Paper to be presented at the

DRUID Society Conference 2014, CBS, Copenhagen, June 16-18

Knowledge Fit and Productivity Gains from Mobility

Karin Hoisl
Ludwig-Maximilians-University
Munich School of Management
hoisl@bwl.lmu.de

Gaétan de Rassenfosse
The University of Melbourne
MIAESR and IPRIA
gaetand@unimelb.edu.au

Abstract

Previous research has established that mobile inventors are more productive than non-mobile inventors. However, the actual reasons for these productivity gains are still the subject of speculation. We use data on an international sample of 1,696 inventors to investigate the sources of these gains. Building on the strategic management literature and the theoretical labor economics literature, we propose that mobility productivity gains are due to match effects between inventor and employer. Our first validation test, a matched difference-in-differences regression model of the productivity of mobile inventors, leads to results that are consistent with the job matching theory. Whereas voluntary moves are associated with productivity gains in the post-move period, involuntary moves are not. Our second validation test involves identifying a direct measure of match quality. We find that a lower degree of ?knowledge fit? is associated with lower productivity gains following a move. We further find that the effect is contingent on the nature of technology fields. The productivity of inventors in science-based fields is more affected by a lower knowledge fit than the productivity of their peers in technology-based fields.

Jelcodes:M50,O31

Knowledge Fit and Productivity Gains from Mobility

DRAFT. COMMENTS WELCOME

This version: February 28, 2014

Abstract

Previous research has established that mobile inventors are more productive than non-mobile inventors. However, the actual reasons for these productivity gains are still the subject of speculation. We use data on an international sample of 1,696 inventors to investigate the sources of these gains. Building on the strategic management literature and the theoretical labor economics literature, we propose that mobility productivity gains are due to match effects between inventor and employer. Our first validation test, a matched difference-in-differences regression model of the productivity of mobile inventors, leads to results that are consistent with the job matching theory. Whereas voluntary moves are associated with productivity gains in the post-move period, involuntary moves are not. Our second validation test involves identifying a direct measure of match quality. We find that a lower degree of 'knowledge fit' is associated with lower productivity gains following a move. We further find that the effect is contingent on the nature of technology fields. The productivity of inventors in science-based fields is more affected by a lower knowledge fit than the productivity of their peers in technology-based fields.

Keywords: inventor mobility; knowledge fit; match effect, productivity.

1 Introduction

Employee mobility is a main source of information diffusion (Arrow 1962) and its role in spreading knowledge is well documented in the empirical literature (Almeida and Kogut 1999; Stolpe 2002; Agrawal et al. 2006; Marx et al. 2009; Breschi and Lissoni 2009). It is now well established that recruiting inventors allows firms tapping into externally-developed ideas thereby facilitating the exploitation of distant knowledge. Management scholars have focused their attention on understanding the *conditions* under which knowledge transfer occurs (Argote and Ingram 2000; Song et al. 2003; Sing and Agrawal 2011). But surprisingly little research has been conducted on the *preconditions* of knowledge transfer, that is on mobility itself.

The management literature seems to rest on the explanation provided by neoclassical labor economic theory that inventors move to firms that are able to employ them at their most productive use – and hence that are able to offer them a higher wage. Empirical validation of this theory is provided by Topel and Ward (1992) who show that a typical job change during the first ten years of market experience in the United States is associated with a 10 percent wage gain. In the specific context of inventors, Hoisl (2007) shows that mobility increases inventor productivity by about 15 percent. In short, mobility would occur because it would allow inventors to raise their productivity. However this claim immediately raises the question of why mobility increases productivity.

Scholars have traditionally answered that question by acknowledging the fact that only a self-selected number of individuals move. Employees who expect productivity improvement by moving quit their job and take another job while the others keep their job, leading to a causal link between mobility and productivity (Johnson 1978; Jovanovic 1979; Mortensen 1986). This theory, known as the job-matching theory, posits that employees who quit their jobs simply poorly 'fit' with their current employers and are likely to increase their fit at another job, thereby increasing their productivity. Extreme cases of this theory are the well-known examples of Harrison Ford, a carpenter-turned-actor, and Andrea Bocelli, an attorney-turned-tenor. To the best of our knowledge, there is limited empirical evidence of the job-matching theory and we are aware of no study that looks specifically at inventors.

In this paper, we seek to document inventor mobility productivity gains and to unravel the sources of these gains. We ask the following questions: (i) what are the productivity effects of mobility; and (ii) to what extent are these productivity gains explained by match effects. We introduce a novel dimension of match quality that we call 'knowledge fit' and define as *the extent to which an inventor's knowledge is applicable to his or her new job*. We hypothesize that knowledge fit adds to the explanation of mobility-productivity gains in R&D-related environments.

Our analysis is based on original survey data obtained from European and U.S. inventors listed on patent applications filed at the European Patent Office (EPO). To trace the productivity of these inventors, survey data were matched with register information from EPO patent applications. The combination of the data sources is unique and enables us to control for individual and organizational characteristics and to uncover largely novel mobility-productivity relationships related to match quality.

The first part of our analysis reproduces and extends earlier findings on mobility productivity gains. Most of the studies in the area report that mobility is 'associated' with productivity gains (Trajtenberg 2005; Shalem and Trajtenberg 2009; Hussinger 2012). As far as we can ascertain, Hoisl (2007) is the only study that establish a causal link between mobility and productivity. However, no explanation is provided as to why the effect occurs. We confirm previous results that mobility increases productivity but show that this effect only holds for voluntary moves. Matched difference-in-differences regression models comparing pre- and post-move productivity of 827 mobile and 827 non-mobile control inventors reveals that voluntary moves (e.g., due to promotion in the new job) are associated with 20-per cent productivity gains in the post-move period whereas involuntary moves (e.g., due to bankruptcy of the former employer) do not affect productivity. This result is consistent with the job matching literatureIIn short, involuntary moves are less likely to result in a better employer-employee match and hence are also less likely to result in productivity gains as compared with voluntary moves.

Given these results, the second part of our analysis aims at identifying determinants of match quality. We adopt a first-difference econometric specification of the post vs. pre-move productivity of the mobile inventors in our sample. The first difference specification allows controlling for inventor-specific effects, thereby dealing with endogeneity concerns. If more productive inventors are also intrinsically better at selecting a suitable environment, at orienting the firm's research trajectory, or at exchanging ideas with their new colleagues (all dimensions that could affect match quality), they were already, in all logic, better at their previous job. However, we also present instrumental variable regressions as robustness to account for correlation between the individual effects and our match quality variable. A strict interpretation of our model suggests that approximately 60 to 65 percent of mobility productivity gains are due to firm effects – that is inventors moving to more productive firms on average – while match quality accounts for the remaining 35 to 40 percent. We provide direct evidence on the existence of match effects by showing that our measure of knowledge fit mitigates the mobility productivity gains. Various robustness checks comforts our finding of a relationship between knowledge fit and mobility productivity gains. In an extension to the analysis we show that knowledge fit is of particular importance in science-based environments such as biotechnology. A possible explanation for this finding is that knowledge accumulation and learning is more costly in these environments compared to technology-based environments (Argote et al. 2003; Zander and Kogut 1995; Szulanski 1996).

