Does Labour Mobility Foster Innovation?

Evidence from Sweden*

Pontus Braunerhjelm
KTH Royal Institute of Technology, SE-100 44 Stockholm, Sweden[1]
pontus.braunerhjelm@indek.kth.se

Ding Ding
KTH Royal Institute of Technology, SE-100 44 Stockholm, Sweden
ding.ding@indek.kth.se

Per Thulin
KTH Royal Institute of Technology, SE-100 44 Stockholm, Sweden
per.thulin@indek.kth.se

Abstract

By utilising a Swedish unique, matched employer-employee dataset that has been pooled with firm-level patent application data, we provide new evidence that knowledge workers' mobility has a positive and strongly significant impact on firm innovation output, as measured by firm patent applications. The effect is particularly strong for knowledge workers that have previously worked in a patenting firm (the learning-by-hiring effect), but firms losing a knowledge worker are also shown to benefit (the diaspora effect), albeit more weakly. Finally, the effect is more pronounced when the joining worker originates in another region.

Keywords: Labour mobility; knowledge diffusion; innovation; social networks

JEL Codes: J24, O31, R23

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* We would like to thank the participants in the workshop "Labor market rigidities, human capital and innovation", held in Washington, D.C. on October 21, 2013, the 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. The project was funded by the KTH Royal Institute of Technology, Sweden.

[1] Pontus Braunerhjelm and Per Thulin are also affiliated with Swedish Entrepreneurship Forum.

I. Introduction

An emerging but scant literature has recently addressed the issue of the influence of labour mobility on innovation. This highly topical and policy-relevant research question considers the faltering growth performance in large parts of the global economy and the call for structural reforms, not least within the European Union, that often targets the labour markets. As innovation is considered the engine of growth, more thorough insights and knowledge regarding the relationship between labour mobility and innovation is obviously a high-priority.

Although most previous studies suggest that labour mobility has a positive effect on innovation, the results in the existing literature remain inconclusive (Agrawal et al., 2006). Similarly, studies on the inter-firm mobility of engineers in Silicon Valley have demonstrated that movers frequently are major patent holders and that such mobility is a crucial part of firm learning processes (Almeida and Kogut, 1999). These results have been corroborated by Oettl and Agrawal (2008), among others, who claim that such knowledge flows accrue not only to the firm receiving employees but also to the firms that lose workers. The latter effect is due to increased knowledge flows and expanded social (knowledge) networks. However, there is evidence that innovative firms have lower turnover rates than other firms when the mobility of highly qualified labour is examined (Balsvik, 2011; Parrotta and Pozzoli, 2012). Thus, the results regarding the effects of labour mobility on innovation are somewhat ambiguous.

The purpose of this paper is to examine the influence of knowledge (R&D) workers' labour mobility on innovation at the firm level. We utilise a unique, matched dataset of employers and employees that features a number of characteristics at the individual, firm and regional levels (including patent applications) and allows us to track the movement of individuals among firms to investigate the ensuing effects on innovation. In our study, only patenting firms qualify as innovative, i.e., those firms that have filed at least one patent application. Non-patenting firms are considered non-innovators.

Building on these unique data, we offer new insights regarding the influence of labour mobility on firm innovativeness in several dimensions. First, we consider not only the firm receiving a new knowledge worker (learning by hiring) but also the firm that has lost a worker (the diaspora effect). Second, we use detailed measures of knowledge workers – function and formal occupation – which bolster the robustness of the results. Third, we emphasise the geographical dimension of knowledge flows, i.e., how inter- versus intra-regional mobility influences innovation output. Finally, we examine whether the effects of labour mobility on innovativeness are different for large firms compared with small firms. Throughout our empirical analysis, we control for a number of factors, such as industry classification and regional variables.

