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Kaiser, Ulrich; Kongsted, H.C. ; Rønde, Thomas

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Ulrich Kaiser
Hans Christian Kongsted
Thomas Rønde

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ULRICH KAISER[*], HANS CHRISTIAN KONGSTED[**], and THOMAS RØNDE[‖]

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Abstract

We measure the quantitative importance of labor mobility as a vehicle for the transmission of knowledge and skills across firms. For this purpose we create 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. The Danish workforce is split into "R&D workers", who hold a bachelor's or a master's degree in a technical field, and "non–R&D workers". We find that mobile R&D workers ("R&D joiners"') contribute more to patenting activity than immobile R&D workers. Furthermore, R&D workers who have previously been employed by a patenting firm ("patent exposed workers") have a larger effect on patenting activity than R&D workers without this experience. Patent exposed R&D joiners constitute the most productive group of workers: for firms that patented prior to 1999, one additional worker of this type relates to an increase in the number of patent applications of the new employer by 0.0646. This corresponds to a 14 percent increase in the mean number of yearly patent applications. We also find that mobility of R&D workers increases the joint patenting activity of the donor and recipient firms, confirming the importance of labor mobility for innovation in the economy.

JEL-classification: O33, O34, C23

Keywords: labor mobility, dynamic count data, patents

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[*]University of Zurich, Institute for Strategy and Business Economics, Plattenstr. 14, 8032 Zurich, Switzerland, email: 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.

[**] University of Copenhagen, Dept. of Economics, Studiestræde 6, 1455 Copenhagen K, Denmark, email: 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.

[‖]Copenhagen Business School, Department of Innovation and Organizational Economics, Kilevej 14A, 2000 Frederiksberg, Denmark, email: 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.

> "A major unresolved issue in the area of economics of technology is the identification and measurement of R&D spillovers, the benefits that one company receives from R&D activity of another." (Griliches, 1990, p. 1,688)

1 Introduction

Knowledge is one of the main sources of the competitive advantage of firms (Kogut and Zander, 1992; Teece, Pisano and Shuen, 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: the knowledge base of a firm can be strengthened by employees joining the firm but weakened by employees leaving. Consistent with this view, mutual funds acquire the resources to introduce new products by hiring managers from the outside (Rao and Drazin, 2002) and semiconductor firms enter markets where experience of new managers is available (Boeker, 1997). Looking at the downside of mobility, Wezel, Cattani and Pennings (2006) show that group exit is a source of 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. Inter-firm mobility is thus a source of knowledge sharing among firms, so–called "technology spillovers", which are identified by macroeconomists as a main driver of sustained economic growth (Romer, 1990; Aghion and Howitt, 1992).[1]

There is a substantial body of evidence from surveys to date (Mansfield, 1985; Zander and Kogut, 1995), patent files (Almeida and Kogut, 1999; Kim and Marschke, 2005; Song, Almeida and Wu, 2003), and litigation (Gilson, 1999; Hoti, McAleer and Slottje, 2006) indicating that mobility is a source of knowledge transfers between firms. However, it is primarily qualititative in nature, and little evidence exists 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 innovation in Danish 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. Some of the questions that we address are: Is labor

[1] See also Fallick, Fleischman, and Rebitzer (2006) for a recent analysis of mobility inside the computer industry in Silicon Valley.

mobility associated with an increase in innovation by the new employer as measured by patent applications? How does the answer to this question depend on the experience of the person moving in terms of her education and the patenting activity of her previous employer? Is mobility associated with an overall increase in the new and old employers' joint innovation? These are central questions for our understanding of mobility as a source of competitive advantage for firms and regions to which the existing literature does not provide answers.

To answer these questions we identify the group of persons who is likely to possess valuable knowledge and measure whether their movements between firms contribute to explaining firm–level patenting activity. Specifically, a firm's work force is split into "R&D workers" and "non–R&D workers" defined according to the level and the subject of their highest educational level. Persons with a bachelor's or a master's degree in natural sciences are, e.g., classified as R&D workers whereas persons with the same level of education in humanities will be termed non–R&D workers. We identify the persons that have recent experience working in an R&D active environment by introducing a second dimension, "patent exposure". A person is "patent exposed" if the firm she was employed by in the previous period applied for a patent during that period. Otherwise, she is "not patent exposed". The idea is here that patent exposed persons are more likely to have accumulated knowledge and skills that can serve as inputs in the production of further innovations than non–exposed persons. 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 the period $t-1$), "joiners" (joined the firm in period t), "leavers" (left the firm after period $t-1$), or "unknown" (entered the Danish labor market in period t).

Our point of departure in the analysis is a standard patent production function at the firm level that maps innovation inputs, the different types of labor and capital, into patent counts and controls for both unobserved and observed firm–specific heterogeneity. To correct for unobserved permanent differences in firms' patent productivity, we utilize the very long "pre–sample" patent histories at our disposal. Specifically, we employ the suggestion of Blundell, Griffith and van Reenen (1995) to use a firm's *average* number of patents over this pre–sample period as an observable proxy for unobservable permanent productivity. Because a prominent feature of our sample is an increasing trend in the overall level of patenting during the pre–sample period, we extend the Blundell, Griffith and van Reenen (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, e.g., the number of patent applications by 0.0112, corresponding to a 184 percent increase in the number of applications for the average firm in the population given a mean number of patents across firms of 0.006. This is more than five times the contribution of a non–R&D joiner with exposure. The increase in the number of patents of 184 percent seems excessive. This figures needs to be, however, interpreted before the background of an average number of workers of this sort of 0.0007 across all firms. As many as 99.2 firms do not employ any R&D joiner with exposure. An increase in the number of R&D joiners with exposure by one thus is a very drastic change for most firms.

For firms that patented prior 1990 the effect of one additional R&D joiner with exposure on the number of patent application is 0.0646 which relates to an increase in the number of patents of this type of firms by 14 percent. These firms apply for 0.45 patents per year on average.

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. Patent exposure is also associated with a 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. Furthermore, the difference between the contribution of exposed and non–exposed workers to patenting is shown to be larger for R&D workers than for non–R&D workers, indicating that workers with an R&D–relevant education have a larger absorptive capacity.

For firm strategy as well as public policy a central question is to what extent the fruits of R&D can be shared among firms. We address this question in two steps. First, we show that the mobility of R&D workers increases the *joint* patenting activity of the donor and the recipient firm. This could either be due to technology spillovers as envisioned in the literature on regional and national growth or be the outcome of a well–functioning labor market that allocates labor to its most productive use. In the second step we develop a stylized model of a competitive labor market to try to disentangle these two explanations. There are two types of workers, patent exposed and not exposed workers. A non–patent exposed worker's labor input is rival (physical labor, human capital, etc.) and can thus be used only by one firm at a time. A patent exposed worker's labor input has an additional, non–rival component, namely knowledge. We show that in equilibrium the recipient firm experiences a larger gain on average when exposed workers join the firm than when non–exposed workers join. More surprisingly, we find that although the knowledge that the patent exposed workers possess is non–rival and stays with the donor firm, the donor firms experience a larger loss on average when exposed workers leave than when non–exposed workers leave. The first prediction of the model is strongly confirmed by the data whereas the evidence for the second implication is somewhat weaker. Overall, our results are consistent with the widely held belief that labor mobility is a source of knowledge sharing among firms.

