WORKING PAPER
2014:30

Does Labor Mobility Foster Innovation? Evidence from Sweden

Pontus Braunerhjelm, Ding Ding and Per Thulin

RESEARCH NETWORK DEBATE
SWEDISH ENTREPRENEURSHIP FORUM

Working Papers Series from Swedish Entrepreneurship Forum

In 2009 Swedish Entrepreneurship Forum started publishing a new series of Working Papers. These are available for download on www.entreprenorskapsforum.se, and are part of our ambition to make quality research available to a wider audience, not only within the academic world.

Scholars from different disciplines are invited to publish academic work with the common denominator that the work has policy relevance within the field of entrepreneurship, innovation and SMEs.

The working papers published in this series have all been discussed at academic seminars at the research institution of the author.

ABOUT SWEDISH ENTREPRENEURSHIP FORUM

Swedish Entrepreneurship Forum is the leading Swedish network organization for generating and transferring policy relevant research in the field of entrepreneurship and small enterprise development.

Swedish Entrepreneurship Forum is a network organization with the aim

- to serve as a bridge between the small business research community and all agents active in development of new and small enterprises.
- to initiate and disseminate research relevant to policy in the fields of entrepreneurship, innovation and SME.
- to offer entrepreneurship researchers a forum for idea sharing, to build national and international networks in the field and to bridge the gap between research and practical application.

Find out more on www.entreprenorskapsforum.se

Does Labor Mobility Foster Innovation?
Evidence from Sweden[1]

October 2014

Pontus Braunerhjelm, Ding Ding and Per Thulin[2]

Abstract

The objective of this paper is to empirically examine the impact of labor mobility on innovation output. An emerging and recent literature provides some, but far from unambiguous, evidence that there may exist a positive relationship between labor mobility and innovativeness, measured as firms' patent applications. Implementing a unique matched employer-employee dataset, which has been pooled with firm level patent application data, we provide new evidence that mobility of knowledge workers has a positive and strongly significant impact on firms' innovation output. The effect is particularly strong for knowledge workers that previously has worked in a patenting firm (the learning by hiring effect), but also the firms losing a knowledge worker is shown to benefit (the diaspora effect), albeit the impact is much weaker. Finally, the effect is more pronounced if the joining worker originates in another region.

Key words: Labor mobility; Innovation; Knowledge flows; Social networks
JEL Codes: J61; O33; O34

[1] We like to thank participants at the workshop "Labor market rigidities, human capital and innovation", held in Washington D.C. October 21, 2013, 15th International Conference of the International Joseph A. Schumpeter Society (ISS) in Jena, Germany July 27–30, 2014, and James Albrecht, Gunnar Eliasson and Hans Lööf, for valuable comments.
[2] All authors are affiliated to KTH The Royal Institute of Technology, Division of Entrepreneurship and Innovation, INDEK, SE-100 44 Stockholm, Sweden. Corresponding author: Pontus Braunerhjelm (pontus.braunerhjelm@indek.kth.se).

Introduction

An emerging but tiny literature has recently addressed the issue of how labor mobility influences innovation. This is a highly topical and policy relevant research question considering the faltering growth performance in large parts of the global economy and the call for structural reforms, not least within the European Union, often targeting the labor markets. Since innovation is supposed to be the engine of growth, more thorough insights regarding the relationship between labor mobility and innovation is obviously a high-priority task.

The results of previous research are inconclusive even though most studies suggest a positive effect of labor mobility on innovation (Agrawal et al., 2006). Similarly, studies on the inter-firm mobility of engineers in Silicon Valley have shown that movers often are major patent holders and that such mobility is a crucial part in firms' learning processes (Almeida and Kogut, 1999). These results have been corroborated by for instance Oettl and Agrawal (2008), who claim that not only does the receiving firm gain from such knowledge flows, but also the firms that loose workers. The latter effect is due to increased knowledge flows and expanded social (knowledge) networks. There is however also evidence that innovative firms have a lower turnover rate than others when we look at the mobility of highly qualified labor (Balsvik, 2011; Parrotta and Pozzoli, 2012). Hence, the result of how labor mobility affects innovation is somewhat ambiguous.

The purpose of this paper is to examine how knowledge generated by labor mobility of high knowledge workers (R&D workers) influences innovation at the firm level. We implement a unique matched dataset of employers and employees. The data set contain a number of characteristics at the individual, firm and regional levels, including patent applications, and allows us to trace how individuals move between firms and the ensuing effects on innovation. To qualify as innovative, firms need to have at least one patent application. Remaining non-patenting firms are considered as non-innovators.

Building on these unique data we offer new insights as regards the influence of labor mobility on firms' innovativeness in several dimensions. First, we take into account not only the firm receiving a new knowledge worker (learning by hiring) but also the firm that has lost a worker (diaspora effect) when analyzing the innovativeness. Second, we use several detailed measures of knowledge workers – function and formal occupation – which further highlight the robustness of the results. Finally, we emphasize the geographical dimension of knowledge flows, i.e. how inter- versus intra-regional mobility influences innovation output, controlling for a number of factors such as industry classification and regional variables.

Our estimations provide strong support for a positive effect of mobility of R&D workers on firms' innovation output. More precisely, when labor mobility of high knowledge worker occurs, both sides (sourcing firms and receiving firms) will benefit from the knowledge flow. If the sourcing firm is considered as an innovator, the knowledge flow is stronger; and if the receiving firm is an innovator, the sourcing firms will receive a stronger backward knowledge flow effect. Both forward and backward effects are stronger if labor mobility takes place across rather than within the regional border. Finally, the results also indicate that large firms benefit more from labor mobility in terms of innovative output than smaller firms.

The rest of the paper is organized in the following way. The next section presents previous research of relevance for the issued addressed in this paper, while the theoretical framework and hypotheses are outlined in the subsequent section. The empirical strategy and description of data follows, which precedes the regression results – separated on the "Firm learning by hiring" and the "Firm learning by diaspora" effects. The last section concludes.

Previous research

Labor market flexibility can be defined in different ways; labor mobility within firms, between firms or in terms of wages. Here we are concerned with labor mobility between firms and the effects on innovation measured as patent applications. Theoretically it can be shown that labor mobility may either increase or decrease innovative performance. In the former case, labor mobility generates better matching and extended networks which increase knowledge flows between firms. The latter effect may occur due to more costly administrative routines and harmful effects on firms' organizational learning and "internal memories" (Zhou et al., 2009). Low mobility may also imply that more power has been transferred to labor, which is likely to raise wages and erode resources that could have been invested in e.g. R&D. Firms could thus find themselves in a hold-up situation (Malcomson, 1997). Overall, previous theoretical models suggest that the effects of labor mobility may go in both directions.

Empirically it has been shown that mobility increase productivity at the firm level (Nicoletti and Scarpetta, 2003; Andersson and Thulin, 2008). The proposed reasons are a better matching between firms' needs and the skills of labor (Bessen and Maskin, 2009), spillover of knowledge embodied in labor, and extended externalities related to network spillovers (Pakes and Nitzan, 1983; Mansfield, 1985; Powell et al., 1996; Zucker et al., 1998; Song et al., 2003; Hoti et al., 2006). As new knowledge, embodied in labor, enters the firm, established processes and methods tend to be challenged. New knowledge provides new insights, increase efficiency and productivity, and may lead to new business opportunities. At a more aggregate level these mechanisms have been extensively discussed in the literature on Jacobian (inter-industry) and Marshallian (intra-industry) externalities (Rosenthal and Strange, 2003), while more micro-oriented studies have looked at recruitment strategies and how mobility enhances learning capacities and learning sharing (von Hippel, 1987; Singh and Agrawal, 2011; Corredoira and Rosenkopf, 2010).

There are good reasons to expect that these results should translate into similar results with regard to firms' innovation activities. A more recent empirical strand in the literature looks specifically at how innovation performance is impacted by labor mobility. Kaiser et al.

