Labor Mobility and Patenting Activity

Ulrich Kaiser
University of Zurich, Institute for Strategy and Business Economics, Plattenstr. 14, 8032 Zurich, Switzerland, ulrich.kaiser@isu.uzh.ch; Centre for Economic and Business Research at Copenhagen Business School, Centre for European Economic Research and Centre for Industrial Economics at the University of Copenhagen.

Hans Christian Kongsted
University of Copenhagen, Dept. of Economics, Studiestræde 6, 1455 Copenhagen K, Denmark, kongsted@econ.ku.dk; Centre for Economic and Business Research at Copenhagen Business School; Centre for Industrial Economics at the University of Copenhagen; Centre for Applied Microeconometrics at the University of Copenhagen.

Thomas Rønde
Copenhagen Business School, Department of Innovation and Organizational Economics, Kilevej 14A, 2000 Frederiksberg, Denmark, thr.ino@cbs.dk; Centre for Economic and Business Research at Copenhagen Business School; Centre for European Economic Research; Centre for Industrial Economics at the University of Copenhagen and Centre for Economic Policy Research.

We measure the quantitative importance of labor mobility as a vehicle for the transmission of knowledge and skills across firms. Our empirical analysis rests upon a theoretical model of labor mobility. We derive empirically testable hypotheses which are tested using a unique data set that matches all applications of Danish firms at the European Patent Office to linked employer–employee register data for the years 1999–2002. We find that mobile R&D workers contribute more to patenting activity than immobile R&D workers. Furthermore, R&D workers who have previously been employed by a patenting firm have a larger effect on patenting activity than R&D workers without this experience. Labor mobility is shown to be important for firm-level invention. For firms that patented prior to 1999, one additional worker joining the firm from an outside patenting firm relates to an increase in the number of patent applications that corresponds to a 14.1 percent increase in the mean number of annual patent applications. We also find that mobility of R&D workers increases the joint patenting activity of the firms involved, confirming the importance of labor mobility for aggregate innovation in the economy.

Key words: labor mobility, dynamic count data, patents

1. Introduction

Knowledge is one of the main sources of the competitive advantage of firms (Kogut and Zander, 1992; Teece et al., 1997). Part of this knowledge resides in the people working in the organization and is only weakly protected by intellectual property rights (Gilson, 1998). Thus, mobility of people represents both a threat and an opportunity to firms: their knowledge base can be strengthened
by employees joining but weakened by employees leaving. Consistent with this view, mutual funds acquire the human resources to introduce new products by hiring managers from the outside (Rao and Drazin, 2002) and semiconductor firms enter markets where the experience of newly hired managers is applicable (Boeker, 1997). Looking at the threat that mobility poses, Wezel, Cattani and Pennings (2006) show that group exit is an important reason for partnership dissolution in the accounting industry.

Inter–firm mobility may not only affect the performance of individual firms but of entire regions. Saxenian (1994) as well as Almeida and Kogut (1999) have documented how engineers and technical workers in Silicon Valley change jobs repeatedly, contributing to knowledge transfer and rapid technological progress.¹ Inter–firm mobility is thus a source of “technology spillovers”, which are identified by macroeconomists as main drivers of sustained economic growth (Romer, 1990; Aghion and Howitt, 1992).

There is a substantial body of evidence from surveys (Mansfield, 1985; Zander and Kogut, 1995), patent files (Almeida and Kogut, 1999; Kim and Marschke, 2005; Song et al., 2003), and litigation (Gilson, 1999; Hoti et al., 2006) indicating that labor mobility is a source of knowledge transfers between firms. However, the evidence is primarily qualitative in nature, and little is known about the quantitative effects of mobility on firm performance.

In this paper we take a step forward towards assessing the quantitative importance of mobility by measuring how labor mobility affects inventions in firms. For this purpose, we have constructed a dataset that combines patent applications by Danish firms to the European Patent Office (EPO) with matched employer–employee register data that contains a complete record of mobility in the Danish labor market. The dataset allows us to estimate the change in the number of inventions, measured by patenting activity, associated with the mobility of different kinds of workers. This represents to our knowledge the first direct evidence on the importance of labor mobility for invention at the firm level. Unlike previous studies, we consider both the threat and the opportunity

¹ See also Fallick et al. (2006) for a recent analysis of mobility inside the computer industry in Silicon Valley.
arising from mobility. Our study shows how much a worker joining the firm adds to inventions but also how much a worker leaving subtracts from it. Furthermore, adding these effects up, we are able to measure whether labor mobility increases the total number of inventions or represents a “zero-sum game” among the firms involved. This is a central question for our understanding of labor mobility as a source of regional competitive advantage to which the existing literature provides few answers.

In our empirical approach, we identify workers who are likely to possess the skills and knowledge to perform R&D and measure whether their movements between firms contribute to firm–level patenting activity. Specifically, workers are split up into “R&D workers” and “non R&D workers” according to the level and the subject of their highest education. Persons, e.g., with a bachelor’s or a master’s degree in natural sciences are classified as R&D workers whereas persons with the same level of education in humanities are termed non R&D workers. We identify the workers that have recent experience working in a R&D active environment by introducing a second dimension, “patent exposure”. A worker is “patent exposed” if her employer in the previous period applied for a patent during that period. Otherwise, she is “non patent exposed”. The idea is here that patent exposed workers are more likely to have accumulated knowledge and skills that can serve as inputs in the production of further inventions than non patent exposed workers. We introduce a third and final dimension in order to keep track of inter–firm mobility. A person belongs in any period $t$ to one of the following groups: “stayers” (worked in firm in period $t − 1$), “joiners” (joined the firm in period $t$), “leavers” (left the firm after period $t − 1$), or “graduates” (entered the Danish labor market in period $t$).

The point of departure in the analysis is a standard firm–level patent production function (Hall et al., 1986; Hausman et al., 1984) that maps the different types of labor, capital and other observed firm characteristics into patent counts. To control for unobserved permanent differences in firms’ patent productivity, we utilize the very long patent histories of firms at our disposal, thereby following a suggestion of Blundell et al. (1995). Because a prominent feature of our sample is an
increasing trend in the overall level of patenting, we extend the Blundell et al. (1995) approach to allow for trending.

Our analysis shows that R&D workers contribute more to patenting activity than non-R&D workers irrespective of exposure status or mobility record. An additional R&D joiner with patent exposure increases the number of patent applications by 0.0111. For firms that patented prior to 1999 the effect of one additional R&D joiner with exposure is 0.0637, which represents a 14.1 percent increase in the number of patent applications for these firms.

Regarding the importance of patent exposure, we find that joiners with patent exposure contribute more to patenting activity than joiners with similar observable characteristics but no patent exposure. One additional patent exposed R&D joiner relates to an increase in the number of patent applications by 0.0637 which is economically and statistically significantly more than a non patent exposed R&D joiner who contributes 0.0433 additional patent applications. Patent exposure is also associated with significantly higher patent productivity for stayers. These findings are consistent with the notion that workers in patenting firms acquire knowledge and skills that increase their productivity in the production of new inventions.

