Technological gatekeepers, regional inventor networks and inventive performance

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Abstract: The paper investigates,in a regional context, the impact of gatekeepers on the quality of inventions at the patent team level based on a social network analysis. Given the lack of consensus in the literature, we explore two definitions of gatekeepers and distinguish their impact from external stars. Our results show that gatekeepers indeedinfluence the quality of the patents to which they participate. However, the quality of their patents is reduced if gatekeepers and their team members are located in the same region compared to multi-location teams and this holds for both definitions. External stars do not contribute to inventive quality even if they work within multi-location teams. Finally, inventor teams benefit from socially close gatekeepers located within their region, even if they have no gatekeepers within their team.

JEL classifications: O31, O33, R11, D85
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1. Introduction

The advantages of industrial clusters to foster innovation is largely documented (Feldman & Kogler 2010). However, an increasing number of papers argue that too much proximity might be detrimental for innovation (Boschma & Frenken 2010; Broekel & Boschma 2012; Cassi & Plunket 2014). Scientific and technological networks have small world structures, that is, linkages are highly clustered as individuals collaborate among themselves and within a community of individuals sharing similar knowledge bases. While this proximity facilitates tacit and complex knowledge exchanges, it may also lead to a lack of new ideas and an increased risk of knowledge redundancy and lock-in (Uzzi 1996; Rychen & Zimmermann 2008; Giuliani 2011).

In contrast, according to Bathelt et al. (2005), successful clusters are characterized by a dense local network offering all the advantages of proximity, combined with extra-cluster collaborations also called global pipelines (Owen-Smith & Powell 2004).

In this context, the geography of innovation literature increasingly emphasizes the specific role played by gatekeepers as a way of escaping the risk of knowledge redundancy and uniformity in the process of knowledge creation.Gatekeepers are depicted as a small number of key actors, who have the capacity of mediating the flow of knowledge between separate groups, namely organizations, technological communities and/or industrial clusters(Allen 1977; Giuliani & Bell 2005; Morrison 2008; Munari et al. 2011; Kauffeld-Monz & Fritsch 2013; Rychen & Zimmermann 2008; Graf & Krüger 2011). In a regional context, gatekeepers endorse this role as they are local actors with wide connections to knowledge produced outside their cluster and as they contribute to translate and diffuse it within their region. As such, they participate to renew the regional knowledge base(Breschi & Lenzi 2015).

Building on these recent findings, the aim of this paper is to further explore if and how gatekeepers contribute to the performance of innovations within clusters. More specifically, based on patent data and inventor networks in the genomic field, we analyze whether gatekeepers affect the quality of patents produced both by the teams to which they belong and by teams to which they are socially connected within regional networks.

We adopt a spatial view of networks by locating each inventor at its declared postal address. We are therefore able to separate, for each individual, its within- and cross-regional network connections. This micro-level approach helps understanding how their embeddedness within regional and global networks influence inventive performance. Further, as teams are increasingly composed of members from multiple regions (von Proff & Dettmann 2013; Hoekman et al. 2009), we are able to evaluate the impact of gatekeepers when all team members are located in the same region compared to their impact in multi-location teams.

Our contribution is threefold. First, we use two definitions of gatekeepers and compare their impact. As there is no consensus in the literature, we choose two approaches largely adopted. In the first one, gatekeepers are considered as local actors with strong connections outside their cluster and with a central position within their cluster, which enables them to diffuse externally produced knowledge within their local context (Giuliani and Bell, 2005; Morrison, 2008). The second approach draws on Gould and Fernandez's (1989) social network analysis, which sees gatekeepers as individuals with unique and non-redundant ties to external actors (Breschi & Lenzi 2015; Graf & Krüger 2011). Second, we contribute to the discussion about the qualitative differences between gatekeepers and external stars, defined as actors with high external linkages but limited local ties (Giuliani 2011; Morrison et al. 2013). Although largely linked to externally produced knowledge, which should contribute to their inventiveness, external stars are not able to increase the quality of inventions within their team as opposed to gatekeepers, probably because differences in local embeddedness play a significant role combined with external knowledge for global pipelines. Third, we explore the channels through which gatekeepers affect inventiveness of other inventors located in their region. Given that knowledge is embedded in individuals and that its diffusion occurs through direct linkages (Singh 2005), we explore the role of social proximity to gatekeepers within regional inventor networks.

Our main results show that gatekeepers indeed influence the patent quality of the team to which they participate. However, the quality of their patents is reduced when gatekeepers and their team members are located in the same region as compared to multi-location teams and this holds for both definitions. External stars do not contribute to the quality of patents even when they work within multi-location teams. Finally, inventor teams benefit from the proximity to gatekeepers located at close social proximity within their region, even if they have no gatekeepers within their team.

The paper is organized as follows. Section 2 provides a review of the literature and develops hypotheses about the impact of gatekeepers on the quality of inventions. Section 3 introduces our data, estimation method and variables. Section 4 presents descriptive statistics on gatekeepers, inventor teams and patents as well as estimation results. Section 5 proposes a discussion and concludes.

2. Literature review

2.1. Proximity versus global pipelines

Because innovation and creativity are highly localized(Feldman & Kogler 2010), individuals and firms can be more innovative if they are embedded in scientific and technological networks within industrial clusters. First, geographical, social and technological proximityto other firms and competitors facilitates the diffusion of knowledge and best-practices through continuous monitoring and imitation and enhances the incentives to innovate and differentiate products (Bathelt et al. 2004;Porter 1998). Second, proximity favors new collaborations and frequent face-to-face interactions. Hence, it reduces coordination and transaction costs and enables the emergence of trust whichfacilitates tacit and complex knowledge exchanges and makes collaborations more efficient(Boschma 2005). Third, collaboration opportunities increase with city size which does also offer the technological and social diversity needed for creativity and inventiveness, the so-called local buzz(Glaeser 1999; Storper & Venables 2004).

Despite the widely documented advantages of industrial clusters, too much proximity may lead to a lack of new ideas and a risk of lock-in(Uzzi & Spiro 2005; Boschma & Frenken 2010; Broekel & Boschma 2012; Cassi & Plunket 2014).

First, the process of knowledge creation is cumulative by nature which leads actors to rely on their prior knowledge(Fleming 2001; Stuart & Podolny 1996) with the risk of being trapped in local search and incremental learning (Rosenkopf & Nerkar 2001). By contrast, technological novelty derives from the ability to recombine familiar components in new ways, that is, new combinations of partly familiar technologies or technological components(Fleming 2001; Hargadon & Sutton 1997). However, this is a difficult task since local search tends to lead inventors towards a familiarity trap(Arts & Veugelers 2015).Hence, individuals may find beneficial to explore new possibilities and ideas preferably outside their organizational and regional boundaries.

Second, local search does also apply to partner selection. Most often, individuals choose past collaborators or their partner's partners in order to lower their search and enforcement costs(Baum et al. 2010). This translates in a tendency of local clustering among actors which means increased connectivity and cohesiveness(Schilling & Phelps 2007). Knowledge sharing and trust are facilitated but the risk of sharing common and redundant knowledge rather than novel ideas is also increased (Uzzi & Spiro 2005).

Given both tendencies of familiarity and redundancy in the process of knowledge production, the capacity to produce successful innovations supposes some brokering position, that is, some openness to more diverse knowledge sources and ideas. This role may be endorsed by specific actors such as technological gatekeepers as we discuss now.

2.2. The role of gatekeepers for innovation

2.2.1.Inventive performance of gatekeepers

Gatekeepers are prone to contribute to knowledge renewal as they act as an interface between local networks and external sources of knowledge(Morrison 2008; Rychen & Zimmermann 2008; Breschi & Lenzi 2015; Allen 1977). They materialize the so-called global pipelines, that is, the channels between local networks and distant actors whichdrives the success of clusters(Owen-Smith & Powell 2004; Bathelt et al. 2004).

Two complementary views of gatekeepers are found in the literature. Following the pioneering work ofAllen(1977), the first approach views gatekeepers as actors serving two functions of mediation and diffusion, namely, sourcing external knowledge and diffusing it within the cluster. Giuliani and Bell(2005) show that only those firms that are close to the technological frontier with high absorptive capacities may be able to reach and maintain wide access to external sources of knowledge. In turn, their local embeddedness enables them to diffuse it within their cluster (Morrison 2008; Giuliani & Bell 2005; Munari et al. 2011). The second approach builds on the definition and methodology proposed byGould and Fernandez(1989) ;gatekeepers are primarily seen as actors having non-redundant ties within a social network as they stand on a unique path between an actor belonging to her group and an actor located outside her group(Lissoni 2010). Applied to a regional context, gatekeepers represent a specific form of brokerage by establishing unique links to actors from other regions(Graf & Krüger 2011; Breschi & Lenzi 2015).