(2011), embarking from a standard patent production function and implementing a matched employer-employee dataset on Danish firms that is pooled with patent data, show that both firms employing knowledge workers from other firms, and those loosing knowledge workers, improve their innovative performance measured as patent applications. They explain the positive outcome to extended and improved networks, accelerating the knowledge flows. It is one of the few studies looking at innovation outputs rather than inputs in terms of citations of previous patents.[3] Also Hoisl et al. (2007) examines how labor mobility influences patenting activities, but the analysis is partial and only considers the receiving firms and suffers from being dependent on questionnaire data. Overwhelmingly the findings, albeit limited, suggest that labor mobility has a positive effect on invention and innovative behavior.[4]

Also the geographical dimension of labor mobility has been addressed in previous studies. Disregarding the plethora of studies looking at how knowledge spillovers diminishes with distance, evidence has also been provided showing that firms are likely to patent more in regions characterized by high labor mobility (Kim and Marschke, 2005). In addition, examining successful clusters and agglomerations, frequent job changes and close interactions between employees of different firms has been stressed as one of the more decisive success factors (Saxenian, 1994; Fallick et al., 2006). On the other hand, it has also been suggested that – due to the similarity of knowledge in the same region – intra-regional movement is slightly less likely to bring new information into the firm and to propel innovation as compared to inter-regional mobility (Essletzbichler and Rigby, 2005). The latter issue has, to our knowledge, not been subject to a rigorous empirical analysis.

Finally, there is also a literature on labor market regulations, firm size and innovativeness. Impediments to mobility may be of an informal or a formal character (Breschi

---

[3] See Song et al. (2003), Rosenkopf and Almeida (2003), Agrawal et al. (2006) and Corredoira and Rosenkopf (2010). At the same time it should be stressed that measuring innovation is a difficult task, where patents and patent application is one but incomplete measure. See Hall (2011) for a review and discussion.

[4] One exception is Cassiman et al. (2011), showing that participation in joint ventures seems more conducive to innovation than labor mobility.

and Lissoni, 2005 and 2009). In the first case firms fear that they will lose some of their proprietary knowledge as employees leave, thereby threatening their competitiveness and profitability, and consequently firms seek to restrain mobility when contracting employees defined as strategically important (Fosfuri and Rønde, 2004; Combes and Duranton, 2006; Marx et al., 2009). These measures seem however to have an ambiguous effect on firms' innovations. While Franco and Mitchell (2008) and Kräkel and Sliwka (2009) conclude that contractual constraints to labor mobility positively influence firms' innovations, other claim the opposite (Samila and Sorenson, 2011).

Formal labor regulation that deters mobility implies administrative costs and, given that at least some of those are fixed, will supposedly hurt smaller firms more than larger firms. Scarpetta and Tressel (2004) present evidence suggesting that labor market regulation influence the incentives to engage in innovation and technology negatively, which can be expected to primarily have a negative effect on innovation in smaller firms. Empirical studies taking into account firms of different sizes are extremely scarce. Zhou et al. (2011) present results that indicate that innovative behavior in smaller firms is positively affected (though the robustness of the results are questionable) by labor being on temporary contracts, albeit their innovation measure is a subjective variable defined by the firms.[5] These findings indicate that for more concentrated industries, i.e. dominated by larger firms, the effects of regulated markets may be quite different than for markets hosting a larger share of smaller firms.

To summarize, theoretical models give some guidance but are far from consensus in their normative conclusions, whereas empirical research – even though results differ – overall seems to support a positive relationship between labor mobility and firms' innovation endeavors.

[5] Ichniowski and Shaw (1995) and Bassanini and Ernst (2002), conclude that primarily smaller firms' innovativeness tend to be negatively affected by labor market regulations.

Theoretical framework and hypotheses

A number of previous contributions have addressed the issue of labor mobility and knowledge flows, departing from the observation that knowledge to a large extent is embodied in employees. Vilalta-Bufi (2008) recently developed a model similar to Romer's (1990) endogenous growth model, where she replaced different types of intermediate goods with different types of human capital. The main features of the model are briefly described below and we refer to Vilalta-Bufi (2008) for details and a complete description of the model.

The economy contains *N* firms, which are identical in all respects except for their firm-specific knowledge (*h*) – assumed to be embodied in its workers. Firms can access knowledge (human capital) in three different ways. First, they can draw upon knowledge among their own experienced employees that remain in the firm (stayers). Second, they can acquire new knowledge by hiring experienced workers from other firms (joiners), and, third, they can hire workers who have just entered the labor market.

Production *Y* is given by,

$$Y_i = H_i^{\alpha} L_i^{1-\alpha}, \quad \alpha \in (0,1) \tag{1}$$

where H_i is a measure of human capital embodied in experienced workers and L_i stands for the amount of workers without any previous work experience; firms are identified by sub-index i. Human capital is defined as a composite of the firm's own experienced workers and experienced workers hired from other firms,

$$H_i = \left(\left(\lambda_i^i h_i \right)^{\alpha} + p \sum_{j \neq i} \left(\lambda_i^j h_j \right)^{\alpha} \right)^{\frac{1}{\alpha}}, \quad p \in [0,1]. \tag{2}$$

In equation (2), λ_i^x shows the amount of labor originating from firm x that is used in production by firm i. Parameter p measures how easily firms can access the external knowledge embodied in their new workers – determined in part by the institutional setting and the absorptive capacity of the hiring firm. Inserting the measure of human capital into the production function and assuming that all firms employ the same amount of new unexperienced workers (here set equal to one for simplicity), production can be written as,

$$Y_i = \left(\lambda_i^i h_i\right)^{\alpha} + p\sum_{j\neq i}\left(\lambda_i^j h_j\right)^{\alpha}. \tag{3}$$

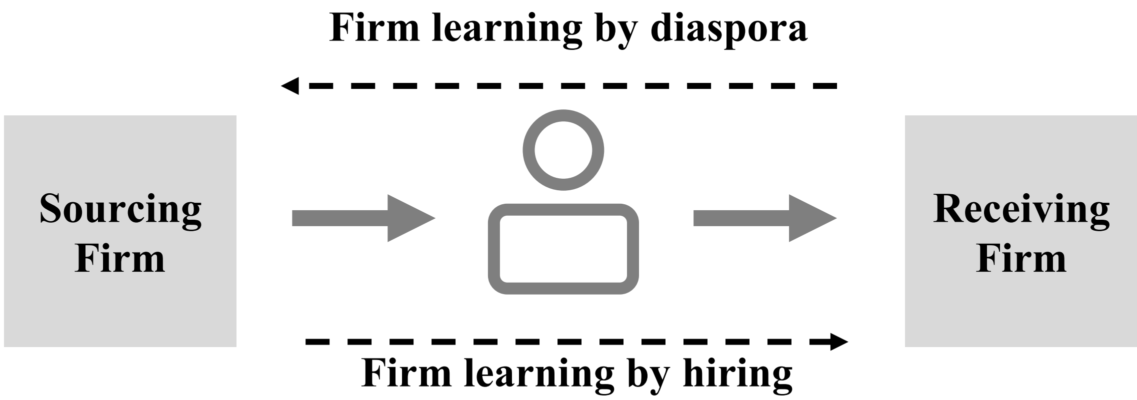
It is costly for a worker to move to a new firm and hence, firms need to pay a wage premium m in order to attract workers from other firms. Firms choose the amount of workers to retain and the amount of experienced workers to hire from other firms in order to maximize their profits. Using the first-order conditions from the profit maximizing problem and imposing market-clearing yields the following equilibrium condition,

$$\alpha\left(1-\left(N-1\right)\lambda^{i*}\right)^{\alpha-1} h_i^{\alpha} = p\alpha\left(\lambda^{i*}\right)^{\alpha-1} h_i^{\alpha} - m \tag{4}$$

where λ^{i*} is the optimal amount of labor to poach by each firm. The solution is interior which ensures positive labor mobility in equilibrium. Hence, the model shows that firms hire workers from other firms in equilibrium in order to enhance their knowledge base. Presumably, this higher knowledge base should also have bearing on firms innovating capacity and thereby establish a causal link between labor mobility and innovation.