We also show that the mobility of R&D workers increases the joint patenting activity of the donor and the recipient firm. The joint effect of mobility has two components: the effect of an R&D joiner for the recipient firm plus the effect of an R&D leaver for the donor firm. An overall positive effect could either be due to technology spillovers or be the outcome of a well-functioning labor market that allocates labor to its most productive use. This gives quantitative support to the notion that inter-firm mobility is an engine for technological progress at the aggregate level.

Turning to the related literature, several studies have used patent data to analyze the importance of mobility for innovation. Almeida and Kogut (1999) track the careers of the most productive research engineers in the semiconductor industry. They provide evidence on the role of inter-firm mobility as a source of technology spillovers by showing that firms cite each other more in their patent applications in regions with high labor turnover. Additional evidence is provided by Kim and Marschke (2005) who show that firms have a higher propensity to patent in regions with high
labor mobility. This is consistent with a theory in which firms patent their inventions to prevent misappropriation by former employees.

Closer to the approach taken in this paper, patent files have been used to track the mobility of inventors across firms. Song et al. (2003) study mobility within and across industries and technology classes using patent citations to explore the conditions under which hiring results in knowledge acquisition for the new employer. Hoisl (2007) combines data on mobility from patent files with background information about the inventors from questionnaires. She shows that mobile inventors are on average more productive and that mobility enhances welfare by increasing inventor productivity.

While patent files are useful in measuring inventions, they are less suitable to trace mobility. The problem here is that only successful moves that result in a patent at the new employer are registered. Moreover, the subject of the analysis are by construction “star scientists” that invent repeatedly. Instead, we consider the average effect of mobility by an average worker with the necessary formal qualifications to perform R&D. We believe that this provides important complementary evidence regarding the trade-offs that firms typically face when managing labor in- and outflows.

Finally, Toivanen and Väänänen (2008) combine Finnish patent data with linked employer–employee data. They find a significant and potentially long–lasting wage premium for inventors of granted patents. Our analysis similarly exploits detailed data on labor movements but the focus is different as we consider the effects of mobility on firms’ innovative productivity.

The rest of the paper is organized as follows. The next section details the hypotheses tested and the theory underlying them. Section 3 describes the data and outlines the definitions used in the analysis. Section 4 characterizes the econometric approach and Section 5 provides some descriptive statistics. The main results are reported in Section 6. Section 7 provides some robustness checks. Finally, Section 8 concludes.
2. Theory and Hypotheses
2.1. The Effects of Mobility

Technology “spillovers”, or “knowledge externalities”, play a central role in modern theories of economic growth (Romer, 1990; Aghion and Howitt, 1992). Once knowledge is created through R&D, it spills over to other firms that can use it as an input in the production of superior goods and new knowledge. Furthermore, since technology spillovers tend to be localized (Audretsch and Feldman, 1996; Keller, 2004), they are a source of agglomeration economies and regional competitive advantage (Porter, 2000; Saxenian, 1994). The importance of technology spillovers stems from knowledge being shareable due to its non–rival nature (Arrow, 1962; David, 1992). If non–rival knowledge is transferred, then inter–firm mobility of personnel should result in a knowledge gain for the recipient firm without a similar loss for the donor firm. We will refer to this as a “spillover effect”.

A worker’s labor input has many other components apart from non–rival knowledge such as physical labor, problem–solving abilities, and human capital. A fraction of the knowledge created when an invention is made may also be embedded in the worker as “intellectual human capital” (Zucker et al., 1998). For our purposes, the key characteristic of these labor inputs is that they are rival in nature.

The labor market should, as any other well–functioning market, induce an efficient match between workers’ labor supply and firms’ labor demand. Workers are employed in firms where they enjoy a high productivity and leave if their labor inputs find a better use elsewhere (Jovanovic, 1979; Mortensen, 1982). There is thus a part of labor mobility that serves to match the workers’ supply of rival labor inputs to firms’ demand. We will refer to the productivity gains that arise from this matching process as a “matching effect”.

Our measure of firms’ inventive output is patent applications. Thus, our hypotheses will focus on the R&D workers who provide the main labor input in this production process. Both the spillover and the matching effect suggest that mobility is associated with a net productivity gain in terms of innovative activity which leads to our first hypothesis:
H. 1. The sum of an R&D joiner’s and an R&D leaver’s contribution to patenting activity is positive.

2.2. The Effects of Exposure

2.2.1. A Stylized Model of a Competitive R&D Labor Market We introduce a simple model along the lines of Pakes and Nitzan (1983) as well as Fosfuri et al. (2001) of a competitive labor market where both matching and spillover effects can arise. The purpose of the model is to guide intuition and to develop further theoretical hypotheses regarding the effects of patent exposure on a worker’s patent productivity.

The value of an R&D worker’s rival labor inputs is $V_{D}$ to the current employer, the potential (D)onor firm. We exclude here intellectual human capital, which is introduced separately below. The worker is matched according to a random matching process to an outside firm, the potential (R)ecipient firm, that values the rival labor inputs as $V_{R}$. We assume $V_{R} = V_{D} + \varepsilon$, where $\varepsilon$ is a random variable distributed in the interval $[-\varepsilon, \varepsilon]$ according to a distribution function $F(\cdot)$ with corresponding density function $f(\cdot)$.

On top of the rival labor inputs, a patent exposed R&D worker also brings knowledge of value $s$. The non-rival part of the knowledge has value $\alpha s$, $\alpha \in [0, 1]$. Rival knowledge is embedded in the worker as intellectual human capital and has value $(1 - \alpha)s$. Hence the degree of non–rivalness of knowledge is measured by parameter $\alpha$. Mobility results in a gain $V_{R} + s$ to the recipient firm and a loss $V_{D} + (1 - \alpha)s$ to the donor firm. There is a fixed cost of mobility $C$ that includes the cost of training for the recipient firm, the cost of finding a replacement for the donor firm, etc. We assume that $-\varepsilon < C - \alpha s < C < \varepsilon$ in order to ensure that the mobility decision depends on the realized value of $\varepsilon$ for both patent exposed and for non patent exposed workers. A fraction $\beta$ of $C$ is carried by the recipient firm and a fraction $(1 - \beta)$ by the donor firm.

Labor market competition is modeled in the following way: firms make a take-it-or-leave-it offer to the worker. The worker is then hired by the firm offering the highest wage. As tie-breaking

\footnote{Assuming that $V_{D}$ and $\varepsilon$ are independent, we disregard complementarities in production between firms and workers that could lead to sorting in the labor market equilibrium. While this is a limitation of the framework, the empirical evidence on the importance of sorting has generally been mixed (Abowd et al., 1999; Melo, 2008).}
rule, we assume that the firm whose valuation of the employee is highest hires her. This ensures an equilibrium in pure strategies. In equilibrium the firm with the highest valuation of the worker hires her paying the valuation of the other firm.

