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# Network stability, connectivity and innovation output

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ABSTRACT

With the patent co-inventing data of top 9 ICT firms with the highest patent application in China, this study establishes the co-inventing network and examines the moderate role of network connectivity, measured by classifying the individuals into two cohorts: inventors in the largest connected component and inventors in other isolated components. The network stability and innovation output demonstrate strong positive interaction, which is significant in not only the largest but also other isolated components. The clustering and centrality demonstrate significant effect on network stability and innovation output in the largest connected component, which is generally the same as that of extant studies. This impact is not significant in the other isolated components, which confirms the moderate role of network connectivity, i.e., fully connected networks constitute the basis for the network structure to be functioning. However, the significantly positive role of the structural hole is not moderated by the network connectivity. The contributions and implications of our findings is discussed at the end of this study.


## 1. Introduction

The effect of individual mobility on knowledge transfer, innovation, and competitive advantage is increasingly becoming an important domain of research (Gardner, 2005; Harris and Helfat, 1997; Rao and Drazin, 2002; Song et al., 2003; Sturman et al., 2008; Wezel et al., 2006). Interorganizational mobility of individuals affects gains or losses in terms of the competitive advantage and performance outcomes (e.g., survival, profitability, effectiveness in head-to-head competition) of organizations that lose individuals (Aime et al., 2010; Phillips, 2002). Therefore, most organizations are trying to curb the mobility and keep the stability of their employee groups, particularly the high-performers. Conversely, the employee's performance may also impact their stability. High-performers usually own high satisfaction with the current job, which makes them less likely to leave, while low-performers are more likely to seek outside opportunities. Although there are reciprocal effects (Shaw et al., 2005a), direct (Glebbeek and Bax, 2004) and indirect (Shaw et al., 2005b) evidence suggests that the effect of employee stability on his/her performance is stronger than the reverse, which may be the main cause that most extant studies focused on the former. However, extant studies did not clearly examine to what extent the reciprocal effect is ignorable. Since there is reciprocal effect, the causal analysis of employee stability and performance should take it into account from both empirical and theoretical perspectives. As the employee's performance and stability interact with and function on each other, this study will make a comprehensive examination of the bidirectional causalities, which is one of the main contributions of this study to extant literatures.

In the context of an organizational network, as the network becomes more connected, distance between any two nodes diminishes, it is possible that information can become more democratized (Ahuja et al., 2012), information can thereby diffuse more quickly, fostering outcomes such as innovation or creativity (Schilling, 2005; Schilling and Phelps, 2007). As the inventors' access to the information and knowledge is to a great extent dependent on the links with each other, the moderate effect of the network connectivity on the inventor stability and his/her performance is indispensable. Although the effect of network structure has been widely discussed by extant studies, e.g., Ahuja (2000), Nerkar and Paruchuri (2005), Paruchuri (2010), Cattani and Ferriani (2008), Zhang et al. (2014a), they are mostly based on the largest connected component within the whole network. As the disconnected components potentially conflate the influences of small-world structure and simple connection (Fleming et al., 2007) and usually take a relatively small ratio compared with the largest component (Casper, 2007), most studies focused on the largest component, while ignored the methods to develop a weighted average across disconnected components proposed by Schilling and Phelps (2007). However, besides the largest component, other components, e.g., the second and third largest, usually own well structured fabric. These components may also exhibit significant network effect, as the links constitute the base for inventor communication. Inventors with key positions may also have advantages in accessing information, and thereby generate higher innovation output in other smaller components. The specific inventive process may lead to the disconnections,

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e.g., pharmaceutical researchers are usually assigned to several groups, which are making mutually independent researches; technicians embarking at two different projects within the same firm may also lead to two isolated components. Obviously, inventors in the largest component represent only part of the firm's inventive activity. As the inventors in other components may also be doing important researches, ignoring these components may lead to a bias of the empirical results. In this sense, the network effect on network stability and performance, particularly in the partly connected contexts, deserves a further study. We will compare the differences of the network effects in the fully connected networks with that in partly connected networks, which formulates another main contribution of this study.

Additionally, extant studies provided only evidences that network connectivity is beneficial by proving that a greater ratio of the largest connected component positively impact innovation, e.g., Fleming et al. (2007), Chen and Guan (2010), Zhang et al. (2014b). As the linkages between individuals are the basic element constituting the network, greater extent of connectivity may be the key for the network indicators, e.g., clustering coefficient, centrality, path length, to be functioning on innovation. However, the moderate role of connectivity is not carefully examined by extant studies and will be another main job of this study.

The remainder of this study is organized as follows: Section 2 presents the hypothesis; Section 3 presents the data and methods; Section 4 provides the empirical results; Section 5 discusses and Section 6 concludes.

## 2. Hypothesis

Because continuous interaction among members is seen as a valuable resource for organizations, turnover has been argued to deplete social capital by damaging firms' internal social fabric (Dess and Shaw, 2001; Shaw et al., 2005a). Kwon and Rupp (2013) found that turnover among individuals who occupy key structural and relational network positions could lead to significant loss of social capital within organizations, resulting in lower firm performance. Individual turnover has been viewed as problematic for firm performance, as individuals' participation in organizational activities has been regarded as a necessary condition for effective firm functioning (Kwon and Rupp, 2013), and the individuals with more work experience usually generate more productions. This may be one of the main causes that firms with higher employee stability usually have higher survival rate (Phillips, 2002; Wezel et al., 2006). However, this positive reciprocal effect may be attenuated by the network connectivity, which determines the access of information and knowledge. For the lack of information and communication, employees in an isolated network are more likely to leave, while employees in a connective network have easier access to heterogeneous team, which is more productive (Hamilton et al., 2012) and makes employees less likely to leave. This gives the following formal hypothesis:

**H1.** *The inventor's network stability positively interacts with his/her innovation performance, while this positive reciprocal effect will be attenuated by the disconnected network.*

The links described in social networks influence one's propensity to stay on their job perhaps through a process of job embeddedness (Holtom et al., 2008), e.g., key individuals usually hold advantageous network position, which bring greater job embeddedness and satisfactions that make them less likely to flow away (Holtom et al., 2008). The individual performance may also be affected by their network positions, which determine the facilitation of information and knowledge acquisition. It has been proved that certain network structure, e.g., medium level clustering and small worldliness, shorter path length would benefit innovation by facilitating the access of information and knowledge (Chen and Guan, 2010; Fleming et al., 2007; Zhang et al., 2014b); Individuals with more structure holes may have lower level innovation output (Ahuja, 2000). As Ahuja (2000) has noted that the optimal structure of the network to a great extent depends on the objectives of the network members, it is necessary to make a further study of the relationships between the innovation performance and network position. We discuss the network position from three measurements: clustering coefficient, structural hole and centrality, which are widely used and discussed by extant studies in measuring the network structures.

