Paper to be presented at

DRUID15, Rome, June 15-17, 2015

(Coorganized with LUISS)

The patent productivity effects of mobility for a panel of Swedish inventors

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Abstract

We investigate how individuals? patent productivity is affected by moving between firms using near-population data on Swedish inventors linked to register data observed between 1990-2007. We find that the average productivity effect following upon a move is not significantly different from zero. This average effect can effectively be decomposed into two parts, depending on whether the move takes place before or after an individual has patented. In general, if the move takes place before the first patent there is a positive effect, whereas the opposite occurs if the first move takes place after a patent. These results suggest a ?convergence? in patenting, where the job-switch is the main explanatory factor. Instrumental variable regressions support the results for the average inventor. They also cancel out significant results for non-patenters and patenters, reinforcing the conclusion that selection is a driving factor of mobility-inducing productivity effects for inventors.

Jelcodes:O31,J62

1 Introduction

During recent years, labor mobility as a channel of knowledge transfer and recombination of knowledge has received a high level of attention. If individuals' mobility raises productivity without lowering it at the originating firm, the societal returns on knowledge increases. Viewed in this way labor mobility may contribute not only to better matching, linked to short-run gains, but also to higher levels of innovation that contribute to long-run growth. Several contributions investigate mobility effects of inventors – a group of individuals whose ability to further knowledge is of significant importance for the productivity of firms and the competitiveness of the economy.

There are two basic arguments for why inventiveness may increase following upon an individual's move between two firms. The first set of explanations emphasizes the individual who moves and any knowledge that this individual brings to the new firm. The literature supports the relevance of this claim by showing that labor mobility increases either the destination firm's inventiveness or the inventiveness of the new employee, by recombining knowledge inherent in the destination firm and in the employee. This literature relates labor mobility to different topics such as; learning-effects on recipient firms (Singh and Agrawal, 2011, Palomeras and Melero, 2010, Song et al., 2003), disagreement as a source of spillovers and labor mobility (Mokyr, 2006, Klepper, 2007, who studies spin-offs), the role of institutional aspects such as non-compete covenants (Marx et al., 2009) and the effect of a move on the person that moves herself (Hoisl, 2007, Hoisl, 2009, Lenzi, 2009). Our study contributes to the estimation of how moving between firms affect the inventor's own productivity (inventiveness).

The second set of explanations for productivity effects stems from labor economics' focus on matching. These perspectives are generally not integrated into empirical analyses of inventor mobility (see Hoisl, 2009 for an exception). According to search theory, a fundamental reason for why job switching takes place is better matching between firms and workers (Borjas, 2008). Nevertheless, information about the quality of a match is imperfect both from an employer's and an employee's viewpoint. It is only through experiencing the match that the quality is revealed. This implies that workers will remain in jobs where their productivity is comparatively high and will change jobs if their relative productivity is low (Jovanovic, 1979), whereas a worker who experiences a bad match is more likely to search for a new job. A worker may also search for a job if the expected gains from the search exceed those of the net present value of current wages (Holmlund, 1984). This implies that from an individual's perspective a job switch takes place if the expected net present value of income becomes higher as a result of the move.

Due to the imperfection of the matching mechanism between firms and workers, workers are induced to search for new jobs and firms to improve on their division of labor. This process is dynamic with job tasks changing over time and worker skills that accumulate and develop over time giving renewed incentives for job-hopping. At the same time, certain skills are idiosyncratic to specific jobs implying that some workers become less mobile as they accumulate more firm-specific knowledge (Becker, 1975).

We contribute in two ways to the literature. The first concerns an improvement in generalizability and precision to the estimation of productivity following upon a move, the second to an explicit analysis of selection. A problem in the existing literature is its reliance on survey data of inventors or on small samples that provide high internal validity for the study but may be less generalizable to other contexts. In a few of these studies, the number of moves prior to any productivity effects is not observable which makes it impossible to study the total effect of potential knowledge spillovers on the inventor's own productivity. Additionally, a common source of bias inherent in survey data is that the response rate may be skewed towards those with higher values of the variable of interest for the researcher.

We use a near-population sample consisting of 80 percent of Swedish inventors listed on European patent office (hereafter, EPO) applications, observed over the period 1990-2007, linked with directories of the whole population using a unique identity number for individuals. Difference-in-difference (DD) regressions allow us to study the effects of a move on the productivity of an individual over time and to eliminate time-invariant ability biases. Also, where prior work had to rely on the patent applicant (Hoisl, 2007, 2009), and required at least two applications by each inventor to observe a move, our material includes data on business group, firm and establishment affiliation which allows us to derive a much more precise definition of mobility. We also include a complete set of inventor covariates such as age, gender and education that reduces problems of omitted variable bias and are not influenced by response bias.

In addition, these data allow us to address the selection into mobility based on ability, as identified in the labor economics literature. We address this problem in two ways. First, we explicitly analyse the role of selection by dividing between inventors with i) no patents prior to their move, and ii) those that have contributed to at least one patent before their move. Second, although difference-in-difference regressions addresses time-invariant heterogeneity, self-selection into mobility remains a problem (Agrawal et al., 2014). We use instrumental variables to address this issue, with the intention to arrive at a causal explanation for mobility on inventiveness. We find that the average productivity effect is not significantly different from zero following upon a move, whether analyzed using standard DD regressions or combined with instrumental variables that use average employment turnover to isolate exogenous variation in the mobility variable. This average effect is decomposed into two parts, depending on whether the move takes place before or after an individual has patented. In general, if the move takes place before the first patent, there is a positive effect, whereas the opposite is found if the first move takes place after a patent. These results suggest a "convergence" in inventiveness, where the job-switch is the main explanatory factor. Instrumental variable regressions cancel out significant results for non-patenters and patenters, reinforcing the conclusion that selection is the driving factor for productivity effects on inventors.