Building on Vilalta-Bufi (2008), Rosenkopf and Almeida (2003) and Song et al. (2003), we refer to the knowledge enhancing effect that occurs through recruiting new employees as the “Firm learning by hiring” effect (Figure 1). Over time, as the new workers’ knowledge is diffused into the new firm, and as their network with former colleagues from the sourcing firm diminishes, the effect gradually peters off. In addition, we extend the model by assuming that workers who left a firm continue to be included in the knowledge creation process by transferring knowledge from their new employers to their old. The mechanism is the same as for the receiving firm; workers often maintain their social relationships after leaving the firm (Crane, 1969; Oettl and Agrawal, 2008). We refer to this process as the “Firm learning by diaspora” effect.

Figure 1: Firm learning process



So far we have considered knowledge upgrading through employees but without taking the geographical dimension into account. Knowledge flows have been shown to be geographically localized (Agrawal and Cockburn, 2003; Almeida and Kogut, 1999; Audretsch and Feldman, 1996; Jaffe et al., 1992; Thompson and Fox-Kean, 2005). To include the effect of geographical distance we classify labor mobility into two different types: intra-regional and inter-regional labor mobility, based on whether the sourcing firm and the receiving firm are located in the same region or not. Firms’ knowledge upgrading thus involves four types of human capital: joiners, leavers, stayers and new workers. Furthermore, joiners and leavers can be divided into two subgroups depending on whether they move across regional borders.

Our hypotheses are based on the theoretical framework outlined above, and the literature review, bearing in mind that both previous theoretical and empirical contributions are scarce and partly ambiguous. However, there are quite compelling indications that labor mobility leads to increased knowledge diffusion and knowledge exchange (within and between firms), positively influencing labor productivity. We expect that for similar reasons labor mobility of workers should be positively associated with firms' innovation activities, particularly if those joining a firm come from an already patenting firm. Moreover, building on results showing that proximity is likely to generate more of knowledge flows, we hypothesize that intra-regional labor mobility is likely to have a stronger effect on a firm's innovation capability than inter-regional labor mobility. Still, there are also results pointing in the opposite direction, i.e. that an inflow of knowledge from more remote environments propels more of innovation. Finally, we argue that it is important to control for market structure in the empirical analysis.

Empirical methodology

R&D workers and labor mobility

The theoretical model highlights the general roll labor mobility plays for knowledge transfers across firms. It is likely though that this effect is particularly strong for more educated workers and workers engaged in R&D. Empirical support for this claim can be found in e.g. Ejermo and Ljung (2014) who show that Swedish inventors tend to be better educated as compared to the average worker, and that their level of education has increased over the years. The percentage of inventors who had a minimum of two years of higher education was 44 percent in 1985 and had increased to 76 percent in 2007. Among these, 14 percent held a PhD degree in 1985 while the corresponding share was 29 percent in 2007. Beside formal education, also the type of job that workers have is likely to influence the extent of knowledge transfers between firms that follows from labor mobility. Consequently, this study focuses on labor mobility of highly educated workers who are more or less directly involved in producing new knowledge within firms. More precisely, the worker should hold at least a bachelor degree in natural, technical, agriculture or health science and be classified as "Professionals" according to the Swedish Standard Classification of Occupations (SSYK=2)[6]. We name this group of workers "R&D workers". We further denote highly educated workers belonging to the group "Technicians and associate professionals" (SSYK=3) as "Associate R&D workers". The group of remaining employees is simply referred to as "Other workers" in the ensuing analysis.

R&D workers are further divided into one of the following seven groups depending on their labor market status:[7]

- *Joiners from patenting firms* (*JP*). R&D-workers who arrived from a patenting firm between year t–1 and t.
- *Joiners from non-patenting firms* (*JNP*). R&D-workers who arrived from a non-patenting firm between year t–1 and t.
- *Leavers to patenting firms* (*LP*). R&D-workers who left the firm at year t–1 and works as a professional at a patenting firm at year t.
- *Leavers to non-patenting firms* (*LNP*). R&D-workers who left the firm at time t–1 and works as a professional at a non-patenting firm at year t.
- *Graduates from tertiary education* (*G*). R&D-workers arriving from tertiary education between year t–1 and t.

[6] The Swedish Standard Classification of Occupations SSYK is based on the International Standard Classification of Occupations (ISCO-88).
[7] The notation in parentheses is subsequently used to identify the different types of workers in the empirical analysis.

- *Other joiners* (*O*). R&D-workers joining the firm where we have no information on their previous job position.
- Stayers (*S*). R&D-workers who are employed by the same firm year *t*–1 and *t*.

Table 1 illustrates the division of workers based on their level of education and occupation.

Table 1: Classification of workers

R&D workers							Associate R&D workers	Other workers
Joiners from patenting firms	Joiners from non-patenting firms	Leavers to patenting firms	Leavers to non-patenting firms	Graduates	Other joiners	Stayers		

Finally, we also classify job switchers as either being intra-regional or inter-regional depending on whether or not the receiving firm and the sourcing firm are located in the same region to test for the effect distance has for knowledge diffusion.

Econometric specification

We departure from a firm-level knowledge production function where physical capital (*K*) and human capital (*H*) are combined to produce new knowledge (*P*) according to,

$$P = AK^{\alpha}H^{\beta}, \quad \alpha, \beta > 0. \tag{5}$$

We define human capital as a weighted composite of the different types of workers who currently are employed by the firm as well as employees who recently left the firm,

$$H = \gamma_{JP}L_{JP} + \gamma_{JNP}L_{JNP} + \gamma_{LP}L_{LP} + \gamma_{LNP}L_{LNP} + \gamma_{G}L_{G} + \gamma_{O}L_{O} + \gamma_{S}L_{S} + \\ + \gamma_{AW}L_{AW} + \gamma_{OW}L_{OW} \tag{6}$$

where sub-script AW and OW denote "Associate R&D workers" and "Other workers", respectively (the other sub-scripts are defined above). L_x stands for the amount of each specific type of labor x used by the firm and the γ-coefficients denote each type of worker's marginal contribution to the composite measure of human capital.

By normalizing the marginal productivity for Stayers to one, we are able to express the knowledge production function as,[8]

$$P = \exp\big[\ln A + \alpha \ln K + \beta \ln L + \beta_{JP}s_{JP} + \beta_{JNP}s_{JNP} \\ + \beta_{LP}s_{LP} + \beta_{LNP}s_{LNP} + \beta_{G}s_{G} + \beta_{O}s_{O} + \beta_{AW}s_{AW} + \beta_{OW}s_{OW}\big] \tag{7}$$

where s stands for number of workers within each category divided by the firm's overall workforce L. The derived knowledge production function constitutes the base for our econometric analysis and it is estimated using the following regression equation,

$$P_{i,t} = \exp\big[\ln A + \alpha \ln K_{i,t} + \beta \ln L_{i,t} + \beta_{JP}s_{JP,i,t} + \beta_{JNP}s_{JNP,i,t} + \\ + \beta_{LP}s_{LP,i,t} + \beta_{LNP}s_{LNP,i,t} + \beta_{G}s_{G,i,t} + \beta_{O}s_{O,i,t} + \beta_{AW}s_{AW,i,t} + \beta_{OW}s_{OW,i,t} + \\ + \mathbf{X}'_{i,t}\boldsymbol{\delta}\big] \tag{8}$$

where subscript i and t denote firm and time, respectively. Vector $\mathbf{X}$ contains variables we need to control for that might otherwise distort the relationship between the labor mobility and innovation.

[8] Note that normalizing marginal productivity for Stayers to one means that we must interpret the effect of the other types of labor as relative to Stayers. See Appendix A for details.

Equation (8) will be estimated using the negative binomial estimator, which is an appropriate estimator in our setting where the dependent variable is count data and the mean number of patents is considerably lower than its standard deviation. Hence, our dependent variable shows obvious sign of over dispersion, which renders the otherwise appropriate Poisson estimator inadequate. The remaining parts of this section present the variables we control for when estimating the relationship between labor mobility and innovation, i.e. the variables contained in vector **X**.

