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Does Mobility Increase the Productivity of Inventors? New Evidence from a Quasi-Experimental Design

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Abstract:

Although labor mobility has been recognized as a key mechanism to transfer tacit knowledge, prior research on inventors has so far neglected to address the question of the consequence of a move on inventive performance. This paper improves on the current R&D literature by presenting a quasi-experimental approach to explore the effect of a specific move of an inventor on his performance. The quasi-experiment provides a favorable setting to test this relationship since it allows interpreting changes of inventive performance causal to a particular move. Results reveal that in the post-move period inventors produce more patentable innovations that are characterized by a higher grant rate and by higher value. However, the gains from movement seem to dissipate over time. Data for the analysis was derived from a survey of German inventors (N = 3,049).

Keywords: Inventor, Productivity, Mobility, Quasi Experiment, Patent

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1 Introduction

Knowledge is one of the most important sources of innovative activity (Feldman 1999). Therefore, an often-discussed phenomenon in the literature is the access to knowledge after hiring a key inventor from another firm. Researchers argue that a move[1] of an inventor to another firm can lead to knowledge transfers (Arrow 1962; Almeida/Kogut 1999). Firms characterized by a "lower technology" level can use this knowledge to catch up and thus are motivated to attract productive inventors (Gilfillan 1935; Song et al. 2003). Especially, the transfer of tacit knowledge that is otherwise immobile is facilitated by inventor mobility (Dosi 1988).

What has so far hardly been addressed in the inventor related literature is the consequence of a move on inventive performance.[2] A change of the employer means that inventors work in a new environment. Human capital literature, e.g., confirms that the work environment has an important effect on the productivity of workers (Rauch 1991). Given that colleagues or the availability of resources, decisively determine inventive output and assuming that one single inventor normally contributes only partly to an invention, it is unclear whether a firm's innovative performance benefits from picking one inventor and transferring this inventor to a new job. This question is of utmost importance to firms since hiring a new inventor is an investment decision under uncertainty.

Labor economics literature provides first evidence to the consequences of labor mobility. Topel and Ward (1992) propose that a move increases the match quality between employer

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1 In the following study, a move of an inventor is defined as a change of his employer.

2 Hoisl (2006) showed that there is a causal relationship between inventor mobility and inventive performance. To deal with this endogeneity problem, instrumental variables techniques were employed. Results showed 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.

and employee. A better match quality should then lead to an increase in the worker's own performance (Jovanovic 1979; Liu 1986). A move can, therefore, be interpreted as a search and sorting process to improve the employer-employee match, resulting in a better performance of the employee. Whether the results of the labor economics literature are also appropriate to R&D personnel in general and to inventors in particular has so far hardly been addressed in the literature.

To shed more light on the relationship between a move of an inventor and his inventive performance and to decrease the uncertainty when hiring a new inventor, this exploratory study provides a quasi-experimental design, which compares the performance of an inventor[3] before and after a selected move relative to a control group. This research methodology improves on the current literature by providing more robust results. Especially, it allows interpreting changes of inventive performance causal to a particular move.

This paper makes use of data collected in a large-scale survey of German inventors, who hold at least one granted European patent. The data include demographic information on more than 3,000 inventors, for instance, the age and the educational degree that will be used to construct an appropriate control group. Patent data from the online EPOLINE database of the European Patent Office (EPO) was further used to trace mobility of inventors over time. All patent applications of the surveyed inventors were included with priority years between 1985 and 1999.

Results reveal that the number of patents, 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. Hence, inventors

[3] To measure inventive performance quantity measures (number of patents per inventor) as well as quality measures (grant rate, opposition rate, and number of citations) will be employed.

not only produce more inventions in the post-move period, the inventions more often meet the requirements for patentability (novelty, inventive step, and usefulness) and are also of higher value. However, the gains from mobility seem to dissipate over time.

The remainder of this paper is organized as follows. Section 2 provides a summary of the previous literature. A description of the methodology used is presented in section 3. Section 4 contains a description of the dataset and of the variables used in the empirical analysis and displays the construction of the control group. Section 5 contains descriptive and multivariate results of the quasi-experiment. Finally, section 6 presents a discussion of the results and provides implications for further research.

