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Does the Mobility of R&D Labor Increase Innovation?

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Abstract

We investigate the effect of mobility of R&D workers on the total patenting activity of their employers. Our study documents how mobile workers affect the patenting activity of the firm they join and the firm they leave. The effect of labor mobility is strongest if workers join from patent-active firms. We also find evidence of a positive feedback effect on the former employer's patenting from workers who have left for another patent-active firm. Summing up the effects of joining and leaving workers, we show that labor mobility increases the total innovative activity of the new and the old employer. Our study which is based on the population of R&D active Danish firms observed between 1999 and 2004 thus provides firm-level support for the notion that labor mobility stimulates overall innovation of a country or region due to knowledge transfer.

JEL-classification: J62, C26

Keywords: labor mobility, innovation, research and development, patenting

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1 Introduction

Knowledge transfer resulting from labor mobility constitutes an important source of innovation and growth. One stream of the literature focuses on the effects of mobility on the innovation activities of individual firms—typically, the firm hiring the worker—and explores the many contingencies that moderate this relationship (Boeker, 1997; Palomeras and Melero, 2010). From a more macro-perspective, studies within economics, management strategy, and economic geography argue that a high level of labor turnover spurs regional innovation performance (Almeida and Kogut, 1999; Fallick et al., 2006). In this paper, we integrate these levels of analysis to study whether labor mobility increases the total R&D output of the firms involved. In other words, we investigate whether the notion that labor mobility stimulates overall innovation has a firm-level micro-foundation.

Various evidence from surveys, patent files, and court cases shows that labor mobility is an important channel of knowledge transfer between firms (Almeida and Kogut, 1999; Hoti et al., 2006; Mansfield, 1985). It is shown that firms exploit the knowledge and skills brought about by new recruitments to increase productivity (Balsvik, 2011, Görg and Strobl, 2005), to enter distant technological areas (Palomeras and Melero, 2010; Rosenkopf and Almeida, 2003; Tzabbar, 2009), to introduce new types of products (Boeker, 1997; Rao and Drazin, 2002), and to boost R&D output (Ejsing et al., 2013). Another strand of the literature looks at worker exits and how these affect firm performance due to interruption of routines and loss of knowledge (Campbell et al., 2011; Wezel et al., 2006). However, as social ties are not necessarily severed by exit, the departure of a worker also represents an opportunity for the firm to access the knowledge available at the worker's new employer (Agrawal et al., 2006; Corredoira and Rosenkopf, 2010).

At the regional level, localized knowledge sharing has long been recognized as a major benefit of agglomeration (Jacobs, 1969; Marshall, 1920). Saxenian (1994) pointed to the particular importance of labor mobility for regional innovation performance. In her comparative analysis of Silicon Valley in California and Route 128 in Massachusetts, she argued that the "job-hopping" culture of Silicon Valley creates tightly coupled social networks through which knowledge flows, causing rapid innovation and growth in that region. Consistent with this view, subsequent studies document the co-existence of high labor turnover and localized knowledge sharing among firms in the semiconductor industry in Silicon Valley (Almeida and Kogut, 1999; Breschi and Lissoni, 2005; Fallick et al., 2006). The importance of labor mobility is underlined by more recent studies showing that regions characterized by strong enforcement of trade secrecy laws and covenants not to compete experience lower rates of labor turnover but also by less patenting and entrepreneurship (Marx et al., 2009; Png, 2012; Samila and Sorenson, 2011).

Although the literature documents the importance of labor mobility for innovation in firms and in regions, to our knowledge, there are no empirical studies providing quantitative evidence of the critical link between these levels of analysis. On the one hand, existing firm-level studies look at the effect of labor mobility on the innovation activities of either the new or the old employer but do not examine the total effect. On the other hand, regional-level studies find a positive relationship between mobility, or variables that influence mobility, and innovation performance and attribute this to a positive total effect of mobility on innovation at the firm level. From a theoretical point of view, however, it is not obvious that labor mobility increases total innovation as the mobility event may hurt the old employer more than it benefits the new employer. We sketch a simple model showing that mobility is more likely to occur in a competitive labor market if it has a positive effect on total innovation. There are, however, circumstances under which mobility does occur in equilibrium even though it reduces total innovation.

Our empirical analysis investigates the effect of mobility of highly skilled workers in Denmark on the total patenting activity of the firms involved. We find a significant and positive effect of labor mobility on total patenting if either of the firms involved has patented before. Mobility from and to patenting firms, that is, firms with a positive stock of existing patents, has the largest marginal effect on total innovation, namely 0.019 additional patent applications in the subsequent year per mobile worker. For the average firm in our sample, this implies a 30 percent increase in the number of patent applications.

Our empirical findings derive from an extensive data set that combines patent applications from Danish firms to the European Patent Office (EPO) with matched employer-employee registry data which essentially contain a complete record of labor mobility in the Danish labor market. This contrasts with most existing studies which trace mobility via patent files, which implies that mobility is observed only if an inventor applies for a patent at two different firms. Mobile inventors who do not patent again, however, are not recorded. We differentiate among workers who joined the firm in the focal year ("joiners"), workers who have been with the firm for at least the previous year ("stayers"), and workers who left in the previous year ("leavers"). The focus is on R&D workers who we define as individuals (i) holding a university degree in natural sciences, engineering and other technical fields, and (ii) who are employed in positions classified as using or producing knowledge at an advanced level. The point of departure of our empirical approach is a standard firm-level patent production function (Hall et al., 1986; Hausman et al., 1984) that maps different types of labor, capital, and other observed firm characteristics into patent counts. To control for unobserved permanent differences in firms' patent productivity, we employ two different count data estimation approaches: the dynamic fixed-effect GMM estimator (Blundell et al. 2002) and the pre-sample mean estimator (Blundell et al. 1995).

We find that a joiner coming from a patenting firm is associated with a significant increase in the number of patent applications by the new employer. In relative terms, this type of R&D worker contributes six times more to patenting than a comparable stayer, while a joiner from a firm with no patent activity is no more productive than a stayer. Our interpretation of this result is that patenting firms on average are more R&D active, and thus constitute a richer source of valuable knowledge. The relative magnitude of the contribution of joiners from patenting firms is sizable given that we consider the effect of mobility of an average R&D worker, whereas most existing studies consider "star scientists" with at least two patented inventions.

In the case of leavers, we find that a worker who left to join a patenting firm, is associated with a significant increase in the number of patent applications by the previous employer. This is evidence that learning from former employees documented by means of patent citations in previous studies (Corredoira and Rosenkopf, 2010, Agrawal et al. 2006) also translates into positive effects on the former employer's patent productivity. In the case of a worker who left to join a non-patenting firm there is no significant concomitant effect on patenting. To sum up, in relation to the effects of joiners and leavers, our analysis provides strong support for the view that mobility of high-skilled workers stimulates total firm-level invention conditional on at least one of the firms involved having been patent active in the past.

The analysis of the effect of mobility on total invention relies on two important advantages of our data set. First, compared to most previous studies that use patent data to track inventor mobility, we have a complete record of worker-level labor mobility. In addition to avoiding possible biases arising from unregistered moves—the “unsuccessful” cases in which a worker does not produce any inventions at the new firm—this allows us to estimate the patent productivity of workers joining, leaving, and staying with a firm. Second, our dependent variable—the number of patent applications—lends itself more naturally to aggregation than other dependent variables which are employed in existing studies such as entry into a new technology class or product area.

While we emphasize the knowledge transfer effects of worker mobility, there is a concern that the observed correlation between mobility and patenting might be partly or even predominantly explained by other factors. To address this issue, in an extension we show that the exchange of labor between two firms is positively associated with firms’ propensity to cite each other’s patents, which we take as an indication that the mobility event resulted in knowledge transfer. Moreover, our GMM estimation applies instruments for labor mobility based on lagged mobility as well as industry averages of different types of mobility. This approach accounts for any contemporaneous firm-specific shocks to patent productivity which would simultaneously increase both hiring and patenting, leading to upward biased estimates. Finally, we also discuss the knowledge protection argument forwarded by Kim and Marschke (2005) and positive assortative matching between firms and R&D workers—the firms that offer the best research conditions hire the best R&D workers—as alternative explanations of a positive correlation between mobility and patenting. We argue that in particular our findings on the leavers’ side are strongly suggestive of a predominant role for knowledge transfer.

The papers closest to ours are Hoisl (2007) and Ejsing et al. (2013) which also study the effect of labor mobility on patenting. Hoisl (2007) combines data on mobility constructed from patent files, with background information on inventors obtained from questionnaires. She shows that mobile inventors are on average more productive and that mobility increases inventor productivity. However, since she does not measure the previous employer’s patent productivity she is unable to address the effect of mobility on the total level of invention. Using similar data to ours, Ejsing et al. (2013) show that hiring researchers from universities has a large effect on firm patenting but they do not address the issue of how worker mobility affects total invention.

