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# The Knowledge Spillover Theory of Intrapreneurship,Labour Mobility and Innovation by Firm Size

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# The Knowledge Spillover Theory of Intrapreneurship, Labour Mobility and Innovation by Firm Size*

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**Abstract**

Presenting The Knowledge Spillover Theory of Intrapreneurship, we examine how labour mobility impacts innovation distributed on firm size. A matched employer-employee dataset, pooled with firm-level patent application data, is implemented in the analysis. We provide new evidence that knowledge workers' mobility has a positive and strongly significant impact on all firms' innovation output, measured as patent applications. The patterns and effects differ between large and small firms. More precisely, for small firms, intraregional mobility of knowledge workers that have previously worked in a patenting firm (the learning-by-hiring effect) are shown to be statistically and economically highly significant, whereas only limited impact could be detected for firms losing knowledge workers (the-learning-by-diaspora effect).

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

*JEL classification*: J24, O31, R23

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## 1. Introduction

According to the knowledge spillover theory of entrepreneurship (Acs et al., 2009), start-ups is one way of diffusing and converting knowledge into societal utility. The underlying mechanism refers to innovation in the Schumpeterian sense, realized by exploiting opportunities originating in knowledge overlooked or neglected by incumbents. A parallel mechanism, not addressed in the original version of the knowledge spillover theory of entrepreneurship (KSTE), has to do with labour mobility. More precisely, R&D-workers that move between firms can be expected to diffuse knowledge and to improve the matching of individuals' heterogenous knowledge, thereby generating more of innovations. We argue that labour mobility associated with engagement in innovative activities, can be defined as a decisive factor in promoting intrapreneurship, which complements regular entrepreneurship in bringing forth innovations. Hence, in the current analysis we will merge insights from the fields of labour market economics, entrepreneurship and innovation to investigate how mobility influence innovation across firms of different size.

There is an overwhelming and convincing literature concluding that new and small firms play a disproportionately large role in forwarding radical innovations. The reasons are allotted a number of factors such as internal organization structures in large incumbents, so called business stealing effects, and individual and cognitive traits, to mention a few.[2] Previous research relating labour mobility to innovation is considerably more limited and remain inconclusive (Agrawal et al., 2006). An early contribution was provided by Almeida and Kogut (1999), showing that inter-firm mobility of engineers in Silicon Valley frequently were major patent holders and that they exerted a strong influence on firms' learning processes. More recently, these results have been corroborated by Oettl and Agrawal (2008), who claim that such knowledge flows accrue not only to the firm receiving employees but also to the firms that

[2] For a survey, see Braunerhjelm (2011).

lose workers. The latter effect is due to increased knowledge flows and expanded social (knowledge) networks. Also, Kaiser et al. (2015) and Braunerhjelm et al. (2014) found a positive association between labour mobility and innovation, measured as patent applications. However, a negative relationship between innovation and mobility of highly qualified labour has also been established in previous literature (Balsvik, 2011; Parrotta and Pozzoli, 2012).[3]

Our prime interest in the current paper is to examine the influence of mobility of knowledge (R&D) workers on innovation on firms distributed on separate size classes; small firms defined as those having less than 50 employees, and medium-sized and large firms defined as those having more than 49 employees.[4] The analysis will take into account both learning by hiring (firms receiving knowledge workers) and the diaspora effect (firms losing knowledge workers). To accomplish this, we will utilise a unique, matched Swedish 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.[5] 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.

We provide a number of new insight regarding the relationship between labour mobility, innovation and how it affects firms of different size. We believe this is the first study to use extensive register data (a population) to investigate the size dimension when analysing how labour mobility influence innovation (and one of the very few addressing this issue at all). Second, we control for other labour market categories, such as newly graduated knowledge

[3] See also Cassiman et al. (2011), who claims that participation in joint ventures is more conducive to innovation than labour mobility.
[4] This is in accordance with the EU's definition of small firms (less than 50 employees).
[5] Similar comprehensive data that are accessible for research can only, as far as we know, be found in Denmark, Finland and Norway.

workers and joiners of unknown origin.[6] This extension could be potentially important since hiring researchers from universities have been shown to impact firms' patenting activities (Ejsing et al., 2013). Third, we have access to a considerably longer time series which comprise the entire business cycle, and a wider set of controls.[7] We also present a separately analysis of the eight most innovative industries to see whether the results differ for high-innovators. Fourth, we emphasise the geographical dimension of knowledge flows, i.e., how inter- versus intraregional mobility influences innovation output, an issue which has not been addressed in previous work but may entail important policy implications. Finally, the issues addressed are highly topical and policy-relevant against the background of faltering growth performance in large parts of the global economy and the call for structural reforms, not least within the European Union. As innovation is considered the engine of growth (Aghion and Howitt, 2009), more thorough insights regarding the relationship between labour mobility and innovation is obviously a high-priority issue.

Our estimations support the proposition that the mobility of R&D workers – whose definition builds on both educational and functional occupation data – has a positive impact on firms' innovation output. Interestingly enough, several distinctive differences emerge when we separate the estimations between small and large firms. More precisely, small firms are shown to be highly dependent on joiners from firms that previously have been engaged in innovation, whereas no such effect could be detected for larger firms. In addition, intraregional mobility is considerably more important for smaller firms while larger firms benefit from both intra- and interregional labour mobility. Smaller firms also benefit (weakly) from labour that have moved to other patenting firms. The opposite patterns by and large prevail for larger firms. For a

[6] Kaiser et al. (2011, p. 21) are aware about this potentially important data omission in their analysis and suggests that an interesting question for future research "… is how the mobility between university and private firms affects the knowledge production in these two sectors, as measured by patents and academic publications."
[7] The Danish study stretches over 2000–2004 while our analysis comprises the years 2001–2008.

number of variables, the results were more pronounced for small firms belonging to the eight most innovative industries.

The rest of the paper is organised as follows. Section 2 reviews the previous research related to the issues addressed in this paper, which is followed by the theoretical framework and hypotheses development in Section 3. Then, we present the empirical strategy in Section 4 and description of the data in Section 5. The regression results, separated into "Firms learning by hiring" and "Firms learning by diaspora", are shown in Section 6. The paper ends with conclusions in Section 7.

## 2. Previous Research

Acs and Audretsch (1988, 1990) were among the first to provide empirical evidence that despite modest R&D investments, small and entrepreneurial firms contribute substantially to innovation in the U.S. Even though large corporations account for the overwhelming share of private R&D outlays, innovative activities differ across industries and large firms did not account for the greatest amount of innovative activity in all industries. For example, Acs and Audretsch conclude that large firms were much more innovative in the aircraft and pharmaceutical industries, while the opposite prevailed in computers and process control instruments where small firms contributed the bulk of innovations. Also Baldwin and Johnson (1999) attribute a particular important role to small firm innovations in certain industries (the electronics, instruments, medical equipment and biotechnology industries). Baldwin (1995) suggests that more successful firms adopt more innovative strategies.[8]

Thus, many entrepreneurs and small firms exploit existing knowledge – through their network and links to other knowledge producers – to satisfy their specific needs in the production of goods and services (Shane 2000, Freel 2003). Almeida and Kogut (1997), and

[8] Large incumbents still play an essential role in economies, not least as creators of "market for ideas" (Gans and Stern 2003).

Almeida (1999), show that small firms innovate in relatively unexplored fields of technology. Before that, Rothwell and Zegveld (1982) claimed that smaller firms more frequently introduced radical innovations. Baumol (2004) makes the same argument. Thereby they also produce new knowledge, even if it does not show up in the R&D-statistics.[9]

These were the insights that formed the base for the KSTE. More precisely, the theory captures how entrepreneurs, taking advantage of their individual and heterogeneous skills and combining that with knowledge originating in R&D-investments by incumbents, become the spillover vehicles required to convert knowledge into societal use. This theoretical foundation can also be used to explain intrapreneurship, i.e. why labour mobility may generate a more productive utilization of knowledge in incumbent firms. A better allocation of certain skills will enhance innovations, thereby promoting growth. We will return to these issues in the theoretical part.

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 (Hoisl, 2007). The implicit assumption is that the effective allocation of knowledge embodied in labour requires mobility, i.e. it is preceded by a search process. On the other hand, a decrease in innovative performance may occur as a result of costlier administrative routines and/or harm to firm organisational learning and "internal memories" (Zhou et al., 2009).

[9] As Christensen (1997) has convincingly shown, large incumbents are not internally organized to adopt changes or produce innovations that may affect the usefulness or value of an existing production structure. Similarly, Aldrich and Auster (1990) make the simpler argument that the larger and older the firm, the less receptive to change the organization becomes. See Braunerhjelm (2011) for a survey.

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 effects (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. New knowledge into the firm is also, in our view, an instrument to promote intrapreneurial innovative activities.

