ETLA Working Papers

No. 27
5 January 2015

Heli Koski
Mika Pajarinen

Mobility of ideas for innovation

The role of inventor-specific knowledge flows

Suggested citation: Koski, Heli & Pajarinen, Mika (5.1.2015). "Mobility of ideas for innovation: The role of inventor-specific knowledge flows". ETLA Working Papers No 27. http://pub.etla.fi/ETLA-Working-Papers-27.pdf

ETLA ELINKEINOELÄMÄN TUTKIMUSLAITOS
THE RESEARCH INSTITUTE OF THE FINNISH ECONOMY

ISSN-L 2323–2420
ISSN 2323–2420 (print)
ISSN 2323–2439 (online)

Mobility of ideas for innovation: The role of inventor-specific knowledge flows

Heli Koski and Mika Pajarinen*

Abstract:

Our data from 351 innovating firms for the years 2001–2012 generally suggest that patentable ideas are strongly linked to the mobility of individual inventors, or that the knowledge flows transmitted are sticky inventor-specific. In other words, the larger the knowledge pool of an inventor entering (leaving) the firm, the more the firm's innovation performance increases (decreases). However, our separate estimations for six different technology classes suggest that this does not apply for all technologies. Our data indicate that the knowledge flows are mobile inventor-specific for chemicals and pharmaceuticals and mechanical engineering such that the mobility of an inventor to a firm increases its innovation performance but the mobility of an inventor from a firm does not affect its innovation performance. We further find that particularly innovation coopetition (i.e., collaboration with a firm's competitors) is an important source of knowledge spillovers. Furthermore, the magnitude of overall localized innovation activity positively relates to the firm's innovation performance providing support for agglomeration externalities.

JEL Classification: J62, D22, D62, L2, O3

Keywords: labor mobility, knowledge spillovers, patents, innovation

* The Research Institute of the Finnish Economy (ETLA). E-mail: heli.koski@etla.fi, mika.pajarinen@etla.fi.
The authors are grateful for the Finnish Funding Agency for Innovation (Tekes) for its financial support.

1. Introduction

The role of knowledge spillovers or externalities in the generation of innovation has gained substantial attention in the economics and management literature (see, e.g., Jaffe et al., 1993; Giuri and Mariani, 2013; Tambe and Hitt, 2014). The questions of the magnitude of knowledge spillovers and the channels via which knowledge spills from one organization to another are not only of interest to academics. These questions are also highly policy relevant as externalities provide a major justification for the allocation of publicly funded R&D subsidies. The argument favoring government R&D subsidies states that without these subsidies firms underinvest in innovation activities as they cannot fully appropriate returns from the output of their investment (i.e., knowledge concerning the production of new goods or services) due to non-rival nature of knowledge. In other words, a firm generating new knowledge cannot, at least not completely, preclude other parties to also use its privately produced knowledge for commercial purposes (e.g., via imitation).

The trend in the empirical literature on knowledge externalities has developed from the aggregate or regional level analysis towards microeconomic approaches capturing the transfer of knowledge at the firm level and, more recently, at the innovator level. Unlike the previous studies, our firm-level empirical study simultaneously controls for knowledge spillover mechanisms at the innovator level via the mobility of employees, at the firm level via the innovation collaboration of a firm with external parties, and at the regional level via the magnitude, diversity and concentration of localized innovation activities. We aim at answering to the questions of what are the channels of mobility of ideas or knowledge generating innovations and whether and how they vary by different technology fields. Particularly, the inventor- and firm-specificity of innovation mobility interests us.

In the empirical part of the study, we use data concerning the patent filings of the Finnish companies acquired from the EPO worldwide statistical database. We match the companies included in the patent dataset to the firm-level financial statements and other background data (industry, geographical location, employment etc.). The combined dataset includes 351 innovating firms and 2536 observations from the years 2001–2012.

We find that knowledge flows generating patentable ideas tend to be generally sticky inventor-specific. In other words, the larger the knowledge pool of an inventor entering (leaving) the firm, the more the firm's innovation performance increases (decreases). However, our separate estimations for six different technology classes suggest that this does not apply for all technologies. Our estimation results indicate that the knowledge flows are mobile inventor-specific for chemicals and pharmaceuticals and mechanical engineering such that the mobility of an inventor to a firm increases its innovation performance but the mobility of an inventor from a firm does not affect its innovation performance.

Our findings also provide support for the literature arguing that a firm's patent stock reflects knowledge base it can use for generating future patentable ideas, and thus a firm's past patenting activity is positively related to its current patenting (see, e.g., Blundell et al, 1995, 2002; Crepon and Duguet, 1997). We develop this idea further by distinguishing a firm's intra-house patenting activities from its collaborative patenting with different parties. Our estimation results suggest that particularly innovation coopetition (i.e., collaboration with a firm's competitors) is an important source of knowledge spillovers. Furthermore, we find that even after controlling for knowledge flows at the inventor-level and the firm-level (i.e., both the firm's own patent stock and spillovers from its innovation collaborators) the magnitude of overall localized innovation activity (i.e., agglomeration externalities) positively relates to the firm's innovation performance.

The rest of the paper is organized as follows. Section 2 briefly summarizes the main findings of previous studies related to our reported research. Section 3 provides conceptual and empirical framework for the analysis, and further introduces the data. Section 4 reports our empirical findings. Section 5 concludes with some policy implications.

2. Related studies

The economic and management literature identifies various potential channels of knowledge spillovers facilitating innovation: i) inter-firm mobility of employees, ii) innovation collaboration of a firm with external partners, and iii) spillovers arising from firms' locational proximity, i.e. knowledge spillovers at the regional level.

The early studies particularly in the fields of geographical economics and applied industrial organization concerning knowledge spillovers typically focused on the existence of localization or agglomeration externalities (see, e.g., Jaffe et al., 1993; Döring and Schellenbach, 2006). It was argued that geographical agglomeration of organizations (such as other firms, universities and research institutes) enabled knowledge to spill over from one organization to another, and therefore those regions with more organizations or knowledge concentrated were likely to have a higher economic growth than others (see, e.g., Feldman and Audrestch, 1999). This happened particularly due to more frequent face-to-face communication – that is required for the distribution of tacit knowledge - across geographically adjacent firms. However, the role of individuals as the transmitters of knowledge flows was not explicitly empirically investigated in these early studies.

