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Inter-firm inventor movements and the optimal structure of co-inventor networks

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Inter-firm inventor movements and the optimal structure of co-inventor networks

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Abstract

There is a growing consensus that high impact innovation requires diverse knowledge access and cohesive groupwork at the same time; however, the role of social and collaboration networks in this phenomenon is still underexplored. In this paper we construct a weighted and time-decayed co-inventor network from all IT-related patents in the harmonized OECD PATSTAT 1977-2013 database. We look at the future impact of firm innovation and apply an inventor mobility framework for the 1990-2000 period to isolate the effect of inventor characteristics from the characteristics of the collaboration network in the firm. Our results imply that highest impact innovations are produced if the firm hires brokers who will work in cohesive networks in the firm. We find evidence that the small world property of networks within the firm exaggerates the effect of incoming brokers and high-impact inventors.

JEL: C31, J69, O31

Keywords: co-inventor network, network constraint, small world network, patent citations, difference-in-differences, predicted margins

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Feltalálók cégek közötti mobilitása
és optimális együttműködési hálózata

Tóth Gergő – Lengyel Balázs

Összefoglaló

Egyre nagyobb az egyetértés azt illetően, hogy a jelentős innovációk születéséhez egyszerre szükséges a diverz tudáshoz való hozzáférés és a kohézív csoportokban való részvétel. Az együttműködési hálózatok szerepe a jelenségben azonban kevésbé feltárt. Tanulmányunkban az OECD PATSTAT adatbázisának 1977-2013 közötti IT-tevékenységekhez kapcsolódó szabadalmai alapján konstruálunk súlyozott és időben késleltetett feltalálói hálózatokat. Az 1990-2010 közötti feltalálói mobilitási hálózat segítségével elkülönítjük a feltalálók egyéni és kollaborációs hálózati jellemzőinek befolyását a cégek jövőbeli innovációira. Vizsgálatunk alapján a legnagyobb hatású innovációk születéséhez olyan brókerek alkalmazására van szükség, akik képesek kohézív kapcsolatrendszerben dolgozni a cégen belül. Eredményeink rámutattak, hogy a vállalaton belüli hálózatok kisvilág-tulajdonsága felnagyítja az újonnan alkalmazott feltalálók hatását.

JEL: C31, J69, O31

Tárgyszavak: együttműködési hálózat, kisvilághálózat, szabadalmi hivatkozások, különbségek-különbsége módszere

1. INTRODUCTION

Collaboration networks are crucial in understanding innovative success, in which the structure of the network and the position of the firm or the inventor determines the variety of knowledge access and therefore are considered as major underlying factors for innovation (Borgatti and Cross 2003, Capaldo 2007, Ibarra 1993, Inkpen and Tsang 2005, Schilling and Phelps 2007, Singh 2005, Sorenson et al. 2006, Sparrowe et al 2001, Uzzi 1997). The structural hole hypothesis is one of the most reflected propositions in this regard claiming that those firms or individuals –often called brokers– produce more radical innovations whose contacts represent non-redundant parts of the network (Burt 2004, Granovetter 1973). However, there is no clear evidence on the above theory because innovation can be produced in a cohesive network and also in a network with structural holes depending on the role of social capital in the process of innovation (Burt 1987). Accordingly, the related empirical evidence is divided in terms of the effect of network constraint. On the one hand, the innovation output of the firm is found to depend more on the number of connections but structural holes were found to have a negative effect (Ahuja 2000, de Vaan et al. 2015). On the other hand, Fleming et al. (2007) found a positive effect of brokering on innovation output of individuals. This still standing puzzle provides opportunities for new questions.

In a more recent discussion, weak ties are confronted with strong ties stressing a diversity-bandwidth trade-off regarding information diffusion in networks (Aral and van Alstyne 2011). In this argument, cohesive networks are claimed to channel complex information if paired with high bandwidth of strong ties as opposed to the classic proposition of Granovetter (1973) where diverse and therefore valuable information can be collected through weak ties that link loosely connected circles in the network. Notwithstanding the high plausibility of the diversity-bandwidth trade-off theory, very few papers provided empirical evidence for the statements. Besides Aral and van Alstyne (2011), Bruggeman (2016) finds strong evidence supporting the diversity-bandwidth above statement by using patent citation networks. Further, Aral (2016) claims that new identification strategies and in particular experimental and quasi-experimental approaches are needed to understand the endogenous relation between social structure and nodal outcomes. In this paper, we take a quasi-experimental approach by taking the case of inter-firm mobility of inventors and by investigating how the network characteristics of mobile inventors and the characteristics of the networks in the firm influence the future impact of the innovation in the firm.

We wish to contribute to the literature by translating the above discussion into two innovation management questions. First, shall the firm hire the broker inventor or the one who has worked in cohesive environments before? The broker might have access to more diverse knowledge while the inventor with cohesive network might have a deeper understanding of specific complex knowledge; and therefore, the firm may face a situation similar to the diversity-bandwidth trade-off. We propose that firms shall choose those inventors who are brokers but only to a certain degree so that they have a medium-diverse or medium-cohesive network. Second, what structure of the network in the receiving firm intensifies the impact of the incoming inventor? New inventors bring new knowledge to the firm that can be exploited more effectively in cohesive groups. In sum, the optimal firm-level outcome can be reached when hiring brokers with some experience in working with cohesive groups and make them work in a tightly knit network. This case the firm can optimize the innovation output by combining diverse knowledge access with complex understanding.

To answer the above questions and provide evidence for the argument, we create a weighted co-inventor network from all IT-related patents in the harmonized OECD PATSTAT 1977-2013 database by projecting inventor co-occurrence in patents using hyperbolic weighting. We introduce an exponential time decay to deflate tie strength and calculate network constraint (Burt, 2004) for every inventor and every year, and the small-worldliness indicator for collaboration networks in every firm and every year (Uzzi and Spiro, 2005). Next, we apply an inter-firm inventor mobility framework for the period 1990-2000, and using a difference-in-differences approach to argue for causal relation between inventor mobility and innovation output. Finally, we look at the cumulated number of citations of the patents at the hiring firm using linear regression models and various values of time-lags and isolate the effect of inventor characteristics from characteristics of networks in firms and investigate how the structure of collaboration network within the firm influences the effect of incoming inventors.Normal paragraph, 0.25 inch indent.

2. LITERATURE AND HYPOTHESES

The mobility of inventors has long been considered a major source of knowledge flow across inventing firms because firms benefit from the tacit or embodied knowledge of incoming inventors (Almeida and Kogut 1999, Arrow 1962, Levin et al. 1987, Palomeras and Melero 2010, Zucker et al. 2002). These mobile inventors are not homogenous and have larger effects on firm-level outcomes if they bring new technological expertise to the receiving firm (Rosenkopf and Almeida 2003, Song et al. 2003). Besides embodied knowledge and skills, incoming inventors can also establish new inter-firm ties by maintaining interaction with previous colleagues at distinct companies (Agrawal et al. 2006, Breschi and Lissoni 2005, 2009). These social and professional connections can provide the hiring firm with additional access to external knowledge (Powell et al. 1996) and are especially important when the research group has to understand complex knowledge (Reagans and McEvily 2003, Sorenson et al. 2006). However, very little is known about the role of network characteristics of incoming inventors in firm-level innovation. In this paper, we aim to open up this question and also aim to understand how collaboration networks within the receiving firm amplify the effect of incoming inventors.