These findings regarding labour mobility and productivity can be expected to prevail also for innovation, not least since innovations is a means to augment productivity. More recently there has also been a few attempts to specifically investigate how innovation performance is impacted by labour mobility. Utilising Danish data, Kaiser et al., (2015) found that firms receiving knowledge workers from other firms, as well as those losing knowledge workers, improved their innovative performance as measured by patent applications. They conclude that the positive outcomes are related to extended and improved networks, accelerating the knowledge flows.[10] However, the authors do not consider firm size or the regional origins of employees nor do they control for knowledge workers coming from the university, or how the market structure influence firm innovativeness.

Hoisl (2007) presents an analysis based on German data for the period 1993 to 1997 where individual data on inventors are combined with a selected number of aggregated industry variables. Her analysis shows a positive association between mobility and inventor

[10] Kaiser et al (2015) is one of the few studies that measures innovation using an output variable. 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.

productivity, indicating a better match between employers and employees and enhanced knowledge spillovers.[11] But Hoisl also concludes that there is a simultaneous relationship where productive inventors become less mobile because they have found good matches. The results seem intuitively appealing, however the representability of the respondents is not well accounted for and, as discussed by Hoisl (2007), may create problems with selection bias. Moreover, the analysis only considers the receiving firms and not those that the inventors have left.

As regards intra- versus interregional mobility, the dominant predicament is that dense areas characterized by mobility are conducive to innovation and productivity. It is well established that knowledge flows are geographically localised (Jaffe et al., 1992; Audretsch and Feldman, 1996; Almeida and Kogut, 1999; Agrawal and Cockburn, 2003; Thompson and Fox-Kean, 2005). It has also been shown that firms are likely to patent more in regions that are characterised by high labour mobility (Kim and Marschke, 2005; Thompson and Fox-Kean, 2005).[12] However, some scholars have suggested that intraregional movement is slightly less likely to yield new information for a firm and to propel innovation compared with interregional mobility due to the similarity of intraregional knowledge (Essletzbichler and Rigby, 2005). The issue of whether interregional mobility is more instrumental in producing innovation than intraregional, and whether firm size differences are important, have 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. Regulatory impediments to mobility may be of an informal or formal character (Breschi and Lissoni, 2005; 2009).[13] Even though firms are operating in the same national

[11] For an early analysis of mobility and matching, see Topel and Ward (1992).
[12] There is huge literature on clusters and agglomerations indicating that frequent job changes and close interactions between employees of different firms are a decisive factor in explaining success of such clusters (Saxenian, 1994; Fallick et al., 2006).
[13] Firms may also seek to contractually restrain the mobility of employees defined as strategically important to guard against the loss of proprietary knowledge. These measures seem to have an ambiguous effect on firm

regulatory context in the current analysis, we claim that there may be divergent effects across firms of different size (Scarpetta and Tressel 2004; Zhou et al., 2011).[14] Ichniowski and Shaw (1995) and Bassanini and Ernst (2002) conclude that primarily smaller firms' innovativeness tend to be negatively affected by labour market regulations.

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. None of these have taken a comprehensive approach using register data to examine the effects on firms of different size or including the regional dimension.

## 3. The Knowledge Spillover Theory of Intrapreneurship

Knowledge is partly embodied in employees, which makes labour mobility relevant from a growth perspective. We argue that increased labour mobility is a way to enhance intrapreneurial activities through improved matching, higher allocation efficiency and extended network effects, thereby accelerating innovative activities.[15] If this allegation is correct, it will be manifested in a positive relationship between labour mobility and innovation output.

According to the endogenous growth theory, R&D-investments and knowledge spillovers can be expected to generate innovation, increased productivity and higher growth (Romer 1990, Aghion and Howitt 1998). Building on the endogenous growth theory, but emphasizing that the spillover mechanism were not well explained, Acs et al. (2009) presented a model where entrepreneurs were shown to constitute that missing link. Here we argue that labour mobility of certain professions or skills, is a complementary channel to diffuse knowledge and to spur

innovation and falls outside the scope of the present analysis (Fosfuri and Rønde, 2004; Franco and Mitchell, 2008; Marx et al., 2009; Samila and Sorenson, 2011.

[14] Zhou et al's (2011) analysis is based on survey data and defines small firms as those having less than 250 employees while the smallest firms (< 5 employees) are excluded.

[15] Labour mobility may also positively affect entrepreneurship through similar mechanism, see Braunerhjelm et al. (2014).

innovation activities. We define intrapreneurs as individuals that are engaged in innovative activities within the firm.

Our theoretical framework builds on Vilalta-Bufi (2008) in which different types of intermediate goods are replaced with different types of human capital. Thus, we adopt a somewhat modified version of the Vilalta-Bufi (2008) model as our base for the knowledge spillover theory of intrapreneurship (KSTI).[16]

*3.1 The knowledge spillover theory of intrapreneurship: A theoretical framework*

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 (graduates). All of these channels have a potential of increasing intrapreneurial and innovative activities.

The introduction of new or modified products and services (*Y*) can be modelled in the following way:

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

$H_i$ 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*. Moreover,

[16] For details, see Vilalta-Bufi (2008). As in the original model we exclude physical capital to make the model more tractable.

human capital is defined as a composite of the firm's own experienced workers and experienced workers hired from other firms that are involved in innovative activities,

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

In equation (2), $\lambda_i^j$ indicates the amount of joiners originating from firm *j* 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 number 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 $\lambda^{i*}$ is the optimal amount of labour to poach by each firm. The solution is interior, which ensures positive labour mobility in equilibrium. Hence, according to the model firms hire workers from other firms in equilibrium to enhance their knowledge base. Presumably, this higher knowledge base should also affect firms´ intrapreneurship 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), and should also peter out over time. 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. To include the effect of geographical distance, we classify labour mobility into two different types: intraregional and interregional labour mobility, based on whether the sourcing and receiving firms are located in the same region. Firms' knowledge upgrading thus involves four types of human capital: joiners, leavers, stayers and graduates. Furthermore, joiners and leavers can be divided into two subgroups depending on whether they move across regional borders.

### *3.2 Hypotheses*

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. For similar reasons, we expect that mobility of knowledge workers should contribute to enhanced intrapreneurship abilities and be positively associated with firm innovation activities, particularly for certain skill cohorts and when those joining a firm come from a patenting firm. Also leavers may contribute to knowledge and a firm's innovative capacity but we expect this influence to be of a lower range. In addition, we argue that a more fluid labour market will primarily benefit smaller firms due to fixed costs in hiring and scouting for relevant knowledge workers. Moreover, building on the results indicating that proximity is likely to generate more knowledge flows, we hypothesise that intraregional labour mobility is likely to have a stronger effect on firm innovation capability than interregional 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.

## 4. Empirical Methodology

### *4.1 R&D Workers and Labour Mobility*

The theoretical model highlights the general role that labour mobility plays in promoting intrapreneurship and 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)[17]. We name this group of workers "R&D workers". In addition, we denote those with the same level of education but belonging to the group "Technicians and associate professionals" (SSYK=3) as "Associate R&D workers". Together, R&D-workers and associate R&D-workers make up the firms' R&D-workforce, i.e. the major share of their intrapreneurs.[18]

R&D workers are further divided into one of the following seven groups, depending on their labour market status:[19]

- *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 $t$.

[17] The Swedish Standard Classification of Occupations SSYK is based on the International Standard Classification of Occupations (ISCO-88).
[18] Henceforth we assume R&D-workers are synonymous with intrapreneurs.
[19] The notation in parentheses is subsequently used to identify the different types of workers in the empirical analysis.

- *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*.

Finally, we also classify job switchers as either intraregional or interregional – 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.

*4.2 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

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

Following Griliches (1967), we specify our quality-adjusted labour input *H* as an additive composite of different types of workers. In particular, we define human capital as a weighted aggregate of the different types of workers who currently are employed by the firm and as employees who recently left the firm,

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

where sub-script *AW* denotes "Associate R&D workers" (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 $\gamma$-coefficients denote each type of worker's marginal contribution to the composite measure of human capital where we have normalized marginal productivity for stayers to one.[20] This enables us to express the knowledge production function as

$$P = \exp\left[\ln A + \alpha \ln K + \beta \ln L + \beta_{JP} s_{JP} + \beta_{JNP} s_{JNP} + \right. \\ \left. + \beta_{LP} s_{LP} + \beta_{LNP} s_{LNP} + \beta_G s_G + \beta_O s_O + \beta_{AW} s_{AW} \right] \tag{7}$$

where $s$ stands for the number of workers within each category divided by the firm's overall R&D workforce (i.e. the sum of R&D workers and Associate R&D workers), $L$. The derived knowledge production function constitutes the base for our econometric analysis, and it is estimated using the following regression equation,

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

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 separately for firms with less than 50 employees and for firms with 50 or more employees to allow the effect of the explanatory variables, and in particular the labour mobility variables, to differ between small and larger firms. The

[20] 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.

relationship between labour mobility and innovation will be estimated using the negative binomial estimator, which is an appropriate estimator given 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 exhibits clear signs of over dispersion, which renders the otherwise appropriate Poisson estimator inadequate. The remaining parts of this section present the control variables contained in vector **X**.