The literature has further stressed the importance of mobility of skilled workers as a key mechanism generating knowledge spillovers (see, e.g., Matusik and Hill, 1998). Various previously reported studies have emphasized the crucial role of individual inventors in the firm’s innovative performance (see, e.g., Gay et al., 2008; Latham et al., 2012). Kaiser et al. (2013) empirically explore the impact of labor mobility in the firms’ innovation output using data from the population of Danish R&D active firms between the years 1999 and 2004. Their study concludes that labor mobility of R&D workers increases statistically significantly firms’ total patenting if either of the firms involved has a history of patenting activity. Relatedly, Hoisl (2007) measuring the inventor productivity by the number of patents per inventor finds that mobility of inventors (measured by the count of firms for which an inventor has worked minus one) increases their productivity but, instead, increase in productivity tends to decrease the inventor’s probability to move from one organization to another.

Similarly, the study of Latham et al. (2012) among five different countries (i.e., France, Germany, Japan, the UK, and the US) suggests that the average number of patents granted per year (over inventor’s career) tends to be higher for inventors of which inter-firm mobility is higher. Furthermore, their study controls for technological mobility of inventors measured by the count of the number of different technological fields in which an inventor has worked and the number of changes from one field to another (HHI at the level of six broad technological classes used). Their results hint that those inventors that are less technologically mobile or more technologically specialized tend to be more productive than others.

The empirical work of Maliranta et al. (2009) suggests that the mobility of a firm’s workers from non-R&D activities to its R&D activities provides a more significant spillover channel boosting both productivity and profitability than the mobility of employees from other firm’s R&D labs to the firm’s own. They interpret this finding as the evidence that a firm’s own workers from non R&D activities transmit relevant knowledge that can be utilized without much effort in the firm's R&D department.

Tambe and Hitt (2014) provide further evidence on the role of the mobility of specialized work-force in the transmission of fundamental knowledge for technological progress. Their empirical findings indicate that the mobility of information technology (IT) workers among firms notably facilitates the diffusion of know-how on the utilization of IT-related innovations and that these IT-specific knowledge spillovers further contribute to the firms' productivity growth. In other words, the movement of IT specialists among firms is a notable source of productivity spillovers.

Relatedly to our study, the strategic management and industrial organization have also explored the firms' knowledge acquisition via collaboration with various parties such as customers, other firms and research institutes and universities. In this literature, the focus has been rather in the relationship between a firm's innovation performance and its knowledge search strategy than in the role of knowledge spillovers (see, e.g, Laursen and Salter, 2006; Love et al., 2013).

3. Mobility of innovations – conceptual and empirical framework

3.1 Conceptual framework

Key or prolific inventors are essential for the development, integration and accumulation of knowledge within the organization, and they further facilitate organizational learning in their employing organization. *Inter-firm mobility* of inventors generates an essential stream of knowledge transfer between organizations. This applies particularly to tacit knowledge of which transfer tends to require face-to-face communications. We propose, however, that when an inventor enters to or leaves from a firm, there are various factors that may impact on whether and how this affects the subsequent innovation performance of the firm.

The impact of the mobility of inventors on a firm's innovation performance depends largely on the type of knowledge that is crucial for innovation and transferred via the inventors as well as on the importance of firm-specific accumulated knowledge for the firm's innovation performance. We identify three cases of the relationship between different types of knowledge and a firm's innovation performance. First, *sticky inventor-specific knowledge* means that the knowledge base of inventors moving into a firm (out from the firm) has a positive (negative) relationship with the firm's subsequent innovation performance. Second, *mobile inventor-specific knowledge* refers to the case in which the knowledge base of inventors moving into a firm is positively related to the firm's subsequent innovation performance, while the order of magnitude of inventors moving out from the firm does not notably affect the firm's innovation performance. Third, *firm-specific knowledge* means that the innovation performance of a firm is not affected by the mobility of inventors.

The degree of tacitness of inventor's knowledge directly influences on its transferability to other R&D personality or inventors employed by the firm. When inventor's knowledge is specialized and not easily transferable, hiring the inventor is likely to increase the firm's innovation performance both due to her/his personal qualities (i.e. know-how, skills and problem-solving abilities) as well due to tacit knowledge (s)he has learned in her/his previous organization. Also, in this case, when the inventor leaves the company, this is likely to generate a decline in the firm's innovation performance. Furthermore, the more productive the inventor a firm hires (loses) is, the larger an increase (decline) in a firm's innovation performance. In other words, knowledge may be inventor-specific and its mobility strongly linked to the mobility of inventors.

Whether the knowledge and ideas of an inventor are easily transferable, it seems credible that inventors entering the firm increase the innovation of their new employer but the innovation performance of a firm from which an inventor leaves from, may not be strongly affected. This may happen as some of the inventor's essential knowledge for generating new innovation can be absorbed by the firm before her skills and problem-solving abilities move to a new organization. In this case, inventor moving into the firm is likely to increase its innovation performance, while the loss of an inventor holding such knowledge may not have notable influence on the firm's innovation output.

Yet another possibility is that knowledge required for innovation tends to be strongly firm-specific. This may be the case if the firm's innovation output is, by and large, based on the accumulated firm-specific knowledge and expertise, and mobility of individual inventors does not substantially affect to it. In other words, neither hiring new inventors to the firm nor the mobility of inventors from the firm to another organization has no substantial influence on the firm's innovation performance.

We consequently propose the following three hypotheses:

Hypothesis 1: *The larger the knowledge pool of an inventor entering (leaving) the firm, the more the firm's innovation performance increases (decreases).*

Hypothesis 2: *The larger the knowledge pool of an inventor entering the firm, the more the firm's innovation performance increases. The mobility of an inventor from a firm does not affect the firm's innovation performance.*

Hypothesis 3: *The mobility of an inventor to a firm or from a firm does not affect the firm's innovation performance.*

Knowledge spillovers arising from the inter-firm mobility of employees is measured by the inflow of (potentially patentable) knowledge at time t to firm i via the vector of inventors j entering the firm from other firms k:

$$SPILL\_INV\_IN_{it} \quad = \sum_{jk} P_{jkt-1}$$

The SPILL_INV_IN variable is the total patent pool (i.e. cumulative sum of patent applications at time t-1) of inventors which moved to a firm at time t. It captures the transfer of *inventor-specific* knowledge moving from one firm to another.

It is also possible that mobile inventors transfer part of the knowledge base of their previous employer to the new one. We therefore test also whether there is a relationship between the mobile inventors' previous employers' patent pool and the new employer's innovation performance. The transfer of *firm-specific* knowledge via mobile inventors is measured by using the variable SPILL_FIRM_IN that captures the patent pool of inventors' previous employers (i.e. cumulative sum of patent applications of the previous employers of mobile inventors at time t-1). This firm-specific measure do not include the patents of the inventors moving into a firm as we aim at separating inter-firm transfer of inventor- and firm-specific knowledge flows.

