TRACING MOBILE INVENTORS –

THE CAUSALITY BETWEEN INVENTOR MOBILITY AND INVENTOR PRODUCTIVITY

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This paper analyzes the causality between inventor productivity and inventor mobility. Whereas existing research implicitly assumes causality to point in one direction, this study ex-ante allows for a simultaneous relationship. To deal with the expected endogeneity problem, instrumental variables techniques will be employed. Additionally a quasi-experimental approach is used to explore the effect of a specific move on inventive performance. Results show that mobile inventors are more than four times as productive as non-movers. Whereas mobility increases productivity, an increase in productivity decreases the number of moves. In addition, difference-in-differences estimation reveals that inventors increase the value of their patent applications in the post-move period.

Keywords: Inventor, Productivity, Mobility, Match Quality, Patent

JEL - codes: J60, J24, O31, O34

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1 Introduction

Krugman (1991) suggests that not only the innovative environment is decisively determined the innovative activity the innovative activity is itself spurred by the environment.

The above mentioned relationship also applies to moving inventors and their inventive environment: moving inventors[1] are exposed to a new environment that affects their activity. For instance, Topel and Ward (1992) propose that mobility can lead to an increase of the match quality between employer and employee. A better match quality should lead to an increase in the inventor's own productivity. A move can, therefore, be interpreted as a search and sorting process to improve the employer-employee match. The importance of match quality is also confirmed by Jovanovic (1979) and Liu (1986). Furthermore, the inventor may profit from the knowledge of his new colleagues. This could also increase the productivity of an inventor. One might, therefore, expect that mobility increases productivity[2].

On the other hand, the literature reveals that hiring a key inventor from another firm can lead to knowledge transfer (Arrow, 1962, Song et al. 2003). Firms characterized by a lower technology level can use this knowledge to catch up and thus are motivated to attract productive inventors (Gilfillan 1935). In particular, the transfer of tacit knowledge, that is otherwise immobile, is facilitated by inventor mobility (Dosi 1988). One could, therefore, assume that the causality runs from productivity to mobility: the more productive an inventor is, the higher the probability to observe a move. Nevertheless, one has to bear in mind that inventors who are very valuable to their employers may be treated with particular attention. In particular, employers try to increase the commitment of these inventors to the firm by providing certain incentives. Gersbach and Schmutzler (2003), e.g., propose that firms can keep their employees from leaving by offering sufficiently high wages. Assuming that the firms are able to observe the quality of an R&D employee one would expect that valuable employees get job offers from competitors but mobility does not actually occur.

With the exception of Trajtenberg (2005) no other research has been carried out on the simultaneous relationship between productivity and mobility of inventors. Trajtenberg (2005) addresses the causality between mobility and productivity of 1,565,780 inventors listed on U.S. patent documents. Overall, 216,581 (33%) of the inventors are movers which means that these inventors changed their employer at least once. Results show that the patents of

[1] Mobile inventors are defined in this paper as inventors who have changed their employer at least once.

[2] The productivity of inventors is measured by relating the number of applications per inventor to the age of the inventor.

inventors who moved receive more citations, and inventors who are responsible for a valuable patent and who ex ante have more information as to the value of this patent compared to their employers are more likely to move since asymmetric information makes it difficult for the employer to impede mobility of high performing inventors.

The following study improves on the current literature by (1) allowing for a simultaneous relationship of productivity and mobility whereas existing research – with exception of Trajtenberg (2005) - implicitly assumes causality to point in one direction (from mobility to productivity *or* from productivity to mobility) and (2) by including inventor characteristics as explanatory variables. One reason for the lack of literature which deals with this causality is the absence of appropriate data. First of all, a matching problem exists with respect to name and address information derived from the patent documents.[3] Furthermore, bibliographic and procedural data hardly suffice to represent the most important determinants of productivity or mobility. Additional information is needed on the inventor himself, for instance, on the inventor's age or educational background. This paper makes use of data collected in a large-scale survey of 3,049 German inventors who hold at least one granted European patent. The inventors were requested to provide demographic information as well as information on the R&D process underlying their patented invention. To trace the mobility and the productivity of each inventor over time, the EPOLINE database of the European Patent Office was used to search for all patent applications belonging to the 3,049 inventors with priority dates between 1977 and 2002, resulting in a total of 39,417 EP patent applications.

To deal with the expected endogeneity problem caused by mobility and productivity, instrumental variables techniques will be employed. The results show that the level of education has no influence on inventor productivity. Making use of external sources of knowledge, on the contrary, has a significant effect on productivity. In particular exploiting the knowledge from scientific literature decreases inventive output. Finally, firm size has a positive impact on productivity. Firm size also influences inventor mobility, although negatively. Furthermore, the temporal concentration of inventive activity and the inventive environment are major determinants of mobility. The number of moves decreases with the temporal concentration of inventive activity and it is higher in large cities compared to rural areas. Overall, results confirm the simultaneous relationship between inventor productivity and inventor mobility. Whereas mobility increases productivity, an increase in productivity decreases the number of moves.

[3] See for instance Hall (2004): The Patent Name-Matching Project, http://emlab.berkeley.edu/users/bhhall/pat/namematch/namematch.html (access on November 28, 2005).

To examine the effect of a particular move on inventive performance an additional quasi-experimental design will be employed comparing the performance of an inventor before and after a selected move. Difference-in-differences estimation reveals that patent applications in the post-move period are more important than those in the pre-move period. In particular, the share of patents granted as well as the share of patents opposed by a third party is higher in the post-move period. Additionally, patents receive more references and also more citations after the move has occurred.

The remainder of this paper is organized as follows. Section 2 contains the derivation of the hypotheses from the literature. A description of the dataset as well as the operationalization of the variables used in the empirical part of the paper are provided in section 3. Section 4 provides descriptive statistics, followed by a two stage least squares regression model to analyze the causality between inventor productivity and inventor mobility. Section 5 contains a difference-in-differences estimation to provide a closer look at the impact of one particular move on inventive performance. Finally, section 6 discusses the estimation results and provides implications for further research.

2 Hypotheses

In the following, hypotheses are derived from the existing literature. First hypotheses as to the determinants of inventor productivity are provided. Subsequently, determinants of inventor mobility will be presented.

- **Inventor Productivity**

Shockley (1957) proposes that productivity is affected by many "mental factors", such as the ability to detect important problems, technical skills and persistence. Since then, a large number of authors considered the dependence between education and ability, especially the appropriateness of education as a proxy for ability.[4] Griliches (1970) suggests to "confess ignorance" with respect to the potential determinants of ability and define ability as gross output of the schooling system. This paper, according to the existing literature, measures intellectual ability using the level of education of the inventors. The following relationship is expected:

[4] See Becker (1964) and Denison (1964) for a survey of the relevant literature.

P.1: Inventors with a high level of education tend to show higher productivity than inventors with a low level of education.

Beyond the level of education, external sources of knowledge can positively influence inventor productivity. Patent documents, for instance, allow inventors not only to catch up on the state-of-the-art but also to collect relevant research information. Los and Verspagen (2003) characterize patent documents as a “potential source of ‘idea-creating’ knowledge spillovers” (Los/Verspagen 2003: 3). Allen (1977), von Hippel (1988) and Freeman (1991) highlight the importance of users and competitors regarding the innovativeness of firms. The literature described above analyzes the influence of knowledge transfer on innovative output at the firm level. However, the results should also apply to the inventor level. Using different sources of knowledge should enable inventors to increase their inventive output. It is therefore hypothesized that

P.2: Inventors making use of patent literature, users’ knowledge or competitors’ knowledge are more productive than inventors who do not use these external sources of knowledge.

Additional external sources of knowledge are university research and the scientific literature. Allen (1977) compares nineteen parallel R&D projects to analyze characteristics, distinguishing engineers from scientists. Two of them are scientific projects, the remaining 17 are technological projects. Results show that scientists receive ideas from the literature, whereas engineers hardly use scientific literature and rather employ customers or suppliers as external sources of knowledge (Allen 1977).

A possible explanation for this difference provides the concept of “absorptive capacity” (Cohen/Levinthal 1989, 1990). Absorptive capacity - the ability of a firm to recognize the value of external information, to assimilate and to apply it to commercial R&D - is required to profit from spillovers. The inventors’ absorptive capacity determines the extent to which the scientific knowledge can be assimilated and employed. Absorptive capacity in turn depends on the extent to which the inventor is used to using scientific sources of knowledge. It is, therefore, assumed that inventors who did doctoral or postdoctoral studies are more able to benefit from scientific research. The following relationship is proposed:

P.3: Inventors who conducted scientific research increase their productivity more by using university research or scientific literature than inventors who do not conduct scientific research.

Idson and Oi (1999) find a positive relationship between labor productivity and firm size because large firms are generally early adopters of new technology. Additionally, they have more resources at their disposal to hire and retain high quality researchers. Kim et al. (2004) use longitudinal worker-firm matched data in the semiconductor and pharmaceutical industries. In both industries the authors find that inventor productivity increases with firm size. Research expenditures, sales and number of employees were used as alternative size measures. Based on the results of the existing literature, the following hypothesis is proposed:

P.4: *Inventors who are employed with a large firm show a higher productivity than inventors working at small firms.*

- **Inventor Mobility**

Spence (1973) suggests that hiring an employee constitutes an investment under uncertainty since the employer is not sure of the capabilities of an employee at the time he hires him. But certain characteristics of the individual are observable and hence can be used to decrease this uncertainty. For instance, the level of education of the inventor can be used as a signal for his qualification. Therefore, inventors with a higher level of education may get more job offers and consequently may move more often. It is, hence, assumed that

M.1: *Inventors with a higher level of education change employers more often than inventors with a lower level of education.*

Additionally, monetary incentives can determine the decision of an inventor to change employers. Allen and Katz (1985) find that career systems of engineers and scientists are completely different. Engineers and scientists are often attracted by higher wages to undertake administrative roles. In general, career prospects are less promising for technical professionals. In cases, where progress in terms of salary or advancement is impossible within the current employment, a change of employer could help sustain their motivations. Therefore, the following relationship is expected:

M.2: *Inventors who classify "increase in salary" and "advancement" as important motives for inventive activity change employers more often than inventors who do not classify these motives as important.*

Furthermore, improvement of working conditions can be a motive to change the employer. Clark et al. (1998) use data of the German Socio-Economic Panel to examine the effects of job satisfaction on employees' future termination behavior. Results show that workers who are dissatisfied with their jobs are more likely to quit compared to highly satisfied workers. Hence the following hypothesis is proposed:

M.3: Inventors who classify "improvement of working conditions" as important as a motive for inventive activity change employers more often than inventors who do not think that "improvement of working conditions" is important for inventive activity.