As the network is becoming more clustered, there is a decline in the formation of bridging new ties (Gulati et al., 2012). The social structure is further characterized by self-containment (Gulati et al., 2012), which makes inventors less likely to change the current state and thereby more likely to be reliant on the network. However, the innovation performance may be affected by the clustering quite differently. Most studies have confirmed a middle-level clustered network encourages, but an extremely low- or high-level clustered network discourages innovation, e.g., Uzzi and Spiro (2005), Chen and Guan (2010), Fowler (2005), and Guimera et al. (2005). The role of a more clustered network maybe two sided: on one hand, it may diffuse knowledge that improves innovation, and on the other hand, it may bring too much common or even negative information that hamper creativity (Chen and Guan, 2010). Hence we make the following hypotheses:

**H2.** *(a). The inventor's clustering coefficient positively correlates with his/her network stability.*

**H2.** *(b). There is an inverted* 'U'-shaped relationship between *inventor's clustering coefficient positively impacts his/her innovation performance.*

The structural holes are gaps in information flows between alters linked to the same ego but not linked to each other (Burt, 1992). A structural hole indicates that the people on either side of the hole have access to different flows of information (Hargadon and Sutton, 1997). Ego networks rich in structural holes imply access to mutually unconnected partners and, consequently, to many distinct information flows (Ahuja, 2000). Therefore, inventors rich in structural hole usually have higher position, which makes them less likely to flow out. However, the effect of structural hole on innovation performance appears to be two sided: on one hand, inventors with extensive relations can foster the development of shared norms of behavior and explicit knowledge-sharing routines (Ahuja, 2000; Dyer and Noboeka, 2000; Uzzi, 1997; Walker et al., 1997), which enhances the innovation performance; on the other hand, the opportunistic actions of the inventor who hold the structural hole is greater, as his/her partners are not directly linked to each other (Ahuja, 2000). The contradictory effects may lead to two opposing point of views, one of which is selected for proposing hypothesis:

**H3.** *(a). The inventor's ego network rich in structural hole positively correlates with his/her network stability.*

**H3.** *(b). The inventor's ego network rich in structural hole positively impacts his/her innovation performance.*

Network centrality is a commonly used indicator of brokerage within social networks (Casper, 2007; Wassermann and Faust, 1994). The centrality is measured with three main indicators: betweenness, closeness and degree centrality, which function on the innovation from different aspects but finally show similar effect. Researches support a link between inventors performance and both number of ties and centrality in networks, with higher performing inventors holding more ties and having more network centrality (Burt, 1992; Cross and Cummings, 2004). Additionally, similar with the role of structural hole, researchers also believe that inventors with greater centrality will have access to more information, have more power and greater influence (Chen and Guan, 2010). Therefore, the centrality is more likely to show positive effect on network stability from the perspective of job embeddedness. The following hypotheses are accordingly proposed:

**H4.** *(a). The inventor's network centrality positively correlates with his/her network stability.*

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**H4.** *(b). The inventor's network centrality positively impacts his/her innovation performance.*

The connected network allows any vertex to be reached from any other vertex by traversing a finite number of edges (Watts, 1999). Network connectivity, which relates to the usefulness of the network in terms of the number of individuals linked together, may confuse the above effects and correlations. If inventors with key network position exit the network, presumably through resignation or retirement, then connectivity within the network will be lost after ties decay (Casper, 2007). The network effect that passes through the inventor will be attenuated if the links are removed due to the inventor's quit decision. Although the network effects may still be significant within any well structured components, it could not go beyond the boundary of the components. The mutually isolated effects in a disconnected network may be quite different from that in connected fully ones. We thereby propose the following hypothesis:

**H5.** *The network effects (structural hole richness, centrality and clustering coefficient) on inventor's network stability and innovation performance are attenuated by the isolation of components.*

The largest connected component is the largest set of inventors in a network who can trace a direct or indirect collaborative path to one another. The largest component usually exhibits inventive small worlds that consist of clusters of cohesive interaction, linked together by occasional bridging connections (Fleming et al., 2007). Network aggregation enables greater opportunities for technological brokerage between previously disconnected technological communities (Burt, 2004; Hargadon, 2003; Stuart and Podolny, 1999), which indicates the advantage of the largest connected component. In comparison, isolates and small clusters will be left without access to new ideas and results (Fleming et al., 2007). As inventors have an incentive to relocate themselves, abandoning disadvantaged positions to join other positions located in a more successful cluster (Casper, 2007), they are more likely to make a leave in case they are isolated. Accordingly, the following hypothesis is proposed:

**H6.** *The largest connected component in the whole network own higher network stability and innovation performance than that of other partly connected components.*

The theoretical framework is presented in Fig. 1.

## 3. Data and method

### *3.1. Data*

The patent co-inventing networks provide a rich opportunity to study the effect of network connectivity because these networks represent a primary conduit of information for inventors. Therefore, we use patent co-inventing data in establishing R&D cooperation networks. The characteristics of the R&D cooperation network are to a great extent reflected by the patent co-inventing network, which is widely used in studying the flow of information and R&D creativity, e.g., Fleming and Marx (2006), Fleming et al. (2007), Chen and Guan (2010), Guan and Chen (2012).

We use the patents by the top 9 ICT firms that filed the largest number of patents for further analysis. These firms are: Huawei, ZTE, Panasonic, Sony, Intel, Philip, IBM, Samsung and LG. We remove the patents with only one inventor that has no contribution to the network structure, and keep the patents with two or more inventors, so that a network with at least two vertices and one edge could be established. To rule out the case that patents with two or more applicants conflate the network, as it is almost impossible to verify if the inventor works in the firm, we omit the patents with over two applicants. However, the patents filed by the firm and its subsidiaries are kept. We take a three year moving window[1] in establishing the dynamic networks. As the patents in our sample have only one applicant, each firm has a dynamic network that is mutually independent. As the networks are not totally connected, we classify the patents into two cohorts: Inventors in the largest connected component, where any pairs of inventors could reach each other by several intermediates, and inventors not in the largest component, where not all pairs of inventors could reach each other. Since the largest component is representative of the whole network by taking the highest weight, we first focus on the largest component and show the connectivity.

