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Labour Mobility, Knowledge Flows and Innovation

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Labour Mobility, Knowledge Flows and Innovation*

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Abstract

By utilising a Swedish unique matched employer-employee dataset, which 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 statistically and economically highly significant for knowledge workers that have previously worked in a patenting firm (the learning-by-hiring effect), whereas only limited impact could be detected for firms losing knowledge workers (the-learning-by-diaspora effect). Finally, the effect is more pronounced when the joining worker originates from within the same region.

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

JEL classification: J24, O31, R23

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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 refers to 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). 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, a negative relationship between innovation and mobility of highly qualified labour has also been established in previous literature (Balsvik, 2011; Parrotta and Pozzoli, 2012).

The purpose of this paper is to examine the influence of mobility of knowledge (R&D) workers on innovation at the firm level taking into account both learning by hiring (firms receiving knowledge workers) and the diaspora effect (firms loosing knowledge workers). We utilise a unique, matched dataset of employers and employees in Sweden 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.[2] 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.

Among previous research contributions, the one most similar to the present analysis is conducted by Kaiser et al. (2015). They implement a similar set of data matching employers and employees for Denmark, where detailed measures of knowledge workers building on both functional occupation and level of education is implemented. However, we extend their analysis in a number of ways, thereby offering new insights regarding the influence of labour mobility on firm innovativeness. First, we include graduates who enter the labour market as a separate category of knowledge workers, while Kaiser et al. (2015) include new graduates together with joiners of unknown origin in a category named “Other joiners”.[3] This extension could be potentially important since hiring researchers from universities have been shown to impact firms’ patenting activities (Ejsing et al., 2013). Second, we have access to a considerably longer time series which comprise the entire business cycle, and a wider set of controls.[4] Whereas these aspects complement and extend the Kaiser et al.’s analysis, we also contribute with some completely new insights regarding the influence of labour mobility on firm innovativeness. Our third contribution is that we emphasise the geographical dimension of knowledge flows, i.e., how inter- versus intra-regional mobility influences innovation output, an issue which has not been addressed in previous work but may entail important policy implications. In addition, throughout the empirical analysis we control for a number of variables at the industry and regional levels. Last but not least we believe that focusing on a country with a different institutional set-up may bolster the robustness of the empirical results

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[2] Similar comprehensive data that are accessible for research can only, as far as we know, be found in Denmark, Finland and Norway.

[3] 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."

[4] The Danish study stretches over 2000–2004 while our analysis comprises the years 2001–2008.

for Denmark. While Denmark ranks high in terms of labour flexibility as measured by the OECD, Sweden is regarded as having a much more rigid labour market.[5] Another difference between the two countries refers to the size distribution of firms, where Sweden has a considerably higher share of large multinational firms.

Our estimations support the proposition that the mobility of R&D workers has a positive impact on firm innovation output. More precisely, primarily firms receiving knowledge workers benefit while no such effect could be detected for firms loosing (sourcing firm) employees in most of the estimations. If both the sourcing and the receiving firm is an innovator, the effect is particularly pronounced. Both forward and backward effects are stronger when labour moves within – rather than across – regional borders, with obvious implications for regional policies.

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 (Hoisl, 2007). The latter

[5] See e.g. Andersson (2012).

effect may occur as a result of costlier 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. Malcomson (1997) refers to this as a hold-up situation where strong labour unions may deter future investments in innovation. Previous theoretical models thus 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 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. 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 firms’ 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., (2015) 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. The authors explain the positive outcomes to extended and improved networks, accelerating the knowledge flows. Kaiser et al. (2015) is one of the few studies that examine innovation outputs rather than inputs in terms of previous patent citations.[6] However, the authors do not consider 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) examines how labour mobility influences patenting activities, or more precisely, inventor productivity. Her analysis, which is based on German data for the period 1993 to 1997, combines individual data on inventors with a selected number of variables aggregated at the industry level. At the individual level the results imply a positive association between mobility and inventor productivity, indicating a better match between employers and employees and enhanced knowledge spill-overs.[7] But Hoisl also concludes that there is a simultaneous relationship where productive inventors become less mobile because they have found good matches. Despite the impressive data gathering behind this analysis it suffers from a number of weaknesses. In particular, the empirical analysis is based on questionnaire data where more than two thirds of the respondents abstained from answering. The representability of the respondents is unclear, and, as discussed by Hoisl (2007), may create problems with selection bias. Less serious is the partial aspect of the analysis, i.e. it only considers the receiving firms and not those that the inventors have left. To summarize, the few previously conducted studies suggest that labour mobility has a positive effect on invention and innovative behaviours.[8]

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[6] 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.

