Effect of Inventor Status on Intra-organizational Innovation Evolution

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Abstract

Innovation is one of the primary characteristics that separates successful from unsuccessful organizations. Organizations have a choice in selecting knowledge that is recombined to produce new innovations. The selection of knowledge is influenced by the status of inventors in an organization's internal knowledge network. In this study, we model knowledge flow within an organization and contend that it exhibits unique characteristics not incorporated in most social network measures. Using the model, we also propose a new measure based on random walks and team identification and use it to examine innovation selection in a large organization. Using empirical methods, we find that inventor status determined by the new measure had a significant positive relationship with the likelihood that his/her knowledge would be selected for recombination. We believe that the new measure in addition to modeling knowledge flow in a scientific collaboration network helps better understand how innovation evolves within organizations.

1. Introduction

Innovation is one of the primary characteristics that separates successful from unsuccessful organizations [1]. It has been described as a problem solving process where the solutions are discovered via the search of existing knowledge and the novel recombination of existing solutions to those problems [2, 3]. Evolution of innovation can be studied and traced by examining this recombinatory process and the various factors that influence it. Organizations have a choice in selecting knowledge that is recombined to produce new innovations. Studies have suggested that this choice is influenced by social networks both within and outside the organization [4-6]. Specifically, the selection of knowledge for recombination is influenced by the status of inventors in an organization's internal knowledge network [7-9]. Organizations (and inventors within) attach more value and recombine knowledge of high-status inventors.

Various social network measures have been used to establish the status of inventors in knowledge networks [5, 10-12]. However, the measures make implicit assumptions about the flow of knowledge within an organization. For instance, the widely used betweenness centrality measure [13] assumes that knowledge flows along shortest paths. Often these assumptions are not valid for modeling knowledge flow within organizations. Establishing the status of inventors (and thus their influence on the recombinatory innovation process) based on these measures may lead to misleading results.

In this paper, we examine the role of inventor status in intra-organizational knowledge networks on the selection of knowledge that is recombined to produce innovation. We focus on intra-organization networks since recombination of internal knowledge helps establish competitive advantage for a longer time [14]. In addition, many innovative organizations are known to build upon their internal knowledge to survive and thrive in their businesses [15]. We model knowledge flow within an organization and contend that it exhibits unique characteristics not incorporated in most social network measures. Using the model, we also propose a new measure based on random walks and team identification and use it to examine innovation selection in a large organization.

In particular, we explore the following research questions:

- How can we effectively model the flow of knowledge within an intra-organizational knowledge network?
- How can we establish the status of an individual in a collaborative knowledge network?
- How does the status of an inventor in a knowledge network affect innovation evolution?

The rest of this paper is organized as follows: Section 2 presents the literature review and background, Section 3 describes the research design and testbed. Section 4 presents the experimental results and discussion. Section 5 concludes and proposes future directions.

2. Literature review

2.1. Innovation and evolution

Innovation has been described in the literature as a problem-solving process wherein solutions are discovered via the search and recombination of existing knowledge [2, 3, 16]. During this process, each innovative organization is faced with a decision to select existing knowledge that is recombined to produce new innovative artifacts. These choices are important as different paths of recombination can lead to different technological capabilities and performance [17, 18]. Thus, the selection of knowledge plays an important role in the direction of innovation evolution and the future success of the organization in a competitive domain.

As the recombination process proceeds, a focal innovation emerges that other innovations build upon [7, 15, 19]. This focal innovation defines an organization's area of expertise [20]. In order to understand innovation evolution, it is necessary to identify the factors leading to the selection of a focal innovation. It has been shown that individuals and organizations do not select innovations just by their technical merits [19, 21], other factors like the expertise of inventors, scope of the innovation, and number of other innovations in the same field play an important role in the selection process. Inventors also select the focal innovation based on the status of the innovation's inventors in the knowledge network [7, 8]. One way to establish the status of an inventor is to use social network measures.

2.2. Social network measures

In the following discussion, knowledge networks are characterized as social networks with inventors as nodes and collaboration as links between them. Various measures to quantify characteristics of social networks have been proposed in the literature [22, 23]. Measures to identify high-status nodes are usually known as centrality or prestige measures.