If both approaches insist on the role of gatekeepers as a source of knowledge transmission and renewal, we lack evidence regarding their impact on the level and quality of innovation. It seems somewhat clear that they become gatekeepers because they are already leading firms and innovators(Munari et al. 2011; Morrison 2008) but the opposite effect still has to be investigated. There are however a few exceptions.Graf and Krüger(2011) find that patent applicants with gatekeeping positions enable to increase the level of patenting in the long run. In the short run, only applicants with a large number of connections manage to take advantage of their position. Regarding the impact of gatekeepers on the quality of innovations, the evidence becomes scarce.Arts & Veugelers (2015)find that technological brokering affects the likelihood of producing breakthrough patents. If this result gives some insights on our specific question, it does not directly tackle the issue of regional gatekeepers. However, if gatekeepers facilitate technological brokering as suggested by Breschi and Lenzi (2015), we should find similar impact between gatekeepers and the quality of patents.

Given these results and the fact that gatekeepers access new external sources of knowledge and increase the opportunities of fruitful creative recombination, we propose the following hypothesis:

Hypothesis 1. Gatekeepers positively affect the quality of inventions of their team

If gatekeepers are key actors for innovation as they transfer external knowledge to their cluster, a number of papers discuss the fact that they behave differently from external stars whoalso have high external linkages but whose local ties are limited(Giuliani 2011). As discussed byMorrison et al.(2013, p. 77), "there is a natural tendency of actors within global pipelines to act as external stars rather than gatekeepers of knowledge" mainly because these actors with tight external links may not be willing to share their externally acquired knowledge with local firms for strategic reasons or because local firms lack absorptive capacities(Giuliani & Bell 2005). Due to insufficient local connections, they cannot affect the technological development of their own regions nor can they benefit from the local buzz. Hence, the qualitative difference with gatekeepers may be questioned and we hypothesize that external stars have more difficulties to produce high quality inventions as follows:

Hypothesis 2. External stars do not positively affect the quality of inventions of their team

Another issue relates to multi-location inventor teams. Most teams are formed by inventors located within the same region ascollaborations rely heavily on geographical and social proximity (Cassi & Plunket 2015; Breschi & Lissoni 2009; Bercovitz & Feldman 2011)as well as local search (Baum et al. 2010). However, a non-negligible proportion of teams are composed by inventors working in separate regions (von Proff & Dettmann 2013; Hoekman et al. 2009) which enjoy a wider access to external knowledge. In their paper on gatekeepers, Breschi & Lenzi (2015)choose to limit their sample to patents for which inventors are all located in a single region in order to mitigate possible endogeneity concerns with reference to the external connections and gatekeeping indicators. As this strategy cannot completely protect from unobserved consequences of mobile inventors, we prefer to explicitly consider the impact of gatekeepers within teams for which all inventors are located in the same region (prior to patenting) versus multi-location teams. However, the sign of the impact is difficult to predict. Because gatekeepers are supposed to provide new sources of knowledge, they should have a positive impact even within a single-region team. In contrast, if they do not manage to recombine it with local knowledge, the impact could well become negative compared to multi-location teams in which the sources of knowledge are much broader and offer more opportunities for innovative recombination.

Hypothesis 3. The impact of gatekeepers on the quality of inventions will be affected by the number of the team members' locations.

2.2.2. Social proximity to gatekeepers

The former section has investigated how gatekeepers may appropriate the benefits of their position for their own invention. However, the literature on gatekeepers is mainly concerned with the social benefits or externalities driven by the presence of gatekeepers within industrial clusters.

Despite the increasing literature on the subject, we still have limited knowledge regarding the indirect influence of gatekeepers on innovation andthe channels through which gatekeepers disseminate their knowledge within clusters. Munari et al.(2011), for example,show that patents belonging to gatekeeping firms are more cited by local firms confirming the role of gatekeepers in the dissemination of technological novelties. Breschi and Lenzi(2015) find that external direct connections outperform external linkages mediated by gatekeepers in explaining the expansion and renewal of a city's knowledge base. This suggests that socially closer interactions are more effective for accessing new knowledge because knowledge is less distorted when there are less intermediaries. Finally,Giuliani(2011) shows that isolated firms within clusters do not benefit from the presence of nearby technological gatekeepers and suggests the need to explore the role of proximity within networks. As knowledge is not in the air but rather flows through interpersonal relationships (Breschi & Lissoni 2009), we hypothesize that being closer to gatekeepers facilitates access to external and non-redundant knowledge sources underlying knowledge recombination and inventive quality. We do also test the moderating effect of multi-location teams as earlier (see hypothesis 3).

Hypothesis 4. Social proximity to gatekeepers increases the inventive performance of patents.

Hypothesis 5. The impact of social proximity to gatekeepers on the quality of inventions is affected by the number of the team members' locations.

3. Data, network construction and variables

3.1. Sample and network analysis

The database used in the paper combines three different sources. Allgenomic European Patents published between 1990 and 2010 are extracted from the Worldwide Patent Statistical Database; the genomic field has been identified based on keywords proposed by a group of experts (Laurens et al. 2010). Genomics is part of the larger biotechnology field, which finds its main applications in health, agriculture and food sectors. It is a science-based technology characterized by a high-level patenting and large international networks. This database iscombined with the OECD REGPAT for the geo-localization of inventors and the OECD EPO indicators for patent quality(Squicciarini et al. 2013). The initial database includes 140,017 observations composed of 38,671 unique patent applications and 61,673 inventors. The name disambiguation for inventors is performed following the methodology proposed byCassi and Carayol(2009).

Networks of inventors are computed based on co-inventorship patterns: they are one-mode projections (inventor by inventor) derived from two-mode affiliation networks (inventor by patent applications). In order to build the network for each period *t*, we followed the common practice of considering co-invention ties formed during the period [*t-5,t-1*] and excluding older ties(Breschi & Lissoni 2009; Breschi & Lenzi 2015; Lobo & Strumsky 2008) based on priority years. Once networks have been built and all interpersonal ties constructed, we have limited our sample to all patents with European EU 15 plus Norway and Switzerland and United States postal addresses.

In order to avoid simultaneity biases, all variables are computed at priority year*t* and based on the network during [*t-5,t-1*]. The well-known drawback of this methodology(Breschi & Lissoni 2009; Lee 2010), is that the final sample only includes patents for which inventors have patented in year *t* and during [*t-5,t-1*]. The final sample includes 11,831 observations based on 10,350 patents as patents are duplicated when there are multiple applicants.

3.2. Variables and estimation strategy

The number of forward citations received by the patent family up to five years after the priority yearis used as an indicator of patent quality and inventive performance; it is considered as an indicator of the social and private value of inventions (Trajtenberg 1990; Harhoff et al. 2003). Since the number of citations is a count variable, a Poisson model could be used but as the variance exceeds the mean as illustrated by the significant dispersion parameter, all estimations are based on a negative binomial model. The model is as follows:

$$E[(y_{ijkt} \,|x_{itjk} , \varepsilon_{ijk}) = \exp(g_{jt}^{'} \theta + x_{it}^{'} \beta + z_{jt}^{'} \gamma + r_k + \mu_t + \varepsilon_{ijkt}) = h_{itjk} \, \lambda_{ijkt}$$

where y_{ijkt} is the number of forward citations for patent *i* produced by team *j* in region *k* in year t; $g_{jt}^{'}$ is a $(1,K_1)$ vector of characteristics containing our variables of interest, i.e. the gatekeeper variables for team *j* for year t; $x_{it}^{'}$ is a $(1,K_2)$ vector of characteristics at the patent level for year t; $z_{jt}^{'}$ is a $(1,K_3)$ vector of characteristics at the inventor and team level; r_k are region-fixed effects; μ_t are time-fixed effects; $h_{ijkt} = \exp(\varepsilon_{ijkt})$ is assumed to have a one parameter gamma distribution with mean 1 and variance κ. This model is estimated using maximum likelihood. Moreover, in order to cope with the fact that errors may be correlated across patents for a given applicant, robust standard errors are adjusted for intra-group correlations (clustered by applicants).