Topel/Ward (1992) use longitudinal employee-employer data containing records for over one million individuals between 1957 and 1972. The authors find that jobs are more stable in large firms. Particularly, the turnover rate in the smallest class is double that of the largest class (1-9 vs. 1000-2499 employees). A reason for this finding may be that large firms provide internal job markets.[5] Careers, therefore, can develop within the firm and the employees need not move out. Allen and Katz (1985) proposed so-called "dual ladder" career systems providing more career chances for engineers. The probability that these career systems are established increases with firm size. Therefore, the following relationship is expected:

M.4: Inventors employed by large firms change employers less often compared to inventors employed with small firms.

Finally, Marshall (1964) recognized that workers may be economically more valuable to one firm than to all other firms. The author stated that firm-specific human capital may be a reason for this phenomenon. Parsons (1972) finds that large investments in firm-specific human capital, either by the firm or the worker, are likely to lead to reduced labor mobility, since the economic cost of worker-job separations is increased. An example for firm specific human capital is the technical specialization of an inventor. A highly firm specific technical concentration of inventive activity can lead to a lower value of an inventor in the labor market. Thus, the following hypothesis is proposed:

M.5: Inventors whose patent applications are concentrated in a small number of technical areas change employers less often than inventors whose patenting activity is diversified.

3 Data Source and Sample

3.1 Description of the Data

Data were collected in the course of the European project (called PatVal) sponsored by the European Commission. Units of observation are inventors who lived in Germany at the time

5 See, for instance, Althauser (1989) for a review of theoretical and empirical studies on internal labor markets.

of application of the respective patents. 10,500 EP patents attributed to inventors living in Germany were chosen as a stratified random sample based on a list of all granted EP patents with priority dates between 1993 and 1997 (15,595 EP patents). A stratified random sample was used in order to oversample potentially important patents.

The first inventor listed on the patent document was chosen as addressee. Each inventor was provided with a cover letter together with a questionnaire. 3,346 responses were received, resulting in a response rate of 32%. The sample contains 2,761 inventors who answered one questionnaire and 288 inventors who filled out two to five questionnaires.[6] Hence, the sample used in this paper contains 3,049 different inventors (representing 3,346 EP patents). The data from the questionnaire was merged with bibliographic and procedural information on the respective patents obtained from the online EPOLINE database. The dataset is a counterpart of the EPOLINE data as of March 1st, 2003 and covers approximately 1,200,000 patent files with application dates ranging from June 1st, 1978 to July 25th, 2002. To trace the productivity and the mobility of each inventor over time, the EPOLINE database was used to search for all patents belonging to the 3,049 inventors with priority dates between 1977 and 2002. The search procedure resulted in a total of 39,417 EP patents. For the instrumental variables technique that is employed to analyze the causality between productivity and mobility the data are aggregated at the inventor level creating cross-sectional data.

For inventors holding only one patent (352 inventors) it is not possible to observe a move. Therefore, these inventors were excluded from the sample. The final sample contains 2,697 inventors who are responsible for at least two patents during the time period under consideration.

Prior to the description of the variables, some limitations of using patent data for tracing mobility und productivity should be mentioned. First of all, a matching problem exists due to a lack of standardization of the spelling of inventors' names. This lack of standardization complicates the identification of inventors, especially of inventors with common last names. This may lead to an underestimation of patents per inventor and, consequently, to an underestimation of the number of moves. Second, identical names may refer to different inventors. Even if additional information, such as the name of the patent applicant, is applied, this could lead to an overestimation of the number of patents per inventor. Third, incomplete address data and female inventors who changed their name due to a marriage may also lead to wrong matches.

[6] Inventors who were responsible for more than one patent in the underlying time period and who were chosen more than once by stratified random sample, were provided with up to five questionnaires.

If the matching procedure works well, it is possible to identify a move, but only if the inventor applied for another patent after he changed the employer. If an inventor moved but did not apply for any patents after this move the data will not reveal the change of the employer. This could result in an underestimation of moves. Furthermore, this may lead to a selection bias since the probability to observe a move increases with the number of patents per inventor, i.e. the probability to observe a move is higher for productive inventors. Information from the PatVal questionnaires on the mobility of less productive inventors was used to reduce this bias. Let us further assume that the patent documents of two successive patents contain different applicants. The fact that different applicants are listed does not automatically mean that the inventor changed jobs. A possible explanation for two different applicants is, for instance, a strategic alliance between two companies or a merger after which patent applications are filed under the applicant name of the new company. These effects may lead to an overestimation of mobility. The classification of “move” and “no move” will be described in more detail in the following section. Furthermore, the results from the PatVal questionnaires, including questions related to the mobility of the inventors, in particular to the employment before, during, and after the invention was made, were utilized to confirm the matching and mobility outcomes. However, the mentioned limitations have to be taken into account when deriving implications from the results.

3.2 Variables

3.2.1 Dependent Variables

PRODUCTIVITY – The variable is defined as the number of applications per inventor, divided by the age of the inventor in 2002 minus 25. A way of justifying this measure would be the assumption that inventors become active at the age of 25 and continue to invent with constant productivity.

$$PRODUCTIVITY = \frac{number\ of\ applications}{age_{2002} - 25}$$

MOBILITY – Based on the full sample, a variable was created indicating the number of moves per inventor. A move is defined as a change of the employer. Since almost two-thirds of the inventors have not moved at all one is added to the number of moves to calculate the logarithm of this variable.

$$MOBILITY = number\ of\ moves + 1$$

The classification of "move" (the inventor changed the employer) and "no move" (the inventor did not change the employer) was corrected manually on the basis of the applicants listed in the EP documents. I made the assumption that the applicant listed on the patent document is also the employer of the respective inventor. To test this assumption, the responses from the PatVal-questionnaire were employed. The questionnaire included a question which asked the inventors whether the applicant listed on the patent document is also their employer. The results revealed that 92% of the questioned inventors are employed with the applicant of the patent. Since the firm applying for the patent is almost surely the employer of the inventors, it is assumed that this assumption should not lead to large biases, assigning it to all patent applications in the sample.

The following three examples of chronological applicant sequences for particular inventors give some insight into the problem of distinguishing between move and no move:

PRIOYEAR	APPLICANT		
1988	SIEMENS		
1989	SIEMENS		
2000	SIEMENS		
2001	Phillips	←	move
2001	SIEMENS	←	no move
2002	Phillips		
2002	Phillips		

Table 1: Example 1 (applicant sequence of inventor 1)

The first example displayed in Table 1 shows a sequence of 7 patents, applied for by two different applicants. Whereas the first change of the applicant is classified as a move, the second change is interpreted as an invention that was made during the employment with SIEMENS, which applied for a subsequent patent. This case was found quite frequently in the data. 26.4% of the mobile inventors have at least one patent application that belongs to this category.

PRIOYEAR	APPLICANT		
1988	SIEMENS		
1989	SIEMENS		
2000	"inventor"	←	no move
2001	SIEMENS		
2001	SIEMENS		
2002	SIEMENS		

Table 2: Example 2 (applicant sequence of inventor 2)

Table 2 shows a second example: in this case, the inventor is the applicant of one of the patents, and additionally, the applicants before and after this patent match completely (here: SIEMENS), it is assumed that this invention is a free invention which means that the applicant did not claim the right to this invention according to the German Employee Invention Act.[7] Therefore, it is taken for granted that the inventor has not changed his employer. The data reveal that 3.7% of the mobile inventors have applied for at least one patent in their own name during employment with another firm.

PRIO DATE	APPLICANT	
	SIEMENS	
01/05/2000	SIEMENS	
01/05/2000	BASF	← no move
	SIEMENS	
	SIEMENS	
	SIEMENS	

Table 3: Example 3 (applicant sequence of inventor 3)

The last example (Table 3) contains two patents from different applicants (SIEMENS and BASF) which were applied for on the same day. This case is also not treated as a move, since it is assumed that these two patents derive from research cooperation between these two firms. The data reveal that about 17.2% of the mobile inventors hold at least one pair of patent applications that belongs to the last category.

3.2.2 Explanatory Variables

AGE - The age of the inventor was obtained from the questionnaire and represents the age at the time of the survey. Age is included in the productivity regression to estimate a coefficient for age instead of assuming the coefficient to be 1, i.e., to take a proportional relationship between adjusted patent counts and age for granted. The age of the inventor is also a control variable in the mobility model.

LEVEL OF EDUCATION - The questionnaire contained a question asking the respondents for their highest attained degree. In order to simplify the analysis, the education variable was aggregated into three groups: (1) secondary school, high school diploma, or vocational

[7] A more detailed description of the German Employee Invention Act is presented in Harhoff and Hoisl (2005).

training (reference group), (2) vocational academy (Berufsakademie) or university studies, and (3) doctoral or postdoctoral studies.

EXTERNAL SOURCES OF KNOWLEDGE - university research, scientific literature, patent literature, users, and competitors. The questionnaire included a question relating to the importance of different sources of knowledge for the development of an invention.[8] Answers were again collected on a scale from one (absolutely not important) to five (very important). A dummy variable was created for each source of knowledge, combining categories 1 (absolutely not important) to 3 (partly important) as well as categories 4 (important) and 5 (very important). The latter implies a use of the respective knowledge source.

INCENTIVES - increase in salary, advancement, improvement of working conditions. The inventors were asked on the importance of different incentives for inventive activity. Answers were collected on a scale from one (absolutely not important) to five (very important). A dummy variable was created for each incentive, combining categories 1 (absolutely not important) to 3 (partly important) as well as categories 4 (important) and 5 (very important). For the latter group the dummy becomes 1; 0 otherwise.

TECHNICAL AREA - Based on their International Patent Classification (IPC) codes, the patent applications were classified into 30 technical areas. This classification was proposed by Schmoch (OECD 1994).