Our estimations support the proposition that the mobility of R&D workers has a positive impact on firm innovation output. More precisely, when high knowledge workers enjoy labour mobility, both firms losing employees (sourcing firms) and firms receiving employees (receiving firms) benefit from the knowledge flow. If the sourcing firm is considered an innovator, the knowledge flow is stronger; however, if the receiving firm is an innovator, the sourcing firms receive a stronger backward knowledge-flow effect. Both forward and backward effects are stronger when labour mobility moves across – rather than within – regional borders. Finally, the results also indicate that large firms benefit more from labour mobility in terms of innovative output than small firms.

The rest of the paper is organised as follows. Section II reviews the previous research related to the issues addressed in this paper, which is followed by the theoretical framework and hypotheses development in Section III. Then, we present the empirical strategy in Section IV and description of the data in Section V. The regression results, separated into "Firms learning by hiring" and "Firms learning by diaspora", are shown in Section VI. The paper ends with conclusions in Section VII.

II. Previous Research

Labour market flexibility can be defined in different ways, such as labour mobility within firms, between firms or in terms of wages. In this study, we are concerned with labour mobility between firms and its effects on innovation, as measured by patent applications. Theoretically, it can be demonstrated that labour mobility may either increase or decrease innovative performance. In the former case, labour mobility generates better matching and extended networks, which increases knowledge flows between firms. The latter effect may occur as a result of more costly administrative routines and/or harm to firm organisational learning and “internal memories” (Zhou et al., 2009). Low mobility may also imply that more power has been transferred to labour, which is likely to result in increased wage levels and the erosion of investments into resources, such as R&D. Firms might thus find themselves in hold-ups (Malcomson, 1997). Previous theoretical models suggest that the effects of labour mobility may travel in both directions.

It has been empirically demonstrated that mobility can increase productivity at the firm level (Nicoletti and Scarpetta, 2003; Andersson and Thulin, 2008). The proposed reasons are better matching between firm needs and the skills of labour (Bessen and Maskin, 2009), spillovers of knowledge that is embodied in labour, 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 that is embodied in labour enters the firm, established processes and methods tend to be challenged. New knowledge provides new insights, increases efficiency and productivity, and may lead to new business opportunities. On a more aggregated level, these mechanisms have been extensively discussed in the literature on Jacobian (inter-industry) and Marshallian (intra-industry) externalities (Rosenthal and Strange, 2003), whereas more micro-oriented studies have examined recruitment strategies and how mobility enhances learning capacities and learning sharing (von Hippel, 1987; Corredoira and Rosenkopf, 2010; Singh and Agrawal, 2011).

It is reasonable to expect that these findings should lead to similar results regarding firm innovation activities. A more recent empirical strand in the literature looks specifically at how innovation performance is impacted by labour mobility. Utilising a standard patent production function that is implemented on a matched employer-employee dataset of Danish firms pooled with patent data, Kaiser et al., (2011) indicate that both firms receiving knowledge workers from other firms and those losing knowledge workers to other firms improve their innovative performance, as measured by patent applications. These authors explain the positive outcomes to extended and improved networks, accelerating the knowledge flows. Kaiser et al. (2011) is one of the few studies that examines innovation outputs rather than inputs in terms of previous patent citations.[2] However, these authors do not consider the regional origins of employees nor how market structures influence firm innovativeness.

Hoisl (2007) examines how labour mobility influences patenting activities, but the analysis is partial, only considers the receiving firms and suffers from its dependence on questionnaire data. Overwhelmingly, the limited findings suggest that labour mobility has a positive effect on invention and innovative behaviours.[3]

