

# Outstanding and ordinary scientists' co-authorship networks in the early career phase

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## ABSTRACT

*How do scientists' ego-centered co-authorship networks affect their research productivity and impact during the early career phase? Do co-authorship networks evolve differently for outstanding scientists vs. ordinary scientists? Our study responded to these questions by demonstrating that scientists' co-authorship network size and betweenness centrality of their co-authorship network positively affected both their research productivity and research impact. Scientists' tie strength diversity of their co-authorship network moderated the relationship between their ego-network size and their research performance. Their co-authorship network's degree centralization moderated the relationship between their betweenness centrality and research performance. Further, the size and betweenness centrality of the co-authorship network were significantly different between the two groups of scientists since their fourth working year. Outstanding scientists had a larger co-authorship network and their positions in the co-authorship network were more central than those of ordinary scientists. Implications for scientists and policy makers in science and higher education are discussed.*

**Keywords:** Co-authorship networks; Research performance; Scientific impact; Early career researchers; Scientometrics assessment.

## INTRODUCTION

Co-authorship is a popular approach to scientific research collaboration in higher education (Feng and Kirkley 2020; Pauli et al. 2019). Previous studies have found that co-authorship is helpful for scientists' performance (Gao, Chen, and Huai 2019; Gonzalez-Brambila, Veloso and Krackhardt 2013; Lee and Bozeman 2005; Li, Liao and Yen 2013) and their academic career (Abbasi, Altmann, and Hossain 2011; Abbasi, Chung,

and Hossain 2012; Abramo, D'Angelo and Murgia 2014; Eisend and Schmidt 2014; He Geng and Campbell-Hunt 2009; Hu, Chen and Liu 2014; Li, Liao and Yen 2013). In addition, co-authorship was found to be a better predictor of building a strong network than the journals one publishes in, or the keywords reflecting one's research area (Zhang 2016). However, the mechanism through which co-authorship affects scientists' performance and their career development is not clear (Letina 2016). In particular, there are several gaps in the literature. First, little research has examined scientists' productivity and impact at the same time (with the exception of Eisend and Schmidt's 2014 study) despite the fact that scientists' performance includes productivity (the number of papers), impact (citation counts, Oguz, Kingsley and John 2014), and the order of authors' names on publications (Abramo, Cicero and D'Angelo 2013). Second, although researchers have analyzed co-authorship networks to describe knowledge flow among co-authors, until recently, most studies have ignored the effect of the characteristics of ego-centered co-authorship networks on scientist performance (Letina 2016; De Stefano and Zaccarin 2015). An ego-centered co-authorship network is a network of a specific scientist (ego) and his/her co-authors (actors) (Letina 2016). A dense ego-centered co-authorship network was found to improve scientists' g-index and citation counts (Abbasi, Altmann and Hossain 2011; Abbasi, Chung and Hossain 2012). Thus, establishing a cohesive ego-centered network (Coleman 1988) or dispersed ego-centered network (Burt 1992) is an important co-authorship strategy for scientists. In addition, an actor's position in the network, which captures his/her social proximity to other actors in a network, is also related to the actor's performance (Gonzalez-Brambila, Veloso, and Krackhardt 2013; Yan and Guan 2018). Given that the characteristics of the network structure and an actor's position in the network should jointly affect the actor's performance (Phelps, Heidl and Wadhw 2012), ego-centered co-authorship networks should be afforded more research attention in order to better understand the effects of co-authorship on scientist performance.

Third, little research has employed longitudinal designs (He Geng and Campbell-Hunt 2009) in examining the evolution of scientists' ego-centered co-authorship networks and their relationship with scientists' career development (Gonzalez-Brambila, Veloso, and Krackhardt 2013). Finally, some important factors for career development such as work experience, age (De Stefano and Zaccarin 2015), gender (Letina 2016), scientific discipline, funding amount, and research team size have generally been ignored in this area. Letina (2016) suggested that such factors should be included in future network models of researchers' performance because being linked with a productive researcher has benefits for the co-author's own productivity.

This study aims to address these gaps. Our sample includes co-authored articles written by a group of outstanding scientists and a group of ordinary scientists, published during their first nine years of working in their fields. We analyzed the impact of scientists' ego-centered co-authorship networks on their productivity and citations and examined how the networks evolved differently between these two groups. Our findings have implications for scientists' early career co-authorship strategies and for policy makers in

science and higher education as well.

## **LITERATURE REVIEW**

### **The Effects of Size and Tie Strength Diversity of Ego-Centered Co-Authorship Networks**

Researchers often collaborate with co-authors to obtain cognitive capital (Xu, Chau and Tan 2014) and diversified knowledge (Feng and Kirkley 2020), and to facilitate creativity (Perry-Smith and Shalley 2003). Research has found that a large collaborative network is associated with improved scientists' performance (Lee and Bozeman 2005). Individuals in collaborative networks can exchange resources and promote cooperation (Nahapiet and Ghoshal 1998); thus, it can be expected that a larger collaborative network will be more likely to possess knowledge and techniques that are novel and non-overlapping, and therefore enhance their ability to engage in creative research (Siciliano, Welch and Feeney 2018).

In addition to the number of ties, it is also important to signify that researchers have worked with each other many times, which facilitates the formation of cooperative norms and trust and, therefore, makes them more productive (Landström and Harirchi 2018). But collaborations that are deeply embedded in one's network are thought to be associated with a homogeneous set of ideas (Zhang 2017), which can hinder creativity (Zhou et al. 2009). Conversely, weak ties can offer individuals embedded in collaborative networks opportunities to access diversified, non-redundant knowledge. But it is worth noting that maintaining a large number of weak ties also requires various costs, such as exchanging high quality information and tacit knowledge. It has been found that weak ties exhibit a reverse U-shaped relationship with creative performance (Perry-Smith and Shalley 2003; Zhou et al. 2009).

Building on this research, Letina (2016) found that whether weak ties or strong ties were beneficial depended on the discipline of the researchers. For instance, in sociology, networks are smaller, and co-authorship is less frequent, especially with regard to collaborating with those from other disciplines and countries. In contrast, in psychology, researchers study more universal subjects and, thus, should be more likely to collaborate with those outside their discipline and country. Letina (2016) reasoned that sociologists may be more dependent than psychologists on their "local" network. Thus, having both strong and weak ties may be beneficial, depending on one's research area.

To help capture both strong and weak ties, in this paper we identify a new tie strength index: tie strength diversity, which refers to the difference in tie strength (e.g. in terms of co-authorship count) between the scientist and each of his/her co-authors. Because tie strength diversity indicates the presence of both strong and weak ties, we expect it to be associated with higher research performance.