*4.3 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.[21] Here, we choose 1987–2000 as our pre-sample period to estimate firm heterogeneity, but we also follow Kaiser et al. (2015) and extend the pre-sample estimator as suggested by Blundell et al. (1995) to account for the proportion of patent applications in a given year,[22]

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

$P_{i,t}$ 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-

[21] This will also account for the so-called zero-inflation problem that arises in settings with an excess number of zeros.

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

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.

*4.4 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*, $\theta$ represents the depreciation rate (assumed to be equal to 0.05 for all firms) and *I* represents investments deflated by the GDP deflator. We choose the pre-sample period 1987–2000 to create the initial capital stocks used in the estimation period beginning in 2001.

*4.5 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, we include dummy variables for industries, years and regions.

## 5. 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.[23] 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 trace 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. Innovation output can then be regressed on these classes of human capital at the firm level.

The dataset contains 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).[24] Patent application data cover the 1987–2008 period, and 8,607 firms owned 154,763 patent

[23] Much data is 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.

[24] 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.

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 sector tends to pay more attention to applied research and experimental research.[25] Furthermore, we only include firms with at least one R&D relevant worker[26], 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 intraregional and interregional labour mobility.[27] 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. The sample is dominated by firms with fewer than 50 employees, which together account for approximately 79 percent of the observations.

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.

[25] The data can be found at the OECD website, science, technology and patents (http://stats.oecd.org).
[26] R&D relevant workers comprise R&D workers and associate R&D workers.
[27] 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 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.

# 6. Results

*6.1 Descriptive Statistics*

Descriptive statistics of the data sample and detailed variable descriptions are presented in Tables A.1–A.7 in the Appendix, in which firms are divided into subgroups based on their pre-sample period innovation status and firm size. This allows us to see the trend of labour mobility between innovators and non-innovators as well as differences across small and large firms.[28]

On average, each firm has 79.8 employees, 7.2 R&D relevant workers and a real capital stock amounting to 67.2 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 304.4 million Swedish Krona) compared with non-patenting firms (54.6 employees, 4.6 R&D relevant workers and a real capital stock of 43 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 also more likely to be innovative in the future compared with non-innovative firms. The same pattern also holds when we divide the sample into small and larger firms as shown in Table A4–A7.

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.

[28] A full correlation matrix is available from the authors upon request.

*6.2 Learning by Hiring and Diaspora effects – small versus larger firms*

The results from the negative binomial regressions are shown in Table 1 and Table 2, where the former refers to firms smaller than 50 employees. The cut-off number of 50 employees has been chosen so as to correspond to OECD's classification of small firms, i.e. 0–49 employees. Starting with small firms in Table 1, the first column distinguishes between joiners and leavers, while column 2 also considers the sourcing and receiving firms' innovative status. The specification in column 3 adds the spatial dimension to the analysis, where we distinguish between intra- and interregional mobility of workers and, finally, regional control variables as well as more detailed industry dummies are added in column 4.

TABLE 1 HERE

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. According to the regression results for firms having less than 50 employees, 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. Interestingly enough, the effect is confined to R&D labour originating from patenting firms (column 2), whereas no such effect could be detected from those arriving from non-patenting firms. The learning by diaspora effect is not supported by our results as shown by the insignificant effect of leavers.

Finally, when we examine other categories of the labour force, both graduates and other joiners fail to achieve statistical significance at any reasonable level. Interacting graduates with a dummy variable for innovative firms in the pre-sample also failed to attain significance

throughout the estimations. Hence, intrapreneurial capacities seems to be limited to a relatively small group of professions and skills where experience plays an important role.

Considering the geographic dimension in column 3 and 4, intraregional joiners from patenting firms dominates even though some significance can also be attributed interregional joiners from patenting firms. As for leavers, no statistically significant effect could be detected, irrespective of geographical unit.

Regarding remaining controls, the results are as expected with regard to the innovation variables (total R&D work force, pre-sample variables and patent dummies). No effect is reported for remaining labour mobility controls or capital stock. Basically, the results are in line with our hypotheses.

Turning to medium-sized and larger firms having at least 50 employees, the pattern looks different (Table 2) even though the overall effect is positive (column 1). However, the effect in this case is dominated by joiners from non-patenting firms, i.e. opposite to what we saw for small firms. This may seem counter-intuitive but several explanations are conceivable. First, smaller firms tend to lack sufficient complementing R&D resources, which combined with the new worker's inexperience from innovation activities might be a too big obstacle for innovation to occur. This is less likely for the larger firm. Second, joiners from non-innovating firms seem more likely to diverge in their knowledge as compared to joiners from innovating firms. Thus heterogeneity may be exploited by larger firms due to higher absorptive capacity related to size. Hence, joiners from non-innovating firms could contribute to a more diversified knowledge base in innovating large firms, resulting in higher innovation activities.

We also note that R&D-workers who previously worked in innovative firms have different effects in smaller and larger firms' patent production. Smaller firms benefit from these joiners while no effect can be detected for larger firms. One reason forwarded in the literature relates to what the employer is willing to do – the disagreement model of innovation and entry

(Klepper and Thomson, 2010) – which causes R&D-workers to look for new opportunities outside their current employer. Joining a smaller innovative firm may give more room to pursue ideas rejected by previous employers. R&D-workers in innovative firms that lack this motive are more likely to be indifferent between the size of their new employer and, hence, we have a selection where workers with more innovative ambitions tend to go to smaller firms. Another plausible reason is that R&D-workers experience of patenting processes simply carries a higher weight in the smaller firm as compared to larger firms.

TABLE 2 HERE

We can however only hypothesize about these alleged reasons; the data does not allow us to dig deeper. In addition, we note that leavers to non-patenting firms exert a weak negative effect on innovation activities in the firms they left. Associate R&D-workers are also shown to have relatively weak but negative effects on innovation relative to stayers in some of the regressions, as is other joiners. Also, regional effects differ across the two groups of firms. For larger firms both intra- and interregional mobility matters, but again solely for joiners from non-patenting firms. As regard the remaining controls they are basically in line with the results for smaller firms.

To summarize, the pattern that emerges for small and larger firm differ considerably, where small firms are shown to be more dependent on joiners from firms with ongoing innovative activities that are located in the region. Large firms on the other hand are not restricted to the region in which they operate and benefit more from joiners recruited from non-patenting firms.

*6.3 Regional control variables*

Neither the regional labour mobility variables nor the share of a region's workers with a completed tertiary education seem to have a significant impact on firms' innovative output according to the estimates in column 4 in Table 1 and 2. Regional density, on the other hand, turns up with an unexpected but minor negative sign in case of small firms, which suggests that more workers per square kilometre has a negative influence on innovation at the firm level. One explanation for this result could be that regional density is highly correlated with the regional dummies, making it hard to separate their individual effects on firms' innovativeness.

Finally, the positive and significant effect shown for the accessibility variable highlights the importance of controlling for spatial autocorrelation when estimating firm level patent production functions – firms located close to firms with high innovative output tend to be more innovative and vice versa.

*6.4 Relative patent productivities*

The estimated coefficients from the negative binomial regressions in Table 1 and 2 enables us to derive the underlying structural parameters of the patent production function, i.e. to calculate the relative patent productivities ($\gamma$ in equation 6). Table 3 provides estimates of the relative patent productivities for our four baseline regression specifications for small firms.

TABLE 3 HERE

Starting with column 2, joiners from patenting firms are on average 4.6 times more patent productive than stayers, while no effect was obtained for joiners from non-patenting firms. Thus, employing R&D workers with experience from an innovating firm have not only a statistically significant effect on innovation, but the effect is also economically important for small firms. We also find that R&D workers leaving a firm to join a patenting firm yield quite

strong effects on innovation; on average, this type of workers are 3.3 times as patent productive as stayers, albeit the significance level is much lower.

Next, when we distinguish between intra- and interregional mobility of R&D workers in column 3 and 4, we find that the positive effect can mainly be attributed intraregional mobility and solely confined to joiners from patenting firms, while no effect could be observed for the other variables.

TABLE 4 HERE

For large firms (Table 4), almost the opposite results are reported. Joiners from non-patenting firms, both intra- and interregional, have the strongest impact on patent productivity, ranging between a factor 6.3 to 3.8 in the different regressions. A considerable sensitivity for leavers to non-patenting firms in other regions is also reported for medium-sized and large firms.

To test the robustness of our results, we have also performed the analysis on two different subsets of our data. The first subset is the manufacturing industry and the second subset comprises the eight most innovative industries as identified by a cluster analysis. The results for small firms are presented in Table 5.

TABLE 5 HERE

When we restrict the analysis to the manufacturing sector (column 1 and 2 which are comparable to column 3 and 4 in Table 3), most of the significance attained in the previous estimations remain, but the magnitudes of the coefficients are on a somewhat lower level. A similarly noteworthy result is that an influx of graduates is shown to have a relatively strong

negative effect on patent productivity in manufacturing firms, suggesting matching problems or that "training on the job" is required before competencies of graduates can be fully utilized.

When we instead look at the most innovative industries, a first observation is that they are composed of both industry and service sectors. Moreover, the results are very similar to those reported in Table 3 and if anything, more accentuated. The negative effects of graduates also disappear. Thus, mobility of R&D-workers exerts its strongest influence on the most innovative industries.