In a related literature stream, registry data is used to test the prediction of human capital theory that workers who acquire valuable knowledge on the job receive a wage premium but pay for this through an initial wage discount. Møen (2005) finds evidence of such a wage profile but Maliranta et al. (2009) find that workers are not able to capitalize on the knowledge acquired from participating in R&D activities. Toivanen and Väänänen (2012) find a significant and potentially long-lasting wage premium for inventors of granted patents, indicating that these workers are perceived by their firms as possessing valuable knowledge and skills. However, our aim is to measure the importance of mobility for total invention.

The remainder of the paper is organized as follows: Section 2 provides the institutional and theoretical background for the analysis. Section 3 describes the data and outlines the definitions used in the analysis. Section 4 discusses our econometric approach and provides descriptive statistics. The main results are reported in Section 5 with some corroborating evidence and robustness checks. Section 6 concludes.

2 Institutional and Theoretical Background

2.1 The Danish labor market

Denmark ranks highly among the OECD countries in terms of worker mobility, on par with e.g. the United States (OECD, 2009). Annual rates of job mobility measured as the proportion of new employees in a firm compared to one year earlier, are in the range of 25 per cent on average (Eriksson and Westergaard-Nielsen, 2009). Indeed, the Danish labor market has been characterized as a "flexicurity" system (European Commission, 2010; Eriksson and Westergaard-Nielsen, 2009) that combines "flexibility" in terms of fairly low levels of job protection—few regulations on layoffs of individual workers and short advance notices for most groups in the labor market—with "security" in terms of an unemployment insurance scheme considered generous both in terms of replacement ratios and the length of insurance coverage and an extensive, publicly subsized job-training program. Hence, although the institutional settings differ appreciably between Denmark and the US, there are few institutional barriers to mobility of labor between firms in both markets.

In regard to knowledge flows by worker mobility, the institutional feature that has attracted most attention is the (non-)enforceability of non-compete agreements. It has been forwarded as a main explanation of differences in terms of innovation and mobility that characterize e.g. the Silicon Valley and Route 128 high-tech clusters (Gilson, 1999). Like the Route 128 case, Denmark does allow the enforcement of covenants not to compete. There is limited evidence on the general prevalence of non-compete clauses in labor contracts in Denmark. A recent report by Dahl and Stamhus (2013) cited a survey of engineers in the private sector, a group of workers highly relevant to our study. It showed that only 14 per cent of engineers are subject to a non-compete clause. Thus, despite the enforceability of non-competes in Denmark, the Danish labor market for R&D workers seems closer to Silicon Valley than to Route 128 in terms of actual restrictions on labor mobility.

2.2 The Effect of Labor Mobility on Firm-Level Invention

We briefly outline the main effects of labor mobility on firms' R&D capabilities identified in the literature.

Reallocation of skills and abilities: R&D workers possess technical skills and problem-solving abilities which constitute important inputs for the production of inventions. Since these skills and abilities can only be applied in one firm at a time, they are rival in nature (Arrow, 1962). That is, when a worker moves from one firm to another, the R&D capability of the new and the old employer are increased and decreased, respectively.

Immediate knowledge transfer: Knowledge differs in the extent to which it is shared among the employees of a firm. Some knowledge is "private," resides within a single individual, and is available only to the current employer. Other pieces of knowledge are "social" and shared among several employees (Spender, 1996). Some social knowledge such as a well-specified technical process can be transferred by a single individual (Liebeskind, 1997) whereas implicit knowledge embedded in the routines, culture, and norms of the firm typically cannot.

If a worker switches firm, the new employer gets access to the worker's private knowledge and the part of the worker's social knowledge that is individually transferable. We refer to this as "forward knowledge transfer" since knowledge and labor flow in the same direction. The old employer loses only the worker's private knowledge. Hence, mobility leads to sharing of social knowledge, which is the fundamental reason why labor mobility is perceived as an important source of aggregate innovation (Saxenian, 1994; Cooper, 2001; Franco and Mitchell, 2008).

Social ties and attention: Agrawal et al. (2006) observe that mobility results in the old and the new employer citing each other's patents more frequently. While the citing behavior of the new employer can be explained by its use of the knowledge that the worker brings, the apparent existence of "reverse knowledge transfer"—i.e. knowledge that flows in the opposite direction to labor—is striking. Two explanations for this phenomenon have been proposed by Corredoira and Rosenkopf (2010). First, the worker may stay in contact with former co-workers, resulting in knowledge exchange among the firms' employees. Second, the old employer's awareness of the worker's new employer may be heightened, causing it to pay closer attention to the new employer's R&D activities. Although our data do not allow us to disentangle these explanations, the theoretical predictions are clear: the increased focus of the involved firms on each other's activities, and the stronger personal ties among employees reinforce the forward knowledge transfer for the new employer. Furthermore, reverse knowledge transfer alleviates the loss of knowledge that the old employer experiences when the worker leaves.

Net effect on the new and old employer: Putting together these three effects of labor mobility suggests that the new employer gains access to new skills and knowledge. These increase the firm's R&D capability and provide new opportunities for knowledge recombination, thereby increasing the inventive output of the firm (Grossman and Helpman, 1991; Schumpeter, 1934). The old employer experiences a loss of the worker's skills and private knowledge but might benefit from reverse knowledge flows. Thus, the overall effect of labor mobility on the old employer's R&D capability and inventive output is theoretically unclear.

2.3 The Effect of Labor Mobility on Aggregate Invention

Our main interest in this paper is how labor mobility affects aggregate invention. The above arguments suggest that the inventive output of the new employer increases while the inventive output of the old employer may decrease, leaving the total effect—the sum of the effects on the new and the old employers—indeterminate.

In order to gain predictions for the total effect, we study mobility that occurs as the result of wage competition among firms. Following Pakes and Nitzan (1984), we consider two firms competing for a worker currently employed by one of the firms. If the current employer keeps the employee, she earns profit π. If the worker moves, the old and the new employer earn $\theta_O\pi$ and $\theta_N\pi$, respectively. The profits $\theta_O\pi$ and $\theta_N\pi$ include all the costs and benefits that arise from labor mobility. Retaining the worker has value $(1-\theta_O)\pi$ to the current employer and hiring the worker has value $\theta_N\pi$ to the potential new employer. Hence, wage competition implies that mobility occurs if and only if $(1-\theta_O)\pi < \theta_N\pi \Leftrightarrow \pi < (\theta_N+\theta_O)\pi$: Mobility occurs if and only if it increases the joint profits of the two firms (Pakes and Nitzan, 1984).

There are opposing effects of labor mobility on the joint profit of the firms (Combes and Duranton, 2006; Fosfuri and Rønde, 2004). First, social knowledge that was in the sole possession of the old employer before the mobility event is shared with the new employer. This leads to increased competition over some commercial uses of the knowledge, reducing the profit of the old employer. Since competition destroys rents, the new employer gains less from entry into these commercial uses than the old employer loses from increased competition. Thus, this effect tends to deter labor mobility. Similarly, more mundane costs related to labor turnover, such as hiring and training costs and costs resulting from interruptions of the workflow, also tend to reduce joint profits and prevent mobility. Second, labor mobility may increase the firms' joint profits through its effect on invention. Firms have different R&D capabilities and strengths, and knowledge sharing increases the likelihood that a piece of knowledge will serve as an input to a new invention (Bessen and Maskin, 2009; Scotchmer, 1991). Therefore, knowledge sharing through labor mobility has the potential to stimulate invention, whether in the form of greater variety, value, or speed of invention. This effect increases the firms' joint profits and tends to facilitate labor mobility.

Putting these arguments together, the theoretical prediction is that labor mobility occurs if and only if the positive effect from an increase in joint invention outweighs the negative effect from more competition and other costs associated with labor mobility. Hence, an increase in joint invention of the firms is a necessary condition for labor mobility to occur in this simple model.[1]

While this result provides a useful benchmark showing the beneficial effects of mobility on total invention, there exist circumstances where it cannot be expected to hold. We will illustrate these using two variations of the above model. First, suppose that the old employer is wealth and credit constrained and cannot pay more than $\bar{W}$ to keep the worker where $\bar{W} < (1-\theta_O)\pi$. Mobility occurs now if $\bar{W} < \theta_N\pi$, but it may decrease total invention as the wage offered by the old employer does not reflect the true value of the worker to the firm. Second, suppose that there are two workers who share valuable knowledge and who can transfer it to a new employer. Then, the old employer has to pay each of these workers $\theta_N\pi$ to keep the knowledge and skills inside the firm. Arguing as above, it is easy to show that mobility occurs if and only if $\pi < (2\theta_N+\theta_O)\pi$. If $(\theta_N+\theta_O)\pi < \pi < (2\theta_N+\theta_O)\pi$, mobility occurs in equilibrium although it reduces the joint profits of the firms.[2] The reduction in joint profits may stem from increased product market competition but also from a reduction in total invention. Mobility does therefore not necessarily increase total invention when valuable knowledge is more widely distributed inside the firm.

These arguments show why endogenous mobility events driven by wage competition do not necessarily increase total invention once we leave the baseline model of the two firms with deep pockets competing for one worker. Obviously, there are also workers switching jobs for reasons exogenous to our model. For example, the partner may find a job in another city, health issues may make a change of career necessary, the worker may develop a preference for

[1]Notice that the knowledge transfer arising from labor mobility is not a true knowledge externality, because the new employer pays (partly) for the knowledge that the worker brings in the form of a higher wage bill.