2 Literature review

Ever since the "re-discovery" of the role of technology for economic growth by Solow (1956), the study of spillovers has been of great interest for economists both empirically (Griliches, 1957, Mansfield, 1961) and theoretically (Nelson, 1959, Romer, 1986). Knowledge spillovers are found to occur through the voluntary exchange of knowledge in lasting customer-supplier relationships, through displays on fairs and exhibitions, through patent documentation, but also through being embodied in goods or in people, whose mobility makes knowledge accessible to others (Feldman, 1999).

Still, pinning down the importance of spillovers to numbers has proved difficult, because it is such a complex phenomenon to study. Yet, the public good nature of knowledge formation has provided a rationale which motivates policies in such diverse areas as the starting of universities, intellectually property rights and subsidies of R&D (Nelson, 1959, Arrow, 1962, Scotchmer, 2004).

In order to estimate the importance of spillovers, many researchers use patent data (Griliches, 1990). Jaffe et al. (1993) investigated the geographical reach of spillovers through matched samples of patent citations, controlling for time patterns and technological similarity. They found that knowledge spillovers tended to be initially geographically localized to a large extent, which puts a limit on the public good nature of new knowledge. Further work recognized that the effects of distance found in Jaffe et al. (1993) may be mitigated by the social network created between firms from the loss or gain of an employee which supersedes, and may be even more important across regional borders (Singh, 2005, Agrawal et al., 2006, Corredoira and Rosenkopf, 2010), although Breschi and Lissoni (2009) found that this knowledge diffusion is hampered by the reluctance of inventors to relocate spatially, which meant that co-invention networks remain intact to a large extent. On the other hand, Breschi and Lenzi (2010) find that even though mobility across firms occurs mainly on the local level, when inventors move across space they are equally likely to move short and long distances, which does not necessarily imply a change of firms (and hence no inter-firm knowledge spillover). The localization of knowledge spillovers from inventor mobility may also differ between regions (Almeida and Kogut, 1999). Hence, the effect of knowledge spillovers through inventor mobility across regions appears to be positive but its significance is uncertain.

Several studies focus on the individual level and the organizational integration of knowledge from spillovers on the firm level. The threat of inter-firm mobility of inventors sometimes induce firms to patent strategically with the intention of appropriating as much of the returns to their innovations as possible, limiting the knowledge spillovers which take place between firms (Kim and Marschke, 2005, Schankerman et al., 2006). Other mechanisms such as non-compete covenants and contracts to retain employees have been used to protect innovations (Marx et al., 2009) as well as a reputed toughness in patent litigations (Agarwal et al., 2009). These factors may hamper the mobility of inventors and the extent of technological progress that could occur through knowledge spillovers and could hence be socially suboptimal (Cooper, 2001).

Kaiser et al. (2015) investigate how mobile R&D workers affect the patenting activities of both the departing and the recipient firm. They find that the effect is strongest if the R&D worker joins from a firm that is already patent-active, rather than from a firm that is not. They also find that the departing firm increases its patenting which may be due to wanting to appropriate the returns to their R&D expenditures. Performing several robustness checks, they show that their results hold. However, they define their R&D workers as those workers who are classified as being either ”professionals” or ”technical workers” according to ISCO, which may thus consist of individuals who are not actively involved in patenting and/or R&D activities and may overstate the results of mobility on patenting.

In the spillover literature on the effects of workers inflows, “learning-by-hiring”-studies focus on firms’ ability to obtain knowledge and learn from an inventor recruited from another firm (Singh and Agrawal, 2011, Palomeras and Melero, 2010, Song et al., 2003). Song et al. (2003) conclude that knowledge transfers through labor mobility are more likely if the hiring firm is less technologically path dependent. Palomeras and Melero (2010) find that the quality of the inventor’s work and the level of complementarity with core competencies of a firm that an inventor is moving to has a positive impact on mobility. Singh and Agrawal (2011) identify the spillover effect from citations by combining Jaffe et al.’s (1993) matched sample approach with the change in citation patterns following a newly recruited inventor’s patents compared to pre-recruitment patents through difference-in-difference estimations. They find a substantial rise in post-recruitment citations within the firm. An important contribution rests in the decomposition of the total inter-firm spillover effect into a) a learning effect resulting in a rising number of citations by new colleagues and

b) an increase in citation rates to the moving inventor herself. In other parts of the literature, the first type is referred to as a peer effect (e.g. Agrawal et al., 2014). Singh and Agrawal (2011) find that a large part of estimated knowledge spillovers is associated with the newly recruited inventor's use of his/her own prior inventions rather than organizational learning.

Other studies focus on the relationship between mobility and productivity and the subsequent patent productivity of the mobile inventor. Trajtenberg and Shiff (2008) find that inventors who hold higher-quality patents are more mobile than inventors producing lesser-quality patents. Furthermore, the patents these inventors produce after moving are of a higher quality than before. This suggests a positive relationship between patent quality and mobility, although no causal link is established in the study. Team experience is further found to exert a negative impact on mobility perhaps due to network effects or good matching. Schettino et al. (2013) find that patent quality is associated with the age of the inventor, being male, having higher education as well as working in teams, although the individual characteristics are not found to influence patent productivity.

Hoisl (2007) investigates whether mobility and productivity are endogenously determined and looks at the causal relationship between the two for a survey-dataset of German inventors. Using two sets of instrumental variable estimations she finds a simultaneous relationship where mobile inventors are more productive than their immobile counterparts, but also that an increase in productivity reduces the likelihood of a move. As instruments for mobility she includes incentives for inventive activities (taken from a questionnaire), the technical concentration of patents and the size of the region the inventor works in. The instruments for productivity are related to external sources of knowledge, i.e. to the extent that inventors use patent documents and scientific literature to get input rather than through personal interaction and are also taken from a questionnaire. However, difficulties to collect comprehensive data put limitations to the generalizability of the study by Hoisl (2007). First, the study only uses inventors with at least two patent applications, although other studies indicate that most inventors only have one patent (Trajtenberg et al., 2006, Ejermo, 2011). Second, with an average patent productivity of 14.7, the sample analyzed in Hoisl (2007) is highly skewed towards the more inventive part of the population distribution.