Turning to the related literature, the main obstacle to the empirical analysis of inter–firm mobility is to find comprehensive data on the movements of individuals across firms. Progress has been made in recent papers where long time–series on mobility inside the semi–conductor industry and the financial services sector have been constructed. These studies have documented how labor inflows can transfer the necessary skills and knowledge to offer products and services outside of the firm's current business areas (Boeker, 1997; Rao and Drazin, 2002) but outflows may disrupt the functioning of the organization (Wezel, Cattani and Pennings, 2006).[2] While these studies show how mobility transfers skills and induces learning across firms, they contain little information regarding the role of mobility in the innovation process.

In order to analyze the importance of mobility for innovation, a number studies have used patent data. Almeida and Kogut (1999) track the careers of the most productive research engineers in the semiconductor industry. They provide evidence on the role of mobility as 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, which is consistent with a theory where 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, Almeida and Wu (2003) study mobility within and across industries and technology classes and use 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 is productivity–enhancing. While providing interesting insights regarding mobility and its effects on innovation, the use of patent files to trace mobility has a major weakness: only moves by inventors that result in a patent at the new employer (successful moves) are registered whereas moves that do not result in

[2]Interestingly, Madsen, Mosakowski and Zaheer (2003) show that the inflow of personnel to trading floors is associated with retention of the current organization in the foreign exchange industry rather than organizational innovations.

a patent (unsuccessful moves) are not. Toivanen and Väänänen (2008) remedy this shortcoming by combining data on inventors of Finnish patents 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 as measured by firms' innovative productivity. This is arguably better suited to answer the questions outlined above regarding the expected (or, average) effect of mobility on innovation in the population of firms.

Our data and empirical analyzes allow us to address new research questions, but we wish to be upfront regarding limitations of our approach. First, the mobility of persons between firms is clearly endogenous. We measure therefore the total effect of mobility resulting from the match between persons' labor supply and firms' labor demand, the effects on the organization of inflows and outflows of personnel, knowledge transfers, etc. We discuss this issue, which is common to the literature, in detail in the text. Second, our approach allows us compare the effects of mobility among different types of workers. However, as previously noted we do not identify the formal inventors as stated in the patent applications. Our results should therefore be interpreted as representing an average person engaged in R&D rather than the star scientist who has been the main focus of the literature until now.

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

We differentiate the labor inputs of workers according to education, patent exposure, and mobility status. In the following we first compare workers within each of the three dimensions and derive theoretical hypotheses regarding their contribution to patenting activity. Afterwards, the interactions between mobility and the other two dimensions are considered, which generates additional hypotheses. Our hypotheses are evaluated in view of the empirical evidence in Section 6.

2.1 Education

Our empirical approach assumes that it is possible to use educational attainment to identify the workers that are central to the production of patentable inventions. Our definitions of R&D workers and non–R&D workers are in accordance with survey evidence on the education of inventors in Denmark (Kaiser, 2006). Still, an important consistency check for our empirical analysis is that R&D workers contribute more to the production of patentable inventions than do non R&D workers. Our first hypothesis simply states as follows:

H. 1: R&D workers contribute more to patenting activity than non R&D workers.

2.2 Exposure

The variable "patent exposure" measures whether a worker has recent experience working for a firm that applied for an EPO patent. From the data it is not possible to infer whether the worker was directly involved in the project that lead to the patent application. We therefore interpret the exposure variable as an indicator of recent experience working in an R&D active environment where valuable knowledge and skills can be acquired. This is in line with the literature showing that not all innovations are patented (Arundel and Kabla, 1998; Brouwer and Kleinknecht, 1999; Cohen, Nelson and Walsh, 2000) but that patents are appropriate indicators for innovative activity (Griliches, 1990).

For R&D workers who are the prime candidates for transferring knowledge, these arguments suggest that joiners with patent exposure will transfer more knowledge to their new employer than joiners without exposure. This should, in turn, translate into a higher innovation output as measured by patent applications for the new employer. Hence, we hypothesize:

H. 2(a): R&D joiners with exposure contribute more to patenting activity than R&D joiners without exposure.

The knowledge resulting from R&D opens up new technical opportunities due to the cumulative nature of innovation. At the same time R&D experience enables the workers to exploit these opportunities better through more efficient search (Nelson, 1982) and use of outside knowledge (Cohen and Levinthal, 1990). These effects suggest that workers with recent R&D experience not only have acquired more knowledge that can be used in the production of new innovation than workers without R&D experience but are also better at using it. Comparing across firms, we hypothesize:

H. 2(b): R&D stayers with exposure contribute more to patenting activity than R&D stayers without exposure.

2.3 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, at least partly, non–rival in nature and therefore shareable among firms (Arrow, 1962; David, 1992). Hence, a central question in the debate regarding the role of labor mobility for innovation is whether it leads to transfer of non–rival knowledge. We will return to this question below. For now notice that 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, e.g., physical labor, problem–solving abilities, and the use of tacit knowledge. For our purposes, the key characteristic of these other components 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. Individuals work in firms where they have a high productivity and leave if their labor inputs find a better use (Jovanovic, 1979; Mortensen, 1982). There will thus be mobility in the labor market that is not driven by knowledge acquisition motives, but primarily serves to match the workers' rival labor inputs to firms' demands. We will refer to the productivity gains that arise from this matching process as a "matching effect."[3]

Both the spillover and the matching effect would suggest that mobility is associated with a net productivity gain:

H. 3(a): The sum of an R&D joiner's and an R&D leaver's contribution to

[3]This is, of course, not to say that employment relations are not discontinued for many other reasons or that the market ensures that all labor is put to its most productive use at all points in time. Still, we would expect that mobility, on average, results in a productivity increase due to better matching.

patenting activity is positive.

H. 3(b): The sum of a non R&D joiner's and a non R&D leaver's contribution to patenting activity is positive.

2.4 Mobility and Exposure

R&D workers with patent exposure are more likely to transfer non–rival knowledge than R&D workers without patent exposure. We would therefore expect that mobility of R&D workers with patent exposure is driven both by spillover and matching effects whereas mobility of R&D workers without patent exposure is driven primarily, or to a larger extent, by the latter effect.

To conceptualize the difference between exposed and non–exposed workers, consider the following stylized model. An individual R&D worker's rival labor inputs contribute to the production of patentable inventions. The value of these inputs is V_D to the current employer, the potential (D)onor firm. The worker is matched according to some matching process to an outside firm, the potential (R)ecipient firm, that values the rival labor inputs V_R. For simplicity, assume that V_D and V_R are independently and uniformly distributed, $V_D \sim U[0, \overline{V}_D]$ and $V_R \sim U[0, \overline{V}_D]$. On top of their rival labor inputs, patent exposed R&D workers also bring knowledge that has value s to the recipient firm. Since this part of the knowledge is non–rival, the donor firm does not experience a loss if the worker leaves.[4] Finally, there is a fixed cost of mobility $\overline{V}$ that includes cost of training for the recipient firm, the cost of finding a replacement for the donor firm, etc.

Assuming that the two firms compete in wages for workers, e.g., modelled as a first price auction, mobility arises if and only if it increases the joint profit of the two firms. Hence an R&D worker switches from the donor to the recipient firm if and only if:

$$
\begin{aligned}
\text{Non-exposed R\&D worker} &: \quad \underbrace{V_R - V_D}_{\text{Net benefit from mobility}} \geq \underbrace{\overline{V}}_{\text{Cost of mobility}}, \\
\text{Exposed R\&D worker} &: \quad \underbrace{V_R + s - V_D}_{\text{Net benefit from mobility}} \geq \underbrace{\overline{V}}_{\text{Cost of mobility}}.
\end{aligned}
$$

Figure 1 illustrates the labor market outcome.

