TRACING MOBILE INVENTORS – THE CAUSALITY BETWEEN INVENTOR MOBILITY AND INVENTOR PRODUCTIVITY

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Tracing Mobile Inventors - The Causality between Inventor Mobility and Inventor Productivity

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Abstract:

This paper analyzes the causality between inventor productivity and inventor mobility. 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. Finally, firm size has a positive impact on productivity. Firm size also influences inventor mobility, although negatively. 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 (IVREG and IVPROBIT) will be employed. Results show that mobile inventors are more productive than non-movers. Whereas a move increases productivity, an increase in productivity decreases the probability to observe a move.

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

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1 Introduction

In 1998, Kai-Fu Lee, an expert on speech recognition and search technologies, moved to Microsoft to found the Chinese Microsoft research division in Beijing. In 2000, he became vice president of interactive services at Microsoft. In July 2005, Lee left Microsoft to work for Google. While working for Microsoft, Lee had signed a non-compete agreement, which barred him from working in research areas competing with Microsoft within one year after leaving the company. On July 19, 2005, after Google had announced that Lee would “serve as President of the company's growing Chinese operations”[1] Microsoft sued Google and Lee. Microsoft claimed that Lee was violating his non-compete agreement, since working for Google would unavoidably lead to the disclosure of technical know-how to Google. On July 28, the Washington State Superior Court enacted a preliminary injunction, which prevented Lee from working on Google projects that competed with Microsoft. On December 22, 2005, Google and Microsoft announced that they had entered into a private agreement, which put an end to the dispute between the two companies.[2]

The Google-Microsoft story gives first insights into possible consequences of a key employee leaving a firm. Kai-Fu Lee is an expert in the field of speech recognition and search technology. A move from Microsoft to Google not only weakened the position of Microsoft in this research field but also strengthened the position of the competitor. For Microsoft a legitimate reason to take court action. Given this story, it would be interesting to learn more about the mobility of productive inventors.

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[1] See http://www.google.com/press/pressrel/rd_china.html (access on January 5, 2007).

[2] See http://news.com.com/Microsoft+sues+over+Google+hire/2100-1014_3-5795051.html as well as http://en.wikipedia.org/wiki/Kai-Fu_Lee (access on August 14, 2006).

On the one hand mobility may effect productivity. R&D personnel[3] 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 in the after-move period. One might, therefore, expect that mobility increases productivity[4].

On the other hand the causality may run in the opposite direction with productivity increasing mobility. 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. Consequently, 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

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

4 The productivity of inventors is measured by relating the number of patent applications per inventor to the age of the inventor.

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's work, no other research focusing on inventors has been carried out on the simultaneous relationship between productivity and mobility. 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 inventors who moved receive more citations. Additionally, 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. A possible explanation is that asymmetric information makes it difficult for the employer to impede mobility of high performing inventors. Especially if another firm has better information and appropriately compensates the inventor.

The following study improves on the current literature by (1) allowing for a simultaneous relationship of productivity and mobility, whereas existing research on inventors – with the exception of Trajtenberg (2005, 2006) - implicitly assumes causality to point in one way (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 dealing 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.[5] 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

[5] 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).

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 increases 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 reduces the probability to observe a move.

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 two models using instrumental variables techniques (IVREG and IVPROBIT) to analyze the causality between inventor productivity and inventor mobility. Finally, section 5 discusses the estimation results and provides implications for further research.

2 Hypotheses

This section derives from the existing literature hypothesised determinants of inventor productivity and mobility

- **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.[6] 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. Assuming productivity is increasing in intellectual ability, the following relationship is expected:

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

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6 See Becker (1964) and Denison (1964) for a survey of the relevant literature.

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 by 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 therefore assumed that

M.1: *Mobility is more common among inventors with a higher level of education than among 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: Mobility rates are higher the more important financial rewards and advancement are to the inventor.

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: The greater the inventor's dissatisfaction with the work environment the greater the likelihood that they change firms.

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.[7] Careers can therefore 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: Mobility is less common among inventors employed with large firms compared to inventors employed with small firms.

