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Knowledge transfer through inventor mobility: The effect on firm-level patenting

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Abstract

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Abstract

Labor mobility is heralded as a key channel of knowledge spillovers between firms. However, the empirical evidence of labor mobility's effects on firm-level innovation performance remains scarce. In this paper, we analyze the effect of inventor mobility on firm-level patenting activity by studying a sample of R&D investing European firms. The empirical results suggest that mobile patent inventors transfer knowledge and improve hiring firm's future innovation performance. Inventor mobility in general does not increase patenting significantly; however, hiring inventors with several prior patents and different kind of technological expertise contributes to firm's future patent output. We also find that hiring inventors especially from actively patenting firms contributes to firm-level patenting in the future. Moreover, we find that outbound mobility weakens the source firm's patenting performance; especially when the firm loses inventors that have been highly productive; have worked in the firm's core field of technology or move to technologically similar firm.

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Keywords: patenting, knowledge transfer, inventor, mobility

1. Introduction

Knowledge spillovers between firms and countries are an important driver of innovation and economic growth. The mechanisms of knowledge spillovers are understood to occur through market transactions, labor mobility, research collaboration, communication at technical conferences, pure externalities, etc. The link between labor mobility and knowledge spillovers has been understood at least since Arrow (1962) and in the recent years there has been an increasing interest on the determinants and consequences of labor mobility. Interfirm labor mobility is now recognized as a key channel of knowledge spillovers. The growth and innovativeness of regions is attributed to labor mobility (Miguélez and Moreno 2013; Samila and Sorenson 2011; Saxenian 1994) and hiring of knowledge carriers, i.e. employees with specific qualifications or expertise, has been shown to improve firm productivity (Balsvik 2011; Maliranta et al. 2009; Parrotta and Pozzoli 2012; Stoyanov and Zubanov 2012). On the other hand, some prior studies have found a negative association between firm productivity and worker turnover (Ilmakunnas et al. 2005). Thus, our understanding of the effects of labor mobility remains incomplete. Especially, the evidence is limited and inconclusive on the effects of labor mobility on firm-level innovation performance.

This paper focuses on the effect of inventor mobility on the innovation output of firms by analyzing a sample of R&D investing European firms and their patenting activity. The study most closely relates to a study by Kaiser et al. (2015), who, using Danish linked employer-employee data, show that R&D worker mobility is positively related with the number of patent applications. In distinction to Kaiser et al. (2015) and other prior studies, the present paper analyses inventor mobility, the prior technological expertise of mobile inventors and the characteristics of their previous employers to explain knowledge transfer between firms. We follow many prior studies by relying on patent data to track mobility. The prior studies have often used patent citation data as an indicator of knowledge flows and knowledge spillovers through inventor mobility (Agarwal et al. 2009; Almeida and Kogut 1999; Corredoira and Rosenkopf 2010; Singh and Agrawal 2011). However, patent citations do not reveal the firm-level effect on innovation output which is the main interest of the present paper.

Prior literature has emphasized learning by hiring; however, outbound mobility is equally important as workers who leave present a knowledge leak and a loss of skills but at the same time they may act as a channel of reverse knowledge spillovers to the firm (Agrawal et al. 2006; Corredoira and Rosenkopf 2010). Therefore, we also need to analyze the outbound mobility of inventors and how its’ effects depend on the characteristics of inventors and their new employers.

In the empirical part of this paper, a patent production function is estimated using negative binomial estimation with pre-sample means to account for unobservable time invariant firm effects. The empirical results reveal that inbound inventor mobility per se does not have a statistically significant effect on firm's patent output. However, the results indicate that firms' patent output is improved when hiring inventors with many past patents and who possess technological knowledge that differs from firm's main field of technology. Similarly, the patent output improves after recruiting inventors from firms that have engaged intensively in patenting in the past, whereas movers from low patenting firms have no significant effect on firm's patenting. Thus, the first group of movers appears to be able to transfer more valuable technological knowledge than the latter group.

In addition, we find that leaving inventors have a negative overall effect on firm's patent output indicating that their skills and expertise cannot be easily replaced. However, the field of technological expertise and patenting experience of leaving inventors matter. Separation of inventors with many patents or experience in firm's core field of technology is especially detrimental for future patenting indicating that inventors possess both inventor-specific and firm-specific knowledge. Moreover, when inventors leave to a high patenting hiring firm, the effect is strongly significant, whereas leavers to low patenting firms do not have negative effect on future patenting. This finding is contrary to the reverse knowledge spillover hypothesis and may indicate that firms systematically engaging in R&D and patenting are able to hire better inventors than firms with less intensive patenting activities.

The rest of the paper is organized as follows. The second section summarizes the theoretical background and the related literature. The third section describes the data and variable formation. The fourth section discusses estimation approach; fifth section presents and discusses the empirical results. The sixth section concludes the paper.

2. Literature background

This chapter discusses the implications of labor mobility for firm's innovation performance and the prior literature thereof. First, the hiring firms benefit from the private skills and expertise of their new employees. These skills are rival in nature and as an employee moves to another firm, the skills will benefit the hiring firm and the old employer, i.e. source firm, will lose access to them. These hires can improve the innovativeness of the hiring firm at the cost of source firm.

Second, labor mobility may enable inter-firm learning through knowledge spillovers (Almeida and Kogut 1999; Moen 2005; Parrotta and Pozzoli 2012). A significant part of firm's R&D related knowledge is tacit and workers acquire this knowledge through job tenure. This part of R&D knowledge cannot be easily codified or protected by patents and thus when employees move they can carry the acquired knowledge to the new employer. However, the knowledge spillovers through labor mobility are not pure externalities, because the new employer pays for the knowledge in form of wages. Moreover, mobility does not necessarily degrade the source firm's knowledge stock, although if employees leave to join a rival firm, the source firm's relative position and competitiveness suffer (Somaya et al. 2008).

Third, the source firm may also enjoy access to new technological knowledge (Agrawal et al. 2006; Oettl and Agrawal 2008). The reason for this is that mobile employees may still retain their existing social contacts at their previous employer which results in continued knowledge transfer (Agrawal et al. 2006). These contacts may be especially useful if employee moves to a customer or a partner firm (Somaya et al. 2008). Another explanation for reverse knowledge spillovers is that employee mobility may enhance the previous employer's awareness of the new employer and the innovations they create (Corredoira and Rosenkopf 2010). Thus, the old employer may enjoy reverse knowledge spillovers and the overall effect of outbound mobility remains unclear.

Fourth, labor mobility may also increase the employer-employee match quality (Jovanovic 1979). Better match quality will lead to higher labor productivity and it can explain a significant share of differences in worker productivity (Jackson 2013). In support of this argument, Hoisl (2007, 2009) and Latham et al. (2011) present evidence that mobility can increase the productivity of inventors.

Fifth, labor mobility may also create significant transaction costs, which is a view traditionally emphasized in labor economics literature. Firm-specific human capital is lost in job changes. When many employees leave the firm, replacing them takes time and the firm's knowledge stock and skills may erode. Also the informal communication structures within the firm are disrupted. .

