Regional innovation clusters and firm innovation performance: an interactionist approach

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ABSTRACT
How is firm innovation affected by location in an innovation cluster? How does the interplay of firm and cluster characteristics matter? We examine these questions by conducting an empirical analysis of firm innovation performance in regional innovation clusters. Our theoretical framework is based on a synthesis of the literature on industrial clustering, regional agglomeration economies and social networks. We test the framework empirically through the analysis of data on patent citations from 578 firms located in 26 European regional clusters in the information technology industry over 10 years. We find that location in these clusters offers benefits and at the same time poses certain constraints. One of the central findings is that connectedness to highly performing firms (in horizontal relationships), research institutions and universities located in a cluster moderates the onset of diminishing returns between firm innovation performance and research and development effort, and helps firms cope with the negative effects of locating in clusters.

KEYWORDS
regional innovation systems; firm innovation performance; European clusters

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INTRODUCTION

With increasing global competition, the survival and success of firms increasingly depends on their ability to innovate (Bartlett & Ghoshal, 1990; Rothaermel, 2008; Schmitz & Strambach, 2009; Zander, 1999). There is evidence that the innovation performance of firms is highly dependent on their ability to absorb knowledge from various external sources (Braczyk, 1998; Chesbrough, 2006; Cortright, 2006; Frost, 2001; Granstrand, Bohlin, Oskarsson, & Sjoberg, 1992; Rosenfeld, 1997; Waits, 1995). Regional innovation clusters represent an important external source for firm innovation (Boix & Galletto, 2009).

While most studies have been focused on examining the specifics of cluster emergence and development (Dunning, 2000; Porter, 1998, 2003; Rugman & D’Cruz, 2000; Scott, 1988) and their implications for regional economic development and competitiveness (Porter, 1998), there is important literature on cluster effects on firm innovation performance. For instance, Baptista and Swann (1998) examined the innovative record of manufacturing firms related to the region where they are located and found that firms are more likely to innovate in a strong cluster. Similarly, Boix and Galletto (2009) explored the effects of industrial clusters on firm innovation performance and found that the innovative output per capita in clusters is 47% above the national average. Beaudry and Breschi (2003) found a strong positive effect on innovation from location in strong clusters where other firms are highly innovative.

It has been argued that clusters have important effects on innovation since firms benefit from a specialized and flexible labour market, competent suppliers in all the phases of the productive chain of a good, as well as easy availability of skills in regional agglomerations (Boix & Galletto, 2009; Keeble & Wilkinson, 1999; Mudambi & Swift, 2012; Porter, 1998). Technology- and knowledge-intensive activities tend to be more geographically concentrated than other types of activities (Brewer, Guisinger, & Young, 2003;
Dunning, 2002). Recent studies also emphasize socially driven mechanisms in clusters such as networking among firms, universities, regional authorities and research institutions that ensure collaboration and enable the sharing of resources and knowledge on specific projects (Lorenzen & Mudambi, 2013; Turkina, Van Assche, & Kali, 2016; Turkina & Van Assche, 2018).

Studies that attempt to explain firm innovation in clusters can be generally divided into two categories: those that analyze firm-level factors and those that focus on cluster-level factors. However, few studies offer a systematic analysis of both groups of factors simultaneously and, most importantly, the interplay between them. For instance, we do not yet know how firm size interacts with cluster characteristics (e.g., whether small firms benefit more from young or mature clusters), or how a firm’s relational capital in a cluster interacts with some of the negative cluster effects discussed in the literature, such as excessive diversity (Orsenigo, 2001). Beugelsdijk (2007), in his conceptual study of regional agglomerations and firm innovation performance, pleads for an ‘interactionist approach’ that would take into account both firm- and region-specific effects and examine interactions between them in a comprehensive manner.

We contribute to the literature by carefully examining the interplay between firm- and cluster-level characteristics in affecting the innovation performance of firms located in innovation clusters. To this end, we first develop a theoretical framework of firm innovation in clusters that draws from the literature on industrial clusters, agglomeration economies and social networks. We then empirically assess the propositions issuing from the theoretical framework by conducting empirical analysis of firm innovation performance in European information technology (IT) clusters. The results indicate important interplays between firm- and cluster-level characteristics.

The paper is organized as follows. The next section defines regional innovation clusters. The third section develops the theoretical framework and hypotheses. The fourth section presents the data and methodology. The fifth section presents the empirical model and the results. The sixth section provides a detailed discussion of findings, conclusions and perspectives for future research.

**REGIONAL INNOVATION CLUSTERS**

Regional innovation clusters have been defined as:

> regional concentrations of large and small companies that develop creative products and services, along with specialized suppliers, service providers, universities, and associated institutions. Ideally, they bring together a critical mass of skills and talent and are characterized by a high level of interaction among these entrepreneurs, researchers, and innovators.

(Wessner, 2011, n.p.)

These clusters are sometimes referred to as technological districts or knowledge clusters (Braczyk, Cooke, & Heidenreich, 1998; Lorenzen & Foss, 2002; Malecki & Oinas, 1999).

Innovation is geographically concentrated in areas that provide agglomeration economies offering a high local density of specialized resources, which enhances and facilitates the innovation process (Muro & Katz, 2010). According to Scott (1988), the formation of agglomerations is particularly intense in research and development (R&D)-intensive industries where flows tend to be small scale and unpredictable, and hence subject to high transaction costs. Appendix A in the supplemental data online presents the European model of regional innovation clusters.

