IBS WORKING PAPERS

Co-inventor networks, mobility and the quality of innovation

Working Paper 2/2015
http://web.ibs-b.hu/research

INTERNATIONAL BUSINESS SCHOOL

Záhony u. 7.

1031 Budapest, Hungary

September 7, 2015

Gergő Tóth[1], Balázs Lengyel[2,3]

[1] MA student, Department of Political Science, Central European University, Nádor u. 9, 1051 Budapest, Hungary

[2]International Business School Budapest, Záhony u. 7, 1031 Budapest, Hungary

[3]Center for Economic and Regional Studies, Hungarian Academy of Sciences, Budaörsi út 45, 1112 Budapest, Hungary

Corresponding author: blengyel@ibs-b.hu

PRELIMINARY DRAFT; PLEASE, DO NOT QUOTE!

Abstract

How does the mobility of inventors and the structure of social networks influence knowledge flow across innovating firms? Do well connected incoming inventors increase the value of innovation at the firm or is this effect coming from those who have access to a diverse pool of knowledge? In order to answer the above central questions of the organizational learning literature we construct a co-inventor network based on all IT-related patents from the harmonized OECD PATSTAT database that contains patents from 1977 to 2013. Variables derived from the network are introduced into a firm level difference-in-differences inventor mobility model, in which the dependent variable is the growth of accumulated number of citations of the receiving firm. Our findings imply that the more contacts an inventor has in the network the higher impact she has on the value of innovation. The model verifies the structural hole hypothesis as well; in general, those inventors have a higher impact on innovation value who have access to non-redundant knowledge. However, a closer look reveals a reverse U-shaped effect of Burt's constraint on innovation quality. Thus, there might be level of redundancy in the inventor's network, which is optimal for creating high quality innovations.

JEL codes: C31, J69, O31

Keywords: degree, Burt's constraint, difference-in-differences, OECD HAN database, patent citations.

Acknowledgement: We thank Tamás Sebestyén for his suggestions and Heléne Dernis for her help in data collection.

1. Introduction

The mobility of inventors has long been considered as the major source of knowledge flow across inventing firms (Almeida and Kogut 1999, Arrow 1962, Levin et al. 1987, Palomeras and Melero 2010).

Mobility of inventors is important because firms benefit from the tacit or embodied knowledge of incoming productive inventors (Zucker et al. 2002). It is also well understood that firms need to hire inventors who possess technological expertise distant from the hiring firm because then the firm obtains inflow new knowledge by the inflow (Rosenkopf and Almeida 2003, Song et al. 2003). Furthermore, incoming inventors also bring their professional networks to the firm (Agrawal et al. 2006, Breschi and Lissoni 2005, 2009); thus, communication with previous colleagues can provide the hiring firm with additional access to external knowledge (Ethridge et al. 2015, Powell et al. 1996). The joint effect of inventors' mobility and their co-inventor networks is a very important though under-researched phenomenon; this is the niche we address in the recent paper.

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). 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.

Certainly, the mobility of inventors and the co-inventor networks are not independent from each other; the network is generated as the inventor moves from one firm to another (Casper 2007, Lee 2010). Networked inventors are more productive and therefore firms can be more motivated in hiring them away (Nakajima et al. 2010). However, evidence shows a reversed causality; mobility increases the productivity of inventors because they learn from job switching, whereas productive inventors and the likelihood (Hoisl 2007). Therefore extra attention shall be paid for the endogen connection between mobility and network formation in an integrated framework.

In this paper we estimate a difference-in-difference inventor mobility model based on all IT-related patents from the harmonized OECD PATSTAT database that contains patents from 1977 to 2013. The dependent variable is the cumulative change of citations to the patents, which is closely associated with the value of innovations (Harhoff et al. 1999), owned by the hiring firm after the observing the inventor mobility. The two explanatory variables in the model are the number of connections (degree) and cohesion in the inventors' ego network (Burt's constraint indicator).

Our findings imply that the more contacts an inventor has in the network the higher impact she has on the value of innovation at the hiring firm. The model verifies the structural hole hypothesis as well; in general, those inventors have a higher impact on innovation value who have access to non-redundant knowledge and whose network is less cohesive. However, a closer look reveals a reverse U-shaped effect of Burt's constraint on innovation quality. Thus, there might be level of redundancy in the inventor's network, which is optimal for creating high quality innovations.

2. Data

Co-inventor network and inventor mobility matrices are constructed from patents filed by the European Patent Office (EPO) from the OECD Patent Database over the 1977-2013 period. We downloaded the dataset directly from the OECD FTP servers in February 2015 and constructed a relational database that merged three kinds of datasets from the OECD Patent Database.

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. The 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 citations of EPO patents in EPO, PCT or USPTO. The data is derived from EPO's PATSTAT database, autumn 2014. The OECD Citation database mainly derives from the infrastructure proposed in Webb et al. (2005). 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 and therefore learning through mobility and social networks might play a more important role than in other technological areas.

The co-inventor network is constructed from an inventor-patent co-occurrence table and two inventors are connected if they co-author a patent together. The edges were created two years prior the year of application because we assume that the inventors work together before they submit the patent application, which is often made in the literature. We also take that supposition that co-inventors stay in contact after inventing together. They might exchange information, ask for advice and follow each other's career or inventing activity.