We now turn to review prior studies that have analyzed the effect of labor mobility on firm-level performance. Management literature has typically found employee turnover to have negative firm performance effects (for a review of the literature see e.g. Hancock et al. (2013)). Ilmakunnas et al. (2005) find that overall employee turnover has a negative effect on firm productivity growth; however, employee churning, i.e. when separations are always replaced by hiring, has a positive effect. Moreover, recent studies using linked employer-employee data have concentrated the analysis on knowledge spillovers through mobility, i.e. they analyze the performance effects of hiring of knowledge carriers. The studies show that the hiring of employees with tertiary education or experience in R&D work improves firm productivity at least in under certain circumstances (Maliranta et al. 2009; Parrotta and Pozzoli 2012). Other firm characteristics matter as well and hiring workers from multinational firms (Balsvik 2011;

Poole 2013) or firms that are more productive (Stoyanov and Zubanov 2012) is shown to act as a channel of knowledge spillovers. Spillovers from IT investments of other firms are also shown to be transmitted through IT worker mobility (Tambe and Hitt 2013). Learning by hiring may also enable the development of new products (Rao and Drazin 2002).

To our knowledge, the studies by Kaiser et al. (2015) and Müller and Peters (2010) are among the few to analyze the firm-level innovation performance effects of R&D labor mobility. In addition, Ejsing et al. (2013) analyze a related theme: the mobility of university scientists. The paper most closely related to the present study is the paper by Kaiser et al. (2015), who using Danish linked employer-employee data show that the patenting activity of Danish firms increases when they hire R&D workers from a patenting firm. R&D worker mobility from or to a non-patenting firm has no effect on firm's patent output. Thus, it is not only mobility but also the availability of technological knowledge that determines the benefits of R&D worker mobility. Müller and Peters (2010) find that the churning of R&D employees has an inverted U-shape relation with firm innovation performance. Mobility increases the probability of innovations but only up to a specific point. Also Koski and Pajarinen (2015) find evidence that mobile inventor specific knowledge contributes to firm patenting, although their results vary across industries.

Several studies have also analyzed the innovation performance effects of labor market flexibility. In contrast to above mentioned studies, these studies tend to find that temporary work contracts and high overall labor turnover have a negative association with new-to-market innovations at firm level (whereas functional flexibility within firm has a positive association) (Giannetti and Madia 2013; Martínez-Sánchez et al. 2011; Michie and Sheehan 2003; Zhou et al. 2011).

In prior empirical literature patent citations are often interpreted as a paper trail of knowledge that reveals how knowledge spills over from one inventor and firm to another (Almeida and Kogut 1999; Jaffe et al. 1993). Analyzing patent citation patterns Almeida and Kogut (1999) show that labor mobility is a driver of growth and innovativeness in Silicon Valley. Also Miguélez and Moreno (2013) show that inventor mobility affects the innovativeness of regions. Studies analyzing citation patterns also provide evidence on the importance of job mobility for the learning by firms (Breschi and Lissoni 2009; Singh and Agrawal 2011). Citation patterns can help to describe the firms' technological search processes; however, they do not represent firms' innovation performance. Moreover, patent citations may contain systematic measurement error as a measure of knowledge flows, e.g. because a great share of citations are added by patent examiners, not inventors or patent applicants (Alcacer and Gittelman 2006; Nelson 2009; Roach and Cohen 2013). The share of examiner citations is especially large in Europe, because the EPO (European Patent Office) does not require the inventors to declare all references (Breschi and Lissoni 2005; Criscuolo and Verspagen 2008).

Related empirical studies suggest that the technological characteristics of firms also matter for knowledge transfer and thus for effects of labor mobility. Song et al. (2003) and Rosenkopf and Almeida (2003) find that inventor mobility is more likely and leads to greater knowledge transfer when mobile inventors possess different kind of technological expertise than the hiring firm. Boschma et al. (2009) find that plant level productivity increases when employees with related, but not too similar, skills are hired. This implies that firms need some degree of technological overlap to maintain absorptive capacity. If the recruited employees bring in knowledge and expertise too different from the firm's existing knowledge base, the firms may struggle to utilize the knowledge. To summarize these arguments, firms are expected to benefit especially from inflow of workers with skills and knowledge that complement their existing expertise[1]. Whether these aspects affect firm level innovation performance is, however, not analyzed by Müller and Peters (2010) or Kaiser et al. (2015).

The effects of outbound employee mobility have received somewhat less attention. Corredoira and Rosenkopf (2010) find evidence of reverse spillovers, i.e. they find that semiconductor firms that lose employees more often cite the patents of firms hiring these employees. At the same time, firms may also suffer from knowledge leaks. Indeed, Kim and Marschke (2005) and Agarwal et al. (2009) show that firms use pre-emptive patenting and patent litigation to protect themselves against potential knowledge leaks. Somaya et al. (2008) find that when employees are hired by cooperators there is a positive effect on firm performance while the effect is negative when employees are hired by competitors, thus implying knowledge leaks. Nevertheless, Kaiser et al. (2015) find evidence that outbound R&D worker mobility to patenting firms increases firm's patenting, while leavers to non-patenting firms have statistically insignificant effect on patenting. Thus, also the effect of outbound mobility may depend on the characteristics of hiring firm. Leaving worker's characteristics may also play a role in the association between worker mobility and performance. Leaving key employees are likely to have a more negative effect on firm performance (Campbell et al. 2012; Siebert and Zubanov 2009). Thus, the expected effect of outbound mobility on firm innovation performance is unclear.

To sum up, the prior empirical evidence points to positive performance effects of labor mobility on regional and individual inventor level. However, the firm-level effects of employee mobility remain rather mixed. Hiring of highly skilled employees contributes to firm productivity but overall effect is not clear.

[1] Parrotta and Pozzoli (2012) find, however, technological proximity to beneficial for learning by hiring.

3. Data

The main dataset used in this study is drawn from the EPO PATSTAT patent database. Additionally, financial and firm ownership data from Bureau van Dijk's Orbis database are also used. From Orbis, we include European manufacturing firms that have consolidated balance sheet data available and report R&D expenditures at least once during time period 2005-2011. For patent data, we use patent applications made to European Patent Office (EPO) after year 1995. In comparison to the national patent applications, the EPO patents have fewer gaps in the inventor and technological field information, which are the key pieces of information for our empirical approach. However, the EPO patents are often second filings and thus there may be a longer time lag between the invention and the patent filing. Only firms that apply for patents are included in the estimation of the patent production function.

Patents are matched to firms based on applicant names. The OECD HAN database and manual matching are used for name matching. The patent data are aggregated at the corporate group level under the assumption that the parent firm (ownership over 50%) is the ultimate owner of its subsidiaries' patents. This aggregation is performed using firm ownership information obtained from the Orbis database and manually checking the merger or acquisition date when subsidiary is observed to file patents.

3.1 Measuring inventor mobility

Patent applications contain information on the inventors and applicants of patents, thus allowing us to trace the employment histories of inventors as the patent applicant is nearly always the employer of the inventor (Hoisl 2007). Patent data has been used to track inventor mobility in several prior studies, e.g. Song et al. (2003), Hoisl (2007), Singh and Agrawal (2011).