In addition, the geographical dimension of labour mobility has been addressed in the previous literature. Disregarding the plethora of studies observing how knowledge spillovers diminish with distance, evidence has also been produced indicating that firms are likely to patent more in regions that are characterised by high labour mobility (Kim and Marschke, 2005). Moreover, studies of successful clusters and agglomerations indicate that frequent job changes and close interactions between employees of different firms are some of the more decisive factors in the success of such clusters (Saxenian, 1994; Fallick et al., 2006). However, some scholars have suggested that intra-regional movement is slightly less likely to yield new information for a firm and to propel innovation compared with inter-regional mobility due to the similarity of intra-regional knowledge (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 labour market regulations, firm size and innovativeness. Impediments to mobility may be informal or formal character (Breschi and Lissoni, 2005, 2009). Informal impediments result when firms seek to contractually restrain the mobility of employees defined as strategically important to guard against the loss of proprietary knowledge – and to protect their competitiveness and profitability – when employees leave (Fosfuri and Rønde, 2004; Combes and Duranton, 2006; Marx et al., 2009). However, these measures seem to have an ambiguous effect on firm innovation. Although Franco and Mitchell (2008) and Kräkel and Sliwka (2009) conclude that contractual constraints to labour mobility

[2] 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.

[3] One exception is Cassiman et al. Arts (2011), who show that participation in joint ventures seems more conducive to innovation than labour mobility.

positively influence firm innovations, others make the opposite claim (Samila and Sorenson, 2011).

Formal labour regulations that deter mobility implies administrative costs; given that at least some of these costs are fixed, they will supposedly hurt smaller firms more than larger firms. Scarpetta and Tressel (2004) empirically show that labour market regulation negatively influences the incentives to engage in innovation and technology, which can be expected to primarily have a negative effect on innovation in smaller firms. Empirical studies considering firms of different sizes are extremely scarce. Zhou et al. (2011) present results that indicate – although the robustness of the results are questionable – that innovative behaviour in smaller firms is positively affected when labour is on temporary contracts; however, their innovation measure is a subjective variable defined by the firms.[4] These findings indicate that for more concentrated industries, i.e., those dominated by larger firms, the effects of regulated markets may be quite different than for markets hosting a larger share of smaller firms.

In summary, theoretical models offer some guidance but are not at a consensus in their normative conclusions, whereas empirical research – although in varying degrees – seems to support a positive relationship between labour mobility and firm innovation.

III. Theoretical Framework and Hypotheses

Knowledge is partly embodied in employees, which makes labour mobility relevant from a growth perspective. If increased labour mobility generates improved matching and higher allocation efficiency, it might also be expected to contribute to more innovation and higher growth. Vilalta-Bufi (2008) recently developed a model similar to Romer's (1990) endogenous growth model, in which 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.

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

The economy contains N firms that are identical in all respects except for their firm-specific knowledge (h), which is assumed to be embodied in each firm's 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 new workers who have just entered the labour 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 represents the number of workers with no 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 indicates the amount of labour 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, which is 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 workers with no experience (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; therefore, firms must pay a wage premium m to attract workers from other firms. Firms choose the number of workers to retain and the number of experienced workers to hire from other firms to maximise their profits. Using the first-order conditions from the profit maximising 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 labour to poach by each firm. The solution is interior, which ensures positive labour mobility in equilibrium. Hence, the model indicates that firms hire workers from other firms in equilibrium to enhance their knowledge base. Presumably, this higher knowledge base should also affect firm innovating capacity and establish a causal link between labour 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. Over time, as new worker knowledge is diffused into the new firm and as their network with former colleagues from the sourcing firm diminishes, the effect gradually tails off. We can 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 employers. The mechanism is the same as for the receiving firm because workers frequently 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.