2 Literature Review

In the following, a review of important results from the knowledge transfer literature will be given. The first paper focuses on the importance of localization to transfer knowledge. The three following papers discuss mechanisms to transfer knowledge such as, for example, labor mobility or alliances. Additionally, the question is addressed whether social ties facilitate the diffusion of knowledge. The last group of papers addresses the characteristics of moving inventors in the pre-move period as well as the characteristics of the patents of mobile inventors.

Almeida and Kogut (1999) use patent citation data to investigate the relationship between inventor mobility and the localization of technological knowledge. The analysis relies on US patent data from 12 top regional clusters (e.g., Silicon Valley) accounting for 95% of the highly cited patents. The authors find that knowledge is transferred through labor markets. However, the knowledge is embedded in regional clusters. The degree of the localization of knowledge varies across regions. For instance, semiconductor knowledge is highly concentrated in the Silicon Valley but less in Southern California. A possible explanation for a strong localization of knowledge in the Silicon Valley is intra-regional mobility of experts. Cross-regional mobility, on the contrary, leads to a wider spread of ideas.

Given that knowledge is geographically and technologically localized, Rosenkopf and Almeida (2001) explore if strategic alliances as well as mobility of inventors in the semiconductor industry enable inter-firm knowledge flows across technical boundaries and technical fields. Results show that mobility and alliances facilitate knowledge transfer regardless of whether the inventor moves inter- or cross-regional. Additionally, knowledge turns out to be localized within technical contexts. Nevertheless, the impact of alliances and mobility increases with technological distance. In particular, it seems that the higher technological similarity of two firms the lower the probability to draw on the other's knowledge. Song et al. (2003) address a similar question by analyzing to which extent inter-firm mobility of R&D engineers can be used to reach beyond current technical and geographical boundaries. The survey relies on 180 mobile US inventors who are responsible for 534 patented inventions. Results show that labor mobility indeed serves as an important mechanism to acquire complex and tacit knowledge from other firms, even if these firms are technologically and geographically distant.

Moen (2000) discusses the link between mobility and spillovers from the point of few of the firm that is loosing an inventor. He argues that labor mobility makes it difficult for firms to appropriate returns to R&D investment and therefore, mobility should lead to an underinvestment in R&D. An empirical test of this hypothesis relying on matched employer-employee data from the Norwegian machinery and equipment industry shows that R&D personnel "pay for the knowledge they accumulate on the job through lower wages in the beginning of their career, and they later earn a return on these implicit investments through higher wages" (Moen 2000, 2). Furthermore, labor mobility has often been considered as a means to catch up with the sate of the art or to transfer knowledge from high-tech to low-tech firms. But the results of this survey show that R&D personnel tends to move to a firm characterized by a similar R&D intensity as the former employer.

Agrawal et al. (2003) go one step further, given that co-location fosters knowledge transfer, the authors analyze whether labor mobility decreases knowledge flows between the moving inventor and his former employer in the after-move period. This question is of special importance since an ongoing exchange of knowledge accommodates for the dynamic character of technology. Using US patent data, the authors find that knowledge transfer also takes place after formerly co-localized inventors are separated because one of the inventors moved to another firm. The authors explain their findings by the fact that social ties that facilitate knowledge transfer persist even after a move.

Palomeras (2004) addresses the issue of which inventor characteristics provide an indication of whether an inventor possesses valuable knowledge for other firms and whether this inventor is able to transfer this knowledge. Based on data of 2,394 inventors at IBM, she finds that patents of movers receive more citations in the pre-move period compared to non-movers. These results seem to indicate that the more important inventors move. However, the author only considers the pre-move period. The post-move period has so far been neglected.

Trajtenberg (2005) is one of the first to analyze the relationship between mobility and labor productivity for R&D personnel. He analyzes the consequences of mobility relying on a sample of 1,565,780 inventors listed on U.S. patent documents. Overall, 216,581 inventors (33%) are movers, which means that these inventors changed their employer at least once. The author finds first evidence that mobility has a positive impact on work performance, in particular, patents of mobile inventors receive more citations. One drawback of this study is that it lacks data on the characteristics of the underlying inventors. Second, the given results are not interpretable causally to a particular move.

