basis of 126 observations (21 regions over 6 years)

Table 3: Network intensity by region

Region	N	Percent	Cum.	N	Percent	Cum.	N	Percent	Cum.
	IntensityTOT			**IntensityGUO**			**IntensitySUB**		
Abruzzo	32	.3	.3	10	.6	.6	22	.3	.3
Basilicata	0	0	.3	0	0	.6	0	0	.3
Bolzano	38	.4	.7	10	.6	1.3	28	.3	.6
Calabria	0	0	.7	0	0	1.3	0	0	.6
Campania	94	1	1.7	28	1.8	3.1	66	.8	1.4
Emilia-Romagna	1584	16.3	18	244	15.6	18.7	1340	16.5	17.9
Friuli-Venezia Giulia	194	2	20	32	2	20.1	162	2	19.9
Latium	512	5.3	25.3	42	2.7	23.5	470	5.8	25.6
Liguria	34	.4	25.7	12	.8	24.3	22	.3	25.9
Lombardy	3724	38.4	64.1	602	38.6	62.9	3122	38.5	64.3
Marche	400	4.1	68.2	56	3.6	66.5	344	4.2	68.5
Molise	28	.3	68.5	6	.4	66.9	22	.3	68.8
Piedmont	1116	11.5	80	150	9.6	76.5	966	11.9	80.6
Apulia	60	.6	80.6	12	.8	77.3	48	.6	81.2
Sardinia	44	.5	81.1	16	1	78.3	28	.3	81.6
Sicily	54	.6	81.7	12	.8	79.1	42	.5	82.1
Tuscany	490	5.1	86.8	84	5.4	84.5	406	5	87.1
Trento	30	.3	87.1	14	.9	85.4	16	.2	87.3
Umbria	46	.5	87.6	18	1.2	86.5	28	.3	87.6
Aosta Valley	0	0	87.6	0	0	86.5	0	0	87.6
Veneto	1218	12.4	100	210	13.5	100	1008	12.4	100
Total	9698			1558			8140		

Note: *N* indicates total number, which is computed on the basis of 54 observations per region (9 manufacturing macro-sectors over 6 years)

Table 4: Network intensity by manufacturing sector

Sector	N	Percent	Cum.	N	Percent	Cum.	N	Percent	Cum.
	IntensityTOT			**IntensityGUO**			**IntensitySUB**		
Chemical	884	9.1	9.1	142	9.1	9.1	742	9.1	9.1
Computer	3080	31.8	40,9	510	32.7	41.8	2570	31.6	40.7
Paper	606	6.2	47.1	70	4.5	46.3	536	6.6	47.3
Food	578	6	53.1	94	6	52.4	484	6	53.2
Furniture	622	6.4	59.5	116	7.4	59.8	506	6.2	59.4
Metal	700	7.2	66.7	196	12.6	72.4	504	6.2	65.6
Plastic	1606	16.6	83.3	176	11.3	83.7	1430	17.7	83.2
Textile	918	9.5	92.8	180	11.5	95.3	738	9.1	92.3
Transport	704	7.2	100	74	4.8	100	630	7.7	100
Total	9698			1558			8140		

Note: *N* indicates total number, which is computed on the basis of 126 observations per sector (21 regions over 6 years)

Table 5: Baseline regression results

	(1) Patent	(2) Patent	(3) Patent	(4) Patent	(5) Patent	(6) Patent	(7) Patent
SPEC	26.984***	26.949***	26.954***	26.949***	26.928***	26.934***	26.931***
	(7.843)	(7.842)	(7.842)	(7.844)	(7.849)	(7.861)	(7.865)
R&D		19.438*	17.828**	17.125**	16.545**	15.972*	15.989*
		(9.379)	(8.097)	(7.314)	(7.433)	(7.906)	(7.929)
HumanCap			3.387**	3.327***	3.371***	3.464***	3.472***
			(1.378)	(1.142)	(1.113)	(1.020)	(1.025)
URB				6.135**	5.779**	5.999***	5.942***
				(2.250)	(2.132)	(2.056)	(2.037)
LUR					-1.340	-1.390	-1.463
					(1.126)	(1.112)	(1.140)
Trade						0.886	1.048
						(1.630)	(1.718)
lnFDI							-0.447
							(1.355)
Obs.	1134	1134	1134	1134	1134	1134	1134
R-squared	0.596	0.597	0.597	0.597	0.597	0.597	0.597
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time/Sector dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors are in parenthesis, clustered by regions.
**** p<0.01, ** p<0.05, * p<0.1*