TECHNICAL CONCENTRATION - share of patent applications in the same technical area. Using the 30 technical areas, a Herfindahl index was calculated. For each inventor, the number of applications in the technical area *i* divided by the total number of applications was calculated, in the following denoted by *p*. The Herfindahl index (HI), consequently, corresponds to the sum of squared shares of applications:

$$HI = \sum_i p_i^2$$

If all applications belong to one technical area, technical concentration is at its maximum and the Herfindahl index is equal to 1.

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8 Although the answers to the questionnaire were related to specific patents, the answers seem to be transferable to all patents of an inventor. It is assumed that inventors basically tend to use special sources of knowledge, for example, due to positive experiences in the past. This assumption proves true, when comparing the answers of inventors who filled out more than one (five at the most) questionnaires. The different sources of knowledge are found to be equally important for all surveyed patents per inventor. Those answers that do not show a perfect match are at least highly correlated. The spearman correlation coefficients for the five different sources of knowledge range between 0.84 and 0.73.

FIRM SIZE - number of employees. The firm size was also obtained from the questionnaire. A set of eight dummy variables was generated in order to account for variation across different firm sizes. The intervals range from “less than 50 employees” to “more than 50,000 employees”. Except for the group “less than 50 employees” (= reference group), the dummies were included in the analysis.

OPPOSITIONS - The variable contains the share of granted patents per inventor that were opposed by a third party within the opposition term of nine months after grant.

STATUS - These variables provide information on the status of the patent applications. Three variables were included representing the shares of applications that were either granted, refused by the examiner or withdrawn by the applicant, for instance, due to the results of the search report. The status variables as well as the opposition variable are included to control for the value of the applications.

CLAIMS - This variable contains the number of claims added up for the total number of patents per inventor. The claims define the scope of an invention for which patent protection is requested. As proposed by Trajtenberg (2005), the number of claims is included as a control variable for an observable characteristic of the inventions at the time of filing.

TEMPORAL CONCENTRATION - This variable controls for temporal effects, i.e. this measure reveals, whether an inventor kept on inventing constantly during his inventive life or whether he carried out his inventions within a short period of time. The index was calculated as follows:

$$TEMP_{CON} = \frac{number\ of\ applications_{t\,(\max)}}{number\ of\ applications}$$

where $t_{(max)}$ is the application year, in which the inventor holds the maximum number of applications. In the event the inventor’s applications are all applied for in the same priority year, the index is at its maximum, and equals 1.

REGIONAL CHARACTERISTICS - This set of dummies indicates whether the inventions were made in a city with more than 1 million inhabitants or in a city with between 500,000 and 1 million inhabitants. The reference group relates to inventions made in rural areas or cities with fewer than 500,000 inhabitants.[9]

[9] Although the answers to the questionnaire were related to specific patents, the answers concerning the environment of the invention seem to be transferable to all patents of an inventor. To test this assumption, 30 mobile inventors were chosen by random to analyze whether the address of these inventors changed over time. Mobile inventors were used since these inventors are rather at risk of changing the home address than

4 Descriptive Statistics and Multivariate Results

4.1 Descriptive Results

Table 4 presents descriptive statistics. The final sample consists of 2,409 different inventors[10], of which 37% changed their employer at least once. In the following, these inventors are classified as mobile. Each inventor is on average responsible for 14.7 EP patents, the number of patents per inventor ranges between a minimum of 2 patents and a maximum of 308 patents. On average 6% of the inventors' granted patents were opposed by a third party, on average 12% of the applications had been withdrawn by the applicant, and 2% had been refused by the patent examiner.

Respondents were aged between 28 and 84 with a mean at 54 at the time they answered the questionnaire. Furthermore, the responding inventors are characterized by a high level of education. 12% have a high school diploma or went through a vocational training, 52% have a university degree, and 36% have a doctoral or post doctoral degree. Users as well as other patent documents turned out to be the most popular sources of knowledge utilized during the invention process: 73% of the inventors believe users to be an important source of knowledge and 66% make use of other patent documents, whereas only 22% of the respondents believe university research to be important for making inventions.

Furthermore, the inventors were asked about the importance of different incentives for their inventive activity. An increase in salary is classified as an important incentive by 67%. Compared to the other incentives, advancement seems to be less critical, as only 59% of all inventors rank advancement to be important for inventive activity. Technical concentration has its mean at 0.68, ranging between 0.14 and 1. This means that the inventors make on average more than two-thirds of their inventions in one technical area. The temporal concentration of the inventive activity has its mean at 0.36, ranging between 0.08 and 1. A mean of 0.36 implies that inventors on average applied for 36% of their patents in one year which means that inventive activity is not too concentrated within a short time.

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inventors who have not changed their employer. Results reveal that only three out of 30 mobile inventors changed their address. Whereas one inventor moved abroad (from a large city in Germany to a small town in Great Britain), the second one moved within Germany (both cities had a comparable size and have been sorted in the same city size group). The third one moved within the same city. The last two moves are thus of no relevance since they were sorted in the correct group. Overall, 1 out of 30 inventors are characterized by a address change relevant for the "inventive environment" variable. This share of inventors (3%) should not lead to large biases when transferring the answers related to one specific patent to all patents of the inventors.

[10] The sample used within this analysis only includes inventors employed with firms. Academic inventors were excluded from the sample. Finally, 2,409 questionnaires were filled out completely with regard to the above mentioned variables.

Variable	Mean	S.D.	Min.	Max.
mobility (dummy variable)	0.37		0	1
number of moves	0.64	1.10	0	12
number of patents	14.69	20.02	2	308
number of claims	157.02	211.91	5	3,027
share of granted patents opposed	0.06	0.11	0	1
share of applications refused	0.02	0.05	0	1
share of applications withdrawn	0.12	0.15	0	1
age of the inventor in 2002	54.04	9.76	28	84
level of education (terminal degree)				
secondary school/vocational training / high school diploma	0.12		0	1
university studies	0.52		0	1
doctoral/post-doctoral studies	0.36		0	1
external sources of knowledge				
universities	0.22		0	1
literature	0.63		0	1
other patents	0.66		0	1
users	0.73		0	1
competitors	0.57		0	1
incentives				
increase in salary	0.67		0	1
advancement	0.59		0	1
improvement of working conditions	0.64		0	1
technical concentration	0.68	0.26	0.14	1
temporal concentration	0.36	0.19	0.08	1
firm size (no. of employees)	48,880	93,488	1	550,000
regional characteristics				
more than 1 million inhabitants	0.10		0	1
500,000 to 1 million inhabitants	0.13		0	1
less than 500,000 inhabitants	0.77		0	1

Table 4: Descriptive statistics (N = 2,409)

On average, the patent assignees' firms have 48,880 employees. The number of employees ranges between 1 and 550,000. In the multivariate analysis firm size groups are used. Finally, the inventors were asked about the environment of the invention that is whether the inventions were made in large cities or in rural areas. 10% of the respondents stated that the inventions were made in a city with more than 1 million inhabitants, while 13% reported that the invention was made in a city with 500,000 to 1 million inhabitants. Finally, 77% of the inventors made their inventions in rural areas or cities with fewer than 500,000 inhabitants.

The following figures aim at a more detailed description of the dependent variables.

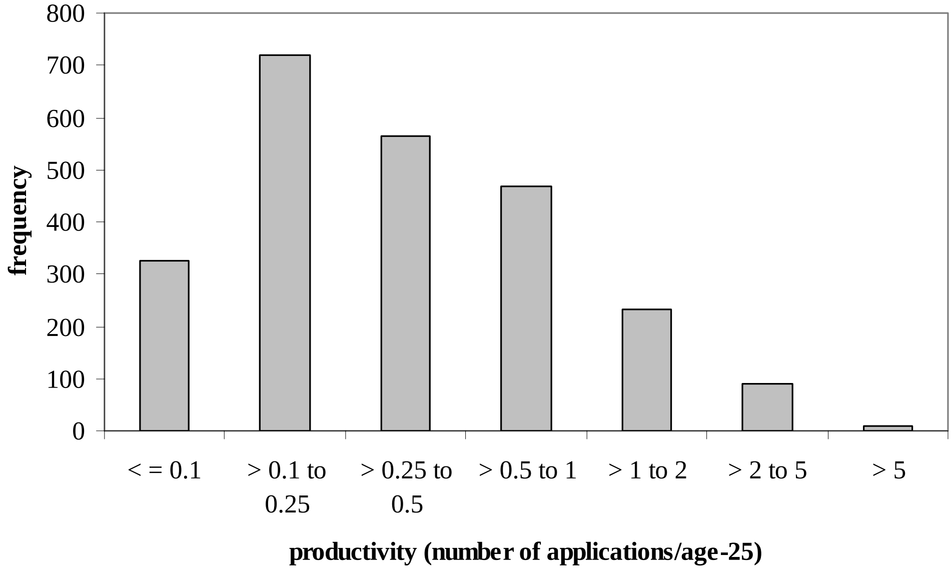

Figure 2: Distribution of inventor productivity (N = 2,409)

Figure 2 provides the distribution of inventor productivity. Productivity was calculated as the cumulative number of applications per inventor divided by the age of the inventor in 2002 minus 25. The histogram displayed in Figure 2 supports the findings of Lotka (1926) that the distribution of productivity among researchers is highly skew. Due to the skewness of the productivity distribution a logarithmic transformation of the productivity variable is used in the following multivariate analysis.