[7] For an early analysis of mobility and matching, see Topel and Ward (1992).

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

In addition, on a more aggregate level of analysis the geographical dimension of labour mobility has been addressed in the previous literature. There is a huge literature providing empirical evidence that knowledge spill-overs diminish with distance, and 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). 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). The dominant predicament is that dense areas characterized by mobility are conducive to innovation and productivity. 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 issue of whether inter-regional mobility is more instrumental in producing innovation than intra-regional has, to our knowledge, not been subject to a rigorous empirical analysis.

Finally, there is also a literature on labour market regulations and innovativeness. Regulatory impediments to mobility may be of an informal or formal character (Breschi and Lissoni, 2005; 2009).[9] As regards regulation we do not consider this to be relevant for the current analysis since firms are operating in the same national regulatory context, even though there may be regional variations due to norms and traditions. Rather, comparing our results with the Danish study seems more relevant.

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.

[9] 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 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).

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.

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.

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.[10] Moreover, human capital is defined as a composite of the firm's own experienced workers and experienced workers hired from other firms,

[10] Following Vilalta-Bufi (2008) we exclude physical capital to make the model more tractable.

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

In equation (2), λ_i^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 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:

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

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, 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 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. Firms' knowledge upgrading thus involves four types of human capital: joiners, leavers, stayers and new workers. Furthermore, joiners and leavers can be divided into two subgroups depending on whether they move across regional borders.

Our hypotheses are based on the theoretical framework outlined above and 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

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)[11]. 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.

R&D workers are further divided into one of the following seven groups, depending on their labour market status:[12]

- *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.

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.

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

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,

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

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 γ-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.[13] This enables us to express the knowledge production function as

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

[13] 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.

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,

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

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 using the negative binomial estimator,[14] 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 control variables contained in vector **X**.

Firm-Specific Heterogeneity

According to Blundell et al. (1995), firm-specific heterogeneity in innovative capacity can be controlled for if we include a dummy variable equal to one if the firm had ever innovated during a pre-sample period and zero otherwise, along with the mean number of

[14] Note that, as shown by Blundell et al. (2002), using fixed effects in a dynamic count data model will yield inconsistent parameter estimates. This renders the negative binomial estimator with fixed effects invalid given our setting where we control for state dependence by using an indicator variable for previous patent applications. Instead, we follow Blundell et al. (2002) and use information about firms' patent application history during a pre-sample period to account for firm heterogeneity.

innovations during the pre-sample period.[15] 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,[16]

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

$P_{i,t}$ 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.

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

[15] This will also account for the so-called zero-inflation problem that arises in settings with an excess number of zeros.
[16] We have also run regressions using the original pre-sample estimator by Blundell et al. (1995), and the results are basically unaltered.

deflator. We choose the pre-sample period 1987–2000 to create the initial capital stocks used in the estimation period beginning in 2001.

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 specialisation (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. 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.

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.[17] 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). 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 sector tends to pay more attention to applied research and experimental research.[18] Furthermore, we only include firms with at least one R&D relevant worker[19], 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

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[17] 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.
[18] The data can be found at the OECD website, science, technology and patents (http://stats.oecd.org).
[19] R&D relevant workers comprise R&D workers and associate R&D workers.

distinguish between intra-regional and inter-regional labour mobility.[20] 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

Descriptive Statistics

Descriptive statistics of the data sample and detailed variable descriptions are presented in Tables A.1–A.3 in the Appendix, in which firms are also divided into two subgroups based on their pre-sample period innovation status. This enables us to get indications of systematic differences in labour mobility for firms that have previously applied for patents and for firms without any previous patent applications.[21]

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 43.0 million Swedish Krona). The average number of

[20] 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 commute. They thus comprise local labour markets and are delineated based on commuting intensities. According to this definition, there are 72 FA-regions in Sweden.

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

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.

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.