Undoubtedly, labor mobility provides access to external knowledge since especially tacit knowledge is embedded in the heads of employees and thus is hardly accessible without transferring the employee. The literature summarized above provides evidence of the existence and of the importance of these knowledge flows. First, studies trace these knowledge flows by employing patent citation data. Second, the literature provides indication that those inventors who move possess of more valuable knowledge compared to non-movers. The question whether an inventor is able to convert this knowledge into new inventions after being transferred into a new work environment remains still unclear. The human resource literature shows that the environment determines the performance of employees. Hence, it is interesting to analyze the consequences of picking a single inventor (even if it is a key inventor) and transferring this inventor to another firm.

The purpose of this paper is to contribute to the knowledge transfer literature by analyzing whether hiring an inventor from another firm is a reasonable mean to increase the firm's innovative performance. The paper improves on the current literature (1) by applying an empirical setting that allows analyzing the after-move performance of an inventor causal to a particular move, and (2) by including inventor characteristics derived from a mail questionnaire. In particular, information on the age and the educational background of the inventors will be used to keep inventor characteristics constant when comparing mobile inventors with non-mobile control inventors.

3 Research Methodology - Quasi Experimental Design

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; Cook/Campbell 1979). One of the most often used quasi-experimental designs is the difference-in-differences estimation approach[4], 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 for the periods before and after the treatment. The difference-in-differences estimator is based on the 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. In the following, the treatment group contains movers (inventors who changed their employer at least once), the control group consists of non-movers, and the treatment is defined as a move. For the time periods three and four year windows before and after the move are employed. To measure the performance of the inventors, quantitative and qualitative measures will be used. The overall number of patent applications per inventor represents a quantity measure. The status of the patent (grant, withdrawal, or refusal), the share of patents opposed, and the number of forward and backward citations form different quality measures.

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

To empirically test whether a move has a positive impact on inventive performance, this paper applies a difference-in-differences estimation approach. The difference-in-differences estimator $\hat{\delta}_1$ is derived by taking the mean value of each group's outcome (treatment and control group) before and after the treatment and then by calculating the difference of the differences of these means (Wooldridge 1999). Therefore, the following equation is constructed:

$$\hat{\delta}_1 = (\overline{mobile}_{post} - \overline{control}_{post}) - (\overline{mobile}_{pre} - \overline{control}_{pre}) = \Delta_{post} - \Delta_{pre} \qquad (1)$$

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 are presented below. The same results as provided by the t-tests can be achieved by using an OLS regression framework. However, an OLS regression has the advantage that additional control regressors can be included in the analysis. Therefore, OLS regression will be used in a second step to control for multiple movements of inventors.

4 Data Description and Construction of a Control Group

4.1 Data

The data used in this study were collected in the course of a project, sponsored by the European Commission, called PatVal[5]. Research groups from six European universities participated in this project. In each of the six countries (France, Germany, Great Britain, Italy, Spain, and the Netherlands) domestic inventors were surveyed simultaneously regarding their granted EP patents. The following exploratory analysis relies only on the German dataset. Units of observation are inventors who lived in Germany at the time of application of the respective patent. 10,500 EP patents were chosen by stratified random sampling[6] 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 information was obtained using a questionnaire. As the addressee of the survey, the first inventor listed on the patent document was chosen. 3,049 responses were received. The data from the questionnaire were merged with bibliographic and procedural information on the respective patents, obtained from the online EPOLINE database. The database contains information on all published EP patent applications as well as all published PCT applications since the founding of the EPO in 1978. The dataset corresponds to the EPOLINE data as of March 1st, 2003. To trace the mobility of each inventor over time, the EPOLINE database was further used to search for all patent applications belonging to the 3,049 inventors with

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[5] PatVal = “The Value of European Patents: Empirical Models and Policy Implications Based on a Survey of European Inventors”

[6] The sample of 10,500 patents includes all opposed patents (1,048) and patents which were not opposed but received at least one citation (5,333), and a random sample of 4,119 patents drawn from the remaining 9,212 patents.

priority dates between 1985 and 1999.[7] Inventors holding only one patent (352 inventors) were removed from the sample since a move is only observable if the inventor is responsible for at least two patent applications during the time period under consideration. Therefore, the final sample contains 2,697 inventors.