Before proceeding to the variables description, some comments are in order. In line with prior empirical research, our level of analysis is the individual patent controlling for team-level and invention characteristics(Singh & Fleming 2009; Bercovitz & Feldman 2011; Arts & Veugelers 2015). However, the reliability of these estimations may be affected by at least three problems. First, the choice of inventors to participate in a team may not be random but depend on the performance of team members. The endogeneity due to team selection is difficult to control for with fixed-effects as team composition changes over time. We nevertheless try to alleviate this effect by introducing a large number of team-level characteristics. Second, patent quality may be influenced by inventors' characteristics which is again difficult to control for using inventor fixed-effects at the team-level. Instead, we try to control for inventor specificities by including prior patenting. Finally, the patent quality can be influenced by the location of inventors. A location fixed-effects could be introduced if all inventors came from the same location. However, thirty-seven percent of the patents used in the final sample are composed by multi-location teams. Therefore, in order to somewhat control for the impact of location and highly productive inventor characteristics (which may not be independent), we attribute to each patent the location of the team's most productive inventor. However, despite all these controls, we are aware that all endogeneity issues are probably not solved, so that our results should be interpreted as correlations rather than causal effects.

3.3. Gatekeeper and external star variables

As mentioned before, there is no clear cut definition of gatekeepers (Graf 2011). Hence,we compare the two dominant approaches found in the literature. Regarding the first approach, Giuliani and Bell (2005, p.55) identify gatekeepers based on two criteria: gatekeepers are actors actively engaged in the transfer of knowledge to other firms operationalized as an in-degree to out-degree centrality lower than one and have above average external openness. Since our network is undirected, we replace the in- and out-degree ratio with betweenness centrality computed within the region; an inventor with a high betweenness centrality has a large influence on knowledge transfers since many shortest paths pass through her. Hence, we define as *gatekeeper 1* an inventor who has *both* a standardized betweenness centrality within her region and a number of direct ties to inventors outside her region above the average compared to other inventors from the region.

The second approach derives from Gould and Fernandez (1989): an inventor located in a region is a *gatekeeper 2* when the shortest path leading from any inventor j in his region to any inventor k in another region passes through this inventor. Based on Butts SNA package (Morris et al 2003), we consider as a *gatekeeper* 2, any inventor with a positive raw absolute brokerage score during [*t-5,t-1*] as inLissoni (2010). Unlike Graf and Krüger (2011), we do not consider the impact of the intensity of the score. These two approaches do not exactly overlap since in Gould and Fernandez (1989), no reference is made to the degree of centrality within the actor's group, only the unique and non-redundant path to an external actor is relevant.

Regarding the geographical boundaries, we follow the literature on inventor networks and attribute each US inventor to a Metropolitan Statistical Area (Lobo & Strumsky 2008; Breschi & Lenzi 2015). For European inventors, both NUTS2 and NUTS3 are found in the literature; however, in order to consider the gatekeeping role, we privilege NUTS2 levels with larger distances between regions for which frequent day to day may be more difficult. We add two dummy variables to control for differences between EU and US teams: *EU team* takes value 1 if all members belong to the EU15 plus Norway and Switzerland, and *US-EU team* for mixed teams.

Since the analysis is performed at the team level, we consider the number of gatekeepers involved in each team (*# of gatekeepers 1* and *# of gatekeepers 2*) and a dummy variable identifying whether the team includes at least one gatekeeper (respectively *gatekeepers 1 dummy* and*gatekeepers 2 dummy*).

As *gatekeepers 1*, external stars have a number of direct ties to inventors outside the region above the average (Giuliani 2011)howeverunlike gatekeepers 1 they have lower than average betweenness centrality. Based on this definition, we compute the number of external stars *(# external stars*), and a dummy variable identifying whether the team includes at least one external star (*External star dummy*).

The social proximity to gatekeepers is based on the matrix of geodesic distances between any two inventors within the network during the period [*t*-5,*t*-1]. In order to avoid double counting, the number of proximate gatekeepers is computed at the team level. We compute for each team, the *number of gatekeepers at distance 1* and the *number of gatekeepers at distance 2 to 4*for each type of gatekeepers that are located in the same region as the team members.

Finally, in order to test the role of multi-location teams, we define a dummy variable *single-region*,which takes the value 1 if all team members report the same location prior to the focal patent and 0 otherwise. *# of regions* is the number of locations within the inventor team and it is introduced in quadratic form as a larger number of regions may increase coordination costs and reduce performance.

3.4. Inventor, team and patent control variables

A number of control variables are considered to cope with inventor team, location and patent value characteristics.

In order to distinguish the specific impact of a gatekeeping position from the overall impact of network connections, we compute for each inventor the *internal* and the *external reachability*. Distance-weighted reachability captures the number of inventors that can be reached by a given individual as well as the path length needed to reach them (Borgatti 2006; Breschi & Lenzi 2015; Schilling & Phelps 2007). It is computed as the sum of the inverse geodesic distances d_{ij} between inventor i and any other inventor j within$i$'s region for the internal reach and d_{ij} between inventor i and any other inventor j located outside his region for external reachability.

$$\text{Distance-weighted reachability} = \sum_j \frac{1}{d_{ij}}$$

FollowingBreschi and Lenzi (2015), it is assumed that no knowledge flow is taking place at a distance above four for which $1/d_{ij}$ is set to 0. As this measure is very sensitive to the size and density of the region, we normalize itby dividing each inventor's reachability by the maximum reachability in his region. Thus, the inventor with the highest reachability has a value of 1 while the other inventors have values lower than 1. The measure is then averaged across inventors within the patent team.

In order to distinguish the impact of gatekeeping position from inventor productivity and more generally relevant inventor and team characteristics, we control for the variables which might affect the number of citations received by the patent in line with prior research (Singh & Fleming 2009): the *average experience* (i.e., the average number of previous patents among team members), the *experience diversity* (i.e., the number of technology classes at digit 3 any inventor has patented before), the team size (i.e., the number of inventors). Following Tzabbar and Vestal (2015), we control for *status asymmetry*, that is, the fact that innovative productivity in a team may be centered on a few key inventors. It is computed as

$$\textit{Status asymmetry} = \left[\left(\sum_{s=2}^{S} \mathrm{Inv}_i^2\right) \times \left(\frac{S}{S-1}\right)\right]$$

where Inv_i refers to the proportion of previous patents inventor *i* earned prior to joining her current team relative to the total number of patents issued by the *S* inventors on the team. Status asymmetry varies from 1/*s* to 2, and a higher score indicates a higher asymmetry.

We also control for geographic, organizational and social proximity among inventors within the team. Geographic proximity is controlled by the average *distance* in kilometers and its quadratic term. Social proximity is controlled for through *relational strength* following Tzabbar and Vestal (2015): it is computed as the average level of collaboration between any two members of team *k* and varies from 0 to 1 where all team members have previously collaborated on a patent.

$$\text{Strength} = 1\,\frac{\sum_{i=1}^{N_k}\sum_{j=1}^{N_k} z_{ijk}\ /\max(z_{ijk})}{N_k(N_k-1)}\,\text{for } j \neq i$$

Organizational proximity is controlled through a dummy indicating whether inventors have applied patents for the *same applicant* prior to the focal patent.

We also introduce a number of invention-level characteristics which are known to affect the number of forward citations, in line with prior research (Singh & Fleming 2009; van Zeebroeck & van Pottelsberghe de la Potterie 2011). We include the *number ofclaims,* which controls for the patent's legal breadth, the *number of backward citations* which captures the degree of cumulativeness within the inventive process, the number of *citations tonon-patent literature,* whichis a proxy for the science-technology links, *the size of the patent family* (i.e. the number of offices in which the patent has been applied for) and *the patent scope* (i.e. the number of International Patent Classification - IPC codes to which the patent refers and proxies the level of pervasiveness). The *number of applicants* on a patent may also increase the number of citations received.

In addition, *year fixed effects* are also included to capture the possible correlation between the number of forward citations and unobserved time-invariant variables responsible for differences in the number of citations over years. We also control for the field characteristics by introducing a *technological field dummy*, which equals one if the patent belongs to the following WIPO 35 technology fields: Organic fine chemistry, Biotechnology, Pharmaceuticals, Macromolecular chemistry, Polymers, Food chemistry, Basic materials chemistry and Chemical engineering. Finally, in order to control for the fact that regions with larger numbers of inventors may have a higher density and buzz, we attribute to each patent the regional dummy of the most productive inventor, that is, the inventor with the highest number of patents filed. In this way, we try to control for the endogeneity of highly productive inventors in highly productive regions. We introduce *region fixed effects* based on these regional dummies.All variables and controls are summarized in Table 1, together with some descriptive statistics.

------ Table 1 Here ------

4. Results

4.1. Descriptive statistics

Table 2 shows descriptive statistics for inventor-year characteristics. Among the 9,699 unique inventors, each inventor can appear more than once, thus we end up with 17,022 inventor-years. Among them 2,408 inventors are *gatekeepers 1*, 5,838 are *gatekeepers 2* and 4,696 are external stars. Although defined on different criteria, *gatekeepers 1* overlap at 99% with *gatekeepers 2*, whereas the opposite is not true, they overlap only at 41% and 35% *gatekeepers 2* are also external stars.