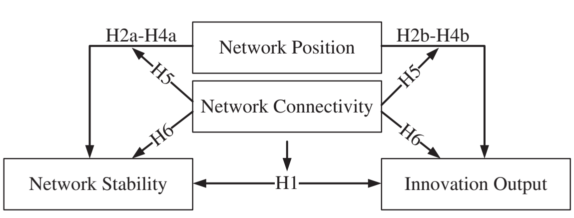


**Fig. 1.** Theoretical framework and hypotheses.

We take the network of Huawei as a special case for further analysis, which is also representative of other firms' networks. Fig. 2 presents the evolution of the largest component in the whole network. The network is becoming more connected before 2008, which is reflected by the increasing weight (blue curve) and scale (green curve) of the largest component. The ratio of the second largest to the largest component has been declining (red curve), which reflects the increasing gap between the largest and other components, and also an increasing weight of the largest component and the network connectivity. However, as the size and weight of largest component drops since 2008 (except the 2012–2014 networks that does not include most patents filed in 2014), the network connectivity slightly declines after 2008. The size of the largest connected component has been growing as Huawei becomes a global telecommunication player. As is shown in Fig. 2, the number of inventors in the largest component is lower than 40 before 2000, but then grows at a fast pace and reaches a peak during 2006–2008. Although the number of inventors falls after 2006–2008, it keeps a smooth trend after 2008–2010. The ratio of the largest component to the whole network also increases before 2006–2008, which suggests a greater connectivity of the network.

Fig. 3 presents the whole 2003–2005 network of Huawei that includes 235 isolated disconnected components, 3323 inventors and 6019 connections. The largest connected component with the inventors being orange in Fig. 3 takes 77% inventors and 85% connections. Other components with other colors have much fewer inventors and connections than that of the largest component, and for many components there are only two inventors. We will make an in-depth analysis of the 2003–2005 network in the following empirical study. Similarly, other firms' 2003–2005 networks are also selected.

Network stability is to a large extent determined by the stability of inventors. In the context of innovation, a high ratio of inventor turnovers from the R&D cooperation network in a short period will lead to an unstable R&D cooperation network. Therefore, we measure the network stability with the inventing life that inventors embarking at innovation (InventLife). The InventLife is measured by the length of period that the inventor first appeared and last appeared in the firm's patents. In detail, the InventLife is measured as follows: As the network to be studied is established with 2003–2005 patents, an inventor is viewed to stay n years in the network if he/she has been absent from and never appeared in the R&D cooperation network since $2004 + n + 1$, e.g., inventor i left the network in 2009 and stayed 4 years in the network since 2004 (2008–$2004 = 4$ years). We take the year 2013 and 2014 as the last observation years. Inventors that own patents filed in 2013 or 2014 are viewed to be still in the R&D cooperation network[2], and his inventing life data are set to

[1] Alternate window sizes, e.g., 4 and 5 years, have also been tested and they had little effect on the results.

[2] As not all the patents filed in 2013 and 2014 are in our data, we choose these two years as the last observation years to ensure the accuracy, i.e., inventors absent from the 2013 patents may appear in 2014.

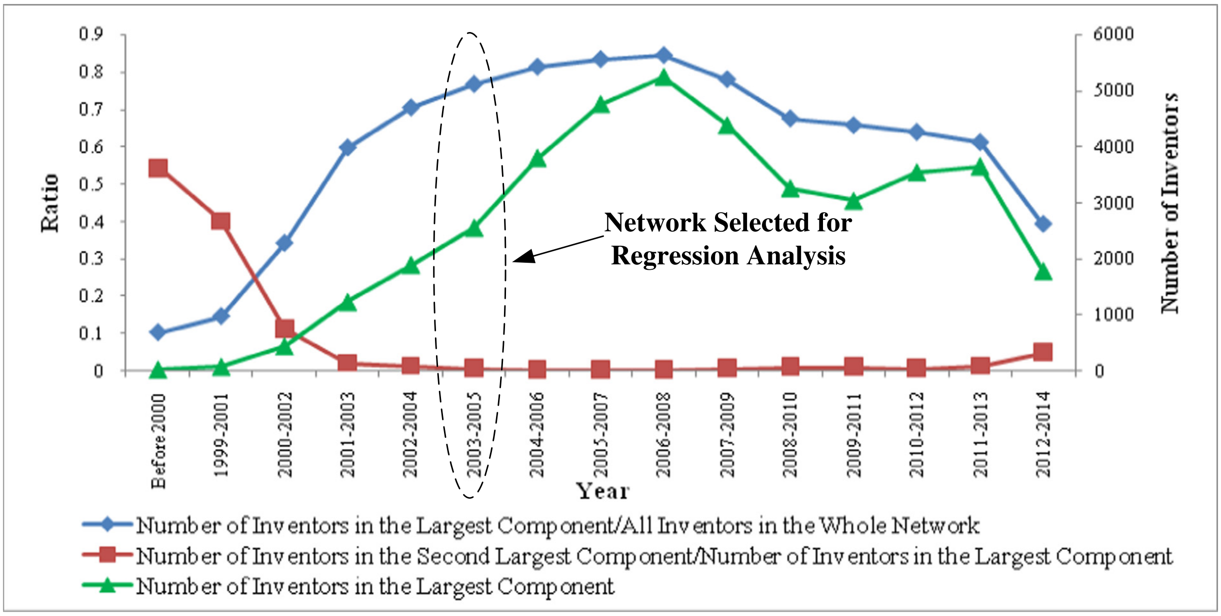


**Fig. 2.** Evolution of network connectivity measured by the size of the largest component in Huawei. Note: Not all the patents filed in 2013 and 2014 are included in the SIPO patent database by the query date 2014.8.30, which leads to a disconnection of the 2012–2014 network and a sharp decline of the size of the largest component.

be censored. Fig. 4 presents the survival curve of the inventing life in the network: Over 60% inventors in the largest component are still in the network one year later, while this ratio is <50% for inventors not in the largest component. In other periods, the survival rates of inventors in the largest component are also higher than inventors not in the largest component, which suggests a more stable network relationship in the largest component than in other components.

### 3.2. Variables

We classify the inventors into two cohorts: Inventors in the largest and not in the largest component, so that we could make a comparison and clarify the impact of network structure on network stability in different context. Table 1 presents the summary statistics and correlation matrix of variables of the 9 ICT firms:

Innovation Output: Following most extant studies, e.g., Fleming et al. (2007), Chen and Guan (2010), Zhang et al. (2014a, b), innovation output is measured by the subsequent patenting in SIPO during 2006–2014. Inventors in the largest component averagely file 10.73 patents, which is twice of the patent output by other inventors (5.01 patents).

InventLife: Table 1 shows that inventors in the largest component averagely stay 3.64 years in the R&D position of the firm (see InventLife), which is longer than that of other inventors (3.07 years).

InLargestComponent: A dummy variable that takes 1 if the inventor is in the largest component and 0 otherwise. A greater weight of largest component will lead to a higher ratio of inventors taking the value 1, which suggests that more inventors could reach each other through a number of intermediates. This variable reflects the network connectivity by telling that if an inventor is either in the largest connected network or in other isolated networks.