Before describing the research methodology, a few limitations of the use of patent data to trace mobility need to be mentioned. First, a lack of standardization of the spelling of inventors' names in the patent documents leads to a name matching problem. This matching problem complicates the search for all patent applications per inventor, especially for inventors with common last names. Identical names may refer to different inventors and different spellings may refer to the same inventor. Incomplete address data and the fact that some female inventors change their names due to marriage lead to wrong matches. Even if the matching procedure works well, it is only possible to identify a move if the inventor applied for another patent after he changed the employer. 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. Furthermore, the fact that different applicants are listed on a patent document 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. To reduce biases, the classification of "move" (the inventor changed the employer) and "no move" (the inventor did not change the employer) was corrected manually.[8] Additionally, the results from the PatVal questionnaires, including questions related to the mobility of the inventors, were utilized to confirm the

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7 See Giuri, Mariani et al. (2005) for a detailed description of the PatVal-EU survey results.

8 For more information according to the name matching procedure, see Hoisl (2006).

matching and mobility outcomes. Given this limitations one has to be cautious when deriving implications from the results.

4.2 Description of the Variables

As already described, the data used in this paper originate from two data sources: first, from a survey of 3,049 German inventors and, second, from the EPOLINE database of the EPO. A brief description of the variables to be used will be given in the following:

Move - Based on the full sample, a variable was created indicating whether the inventor changed his employer or not. The variable was constructed as a dummy variable and takes the value 1 if the inventor moved, and 0 otherwise.

Age - The variable contains the age of the inventors at the time of the survey.

Level of education - The questionnaire included a question asking the respondents for their terminal degree. The education variable was aggregated to three groups: (1) secondary school, high school diploma, or vocational training, (2) vocational academy (Berufsakademie) or university studies, and (3) doctoral or postdoctoral studies.

Technical specialization - 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).

Number of applications - This variable includes the total number of patent applications per inventor. Each inventor was assigned a whole patent irrespective of the number of co-inventors.

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.

Opposition - 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.

Number of references - This variable includes the number of references contained in the search reports provided by the patent examiners at the EPO. References represent subject matter that is held against the claims of a patent application.

Number of citations - This variable includes the number of citations a patent application received within 5 years following the publication of the search report, added up for the total number of patent applications per inventor.

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.

Inventor team size - The number of inventors provided on the patent document was used to measure the size of the inventor team.

4.3 Construction of the Treatment Group and of the Control Group

As mentioned above, 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 EPO 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 was employed.[9]

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 that 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

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9 Since the search report is published about one year after a firm or an individual inventor applied for the EP patent, patent data as of 2005 are needed to calculate five years citation lags for patents with priority year 1999.

effects between the treatment and the control group that are not attributable to the treatment itself. Within this study, three matching criteria were used: the age of the inventor, his educational background as well as the main technical area in which the inventor is active. If it is not possible to identify eligible characteristics for the control group, one could pick inventors randomly from the group of non-treated units. 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 for 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.

5. Results

5.1 Descriptive Results

Table 1, provides descriptive statistics of the above mentioned variables. As already mentioned, the final sample contains 352 mobile inventors and 352 non-mobile control inventors, who have the same age, educational background and technical specialization.

Whereas columns 1 to 4 present descriptive statistics for the full sample, columns 5 to 12 provide summary statistics for the treatment and the control group separately. In the following, the results based on the full sample will be provided. The two sub-samples will only be addressed in case the means of the two sub-samples differ considerably.

Variable	Full sample (N = 704) Mean	S.D.	Median	Max.
number of patent applications	16.01	21.10	10	308
share of granted patents opposed	0.05	0.10	0	0.67
share of applications granted	0.69	0.22	0.69	1
share of applications refused	0.02	0.05	0	0.25
share of applications withdrawn	0.16	0.17	0.13	0.72
cumulative number of references	65.04	81.02	42	1,188
number of references per patent application	4.23	1.09	4.07	9.60
cumulative number of citations	28.34	50.30	13	819
number of citations per patent application	1.51	0.98	1.30	7.25
cumulative number of claims	167.10	218.54	99	2,986
number of claims per patent application	10.64	3.92	9.80	32.50
size of the inventor team (per patent)	3.16	1.37	3.03	10.08

Table 1: Descriptive statistics of the full sample (N = 704) as well as of the treatment group (N = 352) and the control group (N = 352)