Insert Figure 1 about here!

We observe the productivity gains and losses resulting only from the realized moves in our data. For the exposed and the non–exposed R&D workers, this

[4] We assume here that the firms are not competing in the product market.

corresponds to combinations of (V_R, V_D) below the $V_R + s - V_D = \overline{V}$–line and the $V_R + s - V_D = \overline{V}$–line, respectively. The square (dot) illustrates the average value of V_R and V_D conditional on mobility for the exposed and the non–exposed R&D workers, respectively. Looking first at the donor firm, the average value of V_D is larger for exposed than for non–exposed workers. Hence, although the knowledge that the patent exposed workers transfer is non–rival, and therefore remains with the donor firm, the prediction is that firms on average experience a larger loss when exposed workers leave than when non–exposed workers leave. This leads to the following hypothesis:

H. 4: An exposed R&D leaver subtracts more from patenting activity than a non–exposed R&D leaver.

A formal proof for Hypothesis 4 is presented in Appendix A.

Turning to the gain of the recipient firm, the average value of V_R is lower for R&D workers with patent exposure than for R&D workers without patent exposure. In the data, however, we observe the average gain of the recipient firm from the rival labor inputs plus the value of the non–rival knowledge, s. This corresponds to the triangle in the figure, which is north–east of the dot. Therefore, conditional on mobility, hiring an exposed worker results on average in a larger productivity gain for the recipient firm than hiring a non–exposed worker. This implication is tested by Hypothesis 2(a).

2.5 Mobility and Education

Cohen and Levinthal (1990) argue that individuals differ in their abilities to identify valuable knowledge, to assimilate it, and to apply it to a new context (their "absorptive capacity"). Formal training in a relevant field is likely to increase an individual's absorptive capacity. Thus, we would expect that R&D workers have a higher absorptive capacity, and thus benefit more from working in an active R&D environment, than non R&D workers. This leads to the following set of hypotheses:

H. 5(a): The difference in the contribution of joiners with and without exposure is larger for R&D workers than for non–R&D workers.

H. 5(b): The difference in the contribution of stayers with and without exposure is larger for R&D workers than for non–R&D workers.

H. 5(c): The difference in the contribution of leavers with and without exposure is larger for R&D workers than for non–R&D workers.

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 instead of patent applications.

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 11,784 patents 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, Narin, Scherer and Vopel (1999); Lanjouw, Pakes and Putnam (1998), and Hall, Jaffe and Trajtenberg (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. The idea is that valuable patents receive many citations by patents that follow while less valuable patents will receive few citations or no citations at all. 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.[5] Our patent citations data stem from the "EPO/OECD patent citations database" that is available from the OECD (Webb, Dernis, Harhoff and Hoisl, 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 with 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. The corresponding information would have been lost in our analysis anyway since our firm–level data starts in 1999 only.

[5] 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.

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 number of employees and their highest level of education. 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 industrial classification level. We "expand" our patent data such that we obtain one observation for each applicant per year. Firms that did not file for an application at the EPO in a particular year are assigned a 0 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 ones 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' innovation input into patent counts and controls for both unobserved and observed firm–specific heterogeneity. Given that innovation 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, further control variables included in the model, and the functional form of the patent production function.

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 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, Griffith and van Reenen 1995, 2002; Hall, Hausman and Griliches, 1986; Crépon 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. The first concerns the meaning of an "R&D worker", the second the meaning of "mobility" and the third refers to the meaning of "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 B. Our main definition of R&D workers includes both workers with long or medium length R&D educations. This includes workers with a bachelor's, master's or Ph.D. degree in R&D–related subjects like e.g. engineering, chemistry, mathematics, medicin, 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.[6] 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 also comprises of 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 who is employed by firm i at time t but not at time $t-1$. "Leavers" are workers who were 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.

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

[6] 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.

"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 $t-1$. Since the employment history of recent graduates is not tracked, 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:

(1) R&D joiners with patent exposure.

(2) R&D joiners without patent exposure.

(3) R&D stayers with patent exposure.

(4) R&D stayers without patent exposure.

(5) R&D workers without prior employment history.

(6) Non R&D joiners with patent exposure.

(7) Non R&D joiners without patent exposure.

(8) Non R&D stayers with patent exposure.

(9) Non R&D stayers without patent exposure.

(10) Non R&D workers without prior employment history.

(11) R&D leavers with patent exposure.

(12) R&D leavers without patent exposure.

(13) Non R&D leavers with patent exposure.

(14) Non R&D leavers without patent exposure.

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" measured by the shares of each type of labor currently employed, i.e. skill groups (1) through (10) and "leaver" effects in terms 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:[7]

$$\underbrace{\sum_{k=1}^{9} \gamma_k s_k}_{\text{composition effects}} \quad + \quad \underbrace{\sum_{l=11}^{14} \delta_l r_l}_{\text{leaver effects}} \,. \tag{1}$$

[7]Non–exposed non–R&D workers (group 10) 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.

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

The coefficients in Equation (1) do not have a direct economic interpretation such as marginal effects or elasticities. We therefore present our results both in terms of marginal effects — the percentage effects of a one worker change on the expected number of patents — and absolute changes in the number of patents.[8]

4.2 State dependence

The standard treatment of state dependence in patent production, e.g. Blundell, Griffith and van Reenen (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:

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

where P_{it-1} denotes the number of patent applications of firm i at time $t-1$ and ω 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, Griffith and van Reenen (1995) and use a 30 per cent 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, Hall and Griliches (1984); Blundell, Griffith and van Reenen (1995); Blundell, Griffith and Windmeijer (1999), it leaves 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 that constitute the firm's labor force as a part of their "intellectual human capital" (Zucker, Darby and Brewer, 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 labour force. This creates a potential

[8]Appendix C shows how the marginal effects are calculated.

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 cases, and 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, namely 22 years of observations (1977–1998) 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, Griffith and van Reenen (1995) 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" (PSME) yields superior results compared to alternatives that are based on the generalized methods of moments (GMM) framework (Blundell, Griffith and Windmeijer 1999).

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, Griffith and van Reenen (1995) 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 D.

Many of the firms in our data never applied for a single patent. We again follow Blundell, Griffith and van Reenen (1995) as well as Blundell, Griffith and Windmeijer (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).

4.4 Control variables

Our model specification further controls for a number of variables commonly found to be important in the patenting literature. They include measures of firm size (total employment and capital stock, both in logs) as well as sectoral, regional and year dummies. We also include the rate of growth of employment to separate out mobility effects from the effects of firms pursuing "growth strategies".

4.5 Count data models

Our count data models use a common specification of the conditional mean function. We specify the (citation–weighted) mean number of patents applied for, Y_{it}, by firm i in year t by $E(Y_{it}|\boldsymbol{x_{it}}, \eta_i) = e^{\boldsymbol{x_{it}\beta}+\eta_i}$. The exponential specification is standard in the patenting literature. The vector $\boldsymbol{x_{it}}$ denotes observable patent production determinants, including the discounted stock of past patent applications and measures of the size and composition of the labor force as well as standard controls as detailed in the previous sections. The parameter vector $\boldsymbol{\beta}$ contains the corresponding parameters. The term η_i captures unobserved differences between firms in terms of their permanent patent productivity. It is proxied by two observable items, the pre–sample yearly average number of applications relative to the total number of EPO applications and a dummy variable for having at least one EPO patent application in the pre–sample period 1978–1998.

