



# Inter-firm inventor mobility and the role of co-inventor networks in producing high-impact innovation

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## Abstract

Inter-firm mobility of inventors is a major source of embodied knowledge transfer and receiving firms enjoy additional benefits from the collaboration networks of mobile inventors. However, there is still limited understanding on how the firm can maximize the impact of incoming inventors and what structure of co-inventor networks is the most beneficial for that. To answer this question, we construct a weighted and time-decayed co-inventor network from all IT-related patents in the harmonized OECD PATSTAT 1977–2010 database and analyze events of inter-firm inventor mobility. We look at the future impact of firm innovation and isolate the effect of mobile inventors' network characteristics from the characteristics of the collaboration network in the receiving firm. Our results imply that high-impact innovations are produced if the firm hires broker inventors who have diverse networks and thus has the potential to channel a wide pool of knowledge into the firm. We find evidence that cohesive networks within the firm, measured by small world characteristics, exaggerate the effect of incoming brokers and high-impact inventors.

**Keywords** Network constraint · Small world network · Patent citations · Predicted margins

**JEL Classification** C31 · J69 · O31

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## 1 Introduction

The mobility of inventors has long been considered a major source of knowledge flow across inventing firms because they benefit from the tacit or embodied knowledge of incoming inventors (Almeida and Kogut 1999; Arrow 1962; Levin et al. 1987; Palomeiras and Melero 2010; Zucker et al. 2002). According to the central tenet, mobile inventors have larger effects on firm-level outcomes if they bring new technological expertise to the receiving firm (Rosenkopf and Almedia 2003; Song et al. 2003) that is related to the existing expertise in the firm (Boschma et al. 2009; Csáfordi et al. 2018). Besides embodied knowledge and skills, incoming inventors 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 must understand complex knowledge (Reagans and McEvily 2003; Sorenson et al. 2006). Collaboration networks established by employee mobility has been proven to foster growth of higher aggregates such as industry clusters or regions (Almeida and Kogut 1999; Eriksson and Lengyel 2018; Lengyel and Eriksson 2017). However, we need to better understand what structures of collaboration networks firms benefit the most from when they hire new workers or inventors.

In this paper, we argue that the network structure of the individual mobile inventor, the structure of the collaboration network within the receiving firm and finally, the interplay between these structural forms influence the innovation output of the firm. The rationale behind the argument is that mobile workforce is heterogeneous in terms of network structure and consequently provide the firm with access to information of various scale and scope (Kemeny et al. 2016). Those individuals who bridge otherwise unconnected parts of the network—often called brokers—bring diverse new connections to the firm that consequently can combine larger variety of information (Burt 1992, 2000, 2004) and can also control the information flow, which arguably provides additional gains (Granovetter 1973; Newman 2005). The efficiency to absorb external information in the firm (Cohen and Levinthal 2000); however, arguably depends on the internal structure of collaboration (Fleming et al. 2007; Vedres 2017), in which cohesive networks within the firm perform better than loosely knit networks (Aral and van Alstynne 2011; Ter Wal et al. 2016).

Our contribution to the literature is therefore, twofold. Firstly, we connect the recent focus of inventor mobility to already existing ideas in network studies. This is an important step, because the structure of networks and their influence on outcomes are biased by endogeneity and therefore, causality is difficult to disentangle (Aral 2016). The inventor mobility framework provides a novel approach, in which the effect of mobile inventors' characteristics can be isolated from the features of collaboration networks within receiving firms. Secondly, the inventor mobility approach provides recommendations for company managers as well as for policy-makers on what type of inventors should be hired in the firm or attracted to the region and on what type of collaboration network should be built up within the firm or the region to maximize the impact of incoming inventors.

Reflecting on recent discussion in the sociology and innovation studies literature, we establish two hypotheses in the following section. Then, to provide empirical evidence for the argument, we create a weighted co-inventor network from all IT-related patents in the harmonized OECD PATSTAT 1977–2010 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—the measure of brokership in networks

(Burt 2004)—for every inventor and every year, and the small-worldliness indicator—the measure of network cohesion (Uzzi and Spiro 2005)—of collaboration networks within every firm and for every year. Next, we apply an inter-firm inventor mobility framework for the period 1990–2000 and use a difference-in-differences approach to analyze the relation between inventor mobility and innovation output. Finally, we look at the cumulated number of citations of the patents at the hiring firm using a variety of 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. Our findings confirm that firms benefit the most from hiring broker inventors and situating them in cohesive collaboration networks within the firm. This new empirical evidence opens the floor for future research that is discussed in the closing section of this paper.

## 2 Literature and hypotheses

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).