Firm-specific heterogeneity

According to Blundell et al. (1995), firm-specific heterogeneity in innovative capacity can be controlled for if we include a dummy variable equal to one if the firm had ever innovated during a pre-sample period and zero otherwise, along with the mean number of innovations during the pre-sample period. Here we choose 1987–2000 as our pre-sample period to estimate firm heterogeneity, but follow the suggestion by Kaiser et al. (2011) and extend the pre-sample estimator by Blundell et al. (1995) to account for the proportion of patent applications a given year,[9]

$$\ln FE_{i,t} = \ln \left[\frac{\sum_{t=1}^{T} P_{i,t} / P_t}{T} \right]. \tag{9}$$

$P_{i,t}$ denotes the number of patent applications for firm i in year t and P_t the total number of patent applications for all firms in year t. T stands for the total number of years during the

[9] We have also run regressions using the original pre-sample estimator by Blundell et al. (1995) and the results are basically unaltered.

pre-sample period (1987–2000). Hence, if firm *i* innovate in a year where few other firms innovate that will carry a higher weight in the average innovative capacity of the firm.

Firm-specific capital stocks

Due to lack of data we use the Perpetual Inventory Method to reconstruct the physical capital stocks from investments according to,

$$K_{i,t+1} = (1-\theta)K_{i,t} + I_{i,t+1} \tag{10}$$

where $K_{i,t}$ denotes firm *i*'s physical capital stock at time *t*, θ the depreciation rate (assumed to be equal to 0.05 for all firms) and *I* investments deflated by the GDP deflator. The data on investments go back to 1987 and we choose the pre-sample period 1987–2000 to create the initial capital stocks used in the estimation period starting in 2001.

Regional control variables

We include seven regional control variables in the regressions. First we control for the general level of labor mobility within and across regions by including three variables. The first variable – labor inflow to the region – is defined as the total number of employed in the region that worked in a firm located in another region the previous year, divided by the total number of workers in the region. The second variable – labor outflow from the region – is defined as the total number of workers that left the region to take a new job in another region, divided by the total numbers of workers in the region. The third and final variable controls for the general level of labor mobility within regions and is defined as the region's total number of workers who had switched employers within the region divided by the total number of workers in the same region.

We further control for employment density (number of employed per square kilometer), human capital intensity (share of employed with a tertiary education) and industry diversity (Herfindahl index based on regional employment in 3-digit industries) in the regions.

We also include an accessibility variable based on the surrounding regions' patent applications in order to control for potential spatial autocorrelation (see Andersson et al., 2007). Failure to control for this effect in the regression analysis might introduce bias in our estimator. Finally all regressions also include dummy variables for industries[10], years and regions.

Data

An employer-employee dataset

We extracted the personal and firm level data from the Statistics Sweden's Business Register from 1987 to 2008, where the estimation period is 2001–2008 and the pre-sample period 1987–2000.[11] This unique database covers all firms and individuals in Sweden and firms are linked to each other through their hiring activities in the labor market. The matched employer-employee dataset can thus be used to show how networks are generated through labor mobility. In addition, the data contain individual information on educational background, job classification (functions), etc., which enables labor to be distinguished into different types of human capital. Each of these classes of human capital can be regressed on innovation output at the firm level.

[10] These industries are, according to Swedish Standard Industrial Classification 2002: Agriculture; Fishing; Mining and Quarrying; Manufacturing; Electricity, Gas and Water Supply; Construction; Wholesale and Retail Trade; Hotels and Restaurants; Transport, Storage and Communication; Financial Intermediation; Education; Health and Social Work. We edited out the sector of Public Administration and Defense for the reason public sector's innovation activity might be affected by other reasons which we cannot test in this research.

[11] Most data are available also for the period 2008–2013. The empirical analysis is however limited to the period 2001–2008 for the simple reason that several definitions and industry classifications were changed in Statistics Sweden's database on occupations, the Swedish Standard Classification of Occupations (SSYK), in 2009 and onwards.

According to the latest data in November 2013, there are 1,127,832 firms and 1,206,182 establishments, among them, 97.5 percent of the firms are privately owned. The majority of firms are operated as sole proprietorships (53.7 percent) and limited liability companies (33.1 percent).[12] Patent application data cover the years 1987–2008 and 8,607 firms owned 154,763 patent applications in 2008. In the sample, all firms founded during the estimated time period 2001–2008 are excluded for the reason that we need firm's pre-sample innovation activities to distinguish the innovators. Firms from the public sector are also excluded since the differences in patenting activities between the public sector and the private sector are likely to be substantial. The objectives of public firms differ radically from private firms; for example, R&D expenditure is more focused on basic research while the private sector tends to pay more attention to applied research and experimental research.[13] Furthermore, we only include firms with at least one R&D relevant worker[14], which is used to separate firms that have the intention to innovate from other firms.

Those who switch job between firms are also distinguished by the firms' innovation status, i.e. whether they are working in patenting or non-patenting firms. In addition, we separate between intra-regional and inter-regional labor mobility.[15] Pooling the individual and firm level data leaves us with a final sample of 91,668 observations with 21,662 unique firms and 32,742 patent applications between 2001 and 2008.

We use patent applications as a measurement of knowledge output, which is the most commonly used indicator of new knowledge creation (Griliches, 1990; Alcacer and

---

[12] Data are provided by Statistics Sweden's Business Register. Regarding different types of ownership there are 1,076 state-owned, 2,271 municipal-owned, 168 region-owned, 1,009,810 private non-consolidated-owned, 90,412 by private group-owned, and 24,095 foreign-owned.

[13] The data can be found though OECD website, science, technology and patents.PUT IN THE WEB PAGE ADDRESS.

[14] R&D relevant workers comprise R&D workers and Associate R&D workers.

[15] We use functional regions (FA-regions) as our spatial unit of measurement. These regions have been defined by the Swedish Agency for Economic and Regional Growth (Tillväxtverket) as geographical areas in which people can live and work without having to spend too long time commuting. They thus comprise local labor markets and are delineated based on commuting intensities. According to this definition, there are 72 FA-regions in Sweden.

Gittelman, 2006). Despite the limitation of using the patent applications (invention does not always lead to innovation), it is still a better indicator on firm's knowledge creation as compared to granted patents and patent-citations which have a time lag delay.

Results

Descriptive statistics

Descriptive statistics of the data sample are presented in Table B1 and B2 in Appendix B, where firms also are divided into two subgroups based on their pre-sample period innovation status. That allows us to see the trend of labor mobility between innovators and non-innovators.

On average, each firm has 79.8 employees, 7.2 R&D relevant workers and a real capital stock amounting to 60.5 million Swedish Krona. Separating between patenting and non-patenting firms during the pre-sample period reveals that the former type of firms are on average larger and have bigger capital stocks (326.4 employees, 33.1 R&D relevant workers and a real capital stock of 267.7 million Swedish Krona) as compared to non-patenting firms (54.6 employees, 4.6 R&D relevant workers and a real capital stock of 39.3 million Swedish Krona). The average number of patent applications among all firms during the estimation period 2001–2008 is 0.36 while the number of applications for firms that had at least one patent application during the pre-sample period 1987–2000 is much higher (3.7 applications). To sum up, innovative firms are larger, have bigger capital stocks, more human capital and are more likely to be innovative in the future as compared to non-innovative firms.

As regards R&D-worker mobility, firms with pre-sample patents seem more connected with other patenting firms as displayed by their relatively higher shares of joiners from patenting firms as well as leavers to other patenting firms. Moreover, firms that applied for a patent during the pre-sample period have on average a lower share of stayers in the firm as compared to other firms.

Firm learning by hiring

Our panel regression results are presented in Tables 2 and 3. Starting with Table 2, the firm learning by hiring effect (joiners) is basically supported. Joiners contribute positively and significantly to innovation (the number of patent applications) in the firms to which they have moved. The effect is however restricted to R&D labor emanating from an already patenting firm. This illustrates that innovative firms seems to have a more relevant knowledge endowment and organization to exploit new knowledge (compare the absorption parameter in the theoretical model), generating stronger effects of such labor flows.