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. We also consider a negative binomial model that allows the variance to exceed the mean, a phenomenon called "overdispersion". This is commonly found in patent data, and it is economically motivated by unobserved firm–specific heterogeneity. 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 1 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 per cent of the full sample). The latter sample should include most R&D active firms and is be used for checking the robustness of our results in Section 7. It includes 31,193 firm–year observations (15.1 per cent of the full sample) and accounts for 96.7 per cent of the total number of patents. Overall patenting acitivity is fairly modest with the average patenter applying for 1.4 patents per year.

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).

Insert Table 1 about here!

Table 1 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 per cent of workers in patenting firms are classified as R&D workers. Of those workers, around one in five was mobile during any given year. The mobility status could be determined for the vast majority (97 per cent) of R&D workers in patenting firms. For non–patenters the corresponding numbers are lower: only four per cent of workers in non–patenting firms are classified as R&D workers with one in nine being mobile during any given year.

Within the sample of potentially R&D active firms about one in four workers is classified as an R&D worker. Somewhat surprisingly, 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 (one in nine).

6 Results

We report our empirical results in three steps. First, we comment briefly on the estimation results. Although the regression coefficients have no direct economic interpretation, their significance and sign form the basis for later inference. Second, to gain insight into the economic magnitude and significance of effects, we transform our results into more readily interpretable marginal effects. Finally, we present results each of the hypotheses forwarded in Section 2.

6.1 Estimation results

Our main estimation results are presented in Table 2. This is for the full sample of 90.725 firms that (i) have at least one employee and (ii) for which all variables 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 findings are consistent across specifications in terms of sign and magnitude of the estimated parameters.

Insert Table 2 about here!

The variables included to control for scale effects, overall mobility, state dependence and unobserved permanent heterogeneity, are all found to be statistically significant and signed according to expectation.[9] First, the estimated scale effects of the total number of workers and the capital stock (both in logs) are positive and statistically significant. Second, the overall growth rate of the firm's workforce is strongly and positively related to patenting activity, reflecting the prevalence of "growth firms" among patenters. Third, like other existing studies that consider dynamic specifications, 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. Although positive, the term is not significant in the Poisson model. This effect remains an important determinant of patenting even though our specification includes an extended set of human capital variables. This suggests that innovation involves dynamic processes inside the firm and in the product market that are not explained by the changes in the firm's use of human capital.

Finally, our PSME proxies for unobserved permanent heterogeneity, the fixed effect dummy variable for patenting activity prior to 1999, and the continuous measure *ln(fixed effect)* based on the 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.

Our results for composition effects related to the shares of different labor types (relative to the reference share of non–exposed non–R&D workers), are also in line with our expectations. A central finding is that R&D workers in the current workforce (i.e. joiners, stayers, and graduates) contribute positively and significantly to patenting. In contrast, we generally find little effects of non–R&D workers. Only for non–R&D stayers with patent exposure do we find an effect which is statistically significant at the ten per cent level. 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, the picture is mixed for leavers. As expected, we obtain a negative (although insignificant) effect for R&D leavers with patent exposure. For non–R&D leavers with no exposure there is a negative and statistically significant impact on the previous employer. Contrary to our expectations, R&D leavers without patent exposure and non R&D workers leaving firms that did apply for

[9] Our specification also includes 14 sectoral dummies, 14 regional dummies, year dummies for 2001 and 2002, and a constant term.

a patent in the previous period have significant and positive effects on current patenting. An explanation could be that workers leaving facilitate a redirection of R&D activities by opening up positions for workers with different skills and weakening the resistance to change often experienced in established firms (Morrill, 1991).

6.2 Marginal Effects

In a second step, we calculate the marginal effect of changing the number of workers in each group on the number of patent applications. These calculations are based on the RE NegBin estimation results. Table 3 reports the marginal effects in order to obtain an idea about the quantitative significance of the estimation results. These are the absolute changes 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. This calculation is performed for each group of R&D or non–R&D workers.

Insert Table 3 about here!

For the sample that includes all firms, the 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 0.002 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 could be that these workers bring knowledge of the recent developments in the field to the firm, which increases patenting activity.

Restricting attention to firms that already had applied for a patent in the pre–sample period, the marginal effects are generally stronger. The effect of an additional worker ranges here from a 0.06 increase in the number of patent applications for a R&D joiner with patent exposure to a 0.007 increase for a non–R&D stayer without patent exposure. Given the ample evidence for state dependence and the importance of pre–sample patents for current patents, these firms are likely to do more R&D than the average Danish firm in the sample period as well, this shows that acquisition of skills and knowledge through the labor market is more important for R&D active firms.

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 γ and δ coefficients from Equation (1).

Our results for the full model are summarized in Table 4. The first column shows if the estimated differences are in the direction predicted by theory. The second and third columns record the χ^2 statistic and the p-value associated with each hypothesis. We consider a p-value of less than ten per cent as supporting our economic hypotheses. The final column concludes if the economic hypothesis is validated which is the case if the estimated difference is statistically significant and signed according to theory.

First, the empirical evidence strongly corroborates Hypothesis 1 which was forwarded mainly as a consistency check for the R&D worker definition. R&D workers contribute significantly more than non–R&D workers regardless of whether they are joiners or stayers and if they have been previously exposed to patenting or not.

Second, there are strong effects of patent exposure in the directions suggested by theory. For joiners, Hypothesis 2(a), we find a positive productivity differential for R&D workers.[10] This supports the interpretation that knowledge obtained from previous patenting is transferred between firms by worker flows. For stayers, Hypothesis 2(b), we also find evidence that R&D workers with recent experience working in a firm that applied for a patent contribute more to patenting activity than workers with no such experience.

Third, there is strong evidence that the mobility of R&D workers increases the joint patenting of the donor and the recipient firm, Hypothesis 3(a). It is important to notice that this result is not contaminated by observable differences between joiners and leavers. As we have data for the entire Danish labor force, leavers in one firm are joiners in another firm.[11] The additional patenting activity resulting from mobility therefore represents a true increase in patenting. For non–R&D workers the positive effect of mobility on patenting is weaker, presumably because these workers contribute less to innovation. The results are only significant for workers without exposure where the difference is also signed according to theory.

Fourth, there is no strong evidence for the implication of the model that an R&D leaver with exposure subtracts more from the donor firm's patenting activity than a R&D leaver without exposure, Hypothesis 4. The difference has the sign predicted but it is statistically not significant.

Fifth, with regard to "absorptive capacity" our empirical results for Hypotheses 5(a) - (c) point in the direction suggested by theory, although p-values are in the inconclusive range. There is thus weak evidence that formal R&D qual-

[10] While the former is strongly significant, the latter is small and statistically insignificant.

[11] Unemployment rates in the period 1999–2002 have been between 4 per cent and 4.8 per cent.

ifications matter for the ability of individuals to gain from previous patenting exposure and to transfer knowledge, both to a new firm and to future periods within the current firm.

Insert Table 4 about here!

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 very unlikely to patent. In order to check the robustness of our main results we now re–estimate the model on a much more selective sample of firms that employ at least one R&D worker. Estimation results are presented in Appendix E.