Mobile inventors are heterogeneous in terms of their network structure and thus provide the firm with access to information of various scale and scope. For example, Kemeny et al. (2016) showed that the number of connections of incoming managers explains the variations in major firm level outcomes – such as profit – because high degree managers channel more external information into the firm than low degree managers. However, one might expect that the type of ties and the structure of the network can tell us more about information access than the mere number of connections. As it was put forward by Granovetter (1973) in one of the most influential ideas in social science, weak ties provide access to diverse information by linking loosely connected groups (Burt 1992). Consequently, individuals bridging structural holes between communities – who are often called brokers – can combine larger variety of information (Burt 2000) and can also control the information flow, which arguably provides additional gains (Newman 2005). Consequently, brokers are frequently associated with better innovation outputs (Burt 2004) than those with cohesive networks where the access to diverse knowledge is less likely.

However, trust and cohesion between connected individuals are very important for learning as well and one might consider the weak ties argument with limitations (Coleman 1988, Putnam 1995). Burt (2000, at p. 11.) also states that "[…] bridges through structural holes are the source of the ideas of the new inventions but trustful communication due highly connected individuals can be as much as important […]". In a recent discussion, weak ties are confronted with strong ties stressing a diversity-bandwidth trade-off regarding information diffusion in networks (Aral and Van Alstyne 2011). It is claimed in this argument that complex information is easier to access in cohesive or constrained networks and through strong ties due to the high level of trust and bandwidth of communication between alters (Aral 2016). Therefore, the individual is expected to collect complex information from strong and cohesive contacts in rapidly changing environments and shallow but diverse information content from weak ties.

One might anticipate from the above discussion that the combination of weak and strong ties is desirable for firm-level innovation outcomes. For example, Fleming et al. (2007) investigate the new combinations of patent subclasses in the assignments and the re-use of these combinations in order to model generative creativity on the basis of inventor collaborations. They find that broker inventors are more likely to create new combinations in general. However, they also demonstrate that new combinations may arise from cohesive networks as well if these environments are connected to two or more assignees. Yet, an inventor mobility framework can add to the understanding how network cohesion and brokerage of inventors influence firm level innovation because we can disentangle the individual effects of incoming inventors from the effects of collaboration networks within the firm.

With all the above discussion in mind, we wish to contribute to the literature in two ways. First, we pick one from three alternative hypotheses regarding the relation between the network structure of the incoming inventors and the innovation performance of the firm. The "Cohesion hypothesis" would suggest that inventors with cohesive network are more influential than inventors with diverse networks because they might have developed a deep understanding of complex knowledge working in cohesive groups previously (Obstfeld 2005). In contrast, the "Structural hole hypothesis" would imply that broker inventors are more influential for the firm than non-brokers because they have access to diverse knowledge (Burt 2004). Instead of these two traditional approaches, we propose the "Optimal cohesion hypothesis" and argue that inventors with medium value of network cohesion have the greatest influence on the firm not the ones with extremely cohesive or extremely diverse networks. This is a reasonable expectation because too little cohesion in the network might harm the efficiency of knowledge transfer and trust-based relationships (Uzzi 1997), while too much cohesion threatens the innovation effort with isolation from idea flows and with lack of economies of scope (Hansen 1999). Instead, inventors with optimal networks should have access to diverse information by brokering the network and should be able to work in cohesive groups as well to exploit complex knowledge (Aral 2016, Fleming et al. 2007).

Hypothesis 1: The innovation performance of those firms that hire new inventors with medium value of network cohesion is higher than those firms that hire inventors with very diverse or very cohesive networks.

Because networked inventors are more productive and therefore firms might be more motivated in hiring them away (Nakajima et al. 2010), productive inventors are likely to increase their networks (Lee 2010) and in turn, their mobility further increase their productivity because they learn from job switching (Hoisl 2009). This is an important endogenous relation between productivity and collaboration networks, and we argue that the inventor mobility framework allows us to go after this endogenous change. The collaboration network of the mobile inventor is further generated as he/she moves from one firm to another (Casper 2007), thus we can look at how the change in network characteristics influences firm-level innovation outcomes. We posit that the knowledge the new inventor brings into the firm is easier to exploit in cohesive groups than in loosely knit networks. Therefore, those firms are relatively more likely to produce high impact innovation that make new inventors work in groups and consequently, the network of the mobile inventors becomes more cohesive in these situations.

Hypothesis 2: The innovation performance of those firms is higher where the network of mobile inventors become more cohesive than before the mobility event.

Hypotheses 1 can be verified by a reversed U-shape association between network cohesion of the incoming inventors and the firm-level innovation performance, whereas the shift of this optimal value towards cohesion would support Hypothesis 2. This perspective accords well with Uzzi and Spiro (2005) who found similar correspondence between the success of Broadway musicals and the small-worldliness of artist collaboration networks, which indicates cohesive groups brokered by few individuals. We provide new evidence of an optimal network structure at the individual level, which can be really useful in innovation management decisions because individual characteristics are easier to detect than to optimize networks in groups.

In the last step, we further investigate how collaboration networks within the firm influence the effect of new inventors. Based on the diversity-bandwidth literature (Aral 2016, Aral and van Alstyne 2011) and the findings of Fleming et al. (2007), we expect that cohesive networks within the firm intermediate the novel diversity gained by new broker inventors better than loose networks do. We propose that small-world properties of the network shall be investigated to better understand this problem. However, instead of applying the small-worldliness indicator (Uzzi and Spiro, 2005), we focus on two key properties that describe small world networks and analyze the interaction term between the characteristics of new inventors and the characteristics of the intra-firm networks (Watts and Strogatz, 1998).

Hypothesis 3: The effect of mobile brokers is further enhanced by high levels of triadic closure and low levels of average path length of the inventor collaboration network within the firm.

3. MATERIALS AND METHODS

3.1 DATA

We downloaded the OECD Patent Database 1977-2013 directly from the OECD FTP servers in February 2015 and used data of patents filed by the European Patent Office (EPO). The full dataset contains three sources of data. (1) OECD REGPAT database version February 2015 covers patent documents filed by the EPO (derived from PATSTAT 2014 autumn edition). There are unique identifiers for patents, applicants, and inventors in the data that can be matched with other sources in the database. Furthermore, technological classes of the patents as well as the year of application are present in the table. The EPO data contains 2,750,644 patent documents authored by 594,461 inventors. (2) OECD HAN (Harmonized Applicant Names) database version February 2015 contains the cleaned and matched names of patent applicants. Although OECD statisticians warned us that the data might encounter mismatches and errors; this is the best freely available and ready to use dataset that enable researchers to trace patenting firms. There are 2,837,597 unique applicants identified in the

HAN database. (3) OECD Citations database version February 2015 contains those EPO, PCT or USPTO patents that cite the EPO patents we analyze. The data is derived from EPO's PATSTAT database, autumn 2014. There are 99,449,770 unique citations in the data.

These datasets have been merged by the patent identifiers. Then, we narrowed down the database to the G06 IPC[1] code that refers to "Computing, calculating and counting". This technological class suits our research question (Fleming et al. 2007), because programming is a highly innovative process in which fixed costs are relatively low and therefore learning through mobility and social networks might play a more important role than in other technological areas.

Table 1

Number of observations in the data

Data	Observations
Years	36
Countries	68
Firms	28,028
Treated firms	3,370
Mobile inventors	6,396
Mobility	13,519

We exclude those firms that receive more than one new inventor in any of the years the analysis covers because we aim to interpret the effect of nodal characteristics of moving inventors and cannot estimate this effect if more than one inventor arrives to the firm. The remaining dataset contains 28,028 firms located in 68 countries in the period between 1977 and 2013 (Table 1), out of which 3,370 firms that hired exactly one new inventor per year. The number of those inventors who move across firms is 6,396 and there are 13,519 movements in total. Supporting Information 1 contains descriptive figures about the number of inventors, the number of firms, the volume of inventor mobility and the list of countries.