Finally, Marshall (1890) 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

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

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: *The narrower is the application of inventor specific human capital the lower is mobility.*

3 Data Source and Sample

3.1 Description of the Data

Data were collected in the course of a European project (called PatVal) sponsored by the European Commission. Units of observation are inventors who lived in Germany at the time 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.[8] Each inventor was provided with a cover letter together with a questionnaire. 3,346 responses were received,

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[8] The German Employees' Invention Act provides a set of rules that characterize the relationship between an inventor and his employer. In general, the German Employees' Invention Act (GEIA) applies to all inventions made by inventors in organizations which are governed under German law or in German subsidiaries of international organizations. According to § 5 GEIA inventors are obligated to report their inventions to the employer. If the employer does not claim the right to the invention, the invention is released to the inventor. In this case, the inventor can apply for a patent for this invention in his own name. In case of a claim to the invention (which is the case for approximately 95% of all inventions), all rights to the invention are transferred to the employer (§ 6 GEIA), and the employer is obligated to file a national patent application for the invention (§ 7 GEIA). (See http://www.arbeitnehmer-erfindergesetz.de/, access on December 18, 2006).

Both, the applicant and the inventor are mentioned in the patent document. According to Art. 81 European Patent Convention the applicant shall name the inventor(s) in the patent application and affirm that to his knowledge no other person has contributed to the invention. In case the applicant does not fulfil this 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.[9] 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 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

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obligation without cause, the patent office can refuse to grant the patent. (See http://www.european-patent-office.org/legal/epc/e/ma1.html, access on December 18, 2006).

9 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.

address data and female inventors who changed their name due to marriage may also lead to wrong matches.

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. 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[10], 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.

$$PRODUCTIVITY = \frac{number\ of\ applications}{age_{2002} - 25} \tag{1}$$

MOBILITY – Based on the full sample, a dummy variable was created taking the value 1 in case the inventor moved and 0, otherwise. A move is defined as a change of the employer. 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 was also their employer. The results revealed that 92% of the questioned inventors were employed with the applicant of the patent. Since the firm applying for the patent is almost surely the employer of the inventor, 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:

10 Hoisl (2007) shows that citation counts may be a more appropriate measure for inventor productivity. In particular, citations which are a proxy for output quality are more dependent on the inventor himself. Patent counts in contrast are largely determined by the firm that is the R&D management decides whether to file a patent application or how much to spend on R&D. Using citation data, however, requires a five year period after publication of the search report in order to compare citation counts between patents. Whereas Hoisl (2007) applied patent applications between 1978 and 1999, this paper employs applications up to the year 2002. The years between 1999 and 2002 contain important information on mobility, which would otherwise be disregarded due to missing citation data. In the following, the better mobility information is preferred to the improved productivity measure; therefore, the number of patent applications is used as an output measure.

[Table 1 about here]

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.

[Table 2 about here]

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.[11] 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.

[Table 3 about here]

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.

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

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 asked 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 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.[12] Answers were 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 about the importance of different incentives for inventive activity.

[12] 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.

Answers were again 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).

PATENT PROPENSITY – industry specific patenting intensity. Three dummy variables were generated, indicating whether the inventor is mainly active in industries with a low (reference group), medium or high patent propensity.

According to the results of Arundel and Kabla (1998) as well as Brouwer and Kleinknecht (1999)[13], first, the 30 technical areas were categorized as areas with a low, medium, and high patent propensity. In a second step, the patent applications per inventor were summarized over the different categories (low, medium and high patent propensity). For each inventor, the category possessing the largest number of patent applications was chosen as the patent propensity of the sectors in which he is basically active. If one category contained just as many applications as another, one category was chosen by random.