We deem an inventor mobile if she authored at least two patents filed by at least two applicants under our investigated time period. Mobility from applicant A to applicant B is detected at the year when the patent application filed by B is submitted to the EPO.

Appendix 1 and 2 contain descriptive figures about the number of inventors and applicants of the investigated data over the full period.

[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".

3. Methods

3.1 The difference-in-differences approach

The focus of the paper is the effect of incoming inventors on the quality of innovations of the hiring firm. In particular, our intention is to show how the mobility of well-connected inventors and broker inventors with coherent ego networks influence the accumulated number of citations.

A major problem is that highly connected and broker (therefore more productive) inventors are more likely to move to more productive firms because they promise a further step in their career, a new learning possibility and good quality innovation. This is a typical endogeneity issue and our model has to control for observable and unobservable firm attributes that might cause inventor mobility. The difference-in-differences (diff-in-diff) approach is a simple solution for the above problem. These models are applied when the independent variable is available in the data before and after the specific action that the researchers are interested in (Albouy 2004), which are often called treatment or experiment. 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).

In our particular case, the outcome is the accumulated number of citations to the patents owned by a firm and the treatment is the inventor's mobility. The model gives an estimation on the effect of inventor mobility on citation counts by comparing citations before and after the treatment and also by comparing the outcome of the treated firms with the outcome of the non-treated firms. Thus, the observations were assigned into two groups: 1, the treated group, those firms that hired a new inventor from another firm; and 2, a control group of non-treated firms that did not receive inventors. Treatment *T* is a binary variable that determines if the firm gets the treatment or not. An observation are present in the model twice: before (indicated by 0) and after the treatment (indicated by 1).

In a diff-in-diff model the outcome $\mathrm{Y_i}$ is estimated by the following equation:

$$Y_i = \alpha + \beta_i T_i + (\gamma_1 - \gamma_0)t_i + \delta(T_i) + \varepsilon_i, \qquad (1)$$

where $\mathrm{Y_i}$ denoted the number of citations at firm *i;* β_i is the difference between the control and the treatment group which comes from the constant differences between the firms; $\mathrm{T_i} \in \{0,1\}$ equals 1 if the firm is treated and 0 otherwise and ε_i is the error term. The δ term denotes the impact of the mobility of inventors.

This latter impact is calculated by assuming parallel trends of the outcome variable in the treatment and the control group. Making this assumption, we can approximate the value of the outcome in the treatment group that would occur in the absence of the treatment itself. The comparison of outcomes between the treated and control observations is formulated by:

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

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

The assumption of parallel trends is the main limitation of the difference-in-differences approach; the accomplishment of the control group should reflect what would happen to the treated group with the lack of the treatment. The parallel trends assumption that we assigned as $(\gamma_1 - \gamma_0)t_i$ cannot be directly tested because we want to compare two world states of one firm, but this is obviously counterfactual. One cannot observe the dynamics of the treatment group without the treatment; firms are either treated, or they are not. Other problem is that it is often very hard or even impossible to check the suppositions about the unobservable entities and therefore the estimates of the treatment effect may be biased.

There is a recent debate about the validity of the difference-in-differences method. Abadie (2005) discusses group comparisons in non-experimental studies; Athey and Imbens (2002) concern the interference in difference-in-differences because of the linearity assumption, Besley and Case (1994) criticize whether this method really can detangle the possibility of endogeneity and Duflo (2002) focuses on issues related to the standard error of the estimates.

3.2 Explanatory variables: degree and constraint in the co-inventor network

Social capital theory emphasize that personal contacts have value because individual learn from their peers, which can create an advantage and benefits for the individual (Bourdieu and Wacquant 1992, Coleman 1988). For instance Putnam (1995) says social capital can be measured by the amount of trust and “reciprocity” in a community of individuals. The contention comes from what “better connected” means (Burt 2002).

One of the easiest method to measure a node’s social capital and access to knowledge in the network is degree. Because the co-inventor network is non-directed we cannot distinguish indegree (the amount of ties that go to the node) and outdegree (the amount of ties that go from the node). The degree of inventor *i* in the co-worker network at time t is defined as:

$$d_i = \# \, connections, \qquad (3)$$

In the research context, degree means the number of unique inventors whom inventor *i* has worked with. According to a widely accepted proposition, the greater degree the bigger access to knowledge; because a high-degree inventor can collect information or discuss innovation-related issues with many colleagues.

However, degree itself cannot capture all the social capital and knowledge-access characteristics of inventors, which are attributed to the structure of the ego-networks. Therefore, we use the well-known constraint indicator defined by Burt (1992), which measures whether an inventor is situated in a coherent network or in a structural hole. To put this into our context, the question is whether an inventor with access to redundant or non-redundant knowledge have more impact on innovation quality.

According to Burt (1992), non-redundant information flow into a group of individuals through contacts to distant groups and these weak connections between groups are holes in the social structure. These holes represent an opportunity for those broker individuals who connect the groups and control the information flow between the opposite sides of the holes (Burt 2000).

The constraint index C_i is the network constraint on individual *i*, which means the concentration of the individual's connections within a group (Burt 2008) and can be formulated by:

$$C_i = \sum_j C_{ij} \ \ i \neq j, \quad (4)$$

where C_{ij} means i's dependency from j:

$$C_{ij} = \left(p_{ij} + \sum_q p_{iq} p_{qj}\right)^2 \ i \neq q \neq j, \quad (5)$$

where $p_{ij} = z_{ij}/\sum_q z_{iq}$ and z_{ij} assigned to strength of *i*'s effort to connect *j*. So C_{ij} can quantify the resources directly (p_{ij}) or indirectly ($\sum_q p_{iq} p_{qj}$) spent to contact *j*.