Table 2: Regression results with worker shares lagged one year

	(1)	(2)	(3)	(4)	(5)
R&D workers					
Joiners …	1.576*** (7.39)	–	–	–	0.605* (1.67)
… from patenting firms	–	3.612*** (7.42)	–	–	–
… intra-regional	–	–	3.521*** (6.71)	3.769*** (7.18)	–
… inter-regional	–	–	4.104*** (5.12)	4.769*** (6.37)	–
… from non-patenting firms	–	0.501 (1.40)	–	–	–
… intra-regional	–	–	0.174 (0.36)	0.351 (0.75)	–
… inter-regional	–	–	1.472* (2.12)	1.563* (2.30)	–
Leavers …	–0.063 (–0.39)	–	–	–	–1.042* (–1.89)
… to patenting firms	–	0.737* (1.90)	–	–	–
… intra-regional	–	–	0.481 (1.06)	0.647 (1.38)	–
… inter-regional	–	–	1.714* (2.53)	2.536*** (3.37)	–
… to non-patenting firms	–	–1.078* (–1.75)	–	–	–
… intra-regional	–	–	–1.822* (–2.14)	–1.927* (–2.13)	–
… inter-regional	–	–	0.281 (0.32)	–0.138 (–0.14)	–
Graduates	2.174*** (4.21)	2.144*** (4.12)	2.116*** (4.08)	2.524*** (5.43)	2.181*** (3.98)
Other joiners	1.297*** (2.81)	1.277*** (2.80)	1.289*** (2.83)	1.413*** (3.11)	1.276*** (2.70)
Associate R&D workers	0.125 (0.77)	0.113 (0.69)	0.119 (0.72)	0.108 (0.66)	0.133 (0.80)
Other workers	–1.037*** (–6.85)	–1.037*** (–6.83)	–1.021*** (–6.73)	–0.820*** (–5.53)	–0.967*** (–6.15)
Interaction variable between Joiners and firm size (total employment, log.)	–	–	–	–	0.619*** (3.83)
Interaction variable between Leavers and firm size (total employment, log.)	–	–	–	–	0.594* (2.44)
Total employment, logarithm	0.204*** (9.38)	0.205*** (9.43)	0.204*** (9.40)	0.220*** (9.70)	0.189*** (8.35)
Capital stock, logarithm	0.068*** (5.66)	0.067*** (5.66)	0.067*** (5.65)	0.060*** (6.39)	0.068*** (5.61)
FE, logarithm	0.497*** (31.38)	0.498*** (31.45)	0.498*** (31.40)	0.492*** (34.49)	0.498*** (31.72)
FE, dummy	4.529*** (58.35)	4.508*** (58.35)	4.504*** (58.34)	4.745*** (65.90)	4.501*** (57.76)
Patent applications year *t*–1	0.001*** (12.34)	0.001*** (12.22)	0.001*** (12.26)	0.001*** (10.26)	0.001*** (12.23)
Labor mobility into the region	15.48 (1.45)	15.09 (1.41)	14.91 (1.39)	15.92 (1.48)	16.21 (1.51)
Labor mobility out from the region	–0.139 (–0.17)	–0.141 (–0.18)	–0.138 (–0.17)	–0.727 (–0.93)	–0.042 (–0.05)
Intra-regional labor mobility	1.138 (0.71)	1.190 (0.74)	1.208 (0.75)	0.589 (0.43)	1.228 (0.77)
Tertiary education rate	–1.908 (–1.18)	–1.935 (–1.19)	–1.932 (–1.19)	–2.567*** (–4.40)	–1.970 (–1.22)
Regional density	–0.055* (–2.18)	–0.054* (–2.13)	–0.054* (–2.13)	0.007*** (5.96)	–0.058* (–2.31)
Accessibility	0.003 (0.04)	–0.007 (–0.10)	–0.006 (–0.08)	–0.023* (–2.11)	–0.007 (–0.10)
Diversity	16.56* (2.34)	16.72* (2.35)	16.72* (2.36)	2.318* (2.18)	17.45* (2.46)
Constant	–3.503*** (–2.62)	–3.602*** (–2.66)	–3.603*** (–2.67)	–1.407*** (–5.65)	–3.662*** (–2.72)
Industry dummies	YES	YES	YES	NO	YES
Year dummies	YES	YES	YES	NO	YES
Regional dummies	YES	YES	YES	NO	YES
Number of observations	91,668	91,668	91,668	91,668	91,668

Note: ***, ** and * denote statistical significance at the 1-, 5- and 10 percentage level, respectively. t-statistics based on robust standard errors in parentheses. All labor shares are calculated as a fraction of total employment.

Considering the geographic dimension, inter-regional joiners both from patenting firms and non-patenting firms have a higher impact in comparison with intra-regional joiners (the latter however also being strongly significant if they join from an innovating firm), which partly contrast our hypothesis and nuances the results given in previous studies. Above we argued that inter-regional mobility may conceal a selection if the firm needs to pay a premium in order to convince the employee to move to another region. Hence, higher costs should render a more stringent selection process. The alternative explanation is that even though knowledge flows more easily across employees and firms located in the same region, this should not necessarily be interpreted as if the knowledge flows are the most accurate ones from the firm perspective. It may well be the case that less local and more heterogeneous knowledge is of higher importance for firms' innovativeness, or uniqueness of innovations. Again, also at the inter-regional level joiners from patenting firms have the highest impact. Note also that the categories graduates and other joiners are shown to have positive significant effect. Finally, the interaction variable between joiners and firm size in regression 5 shows that larger firms tend to benefit more in terms of innovation output from labor mobility than smaller firms.

Table 3: Regression results with worker shares lagged two years

	(1)	(2)	(3)	(4)	(5)
R&D workers					
Joiners …	2.102*** (8.50)	–	–	–	0.802* (1.87)
… from patenting firms	–	3.947*** (6.33)	–	–	–
… intra-regional	–	–	3.830*** (5.41)	4.160*** (5.65)	–
… inter-regional	–	–	4.500*** (5.44)	5.426*** (6.84)	–
… from non-patenting firms	–	1.127*** (2.73)	–	–	–
… intra-regional	–	–	0.584 (1.09)	0.929* (1.95)	–
… inter-regional	–	–	2.688*** (3.13)	3.042*** (4.17)	–
Leavers …	0.867* (2.52)	–	–	–	0.276 (0.50)
… to patenting firms	–	2.084*** (3.63)	–	–	–
… intra-regional	–	–	1.334* (1.80)	1.877*** (2.68)	–
… inter-regional	–	–	3.341*** (3.82)	4.367*** (5.33)	–
… to non-patenting firms	–	–0.018 (–0.03)	–	–	–
… intra-regional	–	–	–0.662 (–0.70)	–0.236 (–0.30)	–
… inter-regional	–	–	1.063 (0.82)	1.179 (1.02)	–
Graduates	2.424*** (5.21)	2.203*** (4.23)	2.327*** (4.70)	2.570*** (5.53)	2.418*** (4.83)
Other joiners	1.289*** (2.70)	1.276*** (2.61)	1.264*** (2.58)	1.524*** (3.33)	1.212* (2.33)
Associate R&D workers	0.313 (1.56)	0.293 (1.45)	0.289 (1.42)	0.264 (1.29)	0.325 (1.59)
Other workers	–0.294* (–1.83)	–0.279* (–1.74)	–0.269* (–1.67)	–0.085 (–0.60)	–0.226 (–1.37)
Interaction variable between Joiners and firm size (total employment, log.)	–	–	–	–	0.767*** (4.18)
Interaction variable between Leavers and firm size (total employment, log.)	–	–	–	–	0.356 (1.37)
Total employment, logarithm	0.158*** (6.36)	0.158*** (6.37)	0.157*** (6.36)	0.156*** (7.09)	0.141*** (5.44)
Capital stock, logarithm	0.069*** (4.85)	0.068*** (4.83)	0.069*** (4.82)	0.062*** (5.51)	0.070*** (4.79)
FE, logarithm	0.495*** (28.19)	0.496*** (28.21)	0.495*** (28.11)	0.482*** (30.48)	0.497*** (28.37)
FE, dummy	4.436*** (51.11)	4.412*** (50.99)	4.408*** (50.95)	4.604*** (57.81)	4.416*** (50.63)
Patent applications year *t*–1	0.002*** (13.28)	0.002*** (13.39)	0.002*** (13.29)	0.002*** (13.16)	0.002*** (13.02)
Labor mobility into the region	8.891 (0.70)	8.872 (0.70)	8.782 (0.69)	10.83 (0.88)	8.625 (0.68)
Labor mobility out from the region	0.749 (0.73)	0.760 (0.74)	0.781 (0.76)	–1.046 (–0.73)	0.819 (0.79)
Intra-regional labor mobility	1.510 (0.92)	1.536 (0.94)	1.535 (0.93)	0.395 (0.29)	1.606 (0.98)
Tertiary education rate	–1.268 (–0.75)	–1.257 (–0.74)	–1.250 (–0.74)	–2.026*** (–3.46)	–1.319 (–0.78)
Regional density	–0.045 (–1.56)	–0.043 (–1.49)	–0.043 (–1.49)	0.006*** (4.48)	–0.043 (–1.51)
Accessibility	0.052 (0.65)	0.063 (0.79)	0.061 (0.76)	–0.015 (–1.25)	0.058 (0.71)
Diversity	21.25* (2.18)	21.02* (2.15)	21.15* (2.17)	2.659* (2.23)	22.88* (2.34)
Constant	–4.617* (–2.51)	–4.455* (–2.43)	–4.519* (–2.46)	–1.772*** (–6.28)	–4.656* (–2.52)
Industry dummies	YES	YES	YES	NO	YES
Year dummies	YES	YES	YES	NO	YES
Regional dummies	YES	YES	YES	NO	YES
Number of observations	68,505	68,505	68,505	68,505	68,505