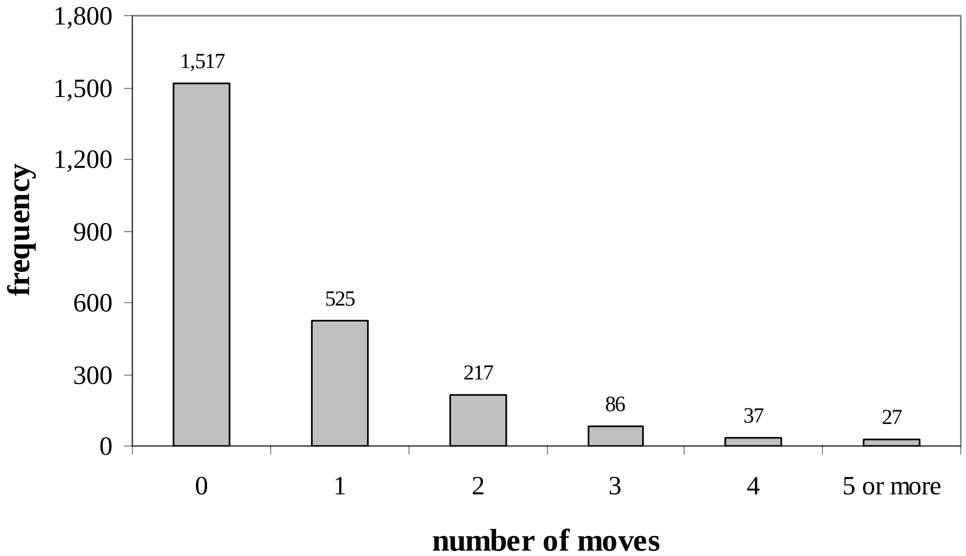

Figure 3: Distribution of the number of moves per inventor (N = 2,409)

Figure 3 reports the distribution of the number of moves per inventor. 1,526 (63%) inventors have not moved at all. 516 (21%) changed their employer once, 217 (9%) inventors changed their employer twice and only 27 (1%) responding inventors moved more than five times. Since Figure 3 also points at a distribution of mobility that is highly skew, the logarithm of the mobility variable is included in the following regression estimation.

4.2 Multivariate Specification

In this paper, an endogenous relationship between productivity and mobility of inventors is expected. To avoid biased results, a method of instrumental variables (IV) is used. In particular, a Two-Stages Least Squares (2SLS) regression is estimated. IV estimation is applicable for simultaneous or causal relationships if it is reasonable to maintain that some regressors are determinants of one dependent variable (e.g., PRODUCTIVITY) but not of the other variable (e.g., MOBILITY). These variables constitute instruments for PRODUCTIVITY in the MOBILITY equation. This strategy permits a consistent estimation of the mobility equation. The productivity equation can be estimated in the same way, using a second IV regression estimation (Mullahy/Sindelar 1996, Wooldridge 1999).

Considering inventor productivity (PRODUCTIVITY) and inventor mobility (MOBILITY), the following equation systems are presumed:

$$MOBILITY = f(PRODUCTIVITY, X_1, ..., X_n, incentives, tech\_con, temp\_con, reg\_char, \kappa)$$

$$PRODUCTIVITY = g(MOBILITY, X_1, ..., X_n, source\_know, \varepsilon)$$

MOBILITY is a function of:

PRODUCTIVITY	the endogenous variable,
$X_1 - X_n$	a number of exogenous variables, which are also assumed to determine PRODUCTIVITY, and
incentives, technical concentration, temporal concentration, and regional characteristics,	which represent additional exogenous variables that only affect MOBILITY. These additional exogenous variables will instrument for MOBILITY in the PRODUCTIVITY equation.

The regional characteristics of the invention (whether the invention was made in a large city or rather in a rural area), for instance, are assumed to serve as instrumental variables. Inventions made in larger cities should have a larger signaling effect leading to a higher probability of getting a job offer by a competitor. The productivity of an inventor, on the contrary, should remain unaffected by environmental differences.

PRODUCTIVITY is a function of:

MOBILITY	the endogenous variable,
$X_1 - X_n$	a number of exogenous variables, which are also assumed to determine MOBILITY, and
external sources of knowledge	which represent additional exogenous variables that only affect PRODUCTIVITY. These additional exogenous variables will instrument for PRODUCTIVITY in the MOBILITY equation.

External sources of knowledge can positively influence inventor productivity. Patent documents, for instance, allow inventors to collect relevant research information about the state of the art or about inventions made by competitors. Additionally, scientific literature is assumed to have a positive impact on inventor productivity. Inventors can use this source of knowledge to catch up on the actual state of basic research. Furthermore, basic research could form a source of idea creating for applied research.

The use of patent and scientific literature should not have a significant influence on the mobility of inventors, since reading patents or scientific articles does not lead to a personal contact between the inventor and the applicant or the author of the article. Thus, there is no reason to believe that the inventors would receive information from job vacancies in a company. Granovetter’s theory of “the strength of weak ties” also confirms that personal contact is needed to establish weak ties (Granovetter 1974, 1983). Montgomery (1991) confirms the applicability of Granovetter’s results to the labor market. In particular, the author describes the importance of personal contacts as a source of employment information.

4.3 Discussion of the Results

Table 7 provides the results of the 2SLS regression estimation. Model (1) contains control variables and explanatory variables required to test the hypotheses. Model (2) additionally includes variables controlling for variation between technical areas. In both models 2(a) and 2(b) technical areas which control for heterogeneity that would otherwise lead to biased results with respect to the estimated coefficients, have additional explanatory power. Therefore, in the following the results of Model (2) are described in more detail.

	Model (1) (industry dummies **not** included)		Model (2) (industry dummies included)	
	(a)	**(b)**	**(a)**	**(b)**
dependent variable	**log(mobility)**	**log(productivity)**	**log(mobility)**	**log(productivity)**
log(productivity)	-0.836*		-0.864*	
	[0.432]		[0.482]	
log(mobility)		0.504***		0.593***
		[0.091]		[0.101]
log(years of inventive activity)	-0.640*	-0.757***	-0.640*	-0.743***
	[0.354]	[0.048]	[0.385]	[0.051]
log(total number of claims)	0.697**	0.763***	0.717**	0.745***
	[0.325]	[0.014]	[0.359]	[0.015]
share of granted patents opposed	-0.133	-0.136*	-0.081	-0.154**
	[0.118]	[0.071]	[0.118]	[0.076]
share of applications refused	0.188	0.094	0.166	0.17
	[0.249]	[0.172]	[0.257]	[0.188]
share of applications withdrawn	0.429***	0.174***	0.429***	0.123*
	[0.143]	[0.060]	[0.147]	[0.063]
level of education, terminal degree (reference group: high school diploma or less)				
university studies	0.071**	-0.019	0.072**	-0.022
	[0.033]	[0.027]	[0.033]	[0.029]
doctoral/postdoctoral studies	0.156***	-0.056	0.117***	-0.076
	[0.045]	[0.045]	[0.043]	[0.048]
incentives				
increase in salary	0.011		0.010	
	[0.030]		[0.030]	
advancement	0.073**		0.070**	
	[0.030]		[0.030]	
improvement working conditions	-0.037		-0.035	
	[0.025]		[0.026]	
sources of knowledge				
knowledge universities		0.012		0.006
		[0.028]		[0.030]
doctoral studies*knowledge_universities		-0.096**		-0.064
		[0.045]		[0.047]
scientific literature		-0.088***		-0.091***
		[0.023]		[0.024]
doctoral studies*scientific_literature		0.124***		0.098**
		[0.044]		[0.046]
other patents		0.040**		0.031
		[0.020]		[0.022]
users		-0.023		-0.007
		[0.020]		[0.021]
competitors		0.007		0.007
		[0.019]		[0.020]
Observations	2409	2409	2409	2409
F-test (df)	10.99(22)	497.81(22)	5.86(51)	206.88(51)

Robust standard errors in brackets / * significant at 10%; ** significant at 5%; *** significant at 1%

Table 7: 2SLS Regression with heteroskedasticity-robust standard errors

	Model (1) (industry dummies **not** included)		Model (2) (industry dummies included)	
	(a)	**(b)**	**(a)**	**(b)**
dependent variable	**log(mobility)**	**log(productivity)**	**log(mobility)**	**log(productivity)**
firm size in number of employees (reference group: less than 51 employees)				
51 - 250 employees	-0.080	0.054	-0.074	0.057
	[0.071]	[0.050]	[0.070]	[0.054]
251 - 500 employees	-0.034	0.218***	-0.061	0.230***
	[0.090]	[0.052]	[0.090]	[0.057]
501 - 1,500 employees	-0.078	0.202***	-0.087	0.212***
	[0.083]	[0.049]	[0.085]	[0.053]
1,501 - 5,000 employees	-0.127	0.284***	-0.164*	0.298***
	[0.091]	[0.051]	[0.090]	[0.056]
5,001 - 10,000 employees	-0.031	0.309***	-0.076	0.299***
	[0.113]	[0.052]	[0.107]	[0.057]
10,001 - 50,000 employees	-0.083	0.423***	-0.135	0.401***
	[0.129]	[0.052]	[0.118]	[0.058]
more than 50,000 employees	-0.094	0.463***	-0.155	0.451***
	[0.140]	[0.053]	[0.131]	[0.060]
technical concentration	-0.196***		-0.210***	
	[0.047]		[0.048]	
temporal concentration	-0.791***		-0.823**	
	[0.301]		[0.326]	
regional characteristics (reference group: less than 500,000 inhabitants)				
city with more than 1 mio. inhabitants	0.088**		0.072*	
	[0.036]		[0.039]	
city with 500.000 to 1 mio. inhabitants	0.222***		0.211***	
	[0.039]		[0.038]	
distribution of patents across technical areas	not included	not included	included	included
Wald test			Chi2(29)=1.91 p=0.002	Chi2(29)=3.86 p=0.000
Constant	-1.442	-2.661***	-1.615	-2.637***
	[0.900]	[0.201]	[0.999]	[0.224]
Observations	2409	2409	2409	2409
F-test (df)	10.99(22)	497.81(22)	5.86(51)	206.88(51)

Robust standard errors in brackets / * significant at 10%; ** significant at 5%; *** significant at 1%

Table 7 continued: 2SLS Regression with heteroskedasticity-robust standard errors

- **Productivity**

I first discuss the results with respect to the productivity equation (Table 7, column 4). *log(age-25)* was included as an independent variable to account for a relationship between age and productivity which may be not proportional. A coefficient of -0.74 implies that the number of applications rises less than proportional with age (slope: 1-0.74 = 0.26). Thus, when age increases by 1%, productivity rises by 0.26%. The effect is significant at the 1% level. It is reasonably to believe that this increase of patent applications over time is an effect of experience. Inventors growing older gain experience which may lead to a higher productivity. An increasing number of patent applications with age may also arise due to the hierarchical position of the inventor. R&D managers increasingly act as advisors in different R&D projects. Consequently, an R&D manager is involved in more projects in parallel, resulting in more patents per inventor. Part of this increase may also occur due to a changing patenting behavior over time. In particular, inventors today tend to patent more than inventors did in the past. Inventors who were in their 40s or 50s or even older at the time of the survey profit from this increasing patent propensity.