Comparing the RE NegBin results on the full sample in Table 2 and the selected sample, we find that the main terms remain strongly significant. The effects of current worker groups remain positive but become smaller in magnitude. The coefficients of the control variables included for firm size, employment growth and pre–sample patenting are very similar between the two sets of results. 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.

The overall robustness of the estimation results is reflected in similar results for the tests of our economic hypotheses. The only changes in terms of overall conclusions that are reported in Table 4, are that hypotheses H.4a and H.5(b) cannot be rejected for 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 F. 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 a narrow definition and become weaker when broadening the definition.

8 Conclusions

In this paper we assess the quantitative importance of mobility for innovation by measuring how labor mobility affects the patenting activity of Danish firms. For this purpose, we have constructed 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 that essentially contains a complete record of mobility in the Danish labor market. The linked employer–employee register data span the period 1999–2002. Unlike previous studies of mobility and innovation that rely on patent data, we are able to observe moves that are "unsuccessful" 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 different types. We differentiate workers along three dimension: (i) R&D workers vs. non–R&D workers, (ii) workers who changed workplaces vs. workers who did not and (iii) workers who were employed by a firm that applied for patent in a previous period vs. who were not employed by such a firm.

The differentiated effects of these worker groups are of central importance when trying to assess the significance of mobility for innovation at the regional or national level. Furthermore, our paper complements previous studies that have focused on star scientist (Almeida and Kogut, 1999) or top–level managers (Boeker, 1997).

We find that R&D joiners coming from a firm that recently applied for a patent contribute more to patenting activity than R&D joiners with similar observable characteristics but coming from a firm that did not previously apply for a patent. Recent patenting experience is also associated with a higher patent productivity for workers staying in the firm. These findings are consistent with the notion that workers employed in patenting firm acquire knowledge and skills that increase their productivity in the production of new inventions. We also find weak evidence for the notion that workers with an R&D–relevant education have a larger absorptive capacity than other workers.

For the average firm, the effects of mobility on patenting activity are generally modest: an increase in the number of R&D joiners who come from a patenting firm — this is the most productive group of workers — is associated with an absolute increase in the number of patents by 0.0112.

This result reflects the fact that only a small fraction of "average" firms are involved in patenting activity. 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: one additional previously "patent–exposed" R&D joiner contributes 0.0646 additional patents on average. 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 more 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 and donor firms. We show that the mobility of R&D workers increases the *joint* patenting activity of the donor and the recipient firm. This is a notable result that provides quantitative support for the notion that interfirm mobility is an engine for innovation also at the aggregate level. Saxenian (1994) has forcefully argued that "job–hopping" is key to the success of Silicon Valley, and our results suggest that something similar, although perhaps to a lesser extent, is 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. A certain labor turnover among the R&D personnel can increase the firm's capacity for innovation. Losing workers to other firms might result in a loss of capacity but this can be more than compensated for by the skills and knowledge of the workers joining the firm.

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Figure 1: Equilibrium mobility outcome for exposed and non–exposed R&D workers

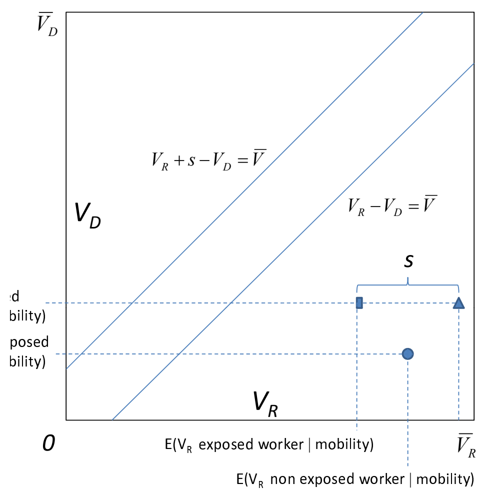

Figure 1 shows the equilibrium mobility outcome for exposed and non–exposed R&D workers.

Table 1: Descriptive statistics

	Full data						Firms w/ at least one R&D worker					
	All firms		w/ patents		w/o patents		All firms		w/ patents		w/o patents	
	Mean	**S.D.**	**Mean**	**S.D.**	**Mean**	**S.D.**	**Mean**	**S.D.**	**Mean**	**S.D.**	**Mean**	**S.D.**
Levels												
Joiners	4.137	35.829	56.217	190.534	3.823	32.502	15.209	90.316	65.402	205.224	13.455	82.950
Stayers	11.311	101.193	213.872	585.800	10.090	89.366	45.980	256.583	248.970	628.613	38.888	229.896
Graduates	1.543	15.630	17.085	49.603	1.449	15.149	5.301	39.303	19.811	53.312	4.794	38.625
Total # of workers	16.991	143.193	287.174	784.236	15.362	128.379	66.490	362.254	334.182	841.554	57.137	329.395
Leavers	2.640	47.219	35.190	162.855	2.444	45.573	9.631	120.816	40.841	175.970	8.541	118.281
Δ ln(# workers) $\cdot$ 100	-0.185	44.247	7.047	48.496	-0.229	44.217	4.564	39.971	9.308	46.844	4.398	39.700
Shares (in percent, relative to total # of employees)												
Joiners	21.57	22.74	22.31	17.39	21.57	22.77	21.59	17.70	22.53	16.80	21.56	17.73
R&D joiners w/ exp.	0.04	1.05	1.35	5.62	0.04	0.95	0.29	2.69	1.59	6.06	0.24	2.48
R&D joiners w/o exp.	0.36	3.25	2.50	6.90	0.35	3.21	2.39	8.06	2.94	7.39	2.37	8.08
Non R&D joiners w/ exp.	0.28	2.71	1.18	2.94	0.28	2.71	0.49	2.22	1.33	3.08	0.46	2.18
Non R&D joiners w/o exp.	13.28	20.12	10.90	12.03	13.29	20.15	11.21	12.57	10.34	10.12	11.24	12.64
Stayers	70.82	29.71	71.31	20.59	70.81	29.76	71.19	23.11	71.14	19.79	71.19	23.22
R&D stayers w/ exp.	0.06	1.61	9.26	16.86	0.01	0.62	0.41	4.13	10.89	17.79	0.05	1.63
R&D stayers w/o exp.	3.09	12.90	6.27	15.53	3.07	12.88	20.45	27.35	7.37	16.59	20.91	27.54
Non R&D stayers w/ exp.	0.20	3.65	29.23	32.87	0.03	1.34	1.09	8.30	29.35	31.84	0.11	2.64
Non R&D stayers w/o exp.	67.47	31.20	26.54	33.79	67.71	31.02	49.23	27.01	23.53	31.52	50.13	26.39
R&D graduates	0.15	1.78	0.55	1.96	0.15	1.78	1.00	4.49	0.65	2.12	1.02	4.55
Non R&D graduates	7.46	11.54	5.83	5.97	7.47	11.56	6.21	7.47	5.68	5.33	6.23	7.54
Leavers	22.27	112.94	19.06	81.36	22.29	113.11	16.86	68.90	15.51	55.21	16.90	69.33
R&D leavers w/ exp.	0.02	2.09	1.91	7.84	0.01	2.00	0.10	5.32	2.01	7.58	0.04	5.21
R&D leavers w/o exp.	0.71	11.29	2.46	28.86	0.70	11.10	2.34	15.66	1.85	22.72	2.36	15.35
Non R&D leavers w/ exp.	0.05	4.64	6.36	33.80	0.02	3.81	0.30	11.78	6.59	36.12	0.08	9.84
Non R&D leavers w/o exp.	21.49	107.85	8.33	50.34	21.57	108.10	14.11	60.85	5.05	19.98	14.42	61.76
# firms	90,725						14,811					