The second inventor-specific measure captures the outflow of knowledge at time t-1 from firm i via the vector of inventors j leaving the firm:

$$SPILL\_OUT_{it} \quad = \sum_{j} P_{ijt-1}$$

The SPILL_OUT variable is the sum of cumulative number of patent applications of inventors leaving the firm. It provides a proxy for innovator level knowledge that spills out from a firm when an innovator leaves.

Our assumption is that innovation related to different technologies may differ in terms of inventor- and firm-specificity of knowledge required for them. Given the lack of prior research on the topic, the inventor- and firm-specificity of knowledge in different technology fields is an empirical question. We undertake estimations separately by each of the six technology classes[1]. In these estimations, the estimated coefficients of the SPILL_INV_IN variable reveal in which technology fields innovators transmit knowledge generating further patentable innovations. The estimated coefficients of the SPILL_OUT variable shows whether (patentable) knowledge related to different technology fields tends to stay or leak out from the firm with the innovators leaving the company. Table 1 outlines the sign of the estimated coefficients of the SPILL_INV_IN and SPILL_OUT variables in relation to the type of transferred knowledge.

[1] The definitions of the technology classes are based on OECD (1994) and Mancusi (2003). Technology classes are 1 ”Electrical engineering”, 2 ”Instruments”, 3 ”Chemicals and pharmaceuticals”, 4 ”Process engineering”, 5 ”Mechanical engineering” and 6 ”Consumer goods and civil engineering”. Technology class 1 includes patent applications related to electronic devices and electrical engineering, audio visual technology, telecommunications, information technology and semiconductors; technology class 2 optics, control and measurement technology and medical technology; technology class 3 organic chemistry, macromolecular chemistry and polymers, pharmaceuticals and cosmetics, biotechnology, materials and metallurgy and food and agriculture; technology class 4 chemical engineering, surfaces, materials processing, thermal processes, oil and basic material chemistry and environmental technology; technology class 5 machines and tools, engines and pumps, mechanical elements, handling, food processing, transport, nuclear engineering and space technology and technology class 6 consumer goods and civil engineering.

Table 1. Innovation and types of knowledge

	SPILL_INV_IN > 0	SPILL_INV_IN = 0
SPILL_OUT < 0	Sticky inventor-specific knowledge	
SPILL_OUT = 0	Mobile inventor-specific knowledge	Firm-specific knowledge

Previous studies suggest that a firm's stock of its past patents reflects knowledge base it can use for generating future patentable ideas, and thus a firm's past patenting activity is positively related to its current patenting. (see, e.g., Blundell et al, 1995, 2002; Crepon and Duguet, 1997). Also, important knowledge for the generation of innovation may "spill" from one firm to another during the R&D collaboration. Generally, according to the resource based view of the management literature, a firm seeks collaboration with external partners that provide complementary inputs for the firm (see, e.g., Miotti and Sachwald, 2003). A firm's joint innovation activities with other firms, research institutes and universities may provide access to knowledge and ideas leading to further innovation.

We go into more detail in our exploration of the role of a firm's own past innovation activities in the firm's contemporary innovation behavior by controlling not only the firm's own patent stock but also spillovers from the patents stocks of the firm's external innovation collaborators (i.e, competitors, other firms, and universities and research institutes). We assume that the greater the knowledge stock of the innovation partners of a firm, the greater the variety of ideas and knowledge that "spills" into the firm.

We further distinguish inter-firm collaboration between the competitors (i.e., collaborating firms active in the same industry with a firm, measured at 3-digit level) and other firms (i.e., collaborator firms that are active in different industries than a firm). In other words, we aim at investigating to what extent *innovation coopetition* vs. *inter-industry innovation collaboration* enhances a firm's subsequent innovation performance. At least partially overlapping technology base of a firm with its coopetition partner may facilitate exchange of information and increase mutual understanding of partners as well as the firms' ability to absorb and use information they obtain from one another. Thus, innovation coopetition may potentially result in more patentable future ideas for a firm than innovation collaboration with those partners that are more distant in the end-user markets or technology-wise. On the other hand, when competitors do joint R&D they may exchange less information than in other collaborative innovation partnerships. This may happen as competitors are likely to have an incentive to minimize other knowledge flows benefiting the competitor in the product markets than those necessary for innovation collaboration.

Furthermore, universities and research institutes may provide important scientific or technological knowledge for a firm's innovation process. The literature presents various reasons why firms collaborate with research organizations such as access to state-of-the-art information, solutions to technical problems and outsourcing R&D (see, e.g., Geisler, 2001; Wang and Shapira, 2012). It thus seems credible that both innovation collaboration and innovation coopetition generate knowledge spillovers but the importance and magnitude of these spillovers, compared to another, is an empirical question.

The above discussion generates two empirically testable hypotheses:

Hypothesis 4 a. The larger the knowledge base or patent pool of a firm, the greater the firm's innovation performance.

Hypothesis 4 b. The larger the knowledge bases or patent pools of a firm's innovation partners, the greater the firm's innovation performance.

We use four variables for measuring the magnitude of firm's past patenting activities. The variable PAT_OWN captures a firm's cumulative number of patent applications it has filed solitarily at time t-1. The variables PATENT_COOP and PATENT_COLLAB capture the cumulative number of patent applications of a firm's past coopetitors and other collaborator firms, respectively, at time t-1. The variable PATENT_RES is a cumulative number of patent applications of those universities and/or research institutes with which a firm has filed joint patent applications in the past. The idea behind generating these variables is that the greater the knowledge base of a firm's innovation partners, the larger potential knowledge spillovers for the firm resulting in patentable ideas.

The geographical agglomeration of organizations has for long been identified as an enabler for the localized knowledge sharing (Jacobs, 1969; Marshall, 1920; Panne, 2004). The quantity of knowledge and new ideas generated in a firm's region determines the magnitude of localized knowledge spillovers available for the firm (see, e.g., Acs et al., 2009). We control for the magnitude of local innovation activities by the variable PAT_LOCAL measuring the total number of patent applications of other firms (i.e., excluding firm's own patent filings) in the ELY center[2] in which the firm is located at time t-1. Given that we control for a firm's past own patenting, this variable provides information on the importance of the magnitude of localized innovation activity for the firm's innovation performance. In other words, this variable captures the short-term influence of localized agglomeration externalities.

