A causal analytic model to evaluate the impact of researchers' individual innovativeness on their collaborative outputs

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Abstract
Purpose – The purpose of this paper is to provide a model that tests to what extent researchers' interactions in the early stage of their collaborative network activities affect the number of collaborative outputs (COs) produced (e.g. joint publications, joint grant proposals and joint patents).

Design/methodology/approach – Using self-reports from 100 tenured/tenure-track faculty at a US-based university, partial least squares (PLS) path models are run to test the extent to which researchers' individual innovativeness (Iinnov) affects the number of COs they produced taking into account the tie strength (TS) of a researcher to other conversational partners. Iinnov is determined by the specific indicators obtained from researchers' interactions in the early stage of their collaborative network activities.

Findings – The results indicate that researchers' Iinnov positively affects the volume of their COs. Furthermore, TS negatively affects the relationship between researchers' Iinnov and the volume of their COs, which is consistent with the famous "Strength of Weak Ties" theory.

Practical implications – By investigating the degree of impact of researchers' Iinnov on their CO, college administration could be informed regarding the extent that the social cohesion formed by interpersonal ties affects or drives the collaboration activity that results in COs. When this paper is extended to the entire university, university administration would know the capability of the different colleges, or even the university as a whole, in transforming the ideas embedded in researchers' networks into a productive work in a collaborative manner.

Originality/value – It is one of the foremost attempts to investigate the relationship between researchers' Iinnov during ideation phase and their CO. Moreover, this paper contributes to the literature regarding the transformation of tacit knowledge into explicit knowledge at a university context.

Keywords Data analysis, Social network analysis, Collaborative networks, Partial least squares (PLS) path modeling, Individual innovativeness, Self-reported data

Paper type Research paper

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1. Introduction

Björk and Magnusson (2009) asserted that "innovation can be seen as ideas that have been developed and implemented". When people interact more, the quality of ideas will increase (Björk and Magnusson, 2009). In addition, working as a group or team stimulates idea generation or ideation (Paulus, 2000). Ideation is a creative process which requires the retrieval of existing knowledge from memory, as well as the combination of various aspects of existing knowledge into novel ideas, where an idea is the basic element of thought that can be either concrete or abstract (Paulus and Brown, 2007). Because of the associative nature of memory, working in a group and attending to the ideas of others could both spark a good idea from an individual's less accessible area of knowledge and could lead to a novel combination of ideas (Paulus and Brown, 2007). Thus, collaboration is necessary for creativity, innovation and problem solving (Paulus and Brown, 2007, John-Steiner, 2000).

From the network perspective, Lovejoy and Sinha (2010) find that individual innovativeness (Iinnov) during the ideation phase is accelerated by two properties:

(1) an individual's participation in a "maximal complete sub-graph" or clique, which maximizes the number of parallel conversations; and

(2) the knowledge gain (KG) of individuals via their conversational churn, which means that an individual constantly changes his/her conversational partners through a large set of conversational partners.

In addition to these two properties, perceived self-innovativeness should also be considered as an accelerator of the Iinnov (Hurt *et al.*, 1977; Keller and Holland, 1978; Cheney *et al.*, 1986; Goldsmith, 1991; Flynn and Goldsmith, 1993; Kleysen and Street, 2001). In the literature, investigating the relationship between researchers' Iinnov during the ideation phase and their collaborative output (CO) is not addressed. This is because the studies in the literature mostly focus on final outputs such as publications and citations because of the major limitation of collecting information with regard to researchers' interaction in the early stage of their collaborative activities. The findings of Lovejoy and Sinha (2010) can be used to test to what extent researchers' Iinnov affects the number of their COs (joint publications, grant proposals and patents). As knowledge creation is an important step which supports idea generation (McAdam, 2004) and the strength of an interpersonal connection affects how easily the created knowledge can be transferred to other individuals (Szulanski, 1996; Uzzi, 1997; Hansen, 1999; Reagans and McEvily, 2003), it is also important to consider the tie strength (TS) of a researcher to other conversational partners while investigating the relationship between researchers' Iinnov and their COs. Thus, this study seeks an answer for the following question:

Q1. What is the impact of researchers' individual innovativeness (as determined by the specific indicators obtained from their communication network) on the volume of their collaborative outputs, taking into account the tie strength of a researcher to other conversational partners?

2. Literature review and hypotheses

2.1 The effect of individual innovativeness on researchers' collaborative outputs

Communication between individuals enhances innovation because they acquire knowledge because of exposure to different and diverse ideas from others (Albrecht and Hall, 1991; Weenig, 1999; Kratzer *et al.*, 2004; Smith *et al.*, 2005). Similarly, Rogers (1995) purported that "we must understand the nature of networks if we are to comprehend the diffusion of innovations fully" because communication involves information exchange in interpersonal networks, whereby individuals accumulate knowledge. Using the network of interpersonal interactions, increasing current knowledge levels by incorporating new inputs from others and implementing new ideas from these inputs is an important source of Iinnov for researchers (Björk and Magnusson, 2009; Paulus and Nijstad, 2003). Thus, acquiring ideas from the repositories of different knowledge sets, selecting and adopting the most useful ones and recombining and transforming these acquired ideas in a novel way are the key steps to be able to innovate. Coleman (1988) viewed the social cohesion engendered by a closed network structure as the source of willingness to transfer knowledge between individuals because this type of network structure reduced the risk of knowledge exchanges because group norms and rules facilitated cooperation between individuals by constraining exploitive behavior (Gargiulo and Benassi, 2000; Reagans and McEvily, 2003; Lovejoy and Sinha, 2010). Additionally, individuals should constantly change their interaction partners to be exposed to different ideas, thereby increasing their current knowledge levels and they should utilize their innate innovativeness. Our study proposes that Iinnov during the ideation phase is accelerated by three properties, each of which is discussed below in detail.

2.1.1 Researchers' rate of participation in "Complete graph(s)". Network structure facilitates the creation of innovation (Rost, 2011). To understand this network structure effect, two competing network views in social capital theory, the network closure effect and structural holes effect, can be visited (Lin, 1999; Burt, 2001; Adler and Kwon, 2002). First, Coleman (1988) highlighted that networks with closure in which every individual is connected, that is, dense sub-groups, is the primary source of the creation of innovation because individuals are more likely to share tacit knowledge (Adler and Kwon, 2002). Second, Burt (1992) purposed that networks with weak network architecture or containing "structural holes" are also the source of the creation of innovation because individuals who locate themselves to close these structural holes can function as a bridging or bonding actor and combine both novel ideas and non-redundant information which flow through different clusters (Ahuja, 2000; Gargiulo and Benassi, 2000; Burt, 2001, 2004; Cowan and Jonard, 2007). In Coleman's view, the presence of cohesive ties (i.e. network closure) promotes a normative environment which helps create trust and cooperation and strengthen the solidarity between individuals (Gargiulo and Benassi, 2000; Rost, 2011). A maximal complete sub-graph, or a clique (Figure 1), is the maximum number of actors who have all possible ties present among themselves (Lovejoy and

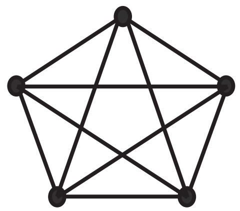


Figure 1.
"A maximal complete sub-graph" consisting of five actors

Sinha, 2010). Referring to Coleman's network closure definition, a clique type of network structures can be used to measure the degree of cohesiveness between individuals. Several studies highlighted that there was a positive impact of the clique type of network structures on individuals' innovativeness (Albrecht and Hall, 1991; Kratzer *et al.*, 2004; Cowan and Jonard, 2004; Hemphälä and Magnusson, 2012). One recent study by Lovejoy and Sinha (2010) also found that Iinnov during the ideation phase was accelerated by the clique type of network structures (called just "complete graphs" in their study).

2.1.2 Researchers' KG via conversational churn. Innovation depends on the availability of knowledge (Du Plessis, 2007). Knowledge is defined as "the state of knowing and understanding", and knowledge management involves building and managing knowledge stocks (Alavi and Leidner, 2001). Bozeman and Rogers (2002) proposed a churn model that is a process during which individual researchers accumulate or gain knowledge, thus enhance their capabilities, as a result of interactions within networks (also called knowledge value collective) that is a set of individuals connected by their uses of a body of scientific and technical knowledge. Lovejoy and Sinha (2010) evaluated the churn model effect by performing a network simulation, in which the knowledge of each individual was represented by binary strings consisting of 1s and 0s and altered through an individual's interaction (or conversational exchanges) with others, which is consistent with the cellular automata theory (Kemper, 2006). Thus, the individual reaches to the "great idea" or "aha moment" when 0s in his/her knowledge string are converted to all 1s. They found that Iinnov during the ideation phase was accelerated by two properties. The first one, discussed in previously, is an individuals' participation in a "maximal complete sub-graph"-type network structure (or a cohesive subunit), which maximizes the number of parallel conversations. The second one is the KG of individuals via their conversational churn which is defined as an individual constantly changing his/her conversational partners through a large set of conversational partners. Our study proposes a formula which calculates an individual's KG via conversational churn using empirical data (Section 3.D).