Nevertheless, trust and cohesion between connected individuals are very important for learning as well and one might consider the structural hole argument with limitations (Coleman 1988; Putnam 1995). Burt (2000, 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 [...]”. Accordingly, some empirical findings demonstrate that the innovation output of the firm is negatively affected by structural holes (Ahuja 2000; de Vaan et al. 2015) and others find a positive relationship between brokering structural holes and innovation output of individuals (Fleming et al. 2007).

In a recent discussion, diverse and cohesive networks are claimed to complement each other (Aral 2016) in a way that loosely knit networks provide access to diverse information (Granovetter 1973); while complex information is channeled more effectively in cohesive structures. The claim was empirically supported by using email data (Aral and van Alstyne 2011), patent citation data (Bruggeman 2016) and by investigating the role of investors’ social networks in the survival of new ventures (Ter Wal et al. 2016). Fleming et al. (2007) investigate the new combinations of patent subclasses in the assignments and the re-use of these combinations 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.

Nevertheless, an inventor mobility framework can add to the understanding on how network cohesion and brokerage of inventors relate to firm level innovation because we can isolate the covariances of innovation performance with individual network

structures of incoming inventors and with collaboration network structure within the firm. One must note, however, that such a framework cannot be used to argue for causality 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) especially while switching jobs (Casper 2007) that further increases their productivity because they learn from this process (Hoisl 2009). This is an important self-reinforcing relation between productivity and collaboration networks, which we do not aim to disentangle in this paper. Instead, we aim to understand which individual network characteristics of the mobile inventor are most beneficial for firms and which structure of collaboration networks within the firm increase these benefits?

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.

Two alternative hypotheses regarding the relation between the network structure of the incoming inventors and the innovation performance of the firm can be stated based on the sociology literature. The “Cohesion hypothesis” suggests that those mobile inventors who have cohesive collaboration networks are favorable because they might have developed a deep understanding of a specific piece of complex knowledge while working in cohesive groups previously and can transfer this specific experience to the firm (Obstfeld 2005). In contrast, the “Structural hole hypothesis” implies that those mobile inventors that broker a diverse network channel a broad scope of new information to the firm and also transfer the skill to manage diverse networks (Burt 2004), which increases the likelihood of novel combinations and the value of innovation (Rosenkopf and Almedia 2003; Song et al. 2003). In our first hypothesis, we confront these classic hypotheses in an inventor mobility framework by formalizing the claim around the “Structural hole hypothesis”.

**Hypothesis 1** The future impact of innovation is higher in those firms that hire new inventors with diverse networks compared to those firms that hire inventors with cohesive networks.

The new knowledge of the mobile inventor must be channeled into the invention processes in the receiving firm, in which collaboration networks play an important role. In this regard, it is widely accepted that cohesive networks are more effective in absorbing new knowledge (Aral 2016; Fleming et al. 2007; Hansen 1999; Uzzi 1997); especially, if the knowledge is complex (Aral and van Alstyne 2011). Consequently, the knowledge the new inventor brings into the firm is easier to exploit in cohesive groups than in loosely knit networks. Further, interaction between the team the mobile inventor works with and the rest of the company where important parts of accumulated knowledge is stored might be necessary for the innovation process, which again calls for cohesive networks that can intermediate knowledge sharing within the firm (Reagans and McEvily 2003). In other words, because the combination of diversity and cohesion produces the best creative outcomes (Uzzi and Spiro 2005), companies might benefit the most from incoming brokers if they are situated in cohesive networks within the firm.

We propose that two key properties of network cohesion of intra-firm collaboration; namely, high transitivity and low path length, further increase company benefits gained from incoming brokers. These indicators together characterize small world networks (Uzzi and Spiro 2005; Watts and Strogatz 1998). Transitive triplets induce trust and reduce the costs of complex knowledge sharing; similarly, knowledge is easier to access if the average path length is low in the network. In our second hypothesis, we focus on the interplay between the characteristics of mobile inventors and the characteristics of the intra-firm networks.

**Hypothesis 2** The future impact of innovation among those firms that hire broker inventors is higher if the inventor collaboration network within the firm has high values of triadic closure and low values of average path length.

### 3 Materials and methods

#### 3.1 Data

We use data of patents filed by the European Patent Office (EPO) that is available in the OECD Patent Database 1977–2013 (version February 2015). The full dataset contains three sources of data. (1) OECD REGPAT database covers patent documents filed by the EPO with unique identifiers for patents, applicants, and inventors. 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 contains the cleaned and matched names of patent applicants. There are 2,837,597 unique applicants identified in the HAN database. (3) OECD Citations database contains those EPO, PCT or USPTO patents that cite the EPO patents we analyze. There are 99,449,770 unique citations in the data. These datasets have been merged by the patent identifiers. We excluded years 2011–2013 from the analysis due to the unexpected fall of number of inventors and applicants in those years in the data (see Supporting Information 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. We narrowed down the database to the G06 IPC 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.