Thus we present the following hypotheses:

**Hypothesis 1.** The size of scientists' ego-centered co-authorship networks will be positively correlated with their performance.

**Hypothesis 2:** Scientists' tie strength diversity will be positively correlated with their performance.

**Hypothesis 3:** Scientists' tie strength diversity will moderate the relationship between the size of scientists' ego-centered co-authorship networks and their performance such that when tie strength diversity is high the positive correlation between the size of their network and their research performance will be higher.

### **The Effect of scientists' Betweenness Centrality of Ego-Centered Co-Authorship Network and the Network's Centralization**

Although the size and tie strength of co-authorship may influence scientists' performance, they do not capture a scientist's position within that collaborative network (Wagner, Whetsell and Mukherjee 2019). Centrality reflects an individual's position in a network in relation to other individuals. The existing literature on co-authorship networks has distinguished between three kinds of centrality. First, degree centrality refers to the number of direct connections that a given actor has with other actors. Second, closeness centrality represents the mean shortest distance by which a given actor is separated from all others in a network. Third, betweenness centrality denotes the percentage of direct ties with other actors who have no direct ties with each other and signifies the network position of a "bridge" (Borgatti 2005). This bridge position helps the actor to access resources from different actors (Otte and Rousseau 2002). Specifically, it involves an actor's relative position in spanning the structural holes, which reflects the fact that the actor maintains a favorable position that yields diversified resources and control advantages. So, scientists in a co-authorship network with high betweenness centrality can improve their scientific performance by taking advantage of non-overlapping information (Wagner, Whetsell, and Mukherjee 2019).

Research on the relationship between betweenness centrality and research productivity has been mixed. Some research has found that betweenness centrality is positively correlated with scientists' *g*-index (Abbasi, Chung, and Hossain 2012) and publication citation counts (Li, Liao, and Yen 2013). However, Abbasi, Altmann, and Hossain (2011) found that betweenness centrality was not associated with researchers' *g* index. We propose that these mixed findings may be reconciled by identifying moderators of the relationship between betweenness centrality and research productivity. First, ego-network centralization may be defined as the difference between the highest centrality and the lowest centrality of all actors in the network (Wasserman 1994). It concerns the degree to which the other actors are connected with each other without the ego actor (McCarty 2002), indicating an extension of node-level centrality. In other words, a highly centralized ego-network is a sparse network where a particular node is connected with all nodes in the network but these other nodes are not connected with each other. On the one hand, if all actors have an equal number of links, then the network would be low in network centralization. In summary, a high betweenness centralized network is a sparse network where actors are connected to others who are

separated (Burt 1992). On the other hand, a low betweenness centralized network is a closed network. One study of the research networks of Italian statisticians found that closed networks had a negative effect on individual scientists' performance (De Stefano and Zaccarin 2015). Research has also found out that central authors have a high level of control, receive more citations (Ortega 2014), and a high *g*-index (Abbasi, Chung, and Hossain 2012; Abbasi, Wigand and Hossain 2014) in sparse ego networks. Hence, we offer the following hypotheses:

**Hypothesis 4:** Scientists' co-authorship network betweenness centrality will be positively correlated with their performance.

**Hypothesis 5:** Scientists' co-authorship network degree centralization will be positively correlated with their performance.

**Hypothesis 6:** Scientists' co-authorship network degree centralization will moderate the relationship between scientists' betweenness centrality and their performance such that when their degree centralization is high, the positive relationship between their betweenness centrality and research performance will be higher.

#### **Evolution of Co-Authorship Network in Scientists' Early Career Phase**

The first nine working years comprise an early stage of scientists' academic careers. During this time period, scientists experience the transition from dependent to independent research and often begin taking on a mentorship role. Little research has examined how one's co-authorship network evolves during this time period and its effect on scientists' career development. A cross-sectional survey study in the Netherlands found that scientists in their 40s exhibited the most active network behavior, after which such behavior declined (Laudel and Gläser 2008).

Taking together this finding with our earlier hypotheses about co-authorship network characteristics likely to affect research productivity, we anticipate that the evolution of co-authorship networks in the early career phase will influence scientists' career development. More specifically, we expect that if scientists are able to establish large ego-centered co-authorship networks with high tie strength diversity quickly, their career development should benefit from these advantages. Thus, we present the following hypotheses:

**Hypothesis 7:** During the early career time period, outstanding scientists will have larger ego-centered co-authorship networks than ordinary scientists.

**Hypothesis 8:** During the early career time period, outstanding scientists will have higher tie strength diversity in their ego-centered co-authorship networks than ordinary scientists.

**Hypothesis 9:** During the early career time period, outstanding scientists will have a higher level of betweenness centrality in their ego-centered co-authorship networks than ordinary scientists.

**Hypothesis 10:** During the early career time period, outstanding scientists will have a higher level of degree centralization in their ego-centered co-authorship networks than ordinary scientists.

The research framework is presented in Figure 1.