2.1.2 The perceived self-innovativeness of researchers. An individual's personality or innate characteristics contribute to his/her innovativeness (Hurt *et al.*, 1977; Keller and Holland, 1978; Cheney *et al.*, 1986; Goldsmith, 1991; Flynn and Goldsmith, 1993; Kleysen and Street, 2001). Rogers (1995) proposed that individuals were characterized as innovative as long as they early adopt an innovation. However, Midgley and Dowling (1978) criticized this notion in a way that innovativeness could not be dependent on observable phenomena such as the time of adoption, rather it existed only "in the mind of the investigator and at a higher level of abstraction". Flynn and Goldsmith (1993) also defended that Iinnov should be measurable from a global perspective called global innovativeness that is "a personality dimension that cut across the span of human behavior". By using a 20-item questionnaire, Hurt *et al.* (1977) first attempted to assess an individual's innovativeness as his/her personality trait which was defined as "perceived willingness to change". We used the questionnaire developed by Hurt *et al.* (1977) to measure the extent to which a researcher's innate characteristics contribute to his/her innovativeness.

Our study investigates the impact of researchers' Iinnov, as determined by the specific indicators obtained from their interactions in the early stage of their collaborative network activities, on the number of COs that can be considered as a measure of innovative output produced. Then, the following hypothesis is purposed:

H1. There is a positive impact of researchers' individual innovativeness on the volume of researchers' collaborative outputs.

2.2 Tie strength of an individual to other conversational partners

Knowledge creation is an important step which supports idea generation (McAdam, 2004). Informal interpersonal connections between individuals play a critical role in knowledge creation and transfer (Reagans and McEvily, 2003). Additionally, the strength of an interpersonal connection affects the ease with which created knowledge is transferred to other individuals (Reagans and McEvily, 2003; Szulanski, 1996; Uzzi, 1997; Hansen, 1999). In the literature, both strong ties and weak ties, two views of TS, have been purported to enhance an individual's knowledge acquisition (Levin and Cross, 2004). Strong ties between individuals promote information flow about activities within an organizational sub-system, while weak ties between individuals promote information flow about activities outside an organizational sub-system (Friedkin, 1982; Weimann, 1983). Hansen (1999) made a similar point which was that the transfer of tacit knowledge is easier between individuals who have strong ties, whereas the transfer of explicit knowledge is easier between individuals who have weak ties. Krackhardt (1992) showed that strong ties are important, as they generate trust. Therefore, strong ties lead to greater knowledge exchange between individuals by ensuring that knowledge seekers sufficiently understand each other (Krackhardt, 1992; Szulanski, 1996; Uzzi, 1997; Levin and Cross, 2004). Strong ties tend to bond similar individuals to each other and cluster them together; hence, individuals are all connected to each other. Therefore, information obtained via strong ties is more likely to be redundant, and this hinders a network from becoming a channel for innovation (Krackhardt, 1992; Uzzi, 1997). In contrast, weak ties behave like local bridges and reach out to non-redundant information from the disparate parts of the system (Granovetter, 1973; Krackhardt, 1992; Levin and Cross, 2004). Then, weak ties combine the ideas from different sources with fewer concerns regarding social conformity, which positively influences individuals toward their innovative propensities (Rogers, 1995; Ruef, 2002). From another viewpoint, Rost (2011) demonstrated that individuals with strong ties but embedded in weak network structures (structural holes or a peripheral network position) came up with the most innovative solutions. Granovetter (1973) proposed that TS was "a (probably linear) combination of the amount of time, the emotional intensity, the intimacy (mutual confiding) and the reciprocal services which characterize the tie" (Marsden and Campbell, 1984). Our study uses the first three of these four indicators (or dimensions). The amount of time spent was measured by asking the question (Q1) "how frequently do you exchange conversations or ideas?" and was called "frequency" (Marsden and Campbell, 1984, Hansen, 1999). "Closeness" is used as a measure of the emotional intensity of a relationship, and the question (Q2) "how close is your relationship between you and your conversational partner?" was asked to assess this dimension (Marsden and Campbell, 1984; Hansen, 1999). Respondents were asked the question (Q3) "how often do you discuss your work or home personal problems with your conversational partner?", which measures the extent of mutual confiding (intimacy) between individuals (Marsden and Campbell, 1984; Petróczi *et al.*, 2007, Mathews *et al.*, 1998). Based on the discussion made so far, it is also important to consider TS and to test the impact of TS on their Iinnov, the volume of their COs and the relationship between researchers' Iinnov and the volume of their COs. Therefore, this study asserts the following three hypotheses:

H2. There is a non-zero impact of TS on the relationship between researchers' individual innovativeness and the volume of researchers' collaborative outputs.

3. Method

3.1 Development of the questionnaire

The research site, a college of engineering, has mainly researchers who hold both tenured and tenure-track faculty positions, research associates, visiting professors and graduate students to run the research. Our study surveyed the entire population which was composed of 107 researchers who hold both tenured and tenure-track faculty positions. The research associates, visiting professors and graduate students were not considered in this study. The dean of the College of Engineering, one researcher who was on leave of absence during the data collection period and five researchers who were recently hired, totaling seven researchers, were excluded. Therefore, the sample size was reduced to 100 researchers. Table I shows the breakdown of the sample size in terms of demographic attributes. There are six departments in the College of Engineering: Chemical and Biomedical Engineering (CBE), Civil and Environmental Engineering (CEE), Computer Science and Engineering (CSE), Electrical Engineering (EE), Industrial and Management Systems Engineering (IMSE) and Mechanical Engineering (ME) (Cimenler *et al.*, 2014).

The questionnaire was in the paper-and-pencil format. It was first designed in a Web format (http://orisurvey.eng.usf.edu/). However, several researchers during the pilot test or others later commented that filling out the questionnaire in a paper-and-pencil format was easier and more comfortable. Before distributing the questionnaire to all researchers, a researcher from each department was randomly chosen and contacted to conduct a pilot test for the questionnaire. Based on the comments and feedback from the

	Gender		
	Male	Female	Total
Sample	86	14	100
Participants	68	8	76

	Race				
	Asian	Black	Hispanic	White	
Sample	35	4	9	52	100
Participants	28	3	5	40	76

	Department						
	CBE	CEE	CSE	EE	IMSE	ME	
Sample	16	19	17	24	10	14	100
Participants	14	13	10	17	10	12	76

Table I. Number of researchers in each demographic attribute researchers, the content and layout of the questionnaire were updated to facilitate gathering the responses (Cimenler *et al.*, 2014).

The questionnaire was three pages long and contained a total of 26 questions. The first page included two questions, and respondents were asked to make a self-report of the number of both in-progress and completed COs with other researchers with whom they engaged in co-authored or joint publications (in-preparation, [re]submitted or rejected and published), joint grant proposals (in-preparation, declined and funded) and joint patents (rejected, submitted and issued), as well as researchers' names. The names of the researchers from six different departments within the college were already populated in six different tables to facilitate the thought process of the respondents. Each table had a different number of rows because of the different number of researchers in each department and five columns. The first two columns contained the last name and first name information of the researchers populated for each department. The third, fourth and fifth columns were the columns into which the respondent put the number of total in-progress and completed joint publications, grant proposals and patents with other researchers. As it might be hard for the respondents to remember the exact number of their total in-progress and completed COs with other researchers, an ordinal scale was used to facilitate the thought process of the respondents. In the scale, the scores 1, 2, 3 and 4 were assigned to the number of COs of 1 to 2, 3 to 5, 6 to 9 and 10-above, respectively (Cimenler *et al.*, 2014).

The second page included four questions and respondents were first asked to report the names of researchers with whom they exchanged conversations or ideas, as well as the frequency of the exchange. A researcher's frequency of communication with other researchers and strength of closeness and intimacy in their communication ties with other researchers were assessed by a second, third and fourth question and were rated based on a six-point Likert-type scale, six-point Likert-type scale and five-point Likert-type scale, respectively. These questions, denoted by Q2, Q3 and Q4, refer to three dimensions of TS in the social network literature. TS can be assessed by three indicators: the frequency of conversational exchange (Q2), the intensity of the conversational exchange (Q3), mutual confiding or level of intimacy between conversational partners (Q4) (Granovetter, 1973; Marsden and Campbell, 1984). The second page was the same as the first page, except that columns next to the columns across which the researchers' names were populated were kept for reporting the answers for Q2, Q3 and Q4. Moreover, the respondent follows the same procedure which was followed to fill out the questionnaire on the first page. For example, a researcher scanned the names in the table, found his/her conversational partner's name and put a score for the frequency of communication and the strength of closeness and intimacy into the cell next to the researcher's name in a given scale. The third page included the assessment of perceived innovativeness measured by 20 questions, each of which was marked in five-point Likert scale (Hurt *et al.*, 1977; Cheney *et al.*, 1986; McCroskey, 2013). Information for the relations of both the communication (i.e. conversational exchange) and COs between researchers was asked for the past six years up to current study date (between 2006 and 2012). This length of time might be reasonable for reporting the relations of the COs but not of communication because two researchers, for example, talk to each other frequently, while they write a journal or proposal, but when they finish writing the journal or proposal, they do not talk as frequently as they talked in the past. However, the main point was to investigate to what extent the researchers were genuinely acquainted with one another on average from the self-perception perspective. In addition, the time frame, six years, must be the same to maintain a balanced comparison between networks constructed from the relations of both the communication and COs (Cimenler *et al.*, 2014).