According to a major claim in innovation studies, a structural hole position provides an inventor with the opportunity to combine non-redundant knowledge and produce radical innovations. However, a variety of evidence illustrates that the picture is far more complex (Fleming et al. 2007, de Vaan et al 2015).

Even Burt (2000, at p. 11) implemented the constraint indicator with limitations:

> *"If a network has lots of structural holes as the source of social capita, then the performance should have a negative association with network constraint. If the network closure is the source of social capital, then performance should have a positive association with constraint.*
>
> *Therefore we can say that bridges through structural holes is the source of the ideas of the new inventions but trustful communication due highly connected individuals can be as much as important to realize the value lies in structural holes."*

An important intuition that one can get from the above statements is that there might be a level of structural holes and coherence in the network, which is optimal for innovation quality.

4. Results

Our results confirm that the more linked inventors have a greater impact on innovation quality at the hiring firm and that broker innovators increase the quality of innovation more than non-brokers. However, we find a reversed U-shape effect regarding the effect of ego-network cohesion on innovation quality.

4.1 Network description

The large co-inventor network resembles the properties of scale-free networks. The degree distribution can be described by a power-law; the relative share of the degree decreases exponentially as *d* grows (Figure 1A). This means that most of the inventors have very few connections and there are very few inventors who have many connections. However, there are certain degrees (around *d*=30) that have a significantly higher shares than the power-law would suggest. These outliers are due to those patents that were co-invented by many inventors who, thus, are all connected to each other and have a high degree. These outliers are not visible when looking at the smoother kernel density figure of degree (Figure 1B).

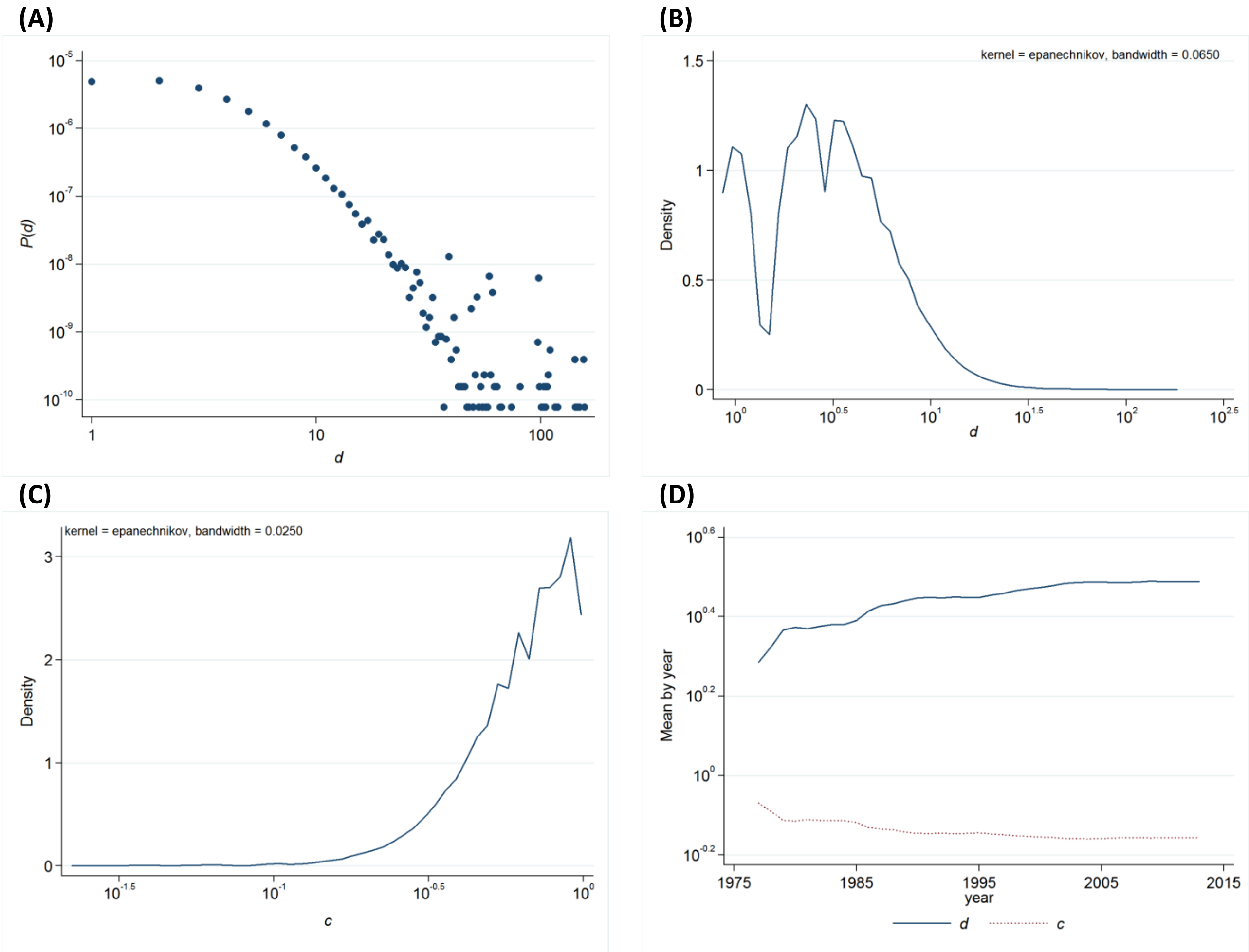


Figure 1. Centrality distributions. (A) Degree distribution of the co-inventor network, logarithmic scale, 2013. **(B)** Kernel density of degree, 2013. **(C)** Kernel density of constraint, 2013. Nodes with degree=2 were excluded from constraint calculation. **(D)** Dynamics of average degree (d) and average constraint (c), 1977-2013. Nodes with degree=2 were excluded from constraint calculation.