Cantwell and Janne (1999) argue that innovation is cumulative and highly sensitive to context. Therefore, it is firm and location specific. The next section analyzes firm- and cluster-specific factors and their interactions that affect firm innovation performance in clusters.

**FIRM INNOVATION PERFORMANCE IN CLUSTERS**

**Firm-related factors**

Capasso and Morrison (2013, p. 1229) found firm size, market segmentation, product differentiation and vertical integration to be important determinants of firm innovation in clusters. As far as firm size is concerned, they argue that small and medium-sized enterprises (SMEs) should benefit more from locating in clusters since they 'have usually a less hierarchical structure, which favors knowledge circulation and provides stronger individual incentive to innovate'. At the same time, some other studies (Boix & Galletto, 2009) have found contradictory evidence that larger firms can be more successful in clusters given their weight in the local system. As far as market segmentation and product differentiation are concerned, Capasso and Morrison (2013) base their analysis on the textile industry, where market segmentation referred to the market niche in which the firm specializes based on the quality of goods produced; product range referred to the number of categories of goods produced. Both had a positive effect on innovation. As far as the degree of vertical integration is concerned, it had a negative effect on innovation implying that flexible specialization enhances innovation.

Another important firm-level factor discussed in the literature is firm absorptive capacity: the ability of a firm to identify, assimilate and exploit knowledge of the environment, as well as the ability to anticipate future technological advances (Cohen & Levinthal, 1989, 1994; Zahra & George, 2002; Schweisfurth & Raasch, 2018). Absorptive capacity is critically important in clusters where interactions among firms are intense and exploiting synergies from the external environment is of particular importance (Expósito-Langa, Molina-Morales, & Capó-Vicedo, 2011). Researchers argue that in high-tech industries R&D indicators are a good approach to defining absorptive capacity (Cohen & Levinthal, 1990). Rocha (1999) used R&D expenditures to evaluate firm absorptive capacity, while other researchers operationalize absorptive capacity with R&D intensity (Stock, Greis, & Fischer, 2001; Tsai, 2001). ’Kim (1997) and Kodama (1995) note the crucial importance of a firm’s internal R&D in determining its
ability to import, comprehend and assimilate external knowledge’ (George, Zahra, Wheatley, & Khan, 2001, p. 215). R&D funds enable the firm to attract and keep talented scientists, as well as to employ outside experts who are knowledgeable in emerging fields, which can reduce the absorption cycle of externally acquired information (Kim, 1997; George et al., 2001).

Numerous studies have found a positive relationship between firm R&D intensity and firm innovation (Almeida, 1996; Almeida & Phene, 2004; Cantwell & Mudambi, 2011; Smeets & Bosker, 2011). At the same time, in the context of industrial clusters, Molina-Morales and Expósito-Langa (2012) found a curvilinear relationship between firm innovation and R&D intensity, demonstrating that there will usually be a saturation level after which decreasing returns occur. However, they also found that firm connectedness to other firms in a cluster has an important moderating effect by giving firms access to external knowledge, thereby strengthening the positive effect of R&D intensity on innovation: while it does not change the slope of the curvilinear relationship, it significantly increases the saturation level. At the same time, recent social network literature suggests that not only does connectedness matter but also it matters even more to whom you are connected (Granovetter, 2005; Turkina & Van Assche, 2018). The argument is that it is better to be connected to highly performing nodes in the network. Firm connectedness to highly performing firms gives access to the best innovators in the industry, thereby giving opportunities to source cutting-edge knowledge and become aware of emerging business opportunities. Therefore, it is logical to suggest that connectedness to highly performing firms in a cluster has a positive effect on firm innovation in clusters. Connectedness to cluster research institutions and universities can be another important source of external knowledge and could therefore have an impact on firm innovation (D’Este & Iammarino, 2010). Local research institutions and universities facilitate connections between firms and external networks and provide access to knowledge and information (Zaheer & McEvily, 1999), thereby reducing search costs related to external knowledge (Maskell, 2001).

We develop hypotheses focusing on relationships previously unexplored in the literature or contradictory findings, while our empirical analysis controls for factors that have been already found as important determinants of firm innovation in clusters.

**Hypothesis 1:** Firm innovation performance is positively affected by connectedness to highly performing firms in the cluster.

**Hypothesis 1a:** Firm innovation performance is positively affected by connectedness to research institutions and universities in the cluster.

**Hypothesis 1b:** Both connectedness to highly performing firms and to research institutions and universities positively moderate the curvilinear relationship between R&D intensity and innovation.

**Cluster-related factors**

One of the central dimensions for evaluating cluster dynamics is cluster specialization (Boix & Galletto, 2009; Breschi & Lissoni, 2001), which reflects the economic effects of the regional cluster in attracting related economic activity from other regions to this location (Breschi & Lissoni, 2001; Turkina et al., 2016). Boix and Galletto (2009) found specialization in manufacturing to have a positive effect on patents at the cluster level, and cluster specialization in general is considered to have positive effect on a region’s economies of scale (Porter, 2003). Nevertheless, overspecialization is viewed as a negative phenomenon since it is likely ‘to result in economic downturns, to prevent the spontaneous creation of inter-industry linkages, and to hamper the creation of innovative ideas through the combination of existing know-how and artifacts than a more diversified economic base’ (Desrochers, Sautet, & Hospers, 2008, p. 234). Overspecialization has been argued to have negative effects on firms located in clusters as it has been linked to long-term lock in, and greater firm vulnerability to external shocks (Yuarra & Ramlogan, 2006; Grabher, 1993).