3.2 NETWORK CREATION AND DETECTION OF INTER-FIRM MOVEMENTS

The co-inventor network is constructed from an inventor-patent co-occurrence table and inventors i and j are connected if they co-author a patent together. If the patent is co-authored by more than two inventors, the network between them will be a fully connected clique by default, which may lead to biased results (Uzzi and Spiro 2005). Therefore, we

[1] The International Patent Classification (IPC) provides for a "hierarchical system of language independent symbols for the classification of patents and utility models according to the different areas of technology to which they pertain".

apply the hyperbolic method suggested by Newman (2001) to project the co-occurrence matrix to one-mode ties. Formally,

$$w_{ij,t} \in (0,1] = e^{(t-u)\lambda} \sum_{k \in u} \frac{\delta_i^k \delta_j^k}{n_k - 1}, \quad (1)$$

where δ_i^k and δ_j^k are 1 if inventor i and inventor j co-author patent k in year u and zero otherwise and nk is the number of inventors authoring patent k. Because inventors i and j might co-author more than one patent in year u, we maximize $\sum_{k \in u} \frac{\delta_i^k \delta_j^k}{n_k - 1}$ at 1. Further, we assume that the strength of the tie weakens over time (Burt 2000) and thus we apply an exponential time decay function between the year of patent publication u and year t. The exponent of time decay is λ and the parameter is set to be equal with 0.1 as it was suggested by Jin et al. (2001). In the last step, we set wij,t to $\sum_{k \in u} \frac{\delta_i^k \delta_j^k}{n_k - 1}$ in case of a new collaboration between i and j and if $w_{ij,t} < \sum_{k \in u} \frac{\delta_i^k \delta_j^k}{n_k - 1}$.

The inter-firm movement of inventors is defined as follows. An inventor moves from company A to company B if at least one patent application authored or co-authored by inventor i has been submitted by company A prior to an application authored or co-authored by inventor i has been submitted by company B. We detect the movement from A to B at the year when the patent application is submitted by B.[2]

The time dimension needs further special care because the data only contains the year of application and the year when the patent was filed, which might be problematic because collaboration typically happens before the application is submitted. In order to remedy this problem, we assume that the edge between inventors i and j is created two years prior the year of patent application because there is substantial time needed to work together before the patent application can be submitted. This approach is not without limitations, and might cause further problems that we have to tackle.

The first problem is that we set wij,t equal to $\sum_{k \in u} \frac{\delta_i^k \delta_j^k}{n_k - 1}$ two years before the patent application and let the weight decay over these two years. One might think that collaboration remains intensive over these years and therefore tie weights should be diminished after the patent application only. Fortunately, this limitation does not cause serious problem in our analysis. In order to check whether the results depend on the procedure of tie-creation, we applied two further alternative ways to define the weight of co-inventor ties. First, we created ties with simple co-occurrence projection and did not introduce time decay. This way, the

[2] We do not consider the date of the application submitted by company A.

weight of each co-inventor tie at every point in time was 1. Second, ties made of simple co-occurrence projection were weighted by the exponential time decay introduced in the main text. This case, the weight of each tie was 1 in the year when the tie was established but the weight then decreased over time.

Since these procedures did not change our results, we chose not to report them and stick to the weight defined in Equation 1 that we think represents the value of ties created long in the past better than any of the other two tie weighting alternatives.

The second problem is the detection of mobility and the simultaneous change of nodal characteristics of mobile inventors versus the structure of collaboration networks within the firm. Because we establish the co-inventor ties two years prior to the application, the network characteristics of the mobile inventor i at time u is dependent on the projects he/she is involved in at company B. We think that this problem offers some interesting insights, and therefore will come back to it in detail in Sections 3.3 and 4.2.

3.3 ESTIMATION STRATEGY

Our focus on inventor mobility as events that influence firm-level outcomes allow us to take a quasi-experimental approach (Mayer and Davis 1999), in which the firm is treated if it hires a new inventor. A major problem is that unlike in controlled experiments, where the assignment into treated and control groups is random, in quasi-experiments the assignment into treated and control groups is not random. In our case, this means that inventors may be motivated to move from less productive to more productive firms because more productive firms promise better career potentials and innovation quality. Thus, those firms are more likely to get assorted to the treated group that have performed better before the event of the treatment, which can lead to biased estimates. To overcome this selection bias, we have to prove the causal relation between hiring a new inventor and the impact of innovation.

To control for the endogeneity issue, we apply a difference-in-differences (diff-in-diff) approach, which is suitable when the independent variable is available in the data before and after the specific action. In the diff-in-diff approach, we first estimate the effect of the new inventor on the recipient firm by comparing the innovation outcome before and after the treatment and also compare the outcome of the treated firms with the outcome of the non-treated firms. This comparison identifies the expected values of the average change and is formulated by:

$$\bar{T} = \left(E\left[\overline{Y^1_{T=1}}\right] - E\left[\overline{Y^1_{T=0}}\right]\right) - \left(E\left[\overline{Y^0_{T=1}}\right] - E\left[\overline{Y^0_{T=0}}\right]\right), \qquad (2)$$

where the first term refers to the differences in outcomes before and after the treatment for the treated group, which may be biased if there are time trends, and the second term uses the differences in outcomes for the control group to eliminate this bias.

The advantage of the diff-in-diff method is that it can avoid many of the emerging endogeneity problems while comparing heterogeneous individuals (Meyer 1995). The main limitation is called the parallel trend assumption, according to which the accomplishment of the control group should reflect what would happen to the treated group with the lack of the treatment. This assumption cannot be directly tested because we want to compare two world states of one firm, but this is obviously counterfactual, one cannot observe the evolution of the treatment group absent the treatment. Further, it is often very difficult to check the suppositions that are made about the unobservable entities and it is possible that despite significant treatment effects, the bias may be too large and consequently lead to wrong estimates.[3]

In the remainder of the analysis, we run linear regression models to measure the effect of inventor and firm-level characteristics on firm-level innovation outcomes. The first specification is

$$Y_{B,t+v} = \alpha + \beta_1 \cdot X_{i,t-3} + \beta_2 \cdot Z_{B,t} + \beta_3 \cdot W_{i,A,B,t} + \beta_4 \cdot T_{B,t} + D_t + \varepsilon_{B,t}, \quad (3)$$

where $Y_{B,t+v}$ is the innovation outcome of receiving firm B at time t+v and v is the applied time lag, $X_{i,t-3}$ denotes network characteristics of the mobile inventor i before the movement, $Z_{B,t}$ stands for the network structure variables of inventor collaboration within receiving firm B at the year of the treatment, $W_{i,A,B,t}$ is the collection of control variables of inventor i and the sending and receiving firms, $T_{B,t}$ equals 1 if firm B receives exactly 1 new inventor at time t and zero otherwise and D_t denotes year fixed effects.

With the introduction of $T_{B,t}$ and D_t into Equation 3, we first compare the outcome of treated firms at time *t+v* to the outcome of non-treated firms. Then, the rest of the co-efficients indicate the comparison within the group of treated firms.

However, because the effects of mobile inventor on firm-level innovation outcomes prevail through collaboration with others in the firm, network characteristics change during mobility. In the second specification, we investigate the role of change in nodal

[3] Accordingly there is a debate about the validity of the diff-in-diff method. Abadie (2005) discusses group comparisons in non-experimental studies, Athey and Imbens (2002) concern the interference in diff-in diff because of the linearity assumption, Besley and Case (1994) criticize whether this method really can detangle the possibility of endogeneity and Bertland et al. (2002) focus on issues related to the standard error of the estimates.

characteristics of the mobile inventor during the event of mobility together with nodal characteristics after mobility:

$$Y_{B,t+v} = \alpha + \beta_1 \cdot X_{i,t} + \beta_2 \cdot (X_{i,t} - X_{i,t-3}) + \beta_3 \cdot Z_{B,t} + \beta_4 \cdot W_{i,A,B,t} + \beta_5 \cdot T_{B,t} + D_t + \varepsilon_{B,t} \quad (4)$$

where $X_{i,t}$ denotes nodal characteristics after and $X_{i,t} - X_{i,t-3}$ the change during mobility.