[2]Rønde (2001) characterizes the equilibrium of this model for all possible values θ_N and θ_O.

working in a different setting, etc. For such mobility events, the decision to leave is not driven by the value of the worker to the firms, leaving the effect of labor mobility on total invention indeterminate.

3 Data

The core of our data set is patent applications to the EPO filed between 1978 and 2006 with at least one applicant and one inventor with Danish residency. These are patents for which we can expect that a substantial part of R&D has taken place within Denmark. The data were retrieved from EPO's "PATSTAT" database.[3] We consider patent applications up to and including 2004 in our analysis since the database for the years after 2004 is incomplete. Our data set includes 12,873 patent applications.

We use patent applications rather than patent grants because the average grant time of four to five years for the patents in our data set (Kaiser and Schneider, 2005) implies that a substantial number of patents applied for during the time period considered for our estimation (2000-2004) would be lost were patent grants used.[4] The "time stamp" of the patent applications is the "priority date," the date of first filing of the invention for patent protection at the EPO or any national patent office.

The EPO data do not have a unique firm identification number of the type used by Statistics Denmark, the provider of our firm-level and employee-level data. Therefore, we mostly manually attached our EPO data to Statistics Denmark's firm identifiers. We were able to assign firm identifiers to 11,280 patent applications. The unmatched applications primarily refer to firms that went out of business before 1999. The corresponding information would in any case have been lost in our analysis since our firm-level data start in 1999. After matching these data with our firm-level information, we are left with 11,031 patent applications applied for by 2,278 unique firms.

Statistics Denmark provided us with firm registry data, most importantly including firms' sectoral and regional affiliations and physical capital book value, and registry data on employee characteristics including, most importantly the end-of-November number of employees and their highest level of education.[5] We discarded sectors with no EPO patent applications between 1978 and 2004. Sectors are defined according to the three-digit NACE Rev. 1 industrial classification. In a final step, we merged the firm-level data with employee-level data, which allows us to track the employment history of individual workers. We excluded firms founded during the estimation period 2000-2004 since, as described further in Section 4, our main estimation results are partly based on an estimator that requires information on firms' patenting behavior prior to 2000. Finally, we discarded firms from the public sector, since its patenting behavior is likely to be very different from that of industry.

[3]For information on this data set, refer to http://www.epo.org/patents/patent-information/raw-data/test/product-14-24.html.

[4]There is a reporting lag between date of application and date of publication of the application in the EPO database. This implies that not all patents applied for after 2004 had been registered in the database at the time of data collection. We excluded these patents in order to avoid biases.

[5]As workers' firm affiliations are registered only once a year, in November, we do not observe within–year mobility.

Our main sample consists of observations for firms that employ at least one worker in an R&D-related occupation. We focus on these since firms with employees in R&D-related occupations are much more likely to patent than firms with no R&D workers. Of the 2,861 patent applications during 2000-2004 that could be definitively assigned to a firm, 2,728—or 95 percent—can be assigned to firms with positive R&D employment. By excluding firms with very little or no current R&D activity, we attempt to compare different varieties of apples rather than apples and oranges. Our main estimation results thus include 42,507 observations for 14,516 unique firms, and 2,728 patents over the period 2000-2004.

We define R&D workers as those employees within a firm who are likely to be engaged in R&D-related tasks. Specifically, we apply two main criteria to identify the relevant group of workers.[6] First, the person must have a Bachelor's, a Master's, or a Doctoral degree in technical or natural sciences, veterinary and agricultural sciences, or health sciences.[7] This criterion is based on the idea that knowledge flows are mainly associated with the mobility of high-skilled workers. The definition corresponds closely to the findings by Kaiser (2006) who uses patent inventor survey (PATVAL) data for Denmark to show that 30.5 percent of the inventors have a Bachelor's degree as their highest level of education, 40.8 percent have Master's degrees and 17.4 percent hold Doctorates. We intend to capture all individuals possessing the formal skills necessary to perform R&D-related activities within a firm. Since some high-skilled workers may never conduct R&D, we introduce the additional criterion that a person's job function must involve the use or production of knowledge at an advanced level. This information is included in our data through the International Standard Classification of Occupations (ISCO) coding published by the International Labour Organization.[8] At its first-digit level, ISCO classifies occupations according to their knowledge content. In particular, we can distinguish between "professionals" (level 2) and "technicians and associate professionals" (level 3).[9] Individuals are categorized in the former group if they work in a position in which they "increase the existing stock of knowledge, apply scientific or artistic concepts and theories, teach about the foregoing in a systematic manner, or engage in any combination of these three activities." We denote this group "R&D professionals". They are the focus of our analysis of mobility since they are most likely to be directly involved in the creation of new knowledge. Individuals categorized as technicians and associate professionals occupy support positions which more likely utilize already existing knowledge. We call this group "R&D support workers". Since they are not directly engaged in developing new knowledge, they are not expected to be the main carriers of knowledge between firms. Therefore, the share of the firm's support workers is included in our model as a control variable only.

To summarize, we define R&D professionals as individuals with a technical or scientific degree who perform job functions with an advanced knowledge content. R&D support workers

[6] Other criteria are that the individual must not be retired, must be aged between 20 and 75 years, and must be employed by a Danish firm (since we only have data on Danish firms at our disposal).

[7] The health sciences category includes many general practitioners and hospital doctors who *a priori* are not expected to perform R&D related activities. Most of these will not be included in our estimations since we exclude the public sector.

[8] http://www.ilo.org/public/english/bureau/stat/isco/intro.htm

[9] We include R&D managers (ISCO 1237) in the group of professionals. The codes are very detailed but a change in the way individuals were classified in 2003 prevents us from using more narrowly defined occupations consistently over time.

have similar formal skills but are employed in positions with less emphasis on the creation of new knowledge. These two groups jointly constitute the current stock of a firm's R&D workers.

We next characterize categories of R&D professionals according to their mobility status. We differentiate between a main group simply termed joiners, who were employed in another firm in year $t-1$, and other joiners, who are workers whose job market status in year $t-1$ is unknown or who graduated between time t and time $t-1$. Stayers are R&D professionals who were employed by firm i both at time $t-1$ and time t. Finally, leavers are workers employed in firm i in year $t-1$ who are employed in a different firm in year t. We also differentiate the joiners and leavers according to the patenting activity of their old and new employers. Specifically, we distinguish between joiners who previously were employed by a "patenting firm", which we define as a firm with a positive patent stock at $t-1$, and joiners who previously were employed by a firm with no patents, a "non-patenting firm". We also distinguish between leavers who joined patenting vs. non-patenting firms. We do this to account for the inherent differences between firms that are patent active and those that are not. Although this is an imperfect measure of firms' R&D activity, patent active firms are likely to possess a workforce that is endowed with a deeper and broader R&D knowledge base than firms that do not patent. When a worker from a patent active firm joins a new employer, she may bring in a set of knowledge that is more valuable for invention.

Insert Table 1 about here.

Table 1 provides descriptive evidence on the basic associations between mobility and patenting in our data. We compare the mean number of patents for firms with a particular status in terms of the mobility of their R&D workers and the remaining firms in our sample. It shows that firms that either received or lost R&D workers have a higher number of patent applications per year than firms with an immobile R&D workforce. The highest number of patents are found for firms that have both joiners and leavers in a given year. These differences are statistically highly significant. Clearly, such comparisons confound a large number of likely determinants of firms' patenting (e.g., firm size, industry, previous patenting) that we will control for in our estimations.

Appendix A displays general descriptive statistics. Most firms in our data are small: the average firm has around eight R&D employees and a capital stock of about DKK78 mill. (the median is DKK2.7 mill.).[10] The overall level of patenting is fairly low. The average firm applies for 0.06 patents per year during the sample period. We also provide descriptive statistics for the subset of firms that patented at least once before the beginning of our sample period, so-called pre-sample patenters. These firms can be expected to patent more regularly than the average firm for several reasons, including state dependence (Blundell et al. 1995) and the likely presence of unobserved firm-specific factors that favor patenting. In addition, observable firm characteristics are conducive to patenting for firms in this sub-sample compared to the average firm in the full sample. We find that firms with one or more pre-sample patents employ an average of 39 R&D workers, employ a stock of capital of DKK400 mill. on average, and produce 0.76 patent applications per year.

In relation to mobility and the composition of the R&D work force, our three groups of joiners (from patenting firms, from non-patenting firms, other joiners) jointly constitute more

[10] $US1 corresponds roughly to DKK5.9.

than 20 per cent of the current year's total employment of R&D professionals (joiners plus the reference category of stayers). The overall level of mobility of R&D professionals is high compared for example to the annual turnover rate of scientists and engineers of 13 per cent reported by Kim and Marschke (2005). The group of R&D supporters amounts to 45.7 per cent of current R&D employment.