3.2 Data collection

The researchers were asked to complete a two-page questionnaire in three steps. First, a mass e-mail from the dean's office was sent out to the researchers in the sample, indicating that each of the researchers would be contacted through either their affiliated department or e-mail. Second, a graduate student from the college of engineering contacted the researchers by either joining their departmental meetings or e-mailing each researcher. The student handed out the paper-and-pencil questionnaire to each researcher in the meeting and made a short presentation about the details of the questionnaire. Additionally, the questionnaire was e-mailed to the researchers who were not present in the meetings as an attachment. Finally, the graduate student followed up with each researcher in the sample in 2-3 weeks for completed questionnaires via e-mail. Completed questionnaires collected from the participants by visiting them directly to protect the confidentiality of their responses. If the questionnaire was not completed yet, then an additional one week was given to the participants for completion before collecting the questionnaires directly from the participants (Cimenler *et al.*, 2014).

Response rates were very low at the end because the number of both fully and partially completed questionnaires received was about ten. Therefore, to increase response rates, each researcher was also contacted personally both to make an in-person delivery of the questionnaire and to explain the purpose of the study and the details. Dillman (2007) discussed the factors improving response rate which can be achieved by in-person delivery. We observed two of those in this study. First, a deliberate effort was made to increase the salience of the experience of receiving the questionnaire; thus, the interaction time required for presenting the questionnaire to the researcher was lengthened. Second, responsibility was assigned to a researcher rather than addressing the request in a general way (Cimenler *et al.*, 2014).

A total of 76 of the 100 tenured/tenure-track faculty members participated in the questionnaire (Table I). It took almost one semester to reach out to our target faculty members and to finalize all responses from the participants. Table II shows the timeline of the steps taken. One potential risk in this study was the low participation rate while collecting the social network data of researchers. If the participation rate is low, then it is difficult to entirely depict connections between researchers, opening up the possibility that the results found in the analyses of the networks will be misleading. However, even if a particular faculty member did not fill out the questionnaire, the connections to non-participants are reported by the participants. Thus, connections of non-participants can be obtained from the perspective of participants. At the end, collaboration information for the full list of researchers is obtained. In this study, information about the connections of 24 non-participants was inferred as explained in the next section.

3.3 Constructing social network data matrixes

Four 100×100 matrixes were constructed from the relational data provided by the researchers: a matrix of communication, joint publications, grant proposals and patents.

Timeline	Steps
During the first week of October, 2012	A pilot test conducted for the questionnaire
In the middle of October, 2012	A mass e-mail from the dean's office was sent out to inform the researchers
During the last two weeks of October, 2012	Questionnaires began to be distributed either in the departmental meetings or through in-person delivery and e-mail
During the first week of November, 2012	A follow-up e-mail was sent to collect the completed questionnaires. The response rate was very low. Therefore, questionnaires were delivered to the researchers in person intensively. An extra one week was given to the participants for uncompleted questionnaires
During the second week of November, 2012	Completed questionnaires continued to be collected and also the questionnaires continued to be delivered in person
During the last week of November and December, 2012	Because of the holiday season, there was minimum response received from the researchers
In the first week of March, 2013	All responses from the participants were finalized

Table II.
Timeline of the steps performed during the data collection

For a particular dyad, the response patterns from the researchers could take one of the five forms:

(1) Both researchers rate each other with an equal score for the frequency of communication and the number of COs.

(2) Both researchers rate each other with a different score for the frequency of communication and the number of COs. In this situation, two cases might happen:
   - One case was that the value of the upper triangle cells was *higher* than the value of the lower triangle cells in the 100 × 100 matrixes.
   - The other was that the value of the lower triangle cells was also *higher* than the value of the upper triangle cells in the 100 × 100 matrixes.

(3) Only one of the researchers rated the other. In this situation, two cases might also happen:
   - One case was that the upper triangle cell contained a value, but lower triangle cell did not in the 100 × 100 matrixes.
   - The other was that the lower triangle cell contained a value, but the upper triangle cell did not in the 100 × 100 matrixes.

Table III summarizes the five possible patterns. "X" and "0" indicate the ratings happening on only one side and non-ratings, respectively. For the purpose of this study, directionality of the networks is not of fundamental importance (Pepe, 2011). This is because the CO networks such as co-authorship networks are analyzed as undirected in the literature. As shown in Table III, we symmetrized the researchers' social network data matrixes by converting the patterns to the undirected edges according to the "maximum" method (Borgatti *et al.*, 2002). All networks constructed from corresponding data matrixes are depicted in Figure 2 using NodeXL version 1.01.229. Table IV illustrates the number of occurrences of these cases in each network. The inter-rater agreement (IRA) percentage in a network was calculated by dividing the total number of occurrences in "Equal-Equal" cases by the total number of occurrences of all cases (e.g. 120 was divided by 1,234 which is the sum of 120, 141, 144, 377 and 452 for the network of communication). In IRA percentage calculation, we omit the cases where both sides did not report a tie to the other, that is, the cases where both sides score 0 (Cimenler *et al.*, 2014).

3.4 Calculation of an individual's knowledge gain

The formula shown in equation (3.1) calculates an individual's KG via conversational churn using empirical data:

$$KG = \sum_{i=1}^{6} n_i + \sum_{i=1}^{6} f(t_i) C_i n_i \tag{3.1}$$

$$f(t) = \frac{2^{\alpha t} - 1}{\max(2^{\alpha t} - 1)} \tag{3.2}$$

Table III.
Five possible cases of reciprocity and the maximum method of symmetrization to undirected edges

Cases	Upper triangle cells	Lower triangle cells	Cases	Upper triangle cells	Lower triangle cells
1	Equal	Equal	1	Equal	Equal
2a	High	Low	2a	High	High
2b	Low	High	2b	High	High
3a	X	0	3a	X	X
3b	0	X	3b	X	X

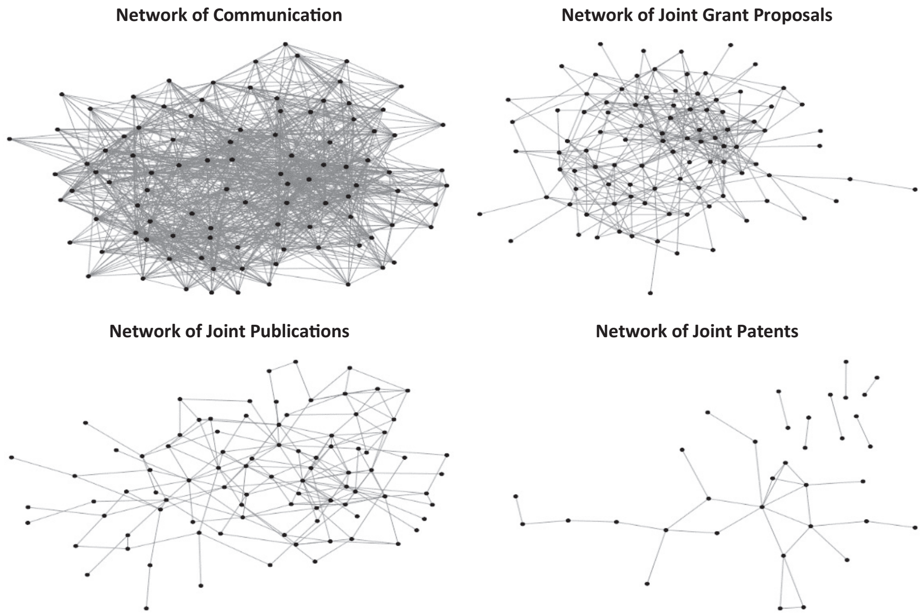


Figure 2.
Visualization of researchers' communication and collaborative output networks

where i refers to the levels (or periods) in the Likert scale. As a six-point Likert scale [once a day(6), once a week(5), once every two week(4), once a month(3), once every two months(2), once every three months(1)] is used in the study, the total number of periods is 6. n_i indicates the total number of conversational partners at each specific level. C_i is the number of conversations a researcher has during a period. For example, in a year, a researcher can have 260 daily conversations (considering business days only), 52 weekly conversations, 26 biweekly conversations, 12 conversations once a month, 6 conversations once every two months and 4 conversations once every three months. $f(t)$ refers to the knowledge growth function by which a researcher accumulates knowledge on a daily basis. As shown in equation (3.2), in this study, 2 was chosen as the base in the function of $f(t)$ and α determines the shape of the parabola capturing the growth rate of knowledge. We used 0.05 for α. By incorporating the denominator into $f(t)$, the maximum value of $f(t)$ a researcher's knowledge can grow is 1, which is during the period of three months (Figure 3). Equation (3.1) has two parts. The first part, $\Sigma_{i=1}^{6} n_i$, computes the total knowledge value a researcher extracts from all of his/her reported conversational partners. For example, when a researcher meets with his/her conversational partner to exchange information on Day 0 (a sort of an initial state) assuming that they have not done so for a while (in this study, we assume for three months), the researcher can obtain the maximum value of knowledge from the conversation, which is 1. Thus, the researcher can obtain the value of 1 from each of his/her conversational partners. The second part, $\Sigma_{i}^{6} f(t_i)C_i n_i$, computes how much total KG a researcher can obtain from the conversations with his/her partner if he/she meets with the same researcher the next day, a week later, two week later, a month later, two