A non patent exposed worker switches from the donor to the recipient firm if and only if:

$$\frac{V_R - \beta C}{\varepsilon} \geq \frac{V_D + (1 - \beta)C}{C}$$

(1)

Notice that the mobility cost decreases the recipient firm’s willingness to pay whereas it increases the donor firm’s willingness to pay, because the donor firm can avoid this cost by retaining the worker. A patent exposed worker leaves the current employer if and only if:

$$\frac{V_R + s - \beta C}{\varepsilon + \alpha s} \geq \frac{V_D + (1 - \alpha)s + (1 - \beta)C}{C}$$

(2)

The donor firm only attaches value to the knowledge embedded in the worker’s intellectual human capital, since the non-rival knowledge stays in the firm if the worker leaves.

Figure 1 illustrates the theoretical hypotheses derived from the model.

2.2.2. Hypotheses Having determined the conditions under which mobility occurs in equilibrium, we derive predictions regarding the productivity of different types of workers in producing patentable inventions.

The value of a non exposed stayer to her current firm is $V_D$ whereas the value of a patent exposed stayer is $V_D + \alpha s$. Notice that non-rival knowledge is not counted as an input provided by the worker, because it stays with the firm if the worker leaves. Similarly, the value of a non patent exposed and a patent exposed leaver are $V_D$ and $V_D + \alpha s$, respectively. Assuming that a worker who contributes more to patenting in terms of value also contributes more in terms of patent counts, we hypothesize:
H. 2: Patent exposed R&D stayers contribute on average more to patenting activity than non patent exposed R&D stayers.

H. 3: Patent exposed R&D leavers subtract on average more from patenting activity than non patent exposed R&D leavers.

One may note that a further implication of our stylized model is that (exposed and non exposed) stayers and leavers have equal patent productivities:

H. 4: The contributions of stayers with patent exposure and leavers with patent exposure are equally large.

H. 5: The contributions of stayers without patent exposure and leavers without patent exposure are equally large.

Hypotheses 4 and 5 are not central to the analysis as they do not concern the effect of patent exposure on patent productivity. It should also be noted that these predictions are not robust across standard models of labor turnover. If the productivity of a firm-worker match is revealed over time (Jovanovic, 1979; Moscarini, 2005), the most productive workers stay whereas the less productive workers leave. Acceptance of Hypotheses 4 and Hypotheses 5 would therefore suggest that firms and workers are able to judge correctly the match quality when the employment relation is initiated.

Our final hypothesis concerns the relationship between the patent productivities of exposed and non exposed joiners at their new firm. The expected value of a non patent exposed joiner to the firm is

\[ \int_{C} (V_D + \varepsilon) f(\varepsilon | \varepsilon \geq C) d\varepsilon, \]  

whereas the expected value of a patent exposed joiner is

\[ \int_{C - \alpha s} (V_D + \varepsilon + s) f(\varepsilon | \varepsilon + \alpha s \geq C) d\varepsilon. \]

Patent exposure has two opposing effects on the expected value of a joiner. First, the knowledge that the worker brings has a positive, direct effect on the value. Second, outside firms bid harder
to hire patent exposed workers in order to acquire their knowledge. There will thus be workers leaving their previous employer that are a relative poor match to their new employer in terms of the value of the rival labor inputs $V_R$. Patent exposure has therefore a negative, indirect effect on the expected value of a joiner as the average match quality is lower. A sufficient condition for the expected value of a patent exposed joiner to be greater than the expected value of a non patent exposed joiner is

$$
\frac{\partial}{\partial s} \left( \int_{C-\alpha s}^{\infty} (V_D + \varepsilon + s)f(\varepsilon)d\varepsilon \right) / \partial s > 0 \Leftrightarrow 1 - \frac{\alpha f(C-\alpha s)}{1 - F(C-\alpha s)} \int_{C-\alpha s}^{\infty} \frac{(\varepsilon + \alpha s - C)f(\varepsilon)}{1 - F(C-\alpha s)}d\varepsilon > 0. \quad (4)
$$

It can be shown that condition (4) is satisfied for the uniform distribution. Numerical calculations confirm that it also holds for the (truncated) normal distribution. Assuming that the positive, direct effect of patent exposure dominates the negative, indirect effect, we derive our final hypothesis:

**H. 6:** Patent exposed R&D joiners contribute on average more to patenting activity than non patent exposed R&D joiners.

### 3. Data

Data on all patent applications to the EPO that were filed for between 1978 and 2002 by at least one applicant with Danish residency constitute the core of our data set. Patent applications are used rather than patent grants because the average grant time at the EPO of four to five years (Kaiser and Schneider, 2005) implies that a substantial number of patents applied for during the time period considered for estimation (1999–2002) would be lost if patent grants were used. The “time stamp” of the patent applications is the “priority date”, the date at which the invention was first filed for patent protection at the EPO or any national patent office. The EPO data consist of

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3 For a uniform distribution $f(\varepsilon) = \frac{1}{2\varepsilon}$ and $F(\varepsilon) = \frac{\varepsilon + \varepsilon^2}{2\varepsilon}$. Hence, condition (4) can be rewritten as:

$$
1 - \frac{\alpha}{\varepsilon - C + \alpha s} \int_{C-\alpha s}^{\infty} \frac{(\varepsilon + \alpha s - C)}{\varepsilon - C + \alpha s}d\varepsilon > 0 \Leftrightarrow 1 - \frac{\alpha}{2} > 0.
$$

Since $\alpha < 1$, this is positive.
11,784 patent applications in total by 2,627 unique non–private Danish applicants over the period 1978–2002.

The distribution of the economic and technological value of patents is heavily skewed in the sense that few patents have a very high value while the bulk of patents have very little value as discussed, e.g., by Harhoff et al. (1999); Lanjouw et al. (1998), and Hall et al. (2005). Trajtenberg (1990) shows that there is a close relationship between the number of citations a patent receives (“forward citations”) and the social value of the inventions in the computer tomography industry. Thus, he suggests to approximate value by patent forward citations since they capture the enormous heterogeneity in the “quality” or “importance” of patents. Like Trajtenberg (1990), we weight each patent by one plus the number of citations the patent received within a three years period after the EPO publication.⁴ Our patent citations data stem from the “EPO/OECD patent citations database” that is available from the OECD (Webb et al., 2005) and covers the period 1978–2006.

The EPO data do not come with a unique firm identifying number of the kind used by Statistics Denmark, the provider of the firm–level and employee–level data. We hence, mostly manually, attached our EPO data to Statistics Denmark’s firm identifiers. As described by Kaiser and Schneider (2005), we exactly matched 95 percent of all unique patent applicants. The unmatched five percent refer primarily to firms that went out of business before 1996 only. The corresponding information would have been lost in our analysis anyway since our firm–level data starts in 1999.

Statistics Denmark provided us with firm registry data, most importantly sector affiliation and the book value of physical capital, and with registry data on employee characteristics, most importantly the end-of-November number of employees and their highest level of education.⁵ Our firm–level data is available for the years 1999–2002. Our control group of non–patenting firms is the universe of firms active in Denmark. We do discard, however, sectors without any EPO patent application between 1978 and 2002. Sectors are defined according to the three digit NACE Rev. 1

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⁴ A time window of five years is often used, but we have chosen a shorter window as our citation data ends less than four years after the patent data.