Our results connect the strategic management literature with labor market research and thereby propose a more comprehensive framework for understanding productivity gains through inventor mobility. We also contribute more specifically to the strategic management literature on search and knowledge recombination by providing a novel insight into the conditions under which individuals successfully transfer their knowledge to, and combine it with, the existing knowledge base of the new employer. Our results are also relevant to the labor economics literature because they are amongst the few number of those that provide direct evidence on match quality. Moreover, the paper provides practical implications for R&D and human resource management by shedding more light into the determinants of productivity-enhancing hires.

2 Theoretical framework

The empirical literature has long provided evidence for productivity gains from employee mobility (e.g., Altonji and Shakotko 1987, Topel and Ward 1992, Jackson 2013). For instance, Topel and Ward (1992) use a U.S. longitudinal employee-employer dataset and show that a typical job change during the first ten years of labor market experience is associated with a 10 percent wage gain.[1] Regarding knowledge workers more specifically, Hoisl (2007) shows that mobility increases inventor productivity by approximately 15 percent.

Several reasons can be put forward to explain the increase in productivity following a move. First, newly-recruited workers may perform better because of a higher intrinsic motivation or because of external incentive systems, such as a probationary period. While increased effort may explain short-term productivity gain, this explanation fails to account for sustained higher productivity that movers enjoy. Second, positive assortative mating (Becker 1973) may occur, whereby only the best employees are able to move and are recruited by better performing firms. Although there is some evidence that such effect may be at play in the labor market of scientists (Agarwal and Ohyama 2013), research has also established the presence of a causal effect of mobility on productivity (Hoisl 2007; Jackson 2013), thereby ruling out assortative mating as the unique explanation for mobility productivity gains.

Another possible explanation for post-move productivity gains comes from the job matching theory from the labor economics literature. The job matching theory starts from the premise that jobs are in Nelson's (1970) terminology 'experience goods' whose value is unknown ex-ante. The worker does not know the relevant characteristics of a job at the date of hire and is thus unable to anticipate

[1] Wage is one measure of productivity. Models of the labor market typically assume that workers are paid at their marginal productivity.

how well he or she fits the job (Johnson 1978; Jovanovic 1979).[2] Although the true value of the realization of match quality is initially unknown to both the worker and the firm, information arises over time that allows the worker to evaluate the job and to make a stay-or-quit decision. The worker decides to quit whenever the value of continuing to work at the job falls below the discounted future income that he or she can expect by trying any other job. It follows that workers poorly matched with their employers are more likely to move because they can reasonably expect a better match (resulting in a higher productivity) with their next employer.

The job matching theory has received recent empirical support from research showing that a worker-firm match effect accounts for variance in productivity as measure by wage data (Woodcock 2008; Sørensen and Vejlin 2012) or output data (Jackson 2013). For instance, Sørensen and Vejlin (2012) attribute around 7 to 9 percent of the wage dispersion in the Danish labor market to the match effect. In the specific context of inventors, Nakijima et al. (2010) show that inventors listed in US patents who move to firms that employ inventors' former collaborators are more productive than inventors who move to firms that were outside their network. If the network acts as an information transfer mechanism, they argue, then match quality should be higher for networked inventors than for non-networked inventors. While this piece of work provides indirect evidence that match quality affects productivity, it does not explicitly measure match quality and remains silent on its actual determinants.

Our first hypothesis directly derives from the job matching theory. If match effects explain productivity gains, it must be that only *voluntary* moves are associated with productivity gains. Voluntary movers select a job because they expect a better match with the new employer. By contrast, inventors who are forced to move (e.g., as a result of a bankruptcy) are less likely than voluntary movers to benefit from the job change. Were they aware of unambiguously more favorable work conditions, they would have moved before being forced to. Accordingly, we hypothesize:

HYPOTHESIS 1: *A voluntary move leads to larger productivity gains from mobility compared to an involuntary move.*

Validation of Hypothesis 1 would bring additional evidence on the existence of match effects. We next seek to identify determinants of match quality. We are particularly interested in a component of match quality that can be assumed to be of particular importance in an R&D environment, namely knowledge fit. Newly-hired inventors transfer their knowledge to the new employer, enabling distant search (Oettl and Agrawal 2008, Rosenkopf and Almeida 2003, Franco and Filson 2006, Paloremas and Melero 2010). Additionally, it allows the interpretation of the new knowledge in the context of the

[2] In Jovanovic's (1979) model, a worker's productivity is a function of the quality of the match with the employer. Match quality follows an exogenously given distribution and the act of changing jobs makes the worker take a new, independent draw from this distribution.

new employer, i.e. to uncodify knowledge (Rosenkopf and Almeida 2003). However, to gain from mobility, individuals have to have knowledge relevant to the new employer. Additionally, they have to tie this knowledge to the knowledge base of the new employer, which requires considerable amount of time and resources (Cohen and Levinthal 1990, Zahra and George 2002). Otherwise the knowledge is lost (Lee and Allen 1982).

A lack of 'employee-employer match', i.e. in case a large share of the knowledge previously accumulated is no longer applicable to the new organization's inventive activities, can occur due to knowledge obsolescence. Obsolescence of knowledge can be caused by technical or economic reasons (Rosen 1975). Technical reasons originating in individuals refer to depreciation of human capital due to aging or non-use of knowledge. Allen and van der Velden (2002) use self-assessments of knowledge obsolescence of 2,723 Dutch workers who obtained tertiary education. The authors find that about one third of the knowledge obtained in tertiary education became obsolete after seven years. The latter was attributed to rapid changes in the work environment and to shortcomings in the education system. Economic reasons refer to changes in the work environment, i.e. to technological or organizational changes or employee mobility (De Grip and Van Loo 2002). Engineers employed with organizations that are technically dynamic exhibit lower vulnerability to obsolescence (Rothman and Perrucci 1971). In case obsolescence is further intensified by a move, human capital (particularly firm- or job-specific human capital) is at risk of becoming obsolete (Beveridge 1930, Hamermesh 1987).