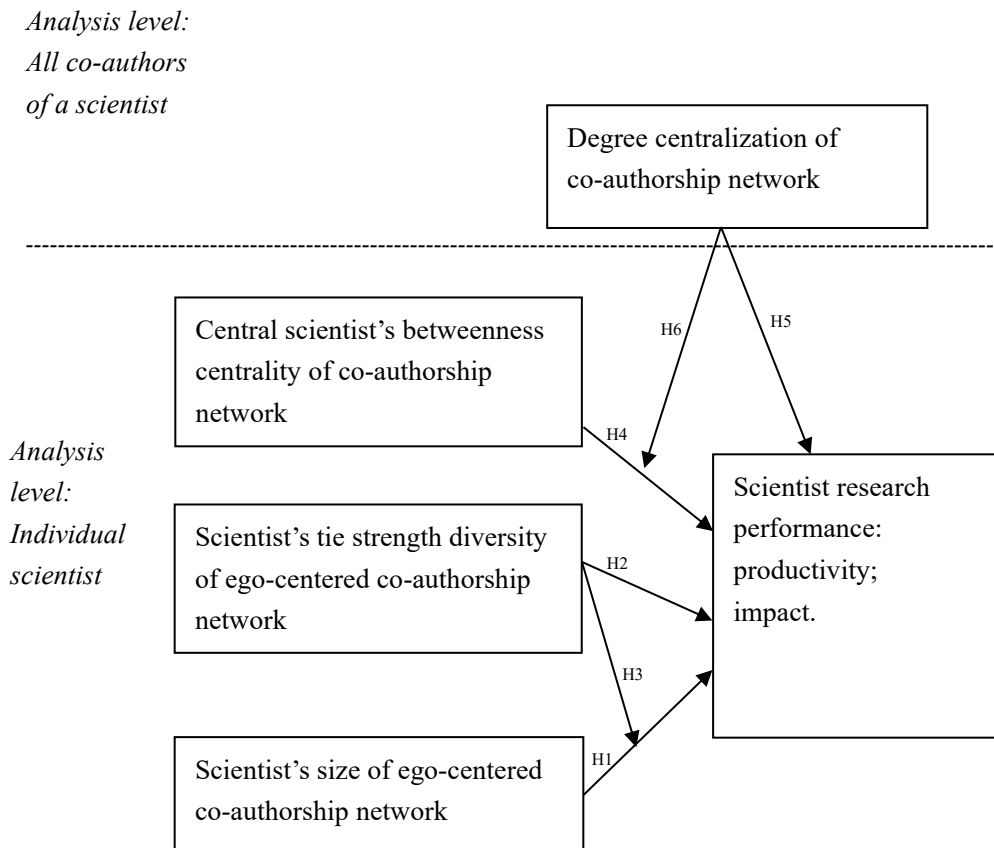


Figure 1: Research Framework and Main Hypotheses

## METHOD

### Sample

With the help of human resources managers in thirty research institutions in China, the pair sampling method was used to select a group of outstanding scientists and a group of ordinary scientists. The sampling strategy of pairs of scientists required that both scientists came from the same research field, earned their Ph.D. degree before 2003, published articles recognized by the Science Citation Index (SCI) or the Engineering Index (EI) during their first nine working years, and both exhibited significant performance in terms of publication productivity, amount of research funding, awards, and promotion speed. In accordance with the requirements of this sampling strategy, 188 pairs of scientists (which means 356 scientists), provided demographic data, including their age, gender, research field, education background, work experience, projects, publications, and overseas visiting scholar experiences. Next, we verified their research field information from the curriculum vitae on their websites (Sabharwal and Hu 2013). After dropping the pairs that could not strictly be matched by research field, pairs with age differences of more than ten years, and those with fewer than nine years of work

experience, the resulting sample included 72 scientists from twelve research institutions<sup>1</sup>. Thirty-nine were categorized as “outstanding” scientists and thirty-three were categorized as “ordinary” scientists. A total of 75 percent were male; 54 percent came from the basic science research field and 46 percent came from the technology development field. The scientists’ ages ranged from 35 to 51 years old (M = 43 years old); 65.3 percent earned their Ph.D. when they were younger than 30 years old, 27.7 percent earned their Ph.D. at 31 to 35 years old, and 7 percent earned their Ph.D. when they were older than 35 years old. A total of 40 percent worked in the same institution where they earned their Ph.D. The scientists were employed by 1 to 4 organizations (M = 1.78); 25 percent of the scientists had visiting scholar appointments overseas for more than 1 year.

The Chi-square and t tests showed that there were no significant differences in the two groups of scientists with regard to gender distribution, home school, age, number of affiliations, oversea experience, and scientific discipline. Academic performance was found to be significantly different between the two groups in terms of the weighted number of articles published in their first nine working years, and weighted citation counts per article in their first nine working years. Taken together, the results indicated it was acceptable to proceed with the two groups for further analyses (See Table 1).

Table 1. Results of Chi-square and t tests

Variable	Outstanding group		Ordinary group			
	Mean	SD	Mean	SD		
<b>Chi-Square test</b>					<b><math>\chi^2</math></b>	<b>Sig.</b>
Gender	1.18	0.38	1.33	0.48	2.26	0.18
Home School	1.69	0.47	1.52	0.51	2.26	0.12
<b>T test</b>					<b>t</b>	<b>Sig.</b>
Age	43.28	4.30	42.45	4.64	0.78	0.44
Number of affiliations	1.79	1.00	1.76	0.94	0.16	0.87
Oversea experience	0.28	0.60	0.21	0.48	0.54	0.60
Scientific discipline	1.51	0.51	1.58	0.50	0.29	0.87
Research productivity	5.75	6.21	2.98	2.05	4.45	0.00
Research impact	23.14	38.18	7.80	10.54	4.09	0.00

### Data Collecting and Cleaning

The sample’s 72 scientists published 3,183 SCI index and EI index articles as of January 1, 2014. Articles that were not published during their first nine working years were not

<sup>1</sup> It should be noted that, 6 institutes provided 2 outstanding scientists and 1 ordinary scientist in a group. Taking into consideration the sample size and difficulty in obtaining matched samples with field data, we accepted this group. Thus, the number of outstanding scientists is slightly larger than that of ordinary scientists.

included. In addition, about 1 percent of the publications had more than fifteen authors. These publications were also not included because having an excessive number of authors makes it difficult to examine network embeddedness (Gonzalez-Brambila, Veloso, and Krackhardt 2013). The final sample included 1,584 articles; 1,501 of which were co-authored with fewer than fifteen authors.

The sample's ego-centered co-authorship networks were established by linking other scientists with our sample's scientists if they co-authored articles together (Uddin, et al. 2012). Each scientist's articles were pooled in a three-year window (Chen and Guan 2010). For example, if a scientist earned the Ph.D. in the year 2000, then the scientists' papers published from 2001 to 2009 were collected. The data from 2001 to 2003, 2004 to 2006, and 2007 to 2009 were used to establish three ego-centered co-authorship networks<sup>2</sup>. The final sample included 205 networks rather than 216 networks (72 scientists \* 3 periods) due to the fact that some scientists had no publications during certain periods.

## **Measures**

### ***Dependent variables***

(a) Research productivity was measured by following the procedure outlined by He, Geng and Campbell-Hunt (2009):

$$\text{Research productivity} = \sum_{i=1}^m A_i.$$

$m$  signifies the number of articles the scientist published in the time period.  $A_i$  is the authorship index, 1 refers to the first or corresponding author, 0.5 is the second author, 0.25 is the third author, and 0.1 refers to all other cases.

(b) Research impact. As suggested by He, Geng and Campbell-Hunt (2009), we excluded self-citations in citation counts of the articles in the subsequent three years of their being published.

### ***Predictor variables***

(a) Network size was measured by the number of non-redundant co-authors of the scientist during the time period.

(b) Tie strength diversity was the standard deviation of all the tie strength between each ego scientist and his/her co-authors. Tie strength was the total co-authorship count an ego scientist had with his/her co-authors during the time period.