⁵ As the firm affiliation of a worker is registered only once a year in November we do not observe within-year mobility.
industrial classification level. Firms that did not file for an application at the EPO in a particular year are assigned a zero for the number of patent applications in that year. In a final step we merge the firm–level data with employee–level data which allows us to track the employment history of each worker across firms.

We lose some observations due to missing values, in particular due to missing values in the firm–level data. We lose the first year of observation for each firm since we use lagged explanatory and endogenous variables.

Our main estimation results are based on 206,645 firm–year observations on 90,725 unique firms. A total of 352 unique firms patented at least once between 2000 and 2002, the total number of patents in that period is 484, and the citations–weighted total is 1,987.

4. Empirical Model

Our point of departure is a standard patent production function that maps firms’ input into patent counts and controls for both unobserved and observed firm–specific heterogeneity. Given that invention is an inherently dynamic process, we also account for possible state dependence in patenting activity: past patenting activity is very likely to have a positive impact on current patenting activity (Flaig and Stadler, 1994).

We discuss in turn the specification of human capital terms, the treatment of state dependence and unobserved heterogeneity, and the functional form of the patent production function.\(^6\)

4.1. Human Capital Variables

We consider the human capital of R&D workers as the most important input factor in patent production. According to German survey data, labor costs make up about two thirds of all R&D costs in German firms (Stifterverband, 2007). We do not have data on R&D expenditures on tangible assets at our disposal but we control for capital stock — as measured by its book value — in the estimations. While existing studies measure R&D inputs either by the overall number of R&D workers or total R&D expenditures (Blundell et al., 1995, 1999; Hall et al., 1986; Crépon

\(^6\)Our model specification also includes standard controls found to be important in the patenting literature such as measures of firm size (total employment and capital stock, both in logs) as well as sectoral, regional and year dummies.
and Duguet 1997; Hall and Ham Ziedonis, 2000; Licht and Zoz, 1998), the richness of our data allows us to take a much more differentiated look at the marginal contributions of different types of labor.

We distinguish human capital effects along three critical dimensions as defined by the concepts of “R&D workers”, “mobility” and “patent exposure”.

R&D workers and non–R&D workers: We define “R&D workers” vs. “non–R&D workers” by using information on the highest level of education attained by the worker. We differentiate between nine skill groups in total, which we describe in more detail in Appendix A. Our main definition of R&D workers includes workers with long or medium length R&D educations. This includes workers with a bachelor’s, a master’s, or a Ph.D. degree in R&D–related subjects like engineering, chemistry, mathematics, medicine, statistics, physics and biology. The definition corresponds most closely to the finding of Kaiser (2006) who uses patent inventor survey data to show that Danish inventors are most likely to hold a bachelor’s degree or higher. As a robustness check we consider in Section 7 a “narrow” definition of R&D workers, which includes only workers with a long R&D-related education (master’s or Ph.D. level), and a “broad” definition, which extends to workers with a short R&D–related education like laboratory technicians or process technicians.

Mobility: We also differentiate workers in terms of their mobility. “Stayers” are workers employed by firm $i$ both at time $t$ and time $t-1$. “Joiners” are workers employed by firm $i$ at time $t$ but not at time $t-1$. “Leavers” are workers employed by firm $i$ at time $t-1$ but no longer at time $t$. A final group of workers are employed with firm $i$ at time $t$ but their employment history is unknown. Although a tiny fraction of the “unknown” workers are workers from foreign countries, most have graduated recently and we shall refer to these workers as “graduates” hereafter.

More precisely, 30.5 percent of the inventors hold a Bachelor’s degree, 40.8 percent a Master’s degree and 17.4 percent a Ph.D. degree.
**Patent exposure:** We define a worker as being “patent exposed” if the firm she was employed with at $t-1$ applied for a patent at time $t-1$. A patent exposed stayer hence is a worker who was employed with firm $i$ at both $t$ and $t-1$ with firm $i$ applying for at least one patent at $t-1$. No distinction can be made here with respect to their patent exposure.

Combining the above three dimensions yields a total of 14 different types of labor which are listed in Table 1. Groups (1) through (10) constitute the firm’s current labor force. Workers in groups (11) through (14) are no longer part of the firm’s labor force.

We specify human capital effects as “composition effects” and “leaver effects”. Composition effects are measured by the share of each type of labor currently employed, skill groups (1) through (10). Leaver effects consist of the ratio of the number of workers in each of the groups (11) through (14) relative to the current total number of workers of the firm:

$$
\sum_{k=1}^{9} \gamma_k s_k + \sum_{l=11}^{14} \delta_l r_l.
$$

Here $s_k$ denotes the share of labor type $k$ in total employment of firm whereas $r_l$ denotes the ratio of leaver group $l$ to total current employment. The sign of each $\gamma$ coefficient indicates the direction of the contribution of each group of workers relative to the comparison group. The $\delta$ coefficients measure the effects of leavers and are therefore expected to be negative.

The coefficients in Equation (5) do not have a simple economic interpretation. We therefore present our results also in terms of the absolute changes in the number of patents from the addition of one worker of a particular type. Appendix B shows how the marginal effects are calculated. We restrict attention to R&D workers since this is the group of workers we are most interested in. Non R&D workers enter our patent production function as control variables only.

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8 Non–exposed non R&D workers (group 9) are left out as the comparison group. The coefficient estimates on the remaining groups are to be interpreted relative to the effects of this comparison group.
4.2. State Dependence

The standard treatment of state dependence in patent production, e.g. Blundell et al. (1995), relies on a measure of a firm’s previous success in patenting: the discounted stock of patents. The discounted patent stock of firm $i$ in period $t-1$ is:

$$G_{it-1} = P_{it-1} + (1 - \omega)G_{it-2},$$

where $P_{it-1}$ denotes the number of patent applications of firm $i$ at time $t-1$ and $\omega$ is a discount factor. State dependence is hence introduced to the model through the term $P_{it-1}$, the lagged number of patent applications. We follow the suggestion of Blundell et al. (1995) and use a 30 percent depreciation rate. Our results remain robust to alternative discount factors.

While such state dependence measures are usually found to be significant even when controlling for firm size (e.g. by the stock of capital, Hausman et al., 1984; Blundell et al. (1995, 1999), they leave open the interpretation of the reasons for state dependence in patenting. With complete longitudinal data on labor flows we can add much more detail. Our approach allows the effects of state dependence (that is, of previous patenting exposure) to reside to different degrees within the different types of workers as a part of their intellectual human capital (Zucker et al., 1998).

4.3. Unobserved Heterogeneity

Unobserved permanent firm heterogeneity implies that firms may differ in terms of their patent productivities irrespective of their previous history in patenting and the size and composition of their current labor force. This creates a potential problem in separating out the contributions of different factors in the patent production function. For example, a firm with high unobservable “patent ability” may attract R&D workers who are also (unobservably) more able than the average R&D worker, or it may employ capital more productively than firms of lower ability. In such a case, with no correction for unobserved patent productivity, one would tend to overestimate the marginal contributions of R&D workers or capital in the patent production function.