We count the number of inventors listed in the firm's patent applications in each year. Of those inventors we count how many have been listed earlier in a patent application by another firm (movers), how many are inventors that appear in the patent data for the first time (new) and how many have been listed in an earlier patent application by the same firm (stayer). Also the number of leaving inventors (leaver) is counted.

Because we do not directly observe an inventor's employment contracts, we need to measure mobility to occur in the year of inventor's first patent application at the new firm. Inventions where the inventor is also the applicant are ignored and not considered as a move, because these do not include a change in employment. An inventor is considered to leave the firm in the year after inventor's last patent at the firm if the inventor appears in a patent application by another firm after that. If an inventor appears only in a single patent application we do not observe either inbound or outbound mobility.

It needs to be recognized that while the patent applicant usually is the inventor's employer, in few occasions e.g. due to strategic alliances or mergers, the applicant may change even though inventor has not changed employment. Unfortunately, these instances cannot be separated in the present study and they may thus overestimate the number of moves. The co-inventions, that is patents that are co-applied by several firms, are ignored when counting mobility to partly address this issue.

This methodology lends itself to measure mobility if the inventor has applied for a patent after the change of employment. Thus, our estimates underestimate the true inventor mobility and cover only successful job switches that result in new patents. The outbound mobility may also be underestimated, because patent data is truncated as new patents are published with time lag and future patenting is unknown. These issues are further discussed in chapter 5.3.

3.2 Identifying individual inventors

The spelling of inventor's name may differ in different patent applications, which needs to be considered in order to track inventor mobility. Identical inventor names may refer to different inventors and different spellings may refer to same inventor. Specifically, we match two records as same inventor if:

1. The records have identical names and the same NUTS3 region or patent assignee
2. The records have similar names (middle names ignored) and the same street address or patent assignee
3. The records have similar names, the same technological field and the same NUTS3 region

The regional location of inventors is based on OECD Regpat database (February 2015 version).

3.3 Patent output

Our dependent variable is the number of patent applications by firm and year. As a robustness test, we also use citation weighted patent output, which is formed by weighting each patent application by one plus the number of citations it receives within three years (citation information is taken from OECD Citations database, February 2015 version). Patent counts, even when weighted with citations, are known to be an imperfect proxy for innovation. Not all inventions are patentable and some firms also prefer to rely on trade secrecy and lead time and do not patent their inventions. These conditions also vary considerable across industries. Therefore, we concentrate the analysis on manufacturing sector, where in general patents are more prevalent. Moreover, we analyse only firms that have applied at least one patent and controls for firm-specific permanent heterogeneity in patenting.

3.4 Source firm's and inventors' past patenting activity

The occurrence of knowledge spillovers is likely to depend on the level of R&D knowledge in the source firm. Ideally, we would like to track the R&D investments of source firms; however, we observe the R&D investments for only a small subset of all possible source firms. Therefore, we need rely on the patent data and measure the extent of source firms' patenting activity. We count as high patenting firms those source firms that have filed more than five patent applications in the year before the inventor moves. Source firms that have fewer patents are classified as low patenting firm. Similarly, we measure the extent of patenting in the firms that hire leaving inventors[2].

We also measure the patenting of mobile inventors prior to the move and classify inventors with more than three prior patents as high patenting inventors and those inventors with fewer patents as low patenting inventors. The threshold is set based on the median number among the mobile inventors. The leaving inventors are similarly classified. Because our variable of interest is firm's patent output, the inventor's past patent output seems the most relevant measure of inventor productivity.

3.5 Technological similarity

The technological similarity between mobile inventor's prior expertise and her new employer is also considered. We also measure the technological similarity between the new employer and the source firm and how it affects the knowledge spillovers.

The International Patent Classification (IPC) at 2-digit level is used to form 52 technology classes based on categorization by Cincera (2005), see Appendix 1. The technological similarity is measured by comparing the most common technology classes in firms and inventors' patents. Some patents have several technology codes which are all used and weighted to find the most common technology class. Following the literature the technological specialization of firms is counted considering all patent applications filed by the firms, while for

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[2] The threshold is set based on the median among the source firms of mobile inventors. Alternative thresholds or considering the regularity of patenting over several years yielded closely similar results.

inventors only patents filed before the move are considered. Inventors are assumed to possess technological expertise in hiring firm's core field of technology when the main technology classes of inventor and firm match. Inventors have technologically related expertise, when their main technology class is different but they have made some inventions in the hiring firm's main technology field. When inventors have no patenting experience in hiring firm's core technology field, they are categorized to possess non-core technological expertise.

The technological similarity of the source firms is measured similarly: the firms are categorized as technologically similar, technologically related and technologically different depending whether their main fields of technology match. The technological similarity of firms recruiting leaving inventors is also measured.

3.6 R&D investments and the number of employees

Data on firms' employees and R&D expenditures are obtained from the Orbis database. The R&D stock measure is constructed using R&D expenditures and the perpetual inventory method with a depreciation rate of 15%, as is typical in the literature (Hall et al. 2010). The initial value of the R&D stock is formed using the R&D expenditure in the first year and scaling it up using the depreciation rate and assumed steady-state growth rate (5%). The R&D investments are deflated to year 2010 prices using country-level GDP deflator obtained from OECD Statistics.

3.7 Descriptive statistics

Our final sample includes 935 firms and 4763 firm-year observations, where the availability of R&D expenditure data is the main delimiting variable leading to unbalanced panel. These firms come from 19 different European countries[3]. We were able to match these firms to 382,315 patent applications in time period 1995-2011. Table 1 provides summary statistics of the sample. Most of our sample firms are large firms with median workforce over 1800 employees, because many smaller firms do not report R&D expenditures. Thus, our results may not readily apply to smaller firms. The median R&D stock is approx. 56 million euros. The median of patent applications per year is 2, while for about a third of the observations we observe no patent applications (in a given year). Table 1 also presents summary statistics of inbound and outbound inventor mobility. Correlations for these variables are presented in Appendix 2. The average

[3] The countries are Austria, Belgium, Denmark, Finland, France, Germany, Hungary, Ireland, Italy, Latvia, Luxemburg, Netherlands, Norway, Spain, Slovenia, Sweden, Switzerland and United Kingdom. Approximately two thirds of the sample firms come from UK, Germany, France and Switzerland.

share of hired inventors is 6.7% of all inventors and about 4.8% of inventors is observed to leave the firm in each year. These figures contain zeros for the observations with no patents and thus no inventors in a given year and hence real rates of mobility are somewhat higher. Nevertheless, the majority of inventors are either first time inventors or inventors who stay at the same firm from year to year. The figures are also quite similar across countries even though labor market conditions vary across countries.

Table 1 here

We divide the inventors and source firms to high and low patenting groups based on the median values of past patenting; hence, these groups are of roughly equal size. However, hired inventors and their source firms are slightly more likely to belong to low patenting groups, whereas the leaving inventors and their hiring firms more often belong to the high patenting groups. Moreover, movers from firms with same or related technological specialization appear more common than movers from technologically different firms. When we look at moving inventors' previous patenting, we observe that a large share of movers have no experience in the firm's core technological field. However, movers with prior experience in firm's main field of technology are the most common group. The figures are similar for outbound inventor mobility. Leaving inventors with patenting experience in firm's core technological field and leavers to technologically similar firms form the largest groups.