There has been a dispute about whether agglomeration externalities are rather intra-industry (i.e., arise from knowledge sharing of firms in the same industry) or inter-industry

[2] In Finland, regional division is based on the areas of the 15 Centres for Economic Development, Transport and the Environment (i.e., ELY Centres) which are responsible for the regional implementation and development tasks of the central government.

(i.e., arise from knowledge sharing of firms across different industries) though. Marshall (1920) argued that knowledge is, by and large, industry-specific. Therefore, regional concentration of firms in the same industry tends to generate (intra-industry) knowledge spillovers called (Marshallian) specialization externalities. We approach the question of specialization externalities from the point of view of firms' innovation activities measured by patent applications in different technology fields. In other words, our underlying idea is that the regional specialization of firms' in innovation activities in a certain technology field may generate knowledge spillovers facilitating further innovation in the same technology field. Our TS index captures the extent of a region's specialization of innovation in technology C across six different technology classes, or the role of Marshallian specialization externalities in innovation production (below time index is dropped for simplicity):

$$TS_{CR} = (P_{CR}/\sum_{C} P_{CR})/(\sum_{R} P_{CR} / \sum_{C}\sum_{R} P_{CR})$$

where C denotes technology class and R denotes region. In other words, TS_{CR} measures the share of patent applications in technology class C in region R relative to the share of patent applications of technology class C of all patent applications. This measure is used in the estimations in which the innovation production function is estimated separately for six different technology classes.

The economic literature (see, e.g., Jacobs, 1969; Glaeser et al, 1992; Neffke et al. 2012) suggests that there may also be local inter-industry spillovers arising from the variety and mix of different ideas across industries (i.e., so called Jacobian diversification externalities). In other words, the more diverse the local pool of ideas is, the greater number of innovations across industries are likely to be generated. We approach the question of diversity of localized ideas via the firms' patenting activities in the region. The technological diversification (TD) index capturing Jabobian diversification externalities can be written as follows (below time index is dropped for simplicity):

$$TD_{CR} = 1 - \sum_{C} (\sum_{R} P_{CR} / \sum_{C} \sum_{R} P_{CR})^2$$

The more diversified the patenting applications of a region are across different technology classes the closer the value of TD is to 1. This measure is used as an explanatory variable both in the estimation of innovation production function for all technologies and in the separate estimations of innovation production functions for six different technology classes.

The specialization and diversification externalities are measured at the regional level assuming that knowledge "spills over" via interaction among localized firms, but without controlling for the actual connections or collaboration among the firms. This is a rather standard approach used in the empirical literature for measuring agglomeration externalities. Our data, however, enables us also to detect intra-industry and inter-industry spillovers arising from innovation collaboration between firms. The variable PAT_COOP measuring the patenting activities of a firm's innovation partners active in the same industry with the firm captures also partially intra-industry spillovers or specialization externalities. Similarly, the variable PAT_COLLAB measuring the patenting activities of a firm's innovation partners active in different industries than the firm captures also partially inter-industry spillovers or diversification externalities. When these variables are used as the explanatory variables in the estimations, the estimated coefficients of the variables TS and TD show the impact of intra-industry and inter-industry knowledge spillovers, respectively, arising from other interactions among firms than formal innovation collaboration generating patentable innovation.

3.2 Data

Our dataset comprises only innovating firms (i.e., those firms that filed at least one patent application during the observation period). We also exclude those firms that had no entering or leaving inventors in the period of study. In addition, we utilize information on only those patent filings in which at least one of the applicants is a company. Our patent dataset covers Finnish firms' patent filings in Europe acquired from the EPO worldwide patent statistical database (EPO PATSTAT[3]). This patent database includes information on both inventors and applicants of the patent filings. We match the companies included in the patent dataset to firm level financial statements and other background data (e.g., industry, geographical location, employment) provided by nationwide business registers of Statistics Finland and Suomen Asiakastieto Oy[4]. These data are available only for the years 2001–2012, so the final combined dataset covers this period.[5] All firm-specific variables are measured at the group level if a company is part of the group. Consistently, we exclude from the mobility variables intra-group transitions (e.g., mobility from a parent company to a subsidiary) of innovators. In total, our final sample covers 351 firms and 2536 observations.

Table 2 shows summary statistics of the main dependent and explanatory variables. The sample firms filed 3.8 applications per year, on average (the variable PAT). Among technology classes, the firms' annual propensity to file a patent was the highest in electrical engineering and process engineering (i.e., about 0.08-0.09). The cumulative sum of patent applications of inventors entering a new company (the variable SPILL_INV_IN) was, on average, 15, while the outflow of knowledge via leaving inventors (the variable SPILL_OUT) was clearly lower, about 7 filed patent application. The average value of the variable

[3] For details of the database, see http://www.epo.org/searching/subscription/raw/product-14-24.html.
[4] Suomen Asiakastieto Oy is a leading private provider of firm level financial statement data in Finland.
[5] In calculations of variables related to patent application stocks we are able to utilize, however, a longer (1995–2012) time period which facilitates us to better take into account past patenting profiles of firms and innovators.

SPILL_FIRM_IN is 156 reflecting notable patent pools of the mobile inventors' previous employers.

Table 2. Description of variables

Variable	Description	Mean	Std. Dev.	Obs
PAT	Number of patent applications at time t	3.790	36.033	2536
PAT_TECH1	Dummy variable that gets value 1 if a firm has filed patent applications in technology class "Electrical engineering" at time t	0.086	0.281	2536
PAT_TECH2	Dummy variable that gets value 1 if a firm has filed patent applications in technology class "Instruments" at time t	0.071	0.257	2536
PAT_TECH3	Dummy variable that gets value 1 if a firm has filed patent applications in technology class "Chemicals and pharmaceuticals" at time t	0.060	0.238	2536
PAT_TECH4	Dummy variable that gets value 1 if a firm has filed patent applications in technology class "Process engineering" at time t	0.080	0.271	2536
PAT_TECH5	Dummy variable that gets value 1 if a firm has filed patent applications in technology class "Mechanical engineering" at time t	0.041	0.198	2536
PAT_TECH6	Dummy variable that gets value 1 if a firm has filed patent applications in technology class "Consumer goods and civil engineering" at time t.	0.015	0.120	2536
SPILL_INV_IN	Cumulative sum of patent applications at t-1 of inventors which moved to a firm at time t	15.295	71.474	2536
SPILL_FIRM_IN	Cumulative sum of patent applications at t-1 of previous employers of inventors which moved to a firm at time t	156.101	878.288	2536
SPILL_OUT	Cumulative sum of patent applications at t-1 of inventors who left a firm at time t	7.051	30.079	2536
PAT_OWN	Firm's cumulative sum of patent applications at t-1	36.573	343.5813	2536
PAT_COOP	Cumulative sum of patent applications of a firm's past coopetitors at t-1	0.607	7.701	2536
PAT_COLLAB	Cumulative sum of patent applications of a firm's past collaborator firms at t-1	13.006	108.257	2536
PAT_RES	Cumulative sum of patent applications of those universities and/or research institutes with which a firm has filed joint patent applications at t-1	7.719	102.521	2536
I	Log of change in intangible assets from t-1 to t	1.380	9.893	2536
PAT_LOCAL	Number of patent applications of the region in which a firm is located at t-1	457.226	470.726	2536
TD	Diversity in the region in which a firm is located at t-1	0.612	0.134	2536
TS_1	Specialization index in tech. "Electrical engineering" in the region in which a firm is located at t-1	0.708	0.467	2536
TS_2	Specialization index in tech. "Instruments" in the region in which a firm is located at t-1	1.546	1.450	2536
TS_3	Specialization index in tech. "Chemicals and pharmaceuticals" in the region in which a firm is	1.075	0.964	2536