To correct for unobserved permanent differences in patent productivity we utilize the fact that we have very long “pre-sample” histories at our disposal (1978–1998) on patenting activity prior
to our “sample” data on workforce characteristics and other observable firm characteristics (1999–2002). Specifically, we employ the suggestion of Blundell et al. (1995, 1999) to use a firm’s average number of patents over this pre-sample period as an observable proxy for unobservable permanent productivity. Their so-called “Pre-Sample Mean Estimator” yields superior results compared to alternatives that are based on the generalized methods of moments (GMM) framework (Blundell et al., 2002).

Since a prominent feature of our data is an overall increase in the level of patenting during the pre-sample period, we extend the Blundell et al. (1995, 1999) approach by normalizing a firm’s number of patents in a pre-sample year by the total number of patents applied for during that year. We provide details on the normalization in Appendix C.

Many of the firms in our data never applied for a single patent. We again follow Blundell et al. (1995, 1999) and include a dummy variable for firms having applied for at least one patent during the pre-sample period. This variable also acts as a remedy for the so-called “zero-inflation problem” that is common to many analyzes of economic count data (Mullahy, 1997). We prefer our approach over the alternative zero inflation model since our model belongs to the family of linear-exponential models which are shown to produce consistent estimates under a large set of circumstances (Gourieroux et al., 1984; Winkelmann, Ch. 3, 2008).

4.4. Count Data Models

Our count data model uses a common specification of the conditional mean function. We specify the (citation-weighted) mean number of patents, $P_{it}$, applied for by firm $i$ in year $t$ as $E(P_{it}|x_{it},\eta_i) = e^{x_{it}\beta + \eta_i}$. The exponential specification is standard in the patenting literature. The vector $x_{it}$ denotes observable patent production determinants, including the discounted stock of past patent applications and measures of the composition of the labor force as detailed in the previous subsections as well as standard controls. The vector $\beta$ contains the corresponding parameters. The term $\eta_i$ captures unobserved differences between firms in terms of their permanent patent productivity. It is proxied by the pre-sample average number of applications relative to the total number of
It is commonplace in the count data literature to consider several different specifications of the conditional variance. We start with a Poisson model, which imposes equality between the mean and the variance, since the conditional mean function of that model is robust to various types of mis-specification such as heteroskedasticity and multiplicative unobserved heterogeneity (Winkelmann, Ch. 3, 2008). We also consider a negative binomial model that allows the variance to exceed the mean as commonly found in patent data. We use a very flexible specification of the negative binomial model, denoted RE NegBin, in which the dispersion parameter can vary randomly between firms.

5. Descriptive Statistics

Table 2 provides descriptive statistics for two different samples: the full estimation sample of 90,725 firms with a total of 206,645 in-sample observations and a subsample of 14,811 firms that employ at least one R&D worker (16.3 percent of the full sample). The latter sample which should include most R&D active firms, is used for checking the robustness of our results in Section 7. It includes 31,193 firm-year observations (15.1 percent of the full sample) and accounts for 96.4 percent of the total number of patents. Overall patenting activity is fairly modest for the full sample with the average patent holder applying for 1.6 patents per year. It is slightly higher for the subsample that employs at least one R&D worker where it is 1.8.

Regarding firm size as measured by the number of employees, the standard picture emerges: patenters are on average much larger than non-patenters although there are very small firms among the patenters (firms with just one employee) as well as very large non-patenting firms (with a maximum of more than 26,000 employees).

Table 2 also details the distribution of (firm, year) observations over groups of workers with differences in terms of the relevance of their education for R&D, their mobility status in the present...
year (joiners vs. stayers), and whether or not they were exposed to patenting in the previous year. For the full sample, the table shows that 21.1 percent of workers in patenting firms are classified as R&D workers. Of those workers, around 19.5 percent were mobile during any given year. A fraction of 7.4 percent of all workers are graduates. For non-patenters the corresponding numbers are lower: 3.8 percent of workers in non-patenting firms are classified as R&D workers with 10.7 percent being mobile during any given year.

Within the sample of “potentially R&D active firms”, firms with at least one R&D worker, 24.8 percent of the workers is classified as R&D workers. This holds equally for patenting and non-patenting firms. Again, one in five R&D workers was mobile during any given year for patenters where mobility was lower among R&D workers employed by non-patenters, 10.7 percent were mobile here.

6. Results

We report our empirical results in three steps. First, we comment briefly on the estimation results in terms of the significance and sign of the regression coefficients. Second, we transform our results into more readily interpretable marginal effects. Finally, we present results regarding each of the hypotheses forwarded in Section 2. Given our sample size, we define a coefficient to be statistically significant if the corresponding $p$-value is 0.05 or lower.

6.1. Estimation Results

Our main estimation results are presented in Table 3. This is for the full sample of 90,725 firms that (i) have at least one employee and (ii) for which all variables are observed. Results are reported both for the standard Poisson model (“Poisson”) and the random effects Negative Binomial model (“RE NegBin”). Our comments focus on the latter because the random effects turn out to be statistically strongly significant. Moreover, our main findings are consistent across specifications in terms of sign and magnitude of the estimated parameters.

The results for composition and leaver effects are in line with our expectations. A central finding is that all groups of R&D workers in the firm’s current workforce contribute positively and
significantly to patenting. By contrast, we generally find little effects of non R&D workers. Only for non R&D stayers with patent exposure do we find a statistically significant impact. The weak effects for non–R&D workers suggest that our classification of R&D workers is sufficiently broad to include most workers that contribute to the production of patentable inventions. Finally, for leavers we generally find weaker effects although the leaver terms are jointly statistically significant. An individually significant leaver effect which is negative in accordance with our expectations, is obtained for non R&D leavers without patent exposure.

The variables included to control for scale effects, state dependence and unobserved permanent heterogeneity are all found to be statistically significant and signed according to our expectations. The estimated scale effects of the total number of workers and the capital stock (both in logs) are positive and statistically significant.

We find ample evidence for positive state dependence in patenting. The standard term included to capture state dependence, the lagged discounted stock of patents, has a positive and statistically significant impact on current patenting activity according to the RE NegBin results. It remains an important determinant of patenting even though our specification includes an extended set of human capital variables.

Our pre-sample mean proxies for unobserved permanent heterogeneity, the fixed effect dummy variable for patenting activity prior to 1999 and the continuous measure \( \ln(\text{fixed effect}) \) based on our mean pre–sample patent count, both add positively and significantly to current patenting activity. This is consistent with the pre–sample level of patenting reflecting permanent differences among firms in their unobserved patent abilities.

### 6.2. Marginal Effects

Table 4 reports the absolute change in the expected number of patents from adding one additional worker of a particular type to the current workforce, or subtracting a worker in the case of leavers.

---

9 Our specification also includes 14 sectoral dummies, 14 regional dummies, and year dummies for 2001 and 2002.

10 Although positive, the term is not significant in the Poisson model.
The calculations are based on the RE NegBin estimation results. We focus on the R&D workers for which we developed theoretical hypotheses in Section 2.

For the sample that includes all firms, the marginal effects are generally modest, ranging from a 0.01 increase in the number of patent applications for one R&D joiner with patent exposure to a 0.004 increase for a non–R&D stayer without patent exposure. Interestingly, R&D graduates have a higher patent productivity than R&D stayers without exposure. A possible interpretation of this result is that graduates bring up-to-date knowledge of the developments in the field.