First, statistics show that gatekeepers are more productive than the average inventor: they apply for roughly twice as much patents (13.57 for *gatekeeper 1* and 9.14 for *gatekeeper 2* compared to 4.59). In contrast, external stars are less productive than the average inventor (4.22) although they have twice as more direct partners outside their location (6.04).Second, both types of gatekeepers have more direct co-inventors within (local degree is respectively 14.53 and 10.45) and outside their region (external degree is respectively 7.45 and 5.94 compared to 3.03). Hence, it is not surprising that they reach more inventors directly and indirectly through network ties within (Internal reachability) and outside (external reachability) their region. Third, they report on average 1.13 and 1.14 locations and 3.08 and 2.61 applicants during the previous period suggesting they are more mobile across locations and organizations.

------ Table 2 Here ------

Table 1 displays summary statistics at the patent-team level. For readability, all the continuous variables are presented in their original format. However, all continuous variables are in a logarithmic form when introduced in the regressions as well as in the correlation table presented in the appendix (Table 1A). Descriptive statistics show that patents receive on average 0.18 citations. Regarding gatekeepers, 41 % of the patents in the sample have at least one *gatekeeper 1* and 68 % have at least one *gatekeeper 2* in their team. Regarding the geographic dispersion of inventor teams, 63% of the teams are located in the same region. Finally, a patent team has on average 2.75 *gatekeeper 1* at geodesic distance 1 with which they have directly collaborated during the previous period and they have on average 4.82 *gatekeeper 1* at geodesic distance 2 to 4. Patents have on average 5.4 gatekeepers 2 at distance 1 and 10.51 *gatekeeper 2* at distance 2 to 4.

Some pairs of variables reported in Table 1A have high correlations, particularly those characterizing inventor teams such as average experience, diversity and network size as inSingh & Fleming (2009) and Arts & Veugelers (2015). First, their introduction within regressions has been carefully considered so thatthey do not cause variance inflation that could affectthe results as shown by the variance inflation ratio, which is lower than 3 on average. Second, it is important to introduce these variables even if correlations are sometimes high in order to avoid gatekeeper variables to catch effects due to inventor team or network embeddedness that cannot be controlled with a real panel model and inventor-team fixed effects.

4.2. Inventive performance of gatekeepers

In Table 3, we consider the inventive performance of gatekeepers. Model 1 introduces only controls: results show the importance of having a large access to external sources of knowledge (i.e. large external reachability)[1]. Patents have also higher quality when the team experience diversity and the number of applicants involved is larger. In contrast, relational strength reporting previous collaborations has a negative impact on quality, maybe due to knowledge redundancy.

Models 2 and 6 test the impact of having at least one gatekeeper within a team and coefficients are not significant. In models 3 and 7, the number of gatekeepers are introduced instead and the results show a positive and significant impact; although only significant at 10% for *gatekeeper 1* type of inventor, it is highly significant (p<0.01) for *gatekeeper 2*. These results support only partly the hypothesis that gatekeepers create more cited patents (hypothesis 1). One may question why having one gatekeeper within the inventor team does not contribute to patent quality whereas having more than one gatekeeper does. Two explanations are possible: either inventive quality needs diversity in external knowledge which supposes that the quality increases when there are at least two gatekeepers even when all gatekeepers belong to the same region, or gatekeepers play a more significant role when they work within multi-location teams. To further explore this issue, columns 4 and 8 test the effect of inventor locations (hypothesis 3) by interacting the number of gatekeepers with the *single-region*dummy. The interaction term is negative and highly significant

[1] The average internal reachability is also highly significant (results not reported here). Given the very high correlation with the average external reachability (i.e. inventors with high internal reach have on average also high external reach), regressions include only external reachability.

for both types of gatekeepers. It indicates that they produce lower quality patents when all team members are located in a single region. This result is further confirmed by models 5 and 9 in which the number of gatekeepers is interacted with the number of regions to which team members belong. Results again strongly confirm hypothesis 3 showing that on average, inventive performance is increased when gatekeepers collaborate with other gatekeepers and inventors located in at least two regions.

------ Table 3 Here ------

Table 4 displays results for the specific impact of external stars on the quality of patents. These regressions tackles the qualitative difference between gatekeepers and external stars regarding the role of external ties *per se* and the possible lack of sufficient local embeddedness which characterizes external stars. Model 1 shows that inventor teams with external stars have on average less citations at a 10% significance level. The results become strongly significant and negative ($p< 0.01$) when considering the impact of the number of external stars in Model 2 confirming hypothesis 2. Unlike regressions with gatekeepers, the interaction between the number of external stars and the location of team members is not significant as shown by Model 3 and 4.

------ Table 4 Here ------

4.3. Proximity to gatekeepers

Table 5 provides the regression estimates for the social proximityof gatekeepers to patent team members. Models 1 and 7 test for the number of gatekeepers at distance 1, that is, gatekeepers with which at least one member has directly collaborated during the previous period. Models 2 and 8 test for the number of gatekeepers at distance 2 to 4. These results offer partial support to hypothesis 4. Regarding proximity to gatekeepers 1, only direct proximity is highly significant ($p< 0.01$) whereas the impact of gatekeepers 2 is highly significant even when geodesic distances are large. These results do not depend on the presence of gatekeepers within the team; said differently, any inventor, even non gatekeepers can benefit from the proximity to gatekeepers[2].

As before, the number of regions to which team members belong has a moderating impact on the quality of patents and this holds whatever the definition of gatekeepers. The interaction between a single-region team and the proximity to any type of gatekeeper is negative and highly significant at distance 1 and only slightly significant at distance 2 to 4 for gatekeeper 1 and not significant for gatekeeper 2. This means again that the quality of patents is lower when inventor teams are close to

[2] This result is not reported in the regression table but available on request

gatekeepers that are all located in their own region compared to multi-location teams. This result is confirmed by the interaction with the number of inventor regions. In other words, the patent quality is enhanced when inventors are located in at least two regions, because than the inventor team benefits from the proximity to gatekeepers located in at least two different regions and this holds even for distances between 2 to 4. All interactions are significant at 5% level at least.

------ Table 5 Here ------

5. Discussion and conclusion

The successful development of industrial clusters is of central importance for economic growth. The role of openness is increasingly emphasized and is of paramount importance to understand how clusters may succeed to find the right balance between local development and external openness. This paper contributes to this discussion by exploring the role of gatekeepers at the very microeconomic level of individual inventors within patent teams.

This paper makes a number of contributions. First, in times of productivity slowdown and increasing fear regarding the low quality of inventions, we provide empirical evidence regarding the positive impact of gatekeepers and proximity to gatekeepers on the quality of patents. Second, we contribute to a better understanding of the characteristics of gatekeepers by contrasting the two most used definitions and comparing them to external stars. Although qualitatively different, both definitions do statistically overlap as gatekeepers with high local embeddedness and large external ties are also gatekeepers in the Gould and Fernandez's (1989) sense. However the opposite is not true, and Gould and Fernandez type of gatekeepers have a more systematic impact on patent quality as it was already the case for technology renewal in Breschi and Lenzi's (2015) paper.

Second, we confirm the qualitative difference between gatekeepers and external stars regarding their impact on inventiveness. Although they both have the potential to act as global pipelines, it does not guarantee increased performance (Morrison et al. 2013); there is also a need for local embeddedness to provide the opportunity for novel technological recombination. In sum, the number of gatekeepers within a research team clearly contributes to the quality of inventions indicating that a larger access to non-local and non-redundant knowledge enables to combine more diverse sources and increase the quality of inventions, whereas the number of inventors with external ties reduces the quality of patents.

Third, the micro approach enables to highlight the complexity of gatekeepers' location. The quality is lower in single-region teams compared to multi-location teams. However, these results raise an open question for future research: does the multi-location simply indicate the advantages of larger access to external knowledge or does it hide the benefits from mobile inventors (Agrawal et al. 2006; Miguélez & Moreno 2013)?

In terms of policy implications, our findings underline the role of gatekeepers for the quality of inventions within clusters. Not only do they have a direct impact when they are in a research team but they also have an indirect impact for socially close inventors. As such, it confirms Graf and Krüger's paper (2011)which suggests that gatekeepers provide a local club good. UnlikeGraf and Krüger' findings, we show that gatekeepers are able to reap the benefits accruing from their brokering position. Our results highlight that the capacity to reap the benefits from global pipelines also depends on within cluster embeddedness. Thus, we can conclude that policies should favor both external and internal interactions to contribute to increase the quality of knowledge within clusters.