Other important dimension for evaluating a cluster’s potential are depth and breadth (Dalum, Pedersen, & Vilumnsen, 2002b). Depth refers to the range of vertically related sub-industries within the cluster. ‘A deep cluster contains an almost complete supply chain whereas a shallow one relies on inputs from outside the region’ (p. 7). The innovation system literature argues that vertical relationships within the cluster can reduce the costs related to communication and the time needed to bring an innovation to the market and can thus significantly enhance innovation growth (Dalum et al. 2002b; Lundvall, 1992). Therefore, deep clusters are argued to be more likely to succeed than ‘shallow’ clusters (Dalum et al., 2002b). While in the past cluster depth could be associated with the degree of vertical integration of cluster firms, recent studies indicate that while some firms can still be highly vertically integrated, a general trend is that firms have started to develop profound networks of qualified suppliers and to outsource a lot of activities along the value chain (Turkina et al., 2016). Therefore, at present there can be deep clusters with extensive value chains, but their vertically related sub-industries can be populated by layers of specialised suppliers rather than be represented by vertically integrated firms.

As far as a cluster’s horizontal dimension (in other words, breadth or diversity) is concerned, a cluster is considered to be broad if the region shows the presence of several horizontally related industries (Dalum et al., 2002b). Horizontally related industries share common technologies, clients and distribution channels (Enright, 2003). Clusters with horizontally related industries may have opportunities to avoid temporary market declines (Dalum et al., 2002b). Audretsch and Feldman (1996) note the significance of technological diversity for the development of regional clusters. In a similar vein, Besant (2008) claim that firm diversity and synergies across sectors (IT, electronics and biotechnology) have contributed to the growth and sustainability of the Bangalore IT cluster. In sum, the strength of the regional innovation cluster resides in its vertical (depth) and the horizontal (breadth) dimensions. Both the depth and breadth of a cluster can be further enhanced...
by appropriate educational organizations and research institutions (Dalum, Pedersen, & Villumsen, 2002a).

On the other hand, as some scholars argue, a cluster’s extreme depth and breadth (i.e., cases in which firm heterogeneity is too large) can prevent the exploitation of inter-firm synergies (Laperche, Sommers, & Uzunidis, 2010). For instance, Tichy (2001) discusses a ‘cluster paradox’. On the one hand, cluster diversity enables the cluster to adapt to changing conditions or to reinvent itself (Menzel & Fornahl, 2007). On the other hand, overly heterogeneous clusters may find it difficult to create positive synergies between firms. Orsenigo (2001) explains the failure of the biotechnology cluster in Lombardy by excessive firm heterogeneity in the region, which prevented firms from engaging in productive cooperation and generating technological synergies. Extreme cluster depth has been linked to insufficient interactions with innovative clusters in other regions (because the focal cluster does not have inputs from outside the region) and the lack of the so called ‘external pipelines’, which are important for acquiring knowledge from distant locations and generating innovation (Bathelt, Malmberg, & Maskell, 2004).

However, scholars agree that a high degree of similarity among firms located in the region is not a good thing either since it decreases the probability of more radical innovations that strengthen the cluster’s ability to adapt to changing external conditions.

To summarize, while there are benefits to each of these cluster characteristics (specialization, depth and breadth), they will each exhibit diminishing returns to scale at some point, holding other factors constant. Since there have been no empirical studies that analyze the effects of breadth, depth and specialization in a systematic manner, we develop the following hypotheses to be tested in the empirical part of the paper:

**Hypothesis 2a:** There is an inverted ‘U’-shaped relationship between firm innovation performance and cluster specialization.

**Hypothesis 2b:** There is an inverted ‘U’-shaped relationship between firm innovation performance and cluster breadth.

**Hypothesis 2c:** There is an inverted ‘U’-shaped relationship between firm innovation performance and cluster depth.

Researchers have found that clusters ‘follow a kind of life cycle with different phases or stages of emergence, growth, and decline’ or renewal with differing characteristics (Menzel & Fornahl, 2010, p. 206). Bergman (2008) proposed a cluster life cycle model based on the industry life cycle model and on the technology life cycle model (Abernathy & Utterback, 1978): in the first stage, a cluster emerges; in the second stage, it expands while innovating aggressively and then consolidating and scaling up; in the final stage, the cluster experiences exhaustion. ‘At this point, the cluster either reinvents itself, triggering a new growth phase, or it stagnates and eventually loses its competitive advantage’ (Sønderregger & Täube, 2010, p. 384).

Another perspective on cluster dynamics comes from the economies of agglomeration (Pouder & St. John, 1996). In this view, young growing clusters are usually highly productive and contribute significantly to regional competitiveness. Consequently, the cluster grows and attracts more firms, capital, and specialized labour, local institutions advance to support the growing cluster and a distinct local cluster culture develops (Malmberg & Maskell, 2002; Utterback, 1974). However, over time co-located firms become myopic (Maskell & Malmberg, 2007) and are subjected to isomorphism through convergence, leading to cognitive lock-in (Grabher, 1993) and overall cluster decline. In other words, active growth and success can be followed by inertia and stagnation. Therefore, it is logical to expect non-linear effects of time in cluster on firm innovation performance.

We summarize this discussion in the form of the following testable hypothesis.

**Hypothesis 3:** There is an inverted ‘U’-shaped relationship between time and firm innovation performance in regional innovation clusters: innovation performance will increase up to a certain point, but then it will turn down.