Note: ***, ** and * denote statistical significance at the 1-, 5- and 10 percentage level, respectively. t-statistics based on robust standard errors in parentheses. All labor shares are calculated as a fraction of total employment.

In Table 3 the same regressions are displayed, but with two years lags in the labor variables. The results are basically confirmed, though somewhat stronger. Also joiners from non-patenting firms are shown to have a positive effect on innovation after some time has elapsed and the impact when we include the regional dimension is stronger. The persistent effect of "firms' learning by hiring" mirrors that the generation of knowledge and its effect on innovation is not simultaneous. Rather there seems to exist a time delay. We would expect the effect to first increase and then, after further time elapse, start to decrease. But here we cannot test it since we only have an eight year panel data and increasing the lag implies that we would lose a considerable number of observations.

Firm learning by the diaspora

To test the effect of firm learning by diaspora, we shall pay attention to the estimation of "leavers". The estimation of leavers that go to patenting firms show a weak positive significance (Table 2), which switches to a weak negative effect if they go to non-patenting firms. Looking at the geographic dimension, the results are not as conclusive for leavers as for joiners. For the latter category a positive and strongly significant result was shown for both intra- and inter-regional mobility, even though the effect was most pronounced for the latter type of mobility. When it comes to leavers, the result is (and considerably more weakly) significant and positive only for inter-regional leavers to patenting firms, while the result is weakly negative for intra-regional movements to non-patenting firms. The explanations are likely to be the same as the ones forwarded above regarding learning by hiring. As was the case for joiners, also the effect of workers leaving the firm tend to have a bigger impact on the innovative output in large firms as compared to smaller firms.

The two-year lagged estimation results are revealed in Table 3. Also in this case the effect of firm learning by the diaspora seems to be persistent and to some extent increasing. Hence, overall the results implies that also the sourcing firm, i.e. those losing R&D-workers, will benefit and that the positive effects will last for at least some years. Overall the results suggest that leavers have a negligible and much smaller instantaneous effect on innovation in their original firms, which however shifts to a positive effect after a few years. The latter effect may reflect that leavers need some time to tap into the knowledge base of their new firms.

Causality

In the theoretical framework we interpreted the causality relationship as going from labor mobility to knowledge flows and innovation, assuming that firms hire experienced workers from other firms to acquire human capital and external knowledge. But we are aware there might exist an endogeneity problem; is it labor mobility that stimulates innovation or the other way around?

We have attempted to avoid this in two ways. First, we have employed a lag distribution on labor mobility encompassing both one and two years. Irrespective of lag structure, the results are still highly significant and persistent. This strongly suggests that the direction is from labor mobility to innovation and not vice versa. Second, we use patent application as the dependent variable, which has the advantage of not being exposed to lengthy time delays, as compared to granted patents. It seems quite unlikely that labor will be attracted by patent applications, given that the outcome is uncertain and could well be associated with higher risks for the employee.

Conclusion

This paper presents an empirical analysis of the relationship between labor mobility, knowledge diffusion and firm's innovation output. We distinguish between three subgroups of workers: R&D workers, Associate R&D workers, and Other workers in order to separate the effect of the mobility of R&D workers. By implementing a unique matched employer-employee dataset, which has been pooled with firm level patent application data, we provide evidence that the mobility of knowledge (R&D) workers have a positive and strongly significant effect on firms' innovativeness. We conclude that there are both forward and backward knowledge flows (between receiving and sourcing firms), but that the former exert a stronger impact on innovation, that the geographical dimension of knowledge flows are important (inter-regional labor mobility have the strongest effect on innovation), and that the impact of knowledge flows seems persistent. When such labor movements occur, the benefit to both sides (sourcing firm and receiving firm) will increase firms are already engaged in innovation. Finally, the results also show that larger firms benefit more than smaller firms from labor mobility.

The results have important and highly relevant policy implications. In the ongoing discussions on how to augment growth, one conclusion is that labor markets should be made more flexible in order to enhance knowledge flows, improve matching and increase innovation.

References

Agrawal, A. and I. Cockburn (2003), "The anchor tenant hypothesis: exploring the role of large, local, R&D-intensive firms in regional innovation systems", *International Journal of Industrial Organization*, 21(9), 1227–1253.

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

Alcacer, J. and M. Gittelman (2006), "How do I know what you know? Patent examiners and the generation of patent citations", *Review of Economics and Statistics*, 88(4), 774–779.

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

Andersson, M. and P. Thulin (2008), "Globalisering, arbetskraftens rörlighet och produktivitet", Research report 23, Globalization Council.

Andersson, M., Gråsjö, U. and C. Karlsson (2007), "Human capital and productivity in a spatial economic system", *Annals of Economics and Statistics*, 87/88, 125–143.

Audretsch, D.B. and M.P. Feldman (1996), "R&D spillovers and the geography of innovation and production", *American Economic Review*, 86(3), 630–640.

Balsvik, R. (2011), "Is labor mobility a channel for spillovers from multinationals? Evidence from Norwegian manufacturing", *The Review of Economics and Statistics*, 93(1), 285–297.

Bassanini, A. and E. Ernst (2002), "Labour market institutions, product market regulation, and innovation: cross-country evidence", OECD Economics Department, Working Papers, No. 316, OECD Publishing. http://dx.doi.org/10.1787/002243151077.

Bessen, J. and E. Maskin (2009), "Sequential innovation, patents, and imitation", *RAND Journal of Economics*, 40(4), 611–635.

Blundell, R., Griffith, R. and J. Von Reenen (1995), "Dynamic count data models of technological innovation", *The Economic Journal*, 105(429), 333–344.

Breschi, S. and F. Lissoni (2005), "Cross-firm inventors and social networks: localized knowledge spillovers revisited", *Annales d´Economie et de Statistique*, 79/80, 189–209.

Breschi, S. and F. Lissoni (2009), "Mobility of skilled workers and co-invention networks: an anatomy of localized knowledge flows", *Journal of Economic Geography*, 9(4), 439–468.

Cassiman, B., Veugelers, R. and S. Arts (2011), "Tracing the effect of links between science and industry: the role of researcher interaction and mobility between firms and research organizations", IESE working paper.

Combes, P.-P. and G. Duranton (2006), "Labour pooling, labour poaching, and spatial clustering", *Regional Science and Urban Economics*, 36(1), 1–28.

Corredoira, R. and L. Rosenkopf (2010), "Should auld acquaintance be Forgot? The reverse transfer of knowledge through mobility ties", *Strategic Management Journal*, 31(2), 159–181.

Crane, D. (1969), "Social structure in a group of scientists: A test of the 'invisible college' hypothesis", *American Sociological Review*, 34(3), 335–352.

Ejermo, O. and T. Jung (2014), "Demographic patterns and trends in patenting: gender, age, and education of inventors", *Technological Forecasting and Social Change*, 86, 110–124.