We created a weighted and time-decayed co-inventor network for variable calculation for the entire period of the data, which will be explained in detail in Sects. 3.2 and 3.3. In the next step, we restricted the investigation of inter-firm inventor mobility to the 1990–2000 period because, on the one hand, ICT technological innovation accelerated in the 1990s, and on the other hand, the remaining 10 years in the citation dataset until 2010 is enough to assess the quality of produced patents.

After trimming the data the sample contains 10,403 uniquely identified firms that has produced at least one patent in the 1990–2000 period (Table 1). To understand the individual effect of incoming inventors, we excluded those 786 firms from the sample that hired

**Table 1** Number of observations in the data

Data	Observations
Years	10
Firms	10,403
Excluded firms	786
Observed firms	9617
Treated firms	1101
Control firms	8516
Observations	96,170
Observations in estimations	95,788

more than one inventor in any of the years in the 1990–2000 period 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. Out of the observed 9617 firms, 1101 firms received exactly one new inventor in any given year and 8516 firms received no new incoming inventor and serve as the control group that is used to quantify the role inventor mobility on the dynamics of firm-level impact. Over the time period, the total number of observations is 96,170, out of which all the variables introduced in Sect. 3.3 have values in the case of 95,788. 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 apply the hyperbolic method suggested by Newmann (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  $w_{ij,t}$  stands for the strength of the tie between inventors  $i$  and  $j$  in year  $t$ ,  $\delta_i^k$  and  $\delta_j^k$  are 1 if inventor  $i$  and inventor  $j$  author patent  $k$  in year  $u$ , such that  $u < t$ , and zero otherwise and  $n_k$  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  $t$  when we calculate the indicators from the network. The exponent of time decay is  $\lambda$  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  $w_{ij,t}$  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 mobility 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 mobility from  $A$  to  $B$  at the year when the patent application is submitted by  $B$ . We do not consider the date of the application submitted by company  $A$ .

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. To remedy this problem, we assume that the edge between inventors  $i$  and  $j$  is created 2 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  $w_{ij,t}$  equal to  $\sum_{k \in u} \frac{\delta_i^k \delta_j^k}{n_k - 1}$  2 years before the patent application and let the weight decay over these 2 years. One might think that collaboration remains intensive over these years and therefore tie weights should be diminished after the patent application only. To check whether the results depend on the procedure of tie-creation, we applied an alternative way to define the weight of co-inventor ties. In this, we created ties with simple co-occurrence projection and did not introduce time decay. This way, the weight of each co-inventor tie at every point in time was 1. Since this procedure did not change our results, we report results only as robustness checks and stick to the weight defined in Eq. 1 that we think represents the value of ties created long in the past better than the latter tie weighting alternative.

The second issue 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 2 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  $B$ . Proposing that this issue can be straightforwardly handled, we will come back to it in detail in Sects. 3.4 and 4.2.

### 3.3 Variables

The dependent variable of our analysis is the cumulative change of citations to the patents owned by the firm over certain time periods (10, 5 and 3 years) starting from the year of patent application. Although criticized in the literature (Beaudry and Schiffauerova 2011), the number of citations has been frequently used to assess patent quality and market value (Castaldi et al. 2015; 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 reduce the potentials of reversed causality discussed later in Sect. 3.4. We used a 10 year time lag for the accumulation of citations received by the firm and also looked at the accumulation over 5 and 3 years. Results appeared to be very similar across time lags used and therefore, we report models with citation growth over 10 years only.

Using the co-inventor network defined in Sect. 3.2, 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:

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



where  $p_{ij,t} = w_{ij,t} / \sum_q w_{iq,t}$  and  $w_{ij,t}$  is the tie weight defined in Eq. 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  $CON_{i,t}$  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  $CON_{i,t}$  denotes a cohesive ego-network of  $i$  because its' neighbors are strongly connected; while a low  $CON_{i,t}$  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 ( $DEG_{i,t}$ ) 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 strong 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  $DEG_{i,t}$  and also for the interaction between  $CON_{i,t}$  and  $DEG_{i,t}$ .

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  $t$  ( $PAT_{B,t}$  and  $CIT_{B,t}$ ), the number of patent applications after the received mobile inventor and within the following 10 years ( $APPI0$ ), the number of mobile inventors received within the following 10 years ( $MOB10$ ), 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 ( $DENS_{B,t}$ ). Descriptive statistics of and Pearson correlation between main variables are presented in Table 2.