4. Empirical approach

This section describes the patent production function and the estimation approach adopted. Following Kaiser et al. (2015), we estimate a patent production function, where the dependent variable is the number of patent applications by firm in a given year. This is a count variable and thus we use a count data model in the estimations. The number of patents is modeled to depend on firm's R&D investment stock, employment, which is also a control for firm size, and number of patent inventors:

$$E\left(P_{it}\right) = \exp\left(\ln A_{it} + \alpha \ln L_{it} + \beta \ln R\&D_{it} + \gamma \ln L^{I}_{i,t-1} + \eta_i\right) \quad (1)$$

where P_{it} refers to the number of patent applications in firm i, L_{it} to the number of employees, $R\&D_{it}$ to firm's R&D stock, $L^{I}_{i,t-1}$ to number of inventors in the previous year and η_i is a firm specific effect. A_{it} captures other factors affecting the production of patentable inventions such as time, sectoral and country effects[4]. The inventors employed in the firm are divided to staying inventors (s), movers from other firms (m), and first time inventors (n): $L^I = L^s + L^m + L^n$. Inventors who leave the firm, L^l, are also considered as distinctive group but they are not counted among the current inventors. Taking logs and using the approximation $\ln(1-x) \approx x$, we can plug the inventor types in the patent production function. This approach normalizes the effect of staying inventors to unity. This leads to a following equation:

$$E\left(P_{it}\right) = \exp\left(\ln A_{it} + \alpha \ln L_{it} + \beta \ln R\&D_{it} + \gamma_0 \ln L^I_{i,t-1} + \gamma_m \frac{L^m_{i,t-1}}{L^I_{i,t-1}} + \gamma_n \frac{L^n_{i,t-1}}{L^I_{i,t-1}} + \gamma_l \frac{L^l_{i,t-1}}{L^I_{i,t-2}} + \eta_i\right) \quad (2)$$

In addition to the above mentioned factors, we will also take into account the state dependency in firm's patenting activity. We control for the previous patenting activity of firm, because past inventions present a stock of knowledge that can be used for future inventions and therefore they can have a substantial effect on current patenting (Blundell et al. 2002). We use as a control the log number of patents lagged by one and two periods and include dummy variables for zero patents. Controlling for past patenting is crucial also because more inventive firms may also be more likely to hire new inventors.

We consider the differences in the characteristics of previous employers and mobile inventors by separating the mobile inventors by type. We will analyze the effect of mobile inventors' past patents, the source firm's patenting, the mobile inventors' technological fit with the hiring firm and the source firm's technological similarity. The characteristics of outbound mobility are similarly analyzed.

Our dependent variable in the estimations is a count variable and thus we need to use Poisson or Negative Binomial regression. The empirical methodology also needs to control for firm-specific permanent heterogeneity in patenting (different patent propensity due to different technological environment, different R&D practices, different R&D investment appropriability conditions etc.). Common approach is to use fixed effect or random effect model. However; because lagged patenting is used as explanatory variable, the strict exogeneity assumption does not hold and random effect Poisson or negative binomial model cannot be used. Therefore we use pre-sample mean estimation suggested by Blundell et al. (1995) and applied for example by Czarnitzki et al. (2009) and Kaiser et al. (2015). The model uses pre-sample patent information to approximate the firm fixed effects in pooled cross-sectional count model. In our model, we use the log of mean patents per year in pre-sample period 1995-2004, and a dummy variable

[4] Estimated model includes dummies for years, industries and countries (based on the location of firm's headquarters).

which indicates firms that had no patents in the pre-sample period. The dummy variable allows the expected number of patents to vary for firms with or without pre-sample patents.

We use negative binomial model to allow over-dispersion in the data. The test for the equality of mean and variance shows that negative binomial model is preferred over Poisson model.

5. Results

5.1 Main results

This section presents and discusses the empirical results. Table 2 presents the results for the baseline model and analyzes the effect of inventors' and source firms' prior patenting. In Table 3, the role of technological characteristics is analyzed. The tables display the coefficients and the cluster robust standard errors in parenthesis. Statistically significant coefficients are presented with asterisks. The coefficients do not directly translate into marginal effects which are reported separately in Table 4; however, the signs and significance levels of coefficient estimates are applicable.

Table 2 here

The first column in Table 2 presents the baseline estimation. Further columns show how the effect of mobility depends on mobile inventors' prior patenting and source firm patenting. Our main control variables in the estimations are firm's previous patenting and R&D stock which have coefficients that are highly significant and have expected signs. The state dependency in firm's patenting is considerable as all variables controlling for firm's past patenting are highly significant. Also pre-sample patenting, which controls for the time-invariant firm-specific heterogeneity, is highly significant. Number of employees is not significant. Neither the log number of inventors has a significant effect on patenting.

Regarding the inventor mobility, we can see that the coefficient of the share of movers is positive but not significant in column 1. This implies that mobile inventors are not significantly more productive for firm's patenting than staying inventors. The coefficient of the share of new inventors is always positive and significant, implying that first time inventors are also associated with higher patenting in the future. However, the share of leaving inventors has a strongly negative and statistically significant coefficient. Thus, inventors who leave the firm to join another firm imply a considerably negative development in firm's future patenting.

In column 2, we separate the mobile inventors with above median prior patenting and those with below median. We notice that hiring inventors with high number of prior patents is associated with significantly higher future patenting, whereas inventors with few patents do not make a difference. Moreover, we can notice that the number of previous patents by leaving inventors is also an important determinant of the losses through outbound mobility. Losing productive inventors has a stronger negative effect on future patenting, whereas leaving inventors with few past patents do not have a significant effect. The past patent productivity thus appears to capture inventors' skills.

Next we take a better look at the characteristics of source and hiring firms. In column 3, we see that inventors who join the firm from a high patenting firm result in an improvement firm's patent output, whereas inventors joining from a low patenting firm have no effect on patenting. This finding implies that inventors from high patenting firms transfer more valuable technological knowledge. We can also notice that leaving inventors have a more negative effect on future patenting when they leave to a high patenting firm. Leavers to low patenting firms do not affect patenting. Leavers to high patenting firms should imply a higher potential for reverse knowledge spillovers. However, their effect is strongly negative which does not support the reverse knowledge spillovers argument. Alternative explanation could be that losing these inventors to high patenting firm entails larger loss in competitiveness or that these inventors are more productive and thus their leaving leads to a greater loss in skills. This might imply that firms investing intensively in patenting are better able to hire the best inventors from their competitors. However, in Appendix 3 we divide mobile inventors both by inventors' and firms' prior patenting and re-estimate the model. Results confirm that both the investor's and the hiring firm's patenting matter for inbound as well as outbound mobility. With respect to outbound mobility, the hiring firms' patenting appears more important in explaining the losses than leaving inventor's productivity. However, the correlations in Appendix 2 show that inventors leaving to high patenting firms are also somewhat more likely to have many prior patents. Therefore, at least based on observable inventor productivity, it appears that poaching of best employees may partly explain why losing inventors to high patenting firms decreases patenting; however, it does not explain it completely.