Table 7 (columns 2 and 4) shows that the level of education is not associated with inventive output. Inventors who have a university or a doctoral degree do not show a higher productivity compared to the reference group (inventors who earned a high school diploma or less). This finding is surprising since many studies have pointed to a positive relationship between the educational degree and inventive output (e.g., Shockley 1957). In case a positive relationship between education and productivity does actually exist, the question poses why the data are not revealing this relationship. Three possible explanations will be given in the following. First, inventive output of productive inventors may be subject to a more severe selection process. Assume that patents of key inventors are often applied for in many different countries leading to higher application costs, this should lead to a more accurate estimation of the probability of a grant or of the market potential of an invention. This could result in a lower number of patent applications of key (highly educated) inventors. Secondly, the most productive inventors are probably involved in larger and more capital-intensive projects. Generally, these projects are long-term projects leading to a smaller number of patents within a certain period of time. Finally, it is possible that the importance of personal attributes or abilities of one single inventor is overstated considerably in the literature since more than 90% of the inventions are made by inventor teams. Possibly inventors, who themselves have no university or doctoral degree but work in an inventor team with university graduates, profit from their colleagues. Therefore, the composition of the inventor team rather than the characteristics of an individual inventor is of importance for inventive output. This assumption has to be analyzed in more detail in future research focusing on the inventor team as unit of observation. Nevertheless, hypothesis P1 is not supported by the data.

Model 1(b) reveals that exploiting the knowledge from other patent documents increases productivity. Inventors who make use of patent documents are 4% (Model 1(b), column 2) more productive than inventors who do not use this source of knowledge (significant at the 5% level). The effect of using patent literature is no longer significant after including the control variables for industry effects (Model 2(b), column 4). Industry effects seem to explain the use of patent documents as external source of knowledge, leaving no explanatory power for this variable. Therefore, hypothesis P2 is also neglected by the data.

Making use of scientific literature hence reduces productivity by 9% (Model 2(b), column 3). The coefficient of the variable "use of scientific literature" is significant at the 1% level. A reason for this negative effect may be that inventors who attach importance to scientific literature conduct basic research rather than applied research. Since basic research compared to applied research results in longer and more extensive R&D processes, basic research should result in a lower application rate per years of inventive activity. Model 2(b) supports the proposition that applying scientific knowledge requires absorptive capacity. Doctoral or post-doctoral studies increase the influence of scientific literature on productivity by 1%[11] (Model 2(b), column 4). The interaction between doctoral studies and spillovers from university research is not significant. These results, at least in part, support hypothesis P3.

Firm size is positively associated with productivity. The coefficients (except for 51 – 250 employees) are significant at the 1% level. Productivity rises almost monotonically with firm size. A productivity increase with firm size can arise due to large firms adopting new technologies earlier. Additionally, they have more resources to hire and retain high quality researchers and to provide incentives for inventive activity. A second reason for this relationship may be that R&D is organized differently in large firms. Possibly, scientists in large R&D departments are highly specialized and play a smaller role in any single R&D project but are involved in different projects at the same time (Kim et al. 2004). Overall, hypothesis P4 is supported by the data.

The control variables: the share of patents opposed and the share of applications withdrawn, contribute to the explanation of inventive productivity. The cumulative number of claims also explains inventor productivity. The share of patents opposed is negatively associated with inventor productivity, the number of claims positively. The share of patents withdrawn by the applicant is also positively associated with the cumulative inventive output (applications and citations).

- **Mobility**

Model 2(a) reported in Table 7 relates mobility to a number of explanatory variables, characterizing the inventor as well as the work environment.

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[11] The overall effect is calculated by adding up the effect of source of scientific literature (-0.091) and the effect of the interaction term doctoral studies * scientific_litarature (0.098).

The set of dummies controlling for the level of education of the inventor shows that an increasing level of education raises the number of moves. A university degree raises the number of moves per inventor by about 7%, a doctoral or post-doctoral degree by about 8% (compared to the reference group: high school or less). These findings support hypothesis M1 that inventors with a higher level of education move more often. This finding complies with the existing literature; in particular, the level of education which is observable is a factor in reducing uncertainty in job negotiations (Spence 1973).

Furthermore, a number of dummy variables were included in the regression estimation to control for the effect of different incentives. An improvement of working conditions does not significantly influence inventor mobility. Advancement, as expected, has a significant effect on mobility. Classification of advancement as important for inventive activity increases the number of moves by 7% (Model 2(a), column 3). Possibly, inventors who regard advancement as an important incentive for inventive activity are more receptive to job offers from competitors. This finding also supports the proposition of Allen and Katz (1985) that career opportunities for technical professionals are often unsatisfactory, resulting in a quit. Whereas hypothesis M3 is not supported, hypothesis M2 is supported by the data.

As expected, an increase in firm size has a negative effect on mobility, although the effect of firm size is not significant at the 10% level. Firms with 1,501 to 10,000 employees form an exception: being employed with these firms decreases the number of moves by 16% (Model 2(a), column 3) compared to the reference group (less than 51 employees). These findings in part support hypothesis M4 that inventors employed with large firms are less likely to move. First of all, jobs with large firms are more stable. Secondly, R&D departments of large firms dispose of more resources which are of great interest to the inventors. It is somewhat surprising that firm size does not significantly affect mobility. Possibly, the productivity variable absorbs part of the firm size effect. Due to strategic reasons large firms tend to patent more per unit R&D compared to small firms (Hall 2004). Using citation counts rather than patent counts to measure productivity will enable to analyze the firm size-mobility relationship more closely. Since the number of citations a patent received is a measure for its quality (Harhoff et al. 1999), citation counts are assumed to be less affected by an increasing patenting activity of firms.

Finally, hypothesis M5 is also supported by the data. Inventors whose inventions are concentrated in a smaller number of technical areas are less likely to move. In particular, an increase in technical concentration by 1% decreases mobility by 0.21 (Model 2(a), column 3). This result is in accordance with the findings in the literature. Technical specialization leads to an increase in firm-specific human capital, resulting in a lower value of the inventor to the job market.

A set of control variables was further factored into the regression. First of all, the age of the inventor was included. Results show that mobility decreases with age. As already proposed by Trajtenberg (2005), inventors tend to move earlier in their patenting career. Kim and Marschke (2005) suggest that inter-firm mobility is observed more often among younger inventors since they have fewer skills and are less productive. Another explanation for the negative relationship may be that at the beginning of their career inventors undergo a search and sorting process to find the right employee-employer match, resulting in more moves.

In addition, temporal concentration of inventive activity is used to show whether an inventor kept on inventing constantly during his inventive life or whether he developed his inventions within a short period of time. Results reveal that a higher temporal concentration decreases the number of moves. An explanation for this finding could be that inventors, who keep on inventing continuously, are more visible and are of more interest to other firms.

Finally, a set of dummy variables was included to control for the environment of the invention. The dummies indicate whether the invention was made in a city with more than 1 million inhabitants or in a city with 500,000 to 1 million inhabitants. The reference group relates to inventions made in rural areas or cities with fewer than 500,000 inhabitants. Both coefficients are highly significant and possess a positive sign which means that inventors who are active in larger cities move more often. Again, this is not surprising, since large cities provide more job opportunities. In rural areas, inter-firm mobility often forces employees to an inter-regional move leading to an increase in mobility costs for the inventor.

- **Causality**

Finally, the findings concerning the causality between inventor productivity and inventor mobility will be provided. Results confirm that there is a simultaneous relationship between inventor productivity and inventor mobility. Model 2(b) shows that in case the number of times an inventor changes his job doubles his productivity will increase by 59.3%. Assuming an inventor who has changed his job once, he will increase his productivity by about 60% if he changes once again. One additional move of an inventor, who has moved twice before, will increase his productivity by 30%. The coefficient is significant at the 1% level. A doubleling of productivity decreases the number of inter-firm moves of an inventor by 86%. Assume, e.g., an inventor who holds 5 patents. An increase by one patent decreases the number moves by about 17%. The effect is significant at the 10% level. Consequently, the data support hypothesis C1 that inventors who move increase their productivity. Hypothesis C2 that inventor productivity affects mobility is also supported. But, the latter relationship shows a different sign as proposed in hypothesis C2. This result may be explained by the fact that productive inventors have found good matches and may not want to move. It is also possible that productive inventors receive job offers from competitors but they do not change because incentive systems within their firm encourage them to stay.

5 Difference-in-Differences Estimation

Results of the 2SLS regression analysis showed that there is a bi-directional causal relationship between inventor mobility and inventor productivity. One of the major drawbacks of the regression analysis described before is that it disregards the time structure of the data. Time series data can help provide a better understanding of the impact of a certain move on inventive performance. The 2SLS results are based on the whole professional life of an inventor and do not reflect the impact of one particular move on the quantity or quality of inventive output in the aftermath of this move. To compare the performance of an inventor before and after a selected move an additional quasi-experimental design will be employed. To distinguish between differences attributable to the move and differences caused by other variables, a comparison group will be constructed containing inventors who have not moved during the time period under consideration but who otherwise are similar to the mobile inventors, for instance, with respect to the age or the educational background.

The use of quasi-experiments to analyze treatment effects in the absence of truly experimental data has gained wide acceptance in empirical research (see e.g., Solon 1985, Krueger 1990, Card/Krueger 1994). Quasi-experiments are characterized by the lack of one of the decisive particularities of a (randomized) experiment: a randomized assignment of the units of observation to the treatment and to the comparison group. The units are rather sorted into the two groups by self-selection (Meyer 1995). One of the most often used quasi-experimental designs is the difference-in-differences estimation approach[12] which aims at analyzing the impact of some treatment on a certain group of subjects under consideration. To do so, the performance of the treatment group is compared relative to the performance of a control group[13] for the periods before and after the treatment. The difference-in-differences estimator is based on the strong assumption that in absence of the treatment, the average outcomes for the treatment and the control group would have followed parallel paths over time (Abadie 2003). Therefore, the control group shows what would have happened to the treatment group in the absence of any treatment.

[12] In psychology this approach is also called the “Before and After Design with an Untreated Comparison Group” (Meyer 1995: 154).

[13] In the literature the terms control group and comparison group are used synonymously. Hereinafter the term control group is used.