When comparing the subsamples of firms with or without any pre-sample patents, the share of support workers is lower for pre-sample patenters (42.3 per cent) than for the other firms in our sample (46 per cent). Pre-sample patenters also attract a larger proportion of their joiners from other patenting firms (2.6 per cent of the current R&D work force compared to 1.3 per cent for firms without pre-sample patents). This is consistent with higher in-sample R&D intensity among "pre-sample patenters". The overall level of mobility is comparable between the two sub-samples with 20 per cent of R&D professionals having joined within a year in the case of pre-sample patenters against 23 per cent for firms without any pre-sample patents.

Appendix B provides the correlations for the variables in our estimations. The table shows that our explanatory variables are moderately correlated. This is confirmed by a variance inflation factor of 1.86, which is well below the critical value of ten (Belsley et al. 1980).

4 Empirical approach

This section describes our patent production function and outlines our econometric approach employed to estimate the relationship between worker mobility and firms' inventive output.

For the patent production function we assume a Cobb-Douglas specification as it is standard in the literature (Blundell et al. 1995; Hausman et al. 1984; Kim and Marschke 2005). Our dependent variable is the total number of a firm's patent applications in a given year, which we denote by P.[11] It is a count variable that takes the value zero or a positive integer which is why we use count data models in the estimations. The mean of the count variable is exponentially linked to the explanatory variable:

$$E(P) \quad = \quad \exp\Big(\ln(A) + \alpha\ln(QL) + \beta\ln(K)\Big) \tag{1}$$

where QL denotes quality-adjusted R&D labor input and K denotes capital input. Our measure of labor input is defined to be specific to a firm's R&D activities. In the case of capital, our data do not allow us to measure the specific input of capital to R&D, hence we interpret capital stock as a general measure of firm size. The variable A summarizes factors other than capital and labor that affect patent production such as sectoral, geographical, and time effects which we also include in our empirical model.[12]

We choose an additive specification for quality-adjusted labor QL, following Griliches (1967). We differentiate between four main types of R&D labor currently employed in the firm, namely stayers (denoted by St), joiners from firms (J), other joiners (O), and support

[11] We omit firm and time indices for brevity in what follows.

[12] Our econometric specification controls for sectoral affiliation (15 sectors), five different geographical regions, and time effects. We lag all explanatory variables except for the time, region and sector dummies by one year to allow for time lags in the R&D process and to alleviate concerns about reverse causality.

workers (Su). Our specification for quality-adjusted labor is:

$$
\begin{aligned}
QL &= L_{St} + \gamma_J L_J + \gamma_O L_O + \gamma_{Su} L_{Su} + \gamma_X L_X \\
&= L\left(1 + (\gamma_J - 1)\frac{L_J}{L} + (\gamma_O - 1)\frac{L_O}{L} + (\gamma_{Su} - 1)\frac{L_{Su}}{L} + \gamma_X \frac{L_X}{L}\right) \qquad (2)
\end{aligned}
$$

where current employment ($L = L_{St} + L_J + L_O + L_{Su}$) does not include leavers (denoted X). We normalize the effect of stayers to unity. The coefficients γ_r measure the contribution of the rth worker type to quality-adjusted labor QL relative to the contribution of stayers.

Taking logs and using the approximation $\ln(1+z) \approx z$ for small z we plug the expression for $\ln(QL)$ into the patent production function. This leads to our basic estimating equation which differentiates between different R&D worker types:

$$
E(P) = \exp\left[\ln(A) + \alpha \ln(L) + \alpha_J \frac{L_J}{L} + \alpha_O \frac{L_O}{L} + \alpha_{Su}\frac{L_{Su}}{L} + \alpha_X \frac{L_X}{L} + \beta \ln(K)\right] \qquad (3)
$$

where $\alpha_r = \alpha(\gamma_r - 1)$ for worker group r currently in the firm and $\alpha_X = \alpha\gamma_X$ for leavers. Our estimations identify the α-coefficients from which we shall back out the productivity ratios γ_r. As discussed in Section 3, our main specification also differentiates between mobile workers who join from or leave to patenting vs. non–patenting firms. This introduces α_r^P and α_r^N as a straightforward extension where the superscripts P and N denote patenting and non-patenting firms, respectively.

The count data models we apply account for both state dependence in patenting activity and unobserved firm heterogeneity. We account for patenting dynamics since existing firm-level studies show that previous patenting activity has substantial positive effects on current patenting (Blundell et al. 1995, 1999, 2002; Crépon and Duguet 1997). Arguing that a firm's stock of past own patents represents knowledge from which future patentable ideas can be derived, Blundell et al. include the lagged discounted stock of patents as a regressor. Due to the relative short time span of our estimation sample, we follow Crépon and Duguet (1997) and use dummy variables that indicate whether or not a firm patented in previous periods as our control for state dependence.

Our empirical approach also allows for fixed effects in order to capture unobserved firm-specific permanent differences such as appropriability conditions for R&D investments or different technological opportunities that might affect current patenting. Estimating a simple model including a dummy variable for each firm would produce consistent estimates only in count data models where all regressors are strictly exogenous, which clearly does not apply to variables directly related to past patenting activity such as our indicators for lagged patent status (Blundell et al. 2002). This is similar to the kind of bias introduced by the simultaneous inclusion of fixed effects and a lagged dependent variable in a linear model which renders the lagged dependent variable endogenous by construction (Nickell 1981). To solve this problem, we consider two different fixed effect approaches for dynamic count data models: a GMM estimator (Blundell et al. 2002, Kim and Marschke 2005) and the Pre-Sample Mean (PSM) estimator of Blundell et al. (1995). We discuss each estimation method in turn.

Blundell et al. (2002) derive a GMM estimator which accounts for both fixed effects and lagged dependent variables. It is best compared to the more popular dynamic panel data estimators for linear models (Arellano and Bond 1991; Arellano and Bover 1995). We follow Kim and Marschke (2005) in applying a quasi-differencing transformation to correct for fixed effects as suggested by Wooldridge (1991). It essentially removes the fixed effects by a non-linear transformation, much like the standard "within transformation" in linear models and uses longer lags of the dependent and independent variables as instruments.[13] Our GMM estimator accounts also for other endogenous variables apart from lagged patent status. One potential concern that we discuss further in Subsection 5.2 is that causality may run not only from mobile workers to patent applications but also in the reverse direction, or that both are caused by common unobserved factors. We address this concern by instrumenting worker shares. As instruments we use the firms' own lagged shares and the average share of each type of worker in other firms in the same sector and in the same region. The intuition is that sector-specific and region-specific labor supply and demand shocks to other firms will affect the demand for each skill group for the focal firm. At the same time, the average shares of the skill groups of other firms are unlikely to be correlated with the error term of our equation of interest—unobserved firm-specific factors that affect the firm's patent production. Tests for dynamic (mis-) specification that we have conducted using the GMM estimator indicate that we need to include two lags of firms' patent status in order to have a dynamically well-specified model.[14] Overall, the data requirements of the GMM approach leaves us with a sample of 23,769 observations for 6,751 firms for GMM estimation.

As an alternative count data approach, we consider the PSM estimator of Blundell et al. (1995). For this specification, the full sample with a total of 42,507 observations for 14,516 firms is available which should enhance the precision of the estimates. The idea behind the PSM estimator is to approximate unobserved time-invariant heterogeneity by using information on the firm's patenting behavior prior to the start of the estimation period. This is exactly the setting in our data: we possess information on all firms' patenting activity from 1978 onwards, while our explanatory variables (allowing for lags) are observed after 1999 only. The PSM estimator approximates the "true" fixed effect by the pre-sample patenting history of each firm, which in our case consists of patents applied for during the period 1978 to 1998. Specifically, the PSM estimator uses the average of the dependent variable over the pre-sample period as a proxy for the correlated effects for each firm. Since a prominent feature of our data is an overall increase in the level of patenting during the pre-sample period, we normalize the firm's number of patents in a pre-sample year by the total number of patents applied for during that year.[15]

In addition to firm fixed effects, both our estimators account for the excess number of zeros commonly found in analyses of economic count data such as patents, the "zero-inflation problem" (Mullahy, 1997). For the GMM, the fixed effects transformation eliminates any time-invariant explanatory variable—including variables that relate to the selection of a firm into patenting or non-patenting. For the PSM estimator, we follow Blundell et al. (1995, 1999) and include a dummy variable for firms that applied for at least one patent during the

[13]To estimate the GMM model we use Windmeijer's (2002) "ExpEnd" program that runs under the software package GAUSS.

[14]For the GMM to be identified, the simultaneous presence of first order serial correlation and absence of second order serial correlation is required (Arellano and Bond 1991; Arellano and Bover 1995; Blundell et al. 2002).

[15]Our approach hence allows for trends in patenting at the general level such as business cycle effects, changes in the propensity of firms to patent rather than to opt for secrecy, or changes in the propensity of Danish firms to patent at the EPO rather than the national patent office.

pre-sample period. This allows the expected number of patents in-sample to differ between pre-sample patenters and non-patenters.[16]

Both the GMM and the PSM estimator were originally designed as Poisson regression models that assume equality of the conditional mean of the dependent variable and its conditional variance. In patent data, however, the conditional variance is greater than the conditional mean (Cincera 1997), which implies over–dispersion that leads to less efficient (but still unbiased and consistent) parameter estimates. More efficient estimates can be obtained by using a Negative Binomial (NegBin) model that allows for over–dispersion. While the PSM estimator is easily extended to a NegBin model, the GMM model is only available in a Poisson regression context.