### 3.4 Estimation strategy

To analyse the relation between inventor mobility and innovation performance of firms, 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 mobility event and compare the outcome of the receiving firms with the outcome of the control group (firms that have not received a new inventor). In a traditional diff-in-diff model the outcome is estimated by the following equation:

$$Y_{B,t} = \alpha + \beta_1 T_B + (\gamma_B - \gamma_A)_t + \delta(T_{B,t}) + u_{B,t}, \quad (3)$$



**Table 2** Descriptive statistics and correlation between main variables

Variable	Obs.	Mean	SD	Min	Max	1	2	3	4	5	6
1 CON <sub>it</sub>	95,788	0.004	0.060	0	1.681	1					
2 DEG <sub>it</sub>	95,788	0.020	0.373	0	26	0.519*	1				
3 Q <sub>Bt</sub>	95,788	0.218	0.390	0	1	-0.014*	0.002	1			
4 DENS <sub>Bt</sub>	95,788	0.462	0.465	0	3	-0.0003	0.004	0.568*	1		
5 INV <sub>Bt</sub>	95,788	0.021	0.335	0	25	0.199*	0.29*	0.017*	0.014*	1	
6 TR <sub>Bt</sub>	95,788	0.311	0.454	0	1	0.004	0.022*	0.829*	0.418*	0.050*	1
7 API <sub>Bt</sub>	95,788	2.175	9.955	0	518.5	0.023*	0.032*	-0.042*	-0.066*	0.068*	0.226*

\**p* < 0.05

where  $Y_{B,t}$  denotes the innovation outcome of receiving firm  $B$  before and after the mobility event,  $\beta_1 T_B$  is the constant difference between the two groups of firms and  $\delta(T_{B,t})$  is our variable of interest, which reflects the time-mobility effect, when  $T_B \in \{0, 1\}$  equals 1 if firm  $B$  received exactly one new inventor during our investigated time period and 0 otherwise.

Using the diff-in-diff method we aim to estimate the exact effect that one particular inventor had on future citations in the firm and disentangle this effect from citation accumulation arising by new mobile inventors coming to the same firm in subsequent years. Therefore, we kept the firms that hired exactly one inventor in the given year and no other inventor in the following time period under which the number of accumulated citations was calculated. Despite the sample size was reduced due to this trimming, we still have a convincing amount of observations for the tested years.

The main limitation of the diff-in-diff method is the parallel trend assumption, marked in Eq. 3. With the  $(\gamma_B - \gamma_A)_t$  term, according to which the accomplishment of the control group should reflect what would happen to the group of receiving firms with the lack of the lack of new incoming inventors (Meyer 1995). 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 receiving firms group absent the inventor mobility. Therefore, to validate the parallel trend assumption, we compare the citations of those firms that receive a new inventor in 1995 or 2000 with firms that hired no inventors. If we find similar trends before the mobility happened we can consider our findings consistent with this assumption. Further, it is often very difficult to check the suppositions that are made about the unobservable entities and it is possible that despite significant mobility effects, the bias may be too large and consequently lead to wrong estimates. 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 can disentangle endogeneity and Bertrand et al. (2002) focus on issues related to the standard error of the estimates.

We first conduct the diff-in-diff analysis with the mobility effect only. Then, to link this exercise to the remaining regression analyses, we include further firm and individual-level variables in the next step of diff-in-diff estimations.

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

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

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 mobility,  $W_{i,A,B,t}$  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 if the firm does not receive a new inventor,  $Year_t$  denotes year fixed effects,  $u_{B,t}$  is an idiosyncratic error that changes over time and across units. With the introduction of  $T_{B,t}$  and  $Year_t$  into Eq. 4, we first compare the outcome of receiving firms at time  $t+v$  to the outcome of the control group. Then, the rest of the co-efficients indicate the comparison within the group of receiving firms.

However, network characteristics of the mobile inventor change during mobility. In the second specification, we investigate the role of change in nodal characteristics of the mobile inventor during the event of mobility together with nodal characteristics after mobility:

$$Y_{B,t+v} = \alpha + \beta_1 \cdot X_{i,t} + \beta_2 \cdot (X_{i,t} - X_{i,t-3}) + \beta_3 \cdot Z_{B,t} + \beta_4 \cdot W_{i,A,B,t} + \beta_5 \cdot T_{B,t} + Year_t + u_{B,t}, \tag{5}$$

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:

$$Y_{B,t+v} = \alpha + \beta_1 \cdot X_{i,t} + \beta_2 \cdot Z_{B,t} + \beta_3 \cdot W_{i,A,B,t} + \beta_4 \cdot T_{B,t} + Year_t + u_{B,t}, \tag{6}$$

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

$$Y_{B,t+v} = \alpha + \beta_1 \cdot X_{i,t-3} \times Z_{B,t} + \beta_2 \cdot X_{i,t-3} + \beta_3 \cdot Z_{B,t} + \beta_4 \cdot W_{i,A,B,t} + \beta_5 \cdot T_{B,t} + Year_t + u_{B,t}, \tag{7}$$

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.