Several measures of node centrality have been developed including degree centrality, closeness, betweenness, information centrality, and influence measures [24, 25]. These measures are not independent of the dynamic processes that unfold within a network [26] and make different implicit assumptions about the path of knowledge flow in a network (we focus on the knowledge flow as this study examines innovation diffusion and selection). However, many studies use these measures without regard to the implicit assumptions made by them. This might lead to poor results or a wrong interpretation of the network phenomenon under study [24]. Thus, it is necessary to model the assumptions pertinent to the network under study prior to selecting the centrality measure.

Based on analysis of previous studies [24, 27, 28], we contend that there are three primary requirements for a measure to correctly identify high-status nodes in a knowledge network of inventor collaborations. These are:

- Account for Diversity of knowledge (D): This implies that a high status inventor is likely to receive diverse knowledge from different parts of the network. In SNA theory, this is best represented by betweenness measures. Betweenness is a measure of the influence a node has on the spread of information through the network [29]. The higher the betweenness, the more frequently a node is likely to receive information from disjoint parts of a network. This is important as the recombination of diverse knowledge from disjoint parts of the network is likely to lead to more innovation [27, 28].
- Random diffusion (R): This implies that the measure should assume that knowledge does not select a preferred path (like the shortest path) of travel through a network. This does not necessarily imply that all paths (of all lengths) are equally important. It has been shown that shorter paths may be important in transferring certain kinds of knowledge [30].
- Parallel duplication (P): This implies that multiple copies of the same knowledge can exist in a network. Thus, when given a choice in the path of travel, knowledge can travel on multiple paths at once [24]. For instance, knowledge is transferred to multiple individuals during team presentations. This assumption is especially important in this study since we are studying inventors within organizations where they are likely to be organized in project teams.

Commonly used social network measures do not satisfy the above assumptions for knowledge flow. For instance, Freeman's betweenness measure [13] does not take into account the duplication of knowledge. Bonacich's power [31] accounts for random diffusion and parallel duplication, however, it is not a betweenness measure and thus does not consider diversity of knowledge. Newman's random walk betweenness [29] assumes D and R however, does not contain a parallel duplication component. A comprehensive discussion of these centrality measures and their assumptions is provided by Borgatti [24]. We propose a measure based on Newman's random walk betweenness centrality to model knowledge flow in the collaboration networks studied here. A team identification component is added to the measure that assumes parallel duplication of knowledge within teams in an organization. Details of the proposed measure are presented in the research design. We believe that the proposed measure satisfies all three requirements for knowledge flow and better identifies high status inventors.

2.3. Knowledge networks and effects on innovation

There have been many studies to examine the relationship between network properties and innovative processes. The studies can broadly be divided into two categories based on the level of analysis: (1) network level studies focus on network topology and its relationship to innovative output and (2) node level studies focus on positional characteristics of individual nodes and relationship to innovation selection and output. In this study, we focus on node level studies to examine the effect of individual status on innovation selection.

Node level studies can also be classified by network extent into intra-organization and inter-organization studies. Intra-organization studies focus on networks of individuals within an organization and examine the effects of the networks on innovative output. Inter-organization studies examine the influence of a network of individuals (both within and outside an organization) or a network of stakeholder or partners outside the boundaries of an organization.

Table 1. Innovation studies using node-level measures

	Network Extent	*Measures*	*Aim/Result*
Patrakosol & Olson, 2007	Inter-org.	Degree centrality	Effect of collaboration on IT innovation. Result: Close collaborations lead to evolutionary innovation
Singh, 2007	Inter-org.	Degree centrality and extensions	Impact of collaboration on innovation selection and future productivity
Bell, 2005	Both	Degree centrality	Impact of managerial network on innovation. Result: higher degree leads to higher innovation
Nerkar & Paruchuri, 2005	Intra-org.	Bonacich power, structural holes	Impact of inventor positions on innovation selection.
Singh, 2005	Both	Shortest paths	Effect of shortest path on innovation selection
Ahuja, 2000	Inter-org.	Node degree, structural holes	Effect of measures on the organizations' innovative output. Result: degree – positive, structural holes – negative.
(Podolny & Stuart, 1995)	Inter-org.	Degree centrality	Study the factors that determine innovation selection

Note: Studies marked in **bold** specifically focused on innovation selection. These are discussed in detail in the text.

