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Network Patterns of Inventor Collaboration and Their Effects on Innovation Outputs

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Abstract: The purpose of this study is to examine how the collaboration structure among inventors in an R and D organization affects its capability to create impactful innovations. Specifically, this study is focused on examining whether a certain type of network mechanism found in collaboration among inventors contributes more to enhancing the future impacts of collaboration outputs, which is represented by the forward citations of their patents. To this end, co-invention networks for R and D organizations are constructed from an inventor-patent database, and the three structural patterns are measured by using network analytic constructs, namely, structural holes, strength of ties, and centralization. The results show that the presence of structural holes and strong ties are positively associated with the increasing forward citations, and that decentralized collaboration has also a positive impact. The findings offer support for both structural hole and network closure perspectives on social capital, which have been considered contradictive in the literature.

Keywords: co-invention networks; network analysis; patent citations; structural holes; strength of ties; centralization

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1. Introduction

Innovation is widely recognized as a process of identifying opportunities for unconventional recombination of diverse technology options that have already existed [1–3]. The process of recombination leads R and D personnel to search beyond their own boundaries for knowledge and skills to complement their capabilities [4]. Typically, innovation processes involve teams of researchers who work together on the same project. While exchanging ideas and sharing information, participants of a research team carry over their knowledge to other members in the same team or other projects that they are involved in. Whenever researchers collaborate with other coworkers, they create knowledge spillovers. The quality and impact of outputs from collaboration processes are inextricably related to who is working with whom; that is, how knowledge spills over among members in an R and D organization. Therefore, knowledge spillover is a causal mechanism linking network structures to organizational performance.

The innovation literature has reported empirical evidence on the relationship between collaboration structures and organizational performance. They find that the transfer of knowledge across boundaries within firms (example, [5]), the combination of technologies from heterogeneous technological origins [3,6,7], and knowledge spillover amongst researchers with different roles (example, [8]) are closely associated with organizational performance and output quality.

In particular, previous research repeatedly stressed the importance of inter-firm alliances and networks for organizational learning and knowledge flows in knowledge-intensive industries. Indeed, numerous previous studies found that R and D alliances are used as an instrument by firms to acquire new skills and to source specialized know-how (see [9] for a nice review). However, these studies were interested in the effects of collaborative R and D on subsequent innovation performance, without putting emphasis on micro-level interactions of how individual inventors collaborate and which co-working structures are more productive. Rather, these previous studies were interested in the fact that collaboration has taken place (as opposed to in-house R and D exclusively) in a certain network structure and in some cases distinguished between the types of partner involved.

This study examines how individual inventors in an R and D organization collaborate with other co-workers in the same organization. We focus on various network mechanisms identified in intra-organizational collaborative invention based on social capital theories. Studies on social capital suggest a variety of possible explanations for the empirically-observed relationship between various network mechanisms and organizational performance. We combine these streams of literature and extend previous research in at least two major ways.

First, we examine in-house R and D collaboration based on social capital theories and focus on how micro-level R and D collaboration among individual inventors affects organizational performance. Second, we explicitly separate three important network mechanisms of strength of ties, dense connectivity, and network centralization and examine how they operate independently and interactively. Although the effects of these network factors have been well studied in the literature, little has been done to disentangle one mechanism from others [10]. Specifically, this study examines whether a firm's patent stock produced under a particular collaboration structure is more impactful on subsequent innovations than other structures. To this end, co-invention networks for R and D organizations are constructed from a patent database, and their structural patterns are examined by using network analytic constructs. Based on the three distinct constructs that represent collaboration patterns, our study seeks to disentangle the effects of two leading network mechanisms, structural hole and tie strength, which have been considered to contradict each other in the extant literature.

2. Hypothesis Development

Although there has been a variety of interrelated definitions of social capital (for differently-focused works, see e.g., [11–13]), most definitions have two elements in common: social capital is embedded in some aspect of social structures, and it facilitates certain actions of actors within the structure [14]. In this sense, social capital refers to the collective value of all social networks and the inclinations that arise from these networks to do things for one other (e.g., [15,16]).

The importance of social capital as an antecedent of innovation has received much theoretical attention over the last few years [17]. It has been shown that social capital and learning have a positive relationship because social capital directly affects the combine-and-exchange process and provides relatively easy access to network resources [18,19]. Relatedly, the overall hypothesis of the social capital theory in the matter of innovation is that firms with a large stock of social capital will have a competitive advantage to the extent that social capital help reduce many forms of communication inefficiencies (e.g., transaction costs, bargaining costs, search costs, and policing costs, *etc.*), cause agreements and cooperation to be honored, and enable employees to share tacit knowledge and place negotiations on the same wavelength [20].

Social capital can take different forms, primarily trust, norm, and network. However, the most distinguishable and relatively easily measurable form is the network structure of relations between and among actors. It is not completely fungible nor exchangeable but may be specific to certain organizations or activities. Depending on diverse organizational characteristics such as culture, routines, and demographic compositions, social capital of organizations inheres in the distinctive structures of collaboration among their members. Thus, the structural features of collaboration must be closely associated with the organizational capability of creating innovations.

Although the contribution of social capital to innovation has been well recognized in the literature, empirical support is scarce owing in the main to: (1) a lack of agreement regarding the content of the concept of social capital and the appropriate way of measuring it [21,22], and (2) the lack of empirical research in the area [23]. This paper aims to fill this research gap by focusing on two issues. First, we separate different network mechanisms, particularly, distinguishing tie strengths (which is at the dyadic level) and density (which as ate the network level), and examines how they affect innovation outputs both independently and interactively. Second, we provide empirical evidence in the context of inventors' collaboration based on a large scale analysis of co-patenting behaviors. In the following sections, we will identify three network constructs that can characterize an R and D organization's social capital and develop hypotheses regarding the structure-performance relationship.

2.1. Structural Holes

The basic idea of a structural hole is that a lack of ties among alters in an ego's social network benefits the ego in terms of accessing diverse information. In a social capital theory, actors who develop ties with disconnected groups are believed to gain access to a broader array of knowledge than those who are connected to a cohesive one [24]. Actors who are in a position of bridging structural holes or gaps between alters, have opportunities to access and assimilate different streams of knowledge and, thus, are likely to play a key role in creating novel ideas [25]. Therefore, the presence of structural holes in a collaboration network indicates that collaboration occurs among R and D personnel with different knowledge backgrounds, providing a greater opportunity for knowledge brokerage that can bring together more diverse knowledge streams and lead to richer contents [26].

Structural hole is also related to information efficiency. In frequent and intense interaction among actors that forms a dense communication structure, much of the information circulating in the system is redundant. Contrastingly, an inventor who spans a structural hole, benefits by brokering and controlling the flow of information between unconnected inventors who have not previously collaborated. Such an inventor is in a position of control since she or he is the only one connected to the other actors in an efficient way, which economizes on the number of ties. This means that inventors who value speed in their search for knowledge have to rely on the focal inventor. Consequently, the presence of structural holes in a collaboration network implies that diverse and non-overlapping knowledge is shared, and knowledge exchange occurs efficiently around the inventors who play the role of knowledge brokers, which results in greater creativity and productivity. This leads to the following hypothesis:

> *H1: All other things being equal, the presence of structural hole in an inventor collaboration network will be positively associated with creating knowledge with a future impact.*

2.2. Strength of Ties

The structural hole perspective focuses on the benefits of transferring and assimilating diverse knowledge (example, [27]) but does not address the problematic nature of such transfers. Presumably, people at opposite ends of a structural hole may have less experience than that of co-workers, which can impede knowledge transfer. On the contrary, individuals who communicate with others frequently or who have a strong emotional attachment to others are more likely to share knowledge than those who communicate infrequently or who are not emotionally attached [28]. As an example, frequent communication can be more effective through the development of relationship-specific heuristics [29].

This view, known as a closure view on social capital [30], focuses on the risks associated with incomplete information in the presence of structural holes. Specifically, closure in a collaboration network is argued to affect easy access to information, and to facilitate sanctions that make it less risky for people in the network to trust each other. Research adopting this view have inferred the network effect on knowledge transfer from the association between tie strength and knowledge transfer [29,31–33]. They primarily focus on how the social dynamics within two-way interactions (example, reciprocity, and commitment) influence knowledge transfer. The effect of tie strength on knowledge transfer is also believed to facilitate the transfer of tacit knowledge [28,33]. Hansen [33] argued that strong ties promote the transfer of complex knowledge than weak ties [29,33,34], because they are more likely be embedded in a dense web of trustworthy relationships [11,20].

The closure and structural hole views have striking parallels in the literature on social capital. Such disagreement originates from a lack of distinction between strong (weak) ties and a dense (sparse) network in the process of operationalization. In fact, research adopting the closure view usually assumes that a dense network represents social cohesion in which most members communicate frequently. Strong ties and social cohesion can be structurally correlated, but it is a mistake to equate their effects because they are conceptually distinct. Burt [35] made a clear conceptual separation between the strength and density of ties. It is very important to acknowledge this, since it is conceivable that sparse ties may be strong, and dense ties may be weak [28]. Specifically, a strong tie can occur in both a cohesive group or in a sparse group [35,36]. Therefore, only by investigating tie strength and cohesion simultaneously, is it possible to dissolve the disagreement.

In this study, we clearly distinguish between tie strength and network closure. The former is related to frequency, depth, or duration of collaboration within a pair of partners, while the latter is associated with a degree or density of overall connectivity; the former then needs to be observed at the dyadic level, but the latter at the network level. By separating them, the following hypothesis does not contradict, but complement, the previous hypothesis:

> *H2: All other things being equal, an inventor collaboration network with many strong ties will be positively associated with creating knowledge with a future impact.*

2.3. Centralization

The third hypothesis developed in this study is about the effects of network centralization. In social network theories, researchers have used the concept of centrality to indicate the status, power, and social capital captured by the location of an actor in a network [37–39]. Unlike centrality, centralization is a network-level measure that examines the extent to which a whole network has a centralized structure. Centralization can tell us whether a network, as a whole, is organized around its most central points.