To check the validity of Hypothesis 1, we predict the marginal effects of  $X_{i,t-3}$  by keeping all other covariates of Eq. 4 fixed. Hypothesis 2 is tested by analyzing the interaction terms in Eq. 7.

## 4 Results

### 4.1 The effect of inventor mobility

The diff-in-diff test proves the positive relationship between inventor mobility and average citation growth after years of the event of mobility (Table 3). The estimations illustrate that patents assigned to firms receiving a new inventor in year 1995 receive 2.5 extra citations on average during the next 3 years compared to patents assigned to control firms and this shift becomes stronger when we increase the time lag. This relationship stands for inventor mobility in year 2000 as well, where the mobility effect is close to 2 extra citations on average after 10 years of the event. Controlling for inventor and firm characteristics applied in Eq. 4 we found very similar results.

**Table 3** Diff-in-diff estimators for inventor mobility and citation growth

Year of mobility	Dependent variable time lag	Diff-in-diff parameter	
		No controls	With controls from Eq. 4
1995	3 years lag	2.564*** (0.072)	2.606*** (0.119)
	5 years lag	4.477*** (0.121)	4.448*** (0.222)
	10 years lag	8.044*** (0.263)	8.572*** (0.660)
2000	3 years lag	0.636*** (0.043)	0.374*** (0.092)
	5 years lag	1.580*** (0.075)	1.354*** (0.062)
	10 years lag	2.097*** (0.196)	1.969*** (0.177)

Standard errors in parentheses

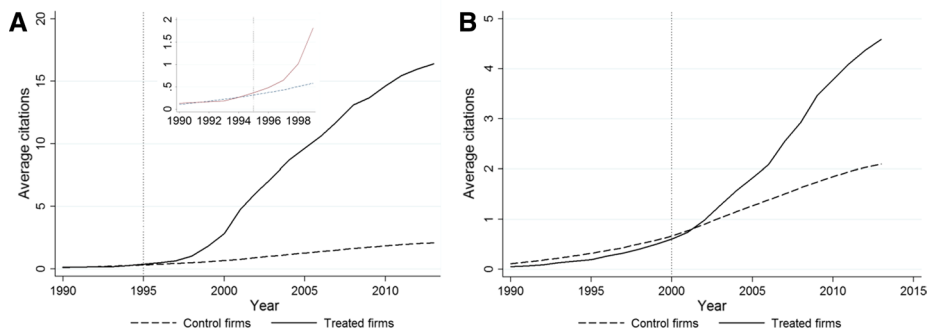
\* $p < 0.05$ ; \*\* $p < 0.01$ ; \*\*\* $p < 0.001$

Further, one can observe in Fig. 1 that receiving firms did not considerably differ on average from control firms before the inventor mobility. In fact, the number of citations starts to strongly deviate from the control group after the mobility. Until that point, the trend in the groups of receiving and control firms are more-or-less parallel and the differences are 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 inventor mobility. This assumption makes the bases for the further estimations in which we aim to explain the variance of the deviation in the group of receiving firms.

## 4.2 Network characteristics of the mobile inventor

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 coefficients and standard errors of point estimates are reported in Table 4. Column 1 reports the coefficients of variables specified in Eq. 4, Column 2 reports the coefficients of variables specified in Eq. 5 and Column 3 reports on the coefficients of variables specified in Eq. 6. The models are stable in terms of the coefficients and explain around 28% of the variation of the independent variable. See Supporting Information 3 for a result table that introduces control and network variables in a step-wise manner.

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  $CON_{it-3}$  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 brokers and had diverse networks before the event of mobility, influence the impact of firm-level innovation more than non-broker inventors who had cohesive networks before the event of mobility. The squared term of  $CON_{it-3}$  was not significant, and therefore, the linear regression alone would infer a linear relationship between being a broker and innovation. We also calculated the marginal effect of  $CON_{it-3}$  with the specification of regression reported in Column 1 to demonstrate the effect of a representative average inventor by keeping all other covariates fixed on the sample mean and plotted it in Fig. 2a. These marginal effects in Fig. 2a suggest that the effect



**Fig. 1** Citation growth in treated and control firms. **a** The citations of those firms that receive a new inventor in 1995 start to deviate from the control group in 1995. Treated firms have 8 more citations on average than non-treated firms in 2005. The subplot zooms into the period until 1998. **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** OLS regression on the impact of nodal characteristics of mobile inventors