	Mobile inventors (N = 352)				Control inventors (N = 352)			
Variable	Mean	S.D.	Median	Max.	Mean	S.D.	Median	Max.
number of patent applications	14.47	15.35	9	119	17.55	25.53	10	315
share of granted patents opposed	0.05	0.09	0	0.50	0.05	0.10	0	0.67
share of applications granted	0.68	0.22	0.70	1	0.69	0.21	0.69	1
share of applications refused	0.02	0.05	0	0.25	0.02	0.05	0	0.25
share of applications withdrawn	0.17	0.17	0.13	0.70	0.16	0.17	0.12	0.72
cumulative number of references	59.91	61.94	40	378	70.17	96.22	44	1,188
number of references per patent appl.	4.29	1.17	4.09	8.50	4.18	1.01	4.01	9.60
cumulative number of citations	26.60	40.48	12	373	30.08	58.51	14	819
number of citations per patent appl.	1.52	1.05	1.33	7.25	1.49	0.91	1.29	5.25
cumulative number of claims	165.23	190.80	97	1,310	168.96	243.40	102.50	2,986
number of claims per patent appl.	11.22	4.05	10.68	26.67	10.05	3.71	9.07	32.50
size of the inventor team (per patent)	3.11	1.34	3	10.08	3.21	1.40	3.08	8

Table 1 (continued): Descriptive statistics of the full sample (N = 704) as well as of the treatment group (N = 352) and the control group (N = 352)

Each of the 704 inventors is on average responsible for about 16 EP patent applications. The total number of applications per inventor ranges between 2 and 308. A median amounting to

10 patents indicates that the distribution of the patents per inventor is highly skewed. The mean number of patents of the mobile inventors amounts to 14.5, whereas the mean number of patents of the control inventors amounts to 17.6 patents. The difference arises at least partially due to the fact that one control inventor holds 315 patents, whereas the mobile inventor with the maximum number of patents is responsible for only 119 patents. The median, however, does not vary distinctly between the two groups ($median_{movers} = 9$, $median_{non\text{-}movers} = 10$).

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 patent examiner. 70% of the applications were finally granted.[10]

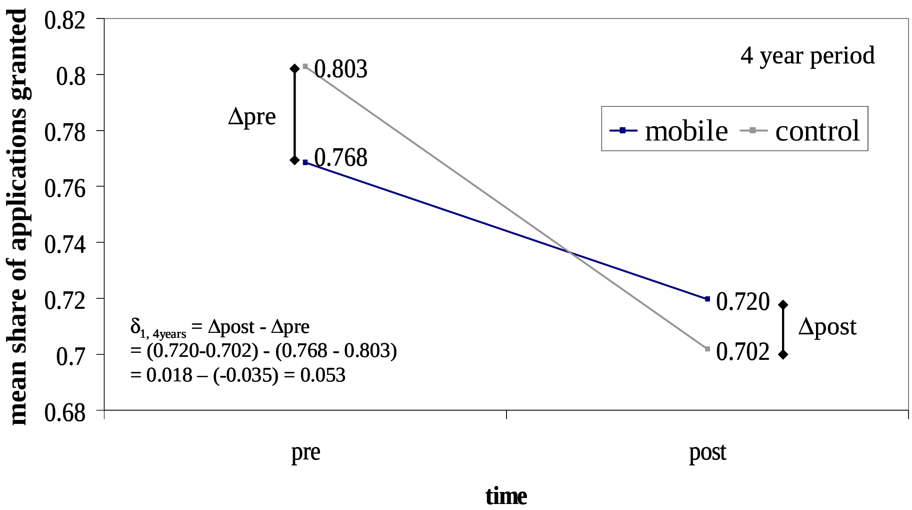
The cumulative number of applications per inventor received an average of 65.04 references made by the patent examiners at the EPO. Each patent application received on average 4.23 references. Furthermore the cumulative number of patent applications per inventor received an average of 28.3 citations from subsequent patents (each application received on average 1.51 citations). The median of the cumulative number of citations amounts to 13. A mean that is more than twice as large as the median also points at a highly skewed distribution of the number of citations. Whereas Table 1 shows that the control inventors' patents altogether received more references and also more citations, the number of references and the number of citations per patent application are almost identical for both groups. The inventors' applications altogether contained an average of 10.64 claims. The number of claims per patent

[10] Even though a number of applications were still pending, the number of granted patents was remarkably high. Wagner (2007) shows that the mean grant rate of the total population of applications at the EPO between 1978 and 2003 calculated, excluding pending applications procedures, amounts to 64%. The high grant rate within this sample (1) occurs due to the over-sampling of important patents during the PatVal-project and (2) is also an effect of the matching procedure, since inventors who hold more patents are more likely to be included in the treatment as well as in the control group.