	located at t-1			
TS_4	Specialization index in tech. "Process engineering" in the region in which a firm is located at t-1	1.235	1.076	2536
TS_5	Specialization index in tech. "Mechanical engineering" in the region in which a firm is located at t-1	1.609	1.699	2536
TS_6	Specialization index in tech. "Consumer goods and civil engineering" in the region in which a firm is located at t-1	2.116	3.674	2536
FOREIGN	1 if firm is foreign-owned firm at t, 0 otherwise	0.177	0.382	2536
EMP	Number of employees in at t	814.080	2642.510	2536
AGE	Age of firm at t	16.013	13.136	2536

The next four variables in the table illustrate the magnitude of a firm's own and its partners' past patenting activities. The mean value of firm's own knowledge pool is 36.6 patent applications (PAT_OWN), while the firm's coopetitors (PAT_COOP), inter-industry collaborators (PAT_COLLAB) and university/research institute cooperators (PAT_RES) filed, on average, 0.6, 13.0 and 7.7 patents, respectively.

We further control for the agglomeration externalities by the variables PAT_LOCAL, TD and TS. The firm-specific control variables include the change in intangible assets (the variable I), the dummy variable for foreign-owned firm (the variable FOREIGN), firm size measured by the number of employees in Finland (the variable EMP) and firm age (the variable AGE). Furthermore, we also include 15 industry-specific control variables and times dummies for each year for the estimated models.

4. Empirical analysis

We first estimate the following innovation production function:

$$PAT_{it} = \alpha_0 + \alpha_1 SPILL_{INV_{IN}\,it-1} + \alpha_2 SPILL_{FIRM_{IN}\,it-1} + \alpha_3 SPILL_{OUT\,it-1} + \alpha_4 PAT_{OWN\,it-1} + \alpha_5 PAT_{COOP\,it-1} + \alpha_6 PAT_{COLLAB\,it-1} + \alpha_7 PAT_{RES\,it-1} + \alpha_8 I_{it} + \alpha_9 PAT_{LOCAL\,Rit-1} + \alpha_{10} TD_{CRit-1} + \alpha_j \sum_j CONTROL_{ijt} + \varepsilon_{it} \qquad \text{MODEL I}$$

where PAT_{it} is the number of patent applications of a firm i at time t and CONTROL is a vector of other control variables. Given that the dependent variable is a count variable, we use the random effects negative binomial model – that allows overdispersion of the dependent variable – for the estimations.

Table 3 summarizes the estimation results. It appeared that the variables SPILL_INV_IN and SPILL_FIRM_IN are highly correlated (rho = 0.87) generating potential multicollinearity problem with unstable parameter estimates. We thus first include only one of these variables at a time to the model (columns 1 and 2) and then estimate the model with both variables (column 3). The estimation results support our hypotheses that mobile inventors are a substantial channel of inter-firm knowledge flows. Positive and statistically significant coefficient of the variable SPILL_INV_IN emphasizes the importance of inventor-specific knowledge transfer (column 1). Also, the estimated coefficient of the variable SPILL_FIRM_IN appears to be statistically significant (column 2) though it is more than ten times smaller than that of the variable SPILL_INV_IN. The estimated coefficient for the variable SPILL_FIRM_IN is not statistically significant though when inventor-specific inter-firm knowledge spillovers are controlled for (column 3). These empirical findings hint that the inventor-specific knowledge spillovers dominate the firm-specific knowledge spillovers from the inventors' previous employers. It is not possible, however, to distinguish to what extent the importance of mobile inventor's patent pool reflects his or her personal capabilities and what part is generated via learning from the inventor's prior employer(s).

The importance of inventors leaving a firm for its subsequent innovation performance further captures the transfer of inventor-specific knowledge flows. The estimated coefficient of the variable SPILL_OUT is negative and statistically significant in all of the estimated models. This means that the more prolific the inventor leaving a firm (measured by the magnitude of his or hers previous patenting activities), the greater the decline in the firm's innovation performance. Our empirical findings indicate that individual inventors play a notable role in a firm's patenting performance, and that their mobility clearly affects positively to the innovation performance of their new employer and negatively to the innovation performance of their old employer. The estimations of the model comprising all technology fields thus support hypothesis 1, or reflect the features of sticky inventor-specific knowledge in the mobility of innovations.

The estimated coefficient for the variables PAT_OWN and PAT_COOP are also positive and statistically significant. The magnitude of the coefficient of PAT_COOP is clearly larger than that of PAT_OWN emphasizing the importance of spillovers arising from intra-industry innovation collaboration. The estimated coefficient for the variables PAT_COLLAB and PAT_RES are not statistically significant suggesting that inter-industry innovation collaboration or a firm's cooperation with universities or research institutes do not generate similarly the transfer of patentable ideas of knowledge across organizations. Our estimation results thus provide support for hypothesis 4a, and also partially for hypothesis 4b. Furthermore, we find that the estimated coefficient of PAT_COOP is clearly larger than the estimated coefficients for variables capturing inventor-specific inter-firm spillovers.[6] This finding suggests that an increase in innovation activities of a firm's coopetition partners tends to generate greater innovation spillovers than an increase in the innovation activities of mobile inventors.