Thus far, we have considered knowledge upgrading through employees without considering the geographical dimension. However, knowledge flows have been shown to be geographically localised (Jaffe et al., 1992; Audretsch and Feldman, 1996; Almeida and Kogut, 1999; Agrawal and Cockburn, 2003; Thompson and Fox-Kean, 2005). To include the effect of geographical distance, we classify labour mobility into two different types: intra-regional and inter-regional labour mobility, based on whether the sourcing and receiving firms are located in the same region. Firm 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 on the literature review, bearing in mind that previous theoretical and empirical contributions are both scarce and ambiguous. However, there are compelling indications that labour mobility leads to increased knowledge diffusion and knowledge exchange (within and between firms) and positively influences labour productivity. We expect that the labour mobility of workers should be positively associated with firm innovation activities for similar reasons, particularly when those joining a firm come from a patenting firm. Moreover, building on the results indicating that proximity is likely to generate more knowledge flows, we hypothesise that intra-regional labour mobility is likely to have a stronger effect on firm innovation capability than inter-regional labour mobility. Nonetheless, there are results pointing in the opposite direction, i.e., that an inflow of knowledge from more remote environments generates more innovation. Finally, we argue that it is important to control for market structure in the empirical analysis.

IV. Empirical Methodology

A. R&D Workers and Labour Mobility

The theoretical model highlights the general role that labour mobility plays in knowledge transfers across firms. It is likely, however, 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 Ejermo and Ljung (2014), who show that Swedish inventors tend to be better educated than 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 per cent in 1985 and had increased to 76 per cent by 2007. Among these, 14 per cent held a PhD degree in 1985, whereas the corresponding share was 29 per cent in 2007. In addition to formal education, the type of job that a worker has is likely to influence the extent of knowledge transfers between firms that follows from labour mobility. Consequently, this study focuses on the labour 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’s degree in natural, technical, agriculture or health science and be classified as “Professionals” according to the Swedish Standard Classification of

Occupations (SSYK=2)[5]. 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 labour market status:[6]

- *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 work as a professional at a patenting firm in year *t*.
- *Leavers to non-patenting firms* (*LNP*). R&D workers who left the firm at time *t*–1 and work as a professional at a non-patenting firm in year *t*.
- *Graduates from tertiary education* (*G*). R&D workers arriving from tertiary education between year *t*–1 and *t*.
- *Other joiners* (*O*). R&D workers joining a firm for whom we have no information on their previous job position.
- Stayers (*S*). R&D workers who are employed by the same firm in year *t*–1 and *t*.

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

TABLE 1 HERE

Finally, we also classify job switchers as either intra-regional or inter-regional – depending on whether the receiving firm and the sourcing firm are located in the same region – to test whether distance has an effect on firm patenting activities.

[5] The Swedish Standard Classification of Occupations SSYK is based on the International Standard Classification of Occupations (ISCO-88).

[6] The notation in parentheses is subsequently used to identify the different types of workers in the empirical analysis.

B. Econometric Specification

We depart from a firm-level knowledge production function in which 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 and as employees who recently left the firm,

$$\begin{aligned} H = {} & \gamma_{JP} L_{JP} + \gamma_{JNP} L_{JNP} + \gamma_{LP} L_{LP} + \gamma_{LNP} L_{LNP} + \gamma_G L_G \\ & + \gamma_O L_O + \gamma_S L_S + \gamma_{AW} L_{AW} + \gamma_{OW} L_{OW} \end{aligned} \tag{6}$$

where sub-script AW and OW denote "Associate R&D workers" and "Other workers", respectively (the other sub-scripts are defined above). L_x denotes the amount of each specific type of labour 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 normalising the marginal productivity for Stayers to one, we are able to express the knowledge production function as[7]

$$\begin{aligned} P = \exp\big[& \ln A + \alpha \ln K + \beta \ln L + \beta_{JP} s_{JP} + \beta_{JNP} s_{JNP} \\ & + \beta_{LP} s_{LP} + \beta_{LNP} s_{LNP} + \beta_G s_G + \beta_O s_O + \beta_{AW} s_{AW} + \beta_{OW} s_{OW} \big] \end{aligned} \tag{7}$$

where s stands for the 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,

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

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

where subscripts i and t denote firm and time, respectively. Vector **X** contains the variables we must control for that might otherwise distort the relationship between labour mobility and innovation.