The constraint indicator (*c*) takes its' value between 0 and 1; the higher the indicator the more knit the ego-network of the inventor, because her connections also know each other. Differently, a low value of *c* means that the inventor is a broker because she connects groups that are otherwise unconnected. One can find a growing distribution of *c* in Figure 1C, which means that only a low share of the inventors are brokers and the majority is located in very cohesive groups where all inventors are connected[2].

Naturally, *d* and *c* are not independent from each other, because the larger number of connections an inventor has the smaller probability that these connections will also know each other. Accordingly, we find a very strong negative correlation (-0.941) between *d* and *c* in year 2013. One can also find a

[2] Constraint calculation is possible for nodes with *d*=2 but interpretation is not straightforward and thus we eliminate these nodes from Figure 1.

divergent trend of average *d* and average *c* over time (Figure 1D), which suggests that there more and more brokers appear in the network over time who connect otherwise disconnected groups.

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. Degree	1	1.957	2.884	4.678	7.138	8.238	8.186	9.001
Avg. Constraint	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 1), 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 1 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 2 by using distinct color codes for each component. Figure 2A reveals that these large components have similar structures; they contain closely connected groups of inventors that are loosely connected to each other in the component. It is very interesting to zoom into the two largest components (Figures 2B and 2C), which can reveal the most important point in our argument.

The largest network in Figure 2B 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. Brokers are claimed to have access to non-redundant knowledge in the network, because their colleagues did not work with each other and therefore have arguably different knowledge. The structural hole hypothesis states that the brokers are more likely to introduce radical innovations than non-brokers, because they can combine non-redundant knowledge in the knowledge creating process.

(A)

(B) (C)