Centralization is related to cohesion, but provides more information than cohesion. In effect, the concepts of cohesion and centralization refer to the differing aspects of the overall "compactness" of a network. Cohesion describes the density of connections within a network, while centralization describes the extent to which such dense connections are organized around particular focal points. Centralization and cohesion, therefore, are important complementary measures.

As a result, in highly-centralized networks, there are a few clusters of inventors that form a strongly cohesive relationship. Research has examined the effect of such central groups on others within the same organization [38,40–42]. Centrality is often perceived as a signal of quality [41]; as a result, central groups of inventors create an attraction for their knowledge to be selected by others in their own inventive activities. Additionally, central groups have a topological advantage in that they have greater access to other parts of the network than less centralized ones. The expanding effects of a few central groups may weaken the activities of those that are local and independent, which mitigate a firm's capability to diversify its technology base and R and D portfolio.

In the innovation literature, the capability of technological diversification has been considered as a critical dimension for impactful innovation creation of many R and D organizations [43–46]. Since many innovations are designed to solve unrelated problems, companies that are more technologically-diversified, capture more opportunities and technical possibilities; as a result, they benefit largely from their own research activities [47]. Organizational learning theory also suggests the benefits of a diverse knowledge base. One such benefit is technological diversification that may play a preventive role against core rigidities [48], by generating and renovating technological trajectories, and taking advantage of cross-fertilization effects between different technologies [49,50].

Many empirical studies have provided evidence supporting these arguments. Ahuja and Lampert [7] demonstrate that, for the chemical industry, experimenting with diverse emerging technologies is a way for organizations to overcome core rigidities, and is associated with the subsequent number of inventions. Katila and Ahuja [51] also reports empirical evidence from the robotics industry, which shows that there is a linear and positive relationship between technological search scope and product innovation. A study by Nicholls-Nixon and Woo [52] examines the relationship between the breadth of technological knowledge and technical output (number of products and patents) in a sample of established pharmaceutical companies. Recently, Nesta and Saviotti [53] state that the scope and coherence of the knowledge base contribute positively to innovation performance, which is estimated by the number of patent applications.

Based on this review, we hypothesize that a highly centralized organization of R and D activities hampers technological diversification, which leads to a weaker performance of knowledge creation. This leads to the next hypothesis:

H3: All other things being equal, highly centralized organization of R and D activities will be negatively associated with creating knowledge with a future impact.

2.4. Additional Test: Interaction Effects

The hypotheses we have developed so far assume that each network mechanism operates independently. However, since we captured the three factors from a single network, it is likely that they are structurally correlated and, thereby, operate interactively. Given the complexity of interactions among the network factors, it is not easily predictable whether one network mechanism boosts or weakens the others. A test for interaction effects between tie strength and two other factors is particularly meaningful in that if we find significant interaction effects among them, this proves that the effects of these factors have distinguishable network mechanisms and that they need to be treated separately. For instance, it is possible that the effects of strong ties diminish as the density of a network increases or the network becomes more centralized. Although we hypothesize that connection strength, itself, will be positively associated with performance, when both clustering coefficient and connection strength are high, the collaboration network becomes exceedingly cohesive, which has negative effects on performance. In this situation, the strong connections at the dyadic level may aggravate the negative effects of cohesive structure at the network level rather than compensate the effects depending on the topological structure of collaboration networks. Similarly, although we hypothesize that decentralized collaboration networks have a positive effect on innovation outputs, if a collaboration network has many strong ties, the effects of decentralization may have diminishing returns on performance. This leads to the following hypothesis:

H4: All other things being equal, the network factors will interact with each other as they affect the firm's capability of creating impactful knowledge.

3. Research Methodology

3.1. Research Sample

The research sample is constructed by using the patent database recently developed by Li *et al.* [54]. Unlike the original United States Patent and Trademark Office (USPTO) database, the patent database by Li *et al.*, includes unique inventor identifiers for patents granted from 1975 through 2010. For each firm, which is identified by a unique assignee code in the inventor database, we first construct a two-mode network consisting of two types of nodes, its patents and inventors. Following this, the two-mode network is converted into a one-mode network of inventors, as shown in Figure 1. The nodes of the converted network are distinct inventors, and there is a link between two different inventor nodes, if they have filed at least one patent together within a given time window. Note that each link may have a value if the pair of inventors has filed more than one patent jointly.

Each co-invention network represents a firm-year observation. Each network changes over time as a firm's patent stock accumulates. Time is needed for a co-invention network to grow to a meaningful size, so that network analysis can be applied; as a result, it is necessary to set a sufficient time window to obtain a single firm-level observation. In this study, a four-year time window has been set for each network following Rappa and Garud (1992) [55]. More specifically, for each firm, co-invention networks are constructed every four years by using patents granted within the last four years from the end of the previous time window.

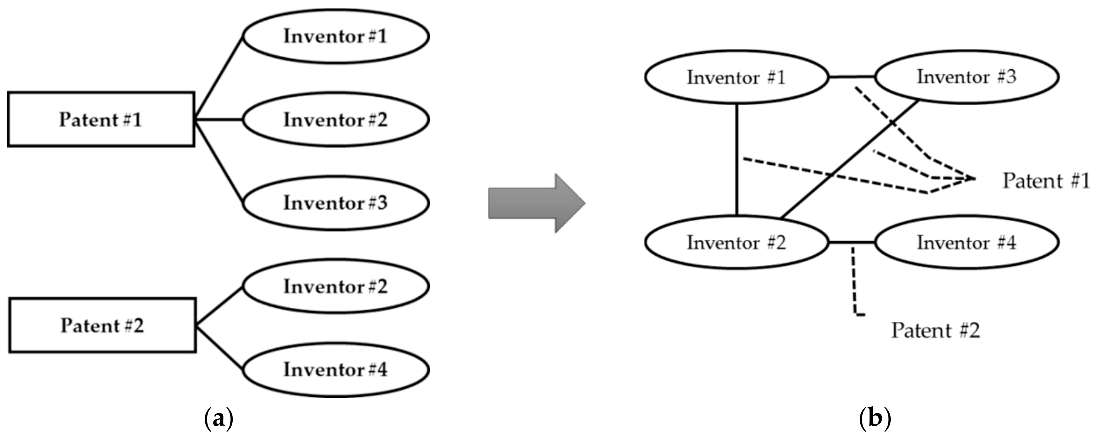


Figure 1. Construction of a co-invention network. (**a**) Patent-Inventor Network (2-mode Network); (**b**) Co-invention Network (1-mode Network).

The sample firms are selected by the following procedure. We first counted the total number of patents of each firm during the total time window (35 years) and selected 500 firms in order of patent counts. Then we built their co-invention networks and again sorted them in order of edge counts in the networks. By examining the individual firm networks we excluded firms that have not filed patents at least one year during the total time window. Specifically, a firm is included in the sample only when the firm has a record of filing patents every year, which means that every firm in the sample has filed at least one patent during the total time window. By doing this, we intend to narrow our focus on firms whose propensity to patent is persistent during the sample period, and that have a sufficient size for an R and D organization. In this way, we finally selected 50 firms that have filed patents more than one patent during 1991–2010. Since we consider five time windows for each firm during the 20-year period, the research sample consists of 250 observations. Information on the sample firms has been included in Appendix A. The sample firms have filed 669,332 patents, which account for 21.4% of the total patents during the period.

3.2. Construction of Measures

3.2.1. Dependent Variable: Patent Citations

The output quality of an R and D organization is measured by the forward citations that its patents stock have received by subsequent inventions until 2010. Patent citations have been considered as excellent measures for technological impact and performance [39,56,57]. We use the total number of citations a patent receives from the time it is granted until the end of 2010 as an indicator of its impact on future knowledge creation. These citations are received from the entire universe of patents, which includes a sample of more than 4,000,000 patents used in this study.

3.2.2. Measures for Structural Holes: Average Degree and Clustering Coefficient

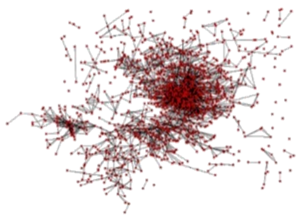
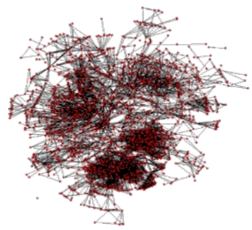
The size of structural holes is measured by average degree and clustering coefficient, which are, in fact, measures for network cohesion. We associate network cohesion with dense connectivity among inventors; as a result, network cohesion is opposite to a structural hole. Thus, more cohesive networks spanned fewer structural holes, so a firm's performance should have a negative association with cohesion according to H1. A popular measure for cohesion is network density, which indicates directly how densely inventors are connected each other. However, network density has a scale problem, in that it underestimates cohesion when a network size is too large. To overcome this problem, average degree is usually considered as a substitute measure of cohesion. Since the average degree does not depend on network size, network cohesion can be compared to the networks of different sizes ([58], p. 74). Clustering coefficient is calculated at both the network level (global) and the node level (local).

A global clustering coefficient represents the number of closed triplets (complete triangles) over the total number of triplets. The local clustering coefficient [59] is given by the proportion of links between nodes within a focal node's neighborhood divided by the maximum number of links that could exist among them. In this study, we combine the two clustering coefficients into one index by using a principal component analysis.

3.2.3. Measures for Centralization: Weighted Degree Centralization, Number of Components, and Component Concentration

Centralization is a macro-level characteristic of a network, which is calculated by using each node's centrality, a node-level characteristic. Centralization indicates how unequal the distribution of node centrality is in a network, or how much variance there is in the distribution of centrality in a network. There are as many centralization measures as centrality measures. This study considers only degree centralization. Note that we use weighted degree centralization (WDC) since a co-invention network is a valued one. To calculate a WDC index, we first calculate the sum of the differences in degree centrality between the most central actor, A, and all the other actors in the network. The sum is then divided by its maximum under the largest possible centralization (that is, a star network). Table 1 compares two co-invention networks with different WDC indices. At a glance, Table 1b looks more centralized around a few inventors. However, the actual WDC index of Table 1a is greater than Table 1b by 0.34. This is because WDC reflects the weights of links.