For larger firms (Table 6), and compared to the results reported in Table 4, the effects are considerably weaker for the manufacturing sector and on par with the previous results when examining the eight most innovative industries.

TABLE 6 HERE

*6.5 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 one-year lag distribution on labour mobility. 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.

Moreover, hiring employees is an active decision made by firm management. If the firm wants to become more innovative, it will search for and hire relevant R&D-workers to help it achieve that goal. Hence, the logical timing of events runs from firm hiring R&D-workers to innovation and not the other way around. Also note that we are interested in the effect of mobile R&D-relevant workers. While innovation may cause firms to hire more or less workers, it is less likely to affect the category of workers which our empirical analysis is based upon. Given the arguments provided above, we claim that reverse causality should not be a problem in our empirical analysis.

## 7. Conclusion

Emanating from a theoretical framework proposed by Acs et al. (2009), we present an empirical analysis of the relationship between labour mobility, knowledge diffusion, firm size and firm innovation output. We distinguish between two subgroups of workers: R&D workers and associate R&D workers to separate the effects of the mobility of knowledge workers which we define as intrapreneurs, i.e. conducive in creating innovations. 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, but that the effects and channels through which these effect works, differ between firms of different sizes.

We conclude that there are primarily forward knowledge flows (between receiving and sourcing firms) but that the existence of backward flows may exist for some industries and some firms. In addition, the geographical dimension of knowledge flows is important for innovation activities and dominated by intraregional labour mobility for smaller firms. For larger firms, also interregional flows have a significant influence on innovation. For the cohort of smaller firms, the effects of R&D labour mobility are shown to be strongest when firms are

already engaged in innovative activities (and again particularly so for the receiving firm). For larger firms, the opposite patterns prevail.

The results have important and highly relevant policy implications. Smaller firms, where previous analyses have provided evidence are the strongest contributions to radical innovations, are by and large dependent on inflows of R&D-workers from other innovating firms. Hence, labour flexibility policies are critically important for innovative activities. Moreover, the marked effect of intraregional mobility carries important policy implications at the regional as well as at the more aggregated levels. Removing obstacles and facilitating intraregional mobility may be a way to enhance cross-fertilization of knowledge, improve matching and strengthening spillovers from knowledge networks.

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 may not only be expected to lead to higher labour participation, higher productivity and better matching, but may also be instrumental in promoting innovation and ultimately higher growth.

## Appendix. Descriptive Statistics

TABLE A.1 HERE

TABLE A.2 HERE

TABLE A.3 HERE

TABLE A.4 HERE

TABLE A.5 HERE

TABLE A.6 HERE

TABLE A.7 HERE

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**Table 1**
Results from negative binomial regressions: Small firms (0–49 employees)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| R&D workers | | | | |
| Joiners … | 0.485*** | | | |
| | (2.79) | | | |
| … from patenting firms | | 0.973*** | | |
| | | (4.68) | | |
| … intraregional | | | 1.116*** | 1.093*** |
| | | | (4.74) | (4.49) |
| … interregional | | | 0.639* | 0.714* |
| | | | (1.70) | (1.96) |
| … from non-patenting firms | | 0.186 | | |
| | | (0.69) | | |
| … intraregional | | | 0.330 | 0.385 |
| | | | (1.06) | (1.56) |
| … interregional | | | –0.267 | –0.208 |
| | | | (–0.69) | (–0.57) |
| Leavers … | 0.122 | | | |
| | (0.69) | | | |
| … to patenting firms | | 0.628 | | |
| | | (1.29) | | |
| … intraregional | | | 0.578 | 0.480 |
| | | | (0.91) | (1.13) |
| … interregional | | | 0.793 | 0.593 |
| | | | (1.18) | (0.87) |
| … to non-patenting firms | | –0.253 | | |
| | | (–0.79) | | |
| … intraregional | | | –0.494 | –0.471 |
| | | | (–1.06) | (–1.07) |
| … interregional | | | 0.128 | 0.155 |
| | | | (0.30) | (0.39) |
| Other joiners | 0.373 | 0.379 | 0.375 | 0.372 |
| | (0.98) | (1.00) | (0.98) | (0.93) |
| Graduates | 0.277 | 0.271 | 0.285 | 0.185 |
| | (0.24) | (0.23) | (0.25) | (0.15) |
| Interaction variable between graduates and a dummy for firms with pre-sample patents | –1.116 | –0.957 | –1.006 | –1.205 |
| | (–0.76) | (–0.65) | (–0.69) | (–0.81) |
| Associate R&D workers | –0.113 | –0.112 | –0.118 | –0.115 |
| | (–0.95) | (–0.95) | (–1.00) | (–0.98) |
| Total R&D work force, logarithm | 0.272*** | 0.273*** | 0.277*** | 0.262*** |
| | (4.60) | (4.62) | (4.69) | (4.39) |
| Capital stock, logarithm | 0.0502 | 0.0498 | 0.0490 | 0.0373 |
| | (1.59) | (1.57) | (1.57) | (1.33) |
| FE, logarithm | 0.291*** | 0.288*** | 0.289*** | 0.289*** |
| | (6.70) | (6.67) | (6.70) | (6.92) |
| FE, dummy | 3.122*** | 3.099*** | 3.102*** | 2.996*** |
| | (17.31) | (17.24) | (17.24) | (16.88) |
| Dummy patent t–1 | 2.791*** | 2.786*** | 2.778*** | 2.634*** |
| | (23.90) | (23.75) | (23.79) | (24.09) |
| Dummy patent t–2 | 0.894*** | 0.884*** | 0.884*** | 0.781*** |
| | (7.25) | (7.17) | (7.19) | (6.91) |
| Labour mobility into the region | | | | 29.50 |
| | | | | (1.23) |
| Labour mobility out from the region | | | | 0.591 |
| | | | | (0.11) |
| Intraregional labour mobility | | | | –2.486 |
| | | | | (–0.55) |
| Tertiary education rate | | | | –2.800 |
| | | | | (–0.84) |
| Regional density | | | | –0.107* |
| | | | | (–1.80) |
| Accessibility | | | | 0.246* |
| | | | | (1.90) |
| Specialisation | | | | –8.784 |
| Industry dummies | 1–digit NACE | 1–digit NACE | 1–digit NACE | 3–digit NACE |
| Year dummies | YES | YES | YES | YES |
| Regional dummies | YES | YES | YES | YES |
| Number of observations | 72,431 | 72,431 | 72,431 | 72,431 |

**Note:** ***, ** and * denote statistical significance at the 1-, 5- and 10 percentage level, respectively. t-statistics based on robust standard errors in parentheses.

**Table 2**

Results from negative binomial regressions: Larger firms (50– employees)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| R&D workers | | | | |
| Joiners … | 0.588** | | | |
| | (2.34) | | | |
| … from patenting firms | | 0.248 | | |
| | | (0.70) | | |
| … intraregional | | | 0.535 | 0.233 |
| | | | (1.26) | (0.58) |
| … interregional | | | 0.519 | 0.0544 |
| | | | (0.81) | (0.09) |
| … from non-patenting firms | | 0.738*** | | |
| | | (2.63) | | |
| … intraregional | | | 0.957*** | 0.778** |
| | | | (2.80) | (2.34) |
| … interregional | | | 1.198*** | 1.058** |
| | | | (2.86) | (2.34) |
| Leavers … | –0.460** | | | |
| | (–1.99) | | | |
| … to patenting firms | | –0.201 | | |
| | | (–0.49) | | |
| … intraregional | | | 0.310 | 0.0354 |
| | | | (0.66) | (0.07) |
| … interregional | | | –0.637 | –1.042 |
| | | | (–0.75) | (–1.58) |
| … to non-patenting firms | | –0.562* | | |
| | | (–1.90) | | |
| … intraregional | | | –0.111 | 0.0439 |
| | | | (–0.30) | (0.14) |
| … interregional | | | –1.187*** | –1.224*** |
| | | | (–2.74) | (–2.67) |
| Other joiners | –0.786* | –0.759* | –0.453 | –0.240 |
| | (–1.75) | (–1.71) | (–1.00) | (–0.55) |
| Graduates | –0.230 | –0.144 | 0.210 | –0.647 |
| | (–0.19) | (–0.12) | (0.18) | (–0.39) |
| Interaction variable between graduates and a dummy for firms with pre-sample patents | 0.939 | 0.876 | 0.218 | 1.206 |
| | (0.55) | (0.53) | (0.13) | (0.59) |
| Associate R&D workers | –0.240** | –0.225** | –0.00187 | –0.111 |
| | (–2.24) | (–2.11) | (–0.02) | (–1.01) |
| Total R&D work force, logarithm | 0.157*** | 0.161*** | 0.226*** | 0.281*** |
| | (6.52) | (6.72) | (9.24) | (9.95) |
| Capital stock, logarithm | –0.0107 | –0.0119 | 0.0457*** | 0.0659*** |
| | (–1.05) | (–1.18) | (3.19) | (4.48) |
| FE, logarithm | 0.594*** | 0.593*** | 0.414*** | 0.350*** |
| | (22.36) | (22.45) | (17.38) | (14.86) |
| FE, dummy | 2.878*** | 2.897*** | 2.528*** | 2.270*** |
| | (24.87) | (25.25) | (22.07) | (19.64) |
| Dummy patent t–1 | 2.556*** | 2.558*** | 2.581*** | 2.362*** |
| | (26.69) | (27.00) | (28.82) | (28.26) |
| Dummy patent t–2 | 0.783*** | 0.782*** | 0.914*** | 0.831*** |
| | (8.47) | (8.51) | (10.64) | (10.44) |
| Labour mobility into the region | | | | –3.240 |
| | | | | (–0.20) |
| Labour mobility out from the region | | | | 1.050 |
| | | | | (0.80) |
| Intraregional labour mobility | | | | –0.786 |
| | | | | (–0.30) |
| Tertiary education rate | | | | –2.350 |
| | | | | (–0.99) |
| Regional density | | | | –0.0241 |
| | | | | (–0.75) |
| Accessibility | | | | 0.183* |
| | | | | (1.92) |
| Specialisation | | | | 12.08 |
| | | | | (0.91) |
| Industry dummies | 1–digit NACE | 1–digit NACE | 1–digit NACE | 3–digit NACE |
| Year dummies | YES | YES | YES | YES |
| Regional dummies | YES | YES | YES | YES |
| Number of observations | 19,237 | 19,237 | 19,237 | 19,237 |