The network indicators that reflect the inventors' centrality are: Betweenness centrality, i.e., the extent to which an inventor is located 'between' other pairs of inventors; Closeness centrality, i.e., the extent of the closeness to every other inventors; Degree centrality, i.e., the number of inventors that an inventor is directly connected with. The estimation methods of the above three centralities are as follows:

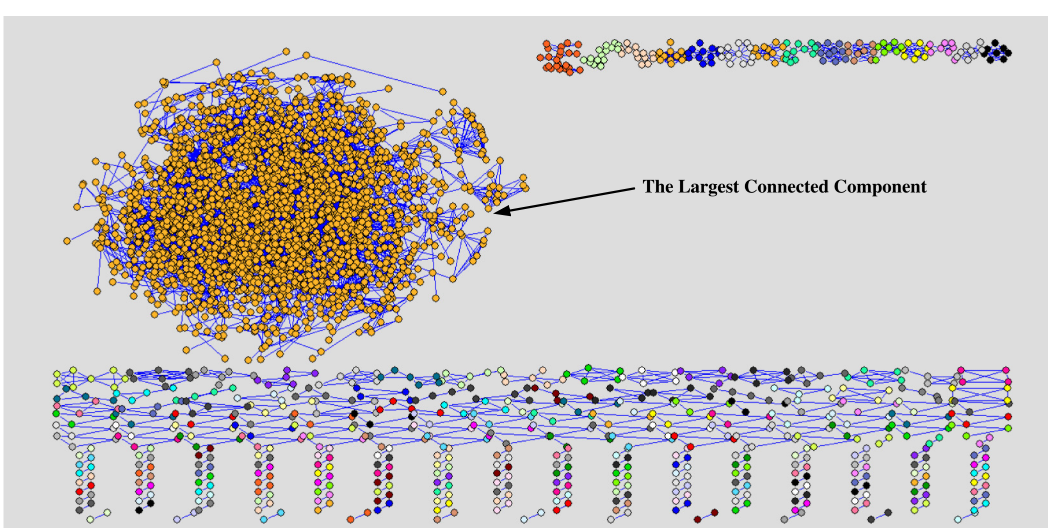


**Fig. 3.** Innovation network with the patent co-authorship data filed during 2003–2005 in Huawei.

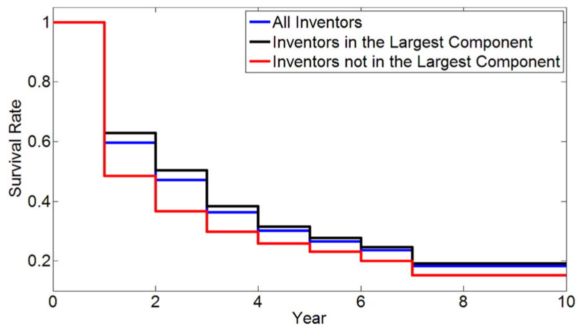


**Fig. 4.** Survival curve of the invent life in the inventive network of Huawei.

The betweenness centrality of inventor i is defined as

$$Betweenness\_Centrality_i = \sum_{s \neq t \neq i \in I} \frac{\sigma(s,t|i)}{\sigma(s,t)}$$

where $\sigma(s,t|i)$ is the total number of shortest paths between $s$ and $t$ that pass through $i$, and $\sigma(s,t) = \sum_I \sigma(s,t|i)$.

The closeness centrality of inventor i is defined as

$$Closeness\_Centrality_i = \frac{1}{\sum_{j \in U} dist(i,j)}$$

where $U$ is the set of all the inventors excluding inventor i, $dist(i,j)$ is the distance between inventor i and j.

The degree centrality of inventor i is measured by the number of inventors directly connected with inventor i.

ClusterCoefficient: The clustering coefficient of inventor i. Let $\tau_\Delta(i)$ denote the number of triangles, which is a complete subgraph of order three, in $I$ into which inventor $i$ falls, and $\tau_3(i)$ the number of connected triples, which is a subgraph of three vertices connected by two edges, in $I$ for which the two edges are both incident to $i$. The clustering coefficient of inventor j can be expressed as (Kolaczyk, 2009):

$$Clustering\_Coefficient_i = \tau_\Delta(j)/\tau_3(j)$$

StructuralHole: The constraint of network connections on inventor, which is measured with the following formula:

$$Structural\_Hole_i = 1 - \sum_{k=1}^{M_i} S_{k,i}^2$$

**Table 1**
Summary statistics and correlation matrix.

| All inventors (N = 23,124) | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Variable | Mean | Std. Dev. | Min | Max | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 1. PatentCount | 9.42 | 14.31 | 1 | 165 | | | | | | | |
| 2. InventLife | 3.51 | 2.90 | 1 | 10 | 0.45 | | | | | | |
| 3. ClusterCoefficient | 0.61 | 0.40 | 0 | 1 | 0.18 | 0.11 | | | | | |
| 4. StructuralHole | 0.40 | 0.30 | −0.13 | 0.49 | 0.37 | 0.16 | 0.09 | | | | |
| 5. InLargestComponent | 0.77 | 0.42 | 0 | 1 | 0.17 | 0.08 | 0.10 | 0.52 | | | |
| 6. BetweenCentrality | 0.0011 | 0.0037 | 0 | 0.09 | 0.45 | 0.14 | −0.23 | 0.40 | 0.16 | | |
| 7. CloseCentrality | 0.09 | 0.05 | 0.0006 | 0.17 | 0.26 | 0.11 | 0.06 | 0.62 | 0.95 | 0.28 | |
| 8. DegreeCentrality | 3.62 | 2.57 | 1 | 16 | 0.19 | 0.03 | 0.32 | 0.71 | 0.28 | 0.25 | 0.36 |
| Inventors in the largest component (N = 17,808) | | | | | | | | | | | |
| Variable | Mean | Std. Dev. | Min | Max | 1 | 2 | 3 | 4 | 5 | 6 | |
| 1. PatentCount | 10.73 | 15.39 | 1 | 165 | | | | | | | |
| 2. InventLife | 3.64 | 2.90 | 1 | 10 | 0.45 | | | | | | |
| 3. ClusterCoefficient | 0.63 | 03786 | 0 | 1 | 0.26 | 0.15 | | | | | |
| 4. StructuralHole | 0.49 | 0.27 | −0.0069 | 0.95 | 0.36 | 0.15 | 0.01 | | | | |
| 5. BetweenCentrality | 0.0014 | 0.0041 | 0 | 0.09 | 0.45 | 0.14 | −0.31 | 0.41 | | | |
| 6. CloseCentrality | 0.11 | 0.0 | 0.06 | 0.17 | 0.27 | 0.10 | −0.13 | 0.53 | 0.42 | | |
| 7. DegreeCentrality | 4.01 | 2.65 | 1 | 16 | 0.16 | 0.02 | 0.25 | 0.68 | 0.23 | 0.36 | |
| Inventors not in the largest component (N = 4616) | | | | | | | | | | | |
| Variable | Mean | Std. Dev. | Min | Max | 1 | 2 | 3 | 4 | 5 | 6 | |
| 1. PatentCount | 5.01 | 8.48 | 1 | 113 | | | | | | | |
| 2. InventLife | 3.07 | 2.84 | 1 | 10 | 0.47 | | | | | | |
| 3. ClusterCoefficient | 0.54 | 0.48 | 0 | 1 | 0.00 | −0.04 | | | | | |
| 4. StructuralHole | 0.12 | 0.23 | −0.13 | 0.73 | 0.22 | 0.07 | 0.19 | | | | |
| 5. BetweenCentrality | 2.72e-7 | 1.70e-6 | 0 | 2.19e-5 | 0.20 | 0.05 | −0.03 | 0.33 | | | |
| 6. CloseCentrality | 0.0012 | 0.0007 | 0.0006 | 0.0036 | 0.17 | 0.03 | 0.53 | 0.85 | 0.33 | | |
| 7. DegreeCentrality | 2.33 | 1.71 | 1 | 9 | 0.11 | −0.01 | 0.61 | 0.74 | 0.14 | 0.89 | |
| Productive inventors in the largest component (N = 1503) | | | | | | | | | | | |
| | Mean | Std. Dev. | Min | Max | 1 | 2 | 3 | 4 | 5 | 6 | |
| 1. PatentCount | 50.97 | 23.87 | 30 | 165 | | | | | | | |
| 2. InventLife | 6.81 | 2.31 | 1 | 10 | −0.03 | | | | | | |
| 3. ClusterCoefficient | 0.43 | 0.31 | 0 | 1 | 0.22 | 0.10 | | | | | |
| 4. StructuralHole | 0.70 | 0.22 | 0 | 0.95 | 0.24 | −0.13 | −0.42 | | | | |
| 5. BetweenCentrality | 0.0060 | 0.01 | 0 | 0.09 | 0.29 | −0.13 | −0.42 | 0.46 | | | |
| 6. CloseCentrality | 0.13 | 0.02 | 0.07 | 0.17 | 0.28 | −0.27 | −0.30 | 0.58 | 0.57 | | |
| 7. DegreeCentrality | 5.08 | 2.88 | 1 | 16 | 0.13 | −0.05 | 0.08 | 0.55 | 0.31 | 0.34 | |