Cases	Network of communication	Network of joint publications	Network of joint grant proposals	Network of joint patents
1	120	38	81	9
2a	141	14	20	2
2b	144	16	21	2
3a	377	68	113	11
3b	452	60	132	11
Inter-rater agreement (%)	9.72	19.39	22.07	25.71

Notes: "1" = the value of the upper and the lower triangle cells were equal; "2a" = the value of the upper triangle cells was higher than the value of the lower triangle cells; "2b" = the value of the lower triangle cells was higher than the value of the upper triangle cells; "3a" = the upper triangle cells contained a value, but lower triangle cells did not; "3b" = the lower triangle cells contained a value, but the upper triangle cells did not

Table IV. The number of occurrences of five possible cases in each network and inter-rater agreement percentage

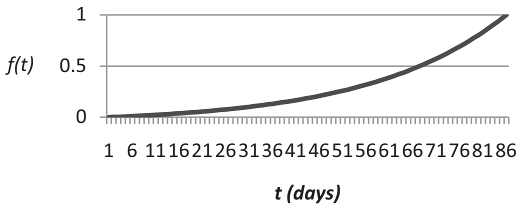


Figure 3. Knowledge growth function

months later or three months later. This part takes into account the fact that if the researcher meets with the same partner next day, then it is less likely that they exchange new information, but if they wait more, then it is more likely that they exchange new information. Therefore, KG of the researcher if he/she waits for one day is less than KG of researcher if he/she waits for a week, and KG of the researcher if he/she waits for a week is less than KG of the researcher if he/she waits for two weeks and so on. Using the values of 0.05 for α and 2 for the base in $f(t)$ ensures that the value of knowledge growth for a researcher are moderately kept low for the interactions: once a day, once a week and once every two week, but maximally high for the interactions: once a month, once every two months and once every three months.

3.5 Sample data for statistical modeling

For the 100 tenured/tenure-track faculty members, nine variables are available. That is, a 100 $\times$ 9 data matrix was compiled. The variables included in the data set are researchers' rate of participation in "complete graph(s)"; researchers' KG via their conversational churn; the perceived self-innovativeness score of researchers; the number of joint publications, grant proposals and patents; and researchers' total scores for the frequency of communication with other researchers and the strength of closeness and intimacy in their communication ties with other researchers. Researchers' rate of participation in "complete graph(s)" was computed from an actor-by-actor clique co-membership matrix using UCINET version 6.308. The perceived self-innovativeness score of researchers was measured by using a 20-item questionnaire and the score received for each researcher was computed (McCroskey, 2013). The number of joint publications, grant proposals and patents was calculated by averaging the rows or columns of data matrixes constructed from CO tie information provided by participants. For a researcher, three dimensions of TS (i.e. "frequency", "closeness" and "intimacy") were recorded in three 100 $\times$ 100 data matrixes constructed via three questions answered by the researchers in the survey. Table V shows three cases that were encountered in the data matrixes.

Total scores for three dimensions of TS should be calculated for each researcher. The calculation was done in two steps. First, three data matrixes constructed for each TS indicator were converted into new data matrixes by a method used in the study of Mathews *et al.* (Mathews *et al.*, 1998). The method was revised and applied to three cases

	Researcher	Researcher's partner
Case 1 (Both scored each other)		
Researcher		X
Researcher's partner	X	
Case 2 (Only a researcher scored his/her partner)		
Researcher		X
Researcher's partner		
Case 3 (Only a researcher's partner scored the researcher)		
Researcher		
Researcher's partner	X	

Table V.
The cases observed in matrixes

in a way as shown in the following method to convert the data matrixes for tie strength indicators:

3.5.1 Case 1 (Both scored each other). Both a researcher and his/her partner get scored **3** in case:

- both the researcher's score for his/her partner is *greater* than the researcher's mean score for all of his/her communication partners; and
- his/her partner's score for the researcher is *greater* than the partner's mean score for all of his/her communication partners.

Both a researcher and his/her partner get scored **2** in case:

- both the researcher's score for his/her partner is *greater* than the researcher's mean score for all of his/her communication partners; and
- his/her partner's for the researcher is *lower* than mean score for the partner's mean score for all of his/her communication partners.

Or:

- both the researcher's score for his/her partner is *lower* than the researcher's mean score for all of his/her communication partners; and
- his/her partner's score for the researcher is *greater* than the partner's mean score for all of his/her communication partners.

Both a researcher and his/her partner get scored **1** in case:

- both the researcher's score for his/her partner is *lower* than the researcher's mean score for all of his/her communication partners; and
- his/her partner's score for the researcher is *lower* than the partner's mean score for all of his/her communication partners.

3.5.2 Case 2 (Only a researcher scored his/her partner). Both a researcher and his/her partner gets scored **2** in case:

- The researcher's score for his/her partner is *greater* than the researcher's mean score for all of his/her communication partners.

Both a researcher and his/her partner gets scored **1** in case:

- The researcher's score for his/her partner is *lower* than the researcher's mean score for all of his/her communication partners.

3.5.3 Case 3 (Only a researcher's partner scored the researcher). Both a researcher and his/her partner gets scored **2** in case:

- His/her partner's score for the researcher is *greater* than the partner's mean score for all of his/her communication partners.

Both a researcher and his/her partner gets scored **1** in case:

- His/her partner's score for the researcher is *lower* than the partner's mean score for all of his/her communication partners.

This method ensures that two researchers get higher credit (e.g. get scored 3) in case both researchers' scores for one another is greater than the average score of their own communication partners. Additionally, by this method, new data matrixes contains researchers' Likert scores for one another at the same scale because Q2, Q3 and Q4, each of which asks for three dimensions of the TS are in different Likert-type scales. Second, either each column or each row of these converted data matrixes was summed to obtain the total score for each TS indicator for a researcher.

4. Results

4.1 Partial least squares path modeling

Structural equation modeling (SEM) is a statistical technique that enables the researchers to construct unobservable variables measured by indicators and to test and estimate the casual relationships between those LVs (Haenlein and Kaplan, 2004). There are two approaches to estimate those relationships: the covariance-based approach and the variance-based [or partial least square (PLS)] approach. The former uses maximum likelihood estimation (MLE) to minimize the difference between the sample covariance matrix and the covariance matrix predicted by the proposed theoretical model, and MLE assumes that the joint distribution of variables in the model follows a multivariate normal distribution, whereas the later maximizes the explanation of variance by estimating the partial model relationships in an iterative sequence of ordinary least squares (OLS) regressions (Urbach and Ahlemann, 2010, Monecke and Leisch, 2012). The PLS approach originally developed by Wold (1985) offers several minimal requirements of restrictive assumptions compared to the covariance-based approach that can primarily be attributed to Jöreskog (1978), who introduced the particular formulation which is the LISREL model (Monecke and Leisch, 2012) (Table VI).

The PLS path modeling is a "soft" SEM technique because it has very few distribution assumptions and few cases can suffice, unlike the "hard" SEM technique, which requires heavy distribution assumptions and several hundreds of cases (Tenenhaus *et al.*, 2005). The PLS path modeling is more suitable for a theoretical framework that is not fully crystallized, a complex model that has a large number of indicators and LVs, a model that has LVs constructed in a formative way (i.e. arrows from indicators are directed to LVs) and data that do not satisfy the assumptions of multivariate normality, independence and large sample size (Chin and Newsted, 1999, Wetzels *et al.*, 2009, Henseler *et al.*, 2009). This study uses social network metrics such as researchers' rate of participation in "complete graph(s)" as variables in the model, meaning that the assumption of independence of observations of each other is violated for those variables. Therefore, running the PLS path modeling over the data set used in

Latent variables	Observable variables		
Tie strength of an individual to others (TS)	Frequency	Closeness	Intimacy
Collaborative outputs (CO)	The number of joint publications	The number of joint grant proposals	The number of joint patents
Individual innovativeness (Iinnov)	Researchers' rate of participation in "complete graph(s)"	Researchers' knowledge gain via their conversational churn	The perceived self-innovativeness score of researchers

Table VI.
Assignment of observable variables to latent variables

this study is more suitable. The model validation in PLS path models is an attempt to assess whether two stages of a model (the measurement model and the structural model) fulfill the quality criteria for empirical work (Urbach and Ahlemann, 2010). Therefore, the path models must be analyzed and interpreted for those two stages (Urbach and Ahlemann, 2010; Henseler *et al.*, 2009; Monecke and Leisch, 2012; Chin, 2010).