**Note:** ***, ** and * denote statistical significance at the 1-, 5- and 10 percentage level, respectively. t-statistics based on robust standard errors in parentheses.

**Table 3**

Estimated relative patent productivities: Small firms (0–49 employees)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| R&D workers, | | | | |
| Joiners … | 2.783*** | | | |
| … from patenting firms | | 4.564*** | | |
| … intraregional | | | 5.029*** | 5.172*** |
| … interregional | | | 3.307* | 3.725* |
| … from non-patenting firms | | 1.681 | | |
| | | | 2.191 | 2.469 |
| … intraregional | | | 0.036 | 0.206 |
| … interregional | | | | |
| Leavers … | 1.449 | | | |
| … to patenting firms | | 3.300 | | |
| … intraregional | | | 3.087 | 2.832 |
| … interregional | | | 3.863 | 3.263 |
| … to non-patenting firms | | 0.073 | | |
| … intraregional | | | –0.783 | –0.798 |
| … interregional | | | 1.462 | 1.592 |
| Other joiners | 2.371 | 2.388 | 2.354 | 2.420 |
| Graduates | | | | |
| … for firms with pre-sample patents | –2.085 | –1.513 | –1.603 | –2.893 |
| … for firms without pre-sample patents | 2.018 | 1.993 | 2.029 | 1.706 |
| Associate R&D workers | 0.585*** | 0.590*** | 0.574*** | 0.561*** |
| Industry dummies | 1–digit NACE | 1–digit NACE | 1–digit NACE | 3–digit NACE |
| Regional control variables | NO | NO | NO | YES |

**Note:** ***, ** and * denote statistical significance at the 1-, 5- and 10 percentage level, respectively.

**Table 4**

Estimated relative patent productivities: Larger firms (50– employees)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| R&D workers, | | | | |
| Joiners … | 4.745** | | | |
| … from patenting firms | | 2.540 | | |
| … intraregional | | | 3.367 | 1.829 |
| … interregional | | | 3.296 | 1.194 |
| … from non-patenting firms | | 5.584*** | | |
| … intraregional | | | 5.235*** | 3.769** |
| … interregional | | | 6.301*** | 4.765** |
| Leavers … | –1.930** | | | |
| … to patenting firms | | –0.248 | | |
| … intraregional | | | 2.372 | 1.126 |
| … interregional | | | –1.819 | –2.708 |
| … to non-patenting firms | | –2.491* | | |
| … intraregional | | | 0.509 | 1.156 |
| … interregional | | | –4.252*** | –3.356*** |
| Other joiners | –4.006* | –3.714* | –1.004 | 0.146 |
| Graduates | | | | |
| … for firms with pre-sample patents | 5.516 | 5.547 | 2.894 | 2.989 |
| … for firms without pre-sample patents | –0.465 | 0.106 | 1.929 | –1.302 |
| Associate R&D workers | –0.529** | –0.398** | 0.992 | 0.605 |
| Industry dummies | 1–digit NACE | 1–digit NACE | 1–digit NACE | 3–digit NACE |
| Regional control variables | NO | NO | NO | YES |

**Note:** ***, ** and * denote statistical significance at the 1-, 5- and 10 percentage level, respectively.

**Table 5**

Estimated relative patent productivities, manufacturing and eight innovative industries: Small firms (0–49 employees)

| | Manufacturing | | Eight innovative industries | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| R&D workers, | | | | |
| Joiners from patenting firms | | | | |
| … intraregional | 3.837** | 3.916** | 5.053*** | 5.114*** |
| … interregional | –1.511 | –1.861 | 3.330* | 3.680** |
| … from non-patenting firms | | | | |
| … intraregional | 3.182 | 2.929 | 2.209 | 2.449 |
| … interregional | 1.169 | 0.679 | 0.124 | 0.287 |
| Leavers to patenting firms | | | | |
| … intraregional | 1.922 | 2.284 | 3.135 | 2.820 |
| … interregional | –3.078 | –4.384 | 3.869 | 3.202 |
| … to non-patenting firms | | | | |
| … intraregional | –2.351 | –2.268 | –0.688 | –0.662 |
| … interregional | 2.176 | 1.755 | 1.489 | 1.599 |
| Other joiners | 0.495 | 0.746 | 2.351 | 2.390 |
| Graduates | | | | |
| … for firms with pre-sample patents | –4.044 | –4.903 | –1.230 | –2.335 |
| … for firms without pre-sample patents | –8.762** | –9.748** | 2.067 | 1.757 |
| Associate R&D workers | 0.780 | 0.513 | 0.631 | 0.614 |
| Industry dummies | 1–digit NACE | 3–digit NACE | 1–digit NACE | 3–digit NACE |
| Regional control variables | NO | YES | NO | YES |

**Note:** ***, ** and * denote statistical significance at the 1-, 5- and 10 percentage level, respectively. The group of eight industries is identified using a cluster analysis based on patenting behaviour and comprises Manufacturing, Mining and quarrying, Electricity, gas and water supply, Construction, Wholesale and retail trade, Transport, storage and communication, Real estate, renting and business activities and Other.

**Table 6**

Estimated relative patent productivities, manufacturing and eight innovative industries: Larger firms (50– employees)

| | Manufacturing | | Eight innovative industries | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| R&D workers, | | | | |
| Joiners from patenting firms | | | | |
| … intraregional | 1.172 | 0.055 | 3.511 | 1.867 |
| … interregional | 3.195 | 1.552 | 3.417 | 1.257 |
| … from non-patenting firms | | | | |
| … intraregional | 3.318 | 2.383 | 5.404*** | 3.824** |
| … interregional | 4.726* | 4.279* | 6.462*** | 4.846** |
| Leavers to patenting firms | | | | |
| … intraregional | 1.283 | 0.974 | 2.372 | 1.104 |
| … interregional | –0.072 | –1.205 | –1.879 | –2.742 |
| … to non-patenting firms | | | | |
| … intraregional | –1.390 | –0.529 | 0.511 | 1.167 |
| … interregional | –3.137** | –2.237** | –4.224*** | –3.305*** |
| Other joiners | –1.069 | –0.153 | –0.812 | 0.226 |
| Graduates | | | | |
| … for firms with pre-sample patents | –1.773 | –6.802 | 1.996 | –1.215 |
| … for firms without pre-sample patents | –1.810 | –1.075 | 3.099 | 3.097 |
| Associate R&D workers | 1.187 | 0.552 | 1.032 | 0.616 |
| Industry dummies | 1–digit NACE | 3–digit NACE | 1–digit NACE | 3–digit NACE |
| Regional control variables | NO | YES | NO | YES |

**Note:** ***, ** and * denote statistical significance at the 1-, 5- and 10 percentage level, respectively. The group of eight industries is identified using a cluster analysis based on patenting behaviour and comprises Manufacturing, Mining and quarrying, Electricity, gas and water supply, Construction, Wholesale and retail trade, Transport, storage and communication, Real estate, renting and business activities and Other.