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where $M_i$ is the number of inventors directly connected with inventor i, and

$$S_{k,i}=\begin{cases}\sum_{n=1}^{B_i}\gamma_i\gamma_n & \text{if i has neighbors who are directly connected with } k\\ \gamma_i & \text{if i has no neighbors who are directly connected with } k\end{cases}$$

where $n$ denotes i's neighbor[3] who are directly connected with $k$, and $B_i$ is the number of i's neighbors who are directly connected with $k$. $\gamma_i$ is the inverse of the number of i's neighbors, including $k$., e.g., i has 4 neighbors, then $\gamma_i = 0.25$, similar explanation applies to $\gamma_n$. A higher value of *Structure_Hole*$_i$ indicates a low constraint on inventor i, which suggests a greater "freedom" inventor i has to withdraw from existing connections or to exploit structural holes (Nooy et al., 2011). This index will have a higher value if inventor owns more structural holes in his/her ego-network.

The largest component has a much different network structure from that of other components, which is illustrated by the differences of clustering, constraints and centrality: Inventors in the largest component are more clustered (Clustering_Coefficient: 0.63 > 0.54) and have more freedom in changing their connections by holding more important network positions (Structure_Hole: 0.49 > 0.12), which may be because inventors in the largest component have more connections with others (Degree_Centrality: 4.01 > 2.33), removing from or adding a connection to an inventor does not basically change his/her ego-network; Inventors in the largest component have greater centrality (Betweenness_Centrality: 0.0014 > 2.72e-7; Closeness_Centrality: 0.1104 > 0.0012; Degree_Centrality: 4.01 > 2.33), which reflects a more important intermediate role of inventors in transmitting information.

The characteristics of the firms are controlled by introducing 8 dummy variables that take 1 if the inventor is in the identified firm and 0 otherwise.

In summary, the network structure of the largest component is much different from other components by owning a greater clustering, lower connection constraint and higher centrality. How this would have impact on the patent output and network stability will be further studied.

### 3.3. The model

As the network stability is measured with the survival data, it is more appropriate to apply the survival model, e.g., Cox, Exponential and Weibull Model. Similarly, count model like Poisson and Negative Binomial Model should be applied to innovation output measured with patent count.

Since we mainly focus on the reciprocal effect between inventor stability and patent output, they will act both as the dependent and independent variables in the above two sets of regressions. We thereby need to find the instrumental variables (IV) to control for the endogeneity brought by the reciprocal effect. Since the patent count is believed to show time unvarying consistency, i.e., inventors who filed large patent count will keep filing in large number, we use an inventor's pre-2003 patent count as the instrumental variable of his/her post-2003 patent count. Similarly, we find a high correlation between pre-2003 and post-2003 inventing life. We thereby use the inventor's pre-2003 inventing life in the firm as the instrumental variable of his/her post-2003 inventing life.

## 4. Empirical results

We use the two stage regressions: First, we get the instrumental variable by regressing the inventor's post-2003 PatentCount on its pre-2003 value and get the estimated value $\widehat{\text{PatentCount}}$. Similarly, we get the InventLife's estimated value $\widehat{\text{InventLife}}$; Second, we regress the InventLife on $\widehat{\text{PatentCount}}$ and other potential impact factors, and make similar regressions with PatentCount being the dependent variable and $\widehat{\text{InventLife}}$ being the instrumental variable.

As the InventLife is the transition data, we regress the InventLife using the Exponential Survival Model, which allows us to run the Accelerated Failure-Time regression in Stata. The Harrell's C index and Schoenfeld Residual tests the null hypothesis that the rate of the failure, i.e., inventor's turnover, remains constant as he/she stays longer in the network (Proportional Hazard Rate). The test in Table 2 suggests that the survival model with all inventors and inventors in the largest component should be based on the fact that a longer time in the network leads to a greater turnover rate, i.e., the failure accelerates as the time flows. However, the transition data of inventors not in the largest component owns a Proportional Hazard Rate in Table 2. As the survival models are based on the hazard rate, which correlates negatively with survival period, the parameter estimates should be oppositely translated, i.e., a negative parameter estimate in Table 2 suggests a positive impact on the survival period.

As large components usually own well organized structure and may exhibit greater effects, we assign the inventors in larger components with greater weight and apply the Weighted Negative Binomial Model to the patent count. We take the edge counts in the component as the weight of its inventors.

The patent count demonstrates positive impact on stability in Model 5 - Model 12 in Table 2. Similarly, the positive impact of inventor stability on patent count can also be found in Model 5 – Model 12 in Table 3. This provides evidence for the former half of H1, i.e., the inventor's network stability positively interacts with his/her innovation performance. However, the significant parameter estimates in both the largest and other components suggest that the positive interaction is not attenuated by the disconnected network, which does not provide evidence for the latter half of Hyopthesis 1.