In a follow-up study using a matched sample approach, Hoisl (2009) determines whether mobility affects high and low productivity inventors differently using jointly estimated quantile regressions. She finds that inventors who are initially more productive benefit more, in terms of their patents receiving more citations from changing jobs than those who are initially less productive. Her results also suggest that inventors who are poorly matched to their employers tend to move to increase their productivity.

Lenzi (2008) uses a different approach to overcome the potential bias stemming from only using patent records to determine mobility by complementing patent documents with CVs. She examines Italian inventors active in the pharmaceutical industry to determine whether inter-firm mobility effects differ for these two types of records. In effect, important knowledge can be gained at one job although no patent is applied for or is kept secret by the inventor, and this knowledge is subsequently used to file a patent at another firm. She finds that patent documents often underestimate the number of moves that inventors actually undertake over the course of their careers as well as misspecify the affiliation of the inventors. Using Poisson regressions, the results suggest a significant positive effect running from mobility on patent documents to both productivity and the number of citations that each patent of the inventor receives, as well as from productivity to patent document mobility (i.e. in the opposite direction). The results for using mobility based on CVs instead show an insignificant effect on productivity and a positive significant effect on the number of citations each patent receives. The effect rather runs from productivity towards mobility using CVs. Lenzi (2009) uses a duration analysis and incorporates more controls into the analysis. The results indicate that life-cycle effects, inventive productivity and the geographical location in which the inventor works are drivers of mobility. It is mainly the most productive inventors who are likely to move. Nevertheless, the results are largely consistent with Hoisl (2007), at least when only considering patent documents, in that mobility seems to be a mechanism which improves the matching between inventors and employers which increases productivity. However, due both to the small sample size (106 inventors in one industry surveyed) and lacking possibilities to causally establish effects, the conclusions may not be generalizable. Le Bas and Haned (2011) consider the effects of both inter-firm and geographical mobility on productivity. They find that more mobile inventors are more productive, but that geographically mobile inventors are less productive. Nevertheless, they do not estimate these in different regressions or consider the potential bias stemming from simultaneity and hence cannot draw any inferences regarding causality in their analysis.

In sum, existing studies have typically found a significant and positive effect of inter-firm mobility on productivity (no matter whether they consider causal effects or not), but a negative effect running from productivity to mobility. Hence, we can expect that Swedish inventors who change jobs will increase their productivity in terms of patenting.

Another aspect which may influence the effect of mobility and patent productivity concerns when the move takes place over the life-cycle of individuals. Rosen (1972) developed a model of human capital accumulation according to which individuals choose between different learning opportunities through job hopping. Later in their career, they capitalize on their endowments of human capital. The length of time over which they benefit from their human capital therefore becomes critical. Early in their careers individuals prefer jobs with much learning relative to their wage level, over jobs with low learning relative to wages. An observed higher patent productivity may therefore also reflect a conscious choice to work in a firm that provides ample learning opportunities early in the career. Møen (2005) found empirical support for this model in that the wage development of Norwegian engineers were slow at the beginning of the career, suggesting instead that they consciously chose low wages in favor of high learning. Following these ideas, we will in this paper focus our attention initially on first-time movers, because we may expect a stronger learning effect for first-time movers. We will later also examine whether the effect differs for second-time movers.

Together, the above studies suggest that selection may be an important part of the reason for why a productivity effect differs following upon a move. In addition, Hoisl (2007) also found that if an individual patented more, this slowed down mobility. Thus, selection may operate both in terms of the selection into mobility and with respect to the outcome itself. It is far from obvious, however, that existing studies can be generalized to (near-)population data and in a panel data setting, which more strongly addresses issues of unobserved heterogeneity. In this paper we will analyze the selection mechanism in more detail by examining the effects on productivity following upon a move by dividing inventors based on past productivity. We will also use instrumental regressions to address selection and endogeneity.

3 Data

The research question stresses the need for a longitudinal perspective. Our dataset, can accommodate these needs. Slightly fewer than 23,000 inventors have been identified from their home addresses as listed on EPO records, commercial address registers and directories of the population that have allowed us to find their social security number. Further details about the matching process can be found in Jung and Ejermo (2014). The dataset combines data from the European Patent Office of all inventors based in Sweden with employer-employee linked longitudinal register data from Statistics Sweden.

The individual records in Statistics Sweden data are linked to information on establishment affiliation, the associated firm, as well as corporate group identifiers. With this information at hand, we can distinguish inventor moves across organizational boundaries. Such moves are defined as taking place if:

(1) an individual in t+1 has a different establishment, a different firm and a separate corporate group from that observed in t; and

(2) both the organization which the inventor departs and enter are observed in both t and t+1.

It could be noted that about half of all inventors' moves to a new establishment involve within-firm or within-business group moves that we judge not to be inter-organizational and hence were excluded from the analysis. Note also that definition (2) implies that moves due to firm exits are excluded. This choice is motivated by that such moves may not be voluntary from the inventor's perspective and that the inclusion may induce a negative productivity bias if the underlying reason for the firm exit correlates with inventor patent productivity. The assumption also implies that moves to firms that start up in the same year are excluded. This choice is based on the motivation that we are interested in the effects of labor mobility and not spin-offs.

The dataset also includes information about the inventor, such as birth year (which can be used to calculate age), educational field and level, as well as yearly observations of establishment and firm affiliation that are used to create tenure variables. The firm data is also connected to the corporation-register which includes information if, and what type of corporation the firm belongs to. More information about the control variables can be found in Appendix A.

We study mobility over the 1990-2007 period. It may be noted that inventor characteristics are also observed in years when not filing for patents. Our study is thus based on the study of the evolution over time of inventive activity and associated mobility across firms on the individual level. We examine for our baseline estimations the effect of the first move in the career. Our control group is therefore individuals that have not (yet) moved. In order to more precisely delineate the first move on the labor market, we require inventors not to be older than 30 years when first appearing in our data. We also exclude inventors under the age of 21 and consistently use this material in our analyses. These restrictions imply that we retain up to 9,846 inventors observed in unbalanced panels in the analyses.