Table 6: Network regression results

	(1) Patent	(2) Patent	(3) Patent	(4) Patent	(5) Patent
R&D	22.025**	19.302**	21.275**	21.074**	21.180**
	(9.648)	(8.462)	(10.076)	(8.955)	(8.616)
HumanCap	3.750***	3.964***	3.807***	4.308***	4.172***
	(1.183)	(1.176)	(1.189)	(1.187)	(1.249)
LUR	-3.256***	-3.030***	-3.200***	-3.385***	-2.869***
	(1.017)	(0.932)	(0.962)	(0.802)	(0.949)
URB	4.072*	5.921***	4.321*	6.182**	6.018***
	(2.033)	(1.716)	(2.204)	(2.295)	(2.104)
Trade	2.265	3.369	2.372	3.123	2.767
	(2.654)	(2.902)	(2.767)	(3.205)	(2.926)
lnFDI	-3.272	-3.420*	-3.431	-1.589	-1.730
	(2.148)	(1.867)	(2.183)	(2.211)	(2.537)
SPEC	23.171***	20.627***	22.927***	23.062***	22.735***
	(6.427)	(5.813)	(6.257)	(6.032)	(5.837)
IntenistyTOT	12.995***		12.614***	12.264***	12.270***
	(2.824)		(3.033)	(2.863)	(2.892)
IntensitySUB		4.361**			
		(1.928)			
IntensityGUO		13.533***			
		(4.127)			
SectTotVar			1.171		
			(3.311)		
SectRelVar				8.787***	6.713***
				(1.812)	(1.761)
SectUnrelVar				-5.407*	-10.024**
				(2.889)	(3.716)
GeoDisp					6.983
					(7.114)
Obs.	1134	1134	1134	1134	1134
R-squared	0.639	0.656	0.640	0.654	0.657
Region dummies	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes
Sector dummies	Yes	Yes	Yes	Yes	Yes
Time/Sector dummies	Yes	Yes	Yes	Yes	Yes

Standard errors are in parenthesis, clustered by region.
**** p<0.01, ** p<0.05, * p<0.1*

Table 7: Regression results by specialization percentiles (IntensityTOT)

Specialisation percentiles	.1	.25	.5	.75	.9
	Patent	Patent	Patent	Patent	Patent
	(1)	(2)	(3)	(4)	(5)
R&D	22.940**	22.566**	22.917**	22.853**	22.617**
	(9.899)	(9.870)	(9.868)	(10.077)	(10.024)
HumanCap	3.922***	4.071***	4.072***	4.058***	3.928***
	(1.091)	(1.075)	(1.091)	(1.135)	(1.171)
LUR	-3.595***	-3.505***	-3.503***	-3.506***	-3.407***
	(1.062)	(1.014)	(1.037)	(1.047)	(1.120)
URB	3.666*	3.878*	4.143**	4.287**	4.090*
	(2.085)	(1.977)	(1.970)	(1.992)	(2.077)
Trade	1.331	1.625	1.707	2.180	2.144
	(2.310)	(2.347)	(2.441)	(2.783)	(2.839)
InFDI	-2.879	-2.745	-2.638	-3.017	-3.276
	(1.893)	(1.908)	(1.933)	(2.104)	(2.237)
SPEC	20.799***	21.295***	21.982***	23.991***	24.631***
	(5.581)	(5.703)	(6.046)	(6.807)	(7.370)
IntensityTOT	-4.715	2.865	6.479***	14.598***	16.345***
	(4.506)	(2.217)	(1.584)	(2.051)	(4.407)
Obs.	1134	1134	1134	1134	1134
R-squared	0.660	0.662	0.662	0.654	0.643
Region dummies	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes
Sector dummies	Yes	Yes	Yes	Yes	Yes
Time/Sector dummies	Yes	Yes	Yes	Yes	Yes

Standard errors are in parenthesis, clustered by region.
**** p<0.01, ** p<0.05, * p<0.1*

Table 8: Regression results by AdvTec percentiles (GeoDisp)

AdvTec percentiles	.1	.25	.5	.75	.9
	Patent	Patent	Patent	Patent	Patent
	(1)	(2)	(3)	(4)	(5)
R&D	12.798	12.793	12.735	12.168	12.001
	(8.123)	(8.109)	(8.020)	(8.305)	(8.069)
HumanCap	4.051***	4.055***	4.008***	4.266***	4.162***
	(1.242)	(1.242)	(1.215)	(1.195)	(1.216)
LUR	-1.086	-1.074	-1.040	-1.138	-0.856
	(0.944)	(0.950)	(0.971)	(1.053)	(1.002)
URB	6.501***	6.572***	6.472***	5.507**	6.042**
	(2.072)	(2.042)	(2.012)	(2.405)	(2.234)
Trade	1.576	1.533	1.451	1.603	1.612
	(2.187)	(2.165)	(2.105)	(2.258)	(2.136)
InFDI	-1.828	-1.775	-1.853	-2.181	-2.351
	(1.794)	(1.754)	(1.695)	(1.526)	(1.593)
SPEC	24.788***	24.766***	24.743***	24.826***	24.878***
	(7.339)	(7.324)	(7.329)	(7.347)	(7.382)
AdvTec	0.720	0.674	0.567	0.741	0.310
	(1.103)	(1.073)	(0.987)	(0.956)	(0.983)
GeoDisp	4.063	4.444	5.524	7.097*	9.895**
	(5.448)	(5.160)	(3.856)	(3.534)	(4.684)
Obs.	1134	1134	1134	1134	1134
R-squared	0.611	0.611	0.611	0.615	0.613
Region dummies	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes
Sector dummies	Yes	Yes	Yes	Yes	Yes
Time/Sector dummies	Yes	Yes	Yes	Yes	Yes