The measurement (or outer) model is defined as the relations between indicators and LVs, and it is evaluated in the first stage. It can be constructed as either reflective way (outwards directed) or formative way (inwards directed) based on the uni-dimensionality or homogeneity of the block of indicators (Diamantopoulos, 2006). All blocks are considered homogenous, if Cronbach's alpha is higher than 0.7 (Tenenhaus *et al.*, 2005, Esposito Vinzi *et al.*, 2010). In this study, Cronbach's alphas in all models were very close to this threshold value, indicating that selecting the reflective way was appropriate. In a reflective model, the relationship between each indicator, p, and its LV, ξ_q, is shown by a simple linear regression in equation (4.1a):

$$x_{pq} = w_{p0} + w_{pq}\xi_q + \varepsilon_{pq} \tag{4.1a}$$

$$E(x_{pq}|\xi_q) = w_{p0} + w_{pq}\xi_q \tag{4.2b}$$

where w_{pq} is the loading (or weight) associated to the p-th indicator for q-th LV and ε_{pq} is the related error term (Esposito Vinzi *et al.*, 2010). The assumption for this model is that the error term ε_{pq} has a zero mean and is uncorrelated with LV, ξ_q. Then, equation (4.1a) is reduced to equation (4.2b).

The structural (or inner) model is defined as the relations between LVs and is evaluated in the second stage. Each LV, $\xi_{q'}$, is regressed on other Q LVs, ξ_q, shown as:

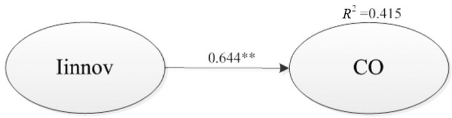
$$\xi_{q'} = \beta_{q'0} + \sum_{q=1}^{Q} \beta_{q'q} \times \xi_q + \nu_q \tag{4.4a}$$

$$E(\xi_{q'}|\xi_q) = \beta_{q'0} + \sum_{q=1}^{Q} \beta_{q'q} \times \xi_q \tag{4.4b}$$

Where $\beta_{q'q}$ are regression coefficients (or inner weights) between LVs and ν_q is the error term related to $\xi_{q'}$ (Esposito Vinzi *et al.*, 2010; Tenenhaus *et al.*, 2005). As the assumption is the error term ν_q which has zero mean and no correlations with LVs $\xi_q$in the model, equation (4.4a) is reduced to equation (4.4b) (Henseler *et al.*, 2009). PLS algorithm first assigns arbitrary initial outer weights and estimates LVs using these initial weights. After the estimation, OLS regression is run between estimated LVs to find the inner weights, and the previously estimated LVs are updated based on these inner weights. In other words, the inner weights are estimated using the calculated LV scores in accordance with the specified network of structural relations. The estimation of the outer weights is iterated until the convergence is observed by means of the alternation of the *outer* and the *inner* estimation steps (Esposito Vinzi *et al.*, 2010). The estimation of outer weights from the updated LV estimates is done using either individual OLS regression per indicator if outer model is a reflective construct or a multiple regression if outer model is a formative construct. The estimation procedure is called partial because it solves block one at a time via alternating the single and multiple linear regressions (Esposito Vinzi *et al.*, 2010). During the step where OLS regression is performed between LVs, PLS regression can be used if LVs are highly correlated (Esposito Vinzi *et al.*, 2010). The PLS path modeling results for Models 1 and 2 are illustrated in Figures 4 and 5 along with Tables VII through X. The next section discusses each stage in detail (Table VII-X).

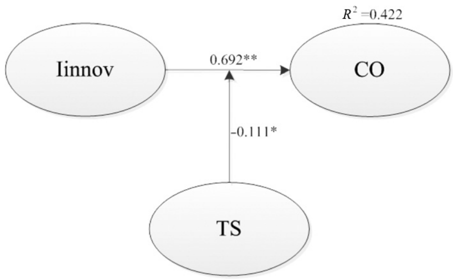
4.2 Analysis and evaluation of partial lease squares models

4.2.1 Assessment of measurement models. A measurement model is assessed with regard to the reliability and validity of the LVs in the model. Once the outer model shows



Notes: 0.05 < **; 0.1 < *

Figure 4. Illustration of Model 1



Notes: 0.05 < **; 0.1 < *

Figure 5. Illustration of Model 2

Table VII. Latent variable loadings and assessment of measurement model for Model 1

	Individual innovativeness (Iinnov)	Collaborative outputs (CO)
Cpart	0.837	0.458
Kgain	0.863	0.630
Sinnov	0.583	0.348
Publication	0.510	0.870
Grant	0.659	0.863
Patent	0.314	0.696
Cronbach's α	0.656	0.756
CR	0.811	0.853
AVE	0.595	0.662
Sqrt (AVE)	0.771	0.814
LV correlations	0.644(Iinnov-CO)	

Notes: Cpart = researchers' rate of participation in "complete graph(s)"; Kgain = researchers' knowledge gain via their conversational churn; Sinnov = the perceived self-innovativeness score of researchers; Publication = the number of joint publications; Grant = the number of joint grant proposals; Patent = the number of joint patents the evidence of sufficient reliability and validity, it will be more meaningful to evaluate the inner path model estimates (Henseler *et al.*, 2009). The measurement models were assessed by the following criteria summed up by Urbach and Ahlemann (2010).

4.2.1.1 Internal consistency reliability (ICR). There are two criteria to assess ICR: a Cronbach's alpha (α) measure and a composite reliability measure. Cronbach's α is a measure of internal consistency, and it is used to measure how closely related a set of items are as a group (Cronbach, 1951). The composite reliability (CR) measure relaxes the Cronbach's α assumption that all scale items are equally related to the attendant LV (Urbach and Ahlemann, 2010). Otherwise, Cronbach's α will tend to underestimate the ICR of LVs. Both of these measures were close and above the threshold value of 0.70, which indicated the adequate internal consistency (Urbach and Ahlemann, 2010).

4.2.1.2 Indicator reliability (IR). A LV should explain a substantial part of each indicator's variance, which is usually at least 50 per cent (Henseler *et al.*, 2009). Then, a variable and set of variables will be consistent about what it really intends to measure. To assess IR, indicator loadings should be both statistically significant at the 0.05 significance level and higher than 0.7 (square root of 50 per cent) (Chin, 1998, Urbach and Ahlemann, 2010). The significance of both LV loadings and the associations between LVs is determined via the bootstrap procedure that is a

	Redundancy	H^2	F^2	GoF
Iinnov	0.000	0.238	0.238	0.361
CO	0.275	0.335	0.244	

Note: H^2 = cross-validated communality, F^2 = cross-validated redundancy and GoF = goodness of fit index

Table VIII. Assessment of structural model for Model 1

	Individual innovativeness (Iinnov)	Collaborative outputs (CO)
Cpart	0.835	0.453
Kgain	0.863	0.629
Sinnov	0.584	0.348
Publication	0.510	0.874
Grant	0.658	0.857
Patent	0.315	0.701
Cronbach's α	0.656	0.756
CR	0.811	0.854
AVE	0.595	0.664
Sqrt (AVE)	0.771	0.815
LV correlations	0.642(Iinnov-CO)	

Table IX. Latent variable loadings and assessment of measurement model for Model 2

	Redundancy	H^2	F^2	GoF
Iinnov	0.000	0.231	0.231	0.287
CO	0.280	0.337	0.263	

Table X. Assessment of structural model for Model 2 resampling method (Efron and Tibshirani, 1993). In this procedure, the proposed model is run several times (this study ran 1,000 times) using repeated random samples of each items to construct a distribution for each association. Thus, where the original value falls in this distribution is investigated by calculating a *t*-value statistics (or related p-value). While running bootstrap resampling procedure in the SmartPLS, the option of "individual changes" for sign changes was selected (Henseler *et al.*, 2009). All LV loadings in two models were significant at the 0.05 level, and they were close to or mostly higher than the threshold value of 0.70.

4.2.1.3 Convergent validity (CV). A set of indicators representing the same underlying construct should converge or demonstrate a unidimensionality compared to the indicators representing other constructs. To assess CV, average variance extracted (AVE) is commonly used, measuring the amount of variance that LV captures from its indicators relative to the amount because of the measurement error (Fornell and Larcker, 1981). AVEs for all LVs across both models were all above 0.50 (threshold value), which indicated sufficient CV. This should be interpreted that all LVs were able to explain more than half of the variance of its indicators on average (Henseler *et al.*, 2009).