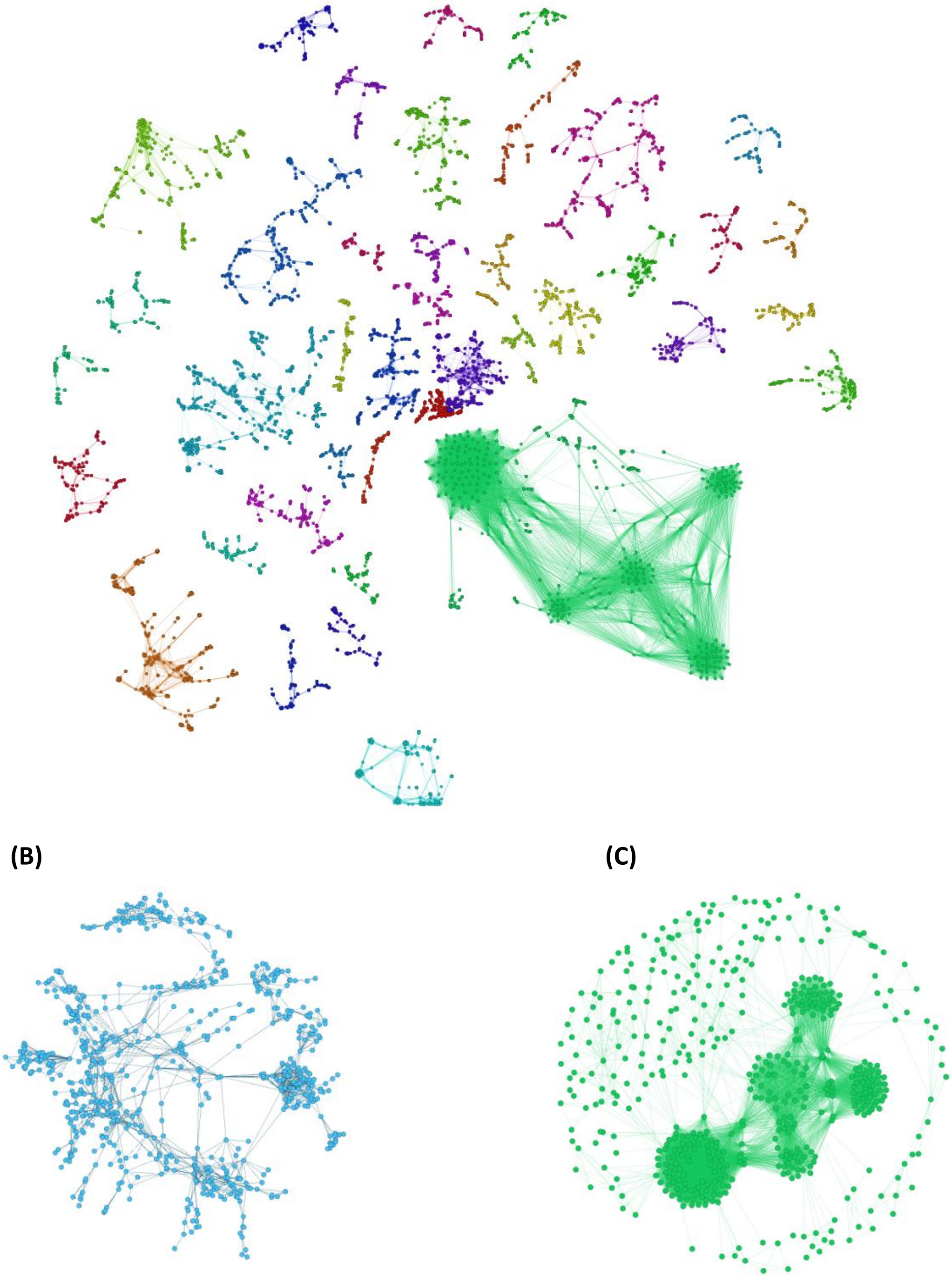


Figure 2. The largest components in the co-inventor network, 2013. (A) The components that have more than 100 inventors, 2013. Force Atlas 2 algorithm was used. **(B)** The largest component containing 717 inventors, 2013. Fruchterman-Reingold algorithm was used. **(C)** The second largest component containing 504 inventors, 2013. Fruchterman-Reingold algorithm was used.

The second largest network in Figure 2C 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 inventors in these cohesive groups have arguable developed a high level of trust because everyone knows everyone and their co-operation among them might be smoother as compared to less connected parts in the network. However, there is a high level of redundancy in the knowledge-access of inventors in these full groups. All the peers of an inventor have similar experience is such groups, which reduces the likelihood of radical innovation produced by the inventor.

Burt's constraint indicator described in section 3.2 is meant to capture if the inventor is situated in a structural hole or in a cohesive network. If the indicator is low, the contacts of the inventor are not connected and she is a broker; if the indicator is high, the contacts of the inventor are connected and she is a cohesive group of the network. Because there are contradictory evidence regarding the role of structural holes and cohesive networks in the quality of innovation, we will discuss the effect of the constraint indicator in an inventor mobility diff-in-diff model.

4.2 Mobility, co-inventor networks and innovation quality

We estimate the diff-in-diff model described in section 3.1, in which the dependent variable is the change of cumulated number of citations received by the patents owned by an applicant over ten years after a treatment. It is important to look at citations over a long period for two reasons. First, the fluctuations of technological change and the jumps in citations can be smoothed out, so that the quality of a patent can be proved by the number of citations to it, indeed. Second, the long term change in the dependent variable the lower chance of endogenity in the model.

Our main explanatory variables are the node indicators of inventors calculated in the co-inventor network for every year. Thus, the co-inventor network is a dynamically changing network, which is due to new edges established in the network by co-authoring new patents, and therefore the number of connections and the cohesiveness of the ego-network of inventors are calculated for every year and for every inventor. However, when estimating the diff-in-diff model, we have to consider the possibility that not only one inventor enters the firm at once because the applicant might submit more than one patent applications and also because the patent itself might be authored by more than one inventor who is new to the firm.

Therefore, the DEGREE variable denotes the mean number of connections and the CONSTR indicator is the mean constraint of the incoming inventors. The number of incoming inventors (INVNR) is also included in the model, which is an additional control for the group size effect. The above mean values are sufficient proxies for capturing the connectedness and broker qualities of the incoming inventors[3]. The higher average degree of the group of inventors the wider access to knowledge by an average group member. In a similar manner, a higher mean value of constraint across incoming inventors denotes a more cohesive network.

Two control variables are used: the number of total citations to the patents owned by the applicant at the time of the treatment (CITCUM) and the number of patent applications within ten years after the

[3] The models have been run with alternative indicators as well, in which the aggregated value of degree and constraint was used as explanatory variables. Because these are linear transformations, the model outcomes did not differ.

treatment (D10PATENTS). All the dependent, explanatory and control variables have been log-transformed.

Table 2. Variable description and Pearson correlation

	Variable	Obs	Mean	Std. Dev.	Min	Max	1	2	3	4
1	INVNR	308,446	0.0401	0.4645	0	40	1.0000			
2	DEGREE	308,446	0.0897	1.4995	0	157	0.3590*	1.0000		
3	CONSTR	308,446	0.0089	0.0809	0	1	0.4896*	0.2621*	1.0000	
4	CITCUM	307,614	7.5383	177.3295	0	25,990	0.1000*	0.0297*	0.0550*	1.0000
5	D10PATENTS	104,117	7.2614	74.1256	0	4,037	0.3195*	0.1685*	0.2006*	0.3030*

Note: * denotes significance of pairwise Pearson correlation at the 0.01 level.

As explained in section 3.1, the observations in the model are firms by year and the data contains all for firms including those who did and also those who did not receive any treatment over the period (Table 3). Therefore, the minimum values of the indicators are zero. The number of observations for D10PATENTS are smaller, because it was not possible to calculate this indicator for firms that were treated after 2003. The low value of Pairwise Pearson correlation coefficients suggests that all the indicators can be introduced into the linear regression models and multicollinearity is not a threat.

The results of the diff-in-diff models can be found in Table 4. Models 1-6 are pooled OLS regressions with year fixed effects and explanatory variables and their quadratic terms are introduced into the models stepwise. The treatment variable (T) has a positive and significant effect in each model, which means that the number of citations grew more in those firms that received treatment as compared to those that didn't.