A second aspect of knowledge fit is the lack of 'recombination match', i.e. the possibility to combine the employees' pre-move knowledge base with that of the new employer. Inventor mobility has long been considered a mechanism for sourcing distant knowledge (Almeida and Kogut 1999, Marx, et al. 2009). Even though the process of innovation critically relies on the recombination of existing ideas (Fleming 2001), recombination boundaries exist between technological domains (von Tunzelmann 1998, Hargadon 2002, Almeida and Kogut 1999). While recombination of knowledge components across technological distances is possible, individuals have to possess absorptive capacity in order to sensibly recombine the knowledge components (Cohen and Levinthal 1990, Fleming 2001). Even though the literature refers to different knowledge domains the same "restrictions" should apply to the recombination of knowledge originating from different organizations. The management literature confirms that inter-firm knowledge flows, to be useful for the receiving firm, need so-called knowledge brokers, i.e. organizations or individuals that link previously unconnected entities by enabling the latter to "interact [...] through the broker" (Fleming et al. 2007, p. 443).
Overall, knowledge fit – either directly (employee-employer match) or indirectly (obsolescence or recombination) – should affect gains from mobility. Accordingly, we hypothesize:

HYPOTHESIS 2: *A lower degree of knowledge fit reduces the productivity gains from mobility.*

3 Dataset and sample

The empirical study uses a sub-sample of the PatVal 2 dataset on inventors, which was collected during a project sponsored by the European Commission ("Innovative S&T indicators combining patent data and surveys: Empirical models and policy analyses" - InnoS&T) (Gambardella et al. 2014).[3]

Our focus is on the 4,916 mobile inventors in the PatVal 2 dataset, defined as inventors who moved once or twice during the last five years prior to the priority date of the surveyed patent application.[4] Answers from 508 Japanese inventors were excluded because it is difficult to distinguish between a genuine move and a so-called secondment. A secondement occurs when an employee is delegated to a firm within the original employer's network (e.g., a supplier). The employee works for this firm until a particular project is concluded and then returns to his or her original employer. The sample was further restricted to inventors who had at least one patent application prior to the move (3,262 inventors dropped) to avoid artificially inflating post-move productivity. By design, inventors are listed on at least one patent application after the move (i.e., the focal patent of the InnoS&T study). Since the risk of false negative (not matching an inventor with his or her patents) is quite high in the pre-move period, the restriction leads to a conservative estimation of the change in productivity. Finally, 277 inventors with missing observations on covariates were dropped from the sample, leading to a final sample containing 869 observations.

To trace productivity over time, we matched the survey data with data from the EPO Worldwide Patent Statistical Database PATSTAT (April 2011 edition). Specifically, we matched each inventor in the survey to its unique PATSTAT identifier. We improved the matching by performing a string match on inventor names and checking the results manually. To avoid double counting we restricted our search to patent applications filed at the EPO.[5] The match resulted in 8,815 patent applications listing at least one of the 869 inventors in our sample and another 10,294 EP patent applications listing the control inventors. Since we combine information from two distinct data sources and since our research question was unknown to respondents at the time of the survey, it is reasonable to argue that our results are preserved from the threat of common method bias (Podsakoff et al. 2003).

[3] In the course of the PatVal 2 project, an online survey of inventors was conducted in 20 European countries (AT, BE, CH, CZ, DE, DK, ES, FI, FR, GB, GR, HU, IE, IT, LU, NL, NO, PL, SE, SI), Israel, the United States, and Japan. One inventor was chosen at random from all patent applications filed at the European Patent Office with priority dates between 2003 and 2005 (124,134 inventors). A total of 23,044 responses were received, yielding a corrected response rate of 22.7% (22,557 letters returned due to wrong addresses).

[4] We excluded inventors who moved more than twice during the period under consideration since the possibility of "unambiguously" attributing productivity gains to a particular move decreases with the number of moves. However, the results regarding sign, size of the coefficient and significance remain the same even if we restrict our sample to single movers or include all movers.

[5] We also searched for patents filed at national patent offices that were not filed at the EPO but it did not lead to a significant improvement in the number of patents identified and introduced a substantial amount of noise in the data.

4 Empirical framework

4.1 Econometric models

Testing for Hypothesis 1

We analyze the productivity-mobility relationship using a 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 and Krueger 1994; Singh and Agrawal 2011; Younge et al. 2011). 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 and Campbell 1979). One of the most often used quasi-experimental designs is the difference-in-differences estimation approach, which aims at analyzing the impact of some treatment on a certain group of subjects under consideration. 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. The treatment group contains movers, the control group consists of non-movers, and the treatment is defined as a move. The treatment group will further be split into voluntary and involuntary movers. We estimate the performance on five-year windows before and after the move.

To construct the control group for the 869 mobile inventors, we used propensity score matching. The control inventors were required to have at least one patent application before and after the move date of their mobile "twin" inventor. Additional matching criteria were personal characteristics of the inventors: their age, gender, level of education, and country of residence. We were not able to find appropriate controls for 42 mobile inventors. Hence, the sample used to test our first hypothesis only contains 827 mobile and 827 non-mobile inventors.[6]

The difference-in-differences estimator is derived by taking the mean value of each group's outcome (treatment and control group) before and after the treatment and calculating the difference of the differences of these means (Wooldridge 1999):

$$\delta_{DID} = \left(\overline{treatment}_{post} - \overline{control}_{post}\right) - \left(\overline{treatment}_{pre} - \overline{control}_{pre}\right) = \Delta_{post} - \Delta_{pre}$$

[6] We conducted a robustness check, which is described in section 5, to make sure that the reduction in our sample does not change the results of our matching regressions.

where a bar indicates an average over the group of inventors and pre and post indices stand for the pre-treatment and the post-treatment period

To test whether δ_{DiD} is statistically different from zero, we use an OLS regression framework. In particular, the following equation is estimated:

$$Q_{it} = \beta_0 + \delta_0 * mobile_i + \delta_1 * post_t + \delta_{DID} * (mobile_i * post_t) + u_{it} \tag{1}$$

where Q_{it} is the productivity of inventor i at time period t (before or after the move), *mobile* is a dummy variable that takes the value 1 of inventors belong to the treatment group and 0 otherwise, and post is a dummy variable that takes the value 1 in the post-treatment period and 0 otherwise. We further split the sample into voluntary and involuntary movers. We expect δ_{DID} to be greater when the regression model is estimated on the sample of voluntary movers.