Table 1. Two co-invention networks with different weighted degree centralization.

	(a) Firm A (1999–2002)	**(b) Firm B (2003–2006)**
Network structure		
Weighted degree centralization	0.54245058	0.20736274
Component concentration	0.50937952	0.59501442
# components	182	119
# inventors	1443	1851

Another important measure for centralization is the number of components. Components represent a part of a network (that is, a sub-network) that is connected within, but disconnected from other parts of a network. If a firm's co-invention network has many components, this means that its R and D is conducted by many independent groups of inventors.

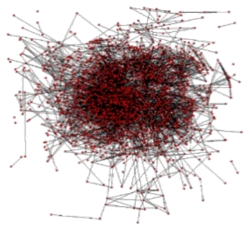
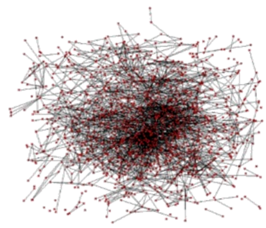
The number of components does not take into account the differences in component sizes. Given networks with the same number of components, the distribution of component sizes in each network may vary significantly. Some networks may have a giant component and many small-sized components, while others only have many components of a similar size. The former may be considered centralized in that many inventors are connected to form a giant component. However, the network can also be considered decentralized, because many small components conduct R and D activities independent of the inventors in the largest component. To quantify this difference we use component concentration, which is represented by Herfindahl–Hirschman index (HHI) for the number of inventors in the components.

Given the number of components n, and the number of inventors I, in a co-invention network, component concentration is calculated as follows:

$$\mathrm{HHI} = \sum_{1}^{n} (C_i/I)^2 \quad (1)$$

In the Equation (1), C_i represents the number of inventors in the i^{th} component. The lower component concentration implies that inventors are more evenly distributed over components in the network. Contrastingly, if inventors are connected in a few large components within a network, then component concentration becomes close to 1. In Table 2, the network in Table 2b has more components, but its component concentration is smaller than the network in Table 2a in which there is a giant component.

Table 2. Two co-invention networks with different component concentrations.

	(a) Firm A (1999–2002)	**(b) Firm B (2003–2006)**
Network structure		
Weighted Degree Centralization	0.25821562	0.22665832
Component concentration	0.62155889	0.34233211
# components	129	225
# inventors	1867	1329

3.2.4. Measure for Strength of Ties: The Ratio of Dyads with Multiple Links

Tie strength represents frequency, depth, and duration of the collaboration, and is measured by the number of patents that two inventors have co-invented. Since tie strength is a value for each dyad, it needs to be converted into a firm or network level index. We consider the ratio of dyads with multiple links (that is, links having weight larger than 1) to the total number of links in a given network. Specifically, it is calculated as follows:

$$\text{Strength of ties} = \frac{\text{The Number of Valued (Weighted) Edges}}{\text{The Number of Total Edges}} \quad (2)$$

3.2.5. Control Variables

To remove truncation effects due to different time horizons, we include period as a control variable. As noted earlier, each period variable represents a four-year time window. For instance, period one refers to the period from 1991 to 1995. The difference in propensity to patent, according to industry, also needs to be controlled. We include an industry control that has one of the following six values based on SIC classification codes: (1) construction; (2) manufacturing; (3) transportation, communication, electric, gas, and sanitary services; (4) wholesale trade; (5) financial, insurance, and real estate; and (6) services. Finally, we control for the effects of firm size by including the number of inventors and patents as control variables.

4. Results

4.1. Descriptive Analysis

Descriptive statistics of variables along with a correlation matrix are presented in Table 3 below. Each # Symbol in our paper means the number of variable (e.g., (9) in Table 3 is the number of patents).

Table 3. Descriptive statistics and correlation matrix.

	Variable	Mean	St. Dev.	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1)	Patent citations	20,234.7	26,650.1	2	192,870	1	−0.256 **	−0.009	0.138 *	−0.122	0.391 **	0.116	0.491 **	0.483 **
(2)	Clustering coefficient	0	1	−2.693	3.553	−0.256 **	1	−0.380 **	−0.516 **	−0.288 **	−0.045	−0.637 **	−0.225 **	−0.402 **
(3)	Average degree	4.58	1.68	1.143	10	−0.009	−0.380 **	1	0.437 **	0.340 **	−0.225 **	0.766 **	0.191 **	0.145 *
(4)	Strength of ties	0.276	0.09	0	0.75	0.138 *	−0.516 **	0.437 **	1	0.545 **	−0.088	0.551 **	0.089	0.261 **
(5)	Weighed degree centralization	0.094	0.094	0.002	0.557	−0.122	−0.288 **	0.340 **	0.545 **	1	−0.403 **	0.385 **	−0.320 **	−0.179 **
(6)	# components	501.652	466.634	2	2794	0.391^{-}	−0.045	−0.225 **	−0.088	−0.403 **	1	−0.179 **	0.722 **	0.718 **
(7)	Component concentration	0.278	0.202	0.001	0.749	0.116	−0.637 **	0.766 **	0.551 **	0.385 **	−0.179 **	1	0.236 **	0.272 **
(8)	# inventors	2617.23	2452.117	5	14,824	0.491 **	−0.225 **	0.191 **	0.089	−0.320 **	0.722 **	0.236 **	1	0.921 **
(9)	# patents	2677.33	2648.071	4	16,338	0.483 **	−0.402 **	0.145 *	0.261 **	−0.179 **	0.718 **	0.272 **	0.921 **	1

Note: * $p < 0.5$; ** $p < 0.01$.

The table shows that an average co-invention network has about 2600 inventors, and they file a similar number of patents. The average degree is 4.58, which means that, on average, an inventor collaborates with about 4.58 inventors. Notably, an average network has about 500 components, implying that each component has about only 5–6 nodes on average. If we consider that component concentration is rarely zero, most components would have an even smaller size. Finally, the ratio of multi-valued edges is about 27.6% on average, which suggests that repeated collaboration is an unusual event. Remarkably, the variables of network centralization have a much larger variation than an average degree or connection strength. This suggests that network centralization is a more effective factor that explains the differences in collaboration structures.

4.2. Estimation Result

The proposed hypotheses are tested by using negative binomial regression with time-dummies. The dependent variable of citation counts takes on only whole number values. The use of a linear regression model on such data can yield inefficient, inconsistent, and biased coefficient estimates. These data, like most count data, exhibit over-dispersion—the variance is greater than the mean. Negative binomial regressions explicitly accommodate this over-dispersion by enabling the variance to be greater than the mean.

We use a time-fixed effect estimation model without firm dummies, unlike typical fixed effects estimations. Fixed effects estimation with firm dummies uses only within-firm differences (which have been pooled in our case), essentially discarding information about differences between firms. In our application where the within-firm variation is small relative to the between-firm variation, use of a negative binomial model with only time-dummies is more suitable. Moreover, patenting behavior (thus, patent citations) is often affected by unobserved time-related factors (which are universally affecting firms) like macro-economic, sociological, or technological situations (e.g., IT bubbles in the late 1990s). By adding time-dummies only, we can estimate between-firm variation by controlling such unobserved time-related factors.

Table 4 displays the regression results, where patent citations are regressed on variables for co-invention network structures. Model 1 contains only the control variables. In the model, the negative coefficients on period dummies show that truncation effects are effectively controlled. Remarkably, industry dummies do not have significant effects on patent citations, implying that our sample shows a consistent patenting behavior regardless of industry type.

Models 2 through 7 test the effects of independent variables individually. At first, the signs on the clustering coefficient and average degree all have negative signs, but the effect of density is not significant. However, in Models 8, 9, and 10, in which the effects of other variables are controlled for, the two cohesion variables show negative and significant coefficients. Specifically, clustering and density, which are associated with network cohesion, have a negative effect on creating inventions with future impact. This offers support for H1, implying that a firm's R and D performance is negatively associated with the extent to which collaboration among inventors forms a dense or cohesive network structure. Consequently, the presence of structural holes in a collaboration network is associated with a much higher innovation performance than those in a dense collaboration structure.

Second, Model 4 shows that strength of ties has positive and significant effects on forward citation frequency. The effect of tie strength is relatively strong and consistent throughout all models (in Models 8 through 10) in which it is included. This offers support for H2, suggesting that frequent and repetitive collaboration between previous partners can significantly improve the likelihood of inventing patents with many citations. Specifically, once a collaboration relationship is established between a particular pair of inventors, this needs to be sustained in the subsequent projects instead of exploring and establishing a new partnership with other partners.

The findings so far support both the structural hole and closure perspectives, as they are operationalized in our terms and methods. The findings clearly show that tie strength and cohesive connectivity have distinct effects (example, [28]). Cohesiveness represents redundancy and inefficiency of knowledge acquisition, which has a negative performance implication, while tie strength reduces coordination costs and facilitates the transfer of complex knowledge.

Table 4. Negative binomial regression results (A sensitivity test for different time-windows is provided in Appendix B).