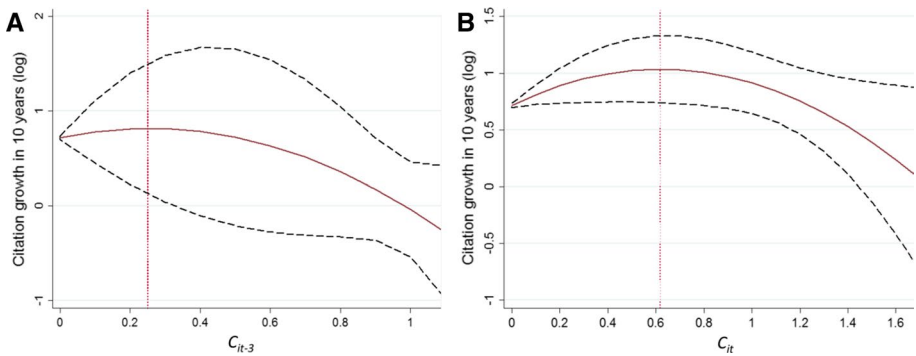
		Cumulative citations of firms 10 years after the treatment		
		(1)	(2)	(3)
Network characteristics of the mobile inventor	CON <sub>it-3</sub>	-0.743*** (0.285)	-0.656** (0.296)	
	CON <sub>it</sub> - CON <sub>it-3</sub>		0.786*** (0.266)	
	CON <sub>it</sub>			1.103** (0.470)
	CON <sub>it</sub> squared			-0.865** (0.389)
	CON <sub>it</sub> × DEG <sub>it</sub>	-0.213*** (0.053)	-0.274*** (0.089)	-0.327*** (0.095)
Quality of the mobile inventor	DEG <sub>it</sub>	0.040** (0.017)	0.049** (0.022)	0.039* (0.021)
	CIT <sub>it</sub>	-0.018 (0.047)	-0.035 (0.048)	-0.031 (0.048)
Quality of the recipient firm	PAT <sub>it</sub>	0.081*** (0.031)	0.074** (0.031)	0.0457 (0.031)
	CIT <sub>Bt</sub>	0.016*** (0.004)	0.016*** (0.004)	0.016*** (0.004)
Quality of the sending firm	PAT <sub>Bt</sub>	0.035*** (0.008)	0.035*** (0.008)	0.035*** (0.008)
	CIT <sub>At</sub>	-0.0001 (0.000)	-0.0001 (0.000)	-0.0001 (0.000)
Mobility and dynamics	PAT <sub>At</sub>	0.0003* (0.000)	0.0003* (0.000)	0.0003* (0.000)
	T	0.223*** (0.043)	0.223*** (0.043)	0.223*** (0.043)
	MOB10	0.205*** (0.059)	0.205*** (0.059)	0.205*** (0.059)
Network in the recipient firm	APP10	0.025*** (0.004)	0.025*** (0.004)	0.025*** (0.004)
	Q <sub>Bt</sub>	2.690*** (0.208)	2.691*** (0.208)	2.691*** (0.208)
	Q <sub>Bt</sub> squared	-2.742*** (0.208)	-2.742*** (0.208)	-2.742*** (0.208)
	DENS <sub>Bt</sub>	-0.010 (0.021)	-0.010 (0.021)	-0.010 (0.021)
	INV <sub>Bt</sub>	-0.017 (0.016)	-0.017 (0.016)	-0.016 (0.016)
	Constant	0.557*** (0.191)	0.557*** (0.191)	0.557*** (0.191)
	Year FE	Yes	Yes	Yes
	Adj. R-sq	0.277	0.277	0.277
N	95,788	95,788	95,788	

Standard errors in parentheses

\**p* < 0.10; \*\**p* < 0.05; \*\*\**p* < 0.01

of  $CON_{it-3}$  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 still significant in this optimal point. However, mobile brokers with low network constraint might increase the impact of innovation at the recipient firm more than mobile non-brokers do; the marginal effect of mobile brokers with cohesive networks is not significant. In sum, we find support for Hypotheses 1.

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  $CON_i$



**Fig. 2** Marginal effects of network constraint ( $CON$ ) on citation growth. **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  $CON_{it-3}=0.22$  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  $CON_{it}=0.61$  denotes the highest predicted margin

between time  $t$  and  $t-3$  into Columns 2 of Table 4. As expected, the coefficient of  $CON_{it} - CON_{it-3}$  takes the positive sign while the sign of  $CON_{it-3}$  does not change. In the final step, we introduce  $CON_{it}$  and its squared term in Column 3 of Table 4. Indeed, both coefficients are significant but with opposite sign and their relation suggest a reverse U-shape. We calculate the marginal effect of  $CON_{it}$  from Column 3 and depict it in Fig. 2b. The finding demonstrates that the reversed U-shape curve shifts to the right, and the optimal point becomes  $CON_{it}=0.61$ . Because all other values were held at sample means, the marginal effect suggests that the number of citations over 10 years is  $10^{0.7}$  in case the constraint of the mobile inventor is close to 0, while citations became  $10^1$  in case constraint is 0.6 at the time of innovation. These findings reported in Table 4 Columns 2 and 3 and the marginal effects together further motivate our Hypotheses 2 because they suggest that new inventors who provide access to new external knowledge through their previous contacts enhance the innovation performance of the firm if they increase their network constraint due to working in cohesive projects in the receiving firm.