Table 1 presents a representative set of previous work [5, 7, 8, 11, 19, 32, 33] that uses node level measures to study knowledge networks and innovation. Among the studies that focused on innovation selection, Singh [8] found that the degree centrality of an inventor did not have a significant effect on the impact of his/her innovation. Podolny & Stuart [19] found that inventor-status did not have a significant positive impact of the selection of their innovation. They also found that the status of other related innovators in the network had a positive association on the impact of the focal innovation. However, both these studies used degree to establish status which may not be an accurate representation of inventor status in a knowledge network and thus may not give the right results. Singh [5] found that as shortest path length between inventors increased, they were less likely to cite each other. The study acknowledged that presence of multiple paths between inventors may have different affects. Nerkar & Paruchuri [7] found that an inventor had a significant positive impact on the selection of his/her innovation. We used a statistical technique similar to their study, however, we proposed a new measure better suited to the problem domain.

Table 2. Key statistics of nanotechnology patents extracted from USPTO

Date range	1976-2006
Patents	97, 562
Assignee institutions (organizations)	26, 304
Inventors (individuals)	189, 045

The testbed in this study included the top organization by the number of inventors

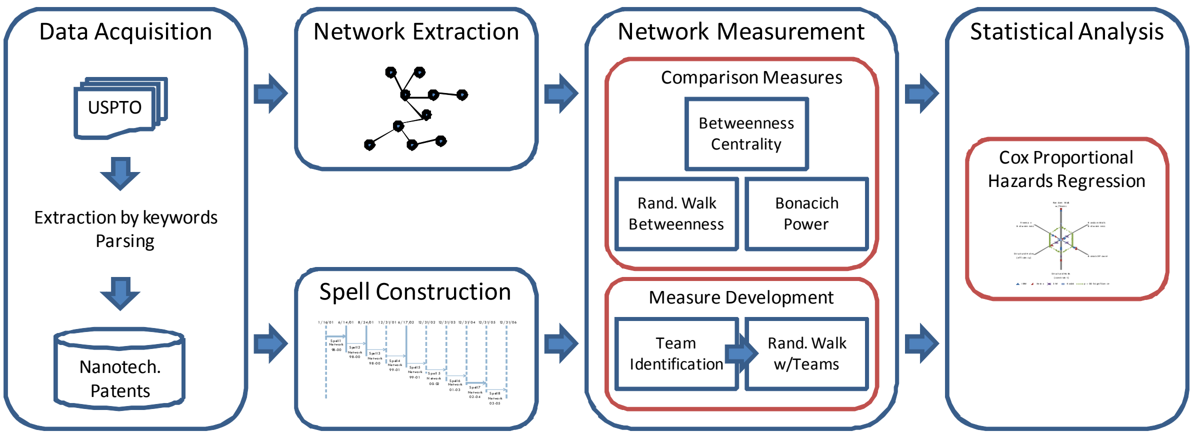

Figure 1. Research design and process

3. Research design and testbed

Figure 1 shows the research design and process used to acquire data, extract knowledge networks, develop the network measures, and statistically evaluate the effect of network measures on innovation selection.

3.1. Data acquisition

This study used nanotechnology related patents from the United States Patent and Trademark Office (USPTO). This is because patents are considered to be excellent indicators of innovation in organizations [7, 34]. We selected nanotechnology as it is an innovative field that promises fundamental changes to a wide variety of research domains [35]. The patents were limited to the nanotechnology field by using a keyword search on the full text of the patent (for details see [36]). Each patent document was downloaded using a web spider and parsed to extract information on assignee organization, inventors, issue and application dates, citation, and other fields. Table 2 shows the statistics of the patents obtained.

(International Business Machines – IBM). Large organizations are usually in business for a longer period of time and tend to have more established knowledge networks and better developed internal knowledge. This is important in this study as an organization with a quality internal knowledge base is likely to specialize in a certain area and recombine its own knowledge to produce innovations.

3.2. Network extraction

A knowledge network based on common affiliations was extracted for inventors in IBM. In the network, each node was represented by an inventor and two inventors were linked to each other if they were listed on the same patent. Such a network reflects strong associations as inventors listed on the same patent are likely to have intense collaboration while working on that innovation. Such an observed collaboration marks the beginning of a strong tie that lasts beyond the collaboration date [5, 37].

3.3 Spell construction

A spell divides the life of a patent (from issue date till the end of the dataset) into time periods. Each time period is used as a data point to determine the effect of various variables on the citation (or no citation) of the patent in that spell. In line with prior research [7, 19], spells of up to 1 year were created for each patent. The first spell began at issue date and ended at either the close of the same year or at the citation date if the patent is cited within that year. The next spell began at the start of the year - if the previous spell ended at the previous year or at the citation date - if the previous spell ended in a citation.