	Dependent Variable:									
	Patent Citations									
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
Clustering coefficient		−0.374 *** (0.050)						−0.814 *** (0.057)		−0.779 *** (0.057)
Average degree			−0.042 (0.028)						−0.240 *** (0.043)	−0.065 * (0.039)
Strength of ties				1.394 ** (0.569)				2.919 *** (0.608)	4.430 *** (0.688)	3.224 *** (0.612)
Weighed degree centralization					−0.782 (0.531)			−2.469 *** (0.539)	−1.453 ** (0.609)	−2.378 *** (0.540)
# components						0.0003 * (0.0001)		0.001 *** (0.0001)	0.001 *** (0.0002)	0.0005 *** (0.0002)
Component concentration							0.254 (0.240)	−1.789 *** (0.333)	1.865 *** (0.374)	−1.391 *** (0.381)
Period 1995–1998	0.050 (0.137)	0.014 (0.129)	0.067 (0.138)	0.013 (0.136)	0.050 (0.137)	0.055 (0.137)	0.034 (0.138)	0.008 (0.113)	−0.064 (0.128)	0.009 (0.114)
Period 1999–2002	−0.248 * (0.140)	−0.303 ** (0.132)	−0.213 (0.141)	−0.304 ** (0.139)	−0.239 * (0.139)	−0.233 * (0.139)	−0.270 * (0.140)	−0.281 ** (0.116)	−0.318 ** (0.132)	−0.272 ** (0.117)
Period 2003–2006	−1.296 *** (0.141)	−1.330 *** (0.133)	−1.253 *** (0.144)	−1.346 *** (0.140)	−1.297 *** (0.141)	−1.293 *** (0.140)	−1.320 *** (0.142)	−1.335 *** (0.118)	−1.363 *** (0.136)	−1.312 *** (0.121)
Period 2007–2010	−3.558 *** (0.141)	−3.551 *** (0.133)	−3.519 *** (0.145)	−3.589 *** (0.140)	−3.561 *** (0.141)	−3.561 *** (0.141)	−3.577 *** (0.142)	−3.469 *** (0.117)	−3.536 *** (0.138)	−3.439 *** (0.123)
Industry (1) Construction	−0.394 (0.277)	−0.326 (0.261)	−0.432 (0.277)	−0.384 (0.275)	−0.407 (0.277)	−0.416 (0.276)	−0.350 (0.280)	−0.569 ** (0.232)	−0.300 (0.261)	−0.556 ** (0.231)
Industry (2) Manufacturing	−0.249 (0.165)	−0.293 * (0.155)	−0.236 (0.165)	−0.282 * (0.165)	−0.212 (0.166)	−0.286 * (0.167)	−0.246 (0.164)	−0.522 *** (0.143)	−0.334 ** (0.164)	−0.498 *** (0.145)
Industry (3) Transportation	0.293 (0.179)	0.401 ** (0.168)	0.280 (0.178)	0.295 * (0.177)	0.305 * (0.178)	0.246 (0.180)	0.320 * (0.180)	0.237 (0.150)	0.311 * (0.170)	0.256 * (0.151)
Industry (4) Wholesale trade	−0.261 (0.185)	−0.222 (0.174)	−0.237 (0.185)	−0.357 * (0.187)	−0.234 (0.187)	−0.281 (0.186)	−0.267 (0.185)	−0.338 ** (0.159)	−0.501 *** (0.179)	−0.337 ** (0.159)

Table 4. *Cont.*

	Dependent Variable:									
	Patent Citations									
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
Industry (5) Financial *etc.*	−0.116 (0.270)	−0.095 (0.254)	−0.131 (0.269)	0.018 (0.273)	−0.153 (0.270)	−0.126 (0.269)	−0.124 (0.270)	0.160 (0.229)	0.075 (0.257)	0.158 (0.228)
Industry (6) Services	−0.235 (0.151)	−0.214 (0.142)	−0.189 (0.155)	−0.286 * (0.151)	−0.202 (0.154)	−0.241 (0.152)	−0.264 * (0.154)	−0.137 (0.137)	−0.397 ** (0.156)	−0.132 (0.138)
# inventors	0.00001 (0.00005)	0.0002 *** (0.00005)	0.00002 (0.00005)	0.0001 (0.0001)	−0.00003 (0.0001)	−0.00001 (0.00005)	0.00001 (0.00005)	0.0003 *** (0.0001)	0.0001 ** (0.0001)	0.0003 *** (0.0001)
# patents	0.0003 *** (0.00004)	0.0002 *** (0.00005)	0.0003 *** (0.00004)	0.0003 *** (0.00005)	0.0004 *** (0.00005)	0.0003 *** (0.00004)	0.0003 *** (0.00004)	−0.0001 (0.00005)	0.0001 (0.0001)	−0.0001 * (0.0001)
Constant	9.583 *** (0.188)	9.682 *** (0.178)	9.721 *** (0.205)	9.278 *** (0.225)	9.645 *** (0.191)	9.581 *** (0.187)	9.539 *** (0.192)	9.773 *** (0.197)	9.242 *** (0.222)	9.831 *** (0.204)
Log Likelihood	−2518.477	−2500.825	−2517.558	−2516.240	−2517.329	−2516.957	−2517.954	−2461.589	−2494.580	−2460.746
theta	2.128 *** (0.179)	2.411 *** (0.204)	2.142 *** (0.180)	2.162 *** (0.182)	2.145 *** (0.180)	2.151 *** (0.181)	2.136 *** (0.179)	3.198 *** (0.275)	2.520 *** (0.214)	3.216 *** (0.276)
Akaike Inf. Crit.	5062.953	5029.650	5063.115	5060.480	5062.657	5061.915	5063.908	4959.178	5025.159	4959.492

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Finally, Models 5, 6, and 7 through 10 show the effects of three variables representing network centralization, which are WDC, number of components, and component concentration. They have an insignificant or marginally significant effect on forward citations in the models in which they are considered individually. However, when other variables are included together as in Models 8 through 10 (that is, the effects of structural holes and tie strength are controlled), the coefficients of all three centralization variables become significant. The sign of each variable offers consistent support for H3, suggesting that a centralized structure of R and D collaboration has a negative effect on the impact of inventions. Both WDC and component concentration that directly measure the extent of network centralization, have significant and negative coefficients. On the contrary, the number of components, which is a measure associated with decentralization, has a positive and significant coefficient. Specifically, an R and D output has a weaker impact when there are highly centralized groups of collaborating inventors. Contrastingly, the impact of the output increases with the number of isolated groups. Supporting this interpretation, the coefficient of component concentration is significant and positive, suggesting that when inventors are distributed evenly in many sub-networks of a similar size, the overall performance of collaboration becomes much greater. Such a decentralized organization of an R and D collaboration indicates that there are no leading groups that manage and control overall inventive processes, and that inventors do not rely on particular groups of inventors. Rather, in decentralized organizations, inventive activities are performed by various independent groups of inventors and those independent groups are likely to have distinct expertise, and to proceed with their own agenda, independent of interventions from central inventor groups. In sum, the findings so far consistently support H1, H2, and H3, which suggest that while cohesive and centralized collaboration structure is not desirable, frequent and repetitive collaboration between existing co-workers can enhance patent quality.

4.3. Interaction Effects

Table 5 displays the results of the negative binomial regression models containing interaction terms between each pair of network variables. In Model 11, it is found that WDC and clustering coefficient have a negative interaction effect, as expected. The fact that both variables have negative effects on performance, it can be naturally expected that one will boost the effect of the other. In Model 12, the interaction effect between WDC and connection strength is tested. The coefficient is significant and positive, suggesting that connection strength, which has a positive effect on performance, also alleviates the negative effect of a centralized collaboration structure. Finally, Model 13 tests the interaction effect between the clustering coefficient and connection strength, and displays the result that connection strength reinforces the negative effects of a cohesive structure. Although connection strength itself is positively associated with performance, when both clustering coefficient and connection strength are high, the collaboration network becomes exceedingly cohesive, which has negative effects on performance. In consequence, the positive effects of connection strength may not be found depending on the topological structure of collaboration networks. The previous findings show that in centralized collaboration networks, strong connections can enhance performance. However, if a collaboration network is already cohesive, the existence of many strong ties in the network may have an adverse effect on performance.

Table 5. Negative binomial regression results: Interaction effects.

	Dependent Variable:			
	Patent Citations			
	(11)	**(12)**	**(13)**	**(14)**
Clustering coefficient	−4.792 *** (0.552)	−4.787 *** (1.263)	−2.988 *** (0.534)	−0.745 (1.893)
Average degree	−0.475 *** (0.072)	−0.781 *** (0.059)	−0.567 *** (0.087)	−0.604 *** (0.149)

Table 5. *Cont.*

	Dependent Variable:			
	Patent Citations			
	(11)	(12)	(13)	(14)
Strength of ties	−0.067 * (0.037)	−0.053 (0.041)	−0.061 (0.039)	0.136 (0.149)
Weighed degree centralization	3.729 *** (0.600)	2.486 *** (0.807)	3.540 *** (0.676)	3.254 (2.037)
# components	0.001 *** (0.0001)	0.0005 *** (0.0002)	0.001 *** (0.0002)	0.002 *** (0.0004)
Component concentration	−0.733 * (0.379)	−1.312 *** (0.381)	−1.441 *** (0.380)	−2.024 (1.438)
WDC : Component concentration	−2.169 *** (0.266)			−4.554 *** (0.708)
WDC : Strength of ties		6.333 ** (2.909)		−10.489 ** (4.263)
Component concentration: Strength of ties			−1.027 *** (0.241)	2.058 *** (0.551)
Period 1995–1998	−0.052 (0.105)	0.001 (0.113)	−0.014 (0.112)	−0.121 (0.098)
Period 1999–2002	−0.367 *** (0.108)	−0.296 ** (0.116)	−0.303 *** (0.115)	−0.476 *** (0.103)
Period 2003–2006	−1.349 *** (0.111)	−1.315 *** (0.120)	−1.324 *** (0.118)	−1.467 *** (0.106)
Period 2007–2010	−3.483 *** (0.113)	−3.457 *** (0.122)	−3.455 *** (0.120)	−3.606 *** (0.108)
Industry (1) Construction	−0.424 ** (0.213)	−0.526 ** (0.229)	−0.498 ** (0.227)	−0.490 ** (0.201)
Industry (2) Manufacturing	−0.446 *** (0.133)	−0.494 *** (0.144)	−0.491 *** (0.142)	−0.474 *** (0.135)
Industry (3) Transportation	0.321 ** (0.139)	0.272 * (0.150)	0.258 * (0.147)	0.263 * (0.136)
Industry (4) Wholesale trade	−0.396 *** (0.147)	−0.334 ** (0.158)	−0.348 ** (0.157)	−0.331 ** (0.148)
Industry (5) Financial *etc.*	−0.007 (0.210)	0.087 (0.231)	0.103 (0.223)	−0.014 (0.202)
Industry (6) Services	−0.220 * (0.128)	−0.146 (0.138)	−0.163 (0.136)	−0.290 ** (0.139)
# inventors	0.0003 *** (0.00005)	0.0003 *** (0.0001)	0.0004 *** (0.0001)	0.0002 *** (0.0001)
# patents	−0.0001 ** (0.00005)	−0.0001 ** (0.0001)	−0.0002 *** (0.0001)	0.00003 (0.0001)
Constant	9.726 *** (0.191)	10.015 *** (0.233)	9.776 *** (0.206)	9.264 *** (0.534)
Log Likelihood	−2437.466	−2458.617	−2455.058	−2412.744
theta	3.810 *** (0.329)	3.266 *** (0.281)	3.355 *** (0.289)	4.558 *** (0.396)
Akaike Inf. Crit.	4914.932	4957.235	4950.115	4893.487