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 Difference-in Difference Estimation Results

Table 2 displays the outcomes of the t-tests. As described before, different measures were employed to account for the performance of an inventor. The number of applications represents a quantitative measure and the status variables, oppositions, and the number of citations provide qualitative measures. First of all, results show that the number of applications does not change due to the move - neither in the 3 nor 4 year window before and after the move. However, the incident of a move has a positive impact on the mean share of applications granted[11]. 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.



Figures 1: Difference-in-differences estimator calculated for the mean share of patents granted (4 year period)

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[11] 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. The mean share of patents pending amounted to 13% in both groups (the mobile inventors and the control inventors).

Figure 1 illustrates the difference-in-differences estimator for the mean share of applications granted for the 4 year period. The Figure shows that 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 cross over is the matching approach. An increasing match quality between employer and employee after the move, as proposed by Topel and Ward (1992), 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% were pending, only 41% of the patents were granted and 38% were pending if the patents were filed in 1997. Finally, when 1999 is the priority year, only 12% of the applications were granted and 77% were pending.

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). This result suggests an increase of the value of the applications or at least an increase of the 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.

	number of applications		share of applications granted		share of applications refused	
	4 years	3 years	4 years	3 years	4 years	3 years
($mobile_{post}$ – $control_{post}$)	-1.293	-1.063	0.018	0.043	-0.005	-0.004
($mobile_{pre}$ – $control_{pre}$)	-1.011	-0.707	-0.034	-0.031	-0.001	0.0002
diff.-in-diff.	-0.281	-0.355	0.052*	0.074**	-0.004	-0.005
t-value	0.57	0.99	1.84	2.51	-0.413	-0.43

	share of applications withdrawn		share of applications opposed		number of references per patent application	
	4 years	3 years	4 years	3 years	4 years	3 years
($mobile_{post}$ – $control_{post}$)	-0.021	-0.026	0.007	0.014	0.275	0.320
($mobile_{pre}$ – $control_{pre}$)	0.038	0.034	-0.016	-0.022	0.035	0.003
diff.-in-diff.	-0.058**	-0.060**	0.021	0.035*	0.240	0.318**
t-value	-2.31	-2.24	1.20	1.83	1.55	2.06

	number of citations per patent application		number of claims per application		number of inventors per patent	
	4 years	3 years	4 years	3 years	4 years	3 years
($mobile_{post}$ – $control_{post}$)	0.134	0.190	1.224	1.357	-0.271	-0.307
($mobile_{pre}$ – $control_{pre}$)	-0.066	-0.099	1.188	1.144	-0.045	-0.073
diff.-in-diff.	0.200	0.289*	0.036	0.214	-0.226**	-0.233**
t-value	1.34	1.85	-0.09	-0.48	2.02	1.97

Table 2: 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)

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 when the 4 year window is considered. Thus, the results suggest that the opposition effect diminishes over time.

In addition to the results described above, reference and citation counts also 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 when the 3 year window is employed. Overall, a move leads to an increase in the number of references by 0.32 references per application. As to citation counts, the difference-in-differences estimator indicates that the number of citations increases 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 seen as a second source of self-citations.

The number of claims per patent is not affected by a 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 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.

Overall, the results of Table 2 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 or the transferred knowledge becomes obsolete. A third explanation may be that inventors who move to a new company bring new know-how, ideas and skills to the company. A combination of existing know-how and skills with new ideas could lead to an increase in innovative activity. Over time, know-how and skills become more and more similar leading to a reduction of inventive activity. It is also possible that the units of observation are inventors during the first years after the move but leave R&D for a job in sales, marketing, or management after about three years. Intra-firm mobility leads to invisibility of the inventor in terms of patents and consequently, the mean inventive performance seems to decrease over time.

5.3 OLS Regression Framework

The t-tests described before considered one particular move that took place before between 1990 and 1995. In case the inventors moved repeatedly during this time, 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. The following equation, including a control dummy for inventors who moved more than once during their inventive life, will be estimated:

$$y = \beta_0 + \delta_0 * mobile + \delta_1 * post + \delta_2 * (mobile * post) + \delta_3 * mult\_mobil + u \qquad (2)$$

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 the interaction between *mobile* and *post*. Hence $\hat{\delta}_2$ is again the difference-in-differences estimator that is the true causal effect of the treatment (= move) on the outcome for the treatment group. *mult_mobile* 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. However, it is important to mention that $\hat{\delta}_3$, the coefficient of the multiple mover dummy, is no longer interpretable causally since the coefficient is no difference-in-differences estimator.