This paper has nevertheless a number of limitations which suggest some caution in interpreting the results. Some of these limitations are common to innovation studies based on patent data. First, the research is based on patents within the genomics field, conclusions may not be generalized to other sectors. Another limitation comes from the characteristics of network ties that are only built on co-inventorship, thus, other types of linkages are not considered, such as publication links, professionnal and personal ties. Third, patent data are only a proxy for innovation output, however innovation outcomes *per se*are ignored due to a lack of other empirical data sources. Finally, unlikeGraf and Krüger's paper (2011), we do not consider the intensity of gatekeeping positions, that is, the number of times they act as gatekeepers or their level of embeddedness and external linkages. This is a limitation when considering social proximity as the impact may be different if inventors are close to high level gatekeepers compared to actors with a few gatekeeping connexions.

Future research could further explore whether non-redundant relational ties do also imply technological and/or organizational brokering. First, the way technological diversity determines these relationships is not tackled explicitly. Second, this research has explored gatekeepers at the patent level controlling for applicant identity. However, an interesting extension could consider the role of gatekeepers not only across regions but also across corporate groups. Finally, we have considered how social proximity explains the way gatekeepers influence other inventors' patent quality, however, if social proximity occurs within industrial groups, the internalization of externalities could limit the social benefit of gatekeepers in a similar way as discussed by Breschi & Lissoni (2009) in their paper on mobile inventors.

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Table 1. Variable definitions and summary statistics

		Mean	SD	Min	Max
Dependent variable					
Forward citations	Number of forward citations over 5 years	0.18	1.20	0.00	79.00
Independent variables					
# of gatekeepers 1	Number of gatekeepers type 1 – over the average external ties and local betweenness centrality	0.80	1.60	0.00	29.00
Gatekeeper 1 (dummy)	Indicator takes 1 if patent invented by at least one gatekeeper type 1	0.41	0.49	0.00	1.00
# of gatekeepers 2	Number of gatekeepers type 2 – non-redundant tie to an inventor located outside the region	1.65	2.69	0.00	43.00
Gatekeeper 2 (dummy)	Indicator takes 1 if patent invented by at least one gatekeeper type 2	0.68	0.47	0.00	1.00
# of external stars	Number of external stars – over the average external ties and lower than average betweenness centrality	1.01	2.05	0.00	27.00
External stars dummy	Teams with external stars	0.48	0.50	0.00	1.00
Single-region	All inventors are from the same region	0.63	0.48	0.00	1.00
# of regions	Number of distinct regions in which the team inventors are located	1.47	0.73	1.00	10.00
# of gatekeepers 1 at distance 1	Number of gatekeepers 1 at distance 1	2.75	5.25	0.00	42.00
# of gatekeepers 1 at distance 2-4	Number of gatekeepers 1 at distance 2 to 4	4.82	8.86	0.00	58.00
# of gatekeepers 2 at distance 1	Number of gatekeepers 2 at distance 1	5.40	10.22	0.00	135.00
# of gatekeepers 2 at distance 2-4	Number of gatekeepers 2 at distance 2 to 4	10.51	21.92	0.00	217.00
Controls at the Inventor team and patent level					
External reachability	sum of inverse geodesic (minimum) distances d_{ij} within the region normalized and averaged	0.22	0.25	0.00	1.00
Internal reachability	sum of inverse geodesic (minimum) distances d_{ij} within the region normalized and averaged	0.33	0.26	0.00	1.00
Average experience (# patent)	Average number of previous patents for the team's inventors	7.86	19.33	0.14	287.00
Experience diversity	Number of technology classes any team inventor has patented in before	4.11	1.61	1.00	14.00
Network size	Number of inventors at distance <=2 in the team's collaborative network	22.56	27.75	0.00	267.00
Status asymmetry	Herfindhal index of concentration of prior patents on a few inventors corrected for small team size bias	0.68	0.33	0.03	1.99
Strength	Team relational strength is the average level of collaboration between any two member of the team	0.19	0.18	0.00	0.50
# of applicants	Number of applicants having applied for the patent	1.33	0.89	1.00	18.00
Team size	Number of inventors who have invented the patent	5.15	4.10	2.00	53.00
Same applicant	Indicator takes 1 if inventors have previously applied for the same applicant	0.92	0.27	0.00	1.00
Distance in Km	Average distance in km between inventors on the team	576	1422	0.00	9637
Technological field dummy	Indicator takes 1 if the patent falls within given technology fields	0.95	0.21	0.00	1.00
EU team	Indicator takes 1 if inventors on the team have all a European address (EU 15 + Norway and Switzerland)	0.28	0.45	0.00	1.00
US-EU team	Indicator takes 1 if the team includes EU and US inventors	0.16	0.36	0.00	1.00
US inventor team	Indicator takes 1 if inventors on the team have all a US address	0.56	0.50	0.00	1.00
Patent scope	The number of IPC codes to which the patent refers and proxies the level of pervasiveness	3.84	2.08	1.00	17.00
Patent family size	The size of the patent family	9.40	6.78	1.00	41.00
# of backward citations	Number of backward citations made by the patent to other patents	4.23	7.62	0.00	123.00
Non-patent literature citations	Number of non-patent references made by the patent	5.80	10.80	0.00	114.00
# of claims	Number of claims made by the patent	25.72	18.67	0.00	314.00

11,831 Observations based on 10,350 patents

Table 2. Characteristics of inventors in the sample

	All inventors				Gatekeeper 1			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Local degree	5.85	9.00	0.00	203.00	14.63	15.48	2.00	203.00
External Degree	3.03	5.95	0.00	172.00	7.45	7.72	1.00	99.00
Number of patents	4.59	11.35	1.00	317.00	13.57	25.10	2.00	317.00
Internal reachability	0.40	0.34	0.00	1.00	0.72	0.27	0.07	1.00
External reachability	0.27	0.33	0.00	1.00	0.50	0.34	0.01	1.00
External stars	0.28	0.45	0.00	1.00	0.00	0.00	0.00	0.00
Gatekeeper 1	0.14	0.35	0.00	1.00	1.00	0.00	1.00	1.00
Gatekeeper 2	0.34	0.47	0.00	1.00	0.99	0.10	0.00	1.00
Number of regions	1.08	0.31	1.00	11.00	1.13	0.40	1.00	9.00
Number of applicants	1.81	1.62	1.00	28.00	3.08	2.36	1.00	28.00
Number of inventors	17,022				2,408			

	Gatekeeper 2				**External Stars**			
	Mean	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**
Local degree	10.45	13.05	0.00	203.00	4.56	8.89	0.00	100.00
External Degree	5.94	8.24	0.00	172.00	6.04	7.92	1.00	172.00
Number of patents	9.14	17.83	2.00	317.00	4.22	7.51	1.00	240.00
Internal reachability	0.55	0.33	0.00	1.00	0.32	0.32	0.00	1.00
External reachability	0.40	0.35	0.00	1.00	0.42	0.36	0.01	1.00
External stars	0.35	0.48	0.00	1.00	1.00	0.00	1.00	1.00
Gatekeeper 1	0.41	0.49	0.00	1.00	0.00	0.00	0.00	0.00
Gatekeeper 2	1.00	0.00	1.00	1.00	0.44	0.50	0.00	1.00
Number of regions	1.14	0.39	1.00	9.00	1.17	0.44	1.00	11.00
Number of applicants	2.61	2.15	1.00	28.00	2.12	2.01	1.00	21.00
Number of inventors	5,838				4,696			

Table 3. Impact of gatekeepers on patent quality (Forward citations 5 years)