In Table 3 we examine the technological similarity of source firms and the technological fields of mobile inventors' expertise. The technological fit of mobile inventors appears to have an effect on firm-level patenting. The results of model 4 show that inventors who bring different technological expertise are helpful for future patenting, whereas bringing additional core expertise by hiring does not have a statistically significant effect on patenting. The technological field of source firm also matters (model 5). Inventors, who move to the firm from an employer with related main field of technology, significantly help to increase patenting in the future.

Inventors from firms in same technological field or completely different field have no significant effect on patenting, i.e. they are equally productive as inventors staying in the firm. Based on these results, it appears that the source firm characteristics are more significant than individual inventor characteristics in explaining gains from mobility. With respect to outbound mobility, both aspects appear equally important predictors.

Table 3 here

With respect to outbound mobility the results in Table 3 show that leaving inventors that have worked in firm's core field of technology have a strongly negative effect on firm's patenting, whereas leaving inventors with non-core technological experience do not have a significant effect. The results conform with the view that losing inventors with core competences is more likely to degrade firm knowledge base and innovativeness. Leaving inventors with non-core technological experience appear less harmful and also have a more positive effect on future performance in the hiring firm. Thus, non-core technological knowledge appears less firm-specific and more general in nature implying wider applicability and easier replacement.

Moreover, when inventors leave to a firm that operates in the same or a related technological field, the effect on patenting is strongly negative in the source-firm. When inventors leave to a firm working in a different technological field, there is no effect. Firms working in the same technological field may be direct competitors of the firm and the negative effect can also be explained by the consequent loss in competitiveness. Mobility to technologically different firms may also enable reverse knowledge spillovers and bring complementing technological expertise and connections for the firm.

The coefficients of a negative binomial model do directly reveal the marginal effects of explanatory variables. Thus, Table 4 presents the marginal effects for some of the key explanatory variables. The marginal effects are estimated at the means of covariates. They show how the expected number of patent applications per year changes with the increase in the explanatory variables. The Table 4 shows an increase of up to 1.8 patent applications due to inbound mobility and decrease up to 3.4 patents due to outbound mobility. With the average share of movers at 0.067, this implies approximately 0.12 more patent applications per year if the inventors are hired from a high patenting firm when compared to no mobility. The median of patents per year is 2 and thus the gain from average mobility can be up to a 6% increase in patenting. Counted similarly, average outbound mobility may decrease patenting about the same amount up to 0.16 patents per year. Thus, the knowledge spillovers through mobility appear somewhat limited in size and in the worst case the drawbacks of outbound mobility may well exceed the benefits.

Table 4 here

Prior literature has mostly analyzed knowledge spillovers through inventor mobility using patent citation data. Our findings show that inventor mobility not only affects the patent citation patterns but also has a significant effect on firm-level patenting. Our finding that transfer of technologically different knowledge is most productive for firm's future patenting is also supported by prior studies (Boschma et al. 2009; Song et al. 2003). However, our findings starkly differ from the results of Kaiser et al. (2015), who found outbound mobility to be positively associated with higher patenting in the future. However, they analyze on average smaller firms that apply also fewer patents. Smaller firms may be able to gain more from mobility (Rao and Drazin 2002). Moreover, larger firms, analyzed in the present study, may also face more risks through outward knowledge spillovers. These differences may partly explain the differing results.

5.2 Robustness

The robustness of our results is tested by excluding in turn firms with few patents or very high number of patents, firms with very high or very low R&D investments, smallest and largest firms in terms of employees and industries with highest and lowest patent intensity. The main results and implications remain unchanged; however, the precision of estimates deteriorates as the sample is narrowed down. Patent production function was also estimated using longer lags of mobility variables and firm's past patenting as explanatory variables. The main findings did not change.

Also country specific estimations of model 1 were conducted. Unfortunately, the number of observations is low for many countries and thus the standard errors are high. However, the point estimates showed that the main findings were replicated in several country-specific estimations whereas for approximately half of the countries the results indicated an inverse U-shape relation between inbound mobility and patent output (and U-shape for outbound mobility). Thus, it appears that despite the country specific differences in labor markets, the inventor mobility is similarly associated with innovative output in many European countries.

Moreover, we re-estimated model using granted patents instead of patent applications as the dependent variable to account for the concern that firms may use patents filing as strategic tool and employee mobility may change firms' patenting strategies rather than their inventive output. Granted patents have gone through the examination process at the patent office and firms' strategic choices are likely to confound them less than patent application numbers.

Granting process may take several years and thus we dropped the last three years of our observation period when re-estimating the model. Overall, using granted patents instead of applications did not change the main results. However, in contrast to our baseline model the effect of inbound mobility was more positive and statistically significant.

We also account for the heterogeneity in the value of patents. It is well documented that the value of patents is heavily skewed (Harhoff et al. 1999; Lanjouw et al. 1998). A common solution has been to use patent citations to approximate patent value. The estimations with quality weighted patent output confirm our main results. The exception is that the role of technological characteristics is less significant in explaining gains from inbound mobility, even though the coefficients have similar magnitudes. The results for these estimations are presented in Appendix 4.

5.3 Identification issues

Despite the above mentioned robustness tests, our results are subject to some endogeneity concerns which do not allow us to make strong causal claims about our results. First, positive assortative matching of firms and inventors is a possible concern (Becker 1973). The most inventive firms may be able attract the most productive inventors, which could lead us to observe positive correlation between mobility and patenting. Also negative effect of overall outbound mobility could be partly biased by the fact that less innovative firms may not be able to keep their inventors or loose best talents. Thus, matching could lead us to overestimate the gains from inbound mobility and the losses from outbound mobility. However, we directly measure the firms' and inventors' past patent productivity to take this into account. Despite this, there could be unobserved differences that could bias our results with respect to overall mobility. However, it is not clear whether the unobserved differences should be similarly correlated with the technological characteristics and thus bias the effect of inflow and outflow of different and similar technological skills.

Second, firms may use patenting to protect themselves against leaving inventors (Kim and Marschke 2005). Thus, the effect of mobility may reflect either research productivity gains or changes in firm's propensity to patent. However, protective patenting hypothesis does not explain e.g. why mobility only from technologically different firms increases patenting. In fact, protective patenting could better explain why mobility to and from technologically similar firms, i.e. possible competitors, would increase patenting, but our findings point to contrary conclusion. Moreover, the argument of Kim and Marschke (2005) suggests that high degree of outbound mobility should have a positive effect on patenting because of higher patenting propensity; however, our results point to a negative overall effect. Thus, while we cannot separate whether mobility affects patent productivity or propensity to patent, it seems that protective patenting hypothesis cannot explain our main findings.

Third, there is a potential selection bias, because we only observe inventors who patent again in their new employer's service. Firms with lower patenting propensity may thus appear to have a lower inventor mobility as well as lower patenting. However, we control for firm effects, which takes time invariant patenting propensity into account. The selection also leads us to observe only more valuable mobility, whereas less valuable mobility, i.e. mobility which does not lead to patents, remains unobserved. This could lead us to overestimate the gains from mobility. However, the overall effect of inbound mobility is not statistically significant and it is not clear whether the partial observation of mobility should affect the results on knowledge transfer from different technological fields or high patenting firms.