5.1 Data Source, Matching, and Descriptive Statistics

The data used in this analysis include patent applications with priority dates between 1985 and 1999. The lower limit was chosen since the years between 1977 and 1984 are characterized by a strong increase in the number of European patent applications, which was caused by the diffusion of the European patent after the founding of the European Patent Office in 1978. Hence, I assume that as of mid 1980, European patent data are a sufficiently reliable source of data to use for a quasi-experimental design. The upper limit was chosen due to the limitations in the availability of citation data. To count the number of citations a patent received from subsequent patents and to compare citations between patents applied for in different years, the number of citations received within a five year time lag from the publication of the search report is employed.[14]

Inventors assigned to the treatment group had to be at least 25 years old in 1986, since it is assumed that inventors do not become active before the age of 25. Additionally, treatment inventors had to have changed their employer at least once between 1990 and 1995. The move-period was chosen in order to analyze three- and four-year windows before and after the move. Since difference-in-differences estimation requires knowledge of the specific point in time when the move took place, information on the applicants of the patents and the priority dates were used to calculate a proxy for the exact date of the move. To identify whether a move actually occurred, applicant names listed on the EP patent documents were employed. In the event two successive patent documents belonging to the same inventor contained two different applicants, it was assumed that the inventor changed his employer in the time period between these two patent applications. Since the exact time of move was not available, the move date was estimated by taking the midpoint between the two application dates (the last patent before and the first patent after the move). In case inventors changed their employer more than once between 1990 and 1995 one of these moves was selected at random. Finally, a sample of 553 mobile inventors was chosen.

To construct the control group for these 553 mobile inventors, a matching approach was used to match each treated unit with a non-treated control unit. In particular, matched treatment-control pairs are necessary to avoid spurious effects of inventor characteristics or industry effects between the treatment and the control group that are not attributable to the treatment itself. In case it is not possible to identify eligible characteristics for the control group, one could pick inventors randomly from the group of non-treated units. The characteristics for the following analysis were chosen based on the findings of the 2SLS regression estimation.

[14] Since the search report is published about one year after the applicant applied for the EP patent, patent data as at 2005 are needed to calculate five years citation lags for patents with priority year 1999.

According to these results relevant matching characteristics that have an effect on inventive output quantity and quality are the age of the inventor, his educational background as well as the main technical area in which the inventor is active. Consequently, the control group was constructed with the help of these three criteria. Additionally, control inventors were chosen who were also responsible for at least one patent before and after the move of the “twin” inventor. This assumption resulted in congruent three and four year windows of the mobile and the matched control inventor. Different time periods could have resulted in biases due to a different patent behavior at different points in time (Hall 2004). In case two or more inventors were potential candidates for matched pairs, one of these inventors was again selected at random. Overall, matched pairs could be found for 352 mobile inventors, resulting in a dataset of 704 inventors who have been responsible for a total of 11,273 patent applications between 1985 and 1999.

Table 8, provides some descriptive statistics of the variables that will be tested in the following difference-in-differences estimation. The variables were selected to compare the inventive performance of the underlying inventors in the pre and post period of the move.

Variable	Mean	S.D.	Min.	Max.
number of patent applications	16.01	21.10	2	308
share of granted applications opposed	0.05	0.10	0	0.67
share of applications granted	0.69	0.22	0.11	1
share of applications refused	0.02	0.05	0	0.25
share of applications withdrawn	0.16	0.17	0	0.72
cumulative number of references	65.04	81.02	2	1,188
number of references per patent application	4.23	1.09	1	9.6
cumulative number of citations	28.34	50.30	0	819
number of citations per patent application	1.51	0.98	0	7.25
cumulative number of claims	167.10	218.54	5	2,986
number of claims per patent application	10.64	3.92	2.33	32.5
size of the inventor team (per patent)	3.16	1.37	1	10.08

Table 8: Descriptive statistics of the treatment and the control group (N = 704)

Each of the 704 inventors (352 mobile inventors and 352 control inventors) is on average responsible for about 16 EP patent applications. The total number of applications per inventor ranges between 2 and 308. On average, 5% of the inventors’ granted patents were opposed by a third party, on average 16% of the applications had been withdrawn by the applicant, and 2% had been refused by the EPO. 70% of the applications were finally granted. The cumulative number of applications per inventor received an average of 65.04 references made by the patent examiners at the EPO. Each patent application received on average 4.23 references. Furthermore the cumulative number of patent applications per inventor received an average of 28.3 citations from subsequent patents (each application received on average 1.51 citations). The inventors' applications altogether contained an average of 10.64 claims. The number of claims per patent had a mean of 10.64. Finally, the average inventor team size varied between 1 and 10.08 with a mean of 3.16.

5.2 Description of the Results

To calculate the difference-in-differences estimator $\hat{\delta}_1$ one has to take the mean value of each group's outcome (treatment and control group) before and after the treatment and then calculate the "differences-in-differences" of the means. Therefore, the following equation is constructed:

$$\hat{\delta}_1 = (\overline{mobile}_{post} - \overline{control}_{post}) - (\overline{mobile}_{pre} - \overline{control}_{pre}) = \Delta_{post} - \Delta_{pre}$$

where the average value of the treatment group is denoted by *mobile* and the average value of the control group by *control*. Pre and post stand for the pre-treatment and the post-treatment period and a bar indicates an average over the inventors.

To test whether $\hat{\delta}_1$ is statistically different from zero one could either conduct a t-test, testing the H_o hypothesis that $\Delta_{post} = \Delta_{pre}$. The results of the t-tests for the variables under consideration are presented below. The same results can be achieved by using an OLS regression framework which will be described later.

As displayed in Table 9 the incident of a move has a positive impact on the mean share of applications granted[15]. In particular, the mean share of applications granted increases by 5% when a window of 4 years before and after the move is considered and by 7% with respect to a 3 year window. Hence the effect of a move on the grant rate seems to decrease over time. Additionally, the trend lines cross over. The important point here is the pattern of switching mean differences. This means that the ex ante low scoring treatment group, including mobile inventors, has overtaken the higher scoring control group. A possible explanation for this

[15] The share of patents which have not been granted include patents which were either refused by the patent examiner or withdrawn by the patent applicant as well as the number of patent applications which are still pending. Analysis of the share of patents pending (applications with priority dates between 1985 and 1999) revealed that in both groups (the mobile inventors and the control inventors) on average 13% of the patents are pending.

cross over is again the matching approach. An increasing match quality between employer and employee after the move could lead to a better performance of the inventor such as, e.g., a higher grant rate. The overall decrease of the mean share of applications granted (between 4% and 10%) - observable for the treatment as well as for the control group – occurs due to truncation of the data. In particular, the average time lag between the application date and the date the application is granted at the EPO is 4.2 years (Harhoff/Wagner 2005). Whereas more than 72% of the patent applications with priority year 1995 were granted and less than 10% are pending, only 41% of the patents were granted and 38% are pending if the patents were filed in 1997. Finally, when 1999 is the priority year, only 12% of the applications were granted and 77% are pending.

	share of applications granted		share of applications refused		share of applications withdrawn	
	4 years	3 years	4 years	3 years	4 years	3 years
($mobile_{post}$ – $control_{post}$)	0.018	0.043	-0.005	-0.004	-0.021	-0.026
($mobile_{pre}$ – $control_{pre}$)	-0.034	-0.031	-0.001	0.0002	0.038	0.034
diff.-in-diff.	0.052*	0.074**	-0.004	-0.005	-0.058**	-0.060**
t-value	1.84	2.51	-0.413	-0.43	-2.31	-2.24

	share of applications opposed		number of references per patent application		number of citations per patent application	
	4 years	3 years	4 years	3 years	4 years	3 years
($mobile_{post}$ – $control_{post}$)	0.007	0.014	0.275	0.320	0.134	0.190
($mobile_{pre}$ – $control_{pre}$)	-0.016	-0.022	0.035	0.003	-0.066	-0.099
diff.-in-diff.	0.021	0.035*	0.240	0.318**	0.200	0.289*
t-value	1.20	1.83	1.55	2.06	1.34	1.85

	number of claims per application		number of applications		number of inventors per patent	
	4 years	3 years	4 years	3 years	4 years	3 years
($mobile_{post}$ – $control_{post}$)	1.224	1.357	-1.293	-1.063	-0.271	-0.307
($mobile_{pre}$ – $control_{pre}$)	1.188	1.144	-1.011	-0.707	-0.045	-0.073
diff.-in-diff.	0.036	0.214	-0.281	-0.355	-0.226**	-0.233**
t-value	-0.09	-0.48	0.57	0.99	2.02	1.97

Table 9: T-Test of difference-in-differences estimations for 4 and 3 year periods before and after the event of a move (* significant at 10%; ** significant at 5%; *** significant at 1%) (N = 352)

Interestingly, a move seems to have no impact on the share of patents refused by the patent examiner. The difference-in-differences estimator is not significant at the 10% level - neither for the 4 year window nor for the 3 year window. Hence, the H_o hypothesis that $\Delta_{post} = \Delta_{pre}$ cannot be rejected. In case the share of patent applications withdrawn by the applicant is considered, a move has a negative impact. Whereas the share of withdrawals prior to the move is larger for the treatment group than for the control group, it becomes smaller afterwards. Overall, the share of applications withdrawn decreases by about 6% (3 and 4 year period). Again this result suggests an increase in the value of the applications or at least an increase of importance of the applications for the new employer. Withdrawals on the part of the applicants take place in case the applicant fears that the invention does not meet the requirements for patentability (novelty and inventive step) or the applicant is no longer interested in receiving patent protection for the invention. One could, therefore, also assume that the inventions of the movers are more in line with the patent portfolio of their new employer compared to the old one.