The clustering demonstrates a weakly inverted U relationship with inventor stability in the largest component, i.e., the estimates of ClusterCoefficient and its square term are only significant at 10% level. It exhibits similar inverted U effect on patent output in Table 3 in the largest component. This suggests that the coexistence of knowledge diffuse that improves innovation and common or even negative information that hampers creativity functions on both innovation performance and network stability. This provides evidence for H2(b), while does not support H2(a).

The structural hole also demonstrates positive impact on inventor stability and patent output in the largest component, which provides evidence for H3(a) and H3(b).

The three measurements of centrality show differing effects. The betweenness and degree centrality show positive impact, while closeness centrality shows insignificant impact on inventor stability in the largest component in Table 2. The effects of three centralities on patent output are basically different, betweenness and closeness centrality show positive impact, while degree centrality shows insignificant impact in the largest component in Table 3. This suggests that centralities function on innovation from multi-perspectives. As there are no significantly negative effects, the empirical results provide evidence for H4(a) and H4(b).

We may find from Tables 2 and 3 that most network indicators demonstrate significant effect on the inventor stability and innovation performance in the largest component, while not significant or the significance level is reduced in the other mutually disconnected components, e.g., clustering coefficient, degree centrality, closeness centrality, degree centrality, which suggests that the disconnected component attenuated the network effect. However, the structural hole is an exception, which exhibits positive effect in both largest and other components. H5 is thereby partly supported, i.e., most but not all the network effects are attenuated by the isolation.

We may be more concerned with the effect of network connectivity. As is shown in Model 1 – Model 4 in Table 2, the negative parameter estimates of InLargestComponent suggests that inventors in the largest component own lower hazard rate, or conversely greater survival

[3] Here the "i's neighbor" denotes the vertices with a direct connection with i.

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**Table 2**
Impact of network connectivity on network stability with exponential survival model.

| Sample | All inventors | | | | Inventors in the largest component | | | | Inventors not in the largest component | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Exponential survival model | | | | Exponential survival model | | | | Exponential survival model | | | |
| Model | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 | Model 7 | Model 8 | Model 9 | Model 10 | Model 11 | Model 12 |
| $\widehat{PatentCount}$ | −0.01***(0.00) | −0.00***(0.00) | −0.01***(0.00) | −0.00***(0.00) | −0.01***(0.00) | −0.00***(0.00) | −0.01***(0.00) | −0.00***(0.00) | −0.01***(0.00) | −0.00***(0.00) | −0.00***(0.00) | −0.00***(0.00) |
| InLargestComponent | −0.02***(0.00) | −0.03***(0.00) | −0.11***(0.03) | −0.02***(0.00) | – | – | – | – | – | – | – | – |
| ClusterCoefficient | −0.29(0.30) | −0.0.22(0.31) | −0.27(0.31) | −0.05(0.30) | −0.71**(0.35) | −0.62*(0.37) | −0.55*(0.32) | −0.55*(0.31) | 0.13(0.08) | 0.13(0.08) | 0.09(0.11) | −0.05(0.12) |
| ClusterCoefficient $^2$ | 0.24(0.28) | 0.11(0.28) | 0.28(0.28) | 0.10(0.28) | 0.60*(0.31) | 0.46*(0.28) | 0.53*(0.32) | 0.47*(0.27) | 0.01(0.00) | 0.01(0.00) | 0.01(0.00) | 0.01(0.00) |
| StructuralHole | −0.56***(0.07) | −0.47***(0.08) | −0.53***(0.08) | −0.82***(0.10) | −0.59***(0.09) | −0.51***(0.10) | −0.55***(0.10) | −0.84***(0.12) | −0.36**(0.17) | −0.30*(0.18) | −0.55(0.37) | −0.87***(0.30) |
| BetweenCentrality | | −19.68***(7.56) | | | | −15.96**(7.78) | | | | −1.39(8.25) | | |
| CloseCentrality | | | 1.39(1.53) | | | | 8.01(6.65) | | | | 0.56(7.97) | |
| DegreeCentrality | | | | −0.04***(0.01) | | | | −0.04***(0.01) | | | | 0.01(0.48) |
| Firm Dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Constant | 1.95***(0.08) | 1.84***(0.09) | 1.91***(0.09) | 2.23***(0.11) | 2.06***(0.14) | 1.92***(0.15) | 0.40(1.39) | 2.33***(0.16) | −1.67***(0.17) | −1.61***(0.1831) | −1.91***(0.45) | −2.27***(0.3301) |
| Log Likelihood | −31,025 | −30,937 | −31,020 | −30,986 | −23,962 | −23,894 | −23,959 | −23,932 | −6061 | −6060 | −6061 | −6059 |
| LR Chi2 | 6516 | 6690 | 6524 | 6593 | 4976 | 5111 | 4980 | 5035 | 990 | 992 | 990 | 994 |
| Prob > Chi2 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.05 | 0.08 | 0.09 | 0.01 |
| No. Obs. | 23,124 | 2124 | 23,124 | 23,124 | 17,808 | 17,808 | 17,808 | 17,808 | 4616 | 4616 | 4616 | 4616 |
| *Proportional-Hazards Assumption Test* | | | | | | | | | | | | |
| Harrell's C Index | | | | | | | | | | | | |
| Harrell's C | 0.59 | 0.59 | 0.59 | 0.59 | 0.60 | 0.60 | 0.60 | 0.60 | 0.52 | 0.52 | 0.52 | 0.51 |
| Somers' D | 0.19 | 0.19 | 0.19 | 0.19 | 0.20 | 0.20 | 0.20 | 0.21 | 0.04 | 0.04 | 0.03 | 0.02 |
| *Test based on Schoenfeld Residuals* | | | | | | | | | | | | |
| Df | 3 | 4 | 4 | 4 | 3 | 4 | 4 | 4 | 2 | 3 | 3 | 3 |
| Chi2 | 32.53 | 40.52 | 33.48 | 38.81 | 35.55 | 39.31 | 37.77 | 43.50 | 0.56 | 0.60 | 0.72 | 0.69 |
| Prob > Chi2 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.75 | 0.90 | 0.87 | 0.87 |
| Hazard Rate | AFT | AFT | AFT | AFT | AFT | AFT | AFT | AFT | PH | PH | PH | PH |

Dependent Variable: InventLife.
Standard Deviation in the Parenthesis.
***, **,*: Parameter estimates are significant at 1%, 5% and 10% respectively.
AFT: The option of Accelerated Failure-Time Metric (AFT) is selected in the Stata package.
PH: Proportional Hazard Rate (PH) is used in the Stata package.