Table 1 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 2: Estimation results

	Poisson		RE NegBin	
	Coeff.	**S.E.**	**Coeff.**	**S.E.**
Disc. stock of applications	0.000	0.000	0.004***	0.001
ln(# workers)	0.321***	0.054	0.494***	0.051
ln(capital stock)	0.136***	0.035	0.061**	0.028
Δ ln(# workers)	0.399***	0.129	0.418***	0.115
ln(fixed effect)	0.468***	0.056	0.489***	0.063
Fixed effect dummy	6.896***	0.553	6.913***	0.551
Constant	-9.005***	0.459	-8.380***	0.446
Worker shares				
Share R&D joiners w/ exp.	3.697***	0.661	4.063***	0.553
Share R&D joiners w/o exp.	3.080***	0.423	2.869***	0.437
Share R&D stayers w/ exp.	2.294***	0.517	2.513***	0.556
Share R&D stayers w/o exp.	1.208***	0.482	1.344***	0.442
Share R&D graduates	2.410***	0.713	2.640***	0.616
Share non–R&D joiners w/ exp.	0.772***	0.333	0.146	0.507
Share non–R&D joiners w/o exp.	0.751***	0.242	0.126	0.261
Share non–R&D stayers w/ exp.	1.052***	0.248	0.432*	0.232
Share non–R&D graduates	0.985**	0.426	0.671	0.450
Share R&D leavers w/ exposure	0.360*	0.212	-0.467	0.986
Share R&D leavers w/o exposure	0.829***	0.167	0.537**	0.246
Share non–R&D leavers w/ exposure	0.118***	0.048	0.221*	0.123
Share non–R&D leavers w/o exposure	-1.499	1.381	-0.741*	0.395
Tests for joint significance				
Sector dummies	46.33	0.000	110.93	0.000
Region dummies	46.01	0.000	13.54	0.484
Year dummies	156.93	0.000	182.77	0.000
# of obs. and specification tests				
# obs.	206,645			
# firms	90,725			
# firms w/ patent	352			
# patents, citations weighted	1,987			
# patents	484			
Pseudo R^2	0.180		0.071	

Table 2 displays coefficient estimates for the Poisson and the random effects NegBin model.

Table 3: Marginal effects

	All firms		**At least one pre–sample patent**	
	M.E.	***p*–val.**	**M.E.**	***p*–val.**
R&D joiners w/ exposure	0.0112	0.000	0.0646	0.004
R&D joiners w/o exposure	0.0085	0.000	0.0476	0.005
R&D stayers w/ exposure	0.0076	0.000	0.0426	0.013
R&D stayers w/o exposure	0.0049	0.001	0.0259	0.023
R&D graduates	0.0079	0.000	0.0444	0.013
Non R&D joiners w/ exposure	0.0022	0.079	0.0089	0.249
Non R&D joiners w/o exposure	0.0021	0.008	0.0086	0.088
Non R&D stayers w/ exposure	0.0028	0.000	0.0129	0.013
Non R&D stayers w/o exposure	0.0018	0.000	0.0068	0.051
Non R&D graduates	0.0034	0.012	0.0163	0.071
R&D leavers w/ exposure	-0.0011	0.638	-0.0066	0.640
R&D leavers w/o exposure	0.0012	0.026	0.0076	0.057
Non R&D leavers w/ exposure	0.0005	0.091	0.0031	0.134
Non R&D leavers w/o exposure	-0.0017	0.000	-0.0105	0.002

Table 3 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 2. 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 calculation of the marginal effects is explained in Appendix C.

Table 4: Hypotheses tests

	Correct sign?	χ^2	p–val.	Hypothesis accepted?
H. 1: R&D workers contribute more to patenting activity than non–R&D workers.	yes	48.78	0.00	yes
1 Joiners	yes	44.66	0.00	yes
1.1 Joiners w/ exposure	yes	23.18	0.00	yes
1.2 Joiners w/o exposure	yes	27.74	0.00	yes
2 Stayers	yes	14.85	0.00	yes
2.1 Stayers w/ exposure	yes	10.54	0.00	yes
2.2 Stayers w/o exposure	yes	9.23	0.00	yes
H. 2(a): R&D joiners with exposure contribute more to patenting activity than R&D joiners without exposure.	yes	3.85	0.05	yes
H. 2(b): R&D stayers with exposure contribute more to patenting activity than R&D stayers without exposure.	yes	4.75	0.03	yes
H. 3(a): The sum of a R&D joiner's and a R&D leaver's contribution to patenting activity is positive.	yes	28.48	0.00	yes
Workers w/ exposure	yes	15.13	0.00	yes
Workers w/o exposure	yes	19.39	0.00	yes
H. 3(b): The sum of a non R&D joiner's and a non R&D leaver's contribution to patenting activity is positive.	no	3.34	0.19	no
Workers w/ exposure	no	0.02	0.88	no
Workers w/o exposure	yes	3.14	0.08	yes
H. 4: An exposed R&D leaver subtracts more from patenting acitivity than a non–exposed R&D leaver.	yes	0.00	0.32	no
H. 5(a): The difference in the contribution of joiners with and without exposure is larger for R&D workers than for non-R&D workers.	yes	3.44	0.06	yes
H. 5(b): The difference in the contribution of stayers with and without exposure is larger for R&D workers than for non-R&D workers.	yes	1.30	0.25	no
H. 5(c): The difference in the contribution of leavers with and without exposure is larger for R&D workers than for non-R&D workers.	yes	2.59	0.10	yes

Table 4 summarizes our hypotheses tests results. Our overall tests combine both the direction of differences in the respective effects and the corresponding statistical significance. We cannot reject our hypotheses if both the signs are correct and if the test is statistically significant in a one–sided test.

Appendix A: formal proof of Hypothesis 4

As a first step in the proof, we determine the outcome of the competition for the workers. Suppose here that the current employer (i.e. donor firm) carries a fraction α of the cost of mobility $\overline{V}$. The donor firm's valuation of an exposed and of a non exposed worker are thus $V_D + s + \alpha\overline{V}$ and $V_D + \alpha\overline{V}$, respectively, because there is no cost of mobility if the worker is retained. The potential employer (i.e. the recepient firm) values both an exposed and a non exposed $V_R - (1-\alpha)\overline{V}$, because the knowledge that the exposed worker possesses remains with the firm if the worker leaves.