6. Conclusions

While labor mobility is heralded as a driver of knowledge diffusion, innovation and economic growth, the detailed evidence on its' effects on firm-level innovation performance remains scarce. This paper provides new empirical evidence on the importance of labor mobility for the innovation output of firms by analyzing the mobility of patent inventors. The study also sheds light on the role of mobile inventors' and source firms' characteristics in enabling knowledge transfer.

The empirical results show that, overall, mobile patent inventors are not more productive than staying inventors in terms of firm's future patent output; however, the gains depend on the characteristics of mobile inventors and their source firms with the latter relatively more important. Hiring inventors with many past patents results in a significant improvement in firm's patenting as well as hiring inventors from firms that have above median patenting. This implies that these mobile inventors possess more valuable skills and expertise and are able to transfer valuable technological knowledge from their previous employers. The estimated marginal effects imply up to 0.12 increase in patent applications per year at average rate of hiring compared to no mobility. As the median of patents per year is 2, this implies 6% increase in patenting. Moreover, we find that it is inventors with different technological expertise and inventors from technologically related but not too similar firms that bring complementary skills and knowledge that benefit firm's patenting in the future. This finding is also in line with earlier results on labor mobility and firm productivity growth (Boschma et al. 2009). Prior literature using patent citations has identified inventor mobility as an important source of knowledge spillovers. Our results confirm these findings and show that inventor mobility not only affects the citation patterns, as shown in earlier literature, but can also have a significant effect on firm-level patenting outcomes.

We also analyze inventors who leave the firm and the characteristics of firms that hire them. Outbound mobility is found to contribute negatively to firm's patent output in the future. The negative effect is stronger when the leaving inventors have been more productive in the past, have worked in firm's core field of technology or leave to a technologically similar firm. These inventors appear to possess skills central to firm's innovation activities and thus leaving leads to deteriorating innovation performance. Inventors possessing non-core technological expertise and inventors leaving to technologically different firms do not have a significantly negative effect on future patenting. The lack of negative effect may be explained by the less firm-specific and thus more easily replaced knowledge these inventors possess. These inventors may also continue to act as source of complementing technological knowledge through reverse knowledge spillovers. Unfortunately, the present study cannot separate these effects; however, this and related questions provide interesting extensions to the present study.

Moreover, the results of the present study show that inventors who leave the firm to join a low patenting firm have no effect on future patenting while leavers to high patenting firms have a strongly negative effect. This finding points, however, not to reverse knowledge spillovers highlighted in prior studies but to knowledge leaks and loss in competitiveness. Our analysis shows that this finding may be partly, but not entirely, due to better firms poaching most productive inventors. Overall, our results do not support the view that the reverse knowledge spillovers could compensate the loss of skills and inventor expertise that is associated with outbound mobility. In this respect our results differ from some of the previous studies, most notably from the results Kaiser et al. (2015).

Some caution is required before interpreting our results as causal. Firms can choose who they hire, and even though we can observe and measure inventors' and firms' past patent productivity, it is possible that positive assortative matching on unobservable characteristics could bias our results. Protective patenting hypothesis (Kim and Marschke 2005) cannot, however, explain our main findings.

Our results have practical implications for firms and the entire economy. We show that employee mobility can be beneficial for firm-level innovativeness and it may thus improve firm productivity and growth in the economy as already argued in the prior literature. Nevertheless, the negative effect of outbound mobility may also cause the firms to invest less in R&D and in their employees, because these investments are lost if employee leaves. However, this study analyzes firm-level performance and ignores the national level benefits of creative destruction. More innovative firms are likely to win market shares and grow in size. This implies that labor market flexibility should to be considered as a tool to facilitate knowledge transfer between firms. Beneficial effects of policies also depend on the future market restructuring through creative destruction as the immediate effects on continuing firms are not unambiguous.

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Table 1. Summary statistics

Variable	Mean	Median	SD
Patents	33.745	2	137.375
No patent dummy	0.341	0	0.474
Citation weighted patents	53.744	3	226.076
Employees	13462.360	1857	37323.290
R&D stock	831.712	55.742	3361.587
Number of inventors	55.394	4	209.836
Share of movers	0.067	0	0.146
Movers, high past patenting	0.027	0	0.087
Movers, low past patenting	0.040	0	0.111
Movers from high patenting firms	0.031	0	0.091
Movers from low patenting firms	0.036	0	0.113
Movers with core tech. expertise	0.031	0	0.103
Movers with related tech. expertise	0.013	0	0.057
Movers with non-core tech. expertise	0.022	0	0.079
Movers from tech. similar	0.029	0	0.102
Movers from tech. related	0.027	0	0.090
Movers from tech. different	0.010	0	0.055
Share of new	0.300	0.300	0.303
Share of leavers	0.048	0	0.122
Leavers, high past patenting	0.029	0	0.094
Leavers, low past patenting	0.019	0	0.069
Leavers to high patenting firms	0.022	0	0.069
Leavers to low patenting firms	0.027	0	0.098
Leavers with core tech. expertise	0.025	0	0.089
Leavers with related tech. expertise	0.012	0	0.059
Leavers with non-core tech. expertise	0.011	0	0.048
Leavers to tech. similar	0.021	0	0.084
Leavers to tech. related	0.019	0	0.068
Leavers to tech. different	0.009	0	0.050

Notes. 4763 observations, 935 firms

Table 2. Effect of inventor mobility on the number of patents at firm level

	1	2	3
L.ln(total inventors)	-0.006	0.002	-0.003
	(0.041)	(0.040)	(0.040)
L.Share of movers	0.143		
	(0.126)		
L.Movers, high past patenting		0.417*	
		(0.218)	
L.Movers, low past patenting		-0.056	
		(0.163)	
L.Movers from high patenting firms			0.535***
			(0.183)
L.Movers from low patenting firms			-0.169
			(0.166)
L.Share of new	0.234**	0.238***	0.238***
	(0.091)	(0.090)	(0.090)
L.Share of leavers	-0.469***		
	(0.148)		
L.Leavers, high past patenting		-0.600***	
		(0.210)	
L.Leavers, low past patenting		-0.292	
		(0.209)	
L.Leavers to high patenting firms			-0.985***
			(0.236)
L.Leavers to low patenting firms			-0.149
			(0.170)
L.ln(patents)	0.535***	0.523***	0.521***
	(0.047)	(0.045)	(0.044)
L2.ln(patents)	0.260***	0.264***	0.272***
	(0.024)	(0.024)	(0.024)
L.No patent dummy	-0.282***	-0.277***	-0.304***
	(0.086)	(0.088)	(0.087)
L2.No patent dummy	-0.463***	-0.465***	-0.450***
	(0.082)	(0.080)	(0.081)
Pre-sample patenting	0.104***	0.105***	0.105***
	(0.023)	(0.022)	(0.023)
No pre-sample patenting dummy	-0.249**	-0.249**	-0.245**
	(0.114)	(0.114)	(0.113)
ln(R&D stock)	0.068***	0.069***	0.068***
	(0.017)	(0.017)	(0.017)
ln(employees)	-0.001	-0.001	0.001
	(0.014)	(0.014)	(0.014)

Notes. 4763 observations. 935 firms. Negative binomial PSM estimation. Dependent variable is the number of patents per year. Standard errors are clustered on firm and are shown in parentheses.* p<0.10, ** p<0.05, *** p<0.01. All estimations include year, industry and country controls as well as a constant term.