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

[13] Arundel and Kabla (1998) use a sample of Europe's largest firms and define the sales-weighted percentages of innovations for which a patent application was filed as a proxy for the firms' patent propensity. Brouwer and Kleinknecht (1999) use data on Dutch firms collected in the course of the Community Innovation Survey (CIS) in 1992. Firms were asked about their rating of the effectiveness of patents as a means to protect their product innovations against imitation. The answers, given on a five-point scale ranging from "insignificant" to "crucial", were used to classify different manufacturing branches according to their propensity to patent.

calculated, in the following denoted by *p*. The Herfindahl index (HI), consequently, corresponds to the sum of squared shares of applications:

$$HI = \sum_i p_i^2 \quad (2)$$

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

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:

$$TEMP_{CON} = \frac{number\ of\ applications_{t\,(\max)}}{number\ of\ applications} \quad (3)$$

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.[14]

4 Descriptive Statistics and Multivariate Results

4.1 Descriptive Results

Table 4 presents descriptive statistics. The final sample consists of 2,409 different inventors[15], 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

[14] 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 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 is 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.

[15] 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.

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 and 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. The industry specific patent propensity is almost equally distributed across the three categories. 28% of the inventors are mainly active in sectors characterized by a low patent propensity. 35% (37%) of the inventors are classified as active in sectors with a medium (high) patent propensity. 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.

[Table 4 about here]

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.

To provide a more detailed description of the productivity variable, Figure 1 shows the distribution of inventor productivity.

[Figure 1 about here]

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 1 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 2 about here]

Figure 2 reports the distribution of the number of moves per inventor. 1,526 inventors (63%) have not moved at all. 516 inventors (21%) changed their employer once, 217 inventors (9%) changed their employer twice and only 27 responding inventors (1%) moved more than five times. Due to the fact that almost two-thirds of the inventors have not moved at all and another 20% changed their employer only once, it is assumed that the aggregation of the number of moves to a dummy variable, only indicating whether the inventor moved or not, does not lead to a loss of important information. Particularly, since the aggregation concerns only about 17% of the inventors, i.e., those who moved more than once.

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, IVREG and IVPROBIT[16] will be employed. 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).

[16] Since mobility is a binary variable, the equation is estimated using the maximum-likelihood version of Stata's IVPROBIT routine.

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
incentives, technical concentration, and regional characteristics,	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, remains unaffected by environmental differences. This result seems to be surprising, since already Marshall (1890) shows that companies within the same industries cluster because industrial districts can benefit from spillovers of specialized knowledge. Additionally, firms in clusters may profit from the same economies of scale that normally only large companies are able to realize (Norton 2000). Since Marshall's seminal work the importance of clusters and agglomeration effects to enhance innovation has been confirmed extensively in the literature (e.g., Brouwer et al. 1999, Saxenian 1994). Nevertheless, local characteristics do not matter with respect to the productivity of an inventor. A possible explanation for this result, mentioned by Gambardella et al. (2006), is that geographic spillovers and local advantages may only be important in particular industries, for instance, in biotechnology or special high-tech industries. However, the data used in this paper cover a large spectrum of industries. Analyzing US patent data, Bettencourt et al. (2007, p. 12) find that larger metropolitan areas have more inventors than smaller ones and generate also more patents. But their results also indicate that "agglomeration […] does not increase on average the productivity of the individual inventor”. It is, therefore, also possible that urban agglomerations cause a selection effect. In particular, large cities may attract and maintain more high quality human capital. Consequently, local characteristics do not significantly affect productivity after controlling for the individual characteristics of the inventor.

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
external sources of knowledge	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.

Due to the fact that PRODUCTIVITY is a continuous variable and MOBILITY is a binary variable, Two Stage Least Squares (2SLS) that estimates two OLS regression models is not applicable. Therefore, in this paper a two-step procedure described by Wooldridge (2001, p. 623-625) is used, for which Wooldridge shows that the standard errors and test statistics remain asymptotically valid:

- PRODUCTIVITY

When estimating productivity, mobility, which is binary, is the only endogenous explanatory variable. Heckman (1978) calls this type of model a dummy endogenous variable model. Using the instruments described before, the following two-step IV method can be employed:

Step 1: Estimation of MOBILITY using a binary response model, i.e. a probit model, which uses maximum likelihood estimation to obtain the fitted probabilities $\hat{\Phi}_i$.

$$P(MOBILITY = 1 \mid x, z) = \Phi(X_1, ..., X_n, incentives, tech\_con, reg\_char) \tag{4.1}$$

where z are the instruments.