Equation (8) will be estimated using the negative binomial estimator, which is an appropriate estimator in our setting in which the dependent variable is count data and the mean number of patents is considerably lower than its standard deviation. Hence, our dependent variable exhibits clear signs 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 labour mobility and innovation, i.e., the variables contained in vector **X**.

C. 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 we also 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 in a given year,[8]

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

$P_{i,t}$ 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 represents the total number of years during the pre-sample period (1987–2000). Therefore, if firm i innovates during a year in which few other firms innovate, it will carry a higher weight in the average innovative capacity of the firm.

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

D. Firm-Specific Capital Stocks

Due to a 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 represents the depreciation rate (assumed to be equal to 0.05 for all firms) and I represents 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 beginning in 2001.

E. Regional Control Variables

We include *seven* regional control variables in the regressions. First, we control for the general level of labour mobility within and across regions by including three variables. The first variable – labour inflow to the region – is defined as the total number of employees in the region who worked in a firm located in another region the previous year, divided by the total number of workers in the region. The second variable – labour outflow from the region – is defined as the total number of workers who 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 labour mobility within regions and is defined as the total number of workers in the region 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 kilometre), 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 that is based on the surrounding regions' patent applications 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 include dummy variables for industries[9], years and regions.

V. Data

We extracted the personal and firm-level data from Statistics Sweden's Business Register from 1987 to 2008, where the estimation period is 2001–2008 and the pre-sample period is 1987–2000.[10] This unique database covers all firms and individuals in Sweden, and firms are linked to one another through their hiring activities in the labour market. The matched employer-employee dataset can thus be used to indicate how networks are generated through labour mobility. In addition, the data contain individual information regarding educational background, job classification (functions), etc., which enables labour 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.

According to the latest data in November 2013, there are 1,127,832 firms and 1,206,182 establishments; among these, 97.5 per cent of the firms are privately owned. The majority of firms are operated as sole proprietorships (53.7 per cent) and limited liability companies (33.1 per cent).[11] Patent application data cover the 1987–2008 period, 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 because we need the firm pre-sample innovation activities to distinguish the innovators. Firms from the public sector are also excluded because 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, whereas the private

[9] These industries are, according to the 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 Defence because public sector innovation activity might be affected by other factors that we cannot test in this research.

[10] Much data are available also for the 2008–2013 period. 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 the following years.

[11] 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 private group-owned, and 24,095 foreign-owned firms.

sector tends to pay more attention to applied research and experimental research.[12] Furthermore, we only include firms with at least one R&D relevant worker[13], which is used to separate firms that have the intention to innovate from other firms.

Those who switch jobs between firms are also distinguished by the firm innovation status, i.e., whether they are working in patenting or non-patenting firms. Moreover, we distinguish between intra-regional and inter-regional labour mobility.[14] 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 Gittelman, 2006). Despite the limitation of using patent applications (invention does not always lead to innovation), it is nevertheless a better indicator of firm knowledge creation compared with granted patents and patent-citations, which are subject to substantial time-lag delays.

VI. Results

A. Descriptive Statistics

Descriptive statistics of the data sample are presented in Tables B.1 and B.2 in Appendix B, in which firms are also divided into two subgroups based on their pre-sample period innovation status. That allows us to see the trend of labour 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 patenting from non-patenting firms during the pre-sample period shows that patenting firms are larger with bigger capital stocks (326.4 employees, 33.1 R&D relevant workers and a real capital stock of 267.7 million Swedish Krona) compared with non-patenting firms

[12] The data can be found at the OECD website, science, technology and patents (http://stats.oecd.org).
[13] R&D relevant workers comprise R&D workers and associate R&D workers.
[14] 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 a lengthy commutes. They thus comprise local labour markets and are delineated based on commuting intensities. According to this definition, there are 72 FA-regions in Sweden.