In the third step, we estimate the effect of nodal characteristics after the mobility event:

$$Y_{B,t+v} = \alpha + \beta_1 \cdot X_{i,t} + \beta_2 \cdot Z_{B,t} + \beta_3 \cdot W_{i,A,B,t} + \beta_4 \cdot T_{B,t} + D_t + \varepsilon_{B,t}, \quad (5)$$

Finally, we introduce the interaction term between characteristics of inventor i and the network structure of company B:

$$Y_{B,t+v} = \alpha + \beta_1 \cdot X_{i,t-3} \times Z_{B,t} + \beta_2 \cdot X_{i,t-3} + \beta_3 \cdot Z_{B,t} + \beta_4 \cdot W_{i,A,B,t} + \beta_5 \cdot T_{B,t} + D_t + \varepsilon_{B,t} \quad (6)$$

where $X_{i,t-3} \times Z_{B,t}$ stands for the interaction between the characteristics of mobile inventors and the network structure of the receiving firm.

In order to check the validity of Hypothesis 1, we predict the marginal effects of $X_{i,t-3}$ by keeping all other covariates of Equation 3 fixed. Hypothesis 2 is tested by Equation 4 and by calculating the marginal effects of $X_{i,t}$ from Equaiton 5. As a result, we can directly measure the change in $Y_{B,t+v}$ as a response to a 1 unit change in $X_{i,t-3}$ and $X_{i,t}$. Hypothesis 3 is tested by analyzing the interaction term in Equation 6.

3.4 VARIABLES

The dependent variable of our analysis is the cumulative change of citations to the patents owned by the firm. Although criticized in the literature (Beaudry and Shiffaeurova 2011) the number of citations has been frequently used to predict patent quality and market value (Hall et al. 2005, Harhoff et al. 1999, Mowery and Ziedonis 2002, Trajtenberg 1990). Further, we think that a sufficiently long period of citation accumulation can help us avoid the potentials of reversed causality discussed in Section 3.3.

We characterize the nodal property of the mobile inventor with the well-known network constraint measure that was proposed by Burt (1992) to distinguish brokers from non-brokers. This indicator measures the cohesiveness of the ego-network around a node and is formulated by:

$$C_{i,t} = \sum_j \left(p_{ij,t} + \sum_q p_{iq,t} p_{qj,t}\right)^2 \; i \neq q \neq j, \quad (7)$$

where $p_{ij,t} = w_{ij,t} / \sum_q w_{iq,t}$ and $w_{ij,t}$ is the tie weight defined in Equation 1. Thus, $p_{ij,t}$ quantifies the relative weight that i is connected with directly and $\sum_q p_{iq,t} p_{qj,t}$ quantifies the relative weight that i is connected with indirectly – through another contact q – to contact j. The indicator $C_{i,t}$ takes a high value if the relative weight of q and j pairs is high; and takes a low value in the contrary case. Consequently, a high $C_{i,t}$ denotes a cohesive ego-network of i because its' neighbors are strongly connected, while a low $C_{i,t}$ denotes that i connects otherwise poorly connected parts of the network and therefore i is a broker.

The network constraint is not totally independent from the number of connections of the node ($D_{i,t}$) because the larger number of connections an inventor has the lower probability that these connections will also know each other (Burt, 2004). Indeed, Supporting Information 2 demonstrates the strongly negative correlation by illustrating the change of these indicators along the different components in the network. In order to evade from the potential bias caused by the variance of the number of connections, we control for $D_{i,t}$ and also for the interaction between $C_{i,t}$ and $D_{i,t}$.

Properties of the network at the receiving firm B are captured by the small-worldliness that consists of the global clustering coefficient (defined also as triadic closure or transitivity, $TR_{B,t}$) and average path length ($APL_{B,t}$) in the inventor collaboration network within the firm. $TR_{B,t}$ compares the number of closed triangles to the possible number of triangles in the network of company B at time t. $APL_{B,t}$ measures the degree of separation between nodes averaged over the full collection of node pairs in company B at time t. Social networks are typically cliquish and only few steps separate two randomly selected individuals in the network. Watts and Strogatz (1998) used these two indicators to describe this phenomenon as the small-world property of social networks. Uzzi and Spiro (2005) further formulated the small-worldliness into a $Q_{B,t} = TR_{B,t} / APL_{B,t}$ ratio and showed that collaborative projects with medium $Q_{B,t}$ produce the best outcomes because social cohesion is paired with diversity in these networks.

To control for the qualities of the mobile inventor i, as well as the sending firm A, we use the total number of patent applications ($PAT_{i,t}$ and $PAT_{A,t}$) and the total number of citations ($CIT_{i,t}$ and $CIT_{A,t}$) the inventors and firms submitted and received until time t. Properties of the receiving firm B include the total number of patent applications and citations cumulated until time t (PAT_{Bt} and $CIT_{B,t}$), the number of patent applications after the treatment and within the following 10 years (*APP10*), the number of treatments received within the following 10 years (*T10*), the number of inventors who author or co-author the patent applications that were submitted by the firm in years t-2, t-1 or t ($INV_{B,t}$) and the density of the collaboration network of these inventors ($DENS_{B,t}$).

Finally, we found a large drop in the total number of citations in years 2011-2013 that we could not explain. Therefore, we decided to exclude these years from the citations dataset, which means that the analysis is restricted to the 1990-2000 period since we look at citation growth over ten years and thus the last year of mobility events is 2000.

Our final sample contains 95,788 observations of firm-year combinations out of which 8,708 observations concern those firms who receive a new inventor. Descriptive statistics of and Pearson correlation between main variables are presented in Table 2.

Table 2

Descriptive statistics and correlation between main variables

	Variable	Obs.	Mean	Std. Dev.	Min	Max	1	2	3	4	5	6
1	C_{it}	95,788	0.004	0.060	0	1.681	1					
2	D_{it}	95,788	0.020	0.373	0	26	0.519*	1				
3	Q_{Bt}	95,788	0.218	0.390	0	1	-0.014*	0.002	1			
4	$DENS_{Bt}$	95,788	0.462	0.465	0	3	-0.0003	0.004	0.568*	1		
5	INV_{Bt}	95,788	0.021	0.335	0	25	0.199*	0.29*	0.017*	0.014*	1	
6	TR_{Bt}	95,788	0.311	0.454	0	1	0.004	0.022*	0.829*	0.418*	0.050*	1
7	APL_{Bt}	95,788	2.175	9.955	0	518.5	0.023*	0.032*	-0.042*	-0.066*	0.068*	0.226*

Note: * $p<0.05$.

4. RESULTS

4.1 THE EFFECT OF INVENTOR MOBILITY

The diff-n-diff test provides a clear proof for the causal relationship between inventor mobility and average citation growth after 10 years of the treatment (Table 3). The estimations illustrate that patents assigned to firms treated in year 1995 receive 8 extra citations on average during the next ten years compared to patents assigned to control firms. This causal relationship stands for treatments in year 2000 as well, where the treatment effect is 2 extra citations. Certainly, the treatment effect might deviate from the average.