Testing for Hypothesis 2

We test the significance of the match quality variable using a framework inspired by the microeconomic job matching literature (e.g. Woodcock 2008). The productivity Q_{ij} of inventor i at firm j is modeled as a Cobb-Douglas production function of the form:

$$Q_{ij} = L_i^{\theta} K_j^{\varphi} M_{ij}^{\phi}$$

where Q_{ij} is the number of inventions produced, L_i is human capital of inventor i (such as the level of education), K_j captures the productive characteristics of the firm (such as the amount of resources available to conduct research and the quality of the management team), and M_{ij} is match quality. The match variable is an inventor-firm specific effect that captures how productive inventor i is in firm j. Taking the expression to the log yields:

$$q_{ij} = \theta l_i + \varphi k_j + \phi m_{ij}$$

where lower case roman letters denote the natural logarithm of variables. We are interested in understanding the productivity gain following a move. Letting j^0 denote the firm prior to the move and j^1 denote the firm after the move, the productivity gain $q_{ij^1} - q_{ij^0}$ is simply:

$$q_{ij^1} - q_{ij^0} = \varphi\left(k_{j^1} - k_{j^0}\right) + \phi\left(m_{ij^1} - m_{ij^0}\right) \tag{2}$$

Equation (2) states that the change in inventor productivity following a move can be decomposed into a change in firm characteristics and a change in match quality. Notations in equation (2) are simplified to:

$$\Delta q_{ij^1j^0} = \varphi \Delta k_{j^1j^0} + \phi \Delta m_{ij^1j^0} \tag{3}$$

The model has the desirable property of being parsimonious. Changes in firms' unobserved effects are captured by the variable $\Delta k_{j^1 j^0}$, while inventor fixed effects are controlled for by taking the first difference.

We believe that the described specification is the best suited for our purpose and given our data. One might argue that we should use a selection model à la Heckman in which the decision to move is estimated in a first stage and the determinants of productivity gains are estimated in a second stage. Selection models are useful to ensure unbiasedness of individual effects estimates and hence valid out-of-sample inference. However, individual effects are not estimated in our regression model – they are wiped out with the first difference specification – and our population of interest is mobile inventors – change in match quality is irrelevant for non-movers.

4.2 Empirical implementation

Dependent variables (H1 and H2 tests). Following Lanjouw and Schankerman (2004), we use a quality-adjusted measure of output to quantify inventor productivity. The variable q_{ij^1} is the log number of citations for patent applications that list employee i as an inventor in firm j^1 and that were filed in a 5-year time window following the move. Similarly, the variable q_{ij^0} is the log number of citations for patent applications filed in a 5-year time window prior to the move. We count citations received in a 5-year time window after the publication of the search report by patent applications. Our dependent variable, labeled 'productivity change', is simply $\Delta q_{ij^1 j^0} = q_{ij^1} - q_{ij^0}$. To measure the performance in the difference-in-difference estimation, quantitative and qualitative measures will be used. The overall number of patent applications per inventor represents a quantitative measure. The number of forward citations received within 5 years after publication of the patent application captures qualitative aspects of the output. Due to the fact that the distribution of inventor productivity is highly skewed to the right, we use a logarithmic transformation of all productivity measures in our regression models in equation (1). Note that the regression model in equation (3) is already expressed in logarithm, such that all the dependent variables are taken to the log.

Match quality variable: knowledge fit (H2 test). Our measure of the change in match quality ($\Delta m_{ij^1 j^0}$) is change in knowledge fit and comes from our questionnaire. In particular we asked inventors the extent to which their previous knowledge was no longer applicable to the new organization's inventive activity. The answers were collected in a 6-point Likert scale, with a high score reflecting a lower degree of knowledge fit.[7]

[7] The exact statement is: "As a result of your last change of employer prior to joining the organization where your invention was made, a significant part of your previous inventive experience was no longer applicable to the new organization's inventive activity". The Likert items were: 0 = "does not apply"; 1 = "fully disagree"; 2 = "disagree"; 3 = "partly agree"; 4 = "agree"; and 5 = "fully agree". To capture quasi-missing

Firm-level variable (H2 test). The regression controls for changes in the productive characteristics between firms ($\Delta k_{j^1 j^0}$), as measured with changes in the log number of citation-weighted patents per employed inventor. We refer to this variable as the 'inter-firm effect'. We show below that this proxy variable adequately captures changes in firms' characteristics.

Let $\bar{Q}_j$ denote the average number of patents per inventor at firm j and N_j the total number of inventors at firm j. We know that:

$$\begin{aligned}
\bar{Q}_j &= \frac{1}{N_j}\sum_{i=1}^{N_j} Q_{ij} \\
&= \frac{1}{N_j}\sum_{i=1}^{N_j} L_i^{\theta} K_j^{\varphi} M_{ij}^{\phi} \\
&= K_j^{\varphi}\left(\frac{1}{N_j}\sum_{i=1}^{N_j} L_i^{\theta} M_{ij}^{\phi}\right)
\end{aligned}$$

such that $\bar{Q}_j$ is correlated with K_j. The term in parenthesis can be interpreted as the average match-adjusted productivity of human capital in firm j, which we denote $\bar{P}_j$. The term $\varphi\Delta k_{j^1 j^0}$ in equation (3) is proxied with the variable $\Delta\bar{q}_{j^1 j^0}$:

$$\begin{aligned}
\Delta\bar{q}_{j^1 j^0} &= \bar{q}_{j^1} - \bar{q}_{j^0} \\
&= \varphi k_{j^1} + \bar{p}_{j^1} - \varphi k_{j^0} - \bar{p}_{j^0} \\
&= \varphi\left(k_{j^1} - k_{j^0}\right) + \bar{p}_{j^1} - \bar{p}_{j^0} \\
&= \varphi\Delta k_{j^1 j^0} + \bar{p}_{j^1} - \bar{p}_{j^0}
\end{aligned}$$

such that we have:

$$\varphi\Delta k_{j^1 j^0} = \Delta\bar{q}_{j^1 j^0} - \bar{p}_{j^1} + \bar{p}_{j^0}$$

and equation (3) becomes:

$$\Delta q_{ij^1 j^0} = \Delta\bar{q}_{j^1 j^0} + \phi\Delta m_{ij^1 j^0} + \varepsilon \tag{4}$$

where ε is an error term that includes changes in the average match-adjusted productivity of human capital between firms ($\bar{p}_{j^0} - \bar{p}_{j^1}$). By design, the average match-adjusted productivity of human capital ($\bar{P}_j$) is orthogonal to the productive characteristics of the firm (K_j) – since any systematic, firm-level difference is included in K_j. As a result, the error term is random with respect to $\Delta\bar{q}_{j^1 j^0}$ and the variable $\Delta\bar{q}_{j^1 j^0}$ is an unbiased proxy of $\Delta k_{j^1 j^0}$.

values in knowledge fit, our regression models include a dummy variable that takes the value 1 if the respondents indicated "does not apply". As a robustness check we also excluded inventors indicated "does not apply" from the dataset. The results regarding, sign, size of the coefficient, and significance remained unchanged.