5 Results

5.1 Main results

Our estimation results are presented in Table 2. We report results for GMM Poisson, PSM Poisson and PSM NegBin count data models.

The GMM approach requires our instruments to be strongly correlated with the mobility terms and to be simultaneously uncorrelated with the error term in the patent production function. We test the first property by running "first stage" regressions (not displayed here for brevity) of our instruments and our exogenous variables on the endogenous variables. F-tests for joint significance of the instruments should be above ten for them to be "sufficiently correlated" with the endogenous variables (Stock et al. 2002). In our case, all F-statistics are substantially above 10. We consider the second property by Hansen J-tests and cannot reject the null hypothesis that our instruments are orthogonal at a marginal significance level of more than 70 percent.

Regarding the choice among estimators and specifications, one reason to prefer PSM over GMM is a sizable increase in the number of observations available for estimation. The choice of a NegBin – rather than a Poisson – is suggested by a test that confirms the presence of overdispersion. However, our results are largely consistent across all three models in terms of signs, magnitude and even significance so we will comment mainly on the PSM NegBin results. The PSM NegBin results will also be used for further calculations.

Looking at the effects of joiners, the statistical significance of the α-coefficients of groups of R&D joiners is to be interpreted relative to the reference group of R&D stayers. The sign tells us whether the corresponding R&D worker type contributes more or less to patenting than stayers. The share of joiners from patenting firms has the largest effect on patent productivity. For joiners from non-patenting firms, we find that their effect is much smaller. In fact, they are not statistically significantly more productive than stayers according to the PSM estimates. The GMM results, however, suggest a positive and marginally significant effect. We interpret this finding of stronger positive effects for joiners from patenting compared to non-patenting firms as reflecting that in the former (but not in the latter) case workers transfer knowledge

[16]This dummy variable also serves to correct for the (arbitrary) small constant added to the number of pre-sample patents to make log-transformation of FE feasible.

valuable for invention.[17] Hence, our results suggest that any negative effects of intellectual property protection and strategic litigation of departing employees by their old firm are outweighed by positive knowledge transfer effects. The heterogeneous group of "other joiners" has a positive effect on patenting which is statistically highly significant although quantitatively smaller than the effect of joiners from patenting firms. This effect is most likely due to the presence of expatriates (who are recorded as "other joiners" since they do not have an employment history in Denmark) and graduates within this group (Ejsing et al. 2013).

For the leaver groups, their α-coefficients show whether R&D workers of this type contribute to the focal firm's patenting activity even though they are no longer employed by that firm. Our results show a positive effect of leavers who left for a patenting firm. The effect is equal in magnitude although statistically insignificant in the less efficient GMM estimation. There are no statistically significant effects of leavers to non-patenting firms. This again suggests that patenting firms constitute richer sources of knowledge.

Table 2 also shows that we find substantial evidence of state dependence as reflected by highly significant dummy variables related to firms' patent status in previous periods. This may reflect sunk costs associated with learning to conduct successful research or more practical knowledge related to patent application process. Our correction for unobserved heterogeneity in the PSM model has a significantly positive impact on current patenting activity: an increase in the number of pre-sample patents by 1 percent is associated with an increase in the number of current patents of around 0.3 percent.

Insert Table 2 about here.

The coefficients in Table 2 do not translate directly into marginal effects as in a linear model. To facilitate the interpretation of the magnitude of these effects, we convert the PSM NegBin estimates into productivity ratios, the γ terms discussed in Section 4. The productivity ratios displayed in Table 3 show that joiners from patenting firms are more than six times more patent productive than R&D stayers, a figure that is statistically highly significant. The related figures for other joiners from and for leavers to patenting firms are 4.9 and 3.3, respectively. The remaining ratios are statistically insignificantly different from 1 indicating that these groups of R&D workers are as productive as stayers.

Insert Table 3 about here.

Finally we evaluate the *total* effect of labor mobility on patenting which is the main focus of the paper. We conduct a thought experiment designed to increase the rate of turnover while keeping R&D employment unchanged. Going from period $t-1$ to t, our experiment replaces an incumbent worker with a joiner, keeping total employment constant. Compared to the situation of no mobility, the effective labor input QL will include an additional joiner effect, γ_J, and an additional leaver effect γ_X, while there will be one stayer less in the firm in period t. The total effect of mobility is then calculated as the marginal effect making

[17] The reverse argument may hold that patenting firms have established a reputation for strict enforcement of patents in order to reduce the risk of knowledge leaks due to worker exit (Agarwal et al. 2009). This would suggest a *smaller* effect of mobility flows involving patenting rather than non-patenting firms, since the firm receiving the knowledge transfer might be reluctant to use proprietary knowledge.

this substitution.[18] Partially differentiating our patent production function, Equation (1), we obtain the total effect of mobility as:

$$\text{Total effect} = \frac{\partial E(P)}{\partial L^i_J} + \frac{\partial E(P)}{\partial L^j_X} - \frac{\partial E(P)}{\partial L_{St}} = \frac{E(P)}{L}(\alpha^i_J + \alpha^j_X), \quad i,j \in \{N,P\}. \tag{4}$$

The α-coefficients are found in Table 2 for different types of workers. The expected number of patents, $E(P)$, and total R&D employment, L, are evaluated for an average firm in our sample as well as the average of firms with at least one pre-sample patent. The results are shown in Table 4. The strongest effect is found for the total effect of one worker leaving for a patenting firm and one worker joining from a patenting firm while keeping total R&D employment constant. This results in an additional 0.019 patents for the average firms in our sample, a 30 percent increase compared to the average number of patents. When evaluated for the average of firms with at least one pre-sample patent, the same type of substitution yields 0.044 additional patents, an increase over the average number of patents for this subset of firms by six percent.

For combinations of leavers and joiners that involve at least one patenting firm, we find a positive and statistically significant effect of mobility on total patenting while mobility between non-patenting firms has no statistically significant effect on total patenting. In fact, these findings are consistent with the theoretical prediction of our basic wage competition model set up in Section 2 that labor mobility increases the total innovative output of the firms involved.

Insert Table 4 about here.

5.2 Identification issues

In this section, we discuss our findings and provide additional evidence to corroborate our interpretation of the main results as being driven by knowledge spillovers from mobility. First, we establish a "paper trail" of patent citation links between firms that are connected by labor flows. Second, we examine the importance of other potential drivers of our results. Specifically, if a firm is ramping up its R&D activities to further exploit an already existing knowledge base within the firm while hiring additional workers to perform the R&D, mobility and innovation could be positively correlated without there being any flow of knowledge between firms. Third, we address the argument in Kim and Marschke (2005) of preemptive patenting in the face of labor mobility. Finally, we discuss the extent to which our results could be affected by positive assortative matching between workers and firms.

First, we want to verify that the probability of citation links between firms increases if there is movement of labor between the firms. The presumption is that if a worker joins another firm and transfers knowledge, there will be an increased likelihood of patent citations between the firms. Mobility between the firms can go in either direction, or there might be a bi-directional exchange of labor. For the event that firm A, say, cites firm B, we distinguish between (i) a forward "joiner" effect if one or more R&D workers join firm A from firm B, and (ii) a reverse "leaver" effect if one or more R&D workers left firm A for firm B in the previous period.

[18]Technically, this measures the total effect of an infinitesimal change in each of the joiner, leaver and stayer groups involved, leaving employment unchanged.

We construct a dyadic data set of all possible combinations of firms that patent within the present period ("firm A") and firms which hold a positive patent stock at the beginning of the period ("firm B"). We define indicator variables for (i) the event of one or more workers joining firm A from firm B, and (ii) one or more R&D workers leaving firm A for firm B. For the case of bi-directional mobility, we define a separate indicator variable coded 1 if such bi-directional exchange occurred (and 0 otherwise). We set the forward and reverse mobility indicators to 0 if the bi-directional variable is coded 1. Finally, we define our dependent variable as an indicator of the existence of one or more citations in firm A's current patent application, to a patent in firm B's patent stock.

Table 5 shows the results of linear regressions of the citations link variable on our three labor mobility indicators.[19] The positive and statistically significant coefficients of our three mobility dummy variables show that labor mobility is positively associated with the probability of firm A citing a firm B patent. This holds for all three types of mobility: a joiner's link, a leaver's link, and the bi-directional link. The key finding holds for the base specification which includes the mobility terms only (1st column), for a specification where we also control for industry and year fixed effects (2nd column), and for further firm characteristics (total number of R&D workers and size of the patent stock of the cited firms, 3rd column) in addition to industry and year controls. The results displayed in Table 5 strongly corroborate our interpretation of the results from the main empirical analysis: both forward and reverse labor mobility appear to be positively associated with "paper trails" of knowledge flows.

Insert Table 5 about here.