Step 2: Estimation of PROBILITY by IVREG including the fitted probabilities $\hat{\Phi}_i$.

$$PRODUCTIVITY = f(\hat{\Phi}_i, X_1, ..., X_n, source\_know, \varepsilon) \tag{4.2}$$

- MOBILITY

To estimate mobility, again the two-step procedure suggested by Wooldridge (2001) is applied. First an OLS regression is used to estimate the continuous endogenous explanatory variable (productivity). In step two again a method of IV is used.

Step 1: Estimation of PRODUCTIVITY using an OLS regression model including regressors that determine PRODUCTIVITY but not MOBILITY (= instruments) to obtain the fitted values $\hat{f}_i$.

$$PRODUCTIVITY = f(X_1,...,X_n, source\_know, \varepsilon) \quad (5.1)$$

Step 2: Estimation of MOBILITY by IVPROBIT including the fitted values $\hat{f}_i$.

$$P(MOBILITY = 1 \mid x, z, \hat{f}_i) = \Phi(\hat{f}_i, X_1,...,X_n, incentives, tech\_con, reg\_char) \quad (5.2)$$

4.3 Discussion of the Results

Table 5 provides the results of the IVREG and the IVPROBIT regression estimations. Model (1) contains control variables and explanatory variables required to test the hypotheses as well as two dummy variables that control for the patent propensity of the industries in which the inventor is mainly active. Model (2) includes variables controlling for the variation between technical areas to check whether the patent propensity dummies, based on the results of Arundel and Kabla (1998) and Brouwer and Kleinknecht (1999), were defined accurately. Comparing the results of Model (1) and Model (2) reveals that the patent propensity dummies work quite well. In particular, the dummies also explain industry effects leading to a decrease of the firm size effects in Model (1) compared to Model (2) (with respect to productivity and mobility). For both models, endogeneity tests were conducted. Endogeneity of the mobility dummy in the productivity regression was tested using the Durbin-Wu-Hausman test of endogeneity (Hausman 1978). To test whether productivity is endogenous in the mobility regression, the Wald test of endogeneity (Wooldridge 2001) was used. The null hypothesis of both tests indicates that the tested regressors are exogenous. A rejection of the null hypothesis means that the endogenous regressors' effects on the estimates are important, and the application of instrumental variables techniques is required. Table 5 (columns 1 and 2) show that both tests reject exogeneity of the tested regressors. Therefore, the application of IV estimation is appropriate. In the following the results of Model (1) are described in more detail.

[Table 5 about here]

- **Productivity**

I first discuss the results with respect to the productivity equation (Table 5, column 1). The *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 -0.82 implies a negative marginal productivity with regard to the age of the inventor. This means that the absolute number of patent applications per inventor increases over time, while the inventors' productivity (defined as the number of patent applications divided by age) decreases. Thus, when age increases by 10%, productivity decreases by 8.2%. The effect is significant at the 1% level. According to the literature a decreasing marginal productivity of R&D personnel may be explained by a decrease of motivation and risk-taking as well as by difficulties in keeping up with technological change (Dalton/Thompson 1971; Lehman 1966; Oberg 1960). Another possible explanation is that inventors are gradually promoted into management positions and therefore spend less time on inventing due to increasing administrative duties.

Table 5 (column 1) 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 is why the data do not reveal this relationship. An explanation for this result may be that the number of patents per inventor (= output quantity) was used as a productivity measure and that output quantity is less dependent on the characteristics of individual inventors (with exception of age and experience) than, e.g., output quality. Especially in large firms, R&D management may determine whether to file a patent application for an invention or how much to spend on R&D. It is also possible that this finding is the result of a selection effect. In particular, assume that inventors need a certain intellectual ability to invent which is also required for higher education. Consequently, most people with high levels of education have a disproportional share of inventions. However, since this study selected inventors who have at least one patented invention, every inventor should be above this threshold of intellectual ability and, consequently, education does not show a significant effect. However, hypothesis P1 is not supported by the data.