**Firm-cluster interactions**

According to the industry life cycle, a firm’s organization and innovative activity change during the cycle (Utterback, 1974; Dalum et al., 2002b). In the early phase of industry growth, there is typically high innovative activity among the firms, especially among smaller firms. In the mature stage, with less product innovation, there is an advantage in the innovative activity of large firms (Dalum, Pedersen, & Villumsen, 2005). Therefore, it is possible to suggest similar effects from cluster life cycles. Small firms are likely to benefit from young clusters and big firms are likely to exhibit high innovation in the mature phase of the cluster. Small size offers advantages in terms of organizational flexibility, which is particularly important during the take-off and high growth of a cluster (Capasso & Morrison, 2013). ‘In such a context, technological trajectories are not yet defined and windows of opportunities are still open for new entrants’ (Capasso & Morrison, 2013, p. 1229). Therefore, because of low entry barriers, small firms can start their business and innovate more easily in growing clusters than in mature clusters with concentrated markets.

**Hypothesis 4:** Small firms show higher innovation in young clusters, while large firms show higher innovation in mature clusters.

In the firm-level effects section we suggested that connectedness to highly performing firms, research institutions and universities positively affects innovation and makes the curvilinear relationship between R&D effort and innovation milder since it gives access to the best innovators and exposes firms to cutting-edge knowledge (Huggins & Johnston, 2010). We also suggest that connectedness to highly performing firms, research institutions, universities and the consequent exposure to cutting-edge
knowledge will make the curvilinear effects of breadth, depth and specialization and time effect milder. If highly performing firms manage to perform well under negative cluster effects, they must have important innovative solutions vis-à-vis other firms in clusters. Exposure to these solutions and the knowledge of these firms can help the focal firm to cope better with negative cluster effects. As far as research institutions and universities are concerned, they are not subjected to the same pressures from the external environment as firms (DiMaggio & Powell, 1983) and can often provide non-standard innovative solutions.

We summarize this discussion by the following hypotheses:

Hypothesis 5: Connectedness to highly performing firms, research institutions and universities make the curvilinear cluster effects (breadth, depth, specialization and time) milder.

DATA AND METHODOLOGY

The IT industry was chosen as the empirical setting for this study. This industry exhibits high geographical clustering of firms. This clustering makes external sourcing of knowledge a characteristic of this industry (Lundvall, 1992; Mansell & Wehn, 1998; Quah, 2000). It is also characterized by price and product competition, with the result that ongoing R&D and innovation is of critical importance (Baptista & Swann, 1999). First, we identify clusters with a high location quotient and also clusters with more modest, but quickly growing location quotient indicates that there is indeed considerable clustering in that particular region; a quickly growing location quotient indicates a quickly growing cluster that has a perspective to turn the region into a highly specialized area over time. We took information on the location quotient from the European Cluster Observatory and identified 26 regional IT clusters at NUTS-2 level. Next, we matched these regions with firms located there using relevant cluster resources, European Patent Register and Orbis databases. We would have liked to include all the firms located in the identified clusters in our analysis, but due to data limitations, the final sample consisted of 578 firms over a 10-year period (2000–09), giving 5780 observations in the sample. The sample is composed of European firms of different sizes. We choose to limit it to European firms to control for economic geography related heterogeneity and for data convenience (our dependent variable is based on data from European patent registry). We choose to focus on the firms that are active over 10 years in the clusters to observe better their innovation performance and the factors that affect it. Firms that do not survive more than 10 years rarely produce patents that receive a lot of citations as innovation is a long-term process and it takes a while to produce a patent and have the patent cited.

Dependent variable: innovation performance

While there are different approaches for measuring innovation performance, ranging from surveys of innovation perception to counting the number of products introduced to market, the two most popular ones (especially in high-tech industries) are counts of raw patent data and patent citations. The use of raw patent counts has been the focus of a debate regarding its biases and shortcomings for the following reasons: there are significant differences in international and sectoral patenting behaviour; differences in patenting between large companies and smaller firms; and in raw patent counts, identical weight is given to some very important patents as well as to secondary patents (Hagedoorn & Clodt, 2003). It is well argued in the literature that patent citations are a more accurate measure of innovation since they represent the impact and quality of innovative activity and the value of the technology (Almeida & Phene, 2004; Frost, 2001; Hall, Jaffe, & Trajtenberg, 2005). In line with prevailing research, we measure firm innovation performance by patent citations. We define the quality of a firm’s innovation output for a particular year as the total number of citations received within the following four years for patents granted in a particular year. A four-year period is considered to be sufficient since afterwards the patent is less likely to be cited than it was in the first years, including the year it was granted (Mehta, Rysman, & Simcoe, 2010). Appendix B in the supplemental data online discusses some trends in our sample.

Independent and control variables

Firm-related variables

R&D intensity. Using the same approach that has been used in some research, including, among others, Cohen and Levinthal (1990), Mowery, Oxley, and Silverman (1996) and Tsai (2001), we measure this variable as follows: R&D expenditures/total revenue.

Firm connectedness. Using information from the European Cluster Observatory, European Innovation Partnership resources, European Commission CORDIS resource, IT cluster reports, and information from the companies’ annual reports, three networks of inter-organizational linkages were constructed for each cluster for three periods: 2000–02, 2003–05 and 2006–09. We use Porter’s (1990), Li’s (2014) and Turkina et al.’s (2016) approach to distinguish between horizontal and vertical linkages: vertical linkages are supply-chain relationships (buyer–supplier relationships), while horizontal linkages are cooperative arrangements between businesses in sharing resources, for example, knowledge management (in the IT industry these are mostly joint ventures and joint R&D projects), as well as minor interactions at cluster conferences, events and discussion platforms that can also serve as important platforms of knowledge sharing (Li, 2014). Owing to data constraints, as well as the time needed to collect the information on all types of networking, we use only publicly available information on inter-organizational (not interpersonal) networking; therefore, the networks that we analyze are formal inter-organizational networks. Another limitation of our network approach is that due to time constraints, we mainly...
focus on the relationships among the firms in our sample (though we include their main partners and suppliers even in cases when they are not in our initial firm sample) and include information only on the main research institutions and organizations.