**Table 3**
Impact of network stability on patent output with Negative Binomial Model.

| Sample | All inventors | | | | Inventors in the largest component | | | | Inventors not in the largest component | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Negative Binomial Model | | | | Negative Binomial Model | | | | Weighted Negative Binomial Model | | | |
| Model | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 | Model 7 | Model 8 | Model 9 | Model 10 | Model 11 | Model 12 |
| ***$\widehat{LengthofPeriod}$*** | 0.22***(0.01) | 0.21***(0.01) | 0.21***(0.00) | 0.22***(0.01) | 0.21***(0.01) | 0.21***(0.01) | 0.21***(0.01) | 0.21***(0.01) | 0.23***(0.01) | 0.23***(0.01) | 0.24***(0.01) | 0.23***(0.01) |
| InLargestComponent | 0.05(0.04) | 0.07*(0.04) | 1.32***(0.11) | 0.05(0.04) | – | – | – | – | – | – | – | – |
| ClusterCoefficient | 0.52**(0.22) | 0.52**(0.21) | 0.93***(0.22) | 0.62***(0.21) | 0.21***(0.04) | 0.20***(0.04) | 0.19***(0.04) | 0.21***(0.04) | 0.00(0.06) | 0.01(0.06) | −0.05(0.09) | 0.03(0.09) |
| ClusterCoefficient $^2$ | −0.98***(0.20) | −0.99***(0.20) | −1.27***(0.20) | −1.06***(0.20) | −0.48**(0.22) | −0.47**(0.21) | −0.47**(0.22) | −0.48**(0.21) | 0.01(0.00) | 0.01(0.00) | 0.01(0.00) | 0.01(0.00) |
| StructuralHole | 1.53***(0.05) | 1.31***(0.06) | 1.12***(0.06) | 1.52***(0.07) | 1.24***(0.07) | 1.13***(0.07) | 1.06***(0.07) | 1.29***(0.09) | 1.02***(0.12) | 0.93***(0.13) | 0.92***(0.26) | 1.20***(0.20) |
| BetweenCentrality | | 34.09***(4.39) | | | | 20.36***(4.14) | | | | 3.15*(16.94) | | |
| CloseCentrality | | | 13.72***(1.03) | | | | 37.31***(4.26) | | | | 6.49(4.93) | |
| DegreeCentrality | | | | 0.00(0.01) | | | | 0.02(0.01) | | | | −0.00(0.03) |
| Firm Dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Constant | 2.30***(0.06) | 2.06***(0.07) | 1.90***(0.07) | 2.29***(0.09) | 3.41***(0.10) | 3.17***(0.11) | −4.49***(0.91) | 3.46***(0.12) | 1.50***(0.12) | 1.41***(0.13) | 1.37***(0.31) | 1.70***(0.22) |
| Log Likelihood | −67,534 | −67,318 | −66,894 | −67,534 | −53,336 | −53,164 | −52,840 | −53,335 | −15,755 | −15,705 | −15,753 | −15,755 |
| LR Chi2 | 18,143 | 18,577 | 19,423 | 18,144 | 14,838 | 15,181 | 15,830 | 14,839 | 4524 | 4624 | 4529 | 4524 |
| Prob > Chi2 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| No. Obs. | 23,124 | 23,124 | 23,124 | 23,124 | 17,808 | 17,808 | 17,808 | 17,808 | 4616 | 4616 | 4616 | 4616 |

Note: ***, **, * denote the parameter estimates are significant at 1%, 5% and 10%, respectively;
Dependent Variable: PatentCount.

period, than those not in the largest component. InLargestComponent exhibits significantly positive effect on patent output in two regressions in Table 3, while the effect is insignificantly positive in the other two regressions in Model 1 – Model 4 in Table 3. This provides insufficient evidence for H6.

As key personnel have greater impact on firm performance and are believed to be more representative, literatures are more concerned with their mobility, e.g., Godart et al. (2014), Groysberg et al. (2008), Kwon and Rupp (2013). We thereby make additional regressions with the productive inventors in the largest component[4] to test the robustness of our empirical results. We define inventors with over 30 patents as the productive inventors.[5] The empirical results are presented in Tables 4 and 5. The structural hole and betweenness centrality exhibits positive impacts on both stability and patent output. Closeness centrality generates positive impact on patent output, while insignificantly impact stability. The insignificantly negative parameter estimate of the square term of clustering coefficient in Table 5 also suggests an inverted U relationship between clustering and paten output, while this inverted U relationship between clustering and stability is significant in Table 4. The structural hole richness positively impacts stability in Table 4 and weakly impacts patent output in Table 5. The closeness and degree centrality demonstrate positive impact on patent output and stability. These empirical results are generally correspondent with that of all inventors in the largest component, which confirms the robustness of our empirical study.

## 5. Discussions and limitations

Since the firms in our data file more patents in USPTO and EPO, the networks with only Chinese patents may only be partly representative of the true network structure, which may lead to a biased empirical result. However, we may preclude this case by making a comparison with other relevant literatures: 1st. There is an inverted U relationship between clustering and patent output, which not only corresponds with Zhang et al. (2014a, b), Chen and Guan (2010) who used either the country level or regional level patent co-inventing data, but also corresponds with Uzzi and Spiro (2005) who used the Broadway musical data. However, Fleming et al. (2007) found an insignificant relationship with the patent co-inventing data; 2nd. The closeness centrality, which is the inverse of the average path length, contributes positively to the patent output. This corresponds with Zhang et al. (2014a, b), Chen and Guan (2010), Fleming et al. (2007); 3rd. The structure hole contributes positively to patent output, which corresponds with Uzzi and Spiro (2005) who also used the individual networked data. However, this contradicts with Schilling and Phelps (2007) who used the inter-firm data. This may be because the negative effect of the opportunism, as is summarized by Schilling and Phelps (2007), brought by the structural holes plays the main role in the inter-firm level network, while the positive effect of structural hole led explicit inter-individual knowledge-sharing plays the main role in the inter-individual level network. Similar differences of the betweenness centrality can also be found in this study and Schilling and Phelps (2007). As our results are generally similar, or at least not contradict with extant literatures, particularly the literatures with the individual networked data, we may conclude that our data is not biased by the unique characteristics of Chinese patents. Therefore, the network effect on inventor stability disclosed by this study is also robust against the single firm sampling.

The network connectivity contributes to both the stability and innovation output, i.e., inventors in the largest connected component produce more patents and have a more endurable stay in the firm than inventors in other isolated components. However, one point that should be noted is that this connectivity effect is different from that of

[4] There are 1503 productive inventors in the largest component, while other components have only 172 productive inventors in sum.
[5] Other thresholds, e.g., 20 and 40, do not basically change the empirical results.