All coefficients of the control variables have the expected signs. We control for the interaction between  $CON_{it}$  and  $DEG_{it}$  because those inventors are more likely to be brokers who have more connections (Burt 2004). We find that  $DEG_{it}$  has a positive effect on the firm-level outcome, which implies that the connectedness of inventors matter, and also find a significant effect of its interaction term with  $CON_{it}$ . 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  $CIT_{A,r}$  is not significant. This means that the quality of the sending firm matters less than the quality of the receiving firm. This finding is intuitive and one might list various reasons for that; e.g. inter-firm knowledge transfer is not automatic and one mobile inventor might transfer only a tiny share of sending firm's knowledge. 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  $CON_{it}$  and  $CON_{it-3}$  and we will come back to this issue later.

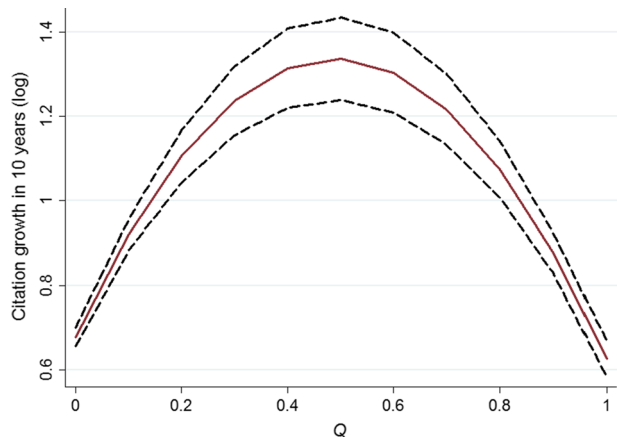
The coefficients of  $T$  are positive and significant in all the models indicating that receiving firms cumulate more citations within 10 years after the event of mobility than control firms. As expected,  $MOBIO$  and  $APPIO$  have positive and significant point estimates, which means that the more mobile inventors the firm receives and the more patent applications it submits over the 10 years after the investigated mobility the more citations the firm will receive.

### 4.3 The network enhancement effect

The remaining coefficients 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 at the sample mean and plotted it in Fig. 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 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 claim that the combination of diversity and cohesion is needed to produce outstanding 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.

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 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 mobility effect of

**Fig. 3** Marginal effect of the small-worldliness ( $Q$ ) of inventor collaboration networks on citation growth. The solid line represents the point estimates and the dashed lines depict 95% confidence interval





incoming inventors. Here, instead of looking at the accelerator effect of small-worldliness  $Q$ , we apply its' components, namely transitivity ( $TR_{Bt}$ ) and average path length ( $APL_{Bt}$ ) and investigate their enhancement effect separately.

To carry out the exercise, we take the number of previously received citations  $CIT_{it}$  as quality indicator of the inventor's knowledge. Further, we also consider whether the mobile inventor brings diverse knowledge into the firm. To do this, we transform the  $CON_{it-3}$  indicator into  $BROKER_{it-3} = 1 - C_{it-3}$  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 Eq. 7 along with further control variables applied in Sect. 4.2. We use pooled OLS regressions with year fixed-effects and clustered standard errors by the receiving firm for estimation. Table 5 summarizes the results.

We find that transitivity of the network increases the positive influence that a new high-impact inventor means for the firm. This is what we would expect because network cohesion is important for trust-based relationships and can thus foster knowledge sharing within the firm. Consequently, the new knowledge brought to the firm by mobile inventors is easier to combine with existing knowledge in the firm in case of highly transitive collaboration networks. We do not find that average path length matters for

**Table 5** OLS regression on the enhancement effect of small world networks

		Cumulative citations over 10 years		
		(1)	(2)	(3)
Inventor quality and transitivity	$CIT_{it} \times TR_{Bt}$	2.923*** (0.852)		4.116*** (1.130)
Inventor quality and average path length	$CIT_{it} \times APL_{Bt}$	-0.010 (0.058)		-0.097 (0.078)
Brokering and transitivity	$BROKER_{it-3} \times TR_{Bt}$		0.363 (0.957)	1.440** (0.626)
Brokering and average path length	$BROKER_{it-3} \times APL_{Bt}$		-0.108** (0.047)	-0.157*** (0.032)
Brokering	$BROKER_{it-3}$	0.845*** (0.246)	1.011*** (0.256)	0.980*** (0.242)
Inventor quality	$CIT_{it}$	-0.052** (0.021)	-0.009 (0.045)	-0.045** (0.021)
Transitivity	$TR_{Bt}$	0.362*** (0.031)	-0.001 (0.957)	-1.078* (0.626)
Average path length	$APL_{Bt}$	-0.017*** (0.005)	0.090* (0.047)	0.140*** (0.032)
	Constant	-0.339 (0.325)	-0.505 (0.332)	-0.474 (0.321)
	Adj. R-sq	0.279	0.279	0.279
	N	95,788	95,788	95,788