PAT_LOCAL which measures the magnitude of localized innovation activity for the firms' innovation performance is positive and statistically significant. However, our proxy for Jacobian diversification externalities (TD) is not statistically significant. These findings hint that there are agglomeration externalities even after controlling for inventor and firm-specific spillovers but they do not appear to link to the localized diversity of ideas or inter-

[6] The Wald tests are in all cases statistically significant at $p<0.01$.

industry spillovers. Among the control variables, firm size (i.e., the variable EMP) is positive and statistically significant indicating that larger firms generate more patent applications than smaller ones.

Table 3. The estimation results of the random effects negative binomial model for innovation production function, dependent variable PAT

	(1) Coef./S.E	(2) Coef./S.E	(3) Coef./S.E
SPILL_INV_IN	0.0023*** (0.0002)		0.0027*** (0.0003)
SPILL_FIRM_IN		0.0002*** (0.0000)	0.0000 (0.0000)
SPILL_OUT	-0.0044*** (0.0010)	-0.0050*** (0.0011)	-0.0041*** (0.0010)
PAT_OWN	0.0004*** (0.0001)	0.0006*** (0.0001)	0.0003*** (0.0001)
PAT_COOP	0.0147*** (0.0029)	0.0120*** (0.0030)	0.0153*** (0.0030)
PAT_COLLAB	0.0002 (0.0004)	0.0005 (0.0004)	0.0002 (0.0004)
PAT_RES	0.0001 (0.0001)	-0.0001 (0.0001)	0.0001 (0.0001)
I	0.0026 (0.0024)	0.0010 (0.0026)	0.0030 (0.0023)
PAT_LOCAL	0.0006*** (0.0001)	0.0006*** (0.0001)	0.0006*** (0.0001)
TD	0.0419 (0.3975)	0.0025 (0.3935)	0.0375 (0.3984)
FOREIGN	0.1144 (0.1379)	0.0994 (0.1386)	0.1205 (0.1378)
EMP	0.0001*** (0.0000)	0.0001*** (0.0000)	0.0001*** (0.0000)
AGE	0.0048 (0.0047)	0.0079 (0.0049)	0.0045 (0.0047)

Years	Yes	Yes	Yes
Industries	Yes	Yes	Yes
Log pseudolikelihood	-2878.163	-2904.459	-2877.207
Wald(Chi2)	613.261***	456.872***	628.325***
Observations	2536	2536	2536

Notes: The table reports the results of random-effects negative binomial regressions, standard errors are in parentheses. Industry and year dummies are included in all estimations. Significance levels are reported in superscript, where *** denotes a significance level of 1%.

We further estimate the model presented in the first column of Table 3 with t-2 lagged values for the variables SPILL_INV_IN and SPILL_OUT to investigate whether the mobility of inventors affects firms' innovation performance with a delay. Table 4 shows the estimation results of this model variation. The greater coefficient of the variable SPILL_IV_IN at time t-1 than at t-2 suggests that a firm's innovation performance is boosted more by the relatively recent inflow of inventors. However, the estimated coefficient for SPILL_INV_IN at t-2 is also positively and highly statistically significant. Instead, the estimation results concerning the variable SPILL_OUT at t-1 and t-2 hint that an inventor leaving a firm tends to reduce the firm's innovation performance more with a two year lag than one year after the loss of an inventor.

Table 4. The role of time lags of SPILL_INV_IN and SPILL_OUT

	Coef./S.E
SPILL_INV_IN	0.0025***
	(0.0002)
SPILL_INV_IN (t-2)	0.0011***
	(0.0002)
SPILL_OUT	-0.0012
	(0.0019)
SPILL_OUT (t-2)	-0.0051**
	(0.0020)

PAT_OWN	0.0004***
	(0.0001)
PAT_COOP	0.0121***
	(0.0030)
PAT_COLLAB	0.0001
	(0.0004)
PAT_RES	0.0000
	(0.0001)
I	0.0029
	(0.0023)
PAT_LOCAL	0.0006***
	(0.0001)
TD	0.0151
	(0.4041)
FOREIGN	0.1420
	(0.1381)
EMP	0.0001***
	(0.0000)
AGE	0.0046
	(0.0047)
Years	Yes
Industries	Yes
Log pseudolikelihood	-2860.376
Wald(Chi2)	663.641***
Observations	2528

Notes: The table reports the results of the random-effects negative binomial regression, standard errors are in parentheses. The explanatory coefficient vector is similar to Column 1 in Table 3 except that there are time lags of t-2 of SPILL_INV_IN and SPILL_OUT. Significance levels are reported in superscript, where *** denotes a significance level of 1% and ** denotes a significance level of 5%.

Second, we empirically analyze whether the dynamics of knowledge spillovers differ across six technology classes and what implications different spillover channels have on the firms' propensity of patenting in different technology fields. We estimate the following innovation production function separately for the six technology classes (k):

$$PAT_{ikt} = \alpha_0 + \alpha_1 SPILL\_INV\_IN_{ikt-1} + \alpha_2 SPILL\_OUT_{ikt-1} + \alpha_3 PAT_{OWN\,ikt-1} + \alpha_4 PAT_{COOP\,ikt-1} + \alpha_5 PAT_{COLLAB\,ikt-1} + \alpha_6 PAT_{RES\,ikt-1} + \alpha_7 I_{it} + \alpha_8 PAT_{LOCAL\,Rikt-1} + \alpha_9 TD_{Rikt-1} + \alpha_k \sum_k TS_{ikt-1} + \alpha_j \sum_j CONTROL_{ijt} + \varepsilon_{ikt} \qquad \text{MODEL II}$$

Here, the dependent variable PAT_{ikt} is a dummy variable which is 1 if a firm has applied for a patent in technology k in year t and 0 otherwise. We further also control for the localized specialization of innovation in technology class k by the variable TS.[7] We use the random effects probit model for the estimations as the number of patent applications per firm is typically either 0 or 1. Consequently, for most technology fields, the dependent variable does not have sufficient count variable structure to allow the estimations of the negative binomial model. Table 5 presents the estimation results.

The estimation results of the model comprising all technologies presented in Tables 3-4 suggest that knowledge of new patentable ideas tend to be sticky inventor-specific. The results reported in Table 5 indicate however that there are differences across technology classes. The variable SPILL_INV_IN is positive and statistically significant in the estimations for all technology classes except for consumer goods and civil engineering (for which the coefficient is not estimable as the variable gets value 0 in all cases). The estimated coefficient of SPILL_OUT is negative and statistically significant for electrical engineering, instruments and process engineering hinting that the knowledge flows crucial for patentable ideas are sticky inventor-specific; the results regarding these technology classes are thus similar to the model comprising all technologies.