Standard errors are in parenthesis, clustered by region.
**** p<0.01, ** p<0.05, * p<0.1*

Table 9: IV-Regression results

	Instrument with lagged regional weights			Instrument with fixed regional weights		
	(1)	(2)	(3)	(4)	(5)	(6)
	Patent	Patent	Patent	Patent	Patent	Patent
2nd stage results						
IntensityTOT	9.033**	9.008**	9.004**	12.412**	12.422**	12.461**
	(4.514)	(4.521)	(4.525)	(5.704)	(5.705)	(5.694)
R&D	20.194**	20.182**	18.535**	21.763**	21.768**	20.038**
	(8.711)	(8.711)	(8.588)	(9.097)	(9.098)	(9.053)
HumanCap	3.665***	3.664***	3.411***	3.737***	3.737***	3.469***
	(1.051)	(1.051)	(1.045)	(1.100)	(1.100)	(1.082)
LUR	-2.714***	-2.711***	-2.502***	-3.180**	-3.182**	-2.966***
	(1.041)	(1.040)	(1.158)	(1.250)	(1.251)	(1.361)
URB	4.640**	4.644**	4.176**	4.154**	4.152**	3.649**
	(1.988)	(1.988)	(1.783)	(2.000)	(2.001)	(1.627)
Trade	1.891	1.889	1.617	2.208	2.209	1.924
	(2.065)	(2.063)	(2.271)	(2.399)	(2.399)	(2.591)
InFDI	-2.413	-2.408	-2.219	-3.148	-3.150	-2.959
	(1.949)	(1.949)	(2.141)	(2.075)	(2.075)	(2.232)
SPEC	24.232***	24.240***	24.248***	23.256***	23.253***	23.249***
	(6.610)	(6.613)	(6.612)	(6.107)	(6.106)	(6.105)
SD EFD		0.824	0.824		0.756	0.756
		(0.631)	(0.632)		(0.639)	(0.639)
Regional Business Services			0.980**			1.041**
			(0.424)			(0.430)
1st stage results						
IV	-1.247***	-1.247***	-1.247***	-4.231***	-4.231***	-4.231***
	(0.230)	(0.230)	(0.230)	(1.307)	(1.306)	(1.304)
R&D	-0.336	-0.336	-0.305	-0.401	-0.401	-0.391
	(0.306)	(0.306)	(0.300)	(0.288)	(0.288)	(0.281)
HumanCap	-0.008	-0.008	-0.003	0.014	0.014	0.015
	(0.032)	(0.032)	(0.028)	(0.031)	(0.031)	(0.028)
LUR	0.121*	0.121*	0.117*	0.089	0.089	0.088
	(0.073)	(0.073)	(0.071)	(0.059)	(0.059)	(0.058)
URB	0.097	0.097	0.106	0.118	0.118	0.121
	(0.121)	(0.121)	(0.112)	(0.108)	(0.108)	(0.107)
Trade	-0.075	-0.075	-0.070	-0.059	-0.058	-0.057
	(0.125)	(0.125)	(0.124)	(0.122)	(0.122)	(0.122)
InFDI	0.173**	0.173**	0.170**	0.201**	0.201**	0.199**
	(0.075)	(0.075)	(0.076)	(0.085)	(0.085)	(0.086)
SPEC	0.263*	0.263*	0.263*	0.254*	0.254*	0.254*
	(0.150)	(0.150)	(0.150)	(0.136)	(0. 136)	(0. 136)
SD EFD		-0.0001	-0.0001		0.031***	0.031***
		(0.011)	(0.011)		(0.011)	(0.011)
Regional Business Services			-0.019			-0.006
			(0.017)			(0.030)
Obs.	1134	1134	1134	1134	1134	1134
R-squared (1st stage)	0.290	0.290	0.290	0.330	0.330	0.330
R-squared (2nd stage)	0.199	0.199	0.199	0.205	0.205	0.205
Under-identification	1.724	1.725	1.725	4.477**	4.776**	4.776**
Weak identification:						
Kleibergen-Paap Wald F-stat	29.32	29.36	29.36	10.48	10.51	10.52
Stock-Yogo 10%	16.38	16.38	16.38	16.38	16.38	16.38
Stock-Yogo 15%	8.96	8.96	8.96	8.96	8.96	8.96
Endogeneity Test	.537	.536	.535	.995	.998	.997
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Sector dummies	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors are in parenthesis, clustered by region.