Firm Learning by Hiring

The results from the negative binomial regressions are shown in Table 1. Column 1 distinguish between joiners and leavers, while column 2 also considers the sourcing and receiving firms' innovative status.[22] The specification in column 3 separates graduates from other joiners and column 4 adds the spatial dimension to the analysis, where we distinguish between intra- and inter-regional mobility of workers. Regional control variables as well as more detailed industry dummies are added in column 5.

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, 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.

[22] The regression results in column 2 are comparable to the specification used in Kaiser et al. (2015).

Table 1
Results from negative binomial regressions

	(1)	(2)	(3)	(4)	(5)
R&D workers					
Joiners …	0.679***	–	–	–	–
	(5.00)				
… from patenting firms	–	0.951***	0.947***	–	–
		(5.25)	(5.23)		
… intra-regional	–	–	–	1.108***	0.942***
				(5.28)	(4.35)
… inter-regional	–	–	–	0.655**	0.469
				(2.05)	(1.56)
… from non-patenting firms	–	0.524***	0.525***	–	–
		(2.94)	(2.94)		
… intra-regional	–	–	–	0.539**	0.518**
				(2.53)	(2.50)
… inter-regional	–	–	–	0.508*	0.484
				(1.68)	(1.61)
Leavers …	–0.0206	–	–	–	–
	(–0.16)				
… to patenting firms	–	0.407*	0.406*	–	–
		(1.66)	(1.66)		
… intra-regional	–	–	–	0.473	0.343
				(1.52)	(1.40)
… inter-regional	–	–	–	0.265	–0.0961
				(0.48)	(–0.20)
… to non-patenting firms	–	–0.335	–0.332	–	–
		(–1.64)	(–1.63)		
… intra-regional	–	–	–	–0.353	–0.256
				(–1.22)	(–1.00)
… inter-regional	–	–	–	–0.300	–0.329
				(–1.00)	(–1.12)
Other joiners incl. graduates	0.175	0.189	–	–	–
	(0.65)	(0.70)			
Other joiners excl. graduates	–	–	0.252	0.249	0.210
			(0.79)	(0.78)	(0.66)
Graduates	–	–	0.484	0.475	0.278
			(0.65)	(0.64)	(0.34)
Interaction variable between graduates and a dummy for firms with pre-sample patents	–	–	–0.869	–0.850	–1.041
			(–0.85)	(–0.83)	(–1.00)
Associate R&D workers	–0.0321	–0.0304	–0.0315	–0.0338	–0.0869
	(–0.39)	(–0.37)	(–0.39)	(–0.42)	(–1.08)
Total R&D work force, logarithm	0.230***	0.231***	0.232***	0.233***	0.257***
	(10.34)	(10.36)	(10.38)	(10.41)	(10.85)
Capital stock, logarithm	0.0541***	0.0546***	0.0544***	0.0545***	0.0587***
	(3.60)	(3.62)	(3.61)	(3.63)	(3.76)
FE, logarithm	0.332***	0.332***	0.331***	0.330***	0.308***
	(15.41)	(15.50)	(15.48)	(15.52)	(14.61)
FE, dummy	2.775***	2.770***	2.778***	2.775***	2.624***
	(26.73)	(26.91)	(26.78)	(26.82)	(25.70)
Dummy patent t–1	2.719***	2.713***	2.714***	2.712***	2.554***
	(36.46)	(36.33)	(36.37)	(36.52)	(36.48)
Dummy patent t–2	0.927***	0.922***	0.922***	0.923***	0.828***
	(12.22)	(12.17)	(12.17)	(12.23)	(11.90)
Labour mobility into the region	–	–	–	–	2.148
					(0.15)
Labour mobility out from the region	–	–	–	–	0.686
					(0.52)
Intra-regional labour mobility	–	–	–	–	–0.432
					(–0.18)
Tertiary education rate	–	–	–	–	–1.518
					(–0.72)
Regional density	–	–	–	–	–0.0618**
					(–2.07)
Accessibility	–	–	–	–	0.218***
					(2.61)
Specialisation	–	–	–	–	5.794
					(0.52)
Industry dummies	1-digit NACE	1-digit NACE	1-digit NACE	1-digit NACE	3-digit NACE
Year dummies	YES	YES	YES	YES	YES
Regional dummies	YES	YES	YES	YES	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.