Table 3

Diff-in-diff test for inventor mobility and citation growth

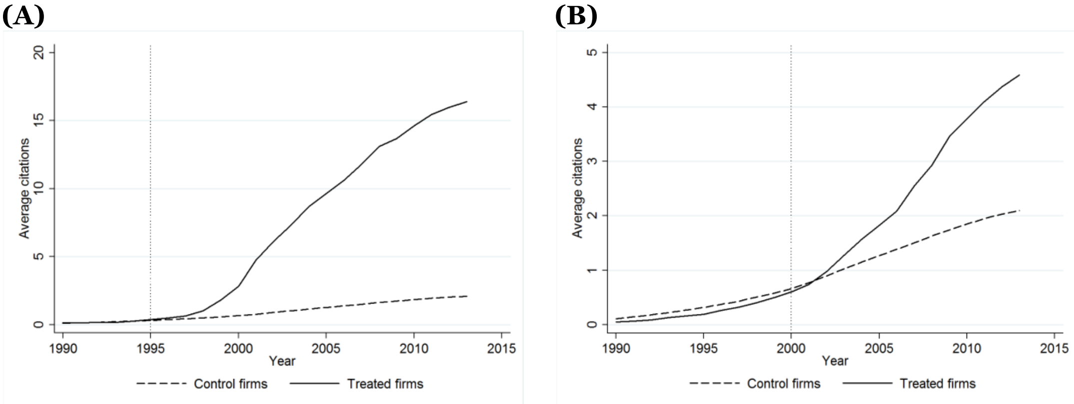
	Treatment 1995				Treatment 2000			
	Y	Std. Error	t	P	Y	Std. Error	t	P
Before								
Control (C)	0.369				0.520			
Treated (T)	1.881				0.783			
Diff (T-C)	1.512	0.152	9.94	0.000***	0.263	0.075	3.49	0.000***
After								
Control (C)	1.099				1.143			
Treated (T)	10.654				3.314			
Diff (T-C)	9.555	0.215	44.44	0.000***	2.170	0.181	12.1	0.000***
Diff-in-Diff	8.044	0.263	30.54	0.000***	1.907	0.196	9.74	0.000***

Further, one can observe in Figure 1 that treated firms did not differ on average from non-treated firms before the treatment. In fact, the number of citations starts to deviate from the control group two years after the treatment. Until that point, the trend in the treatment and control groups are parallel, and the differences are actually nuanced. This observation is very important for our further analysis because we can assume that the observed shift in the dependent variable would not occur in the absence of the treatment. This assumption makes the bases for the further estimations in which we aim to explain the variance of the deviation in the treatment group.

Figure 1

Citation growth in treated and control firms

(A) **(B)**



Note: (A) The citations of those firms that receive a new inventor in 1995 start to increase sharply in 1997. Treated firms have 8 more citations on average than non-treated firms in 2005. (B) The citations of those firms that receive a new inventor in 2000 start to increase sharply in 2002. Treated firms have 2 more citations on average than non-treated firms in 2010.

Table 4

The impact of nodal characteristics of mobile inventors

		Cumulative citations of firms 10 years after the treatment		
		(1)	(2)	(3)
Network characteristics of the mobile inventor	C_{it-3}	-0.743575***	-0.655676**	
		(0.285)	(0.296)	
	C_{it} - C_{it-3}		0.786228***	
			(0.266)	
	C_{it}			1.103024**
				(0.470)
	C_{it} squared			-0.864641**
				(0.389)
	C_{it} × D_{it}	-0.212756***	-0.274054***	-0.326902***
		(0.053)	(0.089)	(0.095)
	D_{it}	0.039537**	0.049212**	0.039174*
		(0.017)	(0.022)	(0.021)
		(0.016)	(0.016)	(0.016)
Quality of the mobile inventor	CIT_{it}	-0.018494	-0.035142	-0.031034
		(0.047)	(0.048)	(0.048)
	PAT_{it}	0.081113***	0.074478**	0.045779
		(0.031)	(0.031)	(0.031)
Quality of the recipient firm	CIT_{Bt}	0.016212***	0.016216***	0.016213***
		(0.004)	(0.004)	(0.004)
	PAT_{Bt}	0.034799***	0.034799***	0.034807***
		(0.008)	(0.008)	(0.008)
Quality of the sending firm	CIT_{At}	-0.000139	-0.000141	-0.000146
		(0.000)	(0.000)	(0.000)
	PAT_{At}	0.000366*	0.000368*	0.000379*
		(0.000)	(0.000)	(0.000)
Treatment and dynamics	T	0.223448***	0.222537***	0.222810***
		(0.043)	(0.043)	(0.043)
	T10	0.205008***	0.204818***	0.204854***
		(0.059)	(0.059)	(0.059)
	APP10	0.024600***	0.024602***	0.024587***
		(0.004)	(0.004)	(0.004)
Network in the recipient firm	Q_{Bt}	2.690093***	2.690847***	2.690724***
		(0.208)	(0.208)	(0.208)
	Q_{Bt} squared	-2.741735***	-2.742346***	-2.741847***
		(0.208)	(0.208)	(0.208)
	$DENS_{Bt}$	-0.009633	-0.009736	-0.010092
		(0.021)	(0.021)	(0.021)
	INV_{Bt}	-0.017001	-0.015714	-0.016300
	Constant	0.556668***	0.556669***	0.556706***
		(0.191)	(0.191)	(0.191)
	YEAR FE	Yes	Yes	Yes
	adj. R-sq	0.277	0.277	0.277
	N	95,788	95,788	95,788

Note: Standard errors in parentheses. * p<0.10. **p<0.05. *** p<0.01.

4.2 NETWORK CHARACTERISTICS OF THE MOBILE INVENTOR

In order to investigate Hypotheses 1 and 2, we run ordinary least squares (OLS) pooled regressions with year fixed effects; standard errors are clustered by the receiving firm. Non-standardized co-efficients and standard errors of point estimates are reported in Table 4.

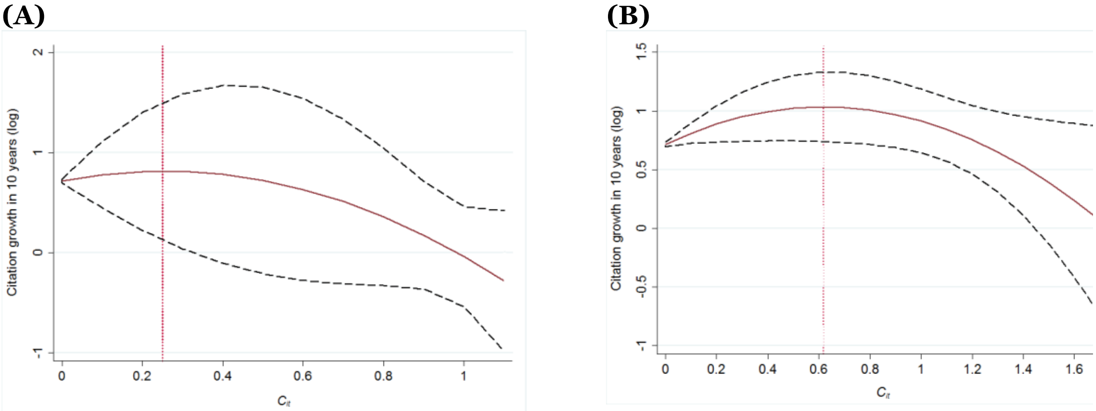
Column 1 reports the co-efficients of variables specified in Equation 3, Column 2 reports the co-efficients of variables specified in Equation 4 and Column 3 reports on the coefficients of variables specified in Equation 5. The models are stable in terms of the co-efficients and explain around 30% of the variation of the independent variable.

Getting to our first research question, we assess whether broker inventors or inventors with cohesive networks enhance the innovation impact of the receiving firm. To start in Column 1 of Table 4, we introduce C_{it-3} and look at the effect of mobile inventors on the basis of their network constraint prior to the event of mobility. The negative coefficient we find means that those inventors who were in broker positions before the event of mobility, influence the impact of firm-level innovation more than non-broker inventors. The squared term of C_{it-3} was not significant, and therefore, the linear regression alone would infer a linear relationship between being a broker and innovation. However, we calculated the marginal effect of C_{it-3} from the regression reported in Column 1 by keeping all other covariates fixed and plotted it in Figure 2A. These marginal effects in Figure 3A suggest that the effect of C_{it-3} is not completely linear. In fact, we find that the mobile inventor has the greatest impact on the recipient firm if his/her network constraint is 0.22, the marginal effect is significant in the optimal point. Despite mobile brokers might induce the impact of innovation at the recipient firm more than mobile non-brokers, a certain degree of cohesiveness amplifies the effect. In sum, calculating the marginal effects, we find support for Hypotheses 1.