Essletzbichler, J. and D. Rigby (2005), "Technological evolution as creative destruction of process heterogeneity: evidence from US plant-level data", *Economic Systems Research*, 17(1), 25–45.

Fallick, B., Fleischman, C.A. and J.B. Rebitzer (2006), "Job-hopping in Silicon Valley: some evidence concerning the microfoundations of a high technology cluster", *The Review of Economics and Statistics*, 88(3), 472–481.

Fosfuri, A. and T. Rønde (2004), "High-tech clusters, technology spillovers, and trade secret laws", *International Journal of Industrial Organization*, 22(1), 45–65.

Franco, A.M. and M.F. Mitchell (2008), "Covenants not to compete, labor mobility, and industry dynamics", *Journal of Economics and Management Strategy*, 17(3), 581–606.

Griliches, Z. (1990), "Patent statistics as economic indicators: a survey", *Journal of Economic Literature*, 28(4), 1661–1707.

Hall, B. (2011), "Using productivity as an innovation indicator", Report for the High Level Panel on Measuring Innovation, DG Research, European Commission.

Hoisl, K. (2007), "Tracing mobile inventors – the causality between inventor mobility and inventor productivity", *Research Policy*, 36(5), 619–636.

Hoti, S., McAleer, M. and D. Slottje (2006), "Intellectual property litigation in the USA", *Journal of Economic Surveys*, 20(4), 715–729.

Ichniowski, C. and K. Shaw (1995), "Old dogs and new tricks: determinants of the adoption of productivity-enhancing work practices", in M. Baily, P. Reiss and C. Winston (eds), Brookings Papers on Economic Activity. Brookings Institute: Washington, DC, 1–65.

Jaffe, A.B., Trajtenberg, M. and R. Henderson (1992), "Geographic localization of knowledge spillovers as evidenced by patent citations", NBER WP 3993, National Bureau of Economic Research.

Kaiser, U., Kongsted, H. and T. Rønde (2011), "Labor mobility, social network effects, and innovative activity", IZA Discussion Paper No. 5664.

Kim, J. and G. Marschke (2005), "Labor mobility of scientists, technological diffusion, and the firm's patenting decision", *RAND Journal of Economics*, 36(2), 298–317.

Kräkel, M. and D. Sliwka (2009), "Should you allow your employee to become your competitor? On non-compete agreements in employment contracts", *International Economic Review*, 50, 117–141.

Malcomson, J.M. (1997), "Contracts, hold-up, and labor markets", *Journal of Economic Literature*, 35(4), 1916–1957.

Mansfield, E. (1985), "How rapidly does new industrial technology leak out?", *The Journal of Industrial Economics*, 34(2), 217–223.

Marx, M., Strumsky, D. and L. Fleming (2009), "Mobility, skills, and the Michigan non-compete experiment", *Management Science*, 55(6), 875–889.

Nicoletti, G. and S. Scarpetta (2003), "Regulation, productivity and growth: OECD evidence", *Economic Policy*, 18(36), 9–72.

Oettl, A. and A. Agrawal (2008), "International labor mobility and knowledge flow externalities", *Journal of International Business Studies*, 39(8), 1242–1260.

Pakes, A. and S. Nitzan (1983), "Optimal contracts for research personnel, research employment and the establishment of 'rival' enterprises", *Journal of Labor Economics*, 1(4), 345–365.

Parrotta, P. and D. Pozzoli (2012), "The effect of learning by hiring on productivity", *RAND Journal of Economics*, 43(1), 167–185.

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

Romer, P.M. (1990), "Endogenous technological change", *The Journal of Political Economy*, 98(5), S71–S102.

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

Rosenthal, S.S. and W.C. Strange (2003), "Geography, industrial organization and agglomeration", *The Review of Economics and Statistics*, 85(2), 377–393.

Samila S. and O. Sorensen (2011), "Noncompete covenants: incentives to innovate or impediments to growth", *Management Science*, 57(3), 425–438.

Saxenian, A. (1994), *Regional advantage: culture and competition in Silicon Valley and Route 128*. Cambridge, Massachusetts: Harvard University Press.

Scarpetta, S. and T. Tressel (2004), "Boosting productivity via innovation and adoption of new technologies: any role for labor market institutions?", World Bank Discussion Paper, 2004.

Singh, J. and A. Agrawal (2011), "Recruiting for ideas: how firms exploit the prior inventions of new hires", *Management Science*, 57(1), 129–150.

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

Thompson, P. and M. Fox-Kean (2005), "Patent citations and the geography of knowledge spillovers: a reassessment", *American Economic Review*, 95(1), 450–460.

Vilalta-Bufí, M. (2008), ”Inter-firm labor mobility and knowledge diffusion: a theoretical approach”, Document de Treball, de La Facultat d'Economica I Empresa, Universitat de Barcelona.

Von Hippel, E. (1987), "Cooperation between rivals: informal know-how trading", *Research Policy*, 16(6), 291–302.

Zhou, J., Shin, S.J., Brass, D.J., Choi, J. and Z.X. Zhang (2009), "Social networks, personal values, and creativity: evidence for curvilinear and interaction effects", *Journal of Applied Psychology*, 94(6), 1544–1552.

Zhou, H., Dekker, R. and A. Kleinknecht (2011), "Flexible labor and innovation performance: evidence from longitudinal firm-level data", *Industrial and Corporate Change*, 20(3), 941–968.

Zucker, L.G., Darby, M.R. and M.B. Brewer (1998), "Intellectual human capital and the birth of U.S. biotechnology enterprises", *American Economic Review*, 88(1), 290–306.

Appendix A. The knowledge production function

New knowledge is produced according to the knowledge production function,

$$P = AK^{\alpha}H^{\beta}, \quad \alpha, \beta > 0 \tag{1}$$

where K denotes physical capital and H the composite measure of human capital defined as,

$$\begin{aligned} H = {} & \gamma_{J,P}L_{J,P} + \gamma_{J,NP}L_{J,NP} + \gamma_{L,P}L_{L,P} + \gamma_{L,NP}L_{L,NP} + \gamma_{G}L_{G} + \gamma_{O}L_{O} + L_{S} + \\ & + \gamma_{AW}L_{AW} + \gamma_{OW}L_{OW} \end{aligned} \tag{2}$$

This can be written as,

$$\begin{aligned} H = L \Bigg[& \gamma_{J,P}\frac{L_{J,P}}{L} + \gamma_{J,NP}\frac{L_{J,NP}}{L} + \gamma_{L,P}\frac{L_{L,P}}{L} + \gamma_{L,NP}\frac{L_{L,NP}}{L} + \gamma_{G}\frac{L_{G}}{L} + \gamma_{O}\frac{L_{O}}{L} + \frac{L_{S}}{L} + \\ & + \gamma_{AW}\frac{L_{AW}}{L} + \gamma_{OW}\frac{L_{OW}}{L} \Bigg] \end{aligned} \tag{3}$$

where

$$L = L_{J,P} + L_{J,NP} + L_{G} + L_{O} + L_{S} + L_{AW} + L_{OW} \,. \tag{4}$$

Human capital can consequently be expressed as,

$$H = L\left[\gamma_{J,P}\frac{L_{J,P}}{L} + \gamma_{J,NP}\frac{L_{J,NP}}{L} + \gamma_{L,P}\frac{L_{L,P}}{L} + \gamma_{L,NP}\frac{L_{L,NP}}{L} + \gamma_G\frac{L_G}{L} + \gamma_O\frac{L_O}{L} + \right. \\ \left. + \left(\frac{L - L_{J,P} - L_{J,NP} - L_G - L_O - L_{AW} - L_{OW}}{L}\right) + \gamma_{AW}\frac{L_{AW}}{L} + \gamma_{OW}\frac{L_{OW}}{L}\right] \tag{5}$$

$$\Leftrightarrow \quad H = L\left[1 + \left(\gamma_{J,P} - 1\right)\frac{L_{J,P}}{L} + \left(\gamma_{J,NP} - 1\right)\frac{L_{J,NP}}{L} + \gamma_{L,P}\frac{L_{L,P}}{L} + \gamma_{L,NP}\frac{L_{L,NP}}{L} + \left(\gamma_G - 1\right)\frac{L_G}{L} + \right. \\ \left. + \left(\gamma_O - 1\right)\frac{L_O}{L} + \left(\gamma_{AW} - 1\right)\frac{L_{AW}}{L} + \left(\gamma_{OW} - 1\right)\frac{L_{OW}}{L}\right] \tag{6}$$

which in turn can be written as,

$$H = L\left[1 + \left(\gamma_{J,P} - 1\right)s_{J,P} + \left(\gamma_{J,NP} - 1\right)s_{J,NP} + \gamma_{L,P}s_{L,P} + \gamma_{L,NP}s_{L,NP} + \left(\gamma_G - 1\right)s_G + \right. \\ \left. + \left(\gamma_O - 1\right)s_O + \left(\gamma_{AW} - 1\right)s_{AW} + \left(\gamma_{OW} - 1\right)s_{OW}\right]. \tag{7}$$