Model (1a) further reveals that exploiting the knowledge from other patent documents has no significant effect on productivity. Basically, making use of scientific literature reduces productivity by 6%. 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. Another explanation may be that absorptive capacity is needed to adequately profit from scientific knowledge. Model (1a) supports the proposition that applying scientific knowledge requires absorptive capacity. In particular, inventors who use scientific literature and who have a doctoral or post-doctoral degree increase their productivity by 4%[17]. The interaction between doctoral studies and spillovers from university research is not significant. These results, at least in part, support hypothesis P3, hypothesis P2 is neglected by the data.

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[17] The overall effect is calculated by adding up the effect of "source of scientific literature" (-0.061) and the effect of the interaction term "doctoral studies * scientific_litarature" (0.100).

Firm size is positively associated with productivity. The coefficients (except for 51 – 250 employees) are significant at the 1% level. Productivity increases 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 inventive output. Finally, as expected, inventors working in industries with a higher patent propensity are more productive that inventors working in industries where patents play a smaller role.

- **Mobility**

Model (1b) reported in Table 5 (columns 2 and 3) relates the probability to observe a move to a number of explanatory variables, characterizing the inventor as well as the work environment.

The set of dummies controlling for the level of education of the inventor shows that an increasing level of education raises the probability of a move. A university degree raises the probability that an inventor changes his employer by about 8.5%, a doctoral or post-doctoral degree by about 9.4% (compared to the reference group: high school or less). These findings support hypothesis M1 that mobility is more common among inventors with a higher level of education. 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 the probability of a move. Classification of advancement as important for inventive activity increases the probability that an inventor changes his employer by 5%. 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 negatively influences the inventors' probability to move. The probability of a move decreases almost monotonically with firm size. For instance, inventors working for firms with 5,001-10,000 employees move 17% less likely compared to the reference group (less than 51 employees). These findings support hypothesis M4 that mobility is less likely in large firms. 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.

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 one unit decreases mobility by 18.4%. 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 age does not significantly influence the probability to observe a move. 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 probability of a move. 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.

Additionally, 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 are more likely to move. 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. Finally, mobility is more common in industries with a medium patent propensity compared to the reference group (low patent propensity).

- **Causality**

After all, 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 (1a) shows that movers are 14.5% more productive than non-movers. The coefficient is significant at the 5% level. This outcome is in accordance with 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, Model (1b) indicates that an increase in productivity by one unit decreases the probability of a move by 18%. The effect is significant at the 1% level. 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. 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.

5 Conclusion

In this paper, the causality between inventor productivity and inventor mobility was analyzed using instrumental variable approaches to deal with the endogeneity problem between productivity and mobility. One of the key findings of this paper is that there exists a simultaneous relationship between inventor mobility and inventor productivity: Movers are more productive than non-moving inventors. In contrast, more productive inventors are less likely to move.

The results concerning the determinants of productivity and mobility provided in 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. 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 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 take advantage of this legal regulation since they receive a compensation for their merits. 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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Table 1

Example 1 (applicant sequence of inventor 1)

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

Table 2

Example 2 (applicant sequence of inventor 2)

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

Table 3

Example 3 (applicant sequence of inventor 3)

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

Table 4

Descriptive statistics (N = 2,409)

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
patent propensity (industry specific patenting intensity)				
low patent propensity	0.28		0	1
medium patent propensity	0.35		0	1
high patent propensity	0.37		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 5