**Table 4**
Impact of Network Structure on the Network Stability of Productive Inventors in the Largest Component.

| Model | Exponential Survival Model | | | |
|---|---|---|---|---|
| | Model 1 | Model 2 | Model 3 | Model 4 |
| ***PatentCount*** | −0.01***(0.00) | −0.01***(0.00) | −0.02***(0.00) | −0.01***(0.00) |
| ClusterCoefficient | −0.39*(0.22) | −0.33*(0.20) | −0.15*(0.09) | −0.48**(0.21) |
| ClusterCoefficient $^2$ | 0.11***(0.00) | 0.24***(0.00) | 0.10***(0.00) | 0.07***(0.00) |
| StructuralHole | −0.62***(0.11) | −0.67***(0.12) | −1.33**(0.10) | −0.82***(0.21) |
| BetweenCentrality | | −6.20***(1.41) | | |
| CloseCentrality | | | −117.12(123.94) | |
| DegreeCentrality | | | | −0.03*(0.01) |
| Firm Dummies | Yes | Yes | Yes | Yes |
| Constant | 0.10(1.07) | 0.40(1.20) | 27.56***(5.44) | 0.31(1.13) |
| Log Likelihood | −1621 | −1620 | −1621 | −1620 |
| LR Chi2 | 71.63 | 73.79 | 71.64 | 73.50 |
| Prob > Chi2 | 0.03 | 0.06 | 0.00 | 0.06 |
| No. Obs. | 1503 | 1503 | 1503 | 1503 |
| *Proportional-Hazards Assumption Test* | | | | |
| Harrell's C Index | | | | |
| Harrell's C | 0.63 | 0.62 | 0.65 | 0.63 |
| Somers' D | 0.26 | 0.24 | 0.30 | 0.26 |
| Test based on Schoenfeld Residuals | | | | |
| df | 3 | 4 | 4 | 4 |
| Chi2 | 6.16 | 6.74 | 6.51 | 7.13 |
| Prob > Chi2 | 0.10 | 0.15 | 0.16 | 0.13 |
| Hazard Rate | AFT | AFT | AFT | AFT |

Note: ***, **, * denote the parameter estimates are significant at 1%, 5% and 10%, respectively;
Dependent variable: InventLife.
The option of accelerated failure-time metric is selected in the Stata package.

the moderate role in the reciprocal effect between network stability and innovation output, which exhibit strong positive correlations that are not attenuated by the disconnected network.

The network effects, e.g., clustering coefficient, betweenness, closeness and degree centrality, are attenuated. This suggests an important role of network connectivity in the network effect. However, the role of structural hole is significant in both fully connected and partly connected networks, which suggests a stronger effect of structural hole than that of other network indicators. As all the above indicators measure how important or how central the individual is in the network from different perspectives, e.g., structural hole richness implies the access to many distinct information flows and the minimization of redundancy between individuals (Burt, 1992); betweenness centrality is based upon the perspective that importance relates to where a vertex is located with respect to the paths between other pairs of vertices; closeness centrality measures the central position that a vertex be close to many other vertices (Kolaczyk, 2009); degree centrality measures are used to estimate the individual' ability to directly access to external knowledge for themselves and their direct power and influence to others in the network (Guan and Chen, 2012), we may thereby need to pay more attention to the individuals with more structural holes by assigning them with greater probability that they exhibit greater effects on innovation.

We may confirm each inventor's inventing life by questionnaire. However, it may not be realistic as there are tens of thousands of inventors, some of whom may have left the firm even over twenty years ago, which makes the employee's mobility information not retrievable. In this study, the individual's inventing life is viewed to be ended if his/her name does not appear in the patent. This measurement is not precise as the inventor may either have left the firm or moved to other positions within the firm. The latter case is not reflected by the patent information. However, the inventors' latter position may be less relevant with the innovation, as his/her inventing behavior is not directly reflected by the patents. Therefore, although it is not precise,

**Table 5**
Impact of Network Stability on Patent Output of Productive Inventors in the Largest Component.

| Model | Negative Binomial Model | | | |
|---|---|---|---|---|
| | Model 1 | Model 2 | Model 3 | Model 4 |
| ***LengthofPeriod*** | 0.01(0.01) | 0.01(0.01) | 0.02*(0.01) | 0.01(0.01) |
| ClusterCoefficient | 0.21**(0.10) | 0.16*(0.10) | 0.18*(0.09) | 0.16*(0.10) |
| ClusterCoefficient $^2$ | −0.11(0.10) | −0.07(0.13) | −0.09(0.20) | −0.004(0.19) |
| StructuralHole | 0.21*(0.12) | 0.16(0.15) | 0.03(0.16) | 0.36*(0.19) |
| BetweenCentrality | | 5.78***(3.00) | | |
| CloseCentrality | | | 22.78***(7.33) | |
| DegreeCentrality | | | | 0.02*(0.01) |
| Firm Dummies | Yes | Yes | Yes | Yes |
| Constant | 4.48***(0.19) | 4.29***(0.21) | −0.70(1.69) | 4.60***(0.21) |
| Log Likelihood | −3474 | −3464 | −3459 | −3473 |
| LR Chi2 | 1388 | 1408 | 1418 | 1390 |
| Prob > Chi2 | 0.00 | 0.00 | 0.00 | 0.00 |
| No. Obs. | 1503 | 1503 | 1503 | 1503 |

Note: ***, **, * denote the parameter estimates are significant at 1%, 5% and 10%, respectively;
Dependent variable: PatentCount.

it is appropriate to measure the inventing life by indexing the first and the last patents an identified inventor applied.

The weights are taken into account in our model, so that the components with greater size and well organized network structure generate greater effect. However, since we are limited by the Stata package, we only add the weight in the Negative Binomial Model. An appropriate option is to add the weight item to both Exponential Survival Model and Negative Binomial Model. This may make our empirical less efficient. Therefore, we need to find or develop an additional package that takes the weight into account in the Exponential Survival Model in our future research.

## 6. Conclusions

Our understanding of the impact of network connectivity remains incomplete. This research makes several theoretical and empirical contributions to our understanding of the moderate role of the network connectivity. Using the patent co-inventing data of top 9 ICT firms that filed the largest number of patents in China, this study establishes the co-inventing network and examines the moderate role of the network connectivity in the reciprocal effect between network stability and innovation output, as well as in the network effects, e.g., clustering, structural hole richness, centrality. The connectivity exhibits positive effect on both patent output and network stability. We further confirm that the clustering and centrality demonstrate significant effect in only the largest connected component, while not significant in other isolated components. This proves the key moderate role of network connectivity, which forms the basis for information transmission and knowledge spillovers. However, the effect structural holes richness demonstrate strong effects, which is not attenuated by network isolation.

Our study has important policy implications: As the largest component plays a major role in the innovation production process in the whole network, it is necessary to maximize the network connectivity. However, Fig. 2 shows a declining trend of the size of the largest component, which should be noted by the firm managers as this will hamper knowledge spillovers and may be harmful to innovation; The positive interaction between network stability and innovation output suggests that a stable network structure is beneficial. How to refrain the employees, particularly the high-performers, from flowing out may always be one of the main focuses of firm managers; Additionally, firm managers should enhance the efficiency of the network by reducing redundant links and communications, which may lead to a network structure filled with more structural holes.

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