The linkages between network actors in horizontal sub-networks were measured on a three-point scale, where ‘2’ is assigned for a strong relationship characterized by intense collaboration through a joint business, programme or partnership; ‘1’ is assigned for minor cooperation through participation in common events, conferences and congresses; and ‘0’ is assigned for the absence of inter-organizational linkages. Network linkages in vertical networks along the value chain are measured on a binary scale, where ‘1’ is assigned for the presence of a relationship; and ‘0’ for the absence of a relationship. The analysis of network linkages based on the scale of the strength of interaction or the binary scale is common in the analysis of inter-organizational networks (Turkina, Van Assche, & Kali, 2016). In this way, 78 inter-organizational network matrices were constructed. As an example, Figure 1 portrays linkages in the Riga region IT cluster for 2006–09 and demonstrates the embeddedness of firms under analysis in the network of relationships.

It is noticeable that each firm maintains a unique pattern of network linkages. Therefore, firms have different levels of integration into the system of relationships in a cluster and are differentially exposed to knowledge, resources, and ideas offered by the cluster.

As far as firm connectedness is concerned, we use closeness centrality to evaluate the degree of embeddedness in vertical networks of relationships, while we test for both betweenness and closeness centrality measures in horizontal relationships. Appendix C in the supplemental data online provides a detailed explanation of this logic. To test for connectedness to highly performing firms we single out the top 10% of firms according to the average number of patent citations for each of the time periods that we study and calculate how strongly each of the firms in our sample is connected to this highly performing group of firms.

As far as research institutions and other relevant organizations are concerned, closeness centrality best reflects the intensity of cooperation with these institutions, because firms are not in competition with these institutions; on the contrary, shared information and resources among local institutions give firms access to a larger pool of external knowledge and resources.

**Firm size.** We operationalize firm size by the number of employees.

**Firm-related controls.** As mentioned above, we test for effects underexplored in the literature and effects with contradictory findings, while controlling for the variables that were found to have effects on innovation in the literature and for which we have the data available: degree of vertical integration operationalized as the number of firm’s production phases and market segmentation operationalized by three categories of price for products/services offered: low–medium–high price based on products/services of firms in the sample (the Boix & Galletto, 2009, approach was used here).

We also control for firm origin with a dummy variable: whether the firm is local or foreign (coming from another European country), as well as for the presence in more than one cluster by the number of clusters in the sample where the firms is present. There is important literature on the importance of not only local but also international networks for innovation performance (Mudambi & Swift, 2012) and, therefore, while bringing this extra layer of international analysis is beyond the scope of this paper, it is important to control for this variable.

**Cluster-related variables**

**Young and mature clusters.** Cluster maturity is operationalized by cluster age (clusters that existed over 30 years are usually approached as mature clusters). Therefore, cluster maturity is operationalized as a dummy variable with the value of 1 for clusters that existed for over 30 years and the value of 0 for clusters that are younger than 30 years. The interaction of firm size operationalized by the number of employees and cluster maturity is used in the analysis to test if big firms show high innovation performance in the maturity phase of the cluster. The interaction of firm size and young clusters (the reverse of the maturity variable) is used to test if small firms benefit from young clusters more than big firms.

**Time in cluster.** The variable time in cluster was measured by the number of years the firm has been in the cluster.

**Cluster specialization, depth and breadth.** Data on cluster specialization, depth and breadth were taken from European Cluster Observatory. The cluster specialization (also known as location quotient) is measured as the ratio of employment in a cluster category to the employment in the region divided by the ratio of the total European employment in that cluster category to the total European employment.

It has been argued that cluster depth refers to the range of vertically related sub-industries within the cluster and cluster breadth is related to the presence of several horizontally related industries with distinct industry codes in the region (Enright, 2001, 2003). Therefore, cluster breadth is measured by the number of horizontally related (with distinct industry codes) concentrated industries in the same region based on European Cluster Observatory location quotient approach (diverse regions would exhibit the presence of concentrated economic activity in several sectors, e.g., aerospace, IT, biotechnology, automobile, etc.), and cluster depth is measured by the number of vertically related subsectors within the IT industry. The European cluster resources provide information on the number of vertically related sub-industries within the cluster.
Cluster-related controls. We control for gross domestic product (GDP) per capita in the region where the cluster is located, population density and business R&D personnel. The data on these variables are taken from the European Union cluster resources.

MODEL AND RESULTS

Since patent citations is a count variable and its distribution approximates the negative binomial distribution and since we have detected overdispersion, we choose the unconditional effects negative binomial regression model for the analysis. We chose the unconditional fixed effects model due to the problems of the conditional negative binomial model and criticisms in the literature that it is not a true fixed effects model (Allison & Waterman, 2002). We use firm, country and time dummies to model dependency between observations. At the same time, for a robustness check, we also conduct a fixed effects Poisson regression with cluster robust standard errors.

Before running the full model, we test and compare the effects of betweenness centrality and closeness centrality in horizontal networks. Closeness centrality turns out to have a significant effect on innovation performance, while betweenness centrality is insignificant. Therefore, we use closeness centrality in all the subsequent regressions. Social network analysts recommend using one centrality measure per subtype of network to avoid collinearity issues.