A second issue is the potential importance of other underlying drivers of both mobility and innovation. The idea is that firms realize a new technological opportunity and prepare to patent by spending heavily on R&D, investing in a laboratory and filling it with R&D workers. If such an alternative interpretation holds, our estimated joiner effect could simply be picking up R&D investments possibly unrelated to knowledge flows. Our GMM results reported in Table 2 apply instruments for firm mobility based on lagged values and industry averages which implies that they are not sensitive to temporary firm-specific shocks. The fact that the GMM results show even larger effects of joiners than the PSM estimation results is therefore supportive of our main interpretation.

A third issue related to the interpretation of our results is the knowledge protection argument proposed by Kim and Marschke (2005). It suggests that firms patent in order to prevent workers from transferring knowledge to other firms. This could go some way in explaining a positive leaver effect. However, the leaver effect in our model on average materializes one year after the worker has left the firm which makes it unlikely that the patenting activity is related to an attempt to protect a specific invention that the departing worker had knowledge of. Furthermore, if we re-estimate the model using two lags instead of just one for all R&D worker related variables, the estimated leaver effect is actually larger than in the one-lag specification although it is slightly less significant which is likely due to a substantial reduction in sample size caused by the additional lag. This suggests that the effect is not primarily driven by any protective measures taken by the old firm since they would need to be put in place soon after the worker departed in order to secure priority over the invention.

[19] Probit regressions regressions generate very similar results and even stronger significance.

Finally, although our data are very detailed with regard to individual characteristics, there is some concern related to the selection of R&D workers with different unobserved ability or human capital endowment into different types of firms. The thought experiment underlying our calculations of the total effect of mobility assumes homogenous unobserved qualities of joiners, leavers, and stayers. We might suspect that firms with the best conditions for conducting research may attract the best workers, so-called "positive assortative matching" (Becker, 1973). In relation to matching R&D workers to firms this would suggest that workers in patenting firms are of higher quality on average than workers in firms with no previous patenting activity. This could explain at least part of the difference between the effects of joiners from these two types of firms that we observe. However, a similar argument would apply to the leavers' side. Leavers to firms with previous patenting activity are on average of higher ability and the old firm suffers a greater loss of human capital for this group than for leavers to firms with no previous patenting. In this interpretation of our results, selection may upwardly bias the effect on joiners from firms with previous patenting activity and likewise downwardly bias the effect on leavers to firms with previous patenting activity. While we cannot assess the actual extent of these biases, they would have opposing effects on the total effect of mobility in Equation (4). More importantly, even if the estimated effects of joiners from patenting and non-patenting firms were entirely due to matching on unobserved differences in worker quality, a positive effect of mobility on total patenting due to knowledge transfers is supported by the finding of a (possibly downward biased) positive leaver effect.

5.3 Robustness checks

We conduct five different robustness checks: (i) accounting for patent heterogeneity by weighing them according to the number of citations received; (ii) discarding the top 20 patenting firms, or alternatively all the biotechnology firms, to check whether our main results are driven by selected firms; (iii) applying a more narrow definition of R&D workers by considering only workers with a Master's or Doctoral degree; (iv) re-running the regressions without correcting for trends in overall patenting behavior; and (v) checking if there are non-linearities in the relationship between mobility and patenting.[20]

First, there might be some concern that our estimates do not account for patent value heterogeneity. It is well known that the distribution of the economic and technological value of patents is heavily skewed in the sense that a few patents are very high value, while most have very little value (see the discussion in, e.g., Hall et al., 2005, Harhoff et al., 1999 and Lanjouw et al., 1998). Trajtenberg (1990) suggests using forward citations, the number of citations a patent receives, to approximate patent value. Like Trajtenberg (1990), we weigh each patent by 1 plus the number of citations a patent received within three years after EPO publication. Our patent citation data are from the "EPO/OECD patent citations database" which is available from the OECD (Webb et al., 2005) and covers the period 1978-2006. The citations-weighted and citations-unweighted estimation results show only slight differences. The significant coefficients in the estimates referring to joiners become slightly larger, while the coefficients of leavers remain almost unchanged. Citation-weighing hence generates results

[20]For reasons of space, the full estimation results are not displayed here but are relegated to a set of additional tables displayed at the end of the paper.

that corroboate our main result that mobility enhances total innovation.

Second, while our sample is representative of firms that employ one or more R&D workers, there is a concern as to the generality of our results. They could be driven primarily by selected industries or firms which are very patent active. When re-estimating our main specification, either excluding the biotechnology sector or the 20 most patent active firms, we find that the results of the estimations on these restricted samples differ very little qualitatively and quantitatively from our main results based on the full data.

A third issue is related to our R&D worker definitions. The main worry is that their definition might be too broad if it includes groups of workers that are unlikely to be engaged in research. The effect, if any, would be to bias our main results downwards. To assess the importance of this argument, we apply a less inclusive definition that selects only workers with a Master's or Ph.D. degree. Somewhat surprisingly, this leads to effects that are generally *smaller* than our main results. We interpret this finding as meaning that workers with a Bachelor's level degree constitute a significant fraction of actual inventors in Denmark, consistent with survey evidence reported by Kaiser (2006).

A fourth robustness check relates to our trend correction of correlated effects as discussed in Section 4. Leaving out the normalization for the general upward trend in patenting activity leads to very similar results in terms of positive and significant effects of both joiners from and leavers to patenting firms. The main difference is that the effect of other joiners is no longer significant. The effect of joiners from non-patenting firms is now significantly different from zero although still appreciably smaller that the effect of joiners from patenting firms.

As a final robustness check, we address potential non-linearities of the relationship between mobility and patenting as considered e.g. by Müller and Peters (2010). To this end, we extended the linear QL specification in Equation (2) by quadratic terms which leads to interaction terms between worker shares and levels of the mobile worker terms in Equation (3). The extended model shows indications of collinear terms and also convex effects which are hard to interpret outside a limited range of adjustments. However, moves of any type that involve ten workers or less account for 98 per cent of all observations in our data and our results for the experiment in Table 4 of substituting joiners for leavers of different types show little qualitative change within that range. Considering substitutions of at most ten R& D workers, we find that the total effect of mobility remains positive if at least one group of workers moves to or from a patenting firm. For moves that involve leavers to patenting firms, the effect loses significance towards the upper end of the range.

6 Conclusions

This paper assesses the quantitative importance of inter-firm labor mobility for invention, using a unique data set that combines patent applications by Danish firms to the European Patent Office with matched employer-employee registry data that track the employment history of R&D workers across time. We estimate the effect of labor mobility on the total patenting activity of the firms involved in labor mobility events.

In line with results in the previous literature, we show that an inflow of workers is associated with an increase in the firm's patenting activity. A worker joining from a patenting firm has a six times higher patenting productivity than a worker who stays with the firm. Interestingly, worker departure is not associated with a decrease in patenting. A worker who left to join a patenting firm contributes three times more to the original firm's patenting activity than a worker that stays, while a worker leaving for a non-patenting firm has no significant concomitant effect on patenting. Most importantly, we show that firms are not involved in a zero-sum game when competing for R&D workers to increase their R&D output. Worker mobility is related to a positive and statistically significant increase in total invention by the old and the new employer. The effect on total invention is strongest for mobility between two patenting firms where a mutual exchange of labor increases the total patenting of the firms involved by 0.019. While this number might seem low, it compares to an average number of 0.064 patents per year for the average firm in our data which implies an increase in total patenting of 30 per cent. Mobility between firms with patenting history is not associated with a significant increase in total patenting.

These results, to the best of our knowledge, provide the first quantitative support for the notion that inter-firm mobility stimulates total innovation. In her study of Silicon Valley, Saxenian (1994) argues that "job-hopping" is crucially important for the innovative performance of the firms in that region, and our results confirm the importance of labor mobility in a much more representative setting covering all types of industries in Denmark.

A key issue is whether it is knowledge transfer related to labor mobility that causes the observed increase in patenting. We provide several pieces of evidence supporting this interpretation. First, we show that mobility is associated with an increase in the probability of the old and the new employer citing each other in subsequent patents, which suggests that mobility does lead to knowledge transfer between the firms. Second, we find both qualitatively and quantitatively very similar results when we instrument labor mobility to reduce concerns that our results might be driven by unobserved factors simultaneously affecting both hiring and patenting. Third, we leverage the complete picture of labor mobility presented by our data to argue that alternative explanations based on knowledge protection or positive assortative matching are unlikely to be predominant explanations of the observed correlations between mobility and patenting.

We regard our results as improving our understanding of the circumstances in which labor mobility stimulates firm-level innovation and aggregate growth. However the results in this paper should be interpreted with caution in relation to drawing conclusions regarding the optimal level of labor turnover in an industry or region. In a small country such as Denmark, firms are likely to face very similar labor market conditions. This is advantageous for the econometric identification but the results represent the association between mobility and patenting given the rate of labor turnover in Denmark. An important factor that must be considered is how labor turnover affects firms' incentives to invest in R&D. It would clearly be an important contribution if future work investigated exogenous variations in mobility rates to analyze how it affects aggregate innovation in an analysis of optimal turnover rates.