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

5. Conclusions

This study offers empirical evidence to show that each firm has a distinctive R and D collaboration structure, which affects the firm's R and D performance and output quality. The findings are in line with the extant literature on the structural hole perspective, and at the same time, provide support for the network closure perspective, by showing the positive impact of information brokerage and efficiency, as well as recurring and intense collaboration. More importantly, our analysis consistently reports the benefits of a decentralized collaboration regardless of the different operationalization of centralized structures.

Our study makes several contributions. First, this is the first attempt to examine a collaboration structure employing a large-scale sample of uniquely identified inventors and their patents data for more than 20 years. Second, this study clearly separates the two structural concepts, tie strength and connectivity, from the traditional closure perspective in which a clear distinction between them has been rarely made. The results show that these two structural concepts examine different aspects of network mechanisms in R and D collaboration and, thus, report that their effects on organization performance are different with firms. As claimed in Reagans and McEvily [28], our findings suggest that structural holes are the source of value added, and strength of ties is essential to realizing the value buried in the holes. Finally, our study employs centralization and component structures, which are rarely found in empirical studies based on social network theories. Taking into account components structures was required from a methodological perspective, because each observation has many isolates or components. Component structures also help to avoid the traditional dichotomous view of social capital, the structural hole, and closure perspectives, by complimenting the two typical network mechanisms in relation with the output quality.

The findings provide some implications for the management of R and D organizations. From the perspective of individual R and D personnel, it is more effective to continue and strengthen collaboration with currently working partners than finding new ones. If they want to find new collaboration partners, it would be beneficial to find inventors who have not been cooperating much with others. At the organization level, managers need to identify and empower distinct groups of collaborators to maintain the decentralization of inventive activities. They need to understand that the excessive reliance on "superstars" may inhibit the capability of creating new inventions, and diversifying the knowledge base. More problematically, that may reduce the incentive to focus on new ideas and cause inventors to maintain their status by relying on the idea of a few key players or the organizational status quo.

There are also some limitations worth noting. First, our findings are not generalizable in the context of inter-firm R and D collaboration. Extending our research framework to the context of inter-firm R and D alliances, it is necessary to examine inventor-level collaboration structures in which each inventor belongs to different organizations. This is hardly considered in current studies on R and D alliances mostly due to the lack of available data. In addition to disambiguating inventors' name in the patent database, we need information on their affiliation. Second, like many other studies on network structures, this study did not take into account demographic features of individual inventors. Detailed information about inventors is typically hard to obtain [8]. If demographic information of inventors is available, research incorporating both network structures and demographic information will provide richer implications on the relationship among collaboration structure, individual characteristics, and organizational performance. Finally, it is also worth noting that although measures of centralization we used are popular, they are not perfect measures for clearly distinguishing centralized and decentralized R and D organizations. For instance, centralization tells us only whether a network is organized around its most central points, but they do not tell us whether these central points comprise of a distinct set of points, which cluster together in a particular part of the network. The individual central points, for example, may be distributed widely throughout the network, and in such cases, a measure of centralization might not be especially informative. Although overcoming this limitation may require new methods and wide empirical tests, reexamining the proposed hypotheses with more sophisticated measures on centralization will be a worthwhile extension to the present study.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A. List of Sample Firms (1991–2010)

Firm	Founded	# Links	# Inventors	# Patents	# Citations
INTERNATIONAL BUSINESS MACHINES	1911	167,637	54,594	53,106	571,419
MATSUSHITA ELECTRIC INDUSTRIAL	1918	136,702	53,932	48,037	333,169
HITACHI LTD	1910	91,468	33,105	22,156	191,322
CANON KABUSHIKI KAISHA	1937	89,595	21,945	33,652	224,142
SAMSUNG ELECTRONICS CO LTD	1969	83,176	25,930	33,425	144,455
KABUSHIKI KAISHA TOSHIBA	1875	61,256	22,612	24,200	193,944
GENERAL ELECTRIC CO	1892	56,337	24,146	20,248	138,294
FUJITSU LTD	1935	54,477	24,053	22,166	146,758
MICROSOFT CORPORATION	1975	52,364	16,238	16,692	111,714
HEWLETT PACKARD COMPANY	1939	48,964	18,551	20,579	166,622
SONY CORPORATION	1946	45,787	21,361	25,569	153,434
INTEL CORPORATION	1968	45,093	15,378	18,577	156,438
MOTOROLA INC	1928	40,186	17,055	15,713	239,520
EASTMAN KODAK COMPANY	1881	36,055	11,087	14,388	105,916
MICRON TECHNOLOGY INC	1978	34,893	4422	18,587	201,065
XEROX CORPORATION	1906	34,322	10,058	11,768	126,900
HONDA GIKEN KOGYO KABUSHIKI KAISHA	1946	33,930	15,015	11,402	50,398
NEC CORPORATION	1899	33,733	16,390	22,541	161,485
BASF AKTIENGESELLSCHAFT	1865	33,651	10,413	7794	28,008
SHARP KABUSHIKI KAISHA	1912	31,048	11,481	11,566	80,433
FUJI PHOTO FILM CO LTD	1934	29,585	8872	14,104	55,910
SIEMENS AKTIENGESELLSCHAFT	1847	29,493	15,909	13,260	60,040
ROBERT BOSCH GMBH	1886	28,931	12,732	10,348	45,856
TEXAS INSTRUMENTS INCORPORATED	1930	28,748	11,184	13,085	150,345
RICOH COMPANY LTD	1936	28,629	8,924	10,052	73,649
BAYER AG	1863	27,444	8109	6622	28,504
SEIKO EPSON CORPORATION	1942	26,542	7796	12,390	53,712
3M INNOVATIVE PROPERTIES COMPANY	1902	25,702	10,443	8744	108,195
THE PROCTER GAMBLE COMPANY	1837	23,943	8784	7385	68,355
ADVANCED MICRO DEVICES INC	1969	22,720	4583	9019	93,482
LG ELECTRONICS INC	1958	19,830	6929	8645	26,866
TOYOTA JIDOSHA KABUSHIKI KAISHA	1937	19,264	8668	6836	41,132
APPLIED MATERIALS INC	1967	18,567	5292	5121	56,430
E I DU PONT DE NEMOURS AND COMPANY	1802	18,219	7875	7697	49,023
MERCK PATENT GMBH	1668	17,646	6422	4427	22,547
SUN MICROSYSTEMS INC	1982	17,279	6390	7579	83,501
THE REGENTS OF THE UNIVERSITY OF CALIFORNIA	1868	16,801	11,357	6075	53,749
SANYO ELECTRIC CO LTD	1947	16,308	7291	5599	25,476
KONINKLIJKE PHILIPS ELECTRONICS N V	1891	16,114	7996	7483	19,943
AT&T CORP	1874	15,764	7389	6368	129,418
HONEYWELL INC	1906	15,454	7484	6502	32,909
TAIWAN SEMICONDUCTOR MANUFACTURING COMPANY	1987	15,372	5834	5317	31,461
GENERAL MOTORS CORPORATION	1908	14,746	7948	6101	47,719
NOKIA CORPORATION	1865	14,350	6968	6917	42,434
FUJI XEROX CO LTD	1962	14,137	5362	4545	24,498
NISSAN MOTOR CO LTD	1933	11,676	5384	4718	30,425
MINOLTA CO LTD	1928	11,049	3383	3994	26,428
BRISTOL MYERS SQUIBB COMPANY	1887	9913	3882	2690	12,702
SUMITOMO CHEMICAL COMPANY LIMITED	1913	9255	3982	2884	9475
THE DOW CHEMICAL COMPANY	1897	7649	3369	2659	29,045

Appendix B. Negative Binomial Regression Results for Different Time Windows

We conducted additional tests to see if changing time windows affect the regression results. In addition to the four-year time window, two additional time windows, three- and five-year, are considered and the regression results are provided in the following tables. The results are not significantly different from the results in the text and they still offer support of our hypotheses.

Table B1. Regression Results for Three-Year Time Window.