It is worth noting that the proxy variable captures all firm-level heterogeneity that affects inventor *i*'s *observed* research productivity. For instance, it is a well-known limitation of patent data that it does not capture an inventor's entire inventive activity, since not all inventions are patented (Griliches 1990). Since the decision to patent an invention is primarily a firm-level decision, our proxy variable accounts for changes in observed productivity that are due to a change in the propensity to patent across firms.

Control variables (H2 test). We control for the age of inventors at the time of the move as well as for their educational degree (whether they earned a PhD). The variables are included to capture systematic differences in inventors' ability to adapt to their new environment. For instance, younger inventors are more flexible than older inventors while older inventors are more experienced (Dane 2010) and this could affect how well they adapt. Similarly, the level of education forms a proxy for the ability of individuals (Spence 1973, Boschma et al. 2009) which could also affect how well they adapt. We also control for systematic differences across technological areas by adding five dummy variables capturing the following areas: electrical engineering; instruments; chemistry/pharmaceuticals (reference group); process engineering; mechanical engineering; and consumer goods. The classification follows the updated nomenclature proposed by the German Fraunhofer Institute for Systems and Innovation Research and the French Intellectual Property Institute (Schmoch 2008). Inventors were assigned to technology areas based on the IPC codes of the surveyed patent.[8] Finally, we control for the number of moves of the inventors, i.e. whether they moved once or twice during the five years prior to the patent application underlying the InnoS&T project.

4.3 Descriptive statistics

Table 1 provides descriptive statistics for our sample. The surveyed inventors received on average 4.15 citations (from a minimum of 0 to a maximum of 100) for their patent applications filed during the 5 years prior to their move. Patent applications filed during the 5 years after the move received on average 6.65 citations (from a minimum of 0 to a maximum of 152). The firms at which the inventors were employed prior to the move exhibit a citation-weighted patent count per employed inventor amounting to 28.11. The equivalent figure for firms in the post-move period amounts to 57.46. It is striking that the citation-weighted patent count in the post-move period is double that in the pre-move period. This increase may reflect a genuine increase in the rate of inventions over time, an increase in the reliance of patents, a better availability of data in the post-move period (e.g. a higher rate of patents matched to inventors), or a combination of these three factors. It is important to note that our inventor-level estimates of productivity gains in H2 are not affected by this general upward trend since our regression model includes the inter-firm effect. The median value of knowledge fit amounts to 1,

[8] IPC stands for International Patent Classification. IPC codes are used by patent examiners to identify the areas of technology to which patents pertain.

meaning that most of the inventors did not experience a (significant) loss of knowledge following the move. The distribution of the knowledge fit variable is displayed in Figure 1. Approximately half the mobile inventors in our sample experienced knowledge obsolescence to some extent.

Inventors were on average 51 years old at the time of the move and 43 percent of them earned a PhD. Inventors are mostly active in electrical engineering (24 percent), followed by chemicals and pharmaceuticals (23 percent), instruments (22 percent), mechanical engineering (14 percent), process engineering (11 percent), and consumer goods (6 percent). Finally, 76 percent of the inventors did not move another time during the 5 years prior to the move under consideration, and 24 percent moved once more. Correlations between independent variables are low, suggesting that collinearity of covariates is not a concern (not reported).

Table 1: Descriptive statistics (N = 869)

Variable	Mean	Std. Dev.	Min	Max
CIT_prior_INV	4.15	7.49	0	100
CIT_post_INV	6.65	12.47	0	152
CIT_prior_FIRM	28.11	155.30	0	2050.92
CIT_post_FIRM	57.46	398.14	0	7876
diff_CIT (dep. var.)	2.50	12.63	-98	122
diffCIT_FIRM	29.35	426.43	-2050.88	7876
knowledge fit♦	1		0	5
knowledge fit = 0 (D)	0.11		0	1
age at move	51.03	9.34	30	85
doctoral degree (D)	0.43		0	1
electrical eng. (D)	0.24		0	1
instruments (D)	0.22		0	1
chemistry/pharma (D)	0.23		0	1
process eng. (D)	0.11		0	1
mechanical eng. (D)	0.14		0	1
consumer goods (D)	0.06		0	1
science-based (D)	0.69		0	1
technology-based (D)	0.31		0	1
number of moves	1.24	0.43	1	2

Notes:
D = dummy variable; ♦ median

Figure 2 provides information about the reasons for moving. Overall, 70 percent of the inventors moved voluntarily, 30 percent involuntarily. The most important reasons for willingly changing the employer were another attractive job offer in R&D (24.7%), an advancement (2.6%), or starting an own company (11.6%). Less important were reasons like an explicit dissatisfaction with the current job (3.5%), an increase in salary (3%), or a move abroad (0.6%). Reasons for unwilling moves were bankruptcy of the current employer (15.7%), reorganization of the current employer resulting in a dismissal of the inventor (8.2%), or family-induced reasons (6.1%).

Figure 1: Distribution of knowledge fit (N = 869)