	Gatekeeper 1					Gatekeeper 2			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Gatekeeper (dummy)		0.25				0.19			
		[0.15]				[0.14]			
# of gatekeepers			0.34+	0.72***	-2.98**		0.47***	0.86***	-1.85**
			[0.18]	[0.23]	[1.21]		[0.16]	[0.22]	[0.90]
Single-region				0.70***				0.92***	
				[0.23]				[0.24]	
Single-region x # of gatekeepers				-0.75***				-0.64***	
				[0.22]				[0.20]	
# of regions					-5.55**				-4.45+
					[2.25]				[2.65]
# of regions sq					1.97+				1.08
					[1.05]				[1.29]
# of gatekeepers x # of regions					5.94**				3.95**
					[2.40]				[1.77]
# of gatekeepers x # of regions sq					-2.33**				-1.35+
					[1.08]				[0.78]
External reachability	1.07***	1.00***	0.92***	1.06***	1.14***	1.06***	0.91***	1.00***	1.10***
	[0.33]	[0.33]	[0.31]	[0.31]	[0.31]	[0.33]	[0.33]	[0.34]	[0.34]
Average experience (# patent)	-0.10	-0.09	-0.13	-0.17	-0.17	-0.09	-0.15	-0.20	-0.20
	[0.20]	[0.20]	[0.20]	[0.19]	[0.19]	[0.20]	[0.19]	[0.19]	[0.18]
Experience diversity	0.63**	0.62**	0.64**	0.71***	0.71***	0.60**	0.59**	0.67**	0.68**
	[0.27]	[0.27]	[0.27]	[0.27]	[0.27]	[0.27]	[0.27]	[0.27]	[0.27]
Network size	-0.19	-0.29**	-0.29+	-0.25	-0.27+	-0.26+	-0.34**	-0.32**	-0.34**
	[0.14]	[0.14]	[0.15]	[0.15]	[0.15]	[0.16]	[0.15]	[0.16]	[0.16]
Status asymmetry	0.80	0.75	0.85	0.71	0.73	0.76	0.97	0.82	0.79
	[0.61]	[0.60]	[0.61]	[0.60]	[0.59]	[0.60]	[0.64]	[0.63]	[0.62]
Strength	-0.72**	-0.74**	-0.76**	-0.84**	-0.76**	-0.73**	-0.82**	-0.93***	-0.84**
	[0.34]	[0.34]	[0.33]	[0.34]	[0.33]	[0.34]	[0.34]	[0.34]	[0.33]
# of applicants	0.78***	0.78***	0.74***	0.67***	0.64***	0.78***	0.75***	0.66***	0.65***
	[0.20]	[0.20]	[0.20]	[0.20]	[0.21]	[0.20]	[0.20]	[0.20]	[0.20]
Team size	0.21	0.19	0.12	-0.00	0.11	0.21	0.08	-0.08	0.02
	[0.28]	[0.28]	[0.28]	[0.27]	[0.27]	[0.28]	[0.27]	[0.26]	[0.25]
Same applicant	0.09	0.07	0.09	0.08	0.07	0.06	0.04	0.02	0.01
	[0.20]	[0.20]	[0.20]	[0.20]	[0.20]	[0.20]	[0.20]	[0.20]	[0.20]
Distance in Km	0.06	0.06	0.06	0.09+	0.09**	0.05	0.05	0.10**	0.10**
	[0.04]	[0.04]	[0.04]	[0.05]	[0.05]	[0.04]	[0.04]	[0.05]	[0.05]
Distance in Km sq	-0.10	-0.10	-0.10	-0.07	-0.05	-0.10	-0.10	-0.08	-0.05
	[0.08]	[0.08]	[0.08]	[0.07]	[0.08]	[0.08]	[0.08]	[0.07]	[0.08]
Technological field dummy	-0.40**	-0.41**	-0.42**	-0.44**	-0.44**	-0.40**	-0.43**	-0.45**	-0.45**
	[0.18]	[0.17]	[0.17]	[0.18]	[0.18]	[0.18]	[0.18]	[0.18]	[0.18]
EU team	0.20	0.17	0.17	0.27	0.25	0.18	0.18	0.29	0.27
	[0.26]	[0.26]	[0.26]	[0.27]	[0.27]	[0.26]	[0.26]	[0.27]	[0.26]
US-EU team	-0.52***	-0.55***	-0.54***	-0.54***	-0.55***	-0.54***	-0.54***	-0.53***	-0.53***
	[0.18]	[0.18]	[0.18]	[0.18]	[0.18]	[0.18]	[0.18]	[0.18]	[0.18]
Patent scope	0.33**	0.33**	0.34**	0.33**	0.31**	0.33**	0.36**	0.34**	0.32**
	[0.14]	[0.14]	[0.14]	[0.14]	[0.14]	[0.14]	[0.14]	[0.14]	[0.15]
Patent family size	-0.15	-0.15	-0.17	-0.19	-0.19	-0.15	-0.17	-0.18	-0.19
	[0.17]	[0.17]	[0.16]	[0.16]	[0.16]	[0.17]	[0.16]	[0.16]	[0.16]
# of backward citations	0.21***	0.22***	0.21***	0.20***	0.20***	0.22***	0.21***	0.21***	0.21***
	[0.07]	[0.07]	[0.07]	[0.07]	[0.07]	[0.07]	[0.07]	[0.07]	[0.07]
Non-patent literature citations	-0.05	-0.05	-0.05	-0.05	-0.05	-0.06	-0.05	-0.06	-0.06
	[0.05]	[0.05]	[0.05]	[0.06]	[0.06]	[0.05]	[0.05]	[0.06]	[0.06]
# of claims	-0.05	-0.04	-0.05	-0.05	-0.05	-0.05	-0.06	-0.05	-0.05
	[0.10]	[0.10]	[0.10]	[0.10]	[0.10]	[0.10]	[0.10]	[0.10]	[0.10]
Constant	-0.74	-0.39	-0.19	-0.43	3.03+	-0.62	-0.16	-0.56	2.78+
	[1.23]	[1.21]	[1.28]	[1.26]	[1.57]	[1.20]	[1.17]	[1.16]	[1.64]
lnalpha constant	2.18***	2.17***	2.17***	2.14***	2.14***	2.17***	2.16***	2.14***	2.14***
	[0.13]	[0.13]	[0.13]	[0.13]	[0.13]	[0.13]	[0.13]	[0.13]	[0.13]
Log Likelihood	-4117	-4115	-4114	-4103	-4101	-4116	-4110	-4100	-4097
Pseudo R-Square	.095	.096	.096	.098	.099	.095	.097	.099	.1

Negative binomial model of forward citations. Robust standard errors in brackets clustered at the applicant level ,
+ 0.10 ** 0.05 ***0.01 11,831 observations and 10,350 patents – Year and region fixed-effects included – lnalpha is the dispersion parameter

Table 4. Impact of external stars on patent quality (Forward citations 5 years)

	(1)	(2)	(3)	(4)
External stars (dummy)	-0.25+			
	[0.13]			
Number of external stars		-0.33***	-0.38**	1.05
		[0.10]	[0.15]	[0.91]
Single-region			0.18	
			[0.27]	
Single-region x Number of external stars			0.17	
			[0.21]	
# of regions				1.33
				[2.94]
Number of external stars x # of regions				-2.62
				[1.79]
# of regions square				-1.02
				[1.45]
Number of external stars x # of regions sq				1.19
				[0.84]
External reachability	1.20***	1.28***	1.32***	1.34***
	[0.34]	[0.34]	[0.34]	[0.34]
Average experience (# patent)	-0.12	-0.11	-0.10	-0.11
	[0.20]	[0.20]	[0.20]	[0.20]
Experience diversity	0.61**	0.60**	0.60**	0.61**
	[0.27]	[0.27]	[0.27]	[0.27]
Network size	-0.17	-0.18	-0.20	-0.19
	[0.14]	[0.14]	[0.14]	[0.14]
Status asymmetry	0.76	0.74	0.72	0.65
	[0.62]	[0.61]	[0.61]	[0.60]
Strength	-0.74**	-0.64+	-0.60+	-0.60+
	[0.33]	[0.34]	[0.34]	[0.33]
# of applicants	0.77***	0.75***	0.76***	0.77***
	[0.21]	[0.20]	[0.21]	[0.21]
Team size	0.22	0.34	0.38	0.36
	[0.28]	[0.28]	[0.27]	[0.28]
Same applicant	0.11	0.11	0.11	0.12
	[0.20]	[0.20]	[0.20]	[0.20]
Distance in Km	0.06	0.06	0.07	0.07
	[0.05]	[0.05]	[0.05]	[0.05]
Distance in Km sq	-0.09	-0.08	-0.05	-0.04
	[0.08]	[0.08]	[0.08]	[0.08]
Technological field dummy	-0.39**	-0.39**	-0.40**	-0.40**
	[0.18]	[0.18]	[0.17]	[0.17]
EU team	0.18	0.18	0.17	0.17
	[0.27]	[0.26]	[0.26]	[0.26]
US-EU team	-0.53***	-0.52***	-0.56***	-0.56***
	[0.19]	[0.19]	[0.18]	[0.19]
Patent scope	0.33**	0.32**	0.31**	0.30**
	[0.14]	[0.14]	[0.14]	[0.14]
Patent family size	-0.15	-0.16	-0.16	-0.16
	[0.17]	[0.17]	[0.17]	[0.17]
# of backward citations	0.21***	0.21***	0.22***	0.22***
	[0.07]	[0.07]	[0.07]	[0.07]
Non-patent literature citations	-0.05	-0.06	-0.06	-0.05
	[0.06]	[0.06]	[0.06]	[0.06]
# of claims	-0.05	-0.05	-0.05	-0.05
	[0.10]	[0.10]	[0.10]	[0.10]
Constant	-0.76	-0.93	-1.20	-1.44
	[1.25]	[1.25]	[1.26]	[1.93]
lnalpha Constant	2.17***	2.16***	2.16***	2.16***
	[0.13]	[0.13]	[0.13]	[0.13]
Log Likelihood	-4114	-4112	-4111	-4109
Pseudo R-Square	.096	.096	.097	.097