Marginal effects evaluated for firms that already applied for a patent in the pre–sample period are generally larger. The effect of an additional worker ranges from a 0.0637 (14.1 percent) increase in the number of patent applications for an R&D joiner with patent exposure to a statistically still significant 0.0197 (2.7 percent) increase for an R&D stayer without patent exposure. Thus, for firms which are likely to do more R&D than the average Danish firm, we find economically sizable effects of labor mobility on patenting activity.

6.3. Tests of Economic Hypotheses

As the final step of our empirical analysis we investigate the validity of the economic hypotheses forwarded in Section 2. We base this inference on the differences in the estimated composition and leaver effects, the $\gamma$ and $\delta$ coefficients from Equation (5).

Our results for the full model are summarized in Table 5. The first column shows if the estimated combination of coefficients is signed according to theory. Hypotheses 1 through 3 and 6 make definite sign predictions. For Hypothesis 4 and Hypothesis 5 our theory predicts no difference between groups. The second and third columns of Table 5 report the $\chi^2$ statistic and the associated $p$-value. The final column concludes if the economic hypothesis is validated statistically. In the case of Hypothesis 1 to Hypothesis 3 as well as for Hypothesis 6, this is the case if the estimated difference is statistically significant and signed according to theory. In the case of Hypothesis 4 and Hypothesis 5, an insignificant value of the the $\chi^2$ statistic is in accordance to our theoretical prediction.
There is strong evidence that the mobility of R&D workers jointly increases the patenting activity of the donor and the recipient firm (Hypothesis 1). It is important to notice that this result is not driven by systematic unobserved differences between joiners and leavers as leavers in one firm are joiners in another firm as we have data for the entire Danish labor force. The fact that leavers in one firm are joiners in another firm is reinforced by a ratio of joiners to leavers of around one at the firm–year level.

There are strong effects of patent exposure in the directions suggested by theory. For stayers, we find evidence that previous patent exposure increases productivity (Hypothesis 2). This also holds for leavers and joiners (Hypotheses 3 and 6). When taken together, these results support the notion that workers acquire knowledge and skills that can be transferred across time within their present firm or across firms. Interestingly, we cannot reject our Hypotheses 4 and 5 that stayers and leavers contribute equally to patent productivity. This holds irrespective of their patenting exposure status and suggests that our results are not driven by workers of different unobserved ability having different probabilities of staying with the firm.

7. Robustness Checks
7.1. R&D Active Firms

We noted in Section 5 that the main analysis is conducted on a very broad sample of firms excluding only firms in sectors with no patenting activity between 1978 and 2002. This clearly includes many firms which are not active in R&D and therefore are very unlikely to patent. In order to check the robustness of our main results we re–estimated the model on a much more selective sample of firms that employ at least one R&D worker. Estimation results and marginal effects for the workforce composition variables are presented in Appendix D.

Comparing the RE NegBin results for the full sample in Table 3 and for the selected sample, we find that the main terms remain strongly significant. The effects of “stayers” remain positive but become smaller in magnitude. In fact, the main differences arise for two groups of non–R&D
workers, the recent graduates and the non exposed leavers. These effects become larger in magnitude and retain their original signs in the selected sample.

7.2. Alternative R&D Worker Definitions

Our main analysis relies on the proper definition of an R&D worker. As noted above, our adopted definition is consistent with survey evidence on the educational level of actual inventors. In this subsection we check the robustness of our results to the scope of this definition.

Specifically, we consider a “narrow” definition of R&D workers including only workers with a long R&D–related education (master’s or Ph.D. level), and a “broad” definition, which comprises also of workers with a short R&D–related education like laboratory technicians or process technicians.

We summarize the results of re–estimating the model for the two additional definitions of R&D workers by presenting the resulting marginal effects in Appendix E. Comparing effects for each worker group across definitions — either for the full sample or for firms with at least one pre–sample patent — we find that the signs for all significant effects are unchanged. In fact, a fairly consistent picture emerges: marginal effects are stronger when using the more narrow definition and become weaker when using the broader one.

8. Conclusions

This paper assesses the quantitative importance of inter-firm mobility of labor for patentable inventions. We use a data set that combines patent applications by Danish firms to the European Patent Office between 1978 and 2002 with matched employer–employee register data. This provides us with a complete record of mobility in the Danish labor market for the period 1999-2002. Unlike previous studies that track inventor mobility using patent files, we are able to observe moves that are "unsuccesful" in the sense of not leading to a patent application by the new employer. Our results pertain therefore to the average effect of mobility for an average worker of a certain type, complementing previous studies that have focused on star scientists (Almeida and Kogut, 1999) or top-level managers (Boeker, 1997).

We differentiate workers along three dimensions: (i) R&D workers vs. non-R&D workers, (ii) mobile workers vs. immobile workers, and (iii) workers employed by a firm that applied for patent
in a previous period vs. workers not employed by such a firm. We find that newly employed R&D workers coming from a firm that recently applied for a patent contribute more to patenting activity than other newly employed R&D workers. Recent patenting experience is also associated with a higher patent productivity for workers staying with the firm. These findings are consistent with the notion that workers employed in patenting firms acquire knowledge and skills that increase their productivity in the production of new inventions.

For the average firm, the effects of mobility on patenting activity are generally modest: an increase in the number of incoming R&D workers with previous patenting experience — which is the most productive group of workers — is associated with an absolute increase in the number of patents by 0.0111. This result reflects the fact that only a small fraction of “average” firms are involved in patenting activity at all. Most of the mobility labor is therefore between firms that never apply for a patent. Restricting attention to firms that already applied for a patent before 1999 (the beginning of our period of analysis) the quantitative effects are stronger: hiring an R&D worker from a firm with recent patenting applications contributes 0.0646 additional patent applications on average. This represents a sizeable 14.1 percent increase in the number of patent applications. Since these firms are likely to do more R&D than the average Danish firm in the sample period, this indicates that acquisition of skills and knowledge through the labor market is important for R&D active firms.

Our study is to the best of our knowledge the first to consider the effect of mobility on the performance of both recipient firms — firms that hire new workers — and donor firms — firms that are left by workers. We show that the mobility of R&D workers increases the joint patenting activity of the firms involved. This is a notable result that provides quantitative support for the notion that inter–firm mobility is an engine for innovation also at the regional level. Saxenian (1994) has forcefully argued that “job-hopping” is of key importance to the success of Silicon Valley. Our results suggest that something similar might be true also outside the world’s most prominent high–tech cluster. More generally, our result show that firms are not involved in a zero–sum game when
competing for labor. Losing workers to other firms might result in a loss of capacity for invention but this is more than compensated for by the skills and knowledge of the workers joining the firm.