The share of oppositions received within the opposition term of nine months after the patent was granted is lower in the treatment group before the move took place and higher afterwards. The difference-in-differences estimator reveals a 4% increase of the opposition rate due to the move. According to Harhoff and Hall (2003) the number of oppositions a patent received is a proxy for the value of the patent. Opposition results hence confirm that patent applications of the mobile inventors become more important after the move. Although the signs point in the same direction, the difference-in-differences estimator is no longer significant in case the 4 year window is considered. The results suggest that this opposition effect diminishes over time.[16]

In addition to the results described above, reference and citation counts underline the proposition that a move has a positive effect on the value of after-move patent applications. However references and citation counts only exhibit a significant difference in case the 3 year window is employed. Table 9 shows that the treatment group and the control group receive the same average number of references during the three years prior to the move. In the post-move period, in contrast, there is a difference between the two groups. Overall, a move leads to an increase in the number of references by 0.32 references per application. As to citation counts Table 9 gives evidence that whereas the control group's patents received slightly more citations per patent in the pre-move period, the mobile inventors are ahead in the post-move period. The difference-in-differences estimator indicates that the number of citations increases

[16] Future research will also include information on the firms that filed the oppositions. In particular, the question will be addressed whether any of the oppositions were filed by former employers of the mobile inventor.

by 0.29 citations per patent as a result of the move. A possible explanation for this outcome could first of all be an increase in the value of the patent applications in the post-move period. Secondly the outcome may be explained by the fact that the inventor who moved works within the same technical area at his new job. Two R&D teams working in the same area produce patent applications which form potential state of the art to be referenced by the patent examiner of the EPO during the search process. The references from the search reports are used to calculate the number of citations from subsequent patents, therefore, more references also lead to more citations. To confirm this assumption, the citing patents have to be analyzed more closely. In particular one would have to find out whether part of the citations received by the after-move patents derive from the former employer of the mobile inventor. The former employer could be interpreted as kind of a second source of self-citations.[17]

The number of claims per patent and the number of applications themselves do not change due to the move - neither in the 3 nor 4 year window before and after the move. Finally, the inventor team size is affected by a move. In general inventors who move work in smaller inventor teams afterwards. This result is surprising since former research confirmed that inventor teams are larger in big firms (especially in large pharmaceutical firms) and inventors working in large firms are less likely to move. Additionally inventors who move typically change from small to larger firms (Topel/Ward 1992, Kim et al. 2004). The difference-in-differences estimator reveals that team size decreases by 0.23 inventors (3 and 4 years) as a result of the move. Although the difference-in-differences estimator is significant at the 5% level, the effect seems to be rather irrelevant since a coefficient of 0.23 corresponds to less than a fourth person. The regression results provided in the next section, however, reveal that the team size effect is no longer significant.

Overall the results of Table 9 show that a move seems to have a larger impact during the 3 year period as compared to the 4 year period. A possible explanation is that inventors who changed their employer do a better job during the first years after the move. Possibly, the inventors make special efforts during their first years to impress their new employer or to gain respect from their colleagues. Over time the differences caused by the move decrease and finally disappear. It is also possible that inventors are able to profit from knowledge they have “transferred” from their former job. Over time this advantage disappears since the inventor faces new tasks and his present knowledge does not suffice to solve these problems. Another explanation may be that the units of observation are still inventors during the first years after the move but leave R&D for a job in sales or marketing after about three years. Intra-firm

[17] Self-citation corrected citation counts will be employed in future research.

mobility (e.g., from R&D to sales) leads to invisibility of the inventor in terms of patents and consequently, the mean inventive performance seems to decrease over time.

The results provided here hence confirm the causal relationship between inventor mobility and patent quality obtained from the 2SLS regression.[18] One of the advantages of the difference-in-differences estimation, which is at the same time a drawback, is that it considers the impact of one specific move on patent quality. As described before, the selected moves took place between 1990 and 1995. In case the inventors moved repeatedly between 1990 and 1995, one of these moves was selected at random. But there are also moves that have taken place before 1990 and/or after 1995. These moves have not been considered at all. To overcome this drawback, an additional dummy regression analysis will be employed. Although an OLS regression framework would lead to the same results as that of the t-tests, it has the advantage that additional control regressors such as multiple moves can be included in the analysis. The following equation including a control dummy for inventors who moved more than once during their inventive life will be estimated:

$$y = \beta_0 + \delta_0 * mobile + \delta_1 * post + \delta_2 * (mobile * post) + \delta_3 * mult\_mobil + u$$

where *mobile* is a dummy variable, taking the value one in case the inventor moved and zero otherwise. *post* is a time dummy variable taking the value one in case the time period after the treatment is considered and zero otherwise. *(mobile * post)* is defined as interaction between *mobile* and *post* and, therefore, is one if the two dummies *mobile* and *post* both take the value one. *mult_mobile*, finally, is defined as a dummy variable taking the value 1 in case the mobile inventors moved more than once during the time under consideration (1985 – 1999). In the following, I will refer to these inventors as multiple movers.

$\hat{\delta}_2$ is the true causal effect of the treatment (= move) on the outcome for the treatment group. Table 10 provides the results of the OLS regression analysis. Whereas Model 1 refers to the results without any further control variables, Model 2 includes a dummy variable for multiple movers. The first column of each model provides the results of the 4 year window, the second column the results of the 3 year window. Model 1 provides the same results as the t-tests with the exception that the number of citations received as well as the team size are no longer significant. Apparently, the other dummy variables leave no explanatory power to the

[18] When only the four year period before and after the move is used to analyze differences in inventive performance, the sample contains 401 matched pairs. To find out whether an increase in the sample by 15% does change the results, the t-tests and the dummy regressions were also conducted using the larger sample. Results show that the absolute values of the coefficients changed only slightly (third position after the decimal point), the signs and the significance remained completely stable. Therefore, in the following the smaller sample is used for the reason of comparison between the two time periods.

interaction term. However, it has to mentioned that the p-value of the interaction term in the citation regression (Model 2f) is only slightly above the 10% level (p = 0.111).

	share of applications granted				**share of applications refused**			
	Model 1a		**Model 2a**		**Model 1b**		**Model 2b**	
	4 years	**3 years**	**4 years**	**3 years**	**4 years**	**3 years**	**4 years**	**3 years**
d_mobile	-0.034	-0.031	-0.035	-0.037	-0.001	0.0002	-0.0002	0.001
	[0.022]	[0.023]	[0.025]	[0.026]	[0.007]	[0.007]	[0.008]	[0.008]
d_post	-0.101***	-0.078***	-0.101***	-0.078***	-0.004	-0.003	-0.004	-0.003
	[0.022]	[0.023]	[0.022]	[0.023]	[0.007]	[0.007]	[0.007]	[0.007]
d_mobile * d_post	0.052*	0.074**	0.052*	0.074**	-0.004	-0.005	-0.004	-0.005
	[0.032]	[0.033]	[0.032]	[0.033]	[0.010]	[0.010]	[0.010]	[0.010]
d_mult_mobile			0.001	0.011			-0.001	-0.002
			[0.022]	[0.023]			[0.007]	[0.007]
Constant	0.803***	0.801***	0.803***	0.801***	0.028***	0.027***	0.028***	0.027***
	[0.016]	[0.016]	[0.016]	[0.016]	[0.005]	[0.005]	[0.005]	[0.005]
Observations	1408	1408	1408	1408	1408	1408	1408	1408
R-squared	0.018	0.008	0.018	0.019	0.002	0.001	0.002	0.001
F-test (df)	8.51(3)	3.86(3)	6.38(4)	2.95(4)	0.78(3)	0.54(3)	0.59(4)	0.42(4)

	share of applications withdrawn				**share of applications opposed**			
	Model 1c		**Model 2c**		**Model 1d**		**Model 2d**	
	4 years	**3 years**	**4 years**	**3 years**	**4 years**	**3 years**	**4 years**	**3 years**
d_mobile	0.038**	0.034*	0.039*	0.036	-0.015	-0.022	-0.019	-0.028*
	[0.019]	[0.020]	[0.021]	[0.022]	[0.013]	[0.014]	[0.014]	[0.016]
d_post	-0.001	-0.002	-0.001	-0.002	-0.023*	-0.027**	-0.023*	-0.027**
	[0.019]	[0.020]	[0.019]	[0.020]	[0.013]	[0.014]	[0.013]	[0.014]
d_mobile * d_post	-0.058**	-0.060**	-0.058**	-0.060**	0.021	0.035*	0.021	0.035*
	[0.027]	[0.028]	[0.027]	[0.028]	[0.018]	[0.020]	[0.018]	[0.020]
d_mult_mobile			-0.003	-0.004			0.009	0.011
			[0.019]	[0.020]			[0.013]	[0.014]
Constant	0.155***	0.157***	0.155***	0.157***	0.072***	0.078***	0.072***	0.078***
	[0.013]	[0.014]	[0.013]	[0.014]	[0.009]	[0.010]	[0.009]	[0.010]
Observations	1408	1408	1408	1408	1408	1408	1408	1408
R-squared	0.007	0.007	0.007	0.007	0.002	0.003	0.003	0.004
F-test (df)	3.42(3)	3.32(3)	2.57(4)	2.50(4)	1.12(3)	1.46(3)	0.96(4)	1.26(4)

Standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 10: Difference-in-differences regression (OLS regression) (N = 1,408)

	number of references per patent application				number of citations per patent application			
	Model 1e		Model 2e		Model 1f		Model 2f	
	4 years	3 years	4 years	3 years	4 years	3 years	4 years	3 years
d_mobile	0.035	0.003	0.074	0.04	-0.066	-0.099	-0.350**	-0.372**
	[0.124]	[0.128]	[0.141]	[0.146]	[0.121]	[0.128]	[0.138]	[0.145]
d_post	0.106	0.064	0.106	0.064	-0.690***	-0.615***	-0.690***	-0.615***
	[0.124]	[0.128]	[0.124]	[0.128]	[0.121]	[0.128]	[0.121]	[0.127]
d_ mobile * d_post	0.240	0.318*	0.24	0.318*	0.200	0.289	0.200	0.289
	[0.175]	[0.181]	[0.175]	[0.181]	[0.172]	[0.181]	[0.171]	[0.180]
d_mult_mobile			-0.071	-0.069			0.520***	0.501***
			[0.124]	[0.128]			[0.121]	[0.128]
Constant	4.202***	4.228***	4.202***	4.228***	1.997***	1.976***	1.997***	1.976***
	[0.088]	[0.090]	[0.088]	[0.090]	[0.086]	[0.090]	[0.085]	[0.090]
Observations	1408	1408	1408	1408	1408	1408	1408	1408
R-squared	0.008	0.009	0.009	0.014	0.034	0.021	0.046	0.031
F-test (df)	3.89(3)	4.11(3)	2.99(4)	3.15(4)	16.23(3)	9.95(3)	16.92(4)	11.38(4)

	number of claims per application				number of applications			
	Model 1g		Model 2g		Model 1h		Model 2h	
	4 years	3 years	4 years	3 years	4 years	3 years	4 years	3 years
d_mobile	1.188***	1.144***	0.818*	0.816*	-1.011*	-0.707	-1.819***	-1.293**
	[0.366]	[0.388]	[0.417]	[0.442]	[0.579]	[0.441]	[0.658]	[0.502]
d_post	0.731**	0.630	0.731**	0.630	1.597***	1.071**	1.597***	1.071**
	[0.366]	[0.388]	[0.366]	[0.388]	[0.579]	[0.441]	[0.577]	[0.440]
d_ mobile * d_post	0.036	0.214	0.036	0.214	-0.281	-0.355	-0.281	-0.355
	[0.518]	[0.549]	[0.518]	[0.549]	[0.818]	[0.624]	[0.817]	[0.623]
d_mult_mobile			0.679*	0.600			1.481**	1.074**
			[0.368]	[0.390]			[0.580]	[0.442]
Constant	9.576***	9.607***	9.576***	9.607***	5.446***	4.460***	5.446***	4.460***
	[0.259]	[0.274]	[0.259]	[0.274]	[0.409]	[0.312]	[0.408]	[0.311]
Observations	1408	1408	1408	1408	1408	1408	1408	1408
R-squared	0.021	0.02	0.023	0.021	0.015	0.012	0.019	0.016
F-test (df)	10.01(3)	9.38(3)	8.37(4)	7.63(4)	6.91(3)	5.53(3)	6.83(4)	5.63(4)