11 831 observations – Year and Region fixed effects included

Table 5. Impact of the proximity to gatekeepers on patent quality (Forward citations 5 years)

	Proximity to gatekeeper 1						Proximity to gatekeeper 2					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
# of gatekeepers at distance 1	0.37***		0.60***		-1.98**		0.32**		0.55***		-2.93***	
	[0.12]		[0.17]		[0.94]		[0.13]		[0.18]		[0.91]	
# of gatekeepers at distance 2-4		0.10		0.25**		-1.62**		0.13**		0.23**		-1.07+
		[0.07]		[0.12]		[0.74]		[0.06]		[0.10]		[0.59]
Single-region			0.66***	0.57**					0.86***	0.56**		
			[0.24]	[0.25]					[0.26]	[0.26]		
Single-region x # of gatekeepers at distance 1			-0.40***						-0.43***			
			[0.15]						[0.13]			
Single-region x # of gatekeepers at distance 2-4				-0.25+						-0.17		
				[0.13]						[0.10]		
# of regions					-7.69***	-7.83***					-12.92***	-7.23**
					[2.44]	[2.66]					[3.55]	[2.83]
# of regions sq					3.21***	3.41***					5.78***	3.10**
					[1.12]	[1.24]					[1.70]	[1.30]
# of gatekeepers at distance 1 x # of regions					4.58**						6.52***	
					[1.98]						[1.98]	
# of gatekeepers at distance 1 x # of regions sq					-2.01**						-3.00***	
					[0.92]						[0.94]	
# of gatekeepers at distance 2-4 x # of regions						3.50**						2.43**
						[1.51]						[1.20]
# of gatekeepers at distance 2-4 x # of regions sq						-1.63**						-1.14**
						[0.68]						[0.54]
External reachability	0.78**	0.97***	0.94***	1.13***	1.00***	1.16***	0.93***	0.95***	1.09***	1.07***	1.12***	1.11***
	[0.34]	[0.34]	[0.32]	[0.33]	[0.32]	[0.33]	[0.34]	[0.34]	[0.33]	[0.33]	[0.32]	[0.33]
Average experience (# patent)	-0.16	-0.11	-0.18	-0.13	-0.17	-0.12	-0.15	-0.11	-0.18	-0.13	-0.16	-0.12
	[0.20]	[0.20]	[0.20]	[0.20]	[0.19]	[0.19]	[0.19]	[0.19]	[0.19]	[0.19]	[0.19]	[0.19]
Experience diversity	0.65**	0.63**	0.70***	0.68**	0.69***	0.66**	0.66**	0.62**	0.75***	0.66**	0.73***	0.65**
	[0.26]	[0.27]	[0.26]	[0.26]	[0.26]	[0.27]	[0.27]	[0.27]	[0.26]	[0.26]	[0.26]	[0.27]
Network size	-0.39***	-0.24+	-0.37**	-0.25+	-0.39***	-0.27**	-0.44***	-0.29**	-0.38**	-0.29**	-0.42***	-0.30**
	[0.15]	[0.14]	[0.15]	[0.13]	[0.15]	[0.13]	[0.16]	[0.14]	[0.16]	[0.14]	[0.16]	[0.14]
Status asymmetry	0.55	0.69	0.45	0.62	0.50	0.68	0.66	0.66	0.53	0.61	0.65	0.67
	[0.58]	[0.59]	[0.57]	[0.59]	[0.57]	[0.59]	[0.59]	[0.60]	[0.57]	[0.60]	[0.57]	[0.60]
Strength	-0.61+	-0.66+	-0.70**	-0.71**	-0.62+	-0.64+	-0.64+	-0.61+	-0.74**	-0.67+	-0.64+	-0.59+
	[0.34]	[0.35]	[0.34]	[0.35]	[0.33]	[0.34]	[0.34]	[0.35]	[0.34]	[0.35]	[0.33]	[0.34]
# of applicants	0.80***	0.79***	0.77***	0.75***	0.73***	0.72***	0.78***	0.80***	0.71***	0.77***	0.66***	0.74***
	[0.20]	[0.20]	[0.20]	[0.20]	[0.20]	[0.20]	[0.20]	[0.20]	[0.20]	[0.21]	[0.19]	[0.20]
Team size	0.06	0.16	-0.06	0.12	0.07	0.23	0.13	0.17	-0.02	0.14	0.13	0.25
	[0.28]	[0.28]	[0.27]	[0.27]	[0.27]	[0.27]	[0.28]	[0.28]	[0.26]	[0.26]	[0.26]	[0.27]

Same applicant	0.07	0.07	0.07	0.07	0.05	0.06	0.07	0.06	0.04	0.05	0.02	0.04
	[0.20]	[0.20]	[0.19]	[0.20]	[0.19]	[0.19]	[0.20]	[0.20]	[0.19]	[0.20]	[0.18]	[0.19]
Distance in Km	0.06	0.06	0.09**	0.09**	0.10**	0.10**	0.06	0.06	0.11**	0.09**	0.11**	0.09**
	[0.04]	[0.05]	[0.05]	[0.05]	[0.05]	[0.05]	[0.04]	[0.05]	[0.05]	[0.05]	[0.05]	[0.05]
Distance in Km sq	-0.10	-0.10	-0.09	-0.10	-0.07	-0.07	-0.10	-0.10	-0.11	-0.09	-0.09	-0.07
	[0.08]	[0.08]	[0.07]	[0.07]	[0.08]	[0.07]	[0.08]	[0.08]	[0.07]	[0.07]	[0.07]	[0.07]
Technological field dummy	-0.40**	-0.39**	-0.41**	-0.42**	-0.41**	-0.41**	-0.41**	-0.39**	-0.44**	-0.41**	-0.44**	-0.40**
	[0.17]	[0.17]	[0.17]	[0.18]	[0.17]	[0.18]	[0.18]	[0.17]	[0.18]	[0.17]	[0.18]	[0.17]
EU team	0.20	0.22	0.28	0.24	0.25	0.22	0.23	0.25	0.30	0.27	0.26	0.24
	[0.26]	[0.26]	[0.27]	[0.27]	[0.27]	[0.26]	[0.26]	[0.27]	[0.26]	[0.27]	[0.26]	[0.26]
US-EU team	-0.51***	-0.51***	-0.47**	-0.52***	-0.49***	-0.54***	-0.50***	-0.51***	-0.44**	-0.52***	-0.46**	-0.54***
	[0.19]	[0.18]	[0.19]	[0.19]	[0.19]	[0.19]	[0.18]	[0.19]	[0.18]	[0.19]	[0.18]	[0.19]
Patent scope	0.30**	0.31**	0.28+	0.29**	0.27+	0.28+	0.31**	0.31**	0.28**	0.29**	0.28+	0.28+
	[0.14]	[0.14]	[0.14]	[0.14]	[0.15]	[0.15]	[0.14]	[0.14]	[0.14]	[0.14]	[0.15]	[0.15]
Patent family size	-0.15	-0.14	-0.16	-0.14	-0.16	-0.14	-0.16	-0.13	-0.17	-0.14	-0.18	-0.14
	[0.17]	[0.17]	[0.17]	[0.17]	[0.16]	[0.17]	[0.16]	[0.17]	[0.16]	[0.17]	[0.16]	[0.16]
# of backward citations	0.21***	0.21***	0.20***	0.21***	0.20***	0.21***	0.21***	0.21***	0.20***	0.21***	0.19***	0.21***
	[0.07]	[0.07]	[0.07]	[0.07]	[0.07]	[0.07]	[0.07]	[0.07]	[0.07]	[0.07]	[0.07]	[0.07]
Non-patent literature citations	-0.04	-0.05	-0.04	-0.05	-0.05	-0.05	-0.05	-0.05	-0.05	-0.05	-0.05	-0.05
	[0.06]	[0.06]	[0.06]	[0.06]	[0.06]	[0.06]	[0.05]	[0.06]	[0.06]	[0.06]	[0.06]	[0.06]
# of claims	-0.05	-0.05	-0.05	-0.05	-0.04	-0.04	-0.05	-0.05	-0.04	-0.04	-0.04	-0.04
	[0.10]	[0.10]	[0.10]	[0.10]	[0.10]	[0.10]	[0.10]	[0.10]	[0.10]	[0.10]	[0.10]	[0.10]
Constant	-0.21	-0.63	-0.58	-1.00	3.69***	3.17**	-0.37	-0.66	-0.82	-1.06	5.98***	2.84+
	[1.18]	[1.20]	[1.14]	[1.17]	[1.42]	[1.49]	[1.16]	[1.19]	[1.13]	[1.17]	[1.72]	[1.56]
Lnalpha												
Constant	2.16***	2.17***	2.14***	2.16***	2.14***	2.15***	2.16***	2.17***	2.14***	2.16***	2.13***	2.15***
	[0.12]	[0.13]	[0.12]	[0.12]	[0.12]	[0.12]	[0.12]	[0.13]	[0.12]	[0.12]	[0.12]	[0.12]
Log Likelihood	-4109	-4116	-4100	-4109	-4098	-4107	-4112	-4114	-4100	-4109	-4095	-4107
Pseudo R-Square	.097	.096	.099	.097	.1	.098	.096	.096	.099	.097	.1	.098
11831 Observations – Year and region fixed effects												