Competition for workers is modeled in the following way: the 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 rule, we assume that the firm whose valuation of the employee is highest hires him. This ensures an equilibrium in pure strategies. In equilibrium the firm with the highest valuation of the worker hires him paying the valuation of the other firm. Therefore, mobility takes place if and only if:

$$\begin{aligned}
\text{Non exposed R\&D worker} &: \quad \underbrace{V_R - V_D}_{\text{Net benefit from mobility}} \geq \underbrace{\overline{V}}_{\text{Cost of mobility}}, \\
\text{Exposed R\&D worker} &: \quad \underbrace{V_R + s - V_D}_{\text{Net benefit from mobility}} \geq \underbrace{\overline{V}}_{\text{Cost of mobility}}.
\end{aligned}$$

Suppose that $\overline{V}_R \geq \overline{V}_D \geq s - \overline{V} > 0$ and $\overline{V}_R - \overline{V} \leq \overline{V}_D$ as in Figure 1. The proofs for the other possible cases are similar. Then, the expected loss of the donor firm conditional on mobility is given by

$$\begin{aligned}
E(V_D \text{ exposed R\&D worker} \quad | \quad &\text{Mobility}) = \\
\int_0^{\overline{V}_D+\overline{V}-s} f(V_R \quad | \quad &\text{Mobility})(V_R + s - \overline{V})/2dV_R + \\
\int_{\overline{V}_D+\overline{V}-s}^{\overline{V}_R} f(V_R \quad | \quad &\text{Mobility})\overline{V}_D/2dV_R,
\end{aligned}$$

where the density function conditional on mobility is given by

$$f(V_R \mid \text{Mobility}) = \frac{V_R + s - \overline{V}}{\overline{V}_D\overline{V}_R - (\overline{V}_D - s + \overline{V})^2/2}.$$

Simplifying expressions, we obtain

$$E(V_D \text{ exposed R\&D worker} \mid \text{Mobility}) = \frac{(\overline{V}_D - s + \overline{V})^2(2\overline{V}_D + s - \overline{V}) - 3\overline{V}_D^2\overline{V}_R}{3((\overline{V}_D - s + \overline{V})^2 - 2\overline{V}_D\overline{V}_R)}.$$

It can be shown that $E(V_D$ exposed R&D worker | Mobility) is increasing in s.

Consider instead a non exposed worker. Here,

$$E(V_D \text{ non exposed R\&D worker} \mid \text{Mobility}) = \int_{\overline{V}}^{\overline{V}_R} g(V_R \mid \text{Mobility})(V_R + s - \overline{V})/2dV_R,$$

where the density function conditional on mobility is given by

$$g(V_R \mid \text{Mobility}) = \frac{V_R - \overline{V}}{(\overline{V}_R - \overline{V})^2/2}.$$

Simplifying expressions, we obtain

$$E(V_D \text{ non exposed R\&D worker} \mid \text{Mobility}) = \frac{\overline{V}_R - \overline{V}}{3}.$$

We are now ready to prove Hypothesis 4 for the example considered.

Proposition 1 *For $\overline{V}_R \geq \overline{V}_D \geq s - \overline{V} > 0$ and $\overline{V}_R - \overline{V} \leq \overline{V}_D$, the expected loss of the donor firm conditional on mobility occurring is greater for an exposed R&D worker than for a non exposed R&D worker.*

Proof. Consider first $s = \overline{V}$ where

$$\underbrace{\frac{\overline{V}_D(3\overline{V}_R - 2\overline{V}_D)}{3(2\overline{V}_R - \overline{V}_D)}}_{E(V_D \text{ exposed R\&D worker}|\text{Mobility})} > \underbrace{\frac{\overline{V}_R - \overline{V}}{3}}_{E(V_D \text{ non exposed R\&D worker}|\text{Mobility})},$$

because $\overline{V}_D > \overline{V}_R - \overline{V}$ and $(3\overline{V}_R - 2\overline{V}_D)/(2\overline{V}_R - \overline{V}_D) > 1$. The proof follows then from $E(V_D$ exposed R&D worker $\mid$ Mobility) being continuous and increasing in s. ■

Appendix B: definition of 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: (1) "Unskilled workers", workers without a completed formal education; (2) "Skilled workers", workers with completed formal education like plumbers, electricians, blacksmiths, carpenters, photographers or waiters; (3) "R&D technicians", workers with a technical education in R&D–related subjects like process technicians, food processing technicians, dairy farm technicians, laboratory technicians or food business engineers; (4) "Other technicians"; workers with a technical education in non–R&D–related subjects like multi media designer, visualizer, actor, real estate agent, hotel technician, transport logistics; (5) "R&D medium length"; workers with a medium length education in R&D–related subjects like machine engineer, electrical engineer, food business engineer, architect, chemists, construction engineer, bio analytic; (6) "Other medium length"; workers with a medium length education in non–R&D–related subjects like social workers, high school teacher, journalist, librarian, photo journalist, language degrees, musician, insurance agent; (7) "R&D long"; workers with a bachelor or master in R&D–related subjects like natural sciences, technology, mathematics, statistics, physics, chemistry, biology; (8) "Non R&D long"; workers with a bachelor or master in non–R&D–related subjects like humanities, theology, religion, history of thought, literature, languages and (9) "Unknown education"; workers with an education unknown to Statistics Denmark. The latter is our "graduate" category.

We consider three different definitions for R&D workers, (i) a "narrow" one which defines R&D workers as workers with a long R&D education (skill group (7)), (ii) a "medium" definition that includes both workers with a long R&D education and and workers with a medium length R&D education (skill groups 5 and 7) and (iii) a "broad" definition that comprises also of workers with a short R&D education (skill groups 3, 5 and 7). We focus attention on the medium definition of R&D workers but present key results for the alternative definitions in Appendix E. Our medium definition corresponds most closely to the finding of Kaiser (2006).

Appendix C: calculation of marginal effects

Recall that the conditional mean function for a count data model is $E(Y_{it}|\boldsymbol{x_{it}}, \eta_i) = e^{X_{it}\boldsymbol{\beta}+\eta_i}$.

Given our definition of human capital variables as in Equation (1), the marginal effect of a worker from the kth skill group related to joiners or stayers on patenting activity — e.g. the absolute change in the number of patents due to a one unit (one worker) change in the number of workers of skill group — then is:

$$\eta_{P,L_k} = \frac{E(\hat{Y_{it}})}{TT}\left(\gamma_k - \frac{\sum_{k=1}^{9}\gamma_k s_k - \sum_{l=11}^{1} 4\delta_l r_l}{TT} + \beta_{\Delta\#\text{ workers}} + \beta_{\#\text{ workers}}\right), \quad (3)$$

where TT denotes the total number of workers and $\beta_{\Delta\#\text{ workers}}$ and $\beta_{\#\text{ workers}}$ denote the coefficients corresponding to the change in the natural logarithm of the number of workers and the natural logarithm of the total number of workers.

The marginal effect of the rth leaver skill group is:

$$\eta_{P,L_r} = \frac{\delta_l}{TT}. \quad (4)$$

We evaluate the marginal effects at the means of the involved variables throughout this paper.

Appendix D: trend correction of the PSME

Let T_P denote the number of pre–sample observations on the dependent variable, let Y_{it} denote the number of patents applied for by firm i in year t, let S_{it} denote latent innovation search activity as in Blundell, Griffith and van Reenen (1995), let A denote a "measure" of all firms and let θ_t aggregate time effect in year t. These are all macro–economic effects including business cycle effects, general patenting propensity (vs. secrecy), the propensity to patent at the EPO, etc. This term is not restricted in any special way across time and it is the same for all firms.