	Negative Binomial Regression Results (Polling of Data in the Three-Year Time Window)									
	Dependent Variable: Patent Citations									
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
Clustering coefficient		−1.507 *** (0.363)						−3.794 *** (0.442)		−3.405 *** (0.439)
Average degree			−0.063 ** (0.029)						−0.216 *** (0.042)	−0.116 *** (0.040)
Strength of ties				1.127 ** (0.452)				1.945 *** (0.469)	3.404 *** (0.495)	2.409 *** (0.492)
Weighted degree centralization					−13.738 *** (1.775)			−19.018 *** (1.993)	−16.861 *** (1.939)	−18.167 *** (1.979)
# component						0.0004 ** (0.0002)		0.001 *** (0.0002)	0.001 *** (0.0002)	0.001 *** (0.0002)
Component concentration							0.083 (0.236)	−0.189 (0.344)	2.249 *** (0.350)	0.444 (0.375)
Industry (1) Construction	−0.381 (0.261)	−0.314 (0.258)	−0.431 * (0.261)	−0.383 (0.259)	−0.466 * (0.248)	−0.410 (0.260)	−0.366 (0.265)	−0.436 ** (0.222)	−0.305 (0.231)	−0.411 * (0.221)
Industry (2) Manufacturing	−0.267 * (0.155)	−0.281 * (0.152)	−0.240 (0.155)	−0.318 ** (0.156)	−0.246 * (0.147)	−0.308 * (0.157)	−0.271 * (0.155)	−0.600 *** (0.138)	−0.567 *** (0.145)	−0.579 *** (0.139)
Industry (3) Transportation	0.230 (0.168)	0.299 * (0.165)	0.215 (0.167)	0.216 (0.167)	0.205 (0.159)	0.171 (0.170)	0.237 (0.169)	0.151 (0.144)	0.172 (0.150)	0.177 (0.143)
Industry (4) Wholesale	−0.278 (0.174)	−0.251 (0.171)	−0.252 (0.173)	−0.363 ** (0.176)	−0.200 (0.166)	−0.317 * (0.176)	−0.280 (0.174)	−0.376 ** (0.154)	−0.504 *** (0.160)	−0.382 ** (0.153)
Industry (5) Financial *etc.*	−0.108 (0.254)	−0.091 (0.250)	−0.133 (0.253)	0.034 (0.257)	−0.242 (0.242)	−0.108 (0.253)	−0.110 (0.254)	0.035 (0.219)	0.023 (0.228)	0.033 (0.218)
Industry (6) Services	−0.263 * (0.142)	−0.247 * (0.139)	−0.201 (0.145)	−0.322 ** (0.144)	−0.279 ** (0.134)	−0.278 * (0.142)	−0.273 * (0.145)	−0.450 *** (0.133)	−0.645 *** (0.140)	−0.447 *** (0.135)

Table B1. *Cont.*

	Negative Binomial Regression Results (Polling of Data in the Three-Year Time Window)									
	Dependent Variable: Patent Citations									
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
Period 1996–1998	0.035 (0.142)	0.012 (0.139)	0.055 (0.141)	−0.028 (0.142)	−0.037 (0.135)	0.048 (0.141)	0.030 (0.142)	−0.208 * (0.120)	−0.269 ** (0.125)	−0.213 * (0.119)
Period 1999–2001	−0.191 (0.143)	−0.252 * (0.141)	−0.146 (0.143)	−0.272 * (0.144)	−0.255 * (0.136)	−0.163 (0.142)	−0.199 (0.144)	−0.520 *** (0.122)	−0.503 *** (0.127)	−0.507 *** (0.122)
Period 2002–2004	−0.828 *** (0.144)	−0.878 *** (0.143)	−0.780 *** (0.145)	−0.889 *** (0.145)	−0.908 *** (0.137)	−0.807 *** (0.143)	−0.834 *** (0.145)	−1.146 *** (0.123)	−1.052 *** (0.129)	−1.105 *** (0.123)
Period 2005–2007	−2.016 *** (0.144)	−2.052 *** (0.142)	−1.960 *** (0.146)	−2.096 *** (0.145)	−2.056 *** (0.137)	−1.994 *** (0.144)	−2.022 *** (0.145)	−2.265 *** (0.122)	−2.229 *** (0.129)	−2.224 *** (0.123)
Period 2008–2010	−4.425 *** (0.145)	−4.435 *** (0.142)	−4.385 *** (0.147)	−4.466 *** (0.144)	−4.505 *** (0.137)	−4.418 *** (0.144)	−4.429 *** (0.145)	−4.597 *** (0.123)	−4.560 *** (0.130)	−4.550 *** (0.125)
# inventor	0.00000 (0.0001)	0.0001 (0.0001)	0.00003 (0.0001)	0.0001 (0.0001)	−0.0001 ** (0.0001)	−0.00001 (0.0001)	0.00000 (0.0001)	0.0001 (0.0001)	0.0001 * (0.0001)	0.0001 ** (0.0001)
# patent	0.0004 *** (0.0001)	0.0004 *** (0.0001)	0.0004 *** (0.0001)	0.0004 *** (0.0001)	0.0005 *** (0.0001)	0.0004 *** (0.0001)	0.0004 *** (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)	0.00004 (0.0001)
Constant	9.357 *** (0.181)	10.293 *** (0.295)	9.561 *** (0.199)	9.099 *** (0.206)	9.909 *** (0.188)	9.354 *** (0.181)	9.349 *** (0.183)	12.169 *** (0.369)	9.779 *** (0.208)	12.086 *** (0.370)
Observations	300	300	300	300	300	300	300	300	300	300
Log Likelihood	−2893.224	−2886.954	−2891.187	−2890.627	−2873.980	−2891.297	−2893.166	−2828.017	−2841.271	−2825.414
theta	1.997 *** (0.154)	2.073 *** (0.160)	2.021 *** (0.156)	2.028 *** (0.156)	2.232 *** (0.173)	2.020 *** (0.156)	1.998 *** (0.154)	2.910 *** (0.228)	2.692 *** (0.210)	2.953 *** (0.231)
Akaike Inf. Crit.	5814.447	5803.907	5812.374	5811.253	5777.961	5812.593	5816.333	5694.033	5720.542	5690.827

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table B2. Regression Results for Three-Year Time Window (interaction effects).

	Negative Binomial Regression Results (Polling of Data in the Three-Year Time Window			
	Dependent Variable: Patent Citations			
	(1)	(2)	(3)	(4)
Clustering coefficient	−0.321 (0.642)	−2.791 *** (0.433)	−3.735 *** (0.719)	−1.372 * (0.751)
Average degree	−0.151 *** (0.041)	−0.116 *** (0.041)	−0.115 *** (0.040)	−0.138 *** (0.042)
Strength of ties	2.131 *** (0.475)	1.020 (0.683)	1.694 (1.509)	−0.520 (1.513)
Weighted degree centralization	18.269 *** (5.965)	−30.562 *** (3.784)	−18.036 *** (1.981)	18.786 ** (7.631)
# component	0.001 *** (0.0002)	0.001 *** (0.0002)	0.001 *** (0.0002)	0.0004 ** (0.0002)
Component concentration	0.887 ** (0.384)	0.549 (0.376)	0.445 (0.375)	0.838 ** (0.399)
CC:WDC	−59.698 *** (8.712)			−61.241 *** (9.460)
ST:WDC		46.146 *** (10.501)		3.461 (10.473)
CC:ST			1.130 (2.046)	3.824 * (2.105)
Industry (1) Construction	−0.436 ** (0.208)	−0.405 * (0.217)	−0.417 * (0.221)	−0.457 ** (0.207)
Industry (2) Manufacturing	−0.556 *** (0.131)	−0.580 *** (0.137)	−0.565 *** (0.143)	−0.503 *** (0.135)
Industry (3) Transportation *etc.*	0.195 (0.135)	0.181 (0.141)	0.183 (0.144)	0.213 (0.135)
Industry (4) Wholesale trade	−0.388 *** (0.145)	−0.407 *** (0.151)	−0.373 ** (0.156)	−0.355 ** (0.147)
Industry (5) Financial *etc.*	−0.037 (0.205)	−0.027 (0.216)	0.036 (0.218)	−0.039 (0.206)
Industry (6) Services	−0.423 *** (0.128)	−0.458 *** (0.133)	−0.433 *** (0.138)	−0.372 *** (0.130)
Period 1996–1998	−0.213 * (0.113)	−0.188 (0.118)	−0.211 * (0.120)	−0.197 * (0.113)
Period 1999–2001	−0.468 *** (0.115)	−0.458 *** (0.121)	−0.505 *** (0.122)	−0.450 *** (0.115)
Period 2002–2004	−1.065 *** (0.116)	−1.064 *** (0.121)	−1.104 *** (0.123)	−1.057 *** (0.116)
Period 2005–2007	−2.160 *** (0.117)	−2.175 *** (0.122)	−2.227 *** (0.123)	−2.156 *** (0.117)
Period 2008–2010	−4.535 *** (0.118)	−4.522 *** (0.123)	−4.553 *** (0.125)	−4.538 *** (0.117)
# inventor	0.0001 ** (0.0001)	0.0002 *** (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)
# patent	0.0001 (0.0001)	0.00003 (0.0001)	0.0001 (0.0001)	0.0002 ** (0.0001)
Constant	10.265 *** (0.466)	11.994 *** (0.380)	12.286 *** (0.521)	10.917 *** (0.541)
Observations	300	300	300	300
Log Likelihood	−2805.317	−2819.324	−2825.308	−2803.890
theta	3.328 *** (0.262)	3.054 *** (0.239)	2.955 *** (0.231)	3.369 *** (0.266)
Akaike Inf. Crit.	5652.633	5680.648	5692.615	5653.779

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table B3. Regression Results for Five-Year Time Window.