4.2.1.4 Discriminant validity (DV). Any single construct (or LV) should be different from the other constructs in a proposed model. In other words, two conceptually different constructs should exhibit sufficient difference (Henseler *et al.*, 2009). There are two commonly applied criteria to assess DV: the cross-loadings and the Fornell–Larcker criterion. In the cross-loading criterion, the loadings of each LV are expected to be higher than all of its cross-loadings with other LVs in the proposed model (Chin, 1998; Henseler *et al.*, 2009). Then, it can be inferred that there is a sufficient difference between constructs. The Fornell–Larcker criterion requires that a LV has to share more variance with its assigned indicators than with any indicators of other LVs (Chin, 1998; Henseler *et al.*, 2009). Then, according to the Fornell–Larcker criterion, DV is assessed by that the AVE of each LV should be greater than squared correlations with other LVs (Henseler *et al.*, 2009). With cross-loadings criteria, the LVs in both models indicated a moderate DV. With the Fornell–Larcker criterion, a square root of AVE for an LV was compared to the LV's squared correlation with any other LV, and it was again observed that the LVs in both models indicated a moderate DV.

4.2.2 Assessment of structural models. Exogenous LVs are the constructs that do not have any predecessors or only have arrows originating from them in the structural model, whereas endogenous LVs are the constructs which has one or more arrows leading into it (Monecke and Leisch, 2012). A structural model (also called inner model) is assessed to determine the significance of the inner paths or hypothesized paths and its explanatory power using the amount of variance accounted for by the endogenous constructs (Hair *et al.*, 2011). The structural models were assessed by the following criteria:

4.2.2.1 Coefficient of determination. R^2 (also called coefficient of determination) measures the amount of variance in the construct that is explained by the model (Chin, 2010). In other words, it measures the relationship of a construct's explained variance to its total variance. Chin (1998) considers R^2 values of 0.67, 0.33 and 0.19 in PLS path model as *substantial*, *moderate* and *weak*, respectively. As seen in both model results, R^2 values were in between the moderate and substantial levels of strength. For example, R^2 value in Model

1 was 0.415, meaning that approximately 42 per cent of variance in construct CO was explained by the exogenous construct Iinnov.

4.2.2.2 Evaluation of path coefficients. The individual path coefficient of the PLS structural model is interpreted as standardized beta coefficients of ordinary least squares regressions (Henseler *et al.*, 2009; Hair *et al.*, 2011). The path coefficients are tested by assessing the direction, strength and the level of significance (the bootstrap resampling method with 1,000 resamples was used to test the significance). Testing the path coefficients provides a partial empirical validation of theoretically assumed relationships (i.e. hypotheses) between constructs (Henseler *et al.*, 2009). Path coefficients showing insignificance and signs contrary to hypothesized direction do not support a prior hypothesis, whereas paths showing significance and a sign fitting empirically support the casual relationship (Hair *et al.*, 2011). The values for the path coefficients in PLS models are given in the standardized form (i.e. between 0 and 1). The path coefficients corresponding to the two hypotheses are statistically significant in both models.

4.2.2.3 Redundancy index (RI) or redundancy. RI is a measure of the quality of the structural model for each endogenous block by taking the measurement model into account (Tenenhaus *et al.*, 2005). In other words, RI measures the portion of variability of the manifest variables connected to the endogenous LV explained by the LVs directly predicting the same endogenous LV (Esposito Vinzi *et al.*, 2010). It is the measure of the quality of structural model for each endogenous construct and calculated by multiplying the average communality of a construct (i.e. AVE) by R^2 of the same construct (Tenenhaus *et al.*, 2005). The following redundancy assessment scale was derived by substituting the minimum average of AVE of 0.50 as suggested by Fornell and Larcker's (1981) and the Chin's (1998) proposed scale for R^2 values at substantial, moderate and weak level in the equation defining redundancy (redundancy = communality $\times$ R^2); $\text{Redundancy}_{\text{substantial}} = 0.34$, $\text{Redundancy}_{\text{moderate}} = 0.17$ and $\text{Redundancy}_{\text{weak}} = 0.10$. Redundancy in both models ranged from moderate to substantial.

4.2.2.4 Cross-validated (communality and redundancy) index. Besides checking the magnitude of R^2 to assess the predictive relevance, the predictive sample reuse technique, called the Stone-Geisser test criterion (or Q^2), can also be used (Chin, 2010). The Q^2 test statistics is a jackknife version of the R^2 statistics (Tenenhaus *et al.*, 2005). Chin (1998) stated that Q^2 statistics is a measure of how well-observed values are reconstructed by the model and its parameter estimates. Calculation of Q^2 involves omitting (or blindfolding) one case at a time, re-estimating the model parameters by using the remaining cases and predicting the omitted case values based on the remaining parameters (Tenenhaus *et al.*, 2005). Q^2 statistics can be obtained through two ways: *cross-validated communality* Q^2, also called H^2, in which prediction of the data points is made by the underlying LV score and *cross-validated redundancy* Q^2, also called F^2, in which prediction is made by those LVs that predict the block in question (Tenenhaus *et al.*, 2005). $Q^2 > 0$ implies the model has predictive relevance, whereas $Q^2 < 0$ represents a lack of predictive relevance. For both models, blindfolding procedure has been performed using $G = 7$ (G is the omission distance. For further discussion of G, please see Tenenhaus *et al.*) (Tenenhaus *et al.*, 2005, p. 175). The value of Q^2 was greater than 0 in both models, indicating that the models has predictive relevance.

4.2.2.5 Goodness of fit index (GoF). GoF index evaluates the model performance by taking both measurement and structural model into consideration and, thus, offer a single measure for the overall prediction performance of the model (Esposito Vinzi *et al.*, 2010). GoF index is calculated by the following formula: GoF $= \sqrt{\overline{AVE} \times \overline{R^2}}$. Threshold values were calculated by plugging a cut-off value of 0.5 for communality and the cut-off values for R^2 proposed by Chin (1998) into the formula. The baseline values for $GoF_{substantial}$, $GoF_{moderate}$ and GoF_{weak} were obtained 0.58, 0.41 and 0.31. Only GoF index for peers has a fit for the weak level. Both models indicated the moderate and weak GoF values, concluding that the models had an adequate explaining power in comparison with baseline values.

5. Discussion

Model 1 corresponding to *H1* presents high and positive value of the path coefficient, indicating that for one-unit change in researchers' Iinnov, COs increases by 0.644. Then, this indicates that the conversion rate of researchers' ideas into the number of their COs is high in the college of engineering. Knowledge is divided into two types: explicit and tacit (Smith, 2001). Explicit or codified knowledge is easily transmittable to another person by either writing it down or articulating it, for example, user manuals, documents, whereas tacit or non-codified knowledge is difficult to transfer by either writing it down or articulating it, and it requires direct experience, for example, using an complex equipment and ability to speak languages (Smith, 2001). Based on the definition of tacit and explicit knowledge, the constructs Iinnov and CO can be considered as tacit and explicit knowledge, respectively. Then, testing *H1* attempts to fill the gap in knowledge creation literature, which is the process of the conversion of tacit knowledge into explicit knowledge (also called "externalization") (Nonaka, 1994, Nonaka and Von Krogh, 2009, Herschel *et al.*, 2001).

Model 2 corresponding to *H2* tests the moderating effect of researchers' strength of interpersonal connections in the impact of researchers' Iinnov on their COs. In PLS, the moderating effect is the interaction term which is built by the products of each indicator of the independent latent variable Iinnov with each indicator of the moderator variable TS (Henseler and Fassott, 2010). From Model 2, it can be observed that there is a low and negative moderating effect of TS, indicating that the theory of "strength of weak ties" proposed by Granovetter (1973) rules the process of the conversion of tacit knowledge into explicit knowledge. This indicates that the weaker ties researchers have with others in the early stages of their collaborative activities, the more COs they have. The result also matches up with the finding of Hansen (1999), which indicated that the transfer of explicit knowledge was easier between individuals who have weak ties.

6. Conclusion

This study proposes two models that investigate the relationship between researchers' Iinnov and their CO. PLS path modeling does not require the assumptions of multivariate normality, independence of observations and large sample size. We used social network metrics such as researchers' rate of participation in "complete graph(s)" as variables in the model, meaning that the assumption of independence of observations is violated, then running the PLS path modeling over the data set used in this study is more suitable. A formula, which measures an individual's KG via conversational churn using empirical data, was proposed. Two properties accelerating Iinnov which was found in the study of Lovejoy and Sinha (2010), participation in a "maximal complete sub-graph" or clique and KG via conversational churn, was empirically tested and found that both of these properties were statistically significant.