(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, whereas the number of applications for firms that had at least one patent application during the 1987–2000 pre-sample period is much higher (3.7 applications). To sum up, innovative firms are larger, have bigger capital stocks and more human capital and are more likely to be innovative in the future compared with non-innovative firms.

Regarding R&D worker mobility, firms with pre-sample patents seem more connected with other patenting firms, as shown by their relatively higher shares of joiners from patenting firms and 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 compared with other firms.

B. Firm Learning by Hiring

Non-mobile R&D workers (Stayers) constitute the base category of R&D workers in the analysis and, hence, the results must be interpreted as relative to stayers. Our panel regression results are presented in Tables 2 and 3. Beginning 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 labour originating from a patenting firm. This illustrates that innovative firms seem to have a more relevant knowledge endowment and organisation to exploit new knowledge (compare the absorption parameter in the theoretical model), which leads to such labour flows having stronger effects.

TABLE 2 HERE

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 contrasts with our hypothesis and nuances the results from previous studies. We argued above that inter-regional mobility may conceal a selection if the firm must pay a premium to convince the employee to move to another region. Hence, higher costs should render a more stringent selection process. The alternative explanation is that although knowledge flows more easily across employees and firms located in the same region, these knowledge flows may not be the most accurate from the firm perspective. It may well be the case that less local and more heterogeneous knowledge is of higher importance for firm innovativeness or innovation uniqueness. 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 demonstrated to have positive significant effects. Finally, the interaction variable between joiners and firm size in regression 5 indicates that larger firms tend to benefit more in terms of innovation output from labour mobility than smaller firms.

TABLE 3 HERE

In Table 3, the same regressions are displayed but with two-year lags in the labour variables. The results are basically confirmed, although to a somewhat stronger extent. In addition, joiners from non-patenting firms are demonstrated 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" shows that the generation of knowledge and its effect on innovation is not simultaneous. Instead, there seems to be a time delay. We would expect the effect to first increase and then, after further time elapses, begin to decrease. However, we cannot test that proposition here because we are restricted to eight years of panel data, and increasing the lag implies that we would lose a considerable number of observations.

C. Firm Learning by Diaspora

To test the effect of firm learning by diaspora, we focus on the estimation of how "leavers" influence innovativeness in the firms they are leaving. The estimation of leavers that go to patenting firms exhibits a weak positive significance (Table 2), which switches to a weak negative effect when they go to non-patenting firms. The results are not as conclusive for leavers as for joiners with respect to the geographic dimension. For joiners, the results demonstrated a positive and strongly significant effect for both intra- and inter-regional mobility, although the effect was most pronounced for the latter type of mobility. In regard to leavers, the result is significant and positive – but considerably weaker – only for inter-regional leavers to patenting firms, whereas the result is weakly negative for intra-regional movements to non-patenting firms. The explanations are likely to be the same (selection effects) as those described above regarding learning by hiring. As was the case for joiners, the effect of workers leaving the firm tends to have a greater impact on the innovative output in large firms compared with smaller firms.

The two-year lagged estimation results are revealed in Table 3. In addition, in this case, the effect of firm learning by diaspora seems to be persistent and to some extent increasing. Hence, the results imply that the sourcing firm, i.e., those losing R&D workers, will also 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.

D. Causality

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

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

VII. Conclusion

This paper presents an empirical analysis of the relationship between labour mobility, knowledge diffusion and firm innovation output. We distinguish between three subgroups of workers: R&D workers, associate R&D workers, and other workers to separate the effects 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 has a strong positive and significant effect on firm innovativeness. We conclude that there are both forward and backward knowledge flows (between receiving and sourcing firms) but that the former exert a greater impact on innovation, that the geographical dimension of knowledge flows are important (inter-regional labour mobility has the strongest effect on innovation), and the impact of knowledge flows seems persistent. In addition, the effects of R&D labour mobility are strongest when firms are already engaged in innovative activities (which holds for both the sourcing and the receiving firm). Finally, the results also indicate that larger firms benefit more than smaller firms from labour mobility.