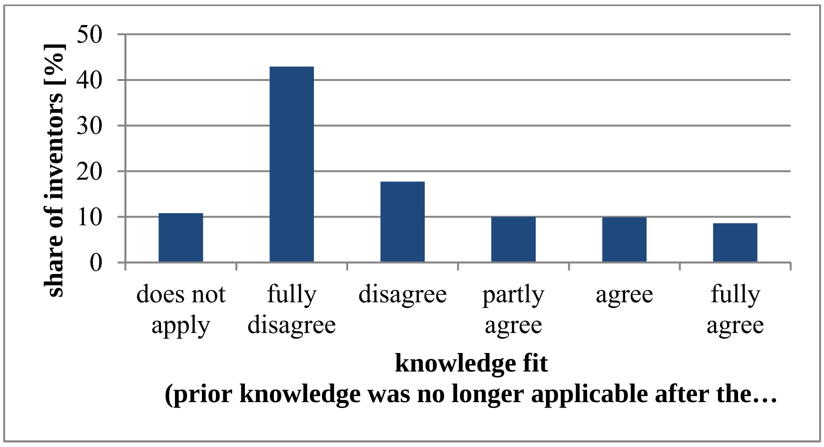
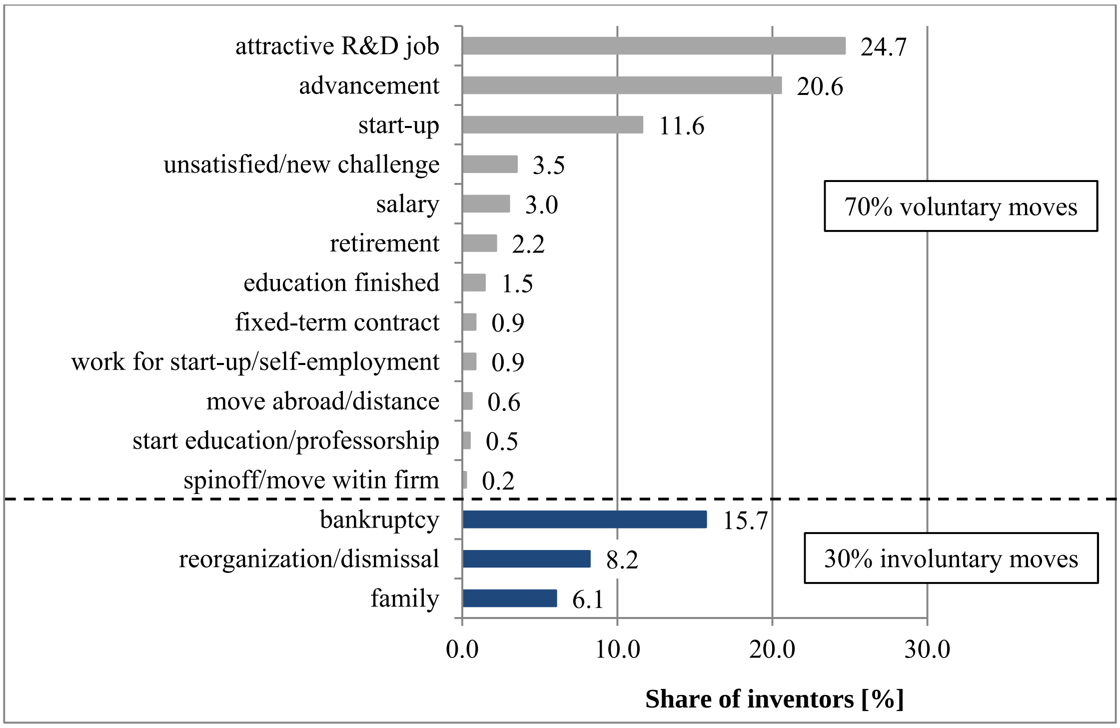


Figure 2: Reasons for moving (N=827)



5 Results

5.1 Baseline results

The results of the difference-in-differences regressions are shown in Table 2. The first two columns refer to all moves in our sample, columns 3 and 4 provide results for voluntary moves and the last two columns display the results for involuntary moves. Models M1, M3, and M5 refer to output quantity (number of patents) and Models M2, M4, and M6 to output quality (number of citations). We do not find any significant effects as regards the quantity of output. However, there is a positive relationship between mobility and output quality. Model M2 reveals that inventors are 13.6 per cent more productive in the post move period. In case we restrict our sample to voluntary movers (Model M4), the move is associated with an increase in quality-adjusted output of 20.5 per cent. In case involuntary moves are considered, we do not find significant results (Models M5 and M6). These results indicate that the underlying mechanism leading to productivity gains in the post-move period is not the move itself. They also allow us to rule out reverse causality as an explanation to observed productivity gains, that is, the fact that movers are more productivity not because of the actual move but because they are intrinsically more productive than non-movers. Because we compare productivity differentials between movers and non-movers (control group) in the pre- and post-move period, reverse causality cannot drive our results. The increase in productivity is consistent with an increase in match quality.. The results are consistent with the job-matching theory. Whereas inventors who move willingly may have found a potentially better match than before, inventors who are forced to move may have less or no options to choose from. Hence, for the latter a move can be seen as a random choice, which may result in the same, a better, or a worse match. We now investigate whether our measure of knowledge fit is a significant determinant of productivity gains.

Table 2: Mobility–productivity-relationship (Difference-in-Differences Estimation)

	all moves		voluntary moves		involuntary moves	
	(Model M1)	(Model M2)	(Model M3)	(Model M4)	(Model M5)	(Model M6)
VARIABLES	**log(PAT_5yr)**	**log(CIT_5yr)**	**log(PAT_5yr)**	**log(CIT_5yr)**	**log(PAT_5yr)**	**log(CIT_5yr)**
move (dummy)	-0.080**	-0.110**	-0.085**	-0.133**	-0.068	-0.059
	[0.033]	[0.056]	[0.039]	[0.067]	[0.061]	[0.102]
post (dummy)	0.308***	0.114**	0.309***	0.096	0.304***	0.159
	[0.035]	[0.057]	[0.042]	[0.069]	[0.064]	[0.102]
move * post	0.040	0.136*	0.063	0.205**	-0.014	-0.026
	[0.050]	[0.080]	[0.059]	[0.096]	[0.090]	[0.146]
Constant	1.395***	1.615***	1.380***	1.601***	1.431***	1.646***
	[0.024]	[0.040]	[0.029]	[0.049]	[0.044]	[0.072]
Observations	3,308	3,308	2,316	2,316	992	992
R-squared	0.052	0.007	0.056	0.009	0.045	0.005
F test	62.01	8.418	46.56	7.568	15.90	1.696

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

A set of baseline regression results is presented in Table 3. A first estimate without the knowledge fit covariate is shown in Model (1a). The inter-firm effect is positive and significant, suggesting that some of the productivity gains enjoyed by the inventor after his or her move are attributable to firm-specific effects (e.g., the inventor may be moving to a more productive environment). The impact of knowledge fit is estimated in Model (1b). The coefficient associated with the knowledge fit variable is negative and significant. Since a high score of our explanatory variable reflects a lower degree of knowledge fit, results indicate that a lower degree of knowledge fit leads to lower post-move productivity gains.[9] In particular, a 10-per cent increase in knowledge fit is associated with a 3-per cent increase in productivity.

[9] We can rule out the possibility that a reduction in post-move productivity is driven by the focal inventor ceasing inventive activity (and thereby exhibiting a poor knowledge fit). By design, all inventors hold at least one patent in the post-move period and are thus 'research-active'. In addition, the knowledge fit variable explicitly asks about relevance of knowledge for the (post-move) organization's *inventive activity*.