IVREG and IVPROBIT Regressions with heteroskedasticity-robust standard errors

	Model (1)		
	(a) IVREG	**(b.1) IVPROBIT**	**(b.2) (dy/dx)♦**
dependent variable	**log(productivity)**	**dummy_mobil**	**dummy_mobil**
productivity_hat [fitted values]		-0.491***	-0.184***
		[0.171]	[0.055]
mobil_hat [Pr(d_mobil)]	0.145*		
	[0.079]		
log(productivity age) (log(age-25))	-0.819***		
	[0.039]		
productivity age (age-25)		0.002	0.001
		[0.003]	[0.001]
log(total number of claims)	0.740***	0.237***	0.089***
	[0.010]	[0.050]	[0.018]
share of patents opposed	-0.155**	-0.19	-0.071
	[0.064]	[0.252]	[0.098]
share of patents refused	0.198	-0.11	-0.041
	[0.157]	[0.544]	[0.223]
share of patents withdrawn	0.242***	0.565***	0.211***
	[0.050]	[0.183]	[0.068]
level of education, terminal degree (reference group: high school diploma or less)			
university studies	0.004	0.228**	0.085**
	[0.022]	[0.091]	[0.034]
doctoral/postdoctoral studies	-0.032	0.249**	0.094**
	[0.035]	[0.102]	[0.038]
incentive - increase in salary		0.045	0.017
		[0.073]	[0.027]
incentive - advancement		0.145**	0.054**
		[0.070]	[0.026]
incentive - improvement of working cond.		-0.035	-0.013
		[0.062]	[0.023]
source of knowledge - universities	0.006		
	[0.023]		
doctoral studies * knowledge_university	-0.049		
	[0.035]		
source of knowledge - literature	-0.061***		
	[0.019]		
doctoral studies * knowledge_literature	0.100***		
	[0.034]		
source of knowledge - other patents	0.018		
	[0.016]		
source of knowledge - user	-0.018		
	[0.016]		
source of knowledge - competitors	0.011		
	[0.015]		
Observations	2409	2409	2409
F-test (df) / Chi2-test (df)	F(25, 2383)=658.56	chi2(24)=223.27	chi2(24)=249.08
R-squared	0.891		
Test of endogeneity: H0: regressor is exogenous			
Durbin-Wu-Hausman test of endogeneity	chi2(1)=5.64, p=0.018		
Wald test of exogeneity		chi2(1)=2.77, p=0.096	

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

♦ marginal effects after ivprobit computed with divprobit; the marginal effect of each independent variable is reported holding the remaining variables at their mean; for dummy variables dy/dx represents the discrete change from 0 to 1

Table 5 continued

IVREG and IVPROBIT Regressions with heteroskedasticity-robust standard errors

	Model (1)		
	(a) IVREG	**(b.1) IVPROBIT**	**(b.2) (dy/dx)♦**
dependent variable	**log(productivity)**	**dummy_mobil**	**dummy_mobil**
firm size in number of employees (reference group: less than 51 employees)			
51 - 250 employees	0.019	-0.204	-0.074
	[0.040]	[0.159]	[0.055]
251 - 500 employees	0.148***	-0.358**	-0.124**
	[0.042]	[0.164]	[0.051]
501 - 1,500 employees	0.137***	-0.375**	-0.131***
	[0.040]	[0.148]	[0.048]
1,501 - 5,000 employees	0.179***	-0.615***	-0.207***
	[0.041]	[0.146]	[0.042]
5,001 - 10,000 employees	0.225***	-0.513***	-0.173***
	[0.042]	[0.159]	[0.046]
10,001 - 50,000 employees	0.283***	-0.705***	-0.235***
	[0.042]	[0.148]	[0.041]
more than 50,000 employees	0.325***	-0.811***	-0.266***
	[0.042]	[0.147]	[0.040]
technical concentration		-0.493***	-0.184***
		[0.112]	[0.042]
temporal concentration	-0.632***	-0.698***	-0.261***
	[0.054]	[0.191]	[0.074]
regional characteristics (reference group: less than 500,000 inhabitants)			
city with more than 1 mio inhabitants		0.291***	0.112***
		[0.092]	[0.036]
city with 500.000 to 1 mio inhabitants		0.497***	0.193***
		[0.081]	[0.032]
patent propensity (patents per R&D expenditures) (reference group: industries with low patent propensty)			
high patent propensity	0.082***	0.131	0.050*
	[0.020]	[0.081]	[0.030]
medium patent propensity	0.019	0.110*	0.041*
	[0.016]	[0.065]	[0.025]
distribution of patents across technical areas Wald test	not included	not included	-
Constant	-1.932***	-0.727**	
	[0.173]	[0.311]	
Observations	2409	2409	2409
F-test (df) / Chi2-test (df)	F(25, 2383)=658.56	chi2(24)=223.27	chi2(24)=249.08
R-squared	0.891		
Test of endogeneity: H0: regressor is exogenous			
Durbin-Wu-Hausman test of endogeneity	chi2(1)=5.64, p=0.018		
Wald test of exogeneity		chi2(1)=2.77, p=0.096	