The effect is stronger for R&D labour originating from a patenting firm as compared to those arriving from non-patenting firms. This illustrates that innovative firms seem to have a more relevant absorptive capacity and are better organised to exploit new knowledge, generating stronger effects for R&D-labour.[23]

Considering the geographic dimension in column 4 and 5, intra-regional joiners both from patenting firms and non-patenting firms tend to have a higher impact on innovation in comparison with inter-regional joiners, a result that is in line with our hypothesis. The effect is particularly strong for intra-regional joiners from patenting firms.

Both graduates and other joiners fail to achieve statistical significance at any reasonable level. Interacting graduates with a dummy for innovative firms in the pre-sample period also failed to attain significance throughout the estimations.

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, which switches to a negative and non-significant 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 as shown in column 4 and 5. For joiners, the results demonstrated a positive and, in most cases, a strongly significant effect for both intra- and inter-regional mobility, although the effect was most pronounced for the former type of mobility. Hence, the general pattern for leavers resembles the one for joiners in the case of R&D-workers going to patenting firms, but the result is not statistically significant. When R&D-workers go to non-patenting firms, the effect switches to negative and remains insignificant. Finally, it can be noted that among the remaining labour-variables distributed on firms, only the stock of firms’ R&D-workers positively affect innovation.

[23] This basically captures absorption capacity in the theoretical model.

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 5 in Table 1. Regional density, on the other hand, turns up with an unexpected negative sign, 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.

The positive and highly 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. Finally, a more specialized local industry structure seems to be conducive to innovation as shown by the positive sign for this variable. However, the specialisation variable is insignificantly estimated and this interpretation must therefore be taken cautiously.

Relative patent productivities

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

Starting with column 2, joiners from patenting and non-patenting firms are on average 5.1 and 3.3 times more patent productive than stayers, respectively. Thus, employing R&D workers has not only a statistically significant effect on innovation, but the effect is also economically large.

Table 2
Estimated relative patent productivities

	(1)	(2)	(3)	(4)	(5)
R&D workers,					
Joiners …	3.952***	–	–	–	–
… from patenting firms	–	5.117***	5.082***	–	–
… intra-regional	–	–	–	5.755***	4.665***
… inter-regional	–	–	–	3.811**	2.825
… from non-patenting firms	–	3.268***	3.263***	–	–
… intra-regional	–	–	–	3.313**	3.016**
… inter-regional	–	–	–	3.180*	2.883
Leavers …	0.910	–	–	–	–
… to patenting firms	–	2.762*	2.750*	–	–
… intra-regional	–	–	–	3.030	2.335
… inter-regional	–	–	–	2.137	0.626
… to non-patenting firms	–	–0.450	–0.431	–	–
… intra-regional	–	–	–	–0.515	0.004
… inter-regional	–	–	–	–0.288	–0.280
Other joiners incl. graduates	1.761	1.818	–	–	–
Other joiners excl. graduates	–	–	2.086	2.069	1.817
Graduates	–	–	0.959	–	–
… for firms with pre-sample patents	–	–	–0.659	–0.609	–1.969
… for firms without pre-sample patents	–	–	3.086	3.039	2.082
Associate R&D workers	0.860	0.868	0.864	0.855	0.662
Industry dummies	1-digit NACE	1-digit NACE	1-digit NACE	1-digit NACE	3-digit NACE
Regional control variables	NO	NO	NO	NO	YES

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

We also find that R&D workers leaving a firm to join a patenting firm yield strong effects on innovation; on average these type of workers are 2.8 times as patent productive as stayers. Our results are rather close to those found by Kaiser et al. (2015) for the Danish labour market where joiners from patenting and non-patenting firms were on average 6.6 and 2.3 times as patent productive than stayers while leavers to patenting firms were found to be 3.3 as productive as stayers in Denmark.

Next, when we distinguish between intra- and inter-regional mobility of R&D workers in column 4, we find that the positive effect can mainly be attributed intra-regional mobility and solely confined to joiners. The difference in relative patent productivities for intra- and inter-regional labour mobility is particularly large for joiners from patenting firms, while we detect almost no difference for joiners from non-patenting firms and leavers. Adding regional control variables and more detailed industry dummies in column 5 reduces the effects somewhat and also renders the estimated effects for inter-regional joiners statistically insignificant.

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.