The findings of this study can offer implications for college and university administrations, as well as for policymakers. For example, by investigating the degree of impact of researchers' Iinnov on their CO, college administration is informed regarding the extent that the social cohesion formed by interpersonal ties affects or drives the collaboration activity that resulted in COs. When this study is extended to the entire university, university administration knows the capability of the different colleges, or even the university as a whole, in transforming the ideas embedded in researchers' networks into a productive work in a collaborative manner. Then, information concerning the extent to which researchers' Iinnov affects their CO can be used for the evaluation of different colleges in a university. In the case of low impact, university administration should initiate to devise policies, for example, polices encouraging informal institutional arrangements or programs in which informal group meetings occur to mediate the exchange of knowledge or ideas informally. In the case of extending the study to the entire university, if small-sized universities have just about the same relative amount of impact as large-sized universities, then there will be no economies of scale in this matter (Melin and Persson, 1996). Furthermore, performance which considers the impact of researchers' interactions in the early stage of their collaborative network activities on their final COs can be compared between different size universities using the model.

This study has three major limitations. First, we intended to capture the in-progress collaborative relations in a self-reported way, as well as the completed collaborative relations; however, there is an issue of accuracy when collecting self-reported data because of biased responses and poor memory (Lee and Bozeman, 2005; Vasileiadou, 2009). For example, respondents do not want to report CO ties, especially joint patents, for confidentiality reasons. Moreover, it is highly possible that respondents might not remember all of their CO ties; therefore, they enter incomplete information. A future study can be made to compare the overlaps of the networks constructed by self-reported data with the networks constructed by database information. Despite these concerns, there are many recent studies using the self-report method (Duque *et al.*, 2005; Sooryamoorthy and Shrum, 2007; Van Rijnsoever *et al.*, 2008; Ynalvez and Shrum, 2011). Second, when this study is applied to other colleges and disciplines, some of these four networks disappear. For example, writing joint grant proposals in a college of business is not as common as in a college of engineering. Moreover, some colleges and disciplines such as college of education and business have a decreased tendency to issue patents, and in some disciplines such as humanities and history, single-authored papers are more valuable than co-authored papers. Furthermore, this study can be run for other colleges of engineering in different universities (e.g. small- or large-sized, research-oriented) to understand whether the findings of this study are more or less specific for the chosen sample. Third, selecting the values of base and α differently in the knowledge growth function, $f(t)$ affects the output obtained from the function itself and the shape of the parabola capturing the growth rate of knowledge. Therefore, a sensitivity analysis can be run for the different values of KG which is obtained by using different $f(t)$s to understand how the results differ in the same model. Moreover, other types of $f(t)$s such as S-shaped functions can also be considered for knowledge growth.

References

Adler, P.S. and Kwon, S.-W. (2002), "Social capital: prospects for a new concept", *The Academy of Management Review*, Vol. 27 No. 1, pp. 17-40.

Ahuja, G. (2000), "Collaboration networks, structural holes, and innovation: a longitudinal study", *Administrative Science Quarterly*, Vol. 45, pp. 425-455.

Alavi, M. and Leidner, D.E. (2001), "Review: knowledge management and knowledge management systems: conceptual foundations and research issues", *MIS Quarterly*, Vol. 25, pp. 107-136.

Albrecht, T.L. and Hall, B. (1991), "Relational and content differences between elites and outsiders in innovation networks", *Human Communication Research*, Vol. 17 No. 4, pp. 535-561.

Björk, J. and Magnusson, M. (2009), "Where do good innovation ideas come from? Exploring the influence of network connectivity on innovation idea quality", *Journal of Product Innovation Management*, Vol. 26 No. 6, pp. 662-670.

Borgatti, S.P., Everett, M.G. and Freeman, L.C. (2002), *Ucinet for Windows: Software for Social Network Analysis*, Analytic Technologies, Harvard, MA.

Bozeman, B. and Rogers, J.D. (2002), "A churn model of scientific knowledge value: internet researchers as a knowledge value collective", *Research Policy*, Vol. 31, pp. 769-794.

Burt, R.S. (1992), *Structural Holes: The Social Structure of Competition*, Harvard University Press, Cambridge, MA.

Burt, R.S. (2001), "Structural holes versus network closure as social capital", in Lin, N., Cook, K.S. and Burt, R.S. (Eds), *Social Capital: Theory and Research*, Transaction Publishers, New Brunswick, NY.

Burt, R.S. (2004), "Structural holes and good ideas", *American Journal of Sociology*, Vol. 110, pp. 349-399.

Cimenler, O., Reeves, K.A. and Skvoretz, J. (2014), "A regression analysis of researchers' social network metrics on their citation performance in a college of engineering", *Journal of Informetrics*, Vol. 8 No. 3 (July), pp. 667-682, ISSN 1751-1577, available at: http://dx.doi.org/10.1016/j.joi.2014.06.004; www.sciencedirect.com/science/article/pii/S1751157714000571

Cheney, G., Block, B.L. and Gordon, B.S. (1986), "Perceptions of innovativeness and communication about innovations: a study of three types of service organizations", *Communication Quarterly*, Vol. 34, pp. 213-230.

Chin, W. (1998), "The partial least squares approach to structural equation modeling", in Marcoulides, G.A. (Ed.), *Modern Methods for Business Research*, Lawrence Erlbaum Associates, Mahwah, NJ.

Chin, W. (2010), "How to write up and report PLS analyses", in Esposito Vinzi, V., Chin, W.W., Henseler, J. and Wang, H. (Eds), *Handbook of Partial Least Squares: Concepts, Methods and Applications*, Springer, Berlin, New York.

Chin, W. and Newsted, P.R. (1999), "Structural equation modeling analysis with small samples using partial least squares", in Hoyle, R. (Ed.), *Statistical Strategies for Small Sample Research*, Sage Publications, Thousand Oaks, CA.

Coleman, J.S. (1988), "Social capital in the creation of human capital", *The American Journal of Sociology*, Vol. 94, pp. 95-120.

Cowan, R. and Jonard, N. (2004), "Network structure and the diffusion of knowledge", *Journal of Economic Dynamics and Control*, Vol. 28 No. 8, pp. 1557-1575.

Cowan, R. and Jonard, N. (2007), "Structural holes, innovation and the distribution of ideas", *Journal of Economic Interaction and Coordination*, Vol. 2 No. 2, pp. 93-110.

Cronbach, L.J. (1951), "Coefficient alpha and the internal structure of tests", *Psychometrika*, Vol. 16 No. 3, pp. 297-334.

Diamantopoulos, A. (2006), "The error term in formative measurement models: interpretation and modeling implications", *Journal of Modelling in Management*, Vol. 1 No. 1, pp. 7-17.

Dillman, D.A. (2007), *Mail and Internet Surveys: The Tailored Design Method*, Wiley, Hoboken, NJ.

Du Plessis, M. (2007), "The role of knowledge management in innovation", *Journal of Knowledge Management*, Vol. 11 No. 4, pp. 20-29.

Duque, R.B., Ynalvez, M., Sooryamoorthy, R., Mbatia, P., Dzorgbo, D.-B.S. and Shrum, W. (2005), "Collaboration paradox: scientific productivity, the internet, and problems of research in developing areas", *Social Studies of Science*, Vol. 35, pp. 755-785.

Efron, B. and Tibshirani, R.J. (1993), *An Introduction to the Bootstrap*, Chapman Hall, New York, NY.

Esposito Vinzi, V., Trinchera, L. and Amato, S. (2010), "PLS path modeling: from foundations to recent developments and open issues for model assessment and improvement", in Esposito Vinzi, V., Chin, W.W., Henseler, J. and Wang, H. (Eds), *Handbook of Partial Least Squares: Concepts, Methods and Applications*, Springer, Berlin, New York, NY.

Flynn, L.R. and Goldsmith, R.E. (1993), "A validation of the Goldsmith and Hofacker innovativeness scale", *Educational and Psychological Measurement*, Vol. 53, pp. 1105-1116.

Fornell, C. and Larcker, D.F. (1981), "Structural equation models with unobservable variables and measurement error: algebra and statistics", *Journal of Marketing Research*, Vol. 18 No. 3, pp. 382-388.

Friedkin, N.E. (1982), "Information flow through strong and weak ties in intraorganizational social networks", *Social Networks*, Vol. 3, pp. 273-285.

Gargiulo, M. and Benassi, M. (2000), "Trapped in your own net? Network cohesion, structural holes, and the adaptation of social capital", *Organization Science*, Vol. 11 No. 2, pp. 183-196.

Goldsmith, R.E. (1991), "The validity of a scale to measure global innovativeness", *Journal of Applied Business Research (JABR)*, Vol. 7 No. 2, pp. 89-97.

Granovetter, M.S. (1973), "The strength of weak ties", *American Journal of Sociology*, Vol. 78 No. 36, pp. 1360-1380.

Haenlein, M. and Kaplan, A.M. (2004), "A beginner's guide to partial least squares analysis", *Understanding Statistics*, Vol. 3 No. 4, pp. 283-297.

Hair, J.F., Ringle, C.M. and Sarstedt, M. (2011), "PLS-SEM: indeed a silver bullet", *The Journal of Marketing Theory and Practice*, Vol. 19 No. 2, pp. 139-152.