**** p<0.01, ** p<0.05, * p<0.1*

Appendix

Tab A1: Manufacturing sectors' classification

Sectors	NACE 2-digit Codes
Chemical	19, 20, 21
Computer	26, 27, 28
Paper	16, 17, 18
Food	10, 11, 12
Furniture	31, 32, 33
Metal	24, 25
Plastic	22, 23
Textile	13, 14, 15
Transport	29, 30

Table A2: Principal Component Analysis results

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	2.142	1.449	0.714	0.714
Comp2	0.693	0.528	0.231	0.945
Comp3	0.165	.	0.055	1.000

Principal components (eigenvectors)

Variable	Comp1	Comp2	Comp3	Unexplained
Life_learning	0.466	0.877	0.119	0
Tertiary_Educ	0.613	-0.417	0.671	0
University	0.638	-0.239	-0.732	0

Table A3: Other controls: Description and sources

Variable	Description	Aggregation level	Source
LUR	Long Unemployment rate	Region/year	OECD
R&D	Regional R&D expenditure over GDP	Region/year	OECD
URB	Proportion of urban waste over total waste production	Region/year	ISTAT
HumanCap	Principal Component Analysis (PCA) on the basis of three indicators: percentage of people with tertiary education, attractiveness of the university system (i.e. students' net migration rate), lifelong learning (i.e. percentage of adults 25-64 who attend educational and/or professional courses over total population 25-64)	Region/year	ISTAT
SPEC	Absolute employment	Region/year/sector	ISTAT
Trade	Imports plus exports over GDP	Region/year	EUROSTAT
InFDI	N. of employees of local foreign-owned firms	Region/year	ISTAT
AdvTec	Percentages of foreign affiliates located in technologically advanced EU-28 countries, except Italy.	Region/year/sector	AMADEUS, EIS

Table A4: Descriptive Statistics

Variable	Obs	Mean	Std.Dev.	Min	Max
Patent	1134	87.197	244.519	0	2197
R&D	1134	6.298	1.411	3.25	8.651
HumanCap	1134	0	1.077	-1.865	2.341
LUR	1134	3.84	2.638	.4	12.3
URB	1134	530.497	77.687	379.9	709.3
Trade	1134	34.509	15.512	2.662	67.839
InFDI	1134	5.292	2.537	1.5	11.8
SPEC	1134	2.238	1.571	.001	238.2
IntensityTOT	1134	8.552	25.149	0	251
IntensitySUB	1134	7.178	22.176	0	204
IntensityGUO	1134	1.374	3.623	0	47
SectTotVar	1134	.579	.903	0	3.772
SectRelVar	1134	.14	.297	0	1.581
SectUnrelVar	1134	.439	.669	0	3.042
GeoDisp	1134	.39	.696	0	2.432
AdvTec	1134	.105	.23	0	1

Tab A5: Correlation matrix

1. R&D	6. InFDI	11. SectTotVar
2. HumanCap	7. SPEC	12. SectRelVar
3. LUR	8. IntensityTOT	13. SectUnrelVar
4. URB	9. IntensitySUB	14. GeoDisp
5. Trade	10. IntensityGUO	15. AdvTec

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1)	1.000														
(2)	0.698	1.000													
(3)	-0.056	0.164	1.000												
(4)	0.329	0.228	-0.455	1.000											
(5)	0.559	0.262	-0.483	0.190	1.000										
(6)	0.583	0.334	-0.456	0.192	0.616	1.000									
(7)	0.801	0.534	-0.042	0.175	0.520	0.413	1.000								
(8)	0.394	0.347	-0.202	0.095	0.401	0.408	0.416	1.000							
(9)	0.378	0.333	-0.196	0.095	0.382	0.393	0.396	0.996	1.000						
(10)	0.420	0.372	-0.201	0.074	0.447	0.428	0.470	0.844	0.794	1.000					
(11)	0.574	0.456	-0.251	0.170	0.554	0.493	0.582	0.674	0.647	0.720	1.000				
(12)	0.480	0.403	-0.203	0.104	0.476	0.415	0.504	0.602	0.563	0.735	0.851	1.000			
(13)	0.562	0.437	-0.248	0.183	0.536	0.482	0.562	0.643	0.624	0.645	0.972	0.705	1.000		
(14)	0.532	0.425	-0.249	0.176	0.535	0.450	0.550	0.625	0.604	0.647	0.921	0.777	0.899	1.000	
(15)	0.281	0.159	-0.166	0.115	0.286	0.232	0.296	0.259	0.246	0.290	0.512	0.313	0.552	0.420	1.000