We find that INVNR has a positive and significant effect while its quadratic term has a negative and significant effect. This finding suggests that the more inventors come to the firm the higher number of citations the firm will get over time. However, decreasing marginal effects are operating, inventor number increases citation growth with decreasing intensity.

DEGREE has a positive and significant effect on citation growth. This implies that the number of inventors whom the incoming inventors have connections to matters for the innovation processes in the firm. The incoming inventors bring their professional ties whom they can contact if an innovation related issue emerges. The finding suggest that social capital increases the effect of inventor mobility on innovation quality, the bigger number of such connections, the higher value of innovation at the firm. However, DEGREE loses significance in Model 6, when introduced together with other regressors.

The most interesting finding concerns the CONSTR variable. It has a significant negative value when introduced alone or with other explanatory variables (Model 3 and Model 5), which means that the structural hole hypothesis of social capital prevails in the inventors' mobility effect on the quality of innovation. Those broker inventors, who establish a link between otherwise unconnected groups and therefore have access and might combine non-redundant knowledge, have a greater impact on innovation quality than non-brokers. However, the introduction of the quadratic term (Models 4 and 6) reveals a very important finding: the general negative effect can be broken into two very strong and contradictory effects. This result implies that the effect of CONSTR on citation counts can be an inversed U-shaped curve; some cohesion is needed in ego-networks but very cohesive networks are not good for innovation quality. Therefore, one might propose that innovation quality might need an optimal level of network cohesion (or broker quality).

Both our control variables have positive and significant effect in all models. Models 7-9 are fixed effect panel regressions that confirms the previous findings.

Table 3. Pooled OLS and FE regressions. dependent variable: 10 years difference of cumulate citation of firms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OLS	OLS	OLS	OLS	OLS	OLS	FE	FE	FE
INVNR	0.105384***				0.094803***	0.085199**			0.033515***
	(0.032)				(0.033)	(0.034)			(0.011)
INVNR2	-0.004850***				-0.004609***	-0.004298***			-0.000452
	(0.002)				(0.002)	(0.002)			(0.000)
DEGREE		0.024902**			0.012128*	-0.000523	0.011793**		-0.000725
		(0.010)			(0.007)	(0.013)	(0.005)		(0.005)
DEGREE2		-0.000213				0.000218	-0.000236		-0.000029
		(0.000)				(0.000)	(0.000)		(0.000)
CONSTR			-0.221012**	0.898829***	-0.211030**	0.672306*		0.368762***	0.236158*
			(0.095)	(0.320)	(0.096)	(0.380)		(0.135)	(0.141)
CONSTR2				-1.107251***		-0.880465**		-0.431191***	-0.303698**
				(0.301)		(0.365)		(0.118)	(0.128)
T	0.805206***	0.888174***	1.082699***	0.941812***	0.873243***	0.823660***	0.087545***	0.102220***	0.059622*
	(0.063)	(0.049)	(0.058)	(0.067)	(0.076)	(0.078)	(0.021)	(0.029)	(0.034)
CITCUM	0.001006***	0.001019***	0.001022***	0.001016***	0.001007***	0.001006***	0.000341***	0.000341***	0.000326***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
D10PATENTS	0.004848***	0.004862***	0.004871***	0.004840***	0.004855***	0.004839***	0.001752***	0.001748***	0.001732***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CONSTANT	0.758407***	0.756356***	0.755084***	0.759662***	0.757452***	0.759838***	0.834747***	0.834728***	0.834778***
	(0.279)	(0.279)	(0.279)	(0.278)	(0.279)	(0.279)	(0.003)	(0.003)	(0.003)
YEAR FE	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No
HAN FE	No	No	No	No	No	No	Yes	Yes	Yes
ADJ. R-SQ	0.182	0.182	0.182	0.182	0.182	0.182	0.030	0.030	0.031
N	104.117	104.117	104.117	104.117	104.117	104.117	104.117	104.117	104.117

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

5. Discussion

In this paper we estimated a difference-in-difference inventor mobility model, in which the dependent variable is the cumulative change of citations to the patents owned by the hiring firm after the observing the inventor mobility. The two explanatory variables in the model are the number of connections (degree) and cohesion in the inventors' ego network (Burt's constraint indicator). Our findings imply that the more contacts an inventor has in the network the higher impact she has on the value of innovation at the hiring firm. The model verifies the structural hole hypothesis as well; in general, those inventors have a higher impact on innovation value who have access to non-redundant knowledge and whose network is less cohesive. However, a closer look reveals a reverse U-shaped effect of Burt's constraint on innovation quality. Thus, there might be level of redundancy in the inventor's network, which is optimal for creating high quality innovations. However, few empirical issues limit the implications of the results and further research steps shall solve these problems.

First of all, edges in the co-inventor network might loose from their weight over time or even cease to exist after few years. Therefore, edge aging has to be taken care of in the next version of the paper and we shall check the robustness of our results by excluding the old ties from the network. Second, recently unobserved effects shall be controlled for in the regression models. For example, productivity or quality of the sending firm and productivity of the mobile inventor might have a positive effect on innovation quality. Inventors who come from highly innovative firms or those mobile inventors themselves who are very productive are very important for innovation and these effects shall be included into the models. Third, alternative dependent variables shall be analyzed. For example, a we might calculate the cumulative change of citations by each patent the firm has because the aggregation to the firm level might be misleading in large firms that have many patents.