Table 1 reports the results of the analysis. Model 1 presents the effects of control variables and model 2 presents the full model.

We also conduct additional tests interacting firm-level control variables with cluster-level variables and cluster-level controls to see if some significant interactions were missed, but none of these interactions was significant.

From the full model with controls and with interaction effects (model 2), we can see that our hypotheses are largely supported. Hypothesis 5 is only partially supported, as connectedness to research institutions and universities makes the curvilinear cluster effects milder, while connectedness to highly performing firms makes the curvilinear cluster effects milder only with respect to horizontal networks. Embeddedness in vertical networks, while having a slightly significant impact on innovation as a stand-alone factor, does not interact with the curvilinear cluster effects. Our robustness check (Poisson model) indicates that even though the significance of some coefficients weakens, the results are largely supported except for the interactions of firm size with cluster maturity and cluster young age (Hypothesis 4).

As far as time in cluster is concerned, we modelled the optimum, which turned out to be 15.6 years, indicating that innovation performance increases over time, but for certain reasons it turns down after around 16 years in cluster. At the same time, connectedness to highly performing firms, research institutions and universities in a cluster moderates the relationship between time in cluster and firm innovation performance by making the curvilinear time effects milder and moving the optimum to 17.3
Table 1. Unconditional fixed-effects negative binomial regression and Poisson regression results.

| Variables                                      | Mean | Standard deviation | Model 1: Unconditional fixed-effects negative binomial | Model 2: Unconditional fixed-effects negative binomial | Model 3: Robustness check with fixed-effects Poisson model (with robust standard errors) |
|------------------------------------------------|------|--------------------|-------------------------------------------------------|-------------------------------------------------------|--------------------------------------------------------------------------------------|
| Time in cluster                                | 15.05| 10.08              | 0.49*** (0.11)                                       | 0.37* (0.34)                                          |
| Time in cluster ^ 2                            | 0.08 | 0.15               | −0.15** (0.06)                                       | −0.12* (0.10)                                         |
| R&D intensity                                  |      |                    | 1.58*** (0.12)                                       | 1.65*** (0.14)                                        |
| R&D intensity ^ 2                               |      |                    | −0.23** (0.14)                                       | −0.20* (0.19)                                         |
| Connectedness to highly performing firms_horiz | 0.07 | 0.15               | 0.66*** (0.015)                                      | 0.41*** (0.011)                                       |
| Connectedness to highly performing firms_vert  | 0.05 | 0.16               | 0.0003* (0.0002)                                     | 0.0001* (0.0001)                                     |
| Connectedness to research institutions and universities |      |                    | 0.35** (0.13)                                       | 0.30* (0.26)                                          |
| Connectedness to highly performing firms_horiz × R&D intensity ^ 2 |      |                    | 0.12*** (0.001)                                     | 0.08** (0.03)                                         |
| Connectedness to highly performing firms_vert × R&D intensity ^ 2 |      |                    | 0.002 (0.004)                                       | 0.001 (0.002)                                         |
| Connectedness to research institutions and universities × R&D intensity ^ 2 |      |                    | 0.007* (0.006)                                     | 0.010* (0.008)                                         |
| Firm size                                      | 71    | 82                 | 1.02 (1.13)                                           | 0.99 (1.01)                                           |
| Cluster maturity                               | 0.42  | 0.53               | 0.11 (0.14)                                           | 0.15 (0.17)                                           |
| Cluster breadth                                | 2.8   | 1.3                | 0.24*** (0.005)                                       | 0.27*** (0.11)                                        |
| Cluster breadth ^ 2                            |      |                    | −0.06*** (0.001)                                     | −0.09* (0.08)                                         |
| Cluster depth                                  | 3.1   | 1.7                | 0.16* (0.12)                                          | 0.12* (0.10)                                          |
| Cluster depth ^ 2                              |      |                    | −0.04*** (0.001)                                     | −0.05** (0.03)                                        |
| Cluster specialization                         | 1.2   | 0.8                | 0.28*** (0.006)                                       | 0.39*** (0.007)                                       |
| Cluster specialization ^ 2                     |      |                    | −0.08*** (0.002)                                     | −0.14** (0.06)                                        |
| Firm size × young clusters                     |      |                    | −0.05** (0.02)                                       | −0.09 (0.09)                                          |
| Firm size × cluster maturity                   |      |                    | 0.41* (0.38)                                          | 0.50 (0.49)                                           |
| Connectedness to highly performing firms_horiz × Cluster depth ^ 2 |      |                    | 0.009* (0.007)                                       | 0.006* (0.005)                                       |
| Connectedness to highly performing firms_vert × Cluster depth ^ 2 |      |                    | 0.10 (0.12)                                           | 0.13 (0.15)                                           |
| Connectedness to research institutions and universities × Cluster depth ^ 2 |      |                    | 0.004* (0.003)                                       | 0.007* (0.006)                                       |
Table 1. Continued.