Table A1 – Correlation table

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32
1	Forward citations 5y	1.00																															
2	# of gatekeepers 1	0.01	1.00																														
3	Gatekeeper 1 (dummy)	0.02	0.88*	1.00																													
4	# of gatekeepers 2	0.01	0.76*	0.63*	1.00																												
5	Gatekeeper 2 (dummy)	0.01	0.51*	0.58*	0.79*	1.00																											
6	# of external stars	-0.01	0.21*	0.11*	0.45*	0.25*	1.00																										
7	External stars (dummy)	-0.01	0.13*	0.09*	0.32*	0.27*	0.85*	1.00																									
8	Single-region	-0.01	-0.13*	-0.09*	-0.20*	-0.13*	-0.48*	-0.47*	1.00																								
9	# of regions	0.01	0.22*	0.14*	0.30*	0.15*	0.58*	0.47*	-0.92*	1.00																							
10	# of gatek. 1 at dist. 1	0.02	0.78*	0.70*	0.65*	0.46*	0.18*	0.11*	-0.05*	0.12*	1.00																						
11	# of gatek. 1 at dist. 2-4	0.01	0.55*	0.48*	0.50*	0.35*	0.15*	0.08*	-0.05*	0.11*	0.76*	1.00																					
12	# of gatek. 2 at dist. 1	0.00	0.71*	0.63*	0.76*	0.58*	0.24*	0.15*	-0.03*	0.11*	0.89*	0.72*	1.00																				
13	# of gatek. 2 at dist. 2-4	0.01	0.54*	0.48*	0.53*	0.40*	0.16*	0.09*	-0.04*	0.10*	0.75*	0.95*	0.77*	1.00																			
14	External reachability	0.05*	0.46*	0.43*	0.40*	0.35*	0.27*	0.28*	-0.23*	0.25*	0.48*	0.32*	0.43*	0.31*	1.00																		
15	Internal reachability	0.02*	0.52*	0.48*	0.44*	0.32*	-0.02*	-0.06*	0.10*	-0.06*	0.57*	0.41*	0.54*	0.41*	0.56*	1.00																	
16	Patent scope	0.01	0.13*	0.10*	0.11*	0.05*	0.05*	0.01	0.02*	0.01	0.17*	0.13*	0.16*	0.11*	0.02*	0.08*	1.00																
17	Patent family size	-0.02	0.16*	0.09*	0.14*	0.06*	0.03*	0.03*	-0.03*	0.03*	0.12*	0.04*	0.13*	0.03*	0.10*	0.08*	0.22*	1.00															
18	# of backward citations	0.01	-0.06*	-0.04*	-0.05*	-0.01	-0.01	0.02*	-0.01	-0.01	-0.08*	-0.05*	-0.05*	-0.04*	-0.05*	-0.08*	-0.03*	0.10*	1.00														
19	Non-patent literature citations	-0.01	-0.13*	-0.08*	-0.11*	-0.03*	-0.01	0.03*	-0.03*	0.00	-0.17*	-0.16*	-0.16*	-0.15*	-0.06*	-0.15*	-0.04*	0.01	0.25*	1.00													
20	# of claims	-0.01	0.04*	0.01	0.03*	0.01	0.03*	0.02*	-0.01	0.03*	0.03*	0.03*	0.04*	0.04*	-0.03*	-0.05*	0.08*	0.02*	0.04*	-0.00	1.00												
21	Average experience (# patent)	-0.00	0.59*	0.50*	0.57*	0.38*	0.11*	0.04*	0.01	0.04*	0.67*	0.51*	0.71*	0.52*	0.42*	0.58*	0.17*	0.08*	-0.12*	-0.21*	0.00	1.00											
22	Experience diversity	0.01	0.42*	0.38*	0.46*	0.37*	0.14*	0.11*	-0.07*	0.10*	0.47*	0.39*	0.50*	0.41*	0.25*	0.29*	0.23*	0.09*	-0.05*	-0.10*	0.06*	0.51*	1.00										
23	Network size	-0.01	0.74*	0.67*	0.75*	0.58*	0.31*	0.24*	-0.12*	0.20*	0.81*	0.66*	0.86*	0.70*	0.45*	0.51*	0.14*	0.11*	-0.06*	-0.15*	0.05*	0.73*	0.57*	1.00									
24	Status asymmetry	0.02*	-0.31*	-0.15*	-0.40*	-0.10*	-0.37*	-0.21*	0.22*	-0.30*	-0.18*	-0.14*	-0.22*	-0.13*	0.02	-0.03*	-0.10*	-0.12*	-0.01	0.03*	-0.04*	-0.06*	-0.12*	-0.29*	1.00								
25	Strength	-0.01	0.07*	0.06*	0.06*	0.01	-0.05*	-0.09*	0.11*	-0.09*	0.05*	-0.03*	0.06*	-0.03*	0.22*	0.36*	0.02*	0.01	-0.05*	-0.07*	-0.03*	0.35*	0.01	0.01	0.16*	1.00							
26	# of applicants	0.03*	0.00	0.02*	0.03*	0.04*	0.13*	0.14*	-0.22*	0.25*	-0.03*	-0.01	-0.04*	-0.03*	0.02*	-0.11*	-0.02	-0.05*	-0.00	0.07*	0.01	-0.14*	-0.00	-0.00	-0.10*	-0.17*	1.00						
27	Team size	-0.01	0.39*	0.24*	0.46*	0.19*	0.41*	0.22*	-0.23*	0.34*	0.31*	0.28*	0.34*	0.27*	-0.08*	-0.05*	0.14*	0.12*	-0.01	-0.05*	0.08*	0.06*	0.21*	0.42*	-0.76*	-0.40*	0.16*	1.00					
28	Same applicant	-0.00	0.14*	0.13*	0.17*	0.13*	0.03*	-0.03*	0.10*	-0.06*	0.13*	0.09*	0.15*	0.09*	0.09*	0.18*	0.04*	0.01	-0.02*	-0.04*	-0.02*	0.18*	0.05*	0.12*	-0.16*	0.31*	-0.07*	0.05*	1.00				
29	Geographical distance	0.01	0.13*	0.10*	0.21*	0.13*	0.39*	0.37*	-0.80*	0.76*	0.08*	0.12*	0.08*	0.12*	0.12*	-0.13*	0.02	0.00	0.00	0.01	0.02*	0.01	0.08*	0.14*	-0.22*	-0.12*	0.23*	0.24*	-0.11*	1.00			
30	EU team	0.05*	-0.11*	-0.07*	-0.13*	-0.06*	-0.04*	0.00	-0.08*	0.05*	-0.19*	-0.22*	-0.23*	-0.24*	0.13*	0.07*	-0.17*	-0.03*	0.01	0.02*	-0.12*	-0.19*	-0.18*	-0.21*	0.07*	0.00	-0.03*	-0.14*	-0.04*	-0.10*	1.00		
31	US-EU team	-0.01	0.07*	0.08*	0.11*	0.07*	0.17*	0.15*	-0.22*	0.25*	0.03*	0.04*	0.03*	0.03*	0.02*	-0.07*	0.06*	-0.01	-0.00	0.05*	-0.00	-0.06*	0.05*	0.07*	-0.12*	-0.19*	0.27*	0.21*	-0.05*	0.29*	-0.27*	1.00	
32	US inventor team	-0.04*	0.05*	0.00	0.04*	0.01	-0.09*	-0.12*	0.23*	-0.22*	0.15*	0.17*	0.19*	0.20*	-0.14*	-0.01	0.11*	0.04*	-0.00	-0.06*	0.11*	0.21*	0.13*	0.14*	0.02*	0.13*	-0.17*	-0.03*	0.07*	-0.12*	-0.71*	-0.48*	1.00

* $p < 0.05$