	Negative Binomial Regression Results (Polling of Data in the Five-Year Time Window)									
	Dependent Variable: Patent Citations									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Clustering coefficient		−2.045 *** (0.417)						−4.845 *** (0.536)		−4.593 *** (0.534)
Average degree			−0.032 (0.032)						−0.172 *** (0.049)	−0.075 * (0.045)
Strength of ties				1.026 * (0.546)				2.029 *** (0.588)	3.175 *** (0.649)	2.320 *** (0.613)
Weighted degree centralization					−11.494 *** (2.415)			−16.696 *** (2.331)	−15.330 *** (2.395)	−16.318 *** (2.322)
# component						0.0002 (0.0002)		0.001 *** (0.0002)	0.001 *** (0.0002)	0.001 *** (0.0002)
Component concentration							0.284 (0.266)	−0.920 ** (0.414)	1.919 *** (0.412)	−0.491 (0.443)
Industry (1) Construction	−0.412 (0.309)	−0.342 (0.300)	−0.442 (0.309)	−0.409 (0.307)	−0.486 (0.299)	−0.439 (0.308)	−0.369 (0.311)	−0.548 ** (0.257)	−0.401 (0.277)	−0.542 ** (0.255)
Industry (2) Manufacturing	−0.239 (0.184)	−0.217 (0.178)	−0.229 (0.184)	−0.300 (0.186)	−0.253 (0.178)	−0.278 (0.187)	−0.231 (0.184)	−0.602 *** (0.160)	−0.512 *** (0.176)	−0.576 *** (0.162)
Industry (3) Transportation *etc.*	0.318 (0.199)	0.411 ** (0.193)	0.306 (0.199)	0.296 (0.199)	0.300 (0.192)	0.261 (0.203)	0.351 * (0.200)	0.175 (0.170)	0.214 (0.185)	0.193 (0.170)
Industry (4) Wholesale trade	−0.261 (0.206)	−0.220 (0.199)	−0.241 (0.206)	−0.345 (0.210)	−0.188 (0.200)	−0.283 (0.207)	−0.265 (0.206)	−0.315 * (0.180)	−0.443 ** (0.195)	−0.303 * (0.180)
Industry (5) Financial *etc.*	−0.092 (0.301)	−0.082 (0.291)	−0.103 (0.300)	0.048 (0.306)	−0.187 (0.291)	−0.092 (0.299)	−0.098 (0.300)	0.130 (0.259)	0.129 (0.279)	0.138 (0.258)
Industry (6) Services	−0.203 (0.167)	−0.154 (0.162)	−0.167 (0.173)	−0.262 (0.171)	−0.224 (0.161)	−0.218 (0.168)	−0.230 (0.170)	−0.289 * (0.153)	−0.537 *** (0.167)	−0.273 * (0.157)
Period 1996–2000	−0.008 (0.138)	−0.075 (0.134)	0.012 (0.139)	−0.078 (0.139)	−0.037 (0.134)	0.007 (0.137)	−0.032 (0.138)	−0.255 ** (0.117)	−0.267 ** (0.127)	−0.253 ** (0.117)

Table B3. *Cont.*

	Negative Binomial Regression Results (Polling of Data in the Five-Year Time Window)									
	Dependent Variable: Patent Citations									
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
Period 2001–2005	−0.789 *** (0.141)	−0.862 *** (0.138)	−0.761 *** (0.143)	−0.852 *** (0.143)	−0.822 *** (0.136)	−0.776 *** (0.140)	−0.812 *** (0.142)	−1.065 *** (0.120)	−0.993 *** (0.131)	−1.042 *** (0.121)
Period 2006–2010	−2.993 *** (0.142)	−3.044 *** (0.138)	−2.965 *** (0.146)	−3.060 *** (0.144)	−2.997 *** (0.137)	−2.982 *** (0.142)	−3.013 *** (0.143)	−3.165 *** (0.119)	−3.139 *** (0.132)	−3.139 *** (0.122)
# inventor	0.00001 (0.00005)	0.0001 (0.00005)	0.00001 (0.00005)	0.0001 (0.0001)	−0.0001 (0.00005)	−0.00001 (0.00005)	0.00000 (0.00005)	0.0001 * (0.00005)	0.0001 (0.0001)	0.0001 ** (0.0001)
# patent	0.0003 *** (0.00004)	0.0002 *** (0.00004)	0.0003 *** (0.00004)	0.0002 *** (0.00004)	0.0003 *** (0.00004)	0.0002 *** (0.00004)	0.0003 *** (0.00004)	0.00004 (0.00004)	0.0001 (0.00005)	0.00003 (0.00004)
Constant	9.794 *** (0.203)	10.908 *** (0.314)	9.905 *** (0.227)	9.521 *** (0.247)	10.224 *** (0.221)	9.798 *** (0.203)	9.728 *** (0.211)	12.875 *** (0.430)	9.757 *** (0.249)	12.807 *** (0.433)
Observations	200	200	200	200	200	200	200	200	200	200
Log Likelihood	−2073.957	−2066.307	−2073.502	−2072.441	−2065.733	−2072.974	−2073.419	−2028.421	−2045.462	−2027.365
theta	2.143 *** (0.201)	2.292 *** (0.215)	2.151 *** (0.201)	2.171 *** (0.203)	2.303 *** (0.217)	2.161 *** (0.202)	2.153 *** (0.202)	3.211 *** (0.307)	2.757 *** (0.262)	3.241 *** (0.310)
Akaike Inf. Crit.	4171.914	4158.614	4173.004	4170.883	4157.465	4171.948	4172.838	4090.841	4124.925	4090.729

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table B4. Regression Results for Five-Year Time Window (interaction effects).

	Negative Binomial Regression Results (Polling of Data in the Five-Year Time Window)			
	Dependent Variable: Patent Citations			
	(1)	(2)	(3)	(4)
Clustering coefficient	−1.172 (0.826)	−3.902 *** (0.536)	−4.645 *** (0.918)	−1.208 (0.996)
Average degree	−0.110 ** (0.046)	−0.068 (0.046)	−0.075 (0.046)	−0.116 ** (0.047)
Strength of ties	1.609 *** (0.591)	1.097 (0.843)	2.229 (1.623)	1.723 (1.725)
Weighted degree centralization	15.979 ** (6.732)	−27.121 *** (5.045)	−16.282 *** (2.337)	21.030 ** (9.765)
# component	0.0004 ** (0.0002)	0.001 *** (0.0002)	0.001 *** (0.0002)	0.0004 * (0.0002)
Component concentration	0.363 (0.471)	−0.241 (0.438)	−0.492 (0.443)	0.379 (0.480)
CC:WDC	−56.009 *** (10.308)			−59.469 *** (11.377)
ST:WDC		33.319 ** (13.482)		−8.618 (13.784)
CC:ST			0.163 (2.389)	0.327 (2.422)
Industry (1) Construction	−0.518 ** (0.243)	−0.522 ** (0.253)	−0.543 ** (0.256)	−0.520 ** (0.243)
Industry (2) Manufacturing	−0.507 *** (0.155)	−0.546 *** (0.161)	−0.573 *** (0.166)	−0.505 *** (0.161)
Industry (3) Transportation *etc.*	0.254 (0.162)	0.215 (0.169)	0.193 (0.171)	0.253 (0.164)
Industry (4) Wholesale trade	−0.298 * (0.172)	−0.309 * (0.178)	−0.303 * (0.183)	−0.299 * (0.174)
Industry (5) Financial *etc.*	0.009 (0.245)	0.045 (0.258)	0.139 (0.258)	0.028 (0.248)
Industry (6) Services	−0.279 * (0.149)	−0.284 * (0.155)	−0.271 * (0.160)	−0.276 * (0.153)
Period 1996–2000	−0.209 * (0.111)	−0.215 * (0.116)	−0.252 ** (0.118)	−0.216 * (0.113)
Period 2001–2005	−0.978 *** (0.115)	−1.005 *** (0.120)	−1.042 *** (0.121)	−0.983 *** (0.116)
Period 2006–2010	−3.079 *** (0.116)	−3.108 *** (0.122)	−3.140 *** (0.122)	−3.084 *** (0.117)
# inventor	0.0001 * (0.00005)	0.0001 ** (0.00005)	0.0001 * (0.0001)	0.0001 * (0.0001)
# patent	0.0001 * (0.00004)	0.00004 (0.00004)	0.00003 (0.0001)	0.0001 (0.0001)
Constant	10.959 *** (0.566)	12.661 *** (0.436)	12.834 *** (0.604)	10.906 *** (0.673)
Observations	200	200	200	200
Log Likelihood	−2016.186	−2024.935	−2027.363	−2016.032
theta	3.598 *** (0.346)	3.314 *** (0.317)	3.241 *** (0.310)	3.602 *** (0.346)
Akaike Inf. Crit.	4070.373	4087.869	4092.726	4074.063