VII. Conclusion

This paper presents an empirical analysis of the relationship between labour mobility, knowledge diffusion 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. 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 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 and dominated by intra-regional labour mobility which has the strongest effect on innovation, even though also inter-regional flows influence innovation in some of the estimations. Finally, 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).

The results have important and highly relevant policy implications. They corroborate and strengthen the results of the Danish analysis since, despite introducing and controlling for a set of new variables, mobility is shown to strongly impact innovation. Moreover, the marked effect of intra-regional mobility carries important policy implications at the regional as well as at the more aggregated levels. Removing obstacles and facilitating intra-regional mobility may be a way to enhance cross-fertilization of knowledge, improve matching and strengthening spill-overs 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

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[24]
Joiners from patenting firms	Joiners who worked at a firm which applied for at least one patent during the pre-sample period[25]
Joiners from patenting firms, intra-regional	Joiners from patenting firms who worked at a firm located in the same region year t–1
Joiners from patenting firms, inter-regional	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, intra-regional	Joiners from non-patenting firms who worked at a firm located in the same region year t–1
Joiners from non-patenting firms, inter-regional	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, intra-regional	Leavers to patenting firms who went to a firm located in the same region year t
Leavers to patenting firms, inter-regional	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, intra-regional	Leavers to non-patenting firms who went to a firm located in the same region year t
Leavers to non-patenting firms, inter-regional	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
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
Intra-regional 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
Specialisation	Herfindahl index based on regional employment in 3-digit industries

[24] The total R&D workforce is defined as the sum of R&D-workers and associate R&D-workers.
[25] 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	0.3895	14.29	0	2,461
Patent *t*–2	0.4034	15.07	0.0	2,879
Dummy patent *t*–1	0.0337	0.18	0	1
Dummy patent *t*–2	0.0347	0.18	0.0	1
Worker shares				
R&D workers				
Joiners …				
… from patenting firms	0.0104	0.08	0	1
… intra-regional	0.0057	0.06	0	1
… inter-regional	0.0047	0.05	0	1
… from non-patenting firms	0.0405	0.16	0	1
… intra-regional	0.0274	0.14	0	1
… inter-regional	0.0131	0.09	0	1
Leavers …				
… to patenting firms	0.0088	0.08	0	9
… intra-regional	0.0048	0.06	0	8
… inter-regional	0.0040	0.05	0	2
… to non-patenting firms	0.0298	0.15	0	9
… intra-regional	0.0188	0.12	0	6
… inter-regional	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	79.7942	449.93	1	19,817
R&D relevant employment	7.2031	76.34	1	7,427
Capital stock, millions SEK	67.2327	790.10	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
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	44.8460	24.29	0	67.8
Accessibility measure, logarithm	–1.9360	2.02	–25.2	2.4
Specialisation	0.1140	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 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	0.3895	4.1064	0.0096
Patent *t*–2	0.4034	4.2718	0.0080
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
… intra-regional	0.0057	0.0151	0.0048
… inter-regional	0.0047	0.0120	0.0040
… from non-patenting firms	0.0405	0.0379	0.0407
… intra-regional	0.0274	0.0207	0.0280
… inter-regional	0.0131	0.0172	0.0127
Leavers …			
… to patenting firms	0.0088	0.0228	0.0073
… intra-regional	0.0048	0.0130	0.0039
… inter-regional	0.0040	0.0098	0.0034
… to non-patenting firms	0.0298	0.0376	0.0290
… intra-regional	0.0188	0.0196	0.0187
… inter-regional	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	79.7942	326.4378	54.5866
R&D relevant employment	7.2031	33.0713	4.5593
Capital stock, millions SEK	67.2327	304.4033	42.9932
Pre-sample variables			
Pre-sample patents (FE)	0.00004	0.0004	0
Dummy, pre-sample patents	0.0927	1.0000	0
Regional control variables			
Labour mobility into the region	0.0015	0.0015	0.0015
Labour mobility out from the region	0.0101	0.0126	0.0098
Intra-regional labour mobility	0.0109	0.0105	0.0109
Tertiary education rate	0.1863	0.1190	0.1285
Regional density, no. of employees per km^2	44.8460	40.4760	45.2927
Accessibility measure, logarithm	–1.9360	–1.7966	–1.9503
Specialisation	0.1140	0.1185	0.1136
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

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