Table 1: Average number of patents per year by mobility status

	Mean	SD	p–value
At least one firm joiner & no firm leavers	0.049	0.626	0.000
At least one firm leaver & no firm joiners	0.036	0.421	0.000
At least one firm joiner & at least one firm leaver	0.414	3.193	0.000

Table 1 shows the mean number of patents and the corresponding standard deviation for firms with particular types of mobile workers. The p-values correspond to two-sided t-tests for statistically significant differences between firms with a specific type of mobile workers and firms with no firm joiners and no firm leavers in a given year. The mean number of patents of firms without mobile workers is 0.011 with a corresponding standard deviation of 0.258.

Table 2: Main estimation results

	GMM Poisson		**Poisson PSM**		**NegBin PSM**	
	Coeff.	**SE**	**Coeff.**	**SE**	**Coeff.**	**SE**
R&D worker shares						
Joiners from patenting firms	2.552**	1.210	1.543***	0.400	1.608***	0.278
Joiners from non–patenting firms	0.858*	0.495	0.506	0.385	0.362	0.336
Other joiners	1.362**	0.638	1.238***	0.337	1.121***	0.274
Support	-0.128	0.282	0.389	0.333	-0.109	0.203
Leavers to pat. firms	0.957	0.884	0.916**	0.464	0.668**	0.321
Leavers to non–pat. firms	0.106	0.267	-0.813	0.773	-0.486	0.424
Capital and R&D labor						
ln(total R&D workers)	0.372*	0.103	0.384***	0.104	0.289***	0.059
ln(capital stock)	0.016	0.029	0.238***	0.068	0.138***	0.036
Lagged patent status and pre–sample variables						
Dummy patent $t-1$	1.482***	0.364	2.026***	0.366	1.308***	0.138
Dummy patent $t-2$	0.628***	0.173	1.080***	0.122	0.842***	0.107
ln(# pre-sample patents)	—	—	0.091	0.120	0.264***	0.087
Dummy pre-sample patent	—	—	-0.081	0.278	0.386	0.247
Number of observations and number of firms						
# of obs.	23,769		42,507		42,507	
# of firms	6,751		14,516		14,516	

Table 2 displays estimation results for GMM fixed effects Poisson, PSM Poisson, and PSM NegBin specifications. "SE" denotes the standard error. Patent citation weights have not been applied. The PSM specifications additionally include sector dummies, year dummies, region dummies and a constant term. These variables are time–invariant and drop out of the fixed effects GMM specification. The GMM specification uses Wooldridge moment conditions and contains year dummies. It uses lagged R&D worker shares and the average share of each type of workers in other firms in the same sector as instruments for R&D worker shares. The asterisks '***', '**' and '*' denote marginal significance at the one, five and ten percent level.

Table 3: Relative patent productivities

	γ_r	p–value
Joiners from patenting firms	6.559	0.000
Joiners from non–patenting firms	2.252	0.286
Other joiners	4.873	0.000
Support	0.624	0.597
Leavers to patenting firms	3.309	0.042
Leavers to non–patenting firms	-0.680	0.253

Table 3 displays the productivities of different types of R&D workers relative to the productivity of R&D stayers. The p-value denotes the marginal significance level for the hypothesis that the relative productivity equals one. These calculations are based on the PSM NegBin results displayed in Table 2. **Reading example:** Joiners from patenting firms are 6.6 times more patent–productive than R&D stayers.

Table 4: Total effects of mobility

	Left for patenting firm		**Left for non–patenting firm**	
	Coeff.	**p–value**	**Coeff.**	**p–value**
Average firm				
Joiners from patenting firms	0.019	0.000	0.009	0.018
Joiners from non–patenting firms	0.009	0.020	-0.001	0.812
Average firm with at least one pre-sample patent				
Joiners from patenting firms	0.044	0.000	0.022	0.018
Joiners from non–patenting firms	0.020	0.020	-0.002	0.812

Table 4 displays our estimates of the total change in the number of patents if one worker left the firm while one worker joins the firm, keeping total R&D employment constant. The upper panel displays our results across all observations and the lower panel shows results for firms with at least one pre–sample patent. These calculations are based on the PSM NegBin results displayed in Table 2. **Reading example:** if one R&D worker leaves for a patenting firm and one worker previously employed by a patenting firm joins, the expected increase in the number of patents is 0.019 for the average firm.

Table 5: Linear regression results for the relationship between R&D worker mobility and citations

	Base specification		**Industry & year dummies**		**Industry & year dummies Firm characteristics**	
	Coeff.	**Std.err.**	**Coeff.**	**Std.err.**	**Coeff.**	**Std.err.**
Forward R&D worker mobility only	0.010***	0.003	0.009***	0.003	0.009***	0.003
Reverse R&D worker mobility only	0.016***	0.006	0.016***	0.006	0.015***	0.006
Bi–directional flows of R&D workers	0.047*	0.026	0.047*	0.026	0.045*	0.026
Year dummies	no		yes		yes	
Industry dummies	no		yes		yes	
Firm characteristics	no		no		yes	

Table 5 displays linear regression results for a firm's probability to cite another firm's patents. The results to the left refer to the base model which includes the three worker flow terms and a constant. The specification in the middle additionally includes year dummies and dummies for firms being in the same industry. The model to the right also includes the log number of R&D workers of the citing firm, the log number of R&D workers of the cited firm, and the lagged log stock of patent applications. Years 2000 through 2004 are included. There are 516,049 dyads, 141 non-zero citation links, 1,011 instances of firms linked by a forward mobility link only, 866 instances of reverse links, and 168 instances of bi-directional mobility links. "SE" denotes the standard errors which are clustered at the firm–level. The asterisks '***' and '*' denote marginal significance at the one and ten percent levels.

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Appendix A: Descriptive statistics

	All obs.		Obs. without pre–sample pat.		Obs. with pre–sample pat.	
	Mean	SD	Mean	SD	Mean	SD
Dependent variable						
# patent appl. t	0.064	—	0.015	—	0.761	—
Dummy patent $t-1$	0.019	—	0.005	—	0.209	—
Dummy patent $t-2$	0.015	—	0.004	—	0.169	—
R&D worker shares (base: R&D stayers)						
Joiners from patenting firms	0.014	0.089	0.013	0.089	0.026	0.089
Joiners from non–patenting firms	0.062	0.199	0.063	0.203	0.046	0.122
Other joiners	0.051	0.182	0.052	0.186	0.043	0.122
Support	0.457	0.441	0.460	0.447	0.423	0.337
Leavers to pat. firms	0.014	0.091	0.013	0.089	0.032	0.110
Leavers to non–pat. firms	0.077	0.244	0.077	0.248	0.074	0.184
Capital and R&D labor						
Total R&D workers	7.693	44.570	5.473	25.694	39.043	140.253
Capital stock (in mio. DKK)	77.50	1'280	54.80	1'140	399.00	2'520
Year dummies (base: 2000)						
2001	0.203	—	0.202	—	0.206	—
2002	0.196	—	0.196	—	0.202	—
2003	0.187	—	0.187	—	0.190	—
2004	0.183	—	0.183	—	0.181	—
Sector dummies (base: wholesale and retail trade)						
Farm & food	0.016	—	0.016	—	0.019	—
Textiles & paper	0.041	—	0.041	—	0.036	—
Plastic & glass	0.026	—	0.023	—	0.072	—
Chemicals	0.014	—	0.011	—	0.054	—
Metals	0.049	—	0.047	—	0.084	—
Machinery	0.069	—	0.057	—	0.233	—
Electrics	0.030	—	0.028	—	0.067	—
Medical technology	0.018	—	0.015	—	0.063	—
Vehicles	0.007	—	0.006	—	0.021	—
Furniture	0.016	—	0.016	—	0.021	—
IT	0.070	—	0.072	—	0.035	—
Technical services	0.140	—	0.141	—	0.127	—
Business related services	0.095	—	0.099	—	0.044	—
Other	0.180	—	0.191	—	0.023	—
Region dummies (base: Greater Copenhagen)						
Sjælland	0.097	—	0.098	—	0.088	—
Syd	0.224	—	0.223	—	0.237	—
Midt	0.207	—	0.208	—	0.196	—
Nord	0.074	—	0.073	—	0.090	—
Pre–sample variables						
# pre–sample patents	0.061	1.465	—	—	0.929	5.625
Dummy pre–sample patent	0.066	—	—	—	1.000	—
# obs.	42'507		39'696		2'811	

The table displays descriptive statistics for the entire set of observations, for observations with a pre–sample patent and for those without a pre–sample patent. "SD" denotes the respective standard deviation.