(c) Betweenness centrality was measured by the method used by Freeman (1979):

$$C_B(n_i) = \sum_{j < k} g_{jk}(n_i) / g_{jk}$$

$$C'_B(n_i) = \frac{2C_B(n_i)}{(g-1)(g-2)}$$

$C_B(n_i)$  refers to the "betweenness centrality" of "ego  $i$ " in the network.  $g_{jk}$  refers to the number of linkage steps from actor " $j$ " to actor " $k$ ".  $g_{jk}(n_i)$  refers to the number

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<sup>2</sup> It should be noted that the co-authorship networks of the three scientists who earned their Ph.D. degree in 2005 only had two years of data; in this case we weighted their network size of the third period with the coefficient 3/2 to maintain a balance.



of linkage steps from actor “j” to actor “k” involving ego “i”. “g” refers to the whole number of network members;  $C_B^i(n_i)$  signifies normalized betweenness centrality.

(d) Co-authorship network's degree centralization. This measure reflects the potential for authors to transmit information about the ego scientist to each other when the scientist is not there (McCarty 2002). When one actor is the intermediary for all other actors, the network's degree centralization would be one. When all authors have the same number of ties within the network, the degree centralization would be zero (McCarty 2002). Degree centralization was calculated by the formula used by Freeman (1979):

$$C_D(n_i) = \sum_j X_{ij}$$

$$C_D = \frac{\sum_{i=1}^{g-1} [C_D(n^*) - C_D(n_i)]}{\max\{\sum_{i=1}^n [C_D(n^*) - C_D(n_i)]\}}$$

$C_D(n_i)$  refers to the “degree centrality” of author “i” in the network.  $X_{ij}$  is zero or one, and refers to whether author  $i$  has a direct connection with author  $j$ .  $C_D$  refers to the overall degree centrality of the co-authorship network;  $C_D(n^*)$  is the maximum of  $C_D(n_i)$ . “g - 1” refers to the number of authors in the network. All network structure variables were calculated using UCINET.

### **Control variables**

Eight variables were used as control variables. First, scientist mobility and overseas working experience have been found to be positively associated with scientists' research output and career development (Cruz-Castro and Sanz-Menéndez 2010; Jonkers and Cruz-Castro 2013), so the “number of affiliations served” (hereafter referred to as *number of affiliations*) and “number of foreign institutions visited longer than a year” (hereafter referred to as *overseas experience*) were included as control variables. In addition, working in the same institution where one earned one's Ph.D. would likely influence one's collaborations, and, thus, was included as a control variable called home school (working in a different institution from one's Ph.D. = 1, working in the same institution as one's Ph.D. = 2).

Because research has found that collaboration tendencies have been influenced by age (Kyvic and Olsen 2008), gender (female = 1, male = 2) (Abramo, Cicero and D'Angelo 2013), and scientific discipline (technology development = 1, basic scientific research = 2) (Abramo, Cicero and D'Angelo 2013), these demographic variables also served as control variables. Moreover, given that scientists' performance would likely be influenced by work experience, the career period (first three work years = 1, second three work years = 2, third three work years = 3) operated as a control variable. Finally, to prevent a group effect on scientists' performance, the group to which they belonged to was coded as a dummy control variable (outstanding group = 1; ordinary group = 2).

## RESULTS

### Correlations

Table 2 shows the descriptive statistics and correlations of the study variables. Research productivity was positively associated with research impact, network size, tie strength diversity and betweenness centrality ( $r = 0.72, p < 0.01$ ;  $r = 0.53, p < 0.01$ ;  $r = 0.44, p < 0.01$ ;  $r = 0.37, p < 0.01$ , respectively). Research impact was positively associated with network size, tie strength diversity and betweenness centrality ( $r = 0.51, p < 0.01$ ;  $r = 0.14, p < 0.05$ ;  $r = 0.23, p < 0.01$ , respectively). Co-authorship network degree centralization had no significant correlation with research performance, but it was positively associated with network size, tie strength diversity and betweenness centrality ( $r = 0.23, p < 0.01$ ;  $r = 0.36, p < 0.01$ ;  $r = -0.17, p < 0.05$ , respectively).

Table 2: Means, Standard Deviations and Correlations (N = 205)

Variable	Mean	SD	Min	Max	1	2	3	4	5
1. Research productivity	4.51	5.00	0.1	34.40					
2. Research impact	16.26	30.14	0	214.70	0.72**				
3. Network size	15.09	13.44	0	89.00	0.53**	0.51**			
4. Ego's tie strength diversity	3.09	7.82	0	79.60	0.44**	0.14*	0.28**		
5. Ego's betweenness centrality	0.44	0.26	0	1.00	0.37**	0.23**	0.28**	-0.01	
6. Co-authorship network degree centralization	0.37	0.25	0	1.00	0.13	0.11	0.23**	0.36**	-0.17*

Note: \*  $p < 0.05$ , \*\*  $p < 0.01$ , two-tailed test.

### Model Testing

The longitudinal design and nested nature of the data required the testing of our hypotheses with a random effects model through hierarchical linear modeling (HLM) rather than ordinary least squares regression (Kenny and Judd 1986). The level-1 variables included the following: size of co-authorship network, central scientist's tie strength diversity, central scientist's betweenness centrality, and degree centralization of the whole co-authorship network. The level-2 variables included all control variables, which were the time-invariant variables of central scientists: gender, age, home school, number of affiliations, overseas experience, scientific discipline, career period, and group. To minimize the likelihood of multi-collinearity, all level-1 predictor variables were grand-mean centered, in keeping with the recommendation of Hofmann and Gavin (1998).

First, we entered all control variables into the model. Next, size, and tie strength diversity were entered. Third, the interaction of size and tie strength diversity was entered. To prevent potentially unstable regression coefficients caused by multi-collinearity, we

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conducted a chi square test of the change in the deviance and the number of estimated parameters to assess the r-squared change associated with the regression coefficient of the new variables entered into the model (e.g. Zhou et al 2009). We used the full maximum likelihood method to estimate the deviance and number of estimated parameters of the models, and the restricted maximum likelihood method to estimate the coefficients of the variables. The predictor variable coefficients were estimations of the fixed effects, with robust standard errors. R-squared was computed using the following equation:  $R^2 = R^2_{\text{within-group}} \times (1 - ICC(1)) + R^2_{\text{between-group}} \times ICC(1)$ . The intra-class correlation coefficients (ICCs) represented the percentage of the total variance in the dependent variables that is between groups (Bryk and Raudenbush 1992). As shown in Table 3, the goodness of fit difference between model 1.2 and model 1.1, as well as between model 1.3 and model 1.2 were both significant ( $\chi^2 (\Delta \text{ Deviance}, \Delta \text{ Number of estimated parameters}) < 0.01$ ;  $\chi^2 (\Delta \text{ Deviance}, \Delta \text{ Number of estimated parameters}) < 0.01$ , respectively).