Further control variables that are not reported in the table include  $DEG_{it}$ ,  $CON_{it} \times DEG_{it}$ ,  $INV_{Bt}$ ,  $DENS_{Bt}$ ,  $CIT_{Bt}$ ,  $PAT_{Bt}$ ,  $CIT_{At}$ ,  $PAT_{At}$ ,  $PAT_{it}$ ,  $APP10$ ,  $T$ ,  $MOB10$ . Year fixed-effects are applied. Standard errors are clustered by the receiving firm

Standard errors in parentheses

\* $p < 0.10$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$

network enhancement. This is surprising because short paths could speed up accessing relevant knowledge in the firm.

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 2.

#### 4.4 Robustness

Several alternative specifications have been tested to check the robustness of the above findings in Sects. 4.2 and 4.3 given the decisions we had to make at various points in the research process. First, we re-calculated the network indicators by applying an un-weighted co-inventor network. Results did not change after applying these different tie weighting procedure. Second, we checked how different time-lags of the dependent variable in Eqs. 4–7 influence the results. We find smaller coefficients of the explanatory variables in case of 3 and 5 years of citation accumulation. However, the general patterns of our findings did not change. Third, we used negative binomial regression as an alternative to the OLS approach introduced above. This regression technique is frequently used to test models in which the dependent variable accumulates over time, and therefore, fits well to our case. This alternative specification did not change our main findings except for two effects: the interaction between inventor quality and average path length became significant in Table 5, while brokers' transitivity loses its explanatory power in the same model. Finally, we applied a multilayer regression approach, in which we introduced region and country layers. Unlike using region and country fixed-effects, which only control for the mean using a set of dummies, these models look at regional and cross-country differences in the distribution of the dependent variable. Although the coefficients of the explanatory variables decreased due to the effects taken by country and regional levels; this last specification has also left our main findings unchanged.

### 5 Conclusions and discussion

A combination of difference-in-differences and pooled OLS regression has been taken in this paper on patent data in the IT sector 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 channels of knowledge transfer between firms.

Network characteristics of mobile inventors who bring new knowledge into the firm have been argued to matter in the innovation process of the receiving firm. Our first finding suggests that those inventors make the largest impact that are brokers and thus can bring diverse inter-firm connections to the company and provide it with a diverse pool of external knowledge. We also argue that the structure of the collaboration network of inventors within the firm scales up the knowledge inflow because new knowledge is easier to combine with existing knowledge in case of cohesive collaboration networks within the company. Our second result implies that small world networks are more efficient in enhancing the effect of incoming high-impact inventors and brokers. The effect 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 recent arguments in sociology and management science (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 network of potential new inventors and selecting the one whose network constraint is low. Since publicly available datasets, such as the one we analyzed, enable firms to deconstruct the network of potential new hires, innovative firms might benefit from looking at the network qualities of their new hires. Second, firms can further enhance the influence of new inventors by establishing cohesive direct environments and quick access through indirect ties to further knowledge produced and stored in other projects of the company.

We can envisage a list of questions that our approach can be extended to. First, further research is needed to show how these results hold in other sectors because the potentials for knowledge transfer through inventor mobility and through co-inventor contacts might differ across industries and our result might be valid for the IT sector only. Second, we shall better understand how new ties established by inventor mobility and existing ties within the firm foster novel combinations and also investigate the role of technological relatedness in this process (Castaldi et al. 2015). Third, research on the spatial dimension of co-inventor ties and the innovation performance of cities or regions might also benefit from the inventor-mobility approach (Anselin et al. 1997; Hoekman et al. 2009; Lobo and Strumsky 2008) and an important policy-relevant question is how regions benefit from the networks of incoming inventors and inventor collaboration within the region. Fourth, one may analyze the content of inter-firm knowledge flows by looking at citation dynamics in the firm induced by the mobility of inventors and the consequential dynamics of collaboration ties (Corredoira and Rosenkopf 2009). Fifth, dynamics of the co-inventor collaboration might be also looked at to highlight the influence of further network effects our analysis could not look at (e.g. the role of forbidden triads put forward by Vedres 2017). Sixth, employment records of inventors might be used to detect inter-firm inventor mobility to disentangle labor mobility from collaborations on patents. Finally, further dimensions of social relations (e.g. friendship ties or advice links) and 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.

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