The "treatment" of inventors consists of the effect of a move on patent productivity. If a move takes place in t, a mobility dummy is created which takes the value zero prior to any move and one in $t+1,\ldots,T$, where T marks the final year the inventor works at the new firm. In our data, firm affiliation is recorded only once per year, in November. We use t+1 for this variable to be sure that the move has been finalized and further distinguish between order of moves by constructing different dummy variables "Move1", "Move2", "Move3" and "Move4" to distinguish between the effects of different move orders. Our dependent variable Patent productivity, is calculated using the sum of the share (or fractions) of applied patents that our focal inventor contributes to in a given year.

Figure 1 depicts average cumulative inventor productivity before and after mobility distinguishing between moves 1-4, without controls for any covariates. Several observations can be made that will be relevant for our regression analyses in the next section of the paper. First, the patent productivity of inventors rises with a steeper slope after their first move. Inventiveness also rises after other moves, but the graph suggests that this rising productivity is rather part of a long-term trend and not attributed to the move per se. Of course, no causal interpretation can be given to these observations. For instance, productivity is higher for individuals before and after higher order moves, because part of the accumulated patent productivity is related to inventor age and firm strategy. In any case, the figure suggests that a focus on the first move is warranted. A second observation concerns the shape of the cumulative productivity line. There is no sign that inventiveness rises suddenly after a move, as would have been expected if inventiveness would rise directly from knowledge transfer. Instead, inventiveness rises for each year following the move compared to before the move. A "before-and-after" perspective on the perceived mobility effect is therefore a valid way of characterizing patent productivity developments and suggests to us that difference-in-difference estimations would be the most relevant starting point for regression analyses.

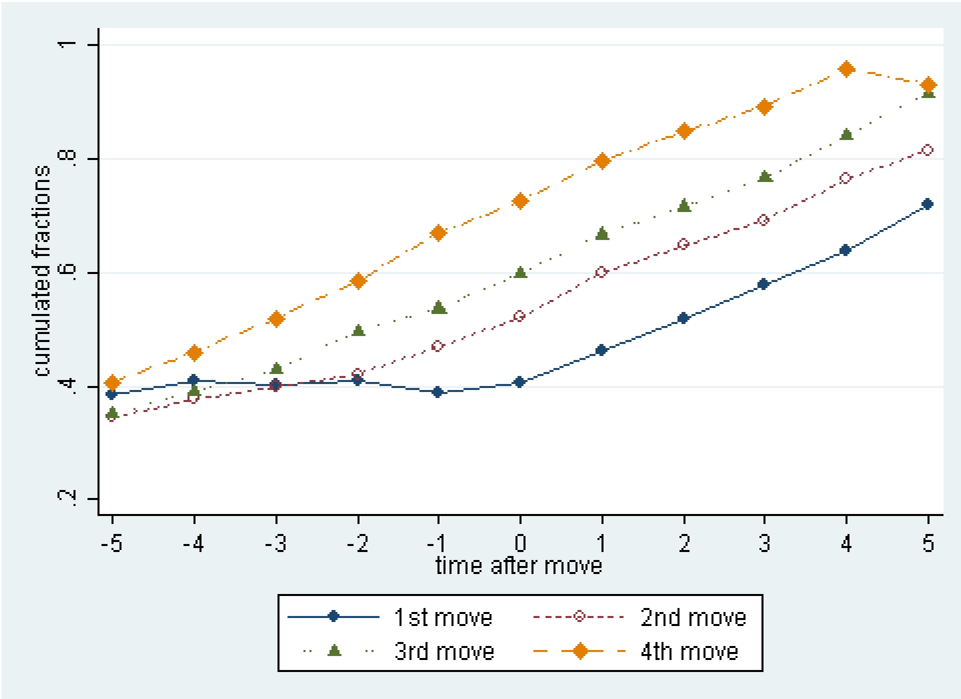

Figure 1 Inventor productivity before and after a move, divided by order of move.

Figure 2 adds to our description by considering the development of patent productivity by age for different types of mobility categories (moves once, moves twice,…). The most distinguishing feature concerns the development of immobile inventors' productivity and some convergence of productivity at higher ages. Before the age of 35, but after the relatively unproductive younger years, never-movers have the highest productivity, probably reflecting an initially good match with the employer. One-time movers' productivity rises to reach the highest level of groups. It is unclear, however, whether this reflects a low number of observed one-time inventors at higher ages (and therefore high variability) or is systematically linked to their one move. For the other groups, convergence seems to be the best way to characterize their patent productivity development. In particular, a relative stagnation can be observed for immobile inventors.

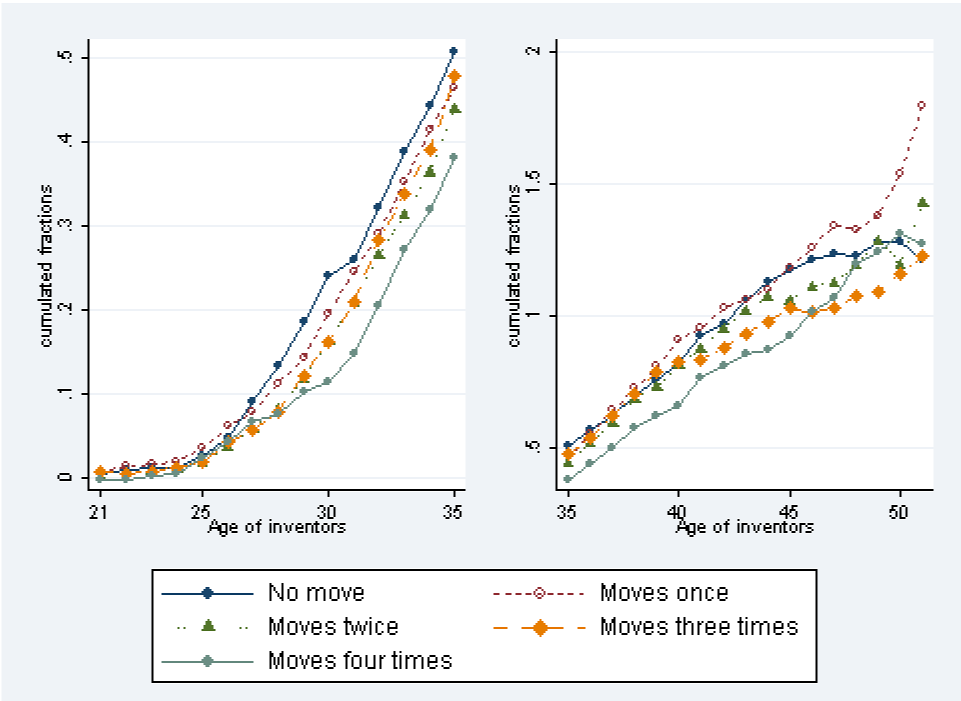

Figure 2 Inventor productivity by age for different move categories. Left panel = age 21-35, right panel = age 35-51.