Figure 2

Marginal effects of network constraint (C) on citation growth.

(A) **(B)**



Note: (A) Network constraint of the mobile inventor at time t_{-3}. The solid line represents estimates and the dashed line is the 95% confidence interval. The dotted vertical line at C_{it}=0.22 denotes the highest predicted margin. (B) Network constraint of the mobile inventor at time t. The solid line represents estimates and the dashed line is the 95% confidence interval. The dotted vertical line at C_{it}=0.61 denotes the highest predicted margin.

However, the mobile inventor establishes new connections with colleagues at the receiving firm while working on new patents, which can alter the value of network constraint. This problem is more pronounced in time-weighted networks, such as our co-inventor network, because newly established ties are stronger by definition and thus can increase constraint. To look at this notion, we introduce the change of C_i between time t and t-3 into Columns 2 of Table 4. As expected, the coefficient of C_{it} - C_{it-3} takes the positive sign while the sign of C_{it-3} does not change. In the final step, we introduce C_{it} and also its squared term in Column 3 of Table 4. Indeed, both of the coefficients are significant but with opposite sign and their relation suggest a reverse U-shape. We calculate the marginal effect of C_{it} from Column 3 and depict it in Figure 2B. The finding demonstrates that the reversed U-shape curve shifts to the right, and the optimal point becomes C_{it} =0.61. These results support Hypotheses 2, we find that new inventors who provide access to new external knowledge through their previous contacts enhance the innovation performance of the firm more if they work in cohesive projects in the recipient firm and thus increase their network constraint.

We control for the interaction between C_{it} and D_{it} because those inventors are more likely to be brokers who have more connections (Burt, 2004). We indeed find a significant effect of the interaction term, which suggest that it is important and makes individual effects clearer. We find that D_{it} has a positive effect on the firm-level outcome, which suggests that the connectedness of inventors matter. Further inventor characteristics are controlled for as well, PAT_{it} has a significant effect but CIT_{it} is not significant. Regarding the firm-level control variables, we find that the firm receives more citations in the future if the new inventor is coming from a firm that has many patent applications and if the receiving firm itself has produced many patent applications and has already accumulated many citations. The coefficients $PAT_{A,t}$ and $CIT_{A,t}$ are lower by two orders of magnitude than the coefficients of $PAT_{B,t}$ and $CIT_{B,t}$ and $CIT_{A,t}$.is not significant. This means that the quality of the sending firm matter less than the quality of the receiving firm. This is intuitive and one might list various reasons that cause it; for example, inter-firm knowledge transfer is not automatic and one mobile inventor might transfer only a tiny share of sending firm's knowledge. More interestingly, we do not find a significant correlation between the number of inventors working for the receiving company. This might be due to the very high correlation between INV_{Bt} and C_{it} and C_{it-3} and we will come back to this issue in a bit.

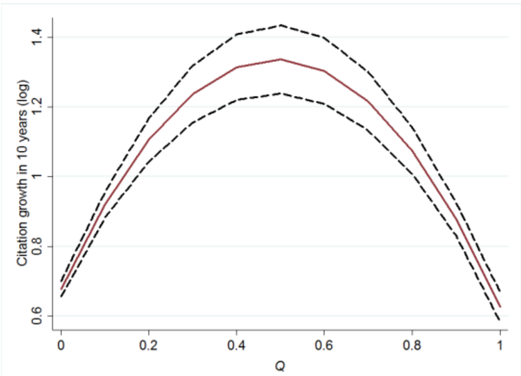
The co-efficients of T is positive and significant in all the models indicating that treated firms cumulate more citations within 10 years after the treatment than non-treated firms. As expected, *T10* and *APP10* have positive and significant point estimates, which means that the more treatment the firm receives and the more patent applications it submits over the 10 years after the investigated treatment the more citations the firm will receive.

4.3 THE NETWORK ENHANCEMENT EFFECT

The remaining co-efficients in Table 4 are related to the network characteristics of the recipient firm. We expected a non-linear correlation between the small-worldliness indicator $Q_{B,t}$ and citation growth (Uzzi and Spiro, 2005). Indeed, $Q_{B,t}$ has a significant positive coefficient while its' squared term has a significant negative coefficient. We calculated the marginal effect of $Q_{B,t}$ from the regression reported in Column 1 of Table 4 by keeping all other covariates fixed and plotted it in Figure 3. One can observe that the margins have an almost perfect reversed U-shape. The reversed U-shape means that the impact of innovation grows if Q increases from 0 to 0.5 but patents get less citations if Q increases from 0.5 towards 1 the patents produced by the firm are likely to get less citations. The result suggests that medium values of small-worldliness are optimal for innovation and our case resembles the example of Uzzi and Spiro (2005). This finding alone supports the idea of the optimal structure of inventor collaboration networks because a combination of weak and strong ties is needed to better outcomes (Aral, 2016). Those co-inventor networks are more productive that contain cohesive groups that can be reached through only few steps because this structure enables effective communication. However, the likelihood to find diverse information in a network is low if the network is too small-worldly.

Figure 3

Marginal effect of the small-worldliness (Q) of inventor collaboration networks on citation growth



Note: The solid line represents the point estimates and the dashed lines depict 95% confidence interval.

The collaboration network of inventors within the receiving firm is an important source of knowledge production because the knowledge of the new inventor can be transmitted to other projects through connections and also because the new inventor can benefit from accessing knowledge of indirect partners. Therefore, we aim to investigate whether cohesive or loosely knit co-inventor networks enhance the treatment effect of incoming inventors. Here, instead of looking at the accelerator effect of small-worldliness Q, we apply its' components, namely high transitivity (TR_{Bt}) and average path length (APL_{Bt}) and investigate their enhancement effect separately.

In order to carry out the exercise, we take the number of previously received citations CIT_{it} as quality indicator of the inventor's knowledge that might spill over to other colleagues in the network. Further, we also consider whether the mobile inventor brings diverse knowledge into the firm. To do this, we transform the C_{it-3} indicator into $1–C_{it-3}$ that is high if the inventor is broker and is low if the inventor is not a broker. This latter transformation will make the interpretation of the results easier. Then, we interact these inventor qualities with TR_{Bt} and APL_{Bt} and introduce these variables into Equation 6 along with further control variables applied in Section 4.2. We use OLS regression with clustered standard errors by the receiving firm for estimation. Table 5 summarizes the results.

We find that transitivity of the network increases the positive shock that a new high-impact inventor means for the firm. This is what we would expect because network cohesion and strong ties are important for understanding and transferring complex knowledge. We do not find that average path length matters for network enhancement. This is surprising because short paths could speed up the spreading of new knowledge.

More importantly, we find that transitivity increases the effect of incoming brokers while smaller average path length favours the spillover of their knowledge. These two findings together suggest that the small world property of inventor collaboration networks within firms enhance the effect of incoming brokers. We verify Hypothesis 3.