Acknowledgments

Financial support from the Danish Social Science Research Council (Forskningsrådet for Samfund og Erhverv) for the research project “Human Capital, Patenting Activity, and Technology Spillovers” is gratefully acknowledged. We are indebted to Steffen Rebien and Jens Peter Schougaard of the Danish Patent and Trademark Office for providing us with the European Patent Office data and for sharing their data expertise with us and to Cédric Schneider for sending us a ready-to-use patent citations database. We gratefully acknowledge helpful comments received at workshops hosted by the Centre for Industrial Economics and the Centre for Business and Economic Research, at the 3rd ZEW Conference on the Economics of Innovation and Patenting, and at the Econometric Society European Meeting in Milan. We particularly benefited from comments by Mogens Fosgerau, Luigi Franzoni, Patrick Legros, Franz Palm, Katharine Rocket, Cédric Schneider, Frederick Schmidt and Rainer Winkelmann. Finally, we thank our student assistants Marie Ebbensgaard, Søren M. Johansen, Simon Lamech and Andreas Sloth for competent research assistance.
9. References


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and Statistics 88, 472–481.
Kaiser, U. (2006), The Value of Danish Patents - Evidence From a Survey of Inventors, Centre for Economic and Business Research Discussion Paper 2006-2; URL:


Toivanen, O., and L. Väänänen (2008), Returns to Inventors, Helsinki School of Economics mimeo.


Figure 1 illustrates the equilibrium mobility outcome for exposed and non–exposed R&D workers. The horizontal axis depicts the value of a worker to the recipient firm. The vertical axis depicts the value of a worker to the donor firm. Mobility occurs to the right of the $C$–line and the $C−s$–line for non patent exposed and for patent exposed workers, respectively. The expected value of a non patent exposed worker is indicated by the two squares. Stayers and leavers have the same expected value to the donor firm. Thus, the two squares are both on the $V_D$-line, which corresponds to Hypothesis 5. The value patent exposed workers' rival labor inputs and total labor inputs are indicated by stars and triangles, respectively. The total expected value of patent exposed stayers and leavers are the same to the donor firm. The triangles indicating the total value of leavers and stayers are therefore both on the $V_D+(1−\alpha)s$–line as stated in Hypothesis 4. Furthermore, patent exposed stayers (leavers) are in expectation more valuable to the donor firm than non patent exposed stayers (leavers) due to rival part of the knowledge. Hypothesis 2 and Hypothesis 3 test this implication. Finally, the expected value of patent exposed joiners' rival labor inputs is lower than that of non patent exposed joiners. Still, the total expected value of the patent exposed joiners’ labor inputs ($V_D+E(|\text{exposed joiner})+s$) is greater to the recipient firm than the total expected value of the non patent exposed joiners’ labor inputs ($V_D+E(|\text{non exposed joiner})$). This corresponds to Hypothesis 6.
<table>
<thead>
<tr>
<th>Currently employed workers</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) R&amp;D joiners with patent exposure</td>
<td></td>
</tr>
<tr>
<td>(2) R&amp;D joiners without patent exposure</td>
<td></td>
</tr>
<tr>
<td>(3) R&amp;D stayers with patent exposure</td>
<td></td>
</tr>
<tr>
<td>(4) R&amp;D stayers without patent exposure</td>
<td></td>
</tr>
<tr>
<td>(5) R&amp;D workers without prior employment history</td>
<td></td>
</tr>
<tr>
<td>(6) Non R&amp;D joiners with patent exposure</td>
<td></td>
</tr>
<tr>
<td>(7) Non R&amp;D joiners without patent exposure (base group)</td>
<td></td>
</tr>
<tr>
<td>(8) Non R&amp;D stayers with patent exposure</td>
<td></td>
</tr>
<tr>
<td>(9) Non R&amp;D stayers without patent exposure</td>
<td></td>
</tr>
<tr>
<td>(10) Non R&amp;D workers without prior employment history</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Leavers</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>(11) R&amp;D leavers with patent exposure</td>
<td></td>
</tr>
<tr>
<td>(12) R&amp;D leavers without patent exposure</td>
<td></td>
</tr>
<tr>
<td>(13) Non R&amp;D leavers with patent exposure</td>
<td></td>
</tr>
<tr>
<td>(14) Non R&amp;D leavers without patent exposure</td>
<td></td>
</tr>
</tbody>
</table>
Table 2 Descriptive statistics

<table>
<thead>
<tr>
<th></th>
<th>All firms w/o patents</th>
<th>All firms w/ at least one R&amp;D worker</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>S.D.</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dependent and explanatory variables unrelated to workforce composition</td>
<td></td>
<td></td>
</tr>
<tr>
<td># of patent applications</td>
<td>0.010</td>
<td>0.569</td>
</tr>
<tr>
<td>Disc. stock of patents</td>
<td>0.159</td>
<td>11.658</td>
</tr>
<tr>
<td>Capital stock (in 1000 DKK)</td>
<td>1.191</td>
<td>24,800</td>
</tr>
<tr>
<td>Fixed effects dummy</td>
<td>0.012</td>
<td>0.108</td>
</tr>
<tr>
<td>Explanatory variables unrelated to workforce composition</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Levels</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Non R&amp;D joiners</td>
<td>0.004</td>
<td>0.034</td>
</tr>
<tr>
<td>Non R&amp;D leavers</td>
<td>0.003</td>
<td>0.028</td>
</tr>
<tr>
<td>Total # of workers</td>
<td>15.448</td>
<td>130.439</td>
</tr>
<tr>
<td>Leavers</td>
<td>2.638</td>
<td>47.215</td>
</tr>
<tr>
<td>Shares (relative to total # of employees)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Joiners</td>
<td>0.150</td>
<td>0.214</td>
</tr>
<tr>
<td>Non R&amp;D joiners</td>
<td>0.000</td>
<td>0.011</td>
</tr>
<tr>
<td>Non R&amp;D leavers</td>
<td>0.003</td>
<td>0.028</td>
</tr>
<tr>
<td>Graduates</td>
<td>0.105</td>
<td>0.188</td>
</tr>
<tr>
<td>Non R&amp;D graduates</td>
<td>0.002</td>
<td>0.029</td>
</tr>
<tr>
<td>Leavers</td>
<td>0.212</td>
<td>1.006</td>
</tr>
<tr>
<td>Non R&amp;D leavers</td>
<td>0.000</td>
<td>0.021</td>
</tr>
<tr>
<td>Mobile R&amp;D leavers</td>
<td>0.008</td>
<td>0.113</td>
</tr>
<tr>
<td>Mobile non R&amp;D leavers</td>
<td>0.001</td>
<td>0.048</td>
</tr>
<tr>
<td># obs.</td>
<td>206,645</td>
<td>1,238</td>
</tr>
<tr>
<td># firms</td>
<td>90,725</td>
<td>352</td>
</tr>
</tbody>
</table>

Table 2 displays descriptive statistics of key variables used in the econometric analysis. Patenting firms are defined as firms who applied for at least one patent between 1999 and 2002.
Table 3