**Table 3: Regressions of Size and Tie Strength Diversity on Scientists' Research Performance (N = 205)**

	Number of articles			Citation counts		
	Model 1.1	Model 1.2	Model 1.3	Model 2.1	Model 2.2	Model 2.3
	coefficient	coefficient	coefficient	coefficient	coefficient	coefficient
Intercept	4.42**	4.46**	4.46**	16.06**	16.23**	16.20**
Gender	-0.02	0.89	0.86	2.44	6.44	6.07
Age	-0.13	0.02	-0.02	-0.74	-0.21	-0.67
Home school	-0.62	-0.90	-0.78	-2.23	-3.77	-2.12
Number of affiliations	1.01*	-0.09	-0.06	9.79**	4.82	5.10
Overseas experience	1.36	0.45	0.31	1.70	-1.36	-3.48
Scientific discipline	-1.06	-1.31	-1.25	3.62	0.38	1.23
Career period	0.88**	-0.54*	-0.48*	4.98*	-1.59	-0.92
Group	2.59**	0.62	0.77	15.42**	7.15	8.94*
Network size		0.22**	0.20**		1.04**	0.84**
Tie strength diversity		0.21**	0.14**		0.26	-0.77
Network size × Tie strength diversity			0.01**			0.09**
Deviance	1174.13	1043.64	1035.24	1917.69	1875.93	1852.44
Number of estimated parameters	11	13	14	11	13	14
$\chi^2 (\Delta \text{ Deviance}, \Delta \text{ Number of estimated parameters})$		0.00	0.00		0.00	0.00
R <sup>2</sup>	0.10	0.21	0.23	0.13	0.28	0.32

Note: \* $p < 0.05$ , \*\* $p < 0.01$ .

The regression results show that size, tie strength diversity, and the interaction term were positively associated with the number of publications ( $\beta_{\text{network size}} = 0.20, p < 0.01$ ;  $\beta_{\text{tie strength diversity}} = 0.14, p < 0.01$ ;  $\beta_{\text{network size} \times \text{tie strength diversity}} = 0.01, p < 0.01$ , respectively). Size and the interaction term were positively associated with citation counts ( $\beta_{\text{network size}} = 0.84,$

$p < 0.01$ ;  $\beta_{\text{network size} \times \text{tie strength diversity}} = 0.09$ ,  $p < 0.01$ , respectively). But tie strength diversity was not associated with citation counts ( $\beta_{\text{tie strength diversity}} = -0.77$ ,  $p > 0.05$ ). Thus, Hypotheses 1 and 3 were supported and Hypothesis 2 was partially supported.

The above interaction effects were graphed using the method suggested by Aiken and West (1991). As shown in Figures 2 and 3, when ego tie strength diversity is high, the effects of network size on research productivity and impact are both positive ( $\beta = 0.25$ ,  $p < 0.01$ ;  $\beta = 1.71$ ,  $p < 0.01$ , respectively). When ego tie strength diversity is low, the effect of network size on research productivity and impact is diminished ( $\beta = 0.13$ ,  $p < 0.01$ ;  $\beta = 0.54$ ,  $p < 0.01$ , respectively).

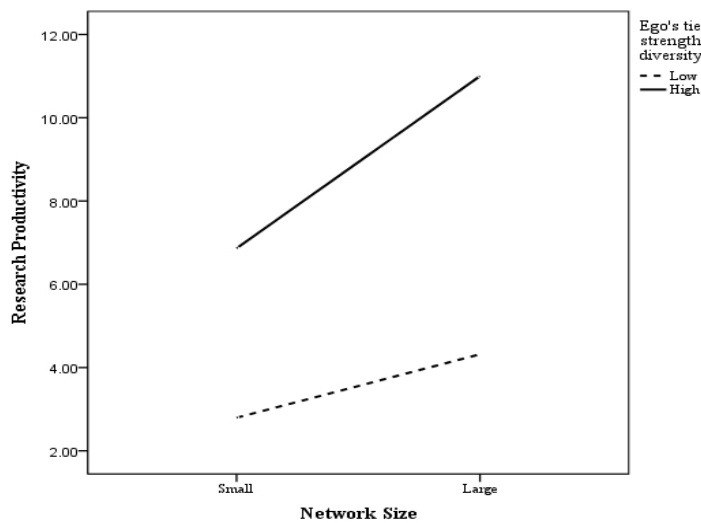


Figure 2: Moderating Effects of Network Size and Ego Tie Strength Diversity on Research Productivity

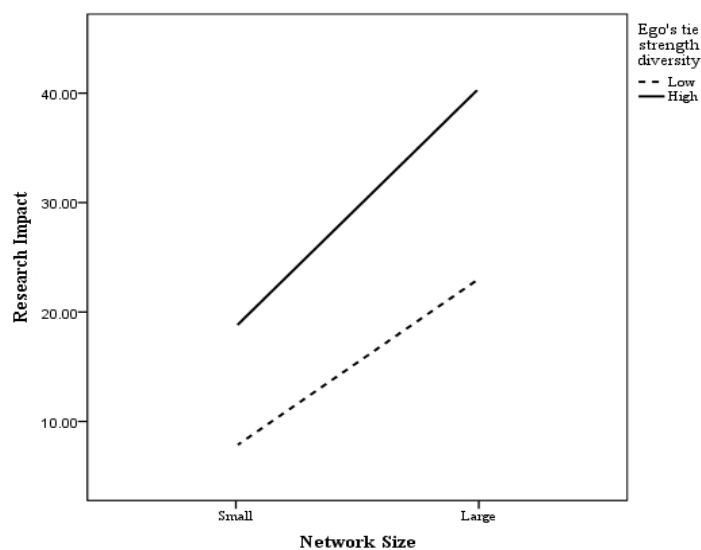


Figure 3: Moderating Effects of Network Size and Ego Tie Strength Diversity on Research Impact

**Outstanding and Ordinary Scientists' Co-Authorship Networks in the Early Career Phase**

The results of the testing of Hypotheses 4, 5 and 6 are presented in Table 4. Ego betweenness centrality, co-authorship network degree centralization, and their interaction were positively associated with research productivity ( $\beta_{\text{ego's betweenness centrality}} = 9.05, p < 0.01$ ;  $\beta_{\text{co-authorship network degree centralization}} = 4.90, p < 0.01$ ;  $\beta_{\text{ego's betweenness centrality} \times \text{overall degree centralization}} = 14.55, p < 0.01$ ). Similar results were found for research impact ( $\beta_{\text{ego's betweenness centrality}} = 32.43, p < 0.01$ ;  $\beta_{\text{co-authorship network degree centralization}} = 25.92, p < 0.01$ ;  $\beta_{\text{ego's betweenness centrality} \times \text{co-authorship network degree centralization}} = 82.51, p < 0.05$ ). Both models fit the data at acceptable levels ( $\chi^2 (\Delta \text{ Deviance}, \Delta \text{ Number of estimated parameters}) < 0.05$ ). Thus, Hypotheses 4, 5 and 6 were supported.