The strategy of dividing time into spells effectively measures the effect of network measures of individuals who coauthored that patent on the citation of a patent through its entire life. The measures were computed on the basis of the network three years prior to the spell. That is, only inventors who had applied for patents in the three years prior to the spell were considered to be part of the network for that spell. This is in line with previous research that shows that inventors are productive for three to five years [38]. We found support for this with the median productive life-span of an inventor being 3-5 years in our dataset.

3.4. Network measurement

In this sub-section, we describe the social network measures that were used to determine the status of inventors in the network. Based on previous studies [7, 19] three measures were selected for comparison: betweenness centrality, Bonacich power, Random walk centrality. We also proposed a new measure called Random Walk w/Teams which is likely to suit this problem domain more than other measures.

3.4.1. Betweenness centrality (BC)

This is a well-known and widely used betweenness measure proposed by Freeman (1979). Intuitively, BC of node *k* is defined as the fraction of times that a node *i* needs the node *k* in order to reach node *j* via the shortest path. BC for a node *k* is calculated as [24]:

$$\sum_{i}\sum_{\substack{j \\ i\neq j\neq k}}\frac{g_{ikj}}{g_{ij}}$$

where, g_{ij} is the number of geodesic paths from *i* to *j* and g_{ikj} is the number of these geodesics that pass through *k*.

3.4.2. Bonacich power (BP)

The BP measure suggests that a node is important to the extent that it is connected to other important nodes. The importance of a node emerges recursively from the pattern of connections among all the inventors (this concept is similar the PageRank [39] algorithm). Details on the implementation of the measure can be found in Bonacich [31].

3.4.3. Random walk centrality (RW)

RW is a relatively new measure that includes contributions from all paths between nodes to calculate betweenness [29]. RW for node k is equal to the number of times a random walk from *i* to *j* passes through *k* - averaged over all *i* and *j*. Thus, the measure includes paths that may not be optimal, though shorter paths still contribute more to the score. Details on the method can be found in Newman (2005). The measure also assumes that on each step during the random walk, information passes from the current node to one adjacent node (i.e., no parallel duplication). However, this assumption may not hold in knowledge networks of the kind studied here. Diffusion of information may happen in parallel within teams and follow a random walk outside them.

3.4.4 Random walk with Teams (RWT)

Innovative organizations generally have teams of inventors working together on projects. The communication levels within these project teams are much higher as compared to between teams [40]. We contend that there is close to parallel duplication of knowledge within teams, i.e., if one member of a team receives knowledge that is pertinent to the project, then all members of the team have access to it. With this assumption, we propose to add team identification to the RW measure to address the issue of parallel duplication.

Team identification

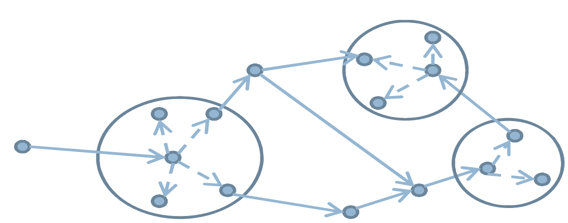

Figure 2. Flow of knowledge within an organization with teams

Figure 2 shows a schematic of the assumed flow of knowledge within an organization with three teams. The circles in the figure indicate teams of inventors. The dashed arrows indicate parallel information duplication (within teams). The solid arrows indicate random walks between teams. As can be seen in the figure, we assume that knowledge diffuses in a parallel fashion within teams and flows through random walks outside them. In order to use this phenomenon to establish the status of inventors, we need to identify teams within an organization. We used the community identification algorithm proposed by Girvan & Newman [41] to identify teams in the collaboration network. The algorithm identifies cohesive communities using an iterative edge removal strategy based on betweenness measures. It has been shown to be superior to other community detection techniques [42] specially in scientific collaboration networks.

RW Betweenness calculation

Once teams are identified, the network is collapsed with each team replaced by a single composite node. This preserves the connections between all team members and individuals outside. Random walk betweenness (using the Newman (2005) procedure for RW) scores are then calculated for each node in each component of the collapsed network. Thus, the RWT measure calculates RW betweenness score for entire teams taken as one node and single inventors who are not part of any teams. For statistical analysis, every individual in a team received the same RWT score. We believe that these new RWT scores will explain innovation diffusion better and identify individuals whose knowledge is valued for recombination within an organization.