The average productivity level in our panel of 147,008 observations of inventors is close to 0.08, reflecting that patenting is relatively rare and that most individuals are listed only once on patents. Inventiveness is even lower before the first move at about 0.069 on a yearly basis, a figure which rises to 0.086 after having moved once. This figure rises slightly to 0.09 following the second move. Mobility is also relatively rare; we find that mobility occurs only in about 10% of the individual year-observations. Of these, 40% of the moves concern the first move, 30% the second, 17% the third, 8% the fourth, with less than 6% of moves representing higher order moves.

Does previous inventiveness influence if an individual chooses to change jobs? Table 1 examines the distribution of our sample with respect patenting productivity and accumulated mobility. The table also shows the corresponding distribution just before an individual moves. It is clear that the vast majority of individuals have no patents before any of their moves. It is also clear that the share of individuals with no patent is higher before the actual move is undertaken. For instance, in 64% of observations no patent before their first move can be observed. By contrast, 75% of movers had no patent. Corresponding figures for the second move are 55 and 64 percent. Thus, we can corroborate the finding by Hoisl (2007) that patenting seems to slow down mobility. The opposite is also true: less patent productive individuals are more likely to change jobs leading to a selection into mobility.

Table 1. Number of individuals and distribution by patenting fractions and accumulated mobility.

Panel A. Distribution of individuals by accumulated patenting in fractions and accumulated mobility.

	Number of moves undertaken			
Patents	0	1	2	3
No patents	42040 (64)	22931 (55)	10844 (48)	4266 (41)
0 < x < 1/4	3842 (6)	3027 (7)	1877 (8)	1110 (11)
1/4 <= x < 1/2	7676 (12)	5990 (14)	3964 (18)	1997 (19)
1/2 <= x < 1	2287 (3)	1702 (4)	1246 (6)	456 (4)
1 <= x < 1.5	5040 (8)	3885 (9)	2343 (10)	1275 (12)
1.5 <= x < 2	1123 (2)	1179 (3)	622 (3)	377 (4)
2 <= x < 5	2711 (4)	2217 (5)	1401 (6)	721 (7)
x >= 5	673 (1)	446 (1)	331 (1)	206 (2)
Total	65392 (100)	41377 (100)	22628 (100)	10408 (100)

Panel B. Distribution of individuals by accumulated patenting, fractions just before a move, and by accumulated mobility.

	Number of moves undertaken			
Patents	0	1	2	3
No patents	4096 (75)	2777 (64)	1382 (55)	606 (47)
0 < x < 1/4	255 (5)	264 (6)	216 (9)	130 (10)
1/4 <= x < 1/2	484 (9)	554 (13)	381 (15)	225 (17)
1/2 <= x < 1	138 (3)	138 (3)	100 (4)	64 (5)
1 <= x < 1.5	269 (5)	298 (7)	237 (9)	131 (10)
1.5 <= x < 2	62 (1)	80 (2)	59 (2)	48 (4)
2 <= x < 5	132 (2)	175 (4)	113 (4)	73 (6)
x >= 5	31 (1)	28 (1)	27 (1)	21 (2)
Total	5467 (100)	4314 (100)	2515 (100)	1298 (100)

Note:
The table includes data up to and including move 3, which encompasses 95 percent of observations.
Relative frequencies are given in brackets.

4 Estimation strategy

Our econometric specification involves estimating the effect on an inventor's patenting propensity from moving to a new establishment based on differences-in-differences (DD). The main identifying assumption is that there should have been no difference between the treated and the control group in the absence of the treatment (which in this case implies mobility between establishments and firms). As such, we estimate an equation of the type:

$$y_{it} = \beta_1 D_{it} + \boldsymbol{\beta}_2' \boldsymbol{X}_{it} + \boldsymbol{\beta}_3' \boldsymbol{F}_{it} + \boldsymbol{\beta}_4' \boldsymbol{\delta}_t + \boldsymbol{\beta}_5' \boldsymbol{\theta}_i + \varepsilon_{it} \,, \qquad (1)$$

where y_{it} represents patent productivity of individual i in period t modeled as a function of **X**, a set of (partially time-varying) inventor characteristics, **F**, a set of firm characteristics, $\boldsymbol{\theta}$ denotes inventor fixed effects, $\boldsymbol{\delta}_t$ are time fixed effects and ε is a classical error term. The binary variable, D_{it}, is defined as follows:

$$D_{it} = \begin{cases} 1 \text{ if individual } i \text{ receives treatment in } t \\ 0 \text{ otherwise} \end{cases}$$

Hence, β_1, is the estimated coefficient of interest. Because the DD-model is essentially a fixed effect model, time-invariant characteristics such as gender or high school grades (to control for ability) cannot meaningfully be included. Among the control variables (**X** and **F**) we include the variables presented in Appendix A.