Table 5

The enhancement effect of small world networks

	Cumulative citations of firms 10 years after the treatment		
	(1)	(2)	(3)
$CIT_{it} \times TR_{Bt}$	2.923299***		4.116214***
	(0.852)		(1.130)
$CIT_{it} \times APL_{Bt}$	-0.009648		-0.097487
	(0.058)		(0.078)
$(1 - C_{it-3}) \times TR_{Bt}$		0.363337	1.440075**
		(0.957)	(0.626)
$(1 - C_{it-3}) \times APL_{Bt}$		-0.107501**	-0.157022***
		(0.047)	(0.032)
$1 - C_{it-3}$	0.844843***	1.011258***	0.980187***
	(0.246)	(0.256)	(0.242)
CIT_{it}	-0.051633**	-0.009491	-0.045144**
	(0.021)	(0.045)	(0.021)
TR_{Bt}	0.362160***	-0.001086	-1.077962*
	(0.031)	(0.957)	(0.626)
APL_{Bt}	-0.017367***	0.090112*	0.139651***
	(0.005)	(0.047)	(0.032)
Constant	-0.338523	-0.504976	-0.473864
	(0.325)	(0.332)	(0.321)
YEAR FE	Yes	Yes	Yes
adj. R-sq	0.279	0.279	0.279
N	95788	95788	95788

Note: Standard errors in parentheses. * $p<0.10$. ** $p<0.05$. *** $p<0.01$. Further control variables that are not reported in the table include D_{it}, $C_{it} \times D_{it}$, INV_{Bt}, $DENS_{Bt}$, CIT_{Bt}, PAT_{Bt}, CIT_{At}, PAT_{At}, PAT_{it}, APP10, T, T10. Standard errors are clustered by the receiving firm.

5. CONCLUSIONS

A quasi-experimental approach has been taken in this paper to assess the role of co-inventor networks on firm-level innovation performance and the events of inter-firm mobility of inventors were used as sources of external variation.

We argue that the nodal characteristics of those new inventors who bring new knowledge into the firm matter and thus we can better understand if individuals with diverse access to external knowledge or those who are located in cohesive groups add more to the innovation process. Our first finding suggests that neither extremely high nor extremely low but moderately low values of network cohesion are optimal for innovation performance. In other words, those inventors make the largest impact who are brokers but have previous experience in working with cohesive groups as well. Further, firm-level outcomes are optimal if the new inventors collaborate in cohesive groups within the firm because this makes the exploitation of the new knowledge more effective. Finally, we argue that the structure of the collaboration network of inventors within the firm scales up the positive shock of knowledge inflow. Indeed, we find that small world networks are more efficient in enhancing the effect of incoming high-impact inventors and brokers. The effects of new inventors are higher if the transitivity of the network is high and if the average path length is low.

The results fit well to the diversity-bandwidth threshold framework that has been recently developed in sociology (Aral and van Alstyne, 2011) because knowledge production is optimal when a large variety of information accessed through diverse networks are understood and processed in cohesive groups that can foster the communication of complex contents. The contributions we make in this paper have high relevancy for innovation management and can be applied in two ways. First, firms might be able to increase the impact of their innovation output by looking at the position of potential new inventors and selecting that one whose network constraint is close to the optimal value. Second, firms can further enhance the influence of new inventors by establishing cohesive direct environments for them and quick access through indirect ties to further knowledge produced and stored in other projects of the company.

Further research is needed to show how these results hold in other situations because the potentials for knowledge transfer through inventor mobility and through co-inventor contacts might differ across industries. Furthermore, real communication flows should be analyzed to shed more light on how knowledge is created and combined in professional networks and to what extent external ties are used by mobile inventors in the recipient firm. Last, instead of the quasi-experimental approach, organized experiments will help us better understand causal relations between co-inventor networks and innovation performance.

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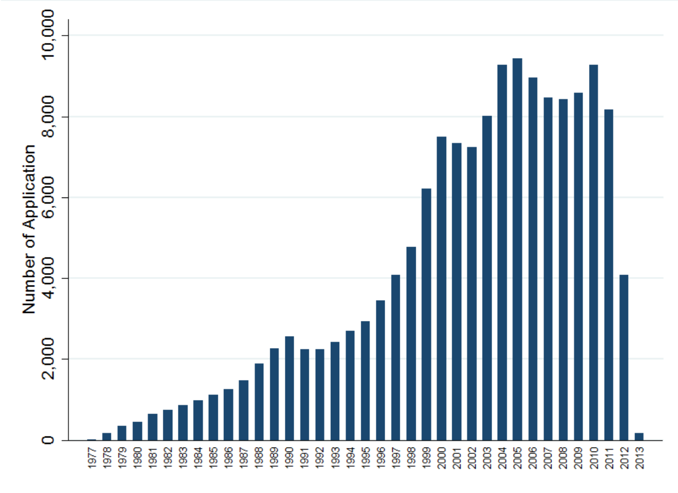
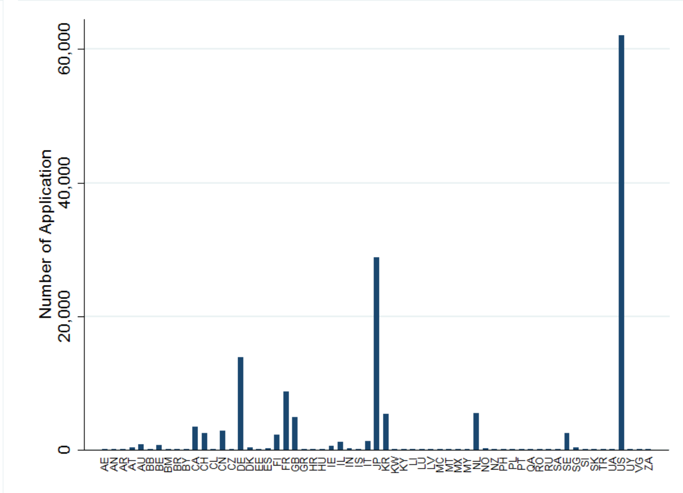
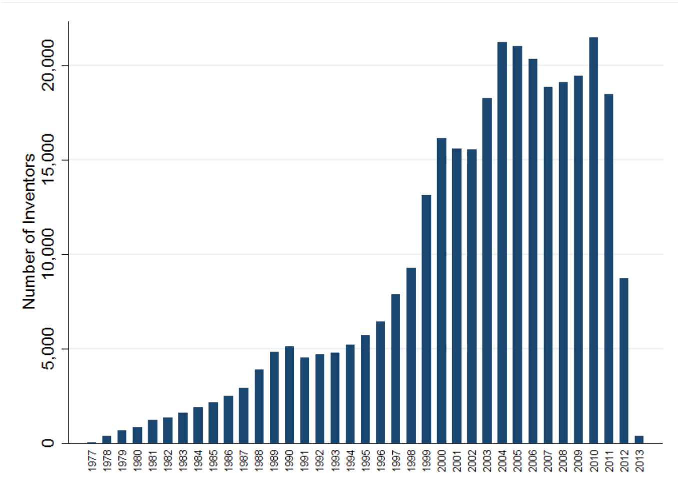
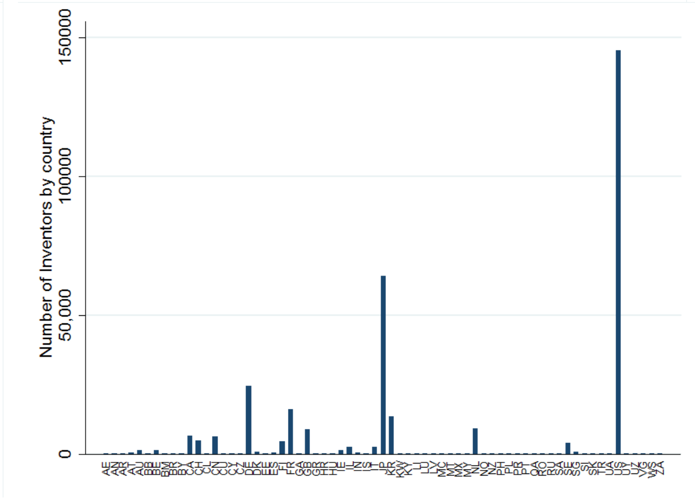
Supporting Figure 1