Hansen, M.T. (1999), "The search-transfer problem: the role of weak ties in sharing knowledge across organization subunits", *Administrative Science Quarterly*, Vol. 44 No. 1, pp. 82-111.

Hemphälä, J. and Magnusson, M. (2012), "Networks for innovation – but what networks and what innovation?", *Creativity and Innovation Management*, Vol. 21 No. 1, pp. 3-16.

Henseler, J. and Fassott, G. (2010), "Testing moderating effects in PLS path models: an illustration of available procedures", in Esposito Vinzi, V., Chin, W.W., Henseler, J. and Wang, H. (Eds), *Handbook of Partial Least Squares*, Springer, Berlin, New York, NY.

Henseler, J., Ringle, C.M. and Sinkovics, R.R. (2009), "The use of partial least squares path modeling in international marketing", *Advances in International Marketing*, Vol. 8, pp. 277-319.

Herschel, R.T., Nemati, H. and Steiger, D. (2001), "Tacit to explicit knowledge conversion: knowledge exchange protocols", *Journal of Knowledge Management*, Vol. 5 No. 1, pp. 107-116.

Hurt, H.T., Joseph, K. and Cook, C.D. (1977), "Scales for the measurement of innovativeness", *Human Communication Research*, Vol. 4 No. 1, pp. 58-65.

John-Steiner, V. (2000), *Creative Collaboration*, Oxford University Press, New York, NY.

Jöreskog, K. (1978), "Structural analysis of covariance and correlation matrices", *Psychometrika*, Vol. 43, pp. 443-477.

Keller, R.T. and Holland, W.E. (1978), "Individual characteristics of innovativeness and communication in research and development organizations", *Journal of Applied Psychology*, Vol. 63 No. 6, pp. 759-762.

Kemper, A. (2006), "Modeling network growth with network theory and cellular automata", *Journal of Modelling in Management*, Vol. 1 No. 1, pp. 75-84.

Kleysen, R.F. and Street, C.T. (2001), "Toward a multi-dimensional measure of individual innovative behavior", *Journal of Intellectual Capital*, Vol. 2 No. 3, pp. 284-296.

Krackhardt, D. (1992), "The strength of strong ties: the importance of philos in organizations", *Networks and Organizations: Structure, Form, and Action*.

Kratzer, J., Leenders, O.T.A.J. and Engelen, J.M.L.V. (2004), "Stimulating the potential: creative performance and communication in innovation teams", *Creativity and Innovation Management*, Vol. 13 No. 1, pp. 63-71.

Lee, S. and Bozeman, B. (2005), "The impact of research collaboration on scientific productivity", *Social Studies of Science*, Vol. 35 No. 5, pp. 673-702.

Levin, D.Z. and Cross, R. (2004), "The strength of weak ties you can trust: the mediating role of trust in effective knowledge transfer", *Management Science*, Vol. 50 No. 11, pp. 1477-1490.

Lin, N. (1999), "Building a network theory of social capital", *Connections*, Vol. 22 No. 1, pp. 28-51.

Lovejoy, W.S. and Sinha, A. (2010), "Efficient structures for innovative social networks", *Management Science*, Vol. 56 No. 7, pp. 1127-1145.

McAdam, R. (2004), "Knowledge creation and idea generation: a critical quality perspective", *Technovation*, Vol. 24 No. 9, pp. 697-705.

McCroskey, J.C. (2013), available at: www.jamescmccroskey.com/measures/innovation.htm

Marsden, P.V. and Campbell, K.E. (1984), "Measuring tie strength", *Social Forces*, Vol. 63 No. 2, pp. 482-501.

Mathews, K.M., White, M.C., Long, R.G., Soper, B. and Von Bergen, C.W. (1998), "Association of indicators and predictors of tie strength", *Psychological Reports*, Vol. 83 No. 3, pp. 1459-1469.

Melin, G. and Persson, O. (1996), "Studying research collaboration using co-authorships", *Scientometrics*, Vol. 36 No. 3, pp. 363-377.

Midgley, D.F. and Dowling, G.R. (1978), "Innovativeness: the concept and its measurement", *Journal of Consumer Research*, Vol. 4, pp. 229-242.

Monecke, A. and Leisch, F. (2012), "semPLS: structural equation modeling using partial least squares", *Journal of Statistical Software*, Vol. 48, pp. 1-32.

Nonaka, I. (1994), "A dynamic theory of organizational knowledge creation", *Organization Science*, 5, 14-37.

Nonaka, I. and Von Krogh, G. (2009), "Perspective-tacit knowledge and knowledge conversion: controversy and advancement in organizational knowledge creation theory", *Organization Science*, Vol. 20, pp. 635-652.

Paulus, P.B. (2000), "Groups, teams, and creativity: the creative potential of idea-generating groups", *Applied Psychology: An International Review*, Vol. 49 No. 2, pp. 237-262.

Paulus, P.B. and Brown, V.R. (2007), "Toward more creative and innovative group idea generation: a cognitive-social-motivational perspective of brainstorming", *Social and Personality Psychology Compass*, Vol. 1 No. 1, pp. 248-265.

Paulus, P.B. and Nijstad, B.A. (2003), *Group Creativity: Innovation Through Collaboration*, Oxford University Press, New York, NY.

Pepe, A. (2011), "The relationship between acquaintanceship and coauthorship in scientific collaboration networks", *Journal of the American Society for Information Science and Technology*, Vol. 62, pp. 2121-2132.

Petróczi, A., Nepusz, T. and Bazsó, F. (2007), "Measuring tie-strength in virtual social networks", *Connections*, Vol. 27 No. 2, pp. 39-52.

Reagans, R. and McEvily, B. (2003), "Network structure and knowledge transfer: the effects of cohesion and range", *Administrative Science Quarterly*, Vol. 48 No. 2, pp. 240-267.

Rogers, E.M. (1995), *Diffusion of Innovations*, Free Press, New York, NY.

Rost, K. (2011), "The strength of strong ties in the creation of innovation", *Research Policy*, Vol. 40 No. 4, pp. 588-604.

Ruef, M. (2002), "Strong ties, weak ties and islands: structural and cultural predictors of organizational innovation", *Industrial and Corporate Change*, Vol. 11 No. 3, pp. 427-449.

Smith, E.A. (2001), "The role of tacit and explicit knowledge in the workplace", *Journal of Knowledge Management*, Vol. 5 No. 4, pp. 311-321.

Smith, K.G., Collins, C.J. and Clark, K.D. (2005), "Existing knowledge, knowledge creation capability, and the rate of new product introduction in high-technology firms", *The Academy of Management Journal*, Vol. 48, pp. 346-357.

Sooryamoorthy, R. and Shrum, W. (2007), "Does the internet promote collaboration and productivity? Evidence from the scientific community in South Africa", *Journal of Computer-Mediated Communication*, Vol. 12 No. 2, pp. 733-751.

Szulanski, G. (1996), "Exploring internal stickiness: impediments to the transfer of best practice within the firm", *Strategic Management Journal*, Vol. 17, pp. 27-43.

Tenenhaus, M., Esposito Vinzi, V., Chatelin, Y.-M. and Lauro, C. (2005), "PLS path modeling", *Computational Statistics & Data Analysis*, Vol. 48 No. 1, pp. 159-205.

Urbach, N. and Ahlemann, F. (2010), "Structural equation modeling in information systems research using partial least squares", *Journal of Information Technology Theory and Application*, Vol. 11 No. 2, pp. 5-40.

Uzzi, B. (1997), "Social structure and competition in interfirm networks: the paradox of embeddedness", *Administrative Science Quarterly*, Vol. 42 No. 1, pp. 35-67.

Van Rijnsoever, F.J., Hessels, L.K. and Vandeberg, R.L.J. (2008), "A resource-based view on the interactions of university researchers", *Research Policy*, Vol. 37 No. 8, pp. 1255-1266.

Vasileiadou, E. (2009), "Stabilisation operationalised: using time series analysis to understand the dynamics of research collaboration", *Journal of Informetrics*, Vol. 3, 36-48.

Weenig, M.W.H. (1999), "Communication networks in the diffusion of an innovation in an organization", *Journal of Applied Social Psychology*, Vol. 29, pp. 1072-1092.

Weimann, G. (1983), "The strength of weak conversational ties in the flow of information and influence", *Social Networks*, Vol. 5 No. 3, pp. 245-267.

Wetzels, M., Odekerken-Schröder, G. and Van Oppen, C. (2009), "Using PLS path modeling for assessing hierarchical construct models: guidelines and empirical illustration", *MIS Quarterly*, Vol. 33, pp. 177-195.

Wold, H. (1985), "Partial least squares", in Kotz, S. (Ed.), *Encyclopedia of Statistical Sciences*, John Wiley & Sons, New York, NY.

Ynalvez, M.A. and Shrum, W.M. (2011), "Professional networks, scientific collaboration, and publication productivity in resource-constrained research institutions in a developing country", *Research Policy*, Vol. 40 No. 2, pp. 204-216.

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