**Table A.1**
Variable descriptions

| Variable | Description |
|---|---|
| Joiners | R&D-workers who joined the firm between year t–1 and t and who worked at another firm year t–1, divided by the firm's total R&D workforce[29] |
| Joiners from patenting firms | Joiners who worked at a firm which applied for at least one patent during the pre-sample period[30] |
| Joiners from patenting firms, intraregional | Joiners from patenting firms who worked at a firm located in the same region year t–1 |
| Joiners from patenting firms, interregional | Joiners from patenting firms who worked at a firm located in another region year t–1 |
| Joiners from non-patenting firms | Joiners who worked at a firm which did not apply for any patents during the pre-sample period |
| Joiners from non-patenting firms, intraregional | Joiners from non-patenting firms who worked at a firm located in the same region year t–1 |
| Joiners from non-patenting firms, interregional | Joiners from non-patenting firms who worked at a firm located in another region year t–1 |
| Leavers | R&D-workers who left the firm between year t–1 and t and who are working at another firm year t, divided by the firm's total R&D workforce |
| Leavers to patenting firms | Leavers who went to a firm which applied for at least one patent during the pre-sample period |
| Leavers to patenting firms, intraregional | Leavers to patenting firms who went to a firm located in the same region year t |
| Leavers to patenting firms, interregional | Leavers to patenting firms who went to a firm located in another region year t |
| Leavers to non-patenting firms | Leavers who went to a firm which did not apply for any patents during the pre-sample period |
| Leavers to non-patenting firms, intraregional | Leavers to non-patenting firms who went to a firm located in the same region year t |
| Leavers to non-patenting firms, interregional | Leavers to non-patenting firms who went to a firm located in another region year t |
| Other joiners | R&D-workers who joined the firm between year t–1 and t and who's background is unknown, divided by the firm's total R&D workforce |
| Graduates | R&D-workers who joined the firm between year t–1 and t and who graduated from a university year t–1, divided by the firm's total R&D workforce |
| Interaction variable between graduates and a dummy for firms with pre-sample patents | Graduates multiplied by a dummy variable which indicates if the firm the graduate starts to work for applied for a patent during the pre-sample period |
| Associate R&D workers | Associate R&D-workers, divided by the firm's total R&D workforce |
| Interaction variable between Joiners and firm size (total employment, log.) | Joiners multiplied by the natural logarithm of the firm's total R&D workforce |
| Interaction variable between Leavers and firm size (total employment, log.) | Leavers multiplied by the natural logarithm of the firm's total R&D workforce |
| Total R&D work force, logarithm | The natural logarithm of the firm's total R&D workforce |
| Capital stock, logarithm | The natural logarithm of the firm's capital stock, where the capital stock is estimated by the perpetual inventory method with a constant depreciation rate of five percent |
| FE, logarithm | Natural logarithm of Blundell et al.'s (1995) pre-sample estimator |
| FE, dummy | A dummy variable indicating if the firm applied for at least one patent during the pre-sample period |
| Dummy patent t–1 | A dummy variable indicating if the firm applied for a patent year t–1 |
| Dummy patent t–2 | A dummy variable indicating if the firm applied for a patent year t–2 |
| Labour mobility into the region | Total number of employees in the region year t who worked in a firm located in another region year t–1, divided by the total number of workers in the region year t |
| Labour mobility out from the region | Total number of workers who left the region year t–1 to take a new job in another region year t, divided by the total numbers of workers in the region year t |
| Intraregional labour mobility | Total number of workers in the region year t who had switched employers within the region between year t–1 and t, divided by the total number of workers in the region year t |
| Tertiary education rate | Share of those employed in the region with a completed tertiary education |
| Regional density | Number of people employed per square kilometre |
| Accessibility | Distance weighted sum of surrounding regions' number of patent applications. Intended to control for potential spatial autocorrelation |
| Diversity | Herfindahl index based on regional employment in 3–digit industries |

[29] The total R&D workforce is defined as the sum of R&D-workers and associate R&D-workers.
[30] The pre-sample period covers the years 1987–2000.

**Table A.2**
Descriptive statistics

| Variable | Mean | Std.dev. | Min | Max |
|---|---|---|---|---|
| Number of patents | 0.3572 | 12.50 | 0 | 1,691 |
| Patent *t*–1 | 0.4084 | 12.64 | 0 | 1,426 |
| Patent *t*–2 | 0.4627 | 13.82 | 0 | 1,426 |
| Dummy patent *t*–1 | 0.0337 | 0.18 | 0 | 1 |
| Dummy patent *t*–2 | 0.0347 | 0.18 | 0 | 1 |
| *Worker shares* | | | | |
| R&D workers | | | | |
| Joiners … | | | | |
| … from patenting firms | 0.0104 | 0.08 | 0 | 1 |
| … intraregional | 0.0057 | 0.06 | 0 | 1 |
| … interregional | 0.0047 | 0.05 | 0 | 1 |
| … from non-patenting firms | 0.0405 | 0.16 | 0 | 1 |
| … intraregional | 0.0274 | 0.14 | 0 | 1 |
| … interregional | 0.0131 | 0.09 | 0 | 1 |
| Leavers … | | | | |
| … to patenting firms | 0.0088 | 0.08 | 0 | 9 |
| … intraregional | 0.0048 | 0.06 | 0 | 8 |
| … interregional | 0.0040 | 0.05 | 0 | 2 |
| … to non-patenting firms | 0.0298 | 0.15 | 0 | 9 |
| … intraregional | 0.0188 | 0.12 | 0 | 6 |
| … interregional | 0.0110 | 0.09 | 0 | 5 |
| Graduates | 0.0056 | 0.04 | 0 | 1 |
| Other joiners | 0.0167 | 0.11 | 0 | 1 |
| Stayers | 0.5708 | 0.45 | 0 | 1 |
| Associate R&D workers | 0.3561 | 0.44 | 0 | 1 |
| *Firm size and capital stock* | | | | |
| Total employment | 79.8 | 449.9 | 1 | 19,817 |
| R&D relevant employment | 7.2 | 76.3 | 1 | 7,427 |
| Capital stock, millions SEK | 67.2 | 790.1 | 0 | 51,014 |
| *Pre-sample variables* | | | | |
| Pre-sample patents (FE) | 0.00004 | 0.0008 | 0 | 0.1 |
| Dummy, pre-sample patents | 0.0927 | 0.29 | 0 | 1 |
| *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 |
| | | | | |
| *Regional control variables* | | | | |
| Labour mobility into the region | 0.001 | 0.005 | 0.000 | 0.099 |
| Labour mobility out from the region | 0.045 | 0.123 | 0.000 | 2.059* |
| Intraregional labour mobility | 0.010 | 0.019 | 0.000 | 0.343 |
| Tertiary education rate | 0.070 | 0.048 | 0.009 | 0.274 |
| Regional density, no. of employees per $km^2$ | 9.240 | 12.664 | 0.036 | 67.845 |
| Accessibility measure, logarithm | –2.924 | 3.885 | –25.164 | 2.376 |
| Diversity | 0.127 | 0.026 | 0.083 | 0.257 |

**Note:** Regional control variables show statistics calculated across the 72 labour market regions.
***** In 2001, 1,618 workers left the labour market region Pajala, while 768 workers remained in the region. Hence, the share of leavers this year is 1,618 divided by 768, which is equal to 2.059.

**Table A.3**
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 | 0.4084 | 4.0323 | 0.0121 |
| Patent *t*–2 | 0.4627 | 4.3651 | 0.0125 |
| Dummy patent *t*–1 | 0.0337 | 0.3134 | 0.0052 |
| Dummy patent *t*–2 | 0.0347 | 0.3313 | 0.0044 |
| *Worker shares* | | | |
| R&D workers | | | |
| Joiners … | | | |
| … from patenting firms | 0.0104 | 0.0271 | 0.0087 |
| … intraregional | 0.0057 | 0.0151 | 0.0048 |
| … interregional | 0.0047 | 0.0120 | 0.0040 |
| … from non-patenting firms | 0.0405 | 0.0379 | 0.0407 |
| … intraregional | 0.0274 | 0.0207 | 0.0280 |
| … interregional | 0.0131 | 0.0172 | 0.0127 |
| Leavers … | | | |
| … to patenting firms | 0.0088 | 0.0228 | 0.0073 |
| … intraregional | 0.0048 | 0.0130 | 0.0039 |
| … interregional | 0.0040 | 0.0098 | 0.0034 |
| … to non-patenting firms | 0.0298 | 0.0376 | 0.0290 |
| … intraregional | 0.0188 | 0.0196 | 0.0187 |
| … interregional | 0.0110 | 0.0179 | 0.0103 |
| Graduates | 0.0056 | 0.0094 | 0.0052 |
| Other joiners | 0.0167 | 0.0165 | 0.0167 |
| Stayers | 0.5708 | 0.4448 | 0.5836 |
| Associate R&D workers | 0.3561 | 0.4643 | 0.3450 |
| *Firm size and capital stock* | | | |
| Total employment | 79.8 | 326.4 | 54.6 |
| R&D relevant employment | 7.2 | 33.1 | 4.6 |
| Capital stock, millions SEK | 67.2 | 304.4 | 43.0 |
| *Pre-sample variables* | | | |
| Pre-sample patents (FE) | 0.00004 | 0.0004 | 0 |
| Dummy, pre-sample patents | 0.0927 | 1.0000 | 0 |
| *Industry dummies* | | | |
| Agriculture | 0.0098 | 0.0028 | 0.0105 |
| Fishing | 0.00002 | 0 | 0.00002 |
| 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 |