Although the panel structure of our data allows us, through fixed-effects regressions, to remove time-invariant heterogeneity, several potential issues warrant an instrumental variable approach. Fixed-effects regressions do not deal with time-varying unobserved heterogeneity. The ability of an inventor may change over time for instance due to favorable work conditions, helpful colleagues, better networks or other (unmeasurable) circumstances. Thus, while ability is to some extent path-dependent it is not deterministically given and therefore not entirely captured by fixed effects. Also, endogeneity may be caused by reverse causality. While mobility may raise productivity, productivity may also affect mobility, because more able inventors self-select into seeking better job opportunities (Hoisl, 2007). One such example is from Klepper's (2007) work that highlights how entrepreneurs with different ideas (abilities) choose to leave their present employer. Instrumental variable techniques can deal with these issues by isolating variation that give rise to a causal interpretation from the variable of interest. Two recent papers by Fabian Waldinger employs instrumental variable techniques to DD-estimation in a setting somewhat related to ours. He uses the dismissal of Jewish scientists from universities in Nazi-Germany in the 1930s as an instrument to estimate the effect of the loss of a supervisor on a PhD-student's scientific productivity (Waldinger, 2010) and for faculty peer effects (Waldinger, 2012). In the first case he distinguishes a long-term negative effect, but not in the second case.

5 Regression results

The first panel fixed-effect regression (A1a, without controls), points to a generally positive effect on inventiveness from inter-firm mobility. The effect is small, but must be compared with an inventor's average patent productivity. Then the increase is about 17% (.012/.069) – a considerable increase. Already, however, with the inclusion of control variables does this turn to a non-significant (though still positive) effect in B1a. Regressions A2a/B2a and A3 examine whether selection was an important factor behind the result in A1a. A2a/B2a show that the strongest increase in patenting is observed for individuals with no prior patenting.

Table 2 presents how productivity changes in response to mobility. In panel A we exclude controls, whereas panel B includes them. In column 1 we include all first-time movers, column 2 and 3 divides those observations into individuals without previous patents and those with any patenting activity, respectively. For columns 1-3 we only observe individuals who have either not moved at all or just moved once. In column 4 we include all inventor observations (i.e. any moves observed) and continue to use the first move as the main explanatory variable of interest.

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Table 2. First move effects on patent productivity.

Panel A - without controls.

Model	A1 All firstmovers	A2 No patents	A3 Yes patents[x)]	A4 Yes patents[y)]
First move (a)	.012 (.004)***	.073 (.003)***	-.120 (.010)***	-.103(.008)***
IV first move (b)	-.052 (.126)	.078 (.0922)	-.340 (.469)	.699 (.871)
Controls	NO	NO	NO	NO

Panel B – with controls.

Model	B1 All firstmovers	B2 No patents	B3 Yes patents[x)]	B4 Yes patents[y)]
First move (a)	.005 (.004)	.070 (.003)***	-.091 (.011)***	-.100 (.009)***
IV first move (b)	-.026 (.145)	.115 (.146)	-.327 (.469)	.694 (1.033)
Controls	YES	YES	YES	YES

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

x) these regressions restrict sample to those that either have not moved or moved just once.

y) these regressions define the treated inventors as those that moved for the first time and include observations for any time beyond

All IV regressions use Highly educated employment growth total in sector as instruments.

By contrast, a distinctively negative effect on inventiveness can be observed for previous inventors (A3a/B3a). This effect is not much different when we extend the post-move period in A4a/B4a. It therefore seems that the regressions reinforce the conclusion that convergence is a correct way of characterizing development of inventiveness, in line with trends in productivity given by age and move-categories in Figure 2, but also importantly that mobility plays a role in contributing to convergence.

In connection with these non-instrumented regressions, it is instructive to observe individual year-effects from the DD-regressions. Normally this is done in order to gauge whether a treated group is subject to pre-trend effects. Here we use these as diagnostics for the size of any selection effects. We can also observe the speed at which a change in inventiveness occurs after a move. These are presented in Figure 3, which shows the size of estimated size coefficients of 10 lead and 10 lag time dummies including control variables, i.e. more elaborate versions of the regressions B1a (top panel) and B2a-B3a (bottom panel). The top panel shows no visible pre-trend as all pre-treatment coefficients' confidence bands cover the line that goes through zero. However, the first two years following treatment show negative coefficients which are almost significantly different from zero. After these two years the effect becomes much more positive. These results suggest that the positive productivity effect follows from an initial adaption process that takes place between the individual and the new firm. When decomposing these results in the bottom panel, the pattern for earlier non-patenters mainly reflect those of the top panel, only on a higher absolute level following upon a move. This is not surprising as most movers in fact have no prior patents. The results for earlier patenters differ, however. Here, there is in fact a clear pre-trend effect where in t-2, t-1 and at t the level of patenting drops to close to zero.[1] Contrasting this is Kim and Marschke (2005), who found that a firm raises its levels of patenting strategically to protect knowledge from disappearing with a person leaving the firm. The only way we can reconcile our results with this is if such strategic patenting takes place through non-leaving individuals listed as inventors, or that our analyzed sample differs substantially from that of Kim and Marschke.

The next set of regressions instrument the mobility variable. We considered many potential instruments. The theoretically best motivated ones were linked to labor market opportunities, which could arguably be viewed as exogenously shifting the number of job opportunities. These variables were all variants on the employment growth in the same sector (two-digit, NACE) of the focal individual, measured on a yearly

[1] Note that given the selection of prior patenters vs. prior non-patenters, we should expect these groups to have positive and negative coefficients prior to moving, but not necessarily to display a trend.

basis. This base variable was decomposed into growth in employment of the region the individual is working in and the rest of the country.[2] We further divided these growth variables into mobility by just those with at least two years of higher education for a total of four possible instruments. Although these instruments are not the same, they also to some extent pick up joint variation because there is correlation between job opportunities across regions. We tried including all four in our instrumental variable regressions, but this was generally rejected by Hansen's J-test for overidentification. In some cases, we had to resort to the use of one instrument. For ease of comparison we present the regressions where we consistently use the generally preferred instrument, Highly educated employment growth total in sector, although in many cases more than one instrument could have been utilized according to the Hansen J-tests and also according to the Kleibergen-Paap (KP) F-statistics for weak instruments. The results in The first panel fixed-effect regression (A1a, without controls), points to a generally positive effect on inventiveness from inter-firm mobility. The effect is small, but must be compared with an inventor's average patent productivity. Then the increase is about 17% (.012/.069) – a considerable increase. Already, however, with the inclusion of control variables does this turn to a non-significant (though still positive) effect in B1a. Regressions A2a/B2a and A3 examine whether selection was an important factor behind the result in A1a. A2a/B2a show that the strongest increase in patenting is observed for individuals with no prior patenting.