Reference list

Abadie, A. (2005). Semiparametric difference-in-differences estimators. *The Review of Economic Studies*, *72*(1), 1-19.

Agrawal. A.. Cockburn. I.. & McHale. J. (2006). Gone but not forgotten: knowledge flows. labor mobility. and enduring social relationships. *Journal of Economic Geography*. 6(5). 571-591.

Ahuja. G. (2000). Collaboration networks. structural holes. and innovation: A longitudinal study. *Administrative Science Quarterly*. 45(3). 425-455.

Albouy, D. (2004). Program evaluation and the difference in difference estimator. *Economics*, *131*.

Almeida. P.. & Kogut. B. (1999). Localization of knowledge and the mobility of engineers in regional networks. *Management Science*, 45(7). 905-917.

Arrow, K.J. (1962). Economic welfare and the allocation of resources for invention. In: Nelson, R.R. (ed) The rate and direction of inventive activity: economic and social factors, 609-625. Princeton Univerity Press, Princeton.

Athey, S., & Imbens, G. (2002). Identification and inference in nonlinear difference-in-differences models.

Bertrand, M., Duflo, E., & Mullainathan, S. (2002). *How much should we trust differences-in-differences estimates?* (No. w8841). National Bureau of Economic Research.

Besley, T., & Case, A. (1994). *Unnatural experiments? Estimating the incidence of endogenous policies* (No. w4956). National Bureau of Economic Research.

Borgatti. S.P.. Cross. R. (2003). A relational view of information seeking and learning in social networks. *Management Science,* 49(4). 432-445.

Breschi. S.. & Lissoni. F. (2005). Knowledge networks from patent data. In: Moed, H.F., Glänzel, W., Schmoch, U. (eds). *Handbook of quantitative science and technology research*, pp. 613-643. Kluwer Academic Publishers, Dordrecht.

Breschi. S.. & Lissoni. F. (2009). Mobility of skilled workers and co-invention networks: an anatomy of localized knowledge flows. *Journal of Economic Geography*. lbp008.

Bourdieu, P., & Wacquant, L. J. (1992). *An invitation to reflexive sociology*. University of Chicago press

Burt. R.S. (1987). Social contagion and innovation: cohesion versus structural equivalence. *American Journal of Sociology*. 92(6). 1287-1335.

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

Burt, R. S. (2000). The network structure of social capital. *Research in Organizational Behavior*, 22, 345-423.

Burt, R. S. (2002). The social capital of structural holes. The new economic sociology: Developments in an emerging field, 148-190.

Burt. R. S. (2004). Structural holes and good ideas. *American Journal of Sociology*. 110(2): 348-399

Burt, R. S. (2008). Industry performance and indirect access to structural holes. *Advances in Strategic Management*, 25, 315-360.

Capaldo. A. (2007). Network structure and innovation: the leveraging of a dual network as a distinctive relational capability. *Strategic Management Journal*. 28(3). 585-608.

Casper. S. (2007). How do technology clusters emerge and become sustainable? Social network formation and inter-firm mobility within the San Diego biotechnology cluster. *Research Policy*. 36(4). 438-455.

Coleman, J. S. (1988). Social capital in the creation of human capital. *American Journal of Sociology*, 94, S95-S120.

de Vaan. M.. Stark. D.. Vedres. B. (2015). Game changer: the topology of creativity. *American Journal of Sociology*. 120(4). 1-51.

Ethridge. F.. Feldman. M.. Kemeny. T.. & Zoller. T. (2015). The Economic Value of Local Social Networks (No. 0170). Spatial Economics Research Centre. LSE.

Fleming, L., Mingo, S., Chen, D. (2007) Collaborative brokerage, generative creativity, and creative success. *Administrative Science Quarterly*, 52(3), 443-475.

Granovetter, M.S. (1973). The strength of wea ties. *American Journal of Sociology*, 78(6), 1360-1380.

Harhoff. D.. Narin. F.. Scherer. F. M.. & Vopel. K. (1999). Citation frequency and the value of patented inventions. *Review of Economics and Statistics*. 81(3). 511-515.

Ibarra. H. (1993). Network centrality. power. and innovation involvement: determinants of technical and administrative roles. *The Academy of Management Journal*. 36(3). 471-501.

Inkpen. A.C.. Tsang. E.W.K. (2005). Social capital. networks. and knowledge transfer. *The Academy of Management Review*. 30(1). 146-165.

Lee. J. J. (2010). Heterogeneity. brokerage. and innovative performance: Endogenous formation of collaborative inventor networks. *Organization Science*. 21(4). 804-822.

Levin, R.C., Klevorick, A.K., Nelson, R.R., Winter, S.G. (1987) Appropriating the returns from industrial research and development. *Brookings Papers on Economic Activity*, 18(3), 783-832.

Meyer, B. D. (1995). Natural and quasi-experiments in economics. *Journal of business & economic statistics*, *13*(2), 151-161.

Nakajima. R.. Tamura. R.. & Hanaki. N. (2010). The effect of collaboration network on inventors' job match. productivity and tenure. *Labour Economics*. 17(4). 723-734.

Palomeras. N.. & Melero. E. (2010). Markets for inventors: learning-by-hiring as a driver of mobility. *Management Science*. 56(5). 881-895.