The results have important and highly relevant policy implications. In the on-going discussions regarding how to augment growth in large parts of Europe, flexibility of the labour market is attributed a strategically important role. Our results show that more flexible labour markets not only may be expected to lead to higher labour participation, higher productivity and better matching, but also may be instrumental in promoting innovation and ultimately higher growth.

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,

$$\begin{aligned} H = L\Bigg[& \gamma_{J,P}\frac{L_{J,P}}{L} + \gamma_{J,NP}\frac{L_{J,NP}}{L} + \gamma_{L,P}\frac{L_{L,P}}{L} + \gamma_{L,NP}\frac{L_{L,NP}}{L} + \gamma_G\frac{L_G}{L} + \gamma_O\frac{L_O}{L} + \\ & + \left(\frac{L - L_{J,P} - L_{J,NP} - L_G - L_O - L_{AW} - L_{OW}}{L}\right) + \gamma_{AW}\frac{L_{AW}}{L} + \gamma_{OW}\frac{L_{OW}}{L}\Bigg] \end{aligned}$$

(5)

$$\Leftrightarrow \quad \begin{aligned} H = L\Bigg[& 1 + \left(\gamma_{J,P} - 1\right)\frac{L_{J,P}}{L} + \left(\gamma_{J,NP} - 1\right)\frac{L_{J,NP}}{L} + \gamma_{L,P}\frac{L_{L,P}}{L} + \gamma_{L,NP}\frac{L_{L,NP}}{L} + \left(\gamma_G - 1\right)\frac{L_G}{L} + \\ & + \left(\gamma_O - 1\right)\frac{L_O}{L} + \left(\gamma_{AW} - 1\right)\frac{L_{AW}}{L} + \left(\gamma_{OW} - 1\right)\frac{L_{OW}}{L}\Bigg] \end{aligned}$$

(6)

which in turn can be written as,

$$H = L\Big[1+\left(\gamma_{J,P}-1\right)s_{J,P}+\left(\gamma_{J,NP}-1\right)s_{J,NP}+\gamma_{L,P}s_{L,P}+\gamma_{L,NP}s_{L,NP}+ \\ \left(\gamma_{G}-1\right)s_{G}+\left(\gamma_{O}-1\right)s_{O}+\left(\gamma_{AW}-1\right)s_{AW}+\left(\gamma_{OW}-1\right)s_{OW}\Big]. \qquad (7)$$

Taking the natural logarithm of (7) yields,

$$\ln H = \ln L + \ln(1+z) \approx \ln L + z \qquad (8)$$

where,

$$z = \Big[\left(\gamma_{J,P}-1\right)s_{J,P}+\left(\gamma_{J,NP}-1\right)s_{J,NP}+\gamma_{L,P}s_{L,P}+\gamma_{L,NP}s_{L,NP}+ \\ \left(\gamma_{G}-1\right)s_{G}+\left(\gamma_{O}-1\right)s_{O}+\left(\gamma_{AW}-1\right)s_{AW}+\left(\gamma_{OW}-1\right)s_{OW}\Big] \qquad (9)$$

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

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

or,

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

Appendix B. Descriptive Statistics

TABLE B.1 HERE

TABLE B.2 HERE

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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		

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)
Labour mobility into the region	15.48 (1.45)	15.09 (1.41)	14.91 (1.39)	15.92 (1.48)	16.21 (1.51)
Labour 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 labour 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 labour shares are calculated as a fraction of total employment.