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

♦ marginal effects after ivprobit computed with divprobit; the marginal effect of each independent variable is reported holding the remaining variables at their mean; for dummy variables dy/dx represents the discrete change from 0 to 1

Table 5 continued

IVREG and IVPROBIT Regressions with heteroskedasticity-robust standard errors

	Model (2)		
	(a) IVREG	(b.1) IVPROBIT	(b.2) (dy/dx)♦
dependent variable	**log(productivity)**	**dummy_mobil**	**dummy_mobil**
productivity_hat [fitted values]		-0.466*** [0.176]	-0.173*** [0.056]
mobil_hat [Pr(d_mobil)]	0.221*** [0.085]		
log(productivity age) (log(age-25))	-0.802*** [0.040]		
productivity age (age-25)		0.002 [0.003]	0.001 [0.001]
log(total number of claims)	0.733*** [0.010]	0.244*** [0.052]	0.091*** [0.018]
share of patents opposed	-0.146** [0.065]	-0.014 [0.260]	-0.005 [0.100]
share of patents refused	0.238 [0.167]	-0.216 [0.544]	-0.080 [0.226]
share of patents withdrawn	0.219*** [0.052]	0.599*** [0.186]	0.223*** [0.070]
level of education, terminal degree (reference group: high school diploma or less)			
university studies	-0.005 [0.023]	0.213** [0.093]	0.079** [0.034]
doctoral/postdoctoral studies	-0.038 [0.036]	0.215** [0.107]	0.081** [0.039]
incentive - increase in salary		0.053 [0.075]	0.020 [0.027]
incentive - advancement		0.138* [0.071]	0.051* [0.026]
incentive - improvement of working cond.		-0.022 [0.063]	-0.008 [0.023]
source of knowledge - universities	0.001 [0.024]		
doctoral studies * knowledge_university	-0.03 [0.035]		
source of knowledge - literature	-0.063*** [0.019]		
doctoral studies * knowledge_literature	0.088** [0.035]		
source of knowledge - other patents	0.017 [0.017]		
source of knowledge - user	-0.007 [0.017]		
source of knowledge - competitors	0.011 [0.015]		
Observations	2409	2409	2409
F-test (df) / Chi2-test (df)	F(52,2356)=316.58	chi2(51)=288.60	chi2(51)=327.58
R-squared	0.888		
Test of endogeneity: H0: regressor is exogenous			
Durbin-Wu-Hausman test of endogeneity	chi2(1)=10.57, p=0.001		
Wald test of exogeneity		chi2(1)=3.19, p=0.074	

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

♦ marginal effects after ivprobit computed with divprobit; the marginal effect of each independent variable is reported holding the remaining variables at their mean; for dummy variables dy/dx represents the discrete change from 0 to 1