---

[7] Estimation results of Table 3 show that the inventor-specific knowledge spillovers dominate the firm-specific knowledge spillovers from the inventors' previous employer. Therefore, the variable SPILL_FIRM_IN that is highly correlated with the variable SPILL_INV_IN is dropped here from the estimations.

Instead, we cannot reject the hypothesis that the coefficient of the variable SPILL_OUT is zero for chemicals and pharmaceuticals, mechanical engineering, and consumer goods and civil engineering. This finding, along with a positive and statistically significant coefficient of SPILL_INV_IN, suggests that the knowledge flows are mobile inventor-specific for chemicals and pharmaceuticals and mechanical engineering. Due to lack of data concerning the inventors entering the firms that file patents in the consumer goods and civil engineering technology class, we cannot make definite conclusions about whether the patentable ideas tend to be based rather on mobile inventor-specific knowledge flows or firm-specific knowledge.

Table 5. The estimation results of the random effects probit model for a firm's propensity to patent by technology classes

	PAT_TECH1 Electrical engineering	PAT_TECH2 Instruments	PAT_TECH3 Chemicals and pharmaceuticals	PAT_TECH4 Process engineering	PAT_TECH5 Mechanical engineering	PAT_TECH6 Consumer goods & civil eng.
	Coef./S.E	Coef./S.E	Coef./S.E	Coef./S.E	Coef./S.E	Coef./S.E
SPILL_INV_IN_k	0.0005*** (0.0001)	0.0014** (0.0006)	0.0010*** (0.0002)	0.0003*** (0.0001)	0.0020** (0.0008)	
SPILL_OUT_k	-0.0075*** (0.0020)	-0.0047** (0.0021)	-0.0004 (0.0003)	-0.0016** (0.0006)	-0.0036 (0.0023)	-0.0028 (0.0034)
PAT_OWN_k	0.0023*** (0.0005)	0.0027*** (0.0008)	0.0005*** (0.0002)	0.0007*** (0.0002)	0.0006** (0.0003)	0.0007** (0.0004)
PAT_COOP_k	0.0071 (0.0081)	-0.0088 (0.0119)	-0.0081 (0.0063)	0.0001 (0.0009)		0.1068 (24.9523)
PAT_COLLAB_k	0.0000 (0.0000)	0.0028 (0.0019)	-0.0003 (0.0004)	0.0001 (0.0001)	-0.0001 (0.0004)	
PAT_RES_k	-0.0116*** (0.0030)	-0.0002 (0.0002)	0.0000 (0.0002)		-0.0004 (0.0014)	
I	0.0009** (0.0004)	0.0009** (0.0004)	0.0000 (0.0003)	-0.0005 (0.0003)	0.0006** (0.0003)	0.0000 (0.0001)
PAT_LOCAL_k	0.0000 (0.0000)	0.0000 (0.0000)	0.0000*** (0.0000)	0.0000*** (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)
TD_k	0.0273 (0.0561)	0.0087 (0.0388)	0.0205 (0.0383)	0.0993** (0.0466)	-0.0178 (0.0267)	-0.0036 (0.0124)

TS_k	0.0718***	0.0020	-0.0003	0.0092**	0.0001	0.0008*
	(0.0224)	(0.0033)	(0.0040)	(0.0038)	(0.0019)	(0.0004)
FOREIGN	-0.0032	-0.0031	0.0019	-0.0127	-0.0003	0.0019
	(0.0153)	(0.0133)	(0.0118)	(0.0137)	(0.0089)	(0.0040)
EMP	0.0000**	-0.0000*	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
AGE	-0.0007	-0.0005	-0.0002	0.0002	0.0004	0.0000
	(0.0005)	(0.0004)	(0.0003)	(0.0004)	(0.0003)	(0.0001)
Years	Yes	Yes	Yes	Yes	Yes	Yes
Industries	Yes	Yes	Yes	Yes	Yes	Yes
Log pseudolikelihood	-491.941	-495.087	-405.794	-475.519	-319.533	-138.060
Wald(Chi2)	193.910***	111.750***	120.260***	103.350***	75.820***	49.790***
Observations	2536	2536	2536	2536	2536	2536

Notes: The reported coefficients are marginal effects of random-effects probit regressions; standard errors are in parentheses. In SPILL_INV_IN_k, SPILL_OUT_k, PAT_OWN_k, PAT_COOP_k, PAT_COLLAB_k, PAT_RES_k, PAT_LOCAL_k, TD_k and TS_k the letter k refers to the same technology class (1-6) as is the technology class of the dependent variable. The blank coefficient cells of the variables indicate that there are no non-zero values of those variables and they are excluded from the regression. Industry and year dummies are included in all estimations. Significance levels are reported in superscript, where *** denotes a significance level of 1%, ** denotes a significance level of 5% and * denotes a significance level of 10%.

The formal firm-level intra-industry and inter-industry innovation collaborator variables do not appear generally statistically significantly in the estimated technology-specific equations. From the regional level variables the estimated coefficient of the variable PAT_LOCAL is positive and statistically significant only for chemicals and pharmaceutical and process engineering reflecting the presence of agglomeration externalities in these technology fields. The variable TD reflecting the localized diversity of patentable ideas gets a positive and statistically significant coefficient for process engineering. The variable TS capturing regional specialization in each technology class is positive and statistically significant in electrical engineering and process engineering and also weakly statistically significant (i.e., at 10 percent level) in consumer goods and civil engineering.

5. Conclusions

This paper has used data from 351 innovating firms for the years 2001–2012 to study the roles of inventor-specific knowledge flows, spillovers from inter-organization innovation collaboration and agglomeration externalities in a firm's innovation performance. Our empirical findings generally suggest that patentable ideas are strongly linked to the mobility of individual inventors, or that the knowledge flows transmitted are sticky inventor-specific. In other words, the larger the knowledge pool of an inventor entering (leaving) the firm, the more the firm's innovation performance increases (decreases). This means that the tacit knowledge of prolific inventors is not easily transferable to the new organization.

We find though that among certain technology fields knowledge is more easily transferable via the mobile inventors. For chemicals and pharmaceuticals and mechanical engineering, the entry of inventors to a firm increases its innovation performance but the firm's innovation performance is not notably affected when the inventors leave the company. In other words, in these technology fields, it seems that firms hiring inventors can absorb some of the inventor's essential knowledge required for generating patentable ideas such that the loss of inventors does not deteriorate the firm's innovation capabilities.