Table 3 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. However, it has to be mentioned that the p-value of the interaction term in the citation regression (Model 2d) is only slightly above the 10% level (p = 0.111).

In the following, only the results of Model 2 are presented. In particular, the impact of multiple movements on inventive output is analyzed. Since multiple moves had no significant effect on the status of the patent applications (share of patents granted, withdrawn and refused), I refrained from displaying these results.

Model 2a 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. 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 not at all.

When considering the number of citations (Model 2d), 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 1 shows 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 2e) – but only when the 4 year period is considered. Table 3 displays that the number of claims per patent increases by 0.7. Comparing this result with the descriptive statistics provided in Table 1 (the mean number of claims per patent amounts to 10.6), 0.7 equals an increase by about 7%.

	number of applications				**share of applications opposed**			
	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	-1.011*	-0.707	-1.819***	-1.293**	-0.015	-0.022	-0.019	-0.028*
	[0.579]	[0.441]	[0.658]	[0.502]	[0.013]	[0.014]	[0.014]	[0.016]
d_post	1.597***	1.071**	1.597***	1.071**	-0.023*	-0.027**	-0.023*	-0.027**
	[0.579]	[0.441]	[0.577]	[0.440]	[0.013]	[0.014]	[0.013]	[0.014]
d_mobile * d_post	-0.281	-0.355	-0.281	-0.355	0.021	0.035*	0.021	0.035*
	[0.818]	[0.624]	[0.817]	[0.623]	[0.018]	[0.020]	[0.018]	[0.020]
d_mult_mobile			1.481**	1.074**			0.009	0.011
			[0.580]	[0.442]			[0.013]	[0.014]
Constant	5.446***	4.460***	5.446***	4.460***	0.072***	0.078***	0.072***	0.078***
	[0.409]	[0.312]	[0.408]	[0.311]	[0.009]	[0.010]	[0.009]	[0.010]
Observations	1408	1408	1408	1408	1408	1408	1408	1408
R-squared	0.015	0.012	0.019	0.016	0.002	0.003	0.003	0.004
F-test (df)	6.91(3)	5.53(3)	6.83(4)	5.63(4)	1.12(3)	1.46(3)	0.96(4)	1.26(4)

	number of references per patent application				**number of citations per patent application**			
	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	0.035	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)

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

Table 3: Difference-in-differences regression (OLS regression) (N = 1,408)

	number of claims per application				number of inventors per patent			
	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	1.188***	1.144***	0.818*	0.816*	-0.045	-0.073	-0.256*	-0.250*
	[0.366]	[0.388]	[0.417]	[0.442]	[0.121]	[0.123]	[0.138]	[0.140]
d_post	0.731**	0.630	0.731**	0.630	0.087	0.056	0.087	0.056
	[0.366]	[0.388]	[0.366]	[0.388]	[0.121]	[0.123]	[0.121]	[0.123]
d_ mobile * d_post	0.036	0.214	0.036	0.214	-0.226	-0.233	-0.226	-0.233
	[0.518]	[0.549]	[0.518]	[0.549]	[0.171]	[0.174]	[0.171]	[0.174]
d_mult_mobile			0.679*	0.600			0.387***	0.323***
			[0.368]	[0.390]			[0.121]	[0.123]
Constant	9.576***	9.607***	9.576***	9.607***	3.202***	3.215***	3.202***	3.215***
	[0.259]	[0.274]	[0.259]	[0.274]	[0.086]	[0.087]	[0.085]	[0.087]
Observations	1408	1408	1408	1408	1408	1408	1408	1408
R-squared	0.021	0.02	0.023	0.021	0.004	0.005	0.011	0.010
F-test (df)	10.01(3)	9.38(3)	8.37(4)	7.63(4)	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 3 (continued): Difference-in-differences regression (OLS regression) (N = 1,408)