Table 5 continued

IVREG and IVPROBIT Regressions with heteroskedasticity-robust standard errors

	Model (2)		
	(a) IVREG	**(b.1) IVPROBIT**	**(b.2) (dy/dx)♦**
dependent variable	**log(productivity)**	**dummy_mobil**	**dummy_mobil**
firm size in number of employees (reference group: less than 51 employees)			
51 - 250 employees	0.022	-0.170	-0.061
	[0.042]	[0.162]	[0.057]
251 - 500 employees	0.152***	-0.430**	-0.146**
	[0.044]	[0.169]	[0.050]
501 - 1,500 employees	0.140***	-0.416***	-0.144**
	[0.041]	[0.152]	[0.047]
1,501 - 5,000 employees	0.183***	-0.706***	-0.231***
	[0.043]	[0.151]	[0.041]
5,001 - 10,000 employees	0.208***	-0.564***	-0.186***
	[0.044]	[0.164]	[0.045]
10,001 - 50,000 employees	0.264***	-0.771***	-0.251***
	[0.044]	[0.154]	[0.041]
more than 50,000 employees	0.307***	-0.915***	-0.292***
	[0.046]	[0.155]	[0.039]
technical concentration		-0.507***	-0.189***
		[0.119]	[0.044]
temporal concentration	-0.605***	-0.775***	-0.288***
	[0.056]	[0.194]	[0.075]
regional characteristics (reference group: less than 500,000 inhabitants)			
city with more than 1 mio inhabitants		0.222**	0.085**
		[0.097]	[0.038]
city with 500.000 to 1 mio inhabitants		0.492***	0.191***
		[0.085]	[0.033]
patent propensity (patents per R&D expenditures) (reference group: industries with low patent propensty)			
high patent propensity			
medium patent propensity			
distribution of patents across technical areas	included	included	-
Wald test	Chi2(29)=3.67 p=0.000	Chi2(29)=73.39 p=0.000	
Constant	-1.974***	-0.911**	
	[0.185]	[0.405]	
Observations	2409	2409	2409
F-test (df) / Chi2-test (df)	F(52,2356)=316.58	chi2(51)=288.60	chi2(51)=327.58
R-squared	0.888		
Test of endogeneity: H0: regressor is exogenous			
Durbin-Wu-Hausman test of endogeneity	chi2(1)=10.57, p=0.001		
Wald test of exogeneity		chi2(1)=3.19, p=0.074	

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

♦ marginal effects after ivprobit computed with divprobit; the marginal effect of each independent variable is reported holding the remaining variables at their mean; for dummy variables dy/dx represents the discrete change from 0 to 1

Figure 1

Distribution of inventor productivity (N = 2,409)

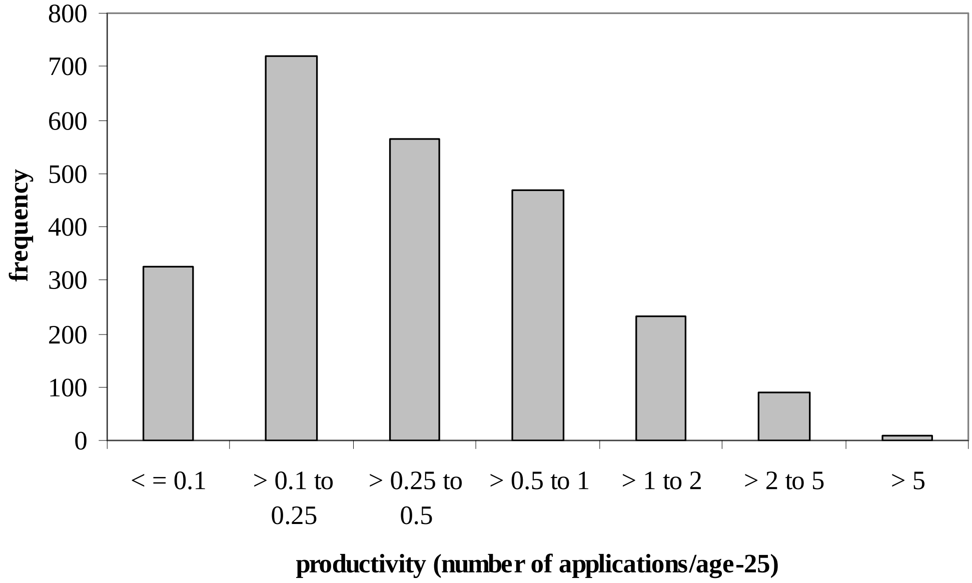

Figure 2

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