Table 4: Moderating Effects of Ego Betweenness Centrality and Co-Authorship Network Degree Centralization on Research Productivity (N = 205)

	Number of papers			Citation counts		
	Model 3.1	Model 3.2	Model 3.3	Model 4.1	Model 4.2	Model 4.3
	coefficient	coefficient	coefficient	coefficient	coefficient	coefficient
Intercept	4.42**	4.43**	4.44**	16.06**	16.07**	16.12**
Gender	-0.02	-0.01	-0.15	2.44	2.04	1.25
Age	-0.13	-0.11	-0.11	-0.74	-0.58	-0.57
Home School	-0.62	-0.54	-0.57	-2.23	-2.77	-2.94
Number of affiliations	1.01*	0.94*	0.91*	9.79**	9.62**	9.43**
Overseas experience	1.36	1.28	1.23	1.70	1.16	0.94
Scientific discipline	-1.06	-1.21	-1.10	3.62	2.83	3.51
Career period	0.88**	0.27	0.13	4.98*	3.15	2.39
Group	2.59**	1.93*	1.74*	15.42**	13.46**	12.46*
Ego's betweenness centrality		6.08**	9.05**		16.13*	32.43**
Co-authorship network's degree centralization		2.81*	4.90**		14.45*	25.92**
Ego's betweenness centrality × Co-authorship network's degree centralization			14.55**			82.51*
Deviance	1174.13	1146.97	1138.94	1917.69	1911.02	1905.83
Number of estimated parameters	11	13	14	11	13	14
$\chi^2 (\Delta \text{ Deviance}, \Delta \text{ Number of estimated parameters})$		0.00	0.00		0.04	0.02
R <sup>2</sup>	0.10	0.21	0.24	0.13	0.14	0.17

Note: \* $p < 0.05$ , \*\* $p < 0.01$

Figures 4 and 5 show that when co-authorship network degree centralization was low, the central scientist's betweenness centrality was positively associated with research productivity and research impact ( $\beta = 5.82, p < 0.01$ ;  $\beta = 12.42, p < 0.01$ , respectively). When co-authorship network degree centralization was high, the positive relationship between the central scientist's betweenness centrality and research productivity and

research impact was stronger ( $\beta = 88.46, p < 0.05, \beta = 13.62, p < 0.01$ , respectively).

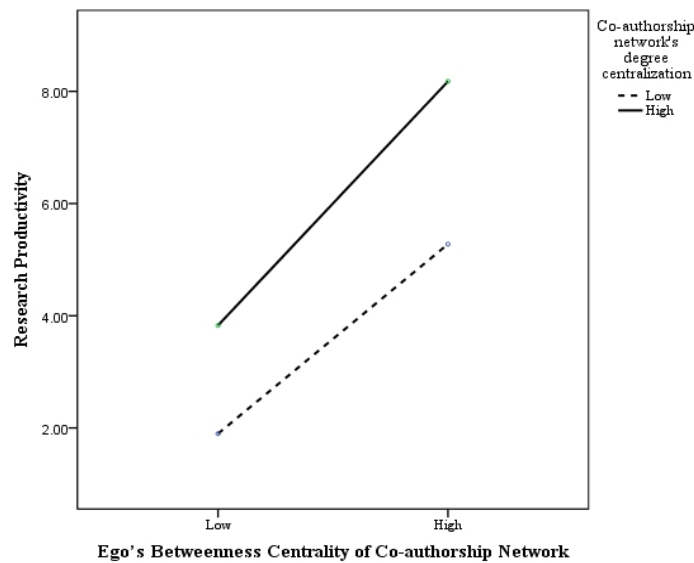


Figure 4: Moderating Effects of Ego Betweenness Centrality and Co-Authorship

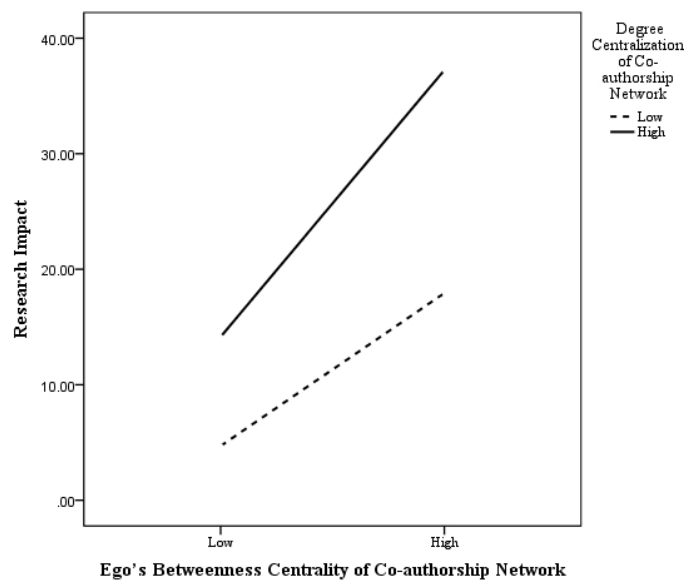


Figure 5: Moderating Effects of Ego Betweenness Centrality and co-Authorship Network Centralization on Research Impact

Next, we used growth models to analyze the evolution of co-authorship networks between two groups of scientists during three career periods. These models are appropriate for analyzing the changes over time and the differences in change patterns (Garson 2013; Lance, Vandenberg and Self 2000; Ployhart, Holtz and Bliese 2002). In the model, time was fixed and regarded as a random effect on individual measurement (Bliese and Ployhart 2002). In this study, time-invariant variables included gender, age, home school, number of affiliations, overseas experience, and scientific discipline. They were entered into the level-2 model as control variables. Group variables were entered in

the level-2 model as moderators.