Table 3: Determinants of productivity change following a move

	Model (1a)	Model (1b)	Model (1c)
Econometric method:	OLS	OLS	2SLS
inter-firm effect ($\Delta\bar{q}_{j^1j^0}$)	1.086***	1.090***	1.104***
	[0.032]	[0.031]	[0.033]
knowledge fit (log)		-0.309**	-1.837*
		[0.155]	[1.026]
knowledge fit = 0 (D)		-0.039	-1.675
		[0.224]	[1.104]
age at move (log)	-0.428	-0.516**	-0.951**
	[0.262]	[0.261]	[0.413]
doctoral degree (D)	0.087	0.089	0.089
	[0.120]	[0.120]	[0.127]
technological areas	*included*	*included*	*included*
	F=1.21; p=0.30	F=1.21; p=0.30	F=4.69; p=0.46
number of moves	0.075	0.074	0.091
	[0.129]	[0.128]	[0.137]
Constant	1.099	1.713*	4.820**
	[0.982]	[1.009]	[2.400]
Observations	869	869	869
R-squared	0.643	0.646	0.601
F test	155.7	133.3	123.02
p-value	0.000	0.000	0.000
F test 1st-stage	-	-	4.88 (p=0.001)
Hansen J statistic	-	-	1.675 (p=0.642)
Instruments	-	-	no. applicants (log), ctryUS (D), ctryGB (D), combine family and work (log)

Notes:
Dependent variable is productivity change ($\Delta q_{ij^1j^0}$).
'D' stands for dummy variable.
Robust standard errors in brackets.
*** p < 0.01, ** p < 0.05, * p < 0.1

Table 4: Determinants of productivity change following a move (robustness checks)

Model:	**(2a)**	**(2b)**	**(2c)**	**(2d)**	**(2e)**	**(2f)**	**(2g)**
inter-firm effect ($\Delta\bar{q}_{j^1j^0}$)	1.105***	1.089***	1.421***	1.111***	1.090***	1.087***	1.093***
	[0.035]	[0.031]	[0.041]	[0.035]	[0.031]	[0.043]	[0.031]
knowledge fit (log)	-0.337*	-0.304*	-0.321*	-0.370**	-0.310**	-0.535***	-0.287*
	[0.172]	[0.156]	[0.167]	[0.176]	[0.155]	[0.189]	[0.155]
knowledge fit = 0 (D)	-0.051	-0.005	-0.193	-0.270	-0.049	-0.253	-0.023
	[0.249]	[0.224]	[0.227]	[0.253]	[0.225]	[0.260]	[0.228]
age at move (log)	-0.723**	-0.442*	-0.336	-0.565*	-0.540**	-0.878***	-0.587**
	[0.313]	[0.264]	[0.283]	[0.288]	[0.267]	[0.328]	[0.262]
doctoral degree (D)	0.073	0.088	0.074	0.045	0.092	0.079	0.103
	[0.138]	[0.121]	[0.129]	[0.132]	[0.120]	[0.151]	[0.121]
technological areas	*included*	*included*	*included*	*included*	*included*	*included*	*included*
	F=2.00; p=0.08	F=1.30; p=0.26	F=1.30; p=0.26	F=0.91; p=0.48	F=1.16; p=0.33	F=1.28; p=0.27	F=1.00; p=0.41
number of moves	0.073	0.065	0.081		0.074	0.158	0.072
	[0.141]	[0.129]	[0.132]		[0.128]	[0.149]	[0.129]
Constant	2.596**	1.428	0.881	2.117*	1.799*	3.131**	1.915*
	[1.191]	[1.021]	[1.085]	[1.105]	[1.028]	[1.248]	[1.016]
Observations	653	860	716	660	866	591	827
R-squared	0.669	0.647	0.578	0.648	0.646	0.639	0.653
F test	106.3	131.9	118.1	124.7	133.2	73.28	134.1
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes:
Dependent variable is productivity change ($\Delta q_{ij^1j^0}$).
'D' stands for dummy variable.
Econometric method is OLS.
Robust standard errors in brackets.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Model (2a): organizations (post-move) with less than 50 employees excluded
Model (2b): top 1% most productive inventors (overall number of inventions, incl. non-patented inventions) excluded
Model (2c): top 10% most productive inventors (number of citations pre- and post-move) excluded
Model (2d): repeated movers excluded
Model (2e): inventors older than 65 years at the time of the move excluded
Model (2f): US inventors excluded
Model (2g): Sample used for the mobility regressions (42 inventors without control inventors excluded)

Although the main specification of equation (3) nets out the human capital of the inventor, it could be argued that inventor-specific characteristics should be controlled for. Indeed, individual characteristics may not only explain the level of productivity (this effect is controlled for by taking the difference in equation (2)), but they could also explain how well inventors are able to adapt to a move (Perrucci and Rothman 1969, Gibbons and Johnston 1974, Fleming and Sorenson 2004). Accordingly, we include the age of the inventor at the time of the move as well as a dummy variable that takes the value 1 if the inventor holds a PhD degree. The coefficient associated with the age variable is negative and significant, suggesting that age decreases the capacity to adapt, i.e. older inventors enjoy lower productivity gains from mobility than younger ones. We find no significant effect related to the level of education.

One might further argue that match quality is endogenous to productivity, meaning that more productive inventors achieve a stronger match than their less productive peers. This would typically occur if highly productive inventors were more able to predict how well they would fit or if more productive inventors were better able to adapt to a new environment. To deal with the possible endogeneity issue, we control for inventor effects by taking the first difference. In all logic, employees that are more able to anticipate match quality for the move under consideration (compared to their less productive peers) were also more able to anticipate match quality for the previous move or at the time they entered the job market for the first time. The same reasoning applies to inventors who are better able to adapt to a new environment. These inventors can be assumed to have already better adapted to their pre-move environment than less productive inventors. It is also unlikely that the colleagues at the new employer try harder to include more able inventors in their projects then 'average' inventors and thereby facilitate the acclimatization of more productive inventors. Hence we are quite confident that the *change* in match quality is not endogenous to the *change* in productivity. One issue that is also worth discussing is reverse causality. Since the knowledge fit variable is a self-reported measure of match quality, inventors who turned out to be less productive than expected after the move may be tempted to report a low degree of knowledge fit. While plausible, we explain in section 3 that our research question was unknown to respondents at the time of the survey. This feature of our research design typically alleviates such threat of reverse causality.