Standard errors in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 10 (continued): Difference-in-differences regression (OLS regression) (N = 1,408)

	number of inventors per patent			
	Model 1i		Model 2i	
	4 years	3 years	4 years	3 years
d_mobile	-0.045	-0.073	-0.256*	-0.250*
	[0.121]	[0.123]	[0.138]	[0.140]
d_post	0.087	0.056	0.087	0.056
	[0.121]	[0.123]	[0.121]	[0.123]
d_ mobile * d_post	-0.226	-0.233	-0.226	-0.233
	[0.171]	[0.174]	[0.171]	[0.174]
d_mult_mobile			0.387***	0.323***
			[0.121]	[0.123]
Constant	3.202***	3.215***	3.202***	3.215***
	[0.086]	[0.087]	[0.085]	[0.087]
Observations	1408	1408	1408	1408
R-squared	0.004	0.005	0.011	0.010
F-test (df)	1.74(3)	2.34(3)	3.86(4)	3.48(4)

Standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 10 (continued): Difference-in-differences regression (OLS regression) (N = 1,408)

In the following, only the results of Model 2 are presented. In particular, the impact of multiple movements on inventive output is analyzed. Results show that the control dummy does not have a significant effect in the regressions with status variables as dependent variables (Models 2a-2c). As explained above, the specific move under consideration has an impact on the share of patents granted and on the share of patents withdrawn. Whether the inventors are single movers or multiple movers does not make any difference. The share of patents opposed by a third party is also not affected by multiple moves (Model 2d), the same applies to the number of references per patent (Model 2e).

In case the number of citations is considered (Model 2f), the coefficient of multiple movements has a significantly positive impact on the dependent variable. In particular, multiple movers receive on average 0.5 more citations (3 year and 4 year window). Table 8 presents that the mean number of citations per patent amounts to 1.51. Therefore, an increase by 0.5 means that the number of citations increases by one third which is quite a large effect. Consequently the patent applications of multiple movers are considerably more valuable compared to single movers or non-movers.

The multiple movers dummy also affects the number of claims per patent (Model 2g) – although only when the 4 year period is considered. Table 8 displays that the number of claims per patent increases by 0.7. Comparing this result with the descriptive statistics provided in Table 8 (the mean number of claims per patent amounts to 10.6), 0.7 equals an increase by about 6%.

Model 2h reveals that multiple movers are responsible for more patent applications. The effect is significant at the 5% level, both for the 3 and the 4 year window. The interesting result here is that an increasing output quantity of multiple inventors seems to be a long running process. In particular, inventors who moved repeatedly, have on average applied for 1.1 (3 year window) and 1.5 (4 year window) more patents as compared to inventors who moved once or less. This result is not surprising, since inventors have to accustom themselves to R&D processes at their new employer and should therefore be able to increase their output over time.

Finally, the multiple mover dummy has also a significantly positive effect on inventor team size (Model 2i). Results show that inventor teams of multiple movers include 0.4 more inventors (0.3 in case the 3 year period is considered). Again comparison with the mean team size provided in Table 8 (the mean team size per patent amounts to 3.16 inventors), reveals that the number of co-inventors increased by 13% (10%). Overall this result implies that inventors who move repeatedly apparently move from smaller firms to larger firms (which are characterized by larger inventor teams) which is again in line with the existing literature (Kim et al. 2004).

Overall, it is shown that the effect of the multiple move dummy is quite large. What has so far not been answered is the question which effects this dummy variable actually captures. First of all, the multiple mover dummy can not be interpreted causally with respect to the move under consideration. It rather refers to the whole time period under consideration (4 years or 3 years before and after the move). Three interpretations of the multiple mover dummy seem possible: first of all, the dummy could represent experience effects. Possibly multiple movers may due to their “move-experience” be able to settle in or to adjust to a new environment faster. In addition, experienced movers may be capable to make better use the knowledge from their new colleagues. Again these results point at the importance of absorptive capacity at the individual inventor level (Cohen/Levinthal 1990). Second, inventors who move repeatedly may be different from single movers or non-movers as to their personal characteristics. For instance, multiple movers may be more flexible or cosmopolitan compared to the reference group (single and non-movers). These characteristics can again help multiple movers to settle in faster and consequently to increase inventive performance. Third, it is possible that the multiple mover-effect reveals that there is another move which has a stronger impact on output quality than the move selected for the difference-in-differences analysis. To shed more light into this discussion further research should analyze multiple movers more closely.

6 Conclusion

In this paper, first the causality between inventor productivity and inventor mobility was analyzed using a 2SLS regression estimation to deal with the endogeneity problem between productivity and mobility. Secondly, to get a better understanding of the impact of one particular move on inventive performance, a quasi-experimental design was employed. In particular, a difference-in-differences estimation was used to compare output quality of a group of mobile inventors and a non-mobile control group in the pre and post move period.

One of the key finding of this paper is that there exists a simultaneous relationship between inventor mobility and inventor productivity: An increase in the number of moves per inventor increases productivity. This outcome confirms the findings of the literature that mobility can lead to a better match between employer and employee, resulting in a higher productivity of the employee. This result could also mean that a move increases the technical skills or the experience of an inventor - for instance, due to knowledge spillovers from colleagues - resulting in a higher productivity.

In contrast, increasing productivity decreases mobility. At first view this could mean that productive inventors are not at risk of being poached. But it could also mean that productive inventors do not want to move. Not because they do not receive any job offers but because incentive systems within their employing firm work quite well. Another possible explanation for the negative causality between productivity and mobility can be special contracts or agreements, for instance, a non-compete agreement between the inventor and his employer. It is common practice that inventors, leaving their employer, are not allowed to work on the same area or project as before one (or more) year(s) after mobility took place. Non-compete agreements restrict employment options of the inventors outside the firm and, therefore, limit the inventors' bargaining power over their employer (Fleming/Marx 2005). This could either keep inventors from leaving at all or at least make the inventors less attractive for the job market.

The difference-in-differences estimation confirmed a positive effect of a particular move on output quality. Inventors are able to increase their grant rate in the aftermath of a move. Granted patents are opposed more frequently and patent applications also receive more references and more citations. Results also suggest that a move has a larger impact during a three year window before and after the move compared to a four year window. A possible explanation is that the inventors make special efforts during their first years to impress their employer or to gain respect from their colleagues. Over time the differences caused by the move decrease and finally disappear. Another explanation may be that inventors leave R&D for another job, e.g., in sales. Intra-firm mobility makes the inventor invisible in terms of patents and leads to an increase in his mean output over time. Finally multiple movers turned out to hold more important patents. To shed more light into the impact of multiple moves on inventive performance, future research should analyze the life cycle of inventors. Possibly, not only the number of moves per inventor has an impact on his performance. Experience from former projects the inventor was involved in or the colleagues the inventor worked together with in the past could also be of importance.

The results of this paper have certain implications for the management of R&D personnel. First, the characteristics of a single individual seem to matter less when considering inventive output. This result suggests that the composition of the inventor team could form a major determinant of inventive output. Therefore, further research should look more closely at inventor teams, especially on the effects of team composition on productivity. Possible determinants of team productivity may be a heterogeneous distribution of the characteristics and skills of the team members as well as team size.

Second, the matching between employee and employer seems to be of particular importance. A good match does not only explain about general differences in the productivity between inventors but also about increases in inventive performance after a certain move. For R&D management as well as for inventors these results imply that both parties should try to maximize match quality. Since match quality is hardly to observe ex ante, R&D management could try to offer different contracts to inventors, resulting in a self-selection of heterogeneous individuals to these contracts.

Finally, another issue relevant to the management of R&D has to be considered. Apart form the findings summarized above, the provided survey reveals that patent documents provide an important source of information for firms to identify valuable patents and also to identify high performing inventors. The number of patents an inventor is responsible for and the number of citations the inventor's patents received from subsequent patents are a good proxy for the productivity of an inventor. Reliable citation counts are only available after five to ten years after the application date which makes them unattractive for the labor market. By contrast, patents are published 18 months after the priority date which turns them into a valuable signal for ingenuity. Since patent applications are published in publicly available databases, information on inventors is actually available at low costs. From the point of view of a firm this "open job market" poses severe threats to loose key inventors who received a job offer from a competitor. Firms would rather like to keep information on inventors secret. However, due to legal regulations this is not possible. Consequently, firms have to undertake special efforts, e.g., they have to provide appropriate motivation and incentive systems or non-compete agreements, to increase the commitment of important inventors to the firm. Inventors probably take advantage of this legal regulation since (1) they receive a compensation for their merits and (2) they are able to increase their power in negations with their employers. On the part of the national economy, this “open job market” has the advantage of promoting job mobility, leading to a better match quality between the employee and the new employer. A better match quality in turn leads to a higher productivity of the employees and consequently to an increase of social welfare.

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