The results indicated that ego network size and betweenness centrality increased as the career period evolved ( $\beta_{\text{Period} \times \text{Group}} = 7.15; p < 0.01$ ;  $\beta_{\text{Period} \times \text{Group}} = 0.09, p < 0.01$ , respectively; see Table 5). The evolution of the two groups' ego network size in three career periods is presented in Figure 6.

Table 5: Growth Patterns of Network Features (N = 205)

	Network size	Tie strength diversity	Degree centralization	Betweenness centrality
	coefficient	coefficient	coefficient	coefficient
Intercept	14.97**	3.02**	0.37**	0.44**
Gender	-3.72	-0.56	0.06	-0.03
Age	-0.42	-0.21	-0.01**	0.00
Home school	1.82	-0.08	0.11**	-0.06
Number of affiliations	4.69**	0.39	0.01	0.01
Overseas experience	2.60	1.82	0.05	-0.01
Scientific discipline	3.93*	-2.65	0.05	0.01
Period	6.16**	0.41	0.03 <sup>+</sup>	0.08**
Group	7.57**	1.42	0.03	0.09*
Period $\times$ Group	7.15**	1.61	0.03	0.09**
Period Square				-0.12**
Period Square $\times$ Group				0.01
Deviance	1518.04	1379.35	-30.83	-36.12
Number of estimated parameters	12	12	12	14
$\chi^2_{(\Delta \text{ Deviance}, \Delta \text{ Number of estimated parameters})}$	0.01	0.22	0.11	0.01
R <sup>2</sup>	0.36	0.02	0.08	0.03

Note: \* $p < 0.05$ , \*\* $p < 0.01$

The relationship between ego betweenness centrality and time exhibited a reverse-U shape ( $\beta_{\text{Period}} = 0.08, p < 0.01$ ;  $\beta_{\text{Period Square}} = -0.12, p < 0.01$ ). In the first career period, betweenness centrality increased quickly. In the second career period, it reached the highest point. Then in the third career period, its increasing speed slowed down in the group of outstanding scientists, and began to decrease in the group of ordinary scientists (see Figure 7). Thus, Hypotheses 7 and 9 were supported.

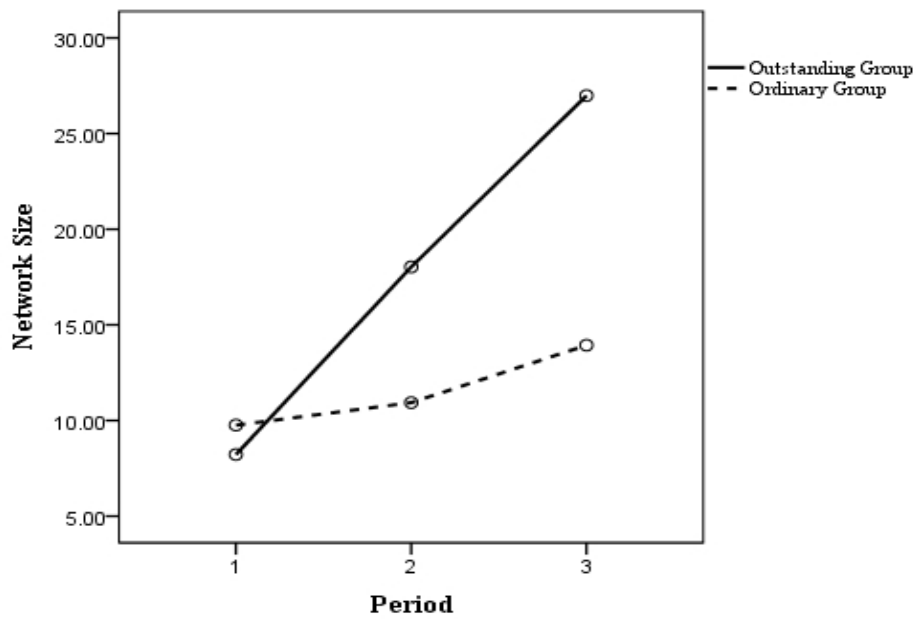


Figure 6: Two Groups of Scientists' Size of Co-Authorship Network in their Three Career Periods

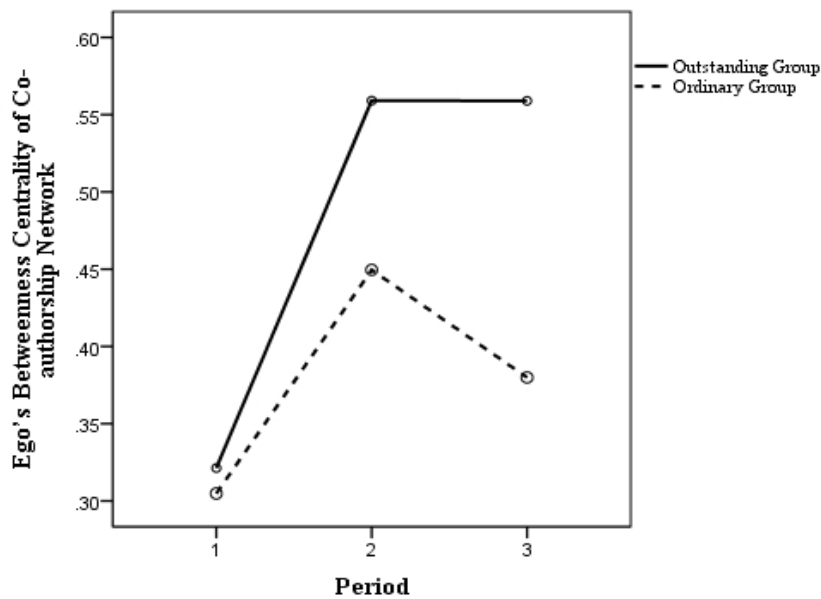


Figure 7. Two Groups of Scientists' Betweenness Centrality of Co-Authorship Network in Three Career Periods

The central scientist's tie strength diversity and co-authorship network degree centralization did not exhibit a significant difference effect during the evolution of the career periods ( $\beta_{\text{Period}} = 1.61, ns$ ;  $\beta_{\text{Period}} = 0.03, ns$ ). Thus, Hypotheses 8 and 10 were not supported.

Taken together, the study's results are summarized in Table 5.