**Table A.4**
Descriptive statistics: Small firms (0–49 employees)

| Variable | Mean | Std.dev. | Min | Max |
|---|---|---|---|---|
| Number of patents | 0.0433 | 0.70 | 0 | 87 |
| Patent *t*–1 | 0.0465 | 0.72 | 0 | 87 |
| Patent *t*–2 | 0.0490 | 0.72 | 0 | 87 |
| Dummy patent *t*–1 | 0.0155 | 0.12 | 0 | 1 |
| Dummy patent *t*–2 | 0.0159 | 0.12 | 0 | 1 |
| *Worker shares* | | | | |
| R&D workers | | | | |
| Joiners … | | | | |
| … from patenting firms | 0.0086 | 0.08 | 0 | 1 |
| … intraregional | 0.0050 | 0.06 | 0 | 1 |
| … interregional | 0.0036 | 0.05 | 0 | 1 |
| … from non-patenting firms | 0.0382 | 0.17 | 0 | 1 |
| … intraregional | 0.0271 | 0.14 | 0 | 1 |
| … interregional | 0.0111 | 0.09 | 0 | 1 |
| Leavers … | | | | |
| … to patenting firms | 0.0063 | 0.07 | 0 | 9 |
| … intraregional | 0.0037 | 0.06 | 0 | 8 |
| … interregional | 0.0026 | 0.04 | 0 | 1 |
| … to non-patenting firms | 0.0243 | 0.14 | 0 | 5 |
| … intraregional | 0.0163 | 0.12 | 0 | 5 |
| … interregional | 0.0080 | 0.08 | 0 | 5 |
| Graduates | 0.0049 | 0.04 | 0 | 1 |
| Other joiners | 0.0163 | 0.11 | 0 | 1 |
| Stayers | 0.6240 | 0.45 | 0 | 1 |
| Associate R&D workers | 0.3081 | 0.44 | 0 | 1 |
| *Firm size and capital stock* | | | | |
| Total employment | 10.3 | 11.9 | 1 | 49 |
| R&D relevant employment | 2.1 | 2.6 | 1 | 37 |
| Capital stock, millions SEK | 8.3 | 115.0 | 0 | 9,683 |
| *Pre-sample variables* | | | | |
| Pre-sample patents (FE) | 0.000004 | 0.00 | 0 | 0.002 |
| Dummy, pre-sample patents | 0.0491 | 0.22 | 0 | 1 |
| *Industry dummies* | | | | |
| Agriculture | 0.0099 | 0.10 | 0 | 1 |
| Fishing | 0.00003 | 0.01 | 0 | 1 |
| Mining and quarrying | 0.0003 | 0.02 | 0 | 1 |
| Manufacturing | 0.0935 | 0.29 | 0 | 1 |
| Electricity, gas and water supply | 0.0048 | 0.07 | 0 | 1 |
| Construction | 0.0166 | 0.13 | 0 | 1 |
| Wholesale and retail trade | 0.1315 | 0.34 | 0 | 1 |
| Hotels and restaurants | 0.0014 | 0.04 | 0 | 1 |
| Transport, storage and communication | 0.0095 | 0.10 | 0 | 1 |
| Financial intermediation | 0.0017 | 0.04 | 0 | 1 |
| Real estate, renting and business activities | 0.4286 | 0.49 | 0 | 1 |
| Education | 0.0181 | 0.13 | 0 | 1 |
| Health and social work | 0.2620 | 0.44 | 0 | 1 |
| Other community, social and personal service | 0.0167 | 0.13 | 0 | 1 |
| Other | 0.0053 | 0.07 | 0 | 1 |
| Number of observations | 72,431 | | | |

**Table A.5**
Mean statistics, distributed on firm's innovative history: Small firms (0–49 employees)

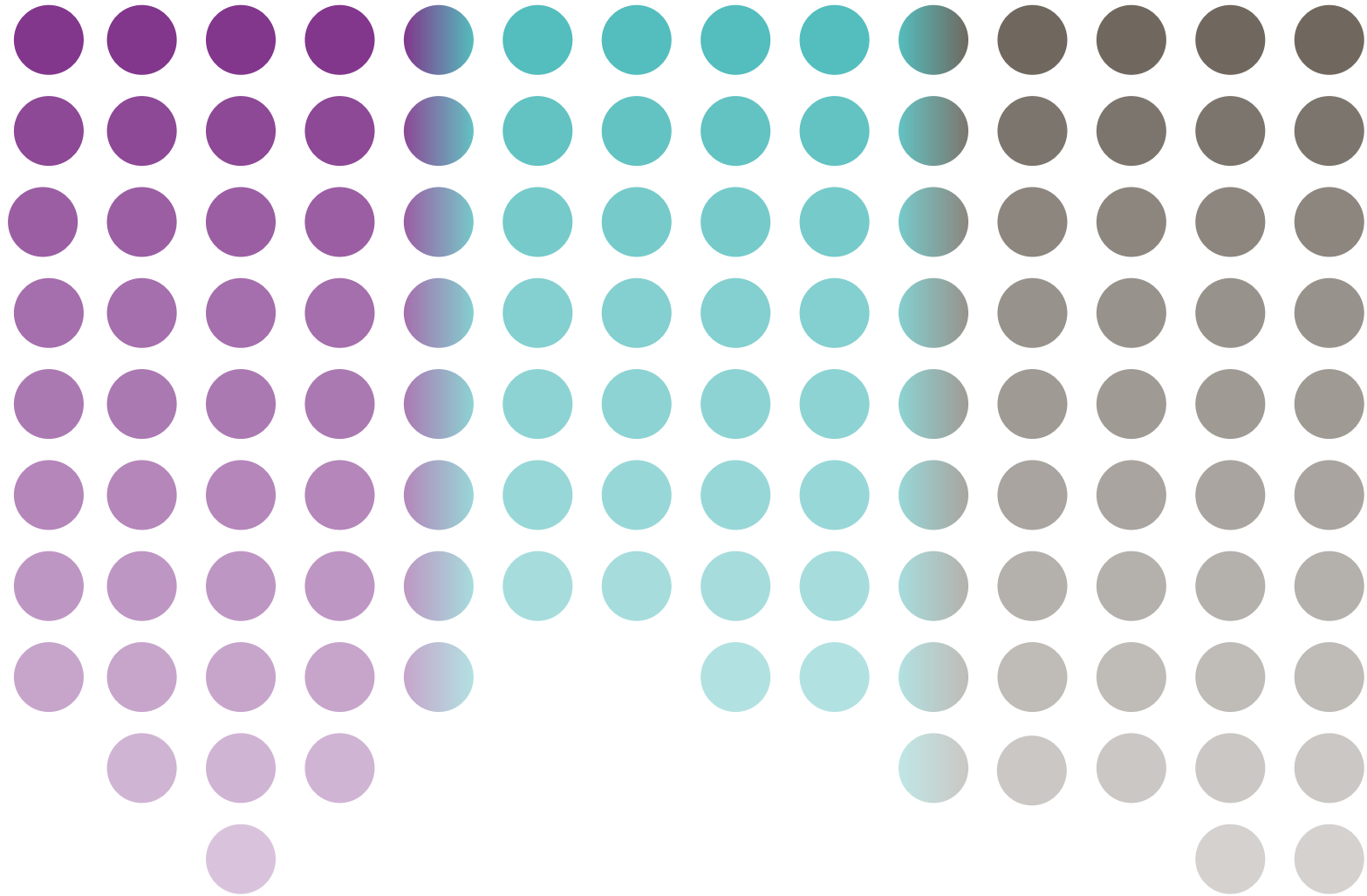
| Variable | All firms | Firms with pre-sample patents | Firms without pre-sample patents |
|---|---|---|---|
| Number of patents | 0.0433 | 0.7633 | 0.0061 |
| Patent *t*–1 | 0.0465 | 0.8142 | 0.0058 |
| Patent *t*–2 | 0.0490 | 0.8495 | 0.0057 |
| Dummy patent *t*–1 | 0.0155 | 0.2570 | 0.0031 |
| Dummy patent *t*–2 | 0.0159 | 0.2744 | 0.0025 |
| *Worker shares* | | | |
| R&D workers | | | |
| Joiners … | | | |
| … from patenting firms | 0.0086 | 0.0306 | 0.0075 |
| … intraregional | 0.0050 | 0.0188 | 0.0043 |
| … interregional | 0.0036 | 0.0118 | 0.0032 |
| … from non-patenting firms | 0.0382 | 0.0417 | 0.0380 |
| … intraregional | 0.0271 | 0.0239 | 0.0273 |
| … interregional | 0.0111 | 0.0178 | 0.0107 |
| Leavers … | | | |
| … to patenting firms | 0.0063 | 0.0228 | 0.0055 |
| … intraregional | 0.0037 | 0.0145 | 0.0031 |
| … interregional | 0.0026 | 0.0082 | 0.0023 |
| … to non-patenting firms | 0.0243 | 0.0376 | 0.0236 |
| … intraregional | 0.0163 | 0.0213 | 0.0160 |
| … interregional | 0.0080 | 0.0163 | 0.0075 |
| Graduates | 0.0049 | 0.0110 | 0.0046 |
| Other joiners | 0.0163 | 0.0194 | 0.0161 |
| Stayers | 0.6240 | 0.4997 | 0.6304 |
| Associate R&D workers | 0.3081 | 0.3976 | 0.3034 |
| *Firm size and capital stock* | | | |
| Total employment | 10.3 | 20.8 | 9.7 |
| R&D relevant employment | 2.1 | 3.3 | 2.0 |
| Capital stock, millions SEK | 8.3 | 11.8 | 8.1 |
| *Pre-sample variables* | | | |
| Pre-sample patents (FE) | 0.000004 | 0.0001 | 0 |
| Dummy, pre-sample patents | 0.0491 | 1 | 0 |
| *Industry dummies* | | | |
| Agriculture | 0.0099 | 0.0062 | 0.0101 |
| Fishing | 0.00003 | 0 | 0.00003 |
| Mining and quarrying | 0.0003 | 0.0006 | 0.0003 |
| Manufacturing | 0.0935 | 0.4023 | 0.0775 |
| Electricity, gas and water supply | 0.0048 | 0.0017 | 0.0050 |
| Construction | 0.0166 | 0.0107 | 0.0169 |
| Wholesale and retail trade | 0.1315 | 0.1875 | 0.1286 |
| Hotels and restaurants | 0.0014 | 0.0000 | 0.0015 |
| Transport, storage and communication | 0.0095 | 0.0028 | 0.0098 |
| Financial intermediation | 0.0017 | 0.0003 | 0.0018 |
| Real estate, renting and business activities | 0.4286 | 0.3669 | 0.4318 |
| Education | 0.0181 | 0.0039 | 0.0189 |
| Health and social work | 0.2620 | 0.0104 | 0.2750 |
| Other community, social and personal service | 0.0167 | 0.0011 | 0.0175 |
| Other | 0.0053 | 0.0056 | 0.0053 |
| Number of observations | 72,431 | 3,557 | 68,874 |