Table 2 should be read as compatible with the corresponding regressions using more than one instrument.

[2] To some extent our instruments capture opportunities to change jobs which is time-varying and linked to population size as in Hoisl (2007), although our instruments should be more specifically linked to an individual's opportunities and also increases variation.

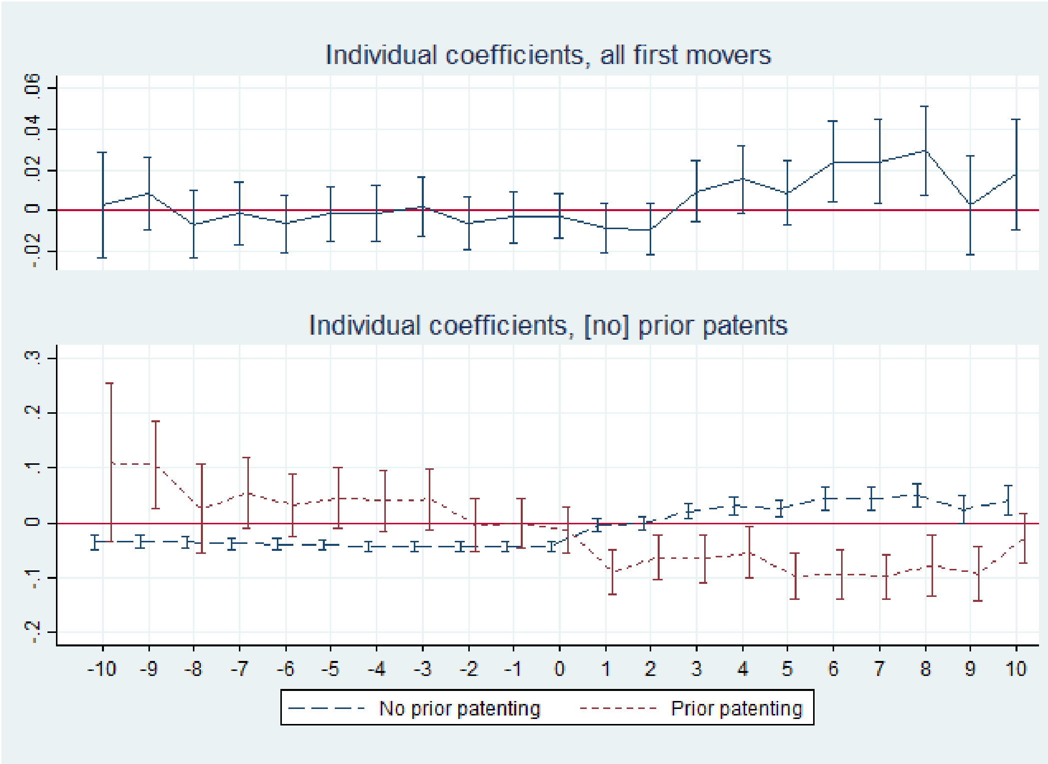

Figure 3. Coefficient estimates for the +/- 10 year effects prior/post to the first move. Top panel shows lead and lag estimates corresponding to B1a. The corresponding versions for B2a and B3a are shown in the bottom panel.

One may wonder whether the results would differ if we reran the above regressions for the second time move, considering our earlier reasoning that any mobility effect should be stronger for the first move. We did this and report the results in Table B, Appendix B. In this case, the control group consists of individuals that already moved once, but stay put. While we find a positive effect in A1a in Table 2, the corresponding coefficient for second time movers is no longer significant, supporting our presumption that first order moves should have stronger effects. Basically, all other results stay qualitatively the same, though for the IV-regressions corresponding to A4b/B4b we find a positive and significant effect when using 3-4 instruments (passing all tests).

With respect to the control variables, we do not put too much focus on them, the main reason being that the fixed effect panel structure absorbs much of their variation, and many of them are just slowly changing, if at all. We tend to find the following results: Age and Tenure capture generally similar aspects. Age increases patent productivity in many estimated models, but at a decreasing rate, i.e. exhibiting an upside-down U-shaped effect. Tenure frequently raises the level of patenting which suggests that on-the-job experience is important. An exception is model A4a, where the effect is significant and negative. This variable is likely to pick up some of the negative "convergence-effects" due to moves as found from A3, and also more negative long term age effects, because the time period observed after a move is longer. Tenure is, however, always insignificant when using instrumental variables. Lagged firm patenting has a positive effect in all non-instrumented regressions, which means that an individual's patenting is indeed affected by past firm patent strategies. It is also positive and significant for the general IV-regression, but it is not significantly different from zero when looking at individuals with patenting prior to their move. There is some tendency that inventor productivity is higher for individuals working in firms with a stronger international orientation. We find a positive effect of this for the dummies Foreign subsidiaries and Swedish business group, foreign subsidiaries.[3] Size effects are generally not significantly different from the base category 1-10 employee firms, except for the second smallest size category (11-50 employees), where we often observe a negative effect. A reason for this could be that for very small firms there is a survival bias, as suggested already by Griliches (1984). This bias is not present for the 11-50 employee category, however. Although outside the scope of this paper, one may speculate that resource constraints that slow their patenting could be a likely explanation for this negative effect (Smith, 2005).

With respect to education we do not generally find results significantly different from zero, though Tertiary education in three cases actually exhibits a negative patent productivity, despite signifying a higher education level than the baseline, somewhat at odds with earlier studies. However, it should be stressed that these education effects are probably to a high extent absorbed by our fixed effects, because they rarely

[3] These results go clearly in line with literature looking at the link between export and learning, cf. Andersson and Lööf (2009) and Ejermo and Bergman (2014).

change in the within sample variation that we use for our estimation. Our results may therefore capture the fact that the few individuals that change educational status may devote less time to inventing.