Table 3. Effect of inventor mobility and technological similarity

	4	5
L.ln(total inventors)	-0.010	-0.007
	(0.042)	(0.040)
L.Movers with core tech. expertise	-0.021	
	(0.197)	
L.Movers with related tech. expertise	0.205	
	(0.261)	
L.Movers with non-core tech. expertise	0.342*	
	(0.191)	
L.Movers from tech. similar		0.003
		(0.197)
L.Movers from tech. related		0.359**
		(0.182)
L.Movers from tech. different		0.028
		(0.255)
L.Share of new	0.228**	0.239***
	(0.091)	(0.091)
L.Leavers with core tech. expertise	-0.484**	
	(0.218)	
L.Leavers with related tech. expertise	-0.654**	
	(0.260)	
L.Leavers with non-core tech. expertise	-0.209	
	(0.268)	
L.Leavers to tech. similar		-0.424**
		(0.199)
L.Leavers to tech. related		-0.720**
		(0.290)
L.Leavers to tech. different		-0.083
		(0.252)
L.ln(patents)	0.538***	0.534***
	(0.048)	(0.045)
L2.ln(patents)	0.261***	0.264***
	(0.024)	(0.024)
L.No patent dummy	-0.289***	-0.282***
	(0.087)	(0.087)
L2.No patent dummy	-0.458***	-0.463***
	(0.082)	(0.081)
Pre-sample patenting	0.104***	0.105***
	(0.023)	(0.023)
No pre-sample patenting dummy	-0.247**	-0.244**
	(0.116)	(0.113)
ln(R&D stock)	0.069***	0.067***
	(0.017)	(0.017)
ln(employees)	-0.002	-0.001
	(0.014)	(0.014)

Notes. 4763 observations. 935 firms. Negative binomial PSM estimation. Dependent variable is the number of patents per year. Standard errors are clustered on firm and are shown in parentheses.* $p<0.10$, ** $p<0.05$, *** $p<0.01$. All estimations include year, industry and country controls as well as a constant term.

Table 4. Marginal effects at means

	1	2	3	4	5
L.Share of movers	0.488 (0.435)				
L.Movers, high past patenting		1.426* (0.757)			
L.Movers, low past patenting		-0.192 (0.556)			
L.Movers from high patenting firms			1.826*** (0.639)		
L.Movers from low patenting firms			-0.578 (0.568)		
L.Movers with core tech. expertise				-0.072 (0.675)	
L.Movers with related tech. expertise				0.703 (0.896)	
L.Movers with non-core tech. expertise				1.169* (0.651)	
L.Movers from tech. similar					0.009 (0.672)
L.Movers from tech. related					1.228* (0.635)
L.Movers from tech. different					0.095 (0.872)
L.Share of new	0.800*** (0.311)	0.814*** (0.308)	0.812*** (0.307)	0.781** (0.309)	0.815*** (0.309)
L.Share of leavers	-1.604*** (0.519)				
L.Leavers, high past patenting		-2.050*** (0.731)			
L.Leavers, low past patenting		-0.998 (0.716)			
L.Leavers to high patenting firms			-3.360*** (0.842)		
L.Leavers to low patenting firms			-0.507 (0.581)		
L.Leavers with core tech. expertise				-1.655** (0.755)	
L.Leavers with related tech. expertise				-2.237*** (0.903)	
L.Leavers with non-core tech. expertise				-0.716 (0.917)	
L.Leavers to tech. similar					-1.451** (0.683)
L.Leavers to tech. related					-2.461** (1.009)
L.Leavers to tech. different					-0.284 (0.861)

Notes. 4763 observations, 935 firms. Standard errors are shown in parentheses.* p<0.10, ** p<0.05, *** p<0.01.

Appendix 1. Technological classification using 2-digit IPC codes

Class	2-digit IPC	Share of patents
1	A01	0.015
2	A21, A22, A23, A24	0.008
3	A41, A42, A42, A44, A45, A46	0.003
4	A47, A63	0.009
5	A61, A62	0.109
6	B01	0.018
7	B02, B03, B04, B05, B06, B07, B08, B090	0.008
8	B21, B22	0.006
9	B23	0.008
10	B24, B24, B26, B27, B28	0.008
11	B29	0.010
12	B30, B31, B32	0.004
13	B41, B42, B43, B44	0.010
14	B60	0.045
15	B61, B62, B63, B64	0.017
16	B65, B66, B67, B68	0.020
17	B81, B82	0.004
18	C01, C06	0.001
19	C02	0.006
20	C03, C04	0.062
21	C05, C07	0.034
22	C08	0.017
23	C09	0.003
24	C10	0.006
25	C11	0.022
26	C12, C13	0.004
27	C21, C22	0.006
28	C23	0.002
29	C25, C30	0.010
30	C40	0.009
31	D01, D02, D03, D04, D05, D06, D07, C14	0.006
32	D21	0.006
33	E01, E02, E03, E04	0.003
34	E05, E06	0.046
35	E21	0.034
36	F01, F02, F03, F04	0.021
37	F15, F16, F17	0.003
38	F21, F22, F23, F24, F25, F26, F27, F28	0.053
39	F41, F42	0.012
40	G01	0.008
41	G02	0.011
42	G03	0.045
43	G04, G05	0.019
44	G06	0.014
45	G07, G08, G09, G10, G12	0.001
46	G11	0.066
47	G21	0.024
48	H01	0.017
49	H02	0.111
50	H03	0.014
51	H04	0.001
52	H05	0.000

Appendix 2. Correlation tables

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Patents	1													
2	Number of inventors	0.976	1												
3	Share of movers	0.003	0.002	1											
4	Movers, high past patenting	0.016	0.015	0.653	1										
5	Movers, low past patenting	-0.009	-0.010	0.806	0.077	1									
6	Movers from high patenting firms	0.041	0.040	0.637	0.498	0.449	1								
7	Movers from low patenting firms	-0.029	-0.030	0.785	0.446	0.684	0.022	1							
8	Movers with core tech. expertise	-0.021	-0.026	0.708	0.484	0.552	0.310	0.668	1						
9	Movers with related tech. expertise	0.026	0.029	0.513	0.447	0.326	0.430	0.319	0.078	1					
10	Movers with non-core tech. expertise	0.013	0.014	0.563	0.255	0.542	0.461	0.359	-0.029	0.104	1				
11	Movers from tech. similar	-0.005	-0.011	0.687	0.471	0.536	0.276	0.669	0.840	0.193	0.053	1			
12	Movers from tech. related	0.012	0.017	0.619	0.441	0.470	0.680	0.256	0.200	0.557	0.473	-0.004	1		
13	Movers from tech. different	-0.003	-0.003	0.366	0.136	0.375	0.063	0.424	-0.009	0.090	0.620	-0.024	0.010	1	
14	Share of new	0.075	0.081	0.057	0.026	0.054	0.048	0.035	0.012	0.043	0.058	0.016	0.045	0.046	1