**Table A.6**
Descriptive statistics: Larger firms (50– employees)

| Variable | Mean | Std.dev. | Min | Max |
|---|---|---|---|---|
| Number of patents | 1.5391 | 27.21 | 0 | 1,691 |
| Patent *t*–1 | 1.6895 | 26.85 | 0 | 1,426 |
| Patent *t*–2 | 1.8416 | 28.69 | 0 | 1,426 |
| Dummy patent *t*–1 | 0.1023 | 0.30 | 0 | 1 |
| Dummy patent *t*–2 | 0.1055 | 0.31 | 0 | 1 |
| *Worker shares* | | | | |
| R&D workers | | | | |
| Joiners … | | | | |
| … from patenting firms | 0.0173 | 0.08 | 0 | 1 |
| … intraregional | 0.0086 | 0.06 | 0 | 1 |
| … interregional | 0.0087 | 0.06 | 0 | 1 |
| … from non-patenting firms | 0.0491 | 0.15 | 0 | 1 |
| … intraregional | 0.0283 | 0.11 | 0 | 1 |
| … interregional | 0.0207 | 0.10 | 0 | 1 |
| Leavers … | | | | |
| … to patenting firms | 0.0180 | 0.09 | 0 | 2 |
| … intraregional | 0.0088 | 0.06 | 0 | 2 |
| … interregional | 0.0092 | 0.07 | 0 | 2 |
| … to non-patenting firms | 0.0507 | 0.19 | 0 | 9 |
| … intraregional | 0.0283 | 0.14 | 0 | 6 |
| … interregional | 0.0224 | 0.11 | 0 | 4 |
| Graduates | 0.0082 | 0.04 | 0 | 1 |
| Other joiners | 0.0181 | 0.09 | 0 | 1 |
| Stayers | 0.3704 | 0.36 | 0 | 1 |
| Associate R&D workers | 0.5369 | 0.39 | 0 | 1 |
| *Firm size and capital stock* | | | | |
| Total employment | 341.6 | 936.7 | 50 | 19,817 |
| R&D relevant employment | 26.5 | 165.2 | 1 | 7,427 |
| Capital stock, millions SEK | 289.2 | 1692 | 0 | 51,013 |
| *Pre-sample variables* | | | | |
| Pre-sample patents (FE) | 0.0002 | 0.002 | 0 | 0.1 |
| Dummy, pre-sample patents | 0.2570 | 0.44 | 0 | 1 |
| *Industry dummies* | | | | |
| Agriculture | 0.0090 | 0.09 | 0 | 1 |
| Fishing | 0.0000 | 0.00 | 0 | 0 |
| Mining and quarrying | 0.0034 | 0.06 | 0 | 1 |
| Manufacturing | 0.4412 | 0.50 | 0 | 1 |
| Electricity, gas and water supply | 0.0233 | 0.15 | 0 | 1 |
| Construction | 0.0424 | 0.20 | 0 | 1 |
| Wholesale and retail trade | 0.1328 | 0.34 | 0 | 1 |
| Hotels and restaurants | 0.0029 | 0.05 | 0 | 1 |
| Transport, storage and communication | 0.0455 | 0.21 | 0 | 1 |
| Financial intermediation | 0.0007 | 0.03 | 0 | 1 |
| Real estate, renting and business activities | 0.1972 | 0.40 | 0 | 1 |
| Education | 0.0219 | 0.15 | 0 | 1 |
| Health and social work | 0.0440 | 0.21 | 0 | 1 |
| Other community, social and personal service | 0.0267 | 0.16 | 0 | 1 |
| Other | 0.0090 | 0.09 | 0 | 1 |
| Number of observations | 19,237 | | | |

**Table A.7**
Mean statistics, distributed on firm's innovative history: Larger firms (50– employees)

| Variable | All firms | Firms with pre-sample patents | Firms without pre-sample patents |
|---|---|---|---|
| Number of patents | 1.5391 | 5.8934 | 0.0334 |
| Patent *t*–1 | 1.6895 | 6.1576 | 0.0408 |
| Patent *t*–2 | 1.8416 | 6.5320 | 0.0424 |
| Dummy patent *t*–1 | 0.1023 | 0.3540 | 0.0153 |
| Dummy patent *t*–2 | 0.1055 | 0.3722 | 0.0133 |
| *Worker shares* | | | |
| R&D workers | | | |
| Joiners … | | | |
| … from patenting firms | 0.0173 | 0.0246 | 0.0148 |
| … intraregional | 0.0086 | 0.0125 | 0.0072 |
| … interregional | 0.0087 | 0.0121 | 0.0076 |
| … from non-patenting firms | 0.0491 | 0.0352 | 0.0539 |
| … intraregional | 0.0283 | 0.0185 | 0.0317 |
| … interregional | 0.0207 | 0.0167 | 0.0221 |
| Leavers … | | | |
| … to patenting firms | 0.0180 | 0.0228 | 0.0163 |
| … intraregional | 0.0088 | 0.0119 | 0.0077 |
| … interregional | 0.0092 | 0.0109 | 0.0086 |
| … to non-patenting firms | 0.0507 | 0.0375 | 0.0552 |
| … intraregional | 0.0283 | 0.0185 | 0.0317 |
| … interregional | 0.0224 | 0.0191 | 0.0235 |
| Graduates | 0.0082 | 0.0083 | 0.0081 |
| Other joiners | 0.0181 | 0.0143 | 0.0194 |
| Stayers | 0.3704 | 0.4054 | 0.3583 |
| Associate R&D workers | 0.5369 | 0.5123 | 0.5455 |
| *Firm size and capital stock* | | | |
| Total employment | 341.6 | 546.4 | 270.8 |
| R&D relevant employment | 26.5 | 54.5 | 16.9 |
| Capital stock, millions SEK | 289.2 | 515.0 | 211.1 |
| *Pre-sample variables* | | | |
| Pre-sample patents (FE) | 0.0002 | 0.0006 | 0.0000 |
| Dummy, pre-sample patents | 0.2570 | 1.0000 | 0.0000 |
| *Industry dummies* | | | |
| Agriculture | 0.0090 | 0.0004 | 0.0120 |
| Fishing | 0.0000 | 0.0000 | 0.0000 |
| Mining and quarrying | 0.0034 | 0.0071 | 0.0021 |
| Manufacturing | 0.4412 | 0.7497 | 0.3345 |
| Electricity, gas and water supply | 0.0233 | 0.0107 | 0.0276 |
| Construction | 0.0424 | 0.0216 | 0.0495 |
| Wholesale and retail trade | 0.1328 | 0.0690 | 0.1548 |
| Hotels and restaurants | 0.0029 | 0.0000 | 0.0039 |
| Transport, storage and communication | 0.0455 | 0.0158 | 0.0558 |
| Financial intermediation | 0.0007 | 0.0000 | 0.0010 |
| Real estate, renting and business activities | 0.1972 | 0.1082 | 0.2279 |
| Education | 0.0219 | 0.0018 | 0.0288 |
| Health and social work | 0.0440 | 0.0016 | 0.0587 |
| Other community, social and personal service | 0.0267 | 0.0097 | 0.0325 |
| Other | 0.0090 | 0.0042 | 0.0106 |
| Number of observations | 19,237 | 4,943 | 14,294 |



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