Getting back to our main results, these are clearly different from those obtained by Hoisl (2009), in that we find no indication that inventors with previous patents see a stronger productivity effect from a move. One of the possible reasons could be that our sample is more general while hers was skewed towards the more productive part of the distribution. Still, the productivity effect could be more nuanced than our rough distinction between "No patents" and "Yes patents" before a move. In order to test this, we reran the regressions in column 3 of The first panel fixed-effect regression (A1a, without controls), points to a generally positive effect on inventiveness from inter-firm mobility. The effect is small, but must be compared with an inventor's average patent productivity. Then the increase is about 17% (.012/.069) – a considerable increase. Already, however, with the inclusion of control variables does this turn to a non-significant (though still positive) effect in B1a. Regressions A2a/B2a and A3 examine whether selection was an important factor behind the result in A1a. A2a/B2a show that the strongest increase in patenting is observed for individuals with no prior patenting.

Table 2 splitting the observations based on the categorization given by Table 1. Also, regressions using the same instrument as above were run. We only reran regressions with controls. Without instruments, we found that the effect of mobility became distinctly more negative the higher the previous patent experience of the inventor. With instruments, no significant effect could be found for mobility whatsoever. Coefficients were very unstable and subject to large standard errors. Therefore, the main message from Table 3 remains: convergence results from mobility stemming from selection.

6 Concluding discussion

In a panel data setting of Swedish inventors we find no evidence that mobility has an effect on the productivity of inventors. Already here our results differ from existing literature. One of the reasons could be the fixed effect structure that control for time-invariant heterogeneity not captured by previous studies, another could be that our evidence is based on a dataset which allow for more generalizable conclusions. Still, this general conclusion masks several underlying patterns that reintroduces a role for mobility. First, individuals with no prior patenting do in fact see an increase in patenting. Since this group is also much larger than the group of movers with prior patenting, circulation of individuals to new firms can in turn more people into inventors. This points to an important role for agglomerations providing such job-changing opportunities, that could be explored in future research. The other important finding of the paper was that individuals with patenting see their patenting go down after a move, with a decline that is stronger the more previous patenting the inventor has been involved in. Also this goes against previous findings. Hoisl (2009) found that the productivity effect of a move was rising with the level of patenting. However, an important difference was that her sample consisted on average of highly productive inventors. We find that the positive effect that inventors obtain of a move takes place mainly because they become inventors, not because their productivity as inventors is unleashed. Productivity effects mostly result for movers without previous patenting that raise their patenting thanks mainly to a better fit or alternatively that they go into an inventing role in their new firm. We view this result as showing that it is mainly better matching that result in higher productivity for first-time movers, rather than knowledge spillovers. However, it should also be mentioned that it is really selection in combination with the move that explains our findings not the move as such; once we instrument mobility by employment growth, all significant effects disappear.

The present study suggests a number of promising research directions. Further research may try to disentangle the matching vs. spillover interpretation of our findings more distinctly, possibly by trying to measure the degree of imperfection in the match between employers and employees.

Finally, one may want to examine the extent to which co-workers are positively affected through a peer effect, or estimate effects on others not directly working on the same patents as the moving inventor either at the firm the inventor leaves (Kim and Marschke, 2005) or at the recipient firm (cf. Agrawal et al., 2014). A different type of research would examine the role of urban agglomerations and the role that job mobility has on patent productivity, which could provide additional evidence on how agglomerations contribute to higher innovativeness through a more elaborated division of labor.

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7 Appendix A. List of control variables.

Tenure measures years at the current job, which is linked to experience and on-the-job training and captures time-varying preferences for job switching. In general, job changes are less likely when a worker has longer tenure, since tenure implies a better matching or when the worker has invested in specific job capital (Becker, 1975).

Lagged firm patenting is a variable which is included to capture any firm strategy of patenting, which can be assumed to influence an individual's propensity to patent positively. We use the lagged value of this variable in order for it not to be directly influenced by a focal inventor moving.

Age and Age^2. These age measures control for linear and non-linear productivity effects that vary over the life-cycle of inventors.

Bachelor degree or above; Tertiary education. These variables control for patent productivity that stem from education. For similar reasons, we include dummies for Education type medicine; natural sciences; and social sciences controlling for education field effects that differ from the baseline category of Education type technical sciences.

We also include dummies for type of the business group the inventor works in, again motivated by the possibilities that they may systematically differ in their patenting strategy. We differentiate between firms belonging to the following categories: Swedish, no business group, Swedish business group, Swedish business group, foreign subsidiary, and Foreign business group with Swedish subsidiaries.

Firm size measures the number of employees of the firm the individual is working in. We divide this variable in the regressions into the same dummy variable categories as Hoisl (2007), i.e. in firm sizes of 11-50, 51-250, 251-500, 501-1,500, 1,501-5,000, 5,001-10,000, 10,001-50,000 and more than 50,000 employees. The base category is 1-10 employees. Larger firms are more likely to target international markets and may therefore have a more pronounced strategy towards patent protection, which is not entirely captured by ownership category.

Public sector is a dummy variable included to capture differences in inventiveness resulting from different incentives for patenting and mobility.

8 Appendix B. Productivity effects on second-time movers.

Table B. Mobility effects on patent productivity for any move, and first to fourth moves.

Panel A - without controls.

Model	A1 All second movers	A2 No patents	A3 Yes patents[x)]	A4 Yes patents[y)]
Second move (a)	-.003 (.005)	.075 (.004)***	-.120 (.014)***	-.080 (.010)***
IV second move (b)	.058 (.058)	.118 (.463)	.525 (.705)	5.913 (33.131)
Controls	NO	NO	NO	NO

Panel B – with controls.

Model	B1 All second movers	B2 No patents	B3 Yes patents[x)]	B4 Yes patents[y)]
Second move (a)	-.002 (.005)	.074 (.004)***	-.106 (.012)***	-.080 (.010)***
IV second move (b)	.144 (.240)	.412 (.585)	.519 (.534)	2.145 (5.218)
Controls	YES	YES	YES	YES

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

x) these regressions restrict sample to those that either have moved once or twice.

y) these regressions define the treated inventors as those that moved for the second time and any time beyond

All IV regressions use Highly educated employment growth total as instruments.