3.5 Statistical analysis

We used patent citation data for statistical analysis since citation leaves a trail of how a patent builds upon previous innovations. Unlike in academic papers, patent citations are not likely to be superfluous [5, 43]. In addition, studies show that correlation between patent citations and actual knowledge diffusion is high [34, 44]. An intra-organizational citation of a patent is a choice made by the organization (and individuals within) to build on knowledge contained in the patent. In this study, we aim to ascertain if the network position of an inventor influences this selection process. Thus, the dependent variable is the citation of a patent by inventors other than those involved in its creation.

Cox proportional hazard models were used to study the effects of network measures on patent citation (other models including Weibull and Exponential were tested however, they were not found to be a good fit). The models used a repeated event hazard rate analysis to incorporate spells. These models were used since they incorporate both censored and uncensored cases, i.e., whether or not the patent was cited. Three kinds of variables were included in the statistical model: dependent variable: patent citation, explanatory variables: each of the social network measures, and control variables: factors (other than network measures) that effect patent citations. Since multiple inventors may be assignees on the same patent, a maximum of the social network scores among all the inventors for that patent was used as an independent variable.

Based on various previous studies, the following control variables were included:

- Calendar age: this controls for improvements in technology since the start of the dataset [19]. As databases and information retrieval techniques improve, patents are easier to find and cite.
- Patent age: a patent is more likely to be cited if it has been around longer.
- Patent age squared: as the age of a patent increases, it may be outdated and less likely to be cited.
- Scope of a patent: The USPTO uses a technology classification system where a patent is classified into one or more technology classes. Studies have used the number of classes to represent the breadth of a patent that has an effect on the patent's impact [45]. We include this variable as the number of USPTO technological classes the patent is classified into.
- Number of claims: the number of claims indicates the value of a patent and the technological spaces it occupies or protects [45].
- Age of prior art: Patents that build on old knowledge have different citation patterns than new ones [46]. This is calculated as the median of the difference between grant year of the focal patent and that of the references cited within that patent.
- Self citation: A self-citation indicates confidence of an individual on his/her work. This may encourage other individuals to cite that work [7]. This is operationalized as a categorical variable which is a '1' if patent has been self-cited before spell, and '0' otherwise.
- Number of patent references/Number of academic references: Patents that cite more prior art may have a different influence than others. They may be in technologically crowded classes and have a different influence as compared to other patents [3].
- Team size: One patent can have multiple

inventors. When determining the effect of social network measures on the citation of a patent, we used the maximum of the measures among all the inventors of that patent. Including team size as a control variable accounts for effects of all inventors on the patent [7] since a heterogeneity in team members can lead to differences in the influence of a patent [47].

- International presence of an inventor: Knowledge flows across international boundaries are different [8] and may affect the citation of a patent. This is operationalized as a variable that is set to '1' if any inventor on patent is outside the U.S. and '0' otherwise.
- Time to grant: A patent that is granted immediately may be uncontroversial and simple. A complex patent may take time to get approved. This might affect citation rates (Nerkar & Paruchuri, 2005).
- Technological effects: This controls for the difference in patenting across technological areas. Certain technological areas may cite a larger number of prior patents than others. This is operationalized as dummy variables for the top 20 classes (with ties retained) each organization patents in.

Based on the results obtained by previous node-level studies and the assumptions for knowledge flow in a network, three hypotheses were examined in this study with each in its own independent model. Each hypothesis tested the effect of an inventor's status (as established by a network measure) on the likelihood of his/her knowledge being selected by other inventors. These are summarized in Table 3.

Table 3. Hypotheses tested

	Measure	*Effect*
H1	Betweenness centrality	No effect
H2	Bonacich power	No effect
H3	Random walk w/Teams (proposed)	Positive effect

4. Experimental results and discussion

In this section, we show the results of the Cox proportional hazards analysis. Four models were constructed for IBM – one for control variables and one for each of the three measures. The correlation matrix (not shown in the paper) shows that all correlations except those between some network measures are low and do not pose multi-collinearity problems. The high correlations between some network measures do not cause problems since each regression model contains only one measure.

Table 4 shows the results for all four Cox regression models for IBM. The first column lists all the network measures and control variables. Each model (from Model 1 - Model 4) contained one network measure. As can be seen in Model 0, the likelihood of a patent being cited decreased (i.e., the hazard ratio < 1.0) with an increase in patent age and time to grant. This may be because as a patent increases in age, its contents become less relevant in a fast moving field like nanotechnology. The likelihood of patent citation increased with an increase in calendar age. The reason behind this may be the better availability of information retrieval technology and databases which make it easier to find a patent and cite it. The likelihood also increased with an increase in the claim count and academic references. As mentioned before, the claims are the number of 'spaces' occupied by the patent. More the spaces occupied, more likely the patent will be cited [45]. The significance of these control variables generally persisted across all models.