Powell. W.W.. Koput. K.W.. Smith-Doerr. L. (1996). Interorganizational collaboration and the locus of innovation: networks of learning in biotechnology. *Administrative Science Quarterly*. 41(1). 116-145.

Putnam, R. D. (1995). Bowling alone: America's declining social capital. *Journal of democracy*, *6*(1), 65-78.

Rosenkopf, L., Almedia, P. (2003) Overcoming local search through alliances and mobility. *Management Science*, 49(6), 751-766.

Schilling. M.A.. Phelps. C.C. (2007). Interfirm collaboration networks: the impact of large-scale network structure on firm innovation. *Management Science*. 53(7). 1113-1126.

Singh. J. (2005). Collaborative networks as determinants of knowledge diffusion patterns. *Management Science*. 51(5). 756-770.

Song, J., Almeida, P., Wu, G. (2003) Learning-by-hiring: when is mobility more likely to facilitate inter-firm knowledge transfer? *Management Science*, 49(4), 351-365.

Sorenson, O., Rivkin, J.W., Fleming, L. (2006). Complexity, networks and knowledge flow. *Research Policy*, 35(7), 994-1017.

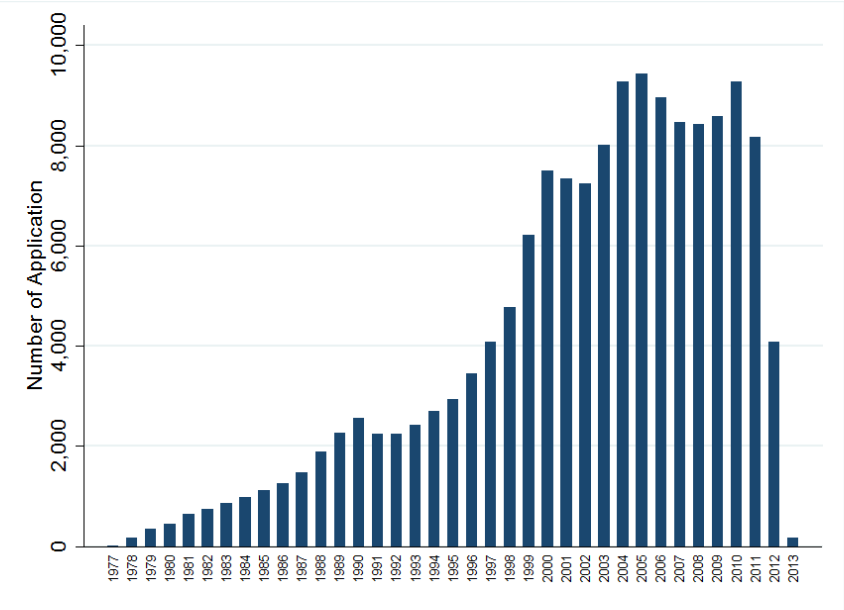
Sparrowe. R.T.. Liden. R.C.. Wayne. S.J.. Kraimer. M.L. (2001). Social networks and the performance of individuals and groups. *The Academy of Management Journal*. 44(2). 316-325.

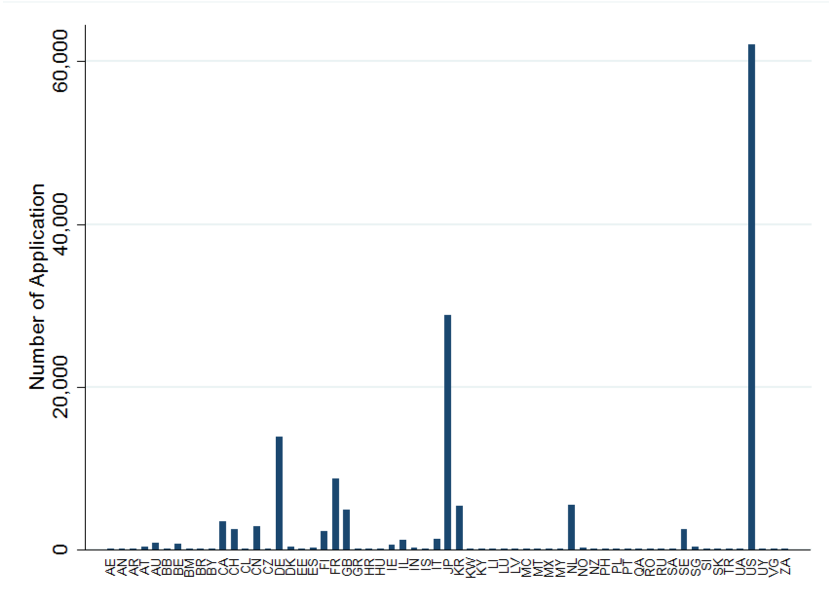
Uzzi. B. (1997). Social structure and competition in interfirm networks: the paradox of embeddedness. *Administrative Science Quarterly*. 42(1). 35-67.

Webb et al. (2005) K-optimal pattern discovery: An efficient and effective approach to exploratory data mining. In: Zhang, S., Jarvis, R. (eds) *Australian Conference on Artificial Intelligence*, *Lecture Notes in Computer Science*, vol 3809, pp 1–2. Springer, Heidelberg.

Zucker, L.G., Darby, R.M., Torero, M. (2002). Labor mobility from academe to commerce. *Journal of Labor Economics*, 20(3), 629-660.

Appendix 1: Number of patent applications by year and country





Appendix 2. Number of inventors by year and country