Taking the natural logarithm of (7) yields,

$$\ln H = \ln L + \ln(1 + z) \approx \ln L + z \tag{8}$$

where,

$$z = \left[\left(\gamma_{J,P} - 1\right)s_{J,P} + \left(\gamma_{J,NP} - 1\right)s_{J,NP} + \gamma_{L,P}s_{L,P} + \gamma_{L,NP}s_{L,NP} + \left(\gamma_G - 1\right)s_G + \right. \\ \left. + \left(\gamma_O - 1\right)s_O + \left(\gamma_{AW} - 1\right)s_{AW} + \left(\gamma_{OW} - 1\right)s_{OW}\right] \tag{9}$$

Substituting (8) and (9) into the knowledge production function gives us,

$$\ln P = \ln A + \alpha \ln K + \beta \ln L + \beta\left(\gamma_{J,P} - 1\right)s_{J,P} + \beta\left(\gamma_{J,NP} - 1\right)s_{J,NP} + \beta\gamma_{L,P}s_{L,P} \\ + \beta\gamma_{L,NP}s_{L,NP} + \beta\left(\gamma_{G} - 1\right)s_{G} + \beta\left(\gamma_{O} - 1\right)s_{O} + \beta\left(\gamma_{AW} - 1\right)s_{AW} + \beta\left(\gamma_{OW} - 1\right)s_{OW} \quad (10)$$

or,

$$\ln P = \ln A + \alpha \ln K + \beta \ln L + \beta_{J,P}s_{J,P} + \beta_{J,NP}s_{J,NP} + \beta_{L,P}s_{L,P} + \\ + \beta_{L,NP}s_{L,NP} + \beta_{G}s_{G} + \beta_{O}s_{O} + \beta_{AW}s_{AW} + \beta_{OW}s_{OW} . \quad (11)$$

Appendix B. Descriptive statistics

Table B1: Descriptive statistics

Variable	Mean	Std.dev.	Min	Max
Number of patents	0.3572	12.50	0	1,691
Patent t–1	0.3895	14.29	0	2,461
Dummy patent t–1	0.0337	0.18	0	1
Worker shares				
R&D workers				
Joiners …				
… from patenting firms	0.0020	0.02	0	1
… intra-regional	0.0012	0.01	0	1
… inter-regional	0.0008	0.01	0	1
… from non-patenting firms	0.0109	0.07	0	1
… intra-regional	0.0083	0.06	0	1
… inter-regional	0.0026	0.02	0	1
Leavers …				
… to patenting firms	0.0016	0.03	0	4.5
… intra-regional	0.0010	0.02	0	4
… inter-regional	0.0006	0.01	0	1
… to non-patenting firms	0.0067	0.06	0	3
… intra-regional	0.0047	0.05	0	3
… inter-regional	0.0020	0.02	0	2.5
Graduates	0.0019	0.02	0	1
Other joiners	0.0047	0.04	0	1
Stayers	0.2687	0.34	0	1
Associate R&D workers	0.0783	0.19	0	1
Other workers	0.6337	0.34	0	0.9998
Firm size and capital stock				
Total employment	79.8	445	1	19,817
R&D relevant employment	7.2	76.3	1	7,427
Capital stock, millions SEK	60.5	744	0	51,000
Pre-sample variables				
Pre-sample patents (FE)	0.0009	0.0008	0	0.1
Dummy, pre-sample patents	0.0927	0.29	0	1
Regional control variables				
Labor mobility into the region	0.0015	0.002	0	0.3
Labor mobility out from the region	0.0101	0.030	0	0.1
Intra-regional labor mobility	0.0109	0.010	0	0.3
Tertiary education rate	0.1863	0.05	0	0.3
Regional density, no. of employees per km^2	44.8	24.29	0	67.8
Accessibility measure, logarithm	–1.94	2.02	–25.2	2.4
Diversity	0.114	0.02	0	0.3
Industry dummies				
Agriculture	0.0098	0.10	0	1
Fishing	0.00002	0.00	0	1
Mining and quarrying	0.0009	0.03	0	1
Manufacturing	0.1664	0.37	0	1
Electricity, gas and water supply	0.0087	0.09	0	1
Construction	0.0220	0.15	0	1
Wholesale and retail trade	0.1318	0.34	0	1
Hotels and restaurants	0.0017	0.04	0	1
Transport, storage and communication	0.0170	0.13	0	1
Financial intermediation	0.0015	0.04	0	1
Real estate, renting and business activities	0.3801	0.49	0	1
Education	0.0189	0.14	0	1
Health and social work	0.2163	0.41	0	1
Other community, social and personal service	0.0188	0.14	0	1
Other	0.0061	0.01	0	1

Table B2: Mean statistics, distributed on firm's innovative history

Variable	All firms	Firms with pre-sample patents	Firms without pre-sample patents
Number of patents	0.3572	3.746	0.0108
Patent *t*–1	0.3895	4.106	0.0096
Dummy patent *t*–1	0.0337	0.3134	0.0052
Worker shares			
R&D workers			
Joiners …			
… from patenting firms	0.0020	0.0045	0.0018
… intra-regional	0.0012	0.0028	0.0010
… inter-regional	0.0008	0.0017	0.0007
… from non-patenting firms	0.0109	0.0059	0.0115
… intra-regional	0.0083	0.0036	0.0088
… inter-regional	0.0026	0.0023	0.0026
Leavers …			
… to patenting firms	0.0016	0.0040	0.0014
… intra-regional	0.0010	0.0025	0.0008
… inter-regional	0.0006	0.0014	0.0006
… to non-patenting firms	0.0067	0.0057	0.0068
… intra-regional	0.0047	0.0034	0.0049
… inter-regional	0.0020	0.0023	0.0019
Graduates	0.0019	0.0024	0.0018
Other joiners	0.0047	0.0028	0.0049
Stayers	0.2687	0.0929	0.2867
Associate R&D workers	0.0783	0.0418	0.0821
Other workers	0.6337	0.8499	0.6116
Firm size and capital stock			
Total employment	79.8	326.4	54.6
R&D relevant employment	7.2	33.1	4.6
Tertiary education workers	13.1	53.0	9.0
Capital stock, millions SEK	60.5	267.7	39.3
Pre-sample variables			
Pre-sample patents (FE)	0.0009	0.0004	0
Dummy, pre-sample patents	0.0927	0.0927	0
Industry dummies			
Agriculture	0.0098	0.0028	0.0105
Fishing	0.00002	0.0000	0.0000
Mining and quarrying	0.0009	0.0044	0.0006
Manufacturing	0.1664	0.6044	0.1217
Electricity, gas and water supply	0.0087	0.0069	0.0089
Construction	0.0220	0.0171	0.0225
Wholesale and retail trade	0.1318	0.1186	0.1331
Hotels and restaurants	0.0017	0.0000	0.0019
Transport, storage and communication	0.0170	0.0104	0.0177
Financial intermediation	0.0015	0.0001	0.0016
Real estate, renting and business activities	0.3801	0.2165	0.3968
Education	0.0189	0.0027	0.0206
Health and social work	0.2163	0.0053	0.2378
Other community, social and personal service	0.0188	0.0061	0.0200
Other	0.0061	0.0048	0.0062

RESEARCH NETWORK DEBATE
SWEDISH ENTREPRENEURSHIP FORUM

WWW.ENTREPRENORSKAPSFORUM.SE