Appendix B: Correlations

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1)	# patent applications	1												
(2)	Share from pat. firms	0.014	1											
(3)	Share from non–pat.	-0.006	-0.032	1										
(4)	Share other joiners	0.001	-0.002	-0.050	1									
(5)	Share support	-0.012	-0.115	-0.253	-0.240	1								
(6)	Share to pat. firms	0.011	0.070	0.022	0.040	-0.084	1							
(7)	Share to non–pat. firms	-0.007	0.024	0.092	0.082	-0.172	0.043	1						
(8)	ln(cap. stock)	0.112	0.016	-0.030	-0.059	0.100	0.025	-0.003	1					
(9)	ln(total R&D workers)	0.193	0.031	-0.017	-0.025	-0.067	0.055	0.030	0.410	1				
(10)	Dummy patent $t-1$	0.319	0.042	-0.007	0.003	-0.029	0.033	-0.009	0.151	0.264	1			
(11)	Dummy patent $t-2$	0.288	0.034	-0.014	-0.003	-0.025	0.039	-0.009	0.139	0.240	0.417	1		
(12)	ln(# pre-sample pat.)	0.269	0.038	-0.020	-0.009	-0.027	0.055	-0.004	0.227	0.349	0.451	0.406	1	
(13)	Dummy pre-sample pat.	0.162	0.036	-0.022	-0.012	-0.020	0.053	-0.003	0.218	0.315	0.375	0.339	0.950	1

Additional tables

Specification with two year lag

	Coeff.		Std. err.
Share joiners from patenting firms	1.877	***	0.344
Share joiners from non-patenting firms	0.115		0.453
Share other joiners	1.397	***	0.323
Share support workers	0.196		0.230
Share leavers to pat. firms	0.762	*	0.403
Share leavers to non-pat. Firms	-0.631		0.422
ln(capital stock)	0.127	***	0.043
ln(total R&D workers)	0.309	***	0.066
Dummy patent t-1	1.233	***	0.148
Dummy patent t-2	1.110	***	0.134
ln(# pre-sample patents)	0.227	**	0.101
Dummy pre-sample patent	0.417		0.304

The table displays NegBin PSME estimation results for our main specification as shown in Table 1 but where all R&D worker related variables are lagged by two instead of one year. It includes 27,199 observations on 9,438 unique firms. The asterisks' `***' and `**' denote marginal significance at the one and five percent level.

Estimation results with citation weights

	Coeff.		Std. err.
Share joiners from patenting firms	1.714	***	0.279
Share joiners from non-patenting firms	0.431		0.338
Share other joiners	1.155	***	0.278
Share support workers	-0.070		0.197
Share leavers to pat. firms	0.629	**	0.322
Share leavers to non-pat. Firms	-0.537		0.428
ln(capital stock)	0.143	***	0.033
ln(total R&D workers)	0.270	***	0.056
Dummy patent t-1	1.257	***	0.140
Dummy patent t-2	0.822	***	0.112
ln(# pre-sample patents)	0.299	***	0.087
Dummy pre-sample patent	0.379		0.292

The table displays NegBin PSME regression results for the number of patent applications weighted by three years. The specification estimated is otherwise identical to the one in the main results table, Table 1. The asterisks' ``***'' and ``**'' denote marginal significance at the one and five percent level, respectively.

Estimation results discarding top 20 patenters and biotechnology firms

	W/o biotech			W/o top 20 patenters		
	Coeff.		Std. err.	Coeff.		Std. err.
Share joiners	1.630	***	0.278	1.519	***	0.282
Share joiners	0.393		0.336	0.250		0.342
Share other jc	1.149	***	0.275	0.975	***	0.273
Share support	-0.086		0.204	-0.200		0.166
Share leavers	0.718	**	0.342	0.710	***	0.275
Share leavers	-0.470		0.424	-0.415		0.409
ln(capital stoc	0.283	***	0.059	0.206	***	0.053
ln(total R&D v	0.150	***	0.036	0.147	***	0.033
Dummy pater	1.320	***	0.140	1.284	***	0.136
Dummy pater	0.841	***	0.108	0.947	***	0.124
ln(# pre-samp	0.260	***	0.088	0.097	*	0.052
Dummy pre-sa	0.367		0.248	1.220	***	0.203
# obs.	42'385			42'389		

The table displays NegBin PSME regression results for samples where biotechnology firms (left panel) and the top 20 patenters (right panel) are discarded. The specification estimated is otherwise identical to the one in the main results table, Table 1. The asterisks' `***' and `**' denote marginal significance at the one and five percent level.

Narrow definition of R&D workers

	Coeff.		Std. err.
Share joiners from patenting firms	1.247	***	0.236
Share joiners from non-patenting firms	0.425	*	0.248
Share other joiners	0.791	***	0.235
Share support workers	0.290		0.221
Share leavers to pat. firms	0.274	**	0.127
Share leavers to non-pat. Firms	-0.775	**	0.334
ln(capital stock)	0.167	***	0.039
ln(total R&D workers)	0.256	***	0.060
Dummy patent t-1	1.271	***	0.156
Dummy patent t-2	0.819	***	0.114
ln(# pre-sample patents)	0.257	***	0.094
Dummy pre-sample patent	0.236		0.284

The table displays NegBin PSME estimation results for a specification that applies a ``narrow'' definition of R&D workers but which is otherwise identical to main results table, Table 1. The estimation involves 16,531 observations on 5,714 unique firms. The asterisks' `***' and `**' denote marginal significance at the one and five percent level.

No correction for time trends

	Coeff.		Std. err.
Share joiners from patenting firms	1.486	***	0.280
Share joiners from non-patenting firn	0.610	**	0.298
Share other joiners	0.502		0.436
Share support workers	-0.120		0.193
Share leavers to pat. firms	0.629	*	0.331
Share leavers to non-pat. Firms	-0.422		0.411
ln(capital stock)	0.140	***	0.035
ln(total R&D workers)	0.255	***	0.058
Dummy patent t-1	1.222	***	0.146
Dummy patent t-2	0.778	***	0.107
ln(# pre-sample patents)	0.347	***	0.084
Dummy pre-sample patent	-2.010	***	0.682

The table displays NegBin PSME results for a specification that does not apply the trend correction for the correlated effects (the term ln(FE)) but which is otherwise identical to the specification shown in the main results table, Table 1. The asterisks' `***' and `**' denote marginal significance at the one and five percent level.

Number and shares of different types of mobile workers

	Joiners from patenting firms		Joiners from non-patenting firms		Leavers to patenting firms		Leavers to non-patenting firms	
	#	Share (%)	#	Share (%)	#	Share (%)	#	Share (%)
0	39'738	57.5	35'239	56.9	39'448	57.8	33'650	64.8
1	1'928	29.6	4'971	29.5	2'027	28.0	5'419	21.5
2	355	5.4	1'018	6.0	459	6.3	1'515	6.0
3-5	316	4.8	778	4.6	361	5.0	1'125	4.5
6-8	77	1.2	217	1.3	105	1.4	325	1.3
9-10	26	0.4	69	0.4	30	0.4	102	0.4
11-15	36	0.6	101	0.6	34	0.5	158	0.6
16-25	14	0.2	66	0.4	27	0.4	113	0.4
26-50	10	0.2	31	0.2	12	0.2	57	0.2
51-75	2	0.0	11	0.1	3	0.0	25	0.1
76-100	3	0.0	3	0.0	0	0.0	12	0.0
>100	2	0.0	3	0.0	1	0.0	6	0.0

Estimation results that include quadratic terms

	Coeff.		Std. err.
Share joiners from patenting firms	1.535	***	0.288
Share joiners from patenting firms# joiners from patenting firms*	-0.017	***	0.003
Share joiners from non-patenting firms	0.164		0.360
Share joiners from non-patenting firms*# joiners from non-patenting firms	0.052		0.033
Share other joiners	0.708	**	0.314
Share other joiners# other joiners*	0.114	***	0.025
Share support workers	-0.137		0.203
Share leavers to pat. firms	0.515		0.330
Share leavers to pat. firms*# leavers to pat. firms	0.027	***	0.004
Share leavers to non-pat. Firms	-0.185		0.410
Share leavers to non-pat. firms*# leavers to non-pat. firms	-0.099	**	0.046
ln(capital stock)	0.142	***	0.036
ln(total R&D workers)	0.277	***	0.062
Dummy patent t-1	1.338	***	0.130
Dummy patent t-2	0.843	***	0.107
ln(# pre-sample patents)	0.235	***	0.070
Dummy pre-sample patent	0.546	***	0.209
Tests for joint significance	**Chi2**		**p-val.**
Joiners from patenting firms	49.24		0.000
Joiners from non-patenting firms	3.18		0.204

The table presents NegBin PSME estimation results. The specification additionally includes sector region and year fixed effects. The specification is else identical to the one in the main text.

Total effects of mobility based on the estimation results that do include nonlinear effects

		Leavers to patenting firms		Leavers to non-patenting firms	
# substitutions		**Coeff.**	***p*-val.**	**Coeff.**	***p*-val.**
1	**Joiners from patenting firms**	0.2685	*0.0000*	0.1446	*0.0136*
	Joiners from non-patenting firms	0.1052	*0.0765*	-0.0188	0.7770
2	**Joiners from patenting firms**	0.5398	*0.0000*	0.2591	0.0279
	Joiners from non-patenting firms	0.2309	*0.0519*	-0.0498	0.7098
5	**Joiners from patenting firms**	1.3705	*0.0000*	0.4223	0.1827
	Joiners from non-patenting firms	0.7320	*0.0173*	-0.2161	0.5584
8	**Joiners from patenting firms**	2.2262	*0.0000*	0.3150	0.5859
	Joiners from non-patenting firms	1.4187	*0.0075*	-0.4926	0.4791
10	**Joiners from patenting firms**	2.8106	*0.0000*	0.0930	0.9073
	Joiners from non-patenting firms	1.9795	*0.0051*	-0.7380	0.4514