Assume that $Y_{it} = S_{it}\theta_t$. We define our *weighted* proxy variable for firm–specific fixed effects, FE_i, by

$$\begin{aligned} FE_i &= \frac{1}{T_P}\sum_{t=1}^{T_P}\frac{Y_{it}}{\sum_{j\in A} Y_{jt}} \\ &= \frac{1}{T_P}\sum_{t=1}^{T_P}\frac{S_{it}\theta_t}{\sum_{j\in A} S_{jt}\theta_t} \end{aligned}$$

Define $S_{it} = \overline{S}_i + u_{it}$ where $\overline{S}_i$ as the Blundell, Griffith and van Reenen (1995) equilibrium value which is proportional to the firm fixed effect, η_i, and u_{it} simply defines the deviation from equilibrium for firm i at time t. Assume further that these deviations add to zero across all firms at any given point in time (note that general business cycles are part of θ_t). Then,

$$\begin{aligned} &= \frac{1}{T_P}\sum_{t=1}^{T_P}\frac{\overline{S}_i + u_{it}}{\sum_{j\in A}(\overline{S}_j + u_{jt})} \\ &= \frac{1}{T_P}\sum_{t=1}^{T_P}\frac{\overline{S}_i + u_{it}}{\sum_{j\in A}\overline{S}_j} \\ &= \frac{1}{\sum_{j\in A}\overline{S}_j}\overline{S}_i + \frac{1}{\sum_{j\in A}\overline{S}_j}\frac{1}{T_P}\sum_{t=1}^{T_P} u_{it} \end{aligned}$$

The last term goes to zero in expectation as T_P increases (which is essentially the same as argument in Blundell, Griffith and van Reenen, 1995). The first term is proportional to $\overline{S}_i$ which in turn proxies η_i as in Blundell, Griffith and van Reenen (1995).

Essentially, we now allow non–stationarity in a way that vanishes once the fixed effect proxies are weighted, is an appropriate representation of business cycle, general patenting propensity (vs. secrecy), EPO patenting propensity effects etc. and is not restricted across time.

Appendix E: estimation result for model that considers only firms with at least one R&D worker

	Poisson		RE NegBin	
	Coeff.	**S.E.**	**Coeff.**	**S.E.**
Disc. stock of applications	0.000	0.000	0.004***	0.001
ln(# workers)	0.245***	0.059	0.372***	0.056
ln(capital stock)	0.123***	0.035	0.048*	0.029
Δ ln(# workers)	0.317***	0.130	0.302***	0.121
ln(fixed effect)	0.474***	0.058	0.517***	0.064
Fixed effect dummy	6.418***	0.551	6.758***	0.564
Constant	-7.238***	0.593	-6.877***	0.511
Skill shares				
Share R&D joiners w/ exp.	3.027***	0.640	3.268***	0.551
Share R&D joiners w/o exp.	2.132***	0.476	1.972***	0.468
Share R&D stayers w/ exp.	1.845***	0.548	1.902***	0.592
Share R&D stayers w/o exp.	-0.035	0.559	0.212	0.508
Share R&D graduates	1.529*	0.816	1.651***	0.649
Share non–R&D joiners w/ exp.	0.624*	0.334	0.222	0.503
Share non–R&D joiners w/o exp.	0.746***	0.285	0.148	0.297
Share non–R&D stayers w/ exp.	0.903***	0.262	0.511**	0.232
Share non–R&D graduates	2.132***	0.557	1.694***	0.575
Share R&D leavers w/ exposure	0.248	0.245	-0.261	0.815
Share R&D leavers w/o exposure	-0.044	0.851	-0.193	0.982
Share non–R&D leavers w/ exposure	0.100**	0.048	0.191*	0.110
Share non–R&D leavers w/o exposure	-4.355**	2.137	-2.140***	0.747
Tests for joint significance				
Sector dummies	39.02	0.000	62.13	0.000
Region dummies	49.67	0.000	13.67	0.475
Year dummies	152.93	0.000	161.21	0.000
# of obs. and specification tests				
# obs.	31,193			
# firms	14,811			
# firms w/ patent	308			
# patents	1,916			
Pseudo R^2	0.104		0.071	

The table displays Poisson and RE NegBin estimation results for our model that considers firms with at least one R&D worker only.

Appendix F: alternative definitions of R&D workers

	All firms		At least one pre–sample patent	
	M.E.	***p*–val.**	**M.E.**	***p*–val.**
Narrow definition of R&D workers				
R&D joiners w/ exposure	0.0139	0.000	0.0824	0.004
R&D joiners w/o exposure	0.0113	0.000	0.0663	0.005
R&D stayers w/ exposure	0.0112	0.001	0.0656	0.015
R&D stayers w/o exposure	0.0064	0.006	0.0359	0.037
R&D graduates	0.0115	0.000	0.0677	0.009
Non R&D joiners w/ exposure	0.0044	0.007	0.0228	0.044
Non R&D joiners w/o exposure	0.0034	0.002	0.0172	0.027
Non R&D stayers w/ exposure	0.0038	0.000	0.0193	0.009
Non R&D stayers w/o exposure	0.0024	0.000	0.0104	0.035
Non R&D graduates	0.0036	0.032	0.0179	0.110
R&D leavers w/ exposure	-0.0059	0.255	-0.0369	0.266
R&D leavers w/o exposure	-0.0041	0.380	-0.0257	0.390
Non R&D leavers w/ exposure	0.0007	0.063	0.0046	0.106
Non R&D leavers w/o exposure	-0.0005	0.173	-0.0032	0.204
Main definition (medium definition) of R&D workers				
R&D joiners w/ exposure	0.0112	0.000	0.0646	0.004
R&D joiners w/o exposure	0.0085	0.000	0.0476	0.005
R&D stayers w/ exposure	0.0076	0.000	0.0426	0.013
R&D stayers w/o exposure	0.0049	0.001	0.0259	0.023
R&D graduates	0.0079	0.000	0.0444	0.013
Non R&D joiners w/ exposure	0.0022	0.079	0.0089	0.249
Non R&D joiners w/o exposure	0.0021	0.008	0.0086	0.088
Non R&D stayers w/ exposure	0.0028	0.000	0.0129	0.013
Non R&D stayers w/o exposure	0.0018	0.000	0.0068	0.051
Non R&D graduates	0.0034	0.012	0.0163	0.071
R&D leavers w/ exposure	-0.0011	0.638	-0.0066	0.640
R&D leavers w/o exposure	0.0012	0.026	0.0076	0.057
Non R&D leavers w/ exposure	0.0005	0.091	0.0031	0.134
Non R&D leavers w/o exposure	-0.0017	0.000	-0.0105	0.002
Broad definition of R&D workers				
R&D joiners w/ exposure	0.0101	0.000	0.0571	0.006
R&D joiners w/o exposure	0.0078	0.000	0.0429	0.006
R&D stayers w/ exposure	0.0072	0.000	0.0393	0.011
R&D stayers w/o exposure	0.0054	0.001	0.0280	0.016
R&D graduates	0.0072	0.001	0.0393	0.018
Non R&D joiners w/ exposure	0.0014	0.300	0.0036	0.667
Non R&D joiners w/o exposure	0.0019	0.016	0.0063	0.170
Non R&D stayers w/ exposure	0.0025	0.000	0.0105	0.021
Non R&D stayers w/o exposure	0.0016	0.001	0.0043	0.129
Non R&D graduates	0.0034	0.009	0.0158	0.068
R&D leavers w/ exposure	-0.0010	0.523	-0.0064	0.529
R&D leavers w/o exposure	0.0009	0.045	0.0055	0.082
Non R&D leavers w/ exposure	0.0006	0.054	0.0037	0.091
Non R&D leavers w/o exposure	-0.0016	0.000	-0.0100	0.003

The Table displays the absolute change in the number of patents due a 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 RE NegBin models that were specified for alternative definitions of R&D workers. 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).