Table 3
Regression results with worker shares lagged two years

	(1)	(2)	(3)	(4)	(5)
R&D workers					
Joiners …	2.102***	–	–	–	0.802*
	(8.50)				(1.87)
… from patenting firms	–	3.947***	–	–	–
		(6.33)			
… intra-regional	–	–	3.830***	4.160***	–
			(5.41)	(5.65)	
… inter-regional	–	–	4.500***	5.426***	–
			(5.44)	(6.84)	
… from non-patenting firms	–	1.127***	–	–	–
		(2.73)			
… intra-regional	–	–	0.584	0.929*	–
			(1.09)	(1.95)	
… inter-regional	–	–	2.688***	3.042***	–
			(3.13)	(4.17)	
Leavers …	0.867*	–	–	–	0.276
	(2.52)				(0.50)
… to patenting firms	–	2.084***	–	–	–
		(3.63)			
… intra-regional	–	–	1.334*	1.877***	–
			(1.80)	(2.68)	
… inter-regional	–	–	3.341***	4.367***	–
			(3.82)	(5.33)	
… to non-patenting firms	–	–0.018	–	–	–
		(–0.03)			
… intra-regional	–	–	–0.662	–0.236	–
			(–0.70)	(–0.30)	
… inter-regional	–	–	1.063	1.179	–
			(0.82)	(1.02)	
Graduates	2.424***	2.203***	2.327***	2.570***	2.418***
	(5.21)	(4.23)	(4.70)	(5.53)	(4.83)
Other joiners	1.289***	1.276***	1.264***	1.524***	1.212*
	(2.70)	(2.61)	(2.58)	(3.33)	(2.33)
Associate R&D workers	0.313	0.293	0.289	0.264	0.325
	(1.56)	(1.45)	(1.42)	(1.29)	(1.59)
Other workers	–0.294*	–0.279*	–0.269*	–0.085	–0.226
	(–1.83)	(–1.74)	(–1.67)	(–0.60)	(–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***	0.158***	0.157***	0.156***	0.141***
	(6.36)	(6.37)	(6.36)	(7.09)	(5.44)
Capital stock, logarithm	0.069***	0.068***	0.069***	0.062***	0.070***
	(4.85)	(4.83)	(4.82)	(5.51)	(4.79)
FE, logarithm	0.495***	0.496***	0.495***	0.482***	0.497***
	(28.19)	(28.21)	(28.11)	(30.48)	(28.37)
FE, dummy	4.436***	4.412***	4.408***	4.604***	4.416***
	(51.11)	(50.99)	(50.95)	(57.81)	(50.63)
Patent applications year *t*–1	0.002***	0.002***	0.002***	0.002***	0.002***
	(13.28)	(13.39)	(13.29)	(13.16)	(13.02)
Labour mobility into the region	8.891	8.872	8.782	10.83	8.625
	(0.70)	(0.70)	(0.69)	(0.88)	(0.68)
Labour mobility out from the region	0.749	0.760	0.781	–1.046	0.819
	(0.73)	(0.74)	(0.76)	(–0.73)	(0.79)
Intra-regional labour mobility	1.510	1.536	1.535	0.395	1.606
	(0.92)	(0.94)	(0.93)	(0.29)	(0.98)
Tertiary education rate	–1.268	–1.257	–1.250	–2.026***	–1.319
	(–0.75)	(–0.74)	(–0.74)	(–3.46)	(–0.78)
Regional density	–0.045	–0.043	–0.043	0.006***	–0.043
	(–1.56)	(–1.49)	(–1.49)	(4.48)	(–1.51)
Accessibility	0.052	0.063	0.061	–0.015	0.058
	(0.65)	(0.79)	(0.76)	(–1.25)	(0.71)
Diversity	21.25*	21.02*	21.15*	2.659*	22.88*
	(2.18)	(2.15)	(2.17)	(2.23)	(2.34)
Constant	–4.617*	–4.455*	–4.519*	–1.772***	–4.656*
	(–2.51)	(–2.43)	(–2.46)	(–6.28)	(–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 labour shares are calculated as a fraction of total employment.

Table B.1
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				
Labour mobility into the region	0.0015	0.002	0	0.3
Labour mobility out from the region	0.0101	0.030	0	0.1
Intra-regional labour 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 B.2

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