Table 5: Results

Hypothesis	Confirmed?
Hypothesis 1: The size of scientists' ego-centered co-authorship networks will be positively correlated with scientists' performance.	Yes
Hypothesis 2: Scientists' tie strength diversity will be positively correlated with their research performance.	Partial yes
Hypothesis 3: Scientists' tie strength diversity will moderate the relationship between the size of scientists' ego-centered co-authorship networks and their performance such that when tie strength diversity is high the positive correlation between the size of their network and their research performance will be higher.	Yes
Hypothesis 4: Scientists' co-authorship network betweenness centrality will be positively correlated with their research performance.	Yes
Hypothesis 5: Degree centralization of scientists' co-authorship network will be positively correlated with their research performance.	Yes
Hypothesis 6: Degree centralization of scientists' co-authorship networks will moderate the relationship between scientists' betweenness centrality and their research performance such that when their degree centralization is high, the positive relationship between scientists' betweenness centrality and research performance will be higher.	Yes
Hypothesis 7: During the early career time period, outstanding scientists will have larger ego-centered co-authorship networks than ordinary scientists.	Yes
Hypothesis 8: During the early career time period, outstanding scientists will have higher tie strength diversity in their ego-centered co-authorship networks than ordinary scientists.	No
Hypothesis 9: During the early career time period, outstanding scientists will have a higher level of betweenness centrality in their ego-centered co-authorship networks than ordinary scientists.	Yes
Hypothesis 10: During the early career time period, outstanding scientists will have a higher level of degree centralization in their ego-centered co-authorship networks than ordinary scientists.	No

## DISCUSSION

One of our key findings was that the size of scientists' co-authorship network was positively correlated with their research productivity and impact. This finding is similar to McFadyen and Cannella's (2004) finding that the number of co-authors had a reverse-U shape relationship with scientists' impact, with the turning point being 93 un-redundant co-authors.

Second, scientists' tie strength diversity was positively associated with scientists' productivity rather than their impact. In addition, it moderated the positive relationship between the size of the network and scientists' performance (both productivity and impact). This result is consistent with the finding that in order to obtain the full benefits

from co-authorship, scientists should manage their cost of co-authors in ways that allow them to benefit from close collaborators (Gonzalez-Brambila, Veloso, and Krackhardt 2013; Letina 2016). Collaboration that is too close may damage the creative thinking process (Zhou et al. 2009). Non-close collaborators should facilitate exploration in the knowledge invention process. Thus, our study's results suggest that tie strength diversity should be a key collaborative strategy of scientists. This finding enriches our understanding of team diversity and research output (Li, Liao and Yen 2013).

Third, we found that scientists' co-authorship network's degree centralization moderated the relationship between betweenness centrality and research performance. This finding is in keeping with the idea that scientists' betweenness centrality increases productivity (De Stefano and Zaccarin 2015) and research impact (Li, Liao and Yen 2013), and that sparse and isolated networks help scientists obtain high  $g$ -indices (Abbasi, Chung and Hossain 2012; Abbasi, Wigand and Hossain 2014). Degree centralization may be enhanced if it includes both prestigious and peripheral scientists. On the one hand, the prestigious scientists will help attract peers' attention. Similar effects have been observed in organizations. Specifically, when the quality of a company's product or service was not well-established, connecting with organizations with good reputations helped organizations build trust from others and improved the acceptance of the product or service (Ahuja, Soda and Zaheer 2012). On the other hand, peripheral scientists should contribute a higher level of efforts and new perspectives in collaboration. Thus, establishing a sparse co-authorship network is another useful collaborative strategy of scientists.

Fourth, in the early career stage of scientists, the size of their co-authorship network increased linearly, while their betweenness centrality increased in a reverse-U shape. In the first three years of employment, the two groups of ordinary and outstanding scientists exhibited no difference in their co-authorship networks. However, later differences started to appear in terms of network size and betweenness centrality. Outstanding scientists increased rapidly in both cases. The betweenness centrality of both groups of scientists decreased after their seventh work year whereas outstanding scientists still had a high level of this variable. We also found that scientists' tie strength diversity and degree centralization had no significant change during the first nine work years. But after their seventh work year, tie strength diversity of co-authorship started to be different between the two groups, with the outstanding group having higher tie strength diversity than the ordinary group. Our findings suggest that expanding one's co-authorship network and adding bridges (i.e. linking co-authors who have not collaborated before) in the network during the early career stage would be helpful for scientists' career development.

## **IMPLICATIONS**

Our study has implications for theory and practice. First, to help capture both strong and weak ties, we identified a new tie strength index: tie strength diversity, which refers to the difference in tie strength (e.g. in terms of co-authorship count) between the scientist and each of his/her co-authors. Our results, using a longitudinal design, suggest that researchers should aim to increase their tie strength diversity.

Another theoretical implication of our study is that co-authorship network management involves not only one's choice of co-authors (e.g. in terms of demographic characteristics, grants, or tenure, Bozeman and Corley 2004) and the ordering of co-authors (Haslam and Laham 2009), but also the characteristics of network structure and relationships. In particular, we suggest that scientists devise appropriate co-authorship network strategies in order to improve their research performance and career development.

First, in the age of open innovation, collaborative research is necessary for scientists, but especially for junior scientists. When establishing and maintaining collaborative partnerships, dividing collaborators into different groups and setting up the collaboration priority for different groups should be a part of scientists' collaboration strategy. Select key collaborators and non-key collaborators in order to maintain tie strength diversity of one's co-authorship network.

Second, in order to improve scientists' betweenness centrality, scientists can collaborate with different authors (Li, Liao and Yen 2013), or those with whom they have not collaborated before (Bishop et al. 2014), in order to obtain a diverse set of knowledge and attention resources from different groups of collaborators.

Our findings also have implications for practice. First, collaborative research project funds could be offered to junior scientists to help them identify collaborators and build their co-authorship networks. Unlike senior scientists who have high academic rank and more work experience, junior scientists encounter more challenges in collaborating with scientists of different levels (Lee and Bozeman 2005). Large collaboration projects are often led by senior, well-known scientists. Building co-authorship networks through these projects should be a key goal of sponsored research.

Second, supporting cross-institutional, cross-discipline long-term visiting scholar programs, and facilitating researchers' mobility should help to improve junior scientists' betweenness centrality of their co-authorship networks.

Several limitations should be considered before generalizing our findings to other contexts. First, our study's sample size was relatively small. With the support of human resources managers we obtained two representative groups of scientists. However, selecting paired samples in a field setting proved challenging. Thus, the study's small sample size influences the robustness of our findings. Second, some scientist

performance factors such as prestige were not taken into account and might have influenced our results (Li et al. 2017). Third, we only compared the two groups of scientists' co-authorship network evolutions in their first nine working years. The senior scientists' co-authorship strategies in their later career stages might also be important for their career development. Whereas our findings preclude drawing conclusions about late career collaborations, they show how scientists manage their co-authorship networks during their early career phase. It is hoped that our findings are informative for junior scientists' career development as well as for science and higher education policy makers.

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