Model 1 shows that the BC score of inventors was found to have an insignificant effect on the citation of their patents. Thus, the measure does not adequately explain the effect inventor status on the selection of his/her knowledge for innovation. As discussed before, BC is based on the assumption that knowledge flows along shortest paths that may not suit this problem domain. Random walk [29] was also found to be insignificant (Model 2). This may be because even though the RW measure incorporates random diffusion and is a betweenness measure, it does not incorporate the influence of teams. Individuals between teams draw knowledge from diverse communities and the RW w/Teams measure is likely to perform better in this problem domain.

The Bonacich power of an inventor was found to be significant in Model 3. The measure has also been found to be significant by prior studies [7]. This implies that an inventor's knowledge is perceived to be more important (and cited) if he/she is connected to other important inventors. However, the absolute effect of the BP measure is very small since the hazard ratio is close to 1.0. A hazard ratio of 1.0 indicates that the variable does not increase or decrease the likelihood of a patent citation.

As can be seen from the table (Model 4), the random walk w/teams measure had a significant positive association with the citation of a patent. A unit increase in the RWT score of an inventor associated with a patent increases the likelihood of the patent being cited by 87%. This shows that the position of the inventor in a network positively effects the selection of his/her knowledge for recombination. There are three components to the

RWT measure that may have contributed to its significance. Firstly, the focus on diversity of knowledge which implies that knowledge of inventors who have high betweenness scores is perceived to be valuable by an organization. Inventors with high betweenness are also likely to obtain knowledge from multiple disparate communities that may increase their innovative potential. Secondly, random diffusion is an important part of the RWT measure and this may have contributed to its positive significance. This is because information may not necessarily flow through shortest paths in a knowledge network (as shown by the insignificance of Freeman's betweenness centrality). A third factor is parallel diffusion, the RWT measure takes into consideration that knowledge can diffuse within a team from one individual to multiple individuals. These three assumptions in the RWT measure make it better suited to explain inventor status in the collaboration networks we study here.

Table 4. Cox regression results for IBM

	Model 0	*Model 1*	*Model 2*	*Model 3*	*Model 4*
Bet. centrality		1.3995			
Random walk			1.1211		
Bonacich power				0.9977**	
RW w/Teams					1.8700*
Patent age	0.9981**	0.9998	0.9998**	0.9998*	0.9998**
Calendar Age	1.3132*	1.5295	1.2942	1.4152	1.5933
Class scope	1 class*	1 class*	1 Class*	1 class*	1 class*
Prior age	0.9999	0.9997*	0.9999	0.9999	0.9999
Patent refs.	1.0012	1.0113	1.0012	1.0014	1.0015
Acad. refs.	1.0205*	1.0172**	1.0204*	1.0204*	1.0200*
Team size	0.9780	1.01567	0.975	0.9798	0.9695
International	1.2651	1.5459*	1.2593	1.2863	1.2544
Time to grant	0.9996**	1.0001	0.9996**	0.9996**	0.9996**
Claim count	1.0131**	1.0088	1.0131**	1.0129**	1.0128**
Self cited	1.5362*	1.8402*	1.5178*	1.5383*	1.4987*
Tech. effects	20 classes**	26 classes**	22 classes**	22 classes**	22 classes**

Note: All correlation values above 0.05 are significant at $p < 0.05$ (*)

5. Conclusions

In this study, we examined the role of inventor status in knowledge networks on the selection of knowledge that is recombined to produce innovation in the nanotechnology field. A new network measure based on random walks and team identification (RWT) was proposed to model knowledge flow within an inventor collaboration network. Using empirical methods, it was found that inventor status as measured by RWT had a significant positive relationship with the likelihood that his/her knowledge would be selected for recombination. We believe that the new measure in addition to modeling knowledge flow in a scientific collaboration network will help better understand how innovation evolves within organizations.

In the future, we plan to test other important social network prestige measures like Burt's Structural Hole measures and information measures like flow centrality to test their effect on innovation selection and compare them to the proposed measure. In addition, we also plan to conduct a similar study on multiple large organizations both individually and combined to a larger dataset to provide more validity to our results.

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