	Variable	1	2	3	4	5	6	7	8	9	10	11	12
1	Patents	1											
2	Share of leavers	0.021	1										
3	Leavers, high past patenting	0.022	0.829	1									
4	Leavers, low past patenting	0.007	0.641	0.102	1								
5	Leavers to high patenting firms	0.069	0.598	0.539	0.324	1							
6	Leavers to low patenting firms	-0.023	0.824	0.652	0.570	0.039	1						
7	Leavers with core tech. expertise	-0.012	0.747	0.633	0.460	0.377	0.665	1					
8	Leavers with related tech. expertise	0.025	0.586	0.556	0.279	0.417	0.436	0.067	1				
9	Leavers with non-core tech. expertise	0.045	0.449	0.259	0.442	0.314	0.338	-0.010	0.127	1			
10	Leavers to tech. similar	0.010	0.706	0.559	0.487	0.394	0.601	0.748	0.217	0.159	1		
11	Leavers to tech. related	0.027	0.607	0.541	0.337	0.540	0.375	0.348	0.485	0.303	0.039	1	
12	Leavers to tech. different	-0.001	0.438	0.354	0.292	0.069	0.497	0.099	0.411	0.420	-0.006	0.060	1

Appendix 3. Inventor mobility divided by inventors' and source firms' prior patenting

L.ln(total inventors)	0.004
	(0.039)
L.Movers, high past patenting & high patenting firm	1.087***
	(0.265)
L.Movers, high past patenting & low patenting firm	-0.413
	(0.271)
L.Movers, low past patenting & high patenting firm	-0.053
	(0.222)
L.Movers, low past patenting & low patenting firm	-0.039
	(0.210)
L.Share of new	0.248***
	(0.089)
L.Leavers, high past patenting & high patenting firm	-1.097***
	(0.286)
L.Leavers, high past patenting & low patenting firm	-0.088
	(0.274)
L.Leavers, low past patenting & high patenting firm	-0.822**
	(0.385)
L.Leavers, low past patenting & low patenting firm	-0.116
	(0.249)
L.ln(patents)	0.507***
	(0.042)
L2.ln(patents)	0.275***
	(0.025)
L.No patent dummy	-0.279***
	(0.089)
L2.No patent dummy	-0.465***
	(0.079)
Pre-sample patenting	0.106***
	(0.022)
No pre-sample patenting dummy	-0.242**
	(0.112)
ln(R&D stock)	0.070***
	(0.016)
ln(employees)	-0.000
	(0.014)

Notes. 4763 observations. 935 firms. Negative binomial PSM estimation. Dependent variable is the number of patents per year. Standard errors are clustered on firm and are shown in parentheses.* p<0.10, ** p<0.05, *** p<0.01. All estimations include year, industry and country controls as well as a constant term.

Appendix 4. Effect of inventor mobility on citation weighted patents

	1	2	3
L.ln(total inventors)	0.051	0.057	0.055
	(0.043)	(0.044)	(0.044)
L.Share of movers	0.116		
	(0.147)		
L.Movers, high past patenting		0.381*	
		(0.225)	
L.Movers, low past patenting		-0.065	
		(0.202)	
L.Movers from high patenting firms			0.531***
			(0.194)
L.Movers from low patenting firms			-0.182
			(0.204)
L.Share of new	0.250**	0.254**	0.250**
	(0.106)	(0.106)	(0.106)
L.Share of leavers	-0.528***		
	(0.161)		
L.Leavers, high past patenting		-0.672***	
		(0.223)	
L.Leavers, low past patenting		-0.332	
		(0.236)	
L.Leavers to high patenting firms			-1.127***
			(0.259)
L.Leavers to low patenting firms			-0.229
			(0.190)
L.ln(Citation weighted patents)	0.456***	0.445***	0.440***
	(0.039)	(0.038)	(0.038)
L2.ln(Citation weighted patents)	0.273***	0.276***	0.284***
	(0.029)	(0.030)	(0.030)
L.No patent dummy	-0.084	-0.080	-0.108
	(0.102)	(0.103)	(0.102)
L2.No patent dummy	-0.335***	-0.336***	-0.319***
	(0.094)	(0.094)	(0.095)
Pre-sample citation weighted patenting	0.105***	0.106***	0.105***
	(0.032)	(0.032)	(0.032)
No pre-sample patenting dummy	-0.220	-0.221	-0.218
	(0.148)	(0.148)	(0.147)
ln(R&D stock)	0.097***	0.098***	0.098***
	(0.021)	(0.021)	(0.021)
ln(employees)	-0.030*	-0.030*	-0.028
	(0.018)	(0.018)	(0.018)

Notes. 4763 observations. 935 firms. Negative binomial PSM estimation. Dependent variable is the number of citation weighted patents per year. Standard errors are clustered on firm and are shown in parentheses.* p<0.10, ** p<0.05, *** p<0.01. All estimations include year, industry and country controls as well as a constant term.

	4	5
L.ln(total inventors)	0.044	0.049
	(0.043)	(0.043)
L.Movers with core tech. expertise	-0.032	
	(0.237)	
L.Movers with related tech. expertise	0.099	
	(0.344)	
L.Movers with non-core tech. expertise	0.343	
	(0.217)	
L.Movers from tech. similar		-0.011
		(0.230)
L.Movers from tech. related		0.319
		(0.194)
L.Movers from tech. different		0.029
		(0.297)
L.Share of new	0.245**	0.253**
	(0.106)	(0.106)
L.Leavers with core tech. expertise	-0.595**	
	(0.238)	
L.Leavers with related tech. expertise	-0.770***	
	(0.280)	
L.Leavers with non-core tech. expertise	-0.085	
	(0.334)	
L.Leavers to tech. similar		-0.632***
		(0.221)
L.Leavers to tech. related		-0.687**
		(0.331)
L.Leavers to tech. different		0.068
		(0.334)
L.ln(Citation weighted patents)	0.460***	0.454***
	(0.040)	(0.039)
L2.ln(Citation weighted patents)	0.274***	0.278***
	(0.029)	(0.029)
L.No patent dummy	-0.089	-0.086
	(0.103)	(0.103)
L2.No patent dummy	-0.330***	-0.330***
	(0.094)	(0.094)
Pre-sample citation weighted patenting	0.105***	0.105***
	(0.032)	(0.032)
No pre-sample patenting dummy	-0.220	-0.214
	(0.149)	(0.148)
ln(R&D stock)	0.098***	0.096***
	(0.021)	(0.021)
ln(employees)	-0.031*	-0.030*
	(0.018)	(0.018)

Notes. 4763 observations. 935 firms. Negative binomial PSM estimation. Dependent variable is the number of citation weighted patents per year. Standard errors are clustered on firm and are shown in parentheses.* p<0.10, ** p<0.05, *** p<0.01. All estimations include year, industry and country controls as well as a constant term.