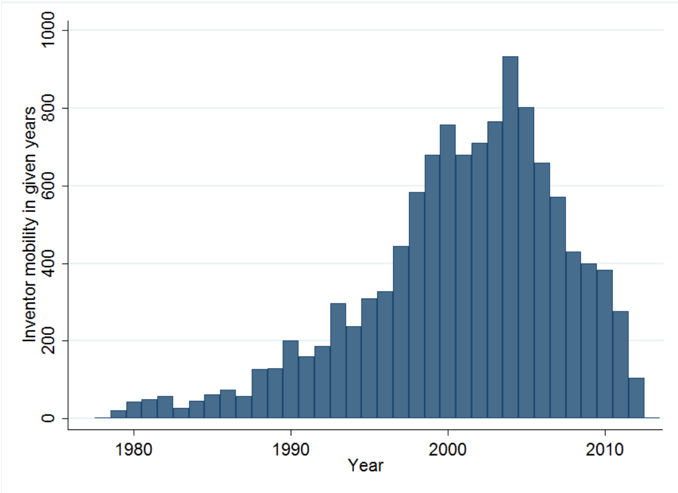
The number of patent applications, inventors and inventor mobility over the period and their country distributions











Countries that are covered in the data: Argentina, Austria, Australia, Bahamas, Barbados, Belarus, Belgium, Bermuda, Brasilia, Brit-Virgin Islands, Canada, Cayman Islands, Chile, China, Croatia, Cuba, Cyprus, Czech-Republic, Denmark, Estonia, Finland, France, Georgia, Germany, Greece, Hungary, Iceland, Ireland, India, Israel, Italy, Japan, Kuwait, Latvia, Liechtenstein, Luxemburg, Malaysia, Malta, Mexico, Monaco, Netherlands, Netherlands Antilles, Norway, New-Zealand, Philippines, Poland, Portugal, Puerto Rico, Qatar, Romania, Russia, Samoa, Saudi Arabia, Singapore, Slovakia, Slovenia, South Africa, South-Korea, Spain, Sweden, Switzerland, Turkey, Ukraine, United Arab Emirates, United Kingdom, United States, Uruguay, Uzbekistan.

Supporting Table 1

Components of the co-inventor network, 2013

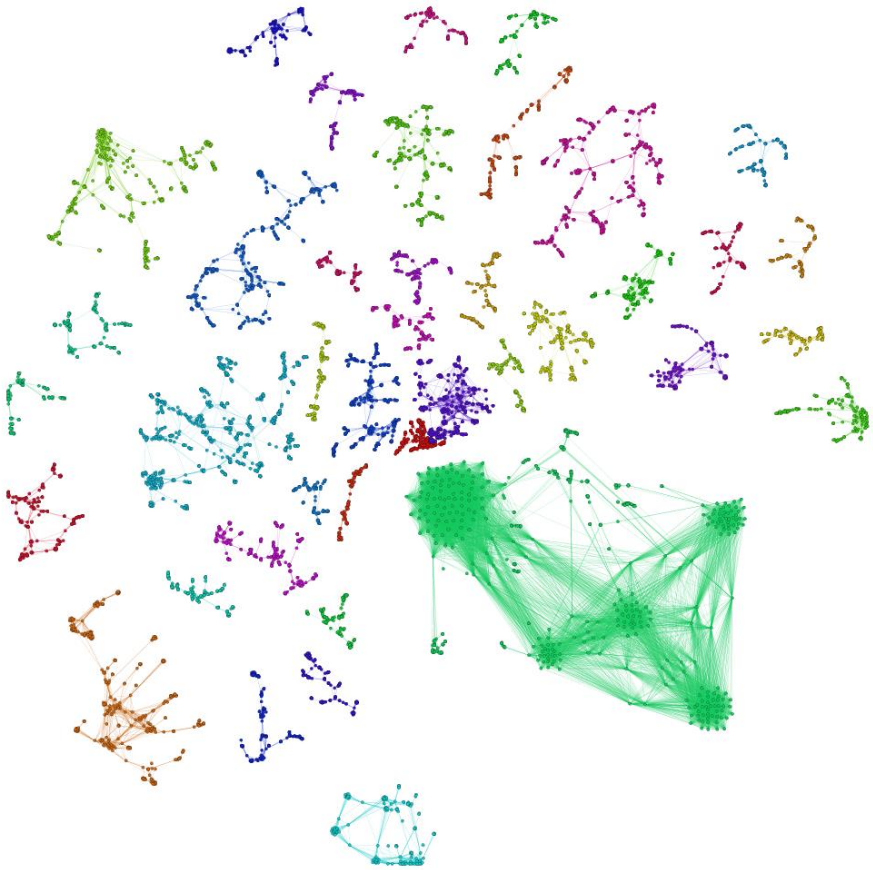
Inventors	2	3	4	5-10	11-20	21-50	51-100	101-
# Components	27,207	17,768	10,276	14,046	1,701	461	62	40
Avg. D_{it}	1	1.957	2.884	4.678	7.138	8.238	8.186	9.001
Avg. C_{it}	N.A.	1	0.921	0.671	0.495	0.467	0.482	0.491

Despite the growing number of brokers, the co-inventor network contained 71,561 isolated components in year 2013. The components of the network are not connected to each other, thus the network has a very fragmented structure. The vast majority of the components contain only a small number of nodes (Table SI3), 77% of the components have less than five nodes. However, there are also a considerable number of large components that account for many inventors. It is illustrated in Table SI3 that the inventors in large components have more connections on average than in small components. The average value of constraint decreases as well as the size of the components grows, which means that brokers might be found in large components. However, the value of average constraint does not seem to decrease monotonously, the value in the largest components are almost identical to the components of 11-20 inventors.

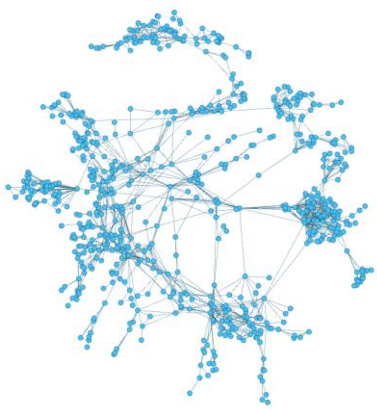
We visualize the largest components of the co-inventor network in Figure SI3 by using distinct color codes for each component. Figure SI3A reveals that these large components have similar structures; they contain closely connected groups of inventors that. The largest network in Figure SI3B contains relatively small closely connected groups, in which inventors have all worked with each other on a patent. These groups are linked by few brokers who have worked with at least one inventor in one closely connected group and at least one inventor in another closely connected group. The second largest network in Figure SI3C has a somewhat different structure. The closely connected groups are large and the networks of these groups are full, which means that all of the concerning inventors have worked with each other.

The largest components in the co-inventor network, 2013.

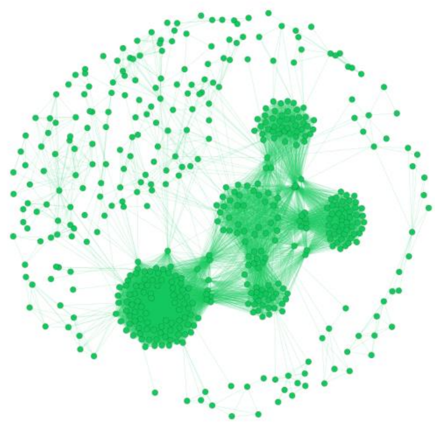
(A)



(B)



(C)



Note: (A) The components that have more than 100 inventors, 2013. Force Atlas 2 algorithm was used. (B) The largest component containing 717 inventors, 2013. Fruchterman-Reingold algorithm was used. (C) The second largest component containing 504 inventors, 2013. Fruchterman-Reingold algorithm was used.