| Variables                                             | Model 1: Unconditional fixed-effects negative binomial | Model 2: Unconditional fixed-effects negative binomial | Model 3: Robustness check with fixed-effects Poisson model (with robust standard errors) |
|-------------------------------------------------------|------------------------------------------------------|------------------------------------------------------|--------------------------------------------------------------------------------------|
|                                                       | Mean        | Standard deviation | Mean        | Standard deviation | Mean        | Standard deviation |
| Connectedness to highly performing firms_horiz × Cluster breadth ^2 | 0.02***(0.001) | 0.09**(0.05)       | 0.02**(0.001) | 0.11 (0.15)     | 0.08 (0.12) | 0.11 (0.15)       |
| Connectedness to highly performing firms_vert × Cluster breadth ^2 | 0.08 (0.12) | 0.11 (0.15)       | 0.02** (0.01) | 0.04* (0.03)     | 0.007*** (0.001) | 0.005** (0.003)   |
| Connectedness to research institutions and universities × Cluster breadth ^2 | 0.02** (0.01) | 0.04* (0.03)     | 0.007*** (0.001) | 0.005** (0.003) | 0.17 (0.21) | 0.22 (0.24)       |
| Connectedness to highly performing firms_horiz × Cluster specialization ^2 | 0.007*** (0.001) | 0.005** (0.003)   | 0.007*** (0.001) | 0.005** (0.003) | 0.003** (0.001) | 0.002* (0.002)   |
| Connectedness to highly performing firms_vert × Cluster specialization ^2 | 0.17 (0.21) | 0.22 (0.24)       | 0.007*** (0.001) | 0.005** (0.003) | 0.003** (0.001) | 0.002* (0.002)   |
| Connectedness to research institutions and universities × Cluster specialization ^2 | 0.007*** (0.001) | 0.005** (0.003)   | 0.007*** (0.001) | 0.005** (0.003) | 0.003** (0.001) | 0.002* (0.002)   |

Control variables

| Variables                              | Mean | Standard deviation | Mean | Standard deviation | Mean | Standard deviation |
|----------------------------------------|------|-------------------|------|-------------------|------|-------------------|
| Origin                                 | 0.62 | 0.48              | 0.62 | 0.45              | 0.62 | 0.48              |
| Presence in other clusters             | 3.2  | 2.4               | 3.2  | 2.4               | 3.2  | 2.4               |
| Vertical integration                    | 1.9  | 2.1               | 1.9  | 2.1               | 1.9  | 2.1               |
| Market segmentation                    | 0.50 | 0.63              | 0.50 | 0.63              | 0.50 | 0.63              |
| Region’s GDP per capita                | US$31,000 | US$14,000 | 0.54** (0.022) | 0.29** (0.012) | 0.37 (0.40) |
| Population density                     | 989  | 1025              | 0.30 (0.36) | 0.38 (0.41) | 0.42 (0.44) |
| Business R&D personnel                 | 1.6  | 0.6               | 0.30 (0.36) | 0.38 (0.41) | 0.42 (0.44) |
| Porb > chi2                            |      |                   | 0.81*** (0.029) | 0.74*** (0.022) | 0.63*** (0.019) |
| Log-likelihood                         |      |                   | 0.81*** (0.029) | 0.74*** (0.022) | 0.63*** (0.019) |
| LR chi2                                |      |                   | 0.81*** (0.029) | 0.74*** (0.022) | 0.63*** (0.019) |
| Log-pseudo-likelihood                  |      |                   | 0.81*** (0.029) | 0.74*** (0.022) | 0.63*** (0.019) |
| Wald chi2                              |      |                   | 0.81*** (0.029) | 0.74*** (0.022) | 0.63*** (0.019) |

Notes: Dependent variable: patent citations.

*p < 0.05, **p < 0.01, ***p < 0.001 (two-tailed).
years in the case of high connectedness to research institutions and universities, and to 20.9 years in cluster in the case of high connectedness to highly performing firms. Moreover, connectedness to highly performing firms make the decline less steep. Figure 2 visualizes these effects. Figures 3 and 4 show how connectedness to highly performing firms and research institutions and universities moderate other curvilinear effects (cluster-level effects of breadth, depth and specialization and firm-level R&D intensity). In each case we do not include other independent variables in the graph modelling; we also normalize model prediction. To determine whether outliers might be driving the curvilinear effects, we test for the significance of slopes (Aiken & West, 1991). The net result of the test is statistically significant curvilinear cluster effects.

**DISCUSSION AND CONCLUSIONS**

An important question in the regional studies, international business and international management literature concerns the strategic objectives of firms regarding their location in regional clusters and the implications of this for their innovation performance. We contribute to the previous research on firm innovation in industrial clusters (e.g., Boix & Galletto, 2009; Capasso & Morrison, 2013; Molina-Morales, 2001) by providing a more nuanced analysis of firm innovation performance in clusters by examining both firm- and cluster-level effects and their interactions to explore which combinations of cluster characteristics and firm characteristics affect innovation performance of firms located in regional innovation clusters.

At the firm level, in line with Molina-Morales and Expósito-Langa (2012), we find that firm connectedness moderates a curvilinear relationship between R&D intensity by increasing the saturation level. At the same time, we advance their analysis further by finding that not only does the number of connections matter but also to whom you are connected is even more important. High connectedness to research institutions and universities and highly performing firms (in horizontal relationships) in particular helps the firm derive more benefits from R&D effort by increasing the saturation level and also makes the slope of the curvilinear relationship between R&D effort and innovation milder, making the eventual downturn of innovation less pronounced.

It is also important to note our contribution to the literature on firm innovation performance and industrial clusters by conducting empirical social network analysis and analyzing connectedness with different network centrality measures. Our findings indicate that a firm’s closeness centrality, reflecting the degree of cooperation, appears to have a positive effect on innovation performance, unlike betweenness centrality, which reflects a position of brokerage. This implies that intense collaboration with well-connected industry peers and collective action is more important for innovation in a cluster than control of information and resources. Therefore, a recommendation for firms located in regional innovation clusters would be to participate in broad inter-firm projects and partnerships rather than to engage in dyadic collaboration. However, to produce most positive effects on innovation, these partnerships have to be with highly performing industry peers.