Finally, the multiple mover dummy also has a significantly positive effect on inventor team size (Model 2f). 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 1 (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 that 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 mover dummy is quite large. What has so far not been answered is the question which effects this dummy variable actually captures. Again, the multiple mover dummy cannot be interpreted causally with respect to one particular move. It rather refers to the whole time period under consideration (4 years or 3 years before and after the move). Nevertheless, three interpretations of the multiple mover dummy seem possible: first, 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 of the knowledge from their new colleagues. These results point to the importance of an absorptive capacity at the individual inventor level (Cohen/Levinthal 1990). Second, inventors who move repeatedly may be different from single movers or non-movers with regard to their personal characteristics. For instance, multiple movers may be more flexible, more cosmopolitan, or more ambitious 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 on this discussion, further research should analyze multiple movers more closely.

6 Conclusion

The objective of this study was to achieve a better understanding of the impact of one particular move of an inventor on his inventive performance, in particular, to interpret the effect of a move on the change of inventive performance causally. This relationship is important in order to answer the question whether it is reasonable to attract inventors from other firms to enable knowledge transfer. To reach this target, a difference-in-differences estimation was employed which compared the output of a group of mobile inventors relative to a non-mobile control group in a pre- and a post-move period.

Data reveal that there are some striking gains from moving, in particular, inventors increase their grant rate due to a move and the patents are also more valuable. Additionally, results show that movers had lower means in almost all measures tested in the difference-in-differences estimation prior to moving compared to in the aftermath of a move. For instance, the grant rate as well as the opposition rate increased due to the move. Consequently, it appears that the "bad matches" move to increase match quality.

Additionally, results suggest that a move has a larger impact during a three year window before and after the move compared to a four year window. Assuming that a move increases match quality, it is surprising that the benefits from moving seem to dissipate over time. Possible reasons for a decrease of the benefits may be that:

(1) During the first years inventors profit from the knowledge they have transferred from their former employer. Over time, knowledge spillovers from other works may dissipate.

(2) "Old knowledge" (knowledge transferred from the former job) that results in new patent applications may also decrease or become obsolete over time.

(3) Inventors may, due to their merits, be promoted into management positions. An increasing administrative workload prevents inventors from spending time on inventions and, consequently, makes them invisible in terms of patents leading to a decrease in the mean output over time.

Finally, multiple movers turned out to perform better than single movers or non-movers. In particular, inventors who moved repeatedly hold more patents that contain more claims and receive more citations. Additionally, they work in larger inventor teams. A possible explanation for the last result is the fact that inventors frequently move from smaller firms to larger firms and R&D is organized differently in large firms. In particular, large firms are characterized by larger inventor teams. The increase in inventive performance may first be attributable to move experience effects, which enable inventors to settle in faster. Secondly, multiple movers may again improve match quality. As mentioned before, the multiple mover coefficient cannot be interpreted causally to a particular move since the effect corresponds to the entire time period under consideration, i.e., the effect does not represent a difference-in-difference estimate. Consequently, it is also possible that multiple movers are “star inventors” who were initially more productive. Future research need to analyze multiple inventors more closely. In particular, surveys should try to identify star inventors and to analyze the effects of multiple movements on both groups (star inventors and average inventors) separately to find out whether repeating movement actually increases inventive performance or whether key inventors rather change their employers more often.

When deriving implications from the results presented within this analysis it has to be taken into account that this study only provides exploratory results. Further research has to control for additional influences on inventive performance such as, e.g., the availability of resources before and after the move. Resources should also have an impact on inventive output. First, larger R&D budgets may result in more output. Secondly, firms that have more resources at their disposal may be more successful in hiring and retaining high quality inventors.

For R&D management the importance of match quality for inventive performance implies that it is important to analyze the inventors’ motives for moving in order to benefit from hiring a new inventor. Possible benefits from moving for inventors may be knowledge spillovers from new colleagues, monetary incentives, advancement, or new areas of application for existing knowledge. This information can be used to achieve a good match between the inventor and the hiring firm. Given a high match quality, it is seems indeed possible to not only transfer the knowledge embedded in an inventor but also to convert this knowledge in valuable inventions.

Finally, this study provides an empirical setting, which turned out to provide interesting and rather robust results. Therefore, quasi-experimental designs could in future also contribute to surveys within other contexts such as, for instance, the promotion of employees in management positions or the analysis of factors for success in the context of mergers, acquisitions or strategic alliances between firms.

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