Interestingly, the strongest spillovers seem to be the intra-industry ones that are generated in the formal innovation collaboration between competitors. This empirical finding supports the idea that the exchange of information and ideas for innovation are facilitated by the collaborating partners' overlapping technology bases. Furthermore, it seems that regional specialization or Marshallian intra-industry externalities matter for the generation of new technologies in certain fields of engineering (i.e., electrical engineering, process engineering, and consumer goods and civil engineering). Our data thus suggest that the majority of intra-industry spillovers across firms leading to patentable ideas happen in direct firm-level collaboration but also Marshallian specialization externalities play role in the generation of new technologies in certain technology fields. Furthermore, the magnitude of overall localized innovation activity is generally positively related to the firm's performance providing further support for the existence of agglomeration externalities.

We find no evidence of significant spillovers arising from either formal inter-industry innovation collaboration or a firm's innovation collaboration with universities or research institutes. At the regional level, the localized technological diversity of ideas is generally neither statistically significantly related to a firm's innovation performance. Our data thus finds no support for Jacobian externalities. Knowledge flows rather tend to transfer from one firm to another via the mobility of individual inventors and via the formal intra-industry collaboration.

From the point of view of technology policy, our findings indicate that encouraging intra-industry innovation collaboration or innovation coopetition can be an efficient means to facilitate the exploitation of knowledge spillovers. Our study hints that R&D subsidies targeted for joint intra-industry innovation projects may be justified due to knowledge spillovers. However, we cannot make any strong statements on this question as our empirical analysis focuses merely on the significance of different channels of knowledge spillovers in the firm's innovation performance, and it does not assess the economic value or magnitude of those spillovers.

Also, in our empirical analysis, we use a rather narrow, though commonly used and important measure of a firm's innovation performance (i.e., the number of patent applications). However, there are a wide range of non-patentable innovations such as organizational and marketing innovations that are out of the scope of our analysis.

Therefore, the estimation results should be interpreted with caution. It is possible that the importance of different spillover channels varies by the type of innovation. Hopefully future empirical work sheds light on this question as well as on the economic value of knowledge spillovers.

References

Acs, Z., Braunerhjelm, P., Audretsch, D. B. and Carlsson, B. (2009). The knowledge spillover theory of entrepreneurship. *Small Business Economics*, 32, 15-30.

Blundell, R., Griffith, R. and van Reenen, J. (1995). Dynamic count data models of technological innovation. *The Economic Journal* 105, 333-344.

Blundell, R., Griffith, R. and van Reenen, J. (2002). Individual effects and dynamics in count data models. *Journal of Econometrics* 108, 113-131.

Castillo, V., Maffioli, A., Rojo, S. and Stucchi, R. (2014). Knowledge spillover of innovation policy through labor mobility: An impact evaluation of the FONTAR program in Argentina. *IDB Working Paper Serier* No. IDB-WP-488. February 2014.

Crepon, B. and Duguet, E. (1997). Estimating the innovation function from the patent numbers: GMM on count panel data. *Journal of Applied Econometrics* 12, 243-263.

Döring, T. and Schellenbach, J. (2006). What do we konow about geographical knowledge spillovers and regional growth? A survey of the literature. *Regional Studies* 40, 375-395.

Feldman, M.P. and Audretsch, D.B. (1999). Innovation in cities: science-based diversity, specialization and localized competition. *European Economic Review* 43, 409-429.

Gay, C., Le Bas, C. and Latham, W. (2008). Collective knowledge, prolific inventors and the value of inventions: An empirical study of French, German and British owned U.S. patents, 1975-1988. *The Economics of Innovation and New Technology* 17, 5-22.

Geisler, E. (2001). Explaining the generation and performance of intersector technology cooperation: A theory of inter-organizational relationships. *Technology Analysis & Strategic Management* 13, 195-206.

Giuri, P. and Mariani, M. (2013). When distance disappears: Inventors, education, and the locus of knowledge spillovers. *Review of Economics And Statistics* 95, 449-463.

Glaeser, E., Kallal, H., Scheinkman, J. and Schleifer, A. (1992). Growth in cities. *Journal of Political Economy* 100, 1126-1152.

Hoisl, K. (2007): Tracing mobile inventors – The causality between inventor mobility and inventor productivity. *Research Policy* 36, 619-636.

Jacobs, J. (1969). *The economy of cities*. Random House, New York.

Jaffe, A.B., Trajtenberg, M., Henderson, R. (1993). Geographic localization of knowledge spillovers as evidenced by patent citations. *Quarterly Journal of Economics*, 63: 577–598.

Kaiser, U., Kongstedt, H.C. and Ronde, T. (2013). Does the mobility of R&D labor increase innovation? Mimeo.

Latham, W. Le Bas, C. and Volodin, D. (2012). Value of invention, prolific inventor productivity and mobility: Evidence from five countries, 1975-2002. *Economies et Societes* 46, 11-40.

Laursen, K. and Salter, A. (2006). Open for innovation: The role of openness in explaining innovation performance among U.K. manufacturing firms. *Strategic Management Journal* 27, 131-150.

Love, J.H., Roper, S. and Vahter, P. 2013. Learning from openness: The dynamics of breadth in external innovation linkages. Strategic Management Journal. Article first published online: 29 AUG 2013.

Maliranta, M., Mohnen, P. and Rouvinen, P. (2009). Is inter-firm labor mobility a channel of knowledge spillovers? Evidence from a linked employer-employee panel. *Industrial and Corporate Change* 18, 1161-1191.

Mancusi, M. (2003). Geographical concentration and the dynamics of countries' specialization in technologies. *Economics of Innovation and New Technology* 12 , 269-291.

Marshall, A. (1920). *Principles of Economics*. Macmillan, London.

Matusik, S.F and Hill, C.W.L. (1998). The utilization of contingent work, knowledge creation, and competitive advantage. *Academy of Management Review* 4, 680-697.

Miotti, L. and Sachwald, E. (2003). Cooperative R&D: why and with whom? *Research Policy* 32, 1481-1499.

Neffke, F., Henning, M. and Boschma, R. (2011). How do regions diversify over time? Industry relatedness and the development of new growth paths in regions. *Economic Geography* 87, 237-265.

OECD (1994). The measurement of scientific and technological activities. Using patent data as science and technology indicators. *Patent Manual, OECD Publication*.

van der Panne, G. (2004). Agglomeration externalities: Marshall versus Jacobs. *Journal of Evolutionary Economics* 14, 593-604.

Tambe, P. and Hitt, L. (2014). Job hopping, information technology spillovers, and productivity growth. *Management Science* 60, 338-355.

Wang, J. and Shapira, P. (2012). Partnering with universities: a good choice for nano-technology start-up firms? *Small Business Economics* 38, 197-215.