<table>
<thead>
<tr>
<th></th>
<th>Poisson Coeff.</th>
<th>Poisson S.E.</th>
<th>RE NegBin Coeff.</th>
<th>RE NegBin S.E.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Disc. stock of applications</td>
<td>0.000</td>
<td>0.000</td>
<td>0.004**</td>
<td>0.001</td>
</tr>
<tr>
<td>ln(# workers)</td>
<td>0.284**</td>
<td>0.052</td>
<td>0.459**</td>
<td>0.050</td>
</tr>
<tr>
<td>ln(capital stock)</td>
<td>0.146**</td>
<td>0.035</td>
<td>0.069*</td>
<td>0.029</td>
</tr>
<tr>
<td>ln(fixed effect)</td>
<td>0.472**</td>
<td>0.059</td>
<td>0.502**</td>
<td>0.064</td>
</tr>
<tr>
<td>Fixed effect dummy</td>
<td>6.963**</td>
<td>0.576</td>
<td>7.062**</td>
<td>0.563</td>
</tr>
<tr>
<td>Constant</td>
<td>-8.989**</td>
<td>0.469</td>
<td>-8.315**</td>
<td>0.454</td>
</tr>
</tbody>
</table>

**Worker shares**

| Share R&D joiners w/ exp. | 4.225**        | 0.624        | 4.351**          | 0.535          |
| Share R&D joiners w/o exp. | 3.219**        | 0.447        | 2.938**          | 0.444          |
| Share R&D stayers w/ exp. | 2.307**        | 0.501        | 2.503**          | 0.553          |
| Share R&D stayers w/o exp. | 1.226**        | 0.465        | 1.309**          | 0.439          |
| Share R&D graduates     | 2.444**        | 0.779        | 2.606**          | 0.627          |
| Share non R&D joiners w/ exp. | 0.533        | 0.357        | 0.127            | 0.508          |
| Share non R&D joiners w/o exp. | 0.677**        | 0.265        | 0.043            | 0.267          |
| Share non R&D stayers w/ exp. | 1.111**        | 0.252        | 0.498*           | 0.232          |
| Share non R&D graduates | 1.021**        | 0.420        | 0.674            | 0.448          |
| Share R&D leavers w/ exposure | -0.267        | 0.844        | -1.776           | 1.101          |
| Share R&D leavers w/o exposure | 0.651**        | 0.247        | 0.478            | 0.284          |
| Share non R&D leavers w/ exposure | 0.049        | 0.051        | 0.170            | 0.123          |
| Share non R&D leavers w/o exposure | -1.738        | 1.545        | -0.970**         | 0.384          |

**Tests for joint significance**

| Leavers | 17.47 | 0.0016 | 120.93 | 0.0000 |
| Sector dummies | 46.83 | 0.0000 | 112.38 | 0.0000 |
| Region dummies | 45.96 | 0.0000 | 13.85  | 0.4613 |
| Year dummies | 160.80 | 0.0000 | 190.11 | 0.0000 |

# of obs. and pseudo $R^2$

| # obs. | 206,645 |
| # firms | 90,725 |
| # firms w/ patent | 352 |
| # patents, citations weighted | 1,987 |
| Pseudo $R^2$ | 0.181 | 0.071 |

Table 3 displays coefficient estimates for the Poisson and the random effects NegBin model. The asterisks ‘**’ and ‘*’ denote marginal significance at the one and five percent level respectively.
Table 4 Marginal effects

<table>
<thead>
<tr>
<th></th>
<th>Firms with at least one patent prior to 1990</th>
<th>All firms</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>M.E.</td>
<td>S.E.</td>
</tr>
<tr>
<td>R&amp;D joiners w/ exposure</td>
<td>0.0111**</td>
<td>0.0026</td>
</tr>
<tr>
<td>R&amp;D joiners w/o exposure</td>
<td>0.0078**</td>
<td>0.0020</td>
</tr>
<tr>
<td>R&amp;D stayers w/ exposure</td>
<td>0.0068**</td>
<td>0.0021</td>
</tr>
<tr>
<td>R&amp;D stayers w/o exposure</td>
<td>0.0040**</td>
<td>0.0015</td>
</tr>
<tr>
<td>R&amp;D graduates</td>
<td>0.0070**</td>
<td>0.0022</td>
</tr>
<tr>
<td>R&amp;D leavers w/ exposure</td>
<td>-0.0042</td>
<td>0.0028</td>
</tr>
<tr>
<td>R&amp;D leavers w/o exposure</td>
<td>0.0011</td>
<td>0.0007</td>
</tr>
</tbody>
</table>

Table 4 displays the absolute change in the number of expected patents due to an increase in the number of workers in the respective skill groups by one. The calculation of these marginal effects is based on the coefficient estimates for the RE NegBin model displayed in Table 3. The marginal effects are calculated for the average firm in our data (left part of the table) and for firms that patented prior to 1999 (right part of the table). The asterisks ‘**’ and ‘*’ denote marginal significance at the one and five percent level, respectively. The calculation of the marginal effects is explained in Appendix B.
Table 5 Hypotheses tests

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Correct sign?</th>
<th>$\chi^2$</th>
<th>$p$-val.</th>
<th>Hypothesis accepted?</th>
</tr>
</thead>
<tbody>
<tr>
<td>H.1: The sum of a R&amp;D joiner's and a R&amp;D leaver's contribution to patenting activity is positive.</td>
<td>yes</td>
<td>12.15</td>
<td>0.00</td>
<td>yes</td>
</tr>
<tr>
<td>H.1.1: Joiners w/ exposure</td>
<td>yes</td>
<td>12.06</td>
<td>0.00</td>
<td>yes</td>
</tr>
<tr>
<td>H.1.2: Joiners w/o exposure</td>
<td>yes</td>
<td>3.55</td>
<td>0.00</td>
<td>yes</td>
</tr>
<tr>
<td>H.2: Patent exposed R&amp;D stayers contribute on average more to patenting activity than non patent exposed R&amp;D stayers.</td>
<td>yes</td>
<td>9.36</td>
<td>0.00</td>
<td>yes</td>
</tr>
<tr>
<td>H.3: Patent exposed R&amp;D leavers subtracts on average more from patenting activity than non patent exposed R&amp;D leavers.</td>
<td>no</td>
<td>0.00</td>
<td>0.00</td>
<td>no</td>
</tr>
<tr>
<td>H.4: Patent exposed R&amp;D joiners contribute on average more to patenting activity than non patent exposed R&amp;D joiners.</td>
<td>yes</td>
<td>4.84</td>
<td>0.00</td>
<td>yes</td>
</tr>
<tr>
<td>H.5: Productivity of stayers with exposure = - productivity of leavers with exposure</td>
<td>—</td>
<td>2.77</td>
<td>0.00</td>
<td>no</td>
</tr>
<tr>
<td>H.6: Productivity of stayers without exposure = - productivity of leavers without exposure.</td>
<td>—</td>
<td>0.12</td>
<td>0.00</td>
<td>yes</td>
</tr>
</tbody>
</table>

Table 5 displays the absolute change in the number of expected patents due to an increase in the number of workers in the respective skill groups by one. The calculation of these marginal effects is based on the coefficient estimates for the RE NegBin model displayed in Table 3. The marginal effects are calculated for the average firm in our data (left part of the table) and for firms that patented prior to 1999 (right part of the table). The asterisks ** and * denote marginal significance at the one and five percent level, respectively. The calculation of the marginal effects is explained in Appendix B.