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

References

1. Kogut, B.; Zander, U. Knowledge of the Firm, Combinative Capabilities, and the Replication of Technology. *Organ. Sci.* **1992**, *3*, 383–397. [CrossRef]
2. Henderson, R.; Cockburn, I. Measuring Competence? Exploring Firm Effects in Pharmaceutical Research. *Strateg. Manag. J.* **1994**, *28*, 128–129. [CrossRef]
3. Fleming, L. Recombinant Uncertainty in Technological Search. *Manag. Sci.* **2001**, *47*, 117–132. [CrossRef]
4. Becker, W.; Dietz, J. R&D Cooperation and Innovation Activities of Firms—Evidence for the German Manufacturing Industry. *Res. Policy* **2004**, *33*, 209–223.
5. Rosenkopf, L.; Nerkar, A. Beyond Local Search: Boundary-Spanning, Exploration, and Impact in the Optical Disk Industry. *Strateg. Manag. J.* **2001**, *22*, 287–306. [CrossRef]
6. Nerkar, A. Old Is Gold? The Value of Temporal Exploration in the Creation of New Knowledge. *Manag. Sci.* **2003**, *49*, 211–229. [CrossRef]
7. Ahuja, G.; Morris Lampert, C. Entrepreneurship in the large corporation: A longitudinal study of how established firms create breakthrough inventions. *Strateg. Manag. J.* **2001**, *22*, 521–543. [CrossRef]
8. Fershtman, C.; Gandal, N. Direct and Indirect Knowledge Spillovers: The "Social Network" of Open-Source Projects. *RAND J. Econ.* **2011**, *42*, 70–91. [CrossRef]
9. Hottenrott, H.; Lopes-Bento, C. Quantity or quality? Knowledge alliances and their effects on patenting. *Ind. Corp Change* **2014**, *24*, 981–1011. [CrossRef]
10. Roda, S. Structural Holes and Managerial Performance: Identifying the Underlying Mechanisms. *Soc. Netw.* **2010**, *32*, 168–179. [CrossRef]
11. Lin, N. *Social Capital: A Theory of Social Structure and Action*; Cambridge University Press: New York, NY, USA, 2002.
12. Adler, P.S.; Kwon, S.-W. *Social Capital: The Good, the Bad, and the Ugly*; Marshall Research Paper Series; Boston, MA, USA, 2000.
13. Borgatti, S.P.; Foster, P.C. The Network Paradigm in Organizational Research: A Review and Typology. *J. Manag.* **2003**, *29*, 991–1013.
14. Coleman, J.S. Social Capital in the Creation of Human Capital. *Am. J. Sociol.* **1988**, *94*, S95–S120. [CrossRef]
15. Putnam, R.D. Bowling Alone: America's Declining Social Capital. *J. Democr.* **1995**, *6*, 65–78. [CrossRef]
16. Putnam, R.D. *Bowling Alone: The Collapse and Revival of American Community*; Simon & Schuster: New York, NY, USA, 2000.
17. Barrutia, J.M.; Echebarria, C. Social Capital, Research and Development, and Innovation: An Empirical Analysis of Spanish and Italian Regions. *Eur. Urban Reg. Stud.* **2010**, *17*, 128–145. [CrossRef]
18. Nahapiet, J.; Ghoshal, S. Social Capital, Intellectual Capital, and the Organizational Advantage. *Acad. Manag. Rev.* **1998**, *23*, 242–266.
19. McFadyen, M.A.; Cannella, A.A., Jr. Social Capital and Knowledge Creation: Diminishing Returns of the Number and Strength of Exchange Relationships. *Acad. Manag. J.* **2004**, *47*, 735–746. [CrossRef]
20. Maskell, P.; Malmberg, A. The Competitiveness of Firms and Regions: "Ubiquitification" and the Importance of Localized Learning. *Eur. Urban Reg. Stud.* **1999**, *6*, 9–25. [CrossRef]
21. Beugelsdijk, S.; Van Schaik, T. Differences in social capital between 54 Western European regions. *Reg. Stud.* **2005**, *39*, 1053–1064. [CrossRef]
22. Pérez, F.; Fernandez de Guevara, J.; Serrano, L.; Montesinos, V. *Measurement of Social Capital and Growth: An Economic Methodology*; University Library of Munich: Munich, Germany, 2012.
23. Evans, M.; Syrett, S. Generating Social Capital?: The Social Economy and Local Economic Development. *Eur. Urban Reg. Stud.* **2007**, *14*, 55–74. [CrossRef]
24. Granovetter, M.S. The Strength of Weak Ties. *Am. J. Sociol.* **1973**, *78*, 1360–1380. [CrossRef]
25. Nerkar, A.; Paruchuri, S. Evolution of R&D Capabilities: The Role of Knowledge Networks within a Firm. *Manag. Sci.* **2005**, *51*, 771–785.
26. Hargadon, A.; Sutton, R.I. Technology Brokering and Innovation in a Product Development Firm. *Adm. Sci. Q.* **1997**, *42*, 716–749. [CrossRef]
27. Stuart, T.E.; Podolny, J.M. Local Search and the Evolution of Technological Capabilities. Strateg. *Manag. J.* **1996**, *17*, 21–38.

28. Reagans, R.; McEvily, B. Network Structure and Knowledge Transfer: The Effects of Cohesion and Range. *Adm. Sci. Q.* **2003**, *48*, 240–267. [CrossRef]
29. Uzzi, B. Social Structure and Competition in Interfirm Networks: The Paradox of Embeddedness. *Adm. Sci. Q.* **1997**, *42*, 35–67. [CrossRef]
30. Coleman, J.S. Social Theory, Social Research, and a Theory of Action. *Am. J. Sociol.* **1986**, *91*, 1309–1335. [CrossRef]
31. Uzzi, B. The Sources and Consequences of Embeddedness for the Economic Performance of Organizations: The Network Effect. *Am. Sociol. Rev.* **1996**, *61*, 674–698. [CrossRef]
32. Uzzi, B. Embeddedness in the Making of Financial Capital: How Social Relations and Networks Benefit Firms Seeking Financing. *Am. Sociol. Rev.* **1999**, *64*, 481–505. [CrossRef]
33. Hansen, M.T. The Search-Transfer Problem: The Role of Weak Ties in Sharing Knowledge across Organization Subunits. *Adm. Sci. Q.* **1999**, *44*, 82–111. [CrossRef]
34. Szulanski, G. Exploring Internal Stickiness: Impediments to the Transfer of Best Practice Within the Firm. Strateg. *Manag. J.* **1996**, *17*, 27–43.
35. Burt, R.S. *Structural Holes: The Social Structure of Competition*; Harvard University Press: Cambridge, MA, USA, 1992.
36. Lin, N.; Ensel, W.M.; Vaughn, J.C. Social Resources and Strength of Ties: Structural Factors in Occupational Status Attainment. *Am. Sociol. Rev.* **1981**, *46*, 393–405. [CrossRef]
37. Podolny, J.M. A Status-Based Model of Market Competition. *Am. J. Sociol.* **1993**, *98*, 829–872. [CrossRef]
38. Brass, D.J.; Burkhardt, M.E. Potential Power and Power Use: An Investigation of Structure and Behavior. *Acad. Manag. J.* **1993**, *36*, 441–470. [CrossRef]
39. Ahuja, G. The Duality of Collaboration: Inducements and Opportunities in the Formation of Interfirm Linkages. *Strateg. Manag. J.* **2000**, *21*, 317–343. [CrossRef]
40. Ibarra, H. Network Centrality, Power, and Innovation Involvement: Determinants of Technical and Administrative Roles. *Acad. Manag. J.* **1993**, *36*, 471–501. [CrossRef]
41. Ahuja, M.K.; Galletta, D.F.; Carley, K.M. Individual Centrality and Performance in Virtual R&D Groups: An Empirical Study. *Manag. Sci.* **2003**, *49*, 21–38.
42. Mehra, A.; Kilduff, M.; Brass, D.J. The Social Networks of High and Low Self-Monitors: Implications for Workplace Performance. *Adm. Sci. Q.* **2001**, *46*, 121–146. [CrossRef]
43. Sorenson, O.; Stuart, T.E. Syndication Networks and the Spatial Distribution of Venture Capital Investments. *Am. J. Sociol.* **2001**, *106*, 1546–1588. [CrossRef]
44. Rosenberg, N. The Direction of Technological Change: Inducement Mechanisms and Focusing Devices. *Econ. Dev. Cult. Change* **1969**, *18*, 1–24. [CrossRef]
45. Dosi, G. Technological Paradigms and Technological Trajectories: A Suggested Interpretation of the Determinants and Directions of Technical Change. *Res. Policy* **1982**, *11*, 102–103. [CrossRef]
46. Nelson, R.R.; Winter, S.G. *An Evolutionary Theory of Economic Change*; Belknap Press of Havard University Press: Cambridge, MA, USA, 1982.
47. Nelson, R. The Simple Economics of Basic Scientific Research. *J. Polit. Econ.* **1959**, *67*, 297–306. [CrossRef]
48. Leonard-Barton, D. Interpersonal Communication Patterns among Swedish and Boston-area Entrepreneurs. *Res. Policy* **1984**, *13*, 101–114. [CrossRef]
49. Granstrand, O. Towards a Theory of the Technology-Based Firm. *Res. Policy* **1998**, *27*, 465–489. [CrossRef]
50. Suzuki, J.; Kodama, F. Technological diversity of persistent innovators in Japan: Two case studies of large Japanese firms. *Res. Policy* **2004**, *33*, 531–549. [CrossRef]
51. Katila, R.; Ahuja, G. Something Old, Something New: A Longitudinal Study of Search Behavior and New Product Introduction. *Acad. Manag. J.* **2012**, *45*, 1183–1194. [CrossRef]
52. Nicholls-Nixon, C.L.; Woo, C.Y. Technology Sourcing and Output of Established Firms in a Regime of Encompassing Technological Change. *Strateg. Manag. J.* **2003**, *24*, 651–666. [CrossRef]
53. Nesta, L.; Saviotti, P.P. Coherence of the Knowledge Base and the Firm's Innovative Performance: Evidence from the U.S. Pharmaceutical Industry. *J. Ind. Econ.* **2005**, *53*, 123–142. [CrossRef]
54. Li, G.C.; Lai, R.; D'Amour, A.; Doolin, D.M.; Sun, Y.; Torvik, V.I.; Yu, A.Z.; Lee, F. Disambiguation and Co-Authorship Networks of the U.S. Patent Inventor Database (1975–2010). *Res. Policy* **2014**, *43*, 941–955. [CrossRef]

55. Rappa, M.A.; Garud, R. Modeling Contribution Spans of Scientists in a Field: The Case of Cochlear Implants. *R&D Manag.* **1992**, *22*, 337–348.
56. Albert, M.B.; Avery, D.; Narin, F.; McAllister, P. Direct Validation of Citation Counts as Indicators of Industrially Important Patents. *Res. Policy* **1991**, *20*, 251–259. [CrossRef]
57. Podolny, J.M.; Stuart, T.E. A Role-Based Ecology of Technological Change. *Am. J. Sociol.* **1995**, *100*, 1224–1260. [CrossRef]
58. De Nooy, W.; Mrvar, A.; Batagelk, V. *Exploratory Social Network Analysis with Pajek*, 2nd ed.; Cambridge University Press: New York, NY, USA, 2011.
59. Watts, D.J.; Strogatz, S.H. Collective Dynamics of "Small-World" Networks. *Nature* **1998**, *393*, 440–442. [CrossRef] [PubMed]