Significant positive effects from connectedness to research institutions and universities indicates that they are an important external source for firm innovation and should not be ignored by firms locating in regional innovation clusters. Although the moderating effect of connectedness to highly performing firms in vertical (supply-chain) networks of relationships is insignificant, its main effect is significant (although with a low impact), indicating that access to highly performing buyers/suppliers may be an important asset and to some degree can help to improve firm innovation performance.

Our findings also indicate the value of the interaction between firm connectedness in horizontal networks in the cluster with cluster-level characteristics. High connectedness to research institutions and universities and to highly performing industry peers (in particular) helps firms to stand against cluster life cycles by increasing the time-related optimum of their innovation performance. An important finding is that the overall relationship between time spent in a cluster and innovation performance has an inverted ‘U’-shape indicating that innovation grows up to an optimum of 16 years and then turns down (as indicated in Figure 2). While it is beyond the scope of this study to identify factors that explain the particular optimum of 16 years, we can speculate that at first firms benefit significantly from agglomeration economies and knowledge spillovers occurring in clusters; however, over time under convergence pressures they might experience cognitive lock-in and without other sources for innovation (e.g., through internal firm opportunities or networks external to clusters) their innovation performance might turn down. Future studies could conduct an in-depth examination of the innovation optimum related to cluster location and the factors that drive it.

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**Figure 2.** Innovation and time in cluster.

Note: Lower curve = baseline; middle curve = high connectedness to research institutions and universities; and upper curve = high connectedness to highly performing firms.
Another important finding concerns curvilinear relationships between firm innovation performance and cluster depth, breadth, and specialization. While some degree of specialization is beneficial for attracting skilled labour and creative positive knowledge spillovers, Desrochers et al. (2008) argued that overspecialization of the regional cluster can lead to a regional economic downturn (and, as a consequence, cluster decline), because the region becomes too dependent on one economic activity and needs a more diversified economic base. Evidently, this negatively affects innovation performance of firms located in overspecialized clusters. At the same time, excessive breadth and depth of the cluster imply excessive firm heterogeneity, which prevents the creation of positive synergies between firms and leads to a downturn in firm innovation performance. Given these findings, when locating their activities in regional innovation clusters, firms need to pay attention to cluster specialization indicators, as well as to the existence of vertically related and horizontally overlapping industries in the region, but to the extent that the firms in the region are not too heterogeneous.

Again, it is crucially important to note the role of firm connectedness to highly performing firms and research institutions and universities to moderate the relationship between cluster breadth, depth, specialization and firm innovation performance by making the negative effects less pronounced.

As far as the interaction between cluster life cycles and firm size is concerned, the results are mixed as the negative binomial model indicates that smaller firms indeed show higher innovation performance in young clusters than bigger firms, while bigger firms benefit more from mature clusters. At same time, the robustness check with a Poisson model does not support these findings. This may indicate that firms of different sizes have opportunities for innovation in clusters and other characteristics, such as the overall time spent in a cluster and firm connectedness, as well as cluster depth, breadth, and specialization, are more important.

Overall, our findings have important managerial implications. They suggest that firm strategic planning needs to take an integrated approach to locating firms in regional clusters by taking into account the interplay between firm- and cluster-level factors since this interaction plays a significant role in determining a firm’s innovation performance.

An important limitation of our research is a potential endogeneity problem as firms in theory do not choose their geographical location randomly, but because they believe it will bring them benefits. Existing research on clusters suggests that firms choose clusters because of positive agglomeration effects such as the availability of skilled labour or the existence of needed infrastructure. This underlies the assumption in our analysis that firms locate in the clusters because they are attracted by cluster agglomeration opportunities. However, the purpose of our analysis is to provide a more nuanced analysis of what makes clusters different from each other and how cluster-related factors, firm-related factors and their interactions affect firms already located in clusters, and why firms need to pay special attention to the combination of their firm-level characteristics with the characteristics of clusters where they locate. However, we admit that while it is beyond the scope of this paper, it is important for future research to consider firm motivation when locating in clusters, or control for firm-level strategic choice differences. Future research should factor in firm strategic choice variables.
Our findings suggest fruitful avenues for future research. Further comparative analyses along the lines of this paper will contribute to identifying patterns across both time and space that lead to superior firm performance in clusters. Another important research limitation of our study is a question of the extent to which evidence from IT clusters applies to other sectors. Therefore, subsequent studies could explore if the same effects hold in other industries. By extending sectoral scope, a more nuanced analysis of firm innovation performance in regional clusters could be obtained. Another important avenue for future research is to bring to this analysis firm networks outside clusters and global cluster connectedness, since the external connectedness of a cluster itself may act as an important pipeline for external knowledge and might mitigate some of the negative effects discussed in this paper.

**DISCLOSURE STATEMENT**

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**NOTES**

1. There are three levels of Nomenclature of Territorial Units for Statistics (NUTS) defined. The current NUTS classification of the European Union, valid from 1 January 2015, lists 98 regions at NUTS-1, 276 regions at NUTS-2 and 1342 regions at NUTS-3 levels. NUTS-2 refers to divisions at the provincial level and is largely used by EUROSTAT and other European Union bodies.

2. Some clusters boast of over 3000 information and communication technology firms.

3. According to European Union cluster resources, European clusters are predominantly populated by European firms. At the same time, we recognize the present focus on firms of only European origin as a data limitation.

4. We use logs where appropriate.

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