Nevertheless, we report results of an instrumental variable (IV) approach in Model (1c) to address potential endogeneity concerns. The instruments that we use are: (i) the number of applicants in the same technological field, as a proxy for the potential number of employers available; (ii) two dummy variables that take the value 1 if the country of birth was the United States or the United Kingdom, as a proxy for the costs of mobility, i.e. native English speakers should face lower costs when moving due to their better communication skills on average; and (iii) the score on the following question: "Amongst your friends, colleagues and people you know more generally, how hard is it to combine family and work for everyone". The answer to this question is also used as a proxy for the costs of mobility. In particular, the question asks the inventors for perceived family-related constraints when moving, which may well lead to a lower perceived match quality. Overall, the IV approach supports the finding that a lower degree of knowledge fit lowers the productivity gains from moving.

The 'exogeneity' of the variable capturing the inter-firm effects ($\Delta\bar{q}_{j^1j^0}$) can also be questioned. Because it includes information from the focal inventor, it depends on the measure of knowledge fit ($\Delta m_{ij^1j^0}$). Concretely, a change in knowledge fit following a move affects an inventor's productivity all else equal, but also affects the average productivity of the firm. However, the risk of endogeneity is very small for two reasons: (i) the productivity effect of interest is the *average* effect over all of the firm's inventors ($\bar{q}_{j^1}$); and (ii) the variables are expressed in difference

($\Delta\bar{q}_{j^1j^0}$). It is difficult to think of a realistic situation under which a change in knowledge fit for one inventor would significantly explain difference in the average productivity of two firms. Nevertheless, we report the results of tree robustness tests aimed at assessing the validity of the baseline result. Models (2a) and (2b), displayed in Table 4, seek to exclude situations in which individual inventors could have a noticeable impact on the average productivity of the firm. First, we restrict the sample to inventors who move to large companies (firms with at least 50 employees). Second, we exclude inventors with a disproportionately high quantitative productivity (top 1 percent most productive inventors in terms of number of inventions). Third, we also excluded the most productive inventors with respect to output quality (top 10 percent most productive inventors in terms of citation corrected patent counts were excluded) in any of the two periods. Our results are robust to these specifications (also using IV regressions, not reported).[10]

As mentioned earlier, the sample is restricted to inventors who moved maximum twice, i.e. once more in the 5-year time window prior to the observed move. This restriction is required to ensure that the productivity variable in the pre-move period (q_{ij^0}) and the firm effect in the pre-move period ($\bar{q}_{j^0}$) are computed with a reasonable degree of accuracy. It is possible to further increase the accuracy of the dependent variable by restricting the sample to inventors who moved only once. Doing so reduces the sample by 209 observations and leads to estimates that are again robust, as indicated in Model (2d).[11] One limitation of our data is that we do not observe whether the inventor moved *after* the move under consideration, such that we cannot fully rule out an inaccuracy of the productivity variable in the post-move period (q_{ij^1}) and the firm effect in the post-move period ($\bar{q}_{j^1}$). It is, however, reasonable to assume that an inventor's move behavior is consistent over time. Hoisl (2007) for instance, finds no significant effect of age on the probability of a move. Hence, those inventors who moved rarely during the five years prior to the move under consideration should also be characterized by low a probability of moving in the post-move period. In addition, this limitation is likely to bias downward (if at all) estimates of the effect of knowledge fit on productivity. If inventors who experienced poor knowledge fit were also more likely to move after the reported move, they presumably increased their productivity, limiting the impact that a lack of knowledge fit has on productivity. Hence our results depict conservative estimates.

We conducted three more robustness checks. First, we excluded inventors older than 65 years at the time of the move from our sample (Model 2e) to make sure that our results are not driven by special characteristics of retired inventors. Second, we excluded US inventors from our sample (Model

[10] We refrain from reporting IV results for our robustness checks, since we lack a consistent set of strong instruments for all different regressions—IV tests sometimes suggest that the instruments are weak.

[11] We have decided to use the sample of inventors who moved once or twice for our baseline estimates because of our limited sample size, and given that the results are not altered by the inclusion of inventors who moved twice. Note that the baseline regression includes a dummy variable that controls for the number of moves.

2f), since the fact that we base our productivity measure on citations to EP patents rather than to US patents could again lead to biases. Finally, we excluded the 42 mobile inventors for whom we could not find an appropriate control group for the sake of consistency with Hypothesis 1 (Model 2g). Again, the results stay robust as regards sign and significance of the coefficients.

5.2 Additional results: science-based vs. technology-based fields

In an extension to the analysis, we investigate whether the mitigating effect that knowledge fit has on mobility-productivity gains depends on a set of conditioning factors. In particular, we suspect that knowledge fit may matter more in fields that rely heavily on science. The reason for this is that knowledge is harder to transfer in areas where knowledge has not (yet) been codified (Argote et al. 2003, Zander and Kogut 1995) or where knowledge is not (yet) well-understood (Szulanski 1996). Knowledge in science-based fields often comes from basic research, which is by definition characterized by higher uncertainty, whereas technology-based fields often rely on applied knowledge, which is typically better understood. In case knowledge transfer is more difficult in science-based compared to technology-based fields, knowledge fit should be even more important in science based fields.

We measure the science dependence of technologies by looking at the proportion of references from scientific literature listed in patent documents (estimation based on the population of patents filed at the EPO). Table 5 shows that three fields clearly stand out: electrical engineering, instruments, and chemistry and pharmaceuticals with between 17 and 18 percent of the listed references pointing to the scientific literature. For the other technologies in our sample (process engineering, mechanical engineering and consumption), the proportion of listed references pointing to the scientific literature ranges between 2 and 5 percent. Overall, 69 percent of the inventors were active in science-based fields (the rest worked in technology-based fields).

Table 5: Technological environment (N=869)

		share of non-patent references
science-based	Electrical Engineering	**0.17**
	Instruments	**0.18**
	Chemistry/Pharma	**0.18**
technology-based	Process engineering	**0.05**
	Mechanical engineering	**0.05**
	Consumption	**0.02**

Note: The classification is based on all EP patent applications filed between 1978 and 2011

Before providing the results with respect to knowledge fit, we report the outcomes of additional difference-in-differences regressions displayed in Table 6, which split the sample according to science- versus technology-based fields. For science-based fields we find an increase of qualitative productivity in the post-move period amounting to 21.6 percent (Model M8). We do not find productivity gains in the post-move period for technology-based fields. Voluntary moves to science-based fields result in an increase in post-move productivity amounting to 32.2 percent in terms of output quality (Model M12) and to 13.6% in terms of output quantity (Model M11). In case of technology-based fields, we again do not observe productivity gains from moving (Models M13 and M14). The same applies to involuntary moves – for both types of technology fields (Models M15 to M18).

Table 6: Mobility–productivity-relationship (Difference-in-Differences Estimation); by environment

	all moves science based		technology based	
	(Model M7)	(Model M8)	(Model M9)	(Model M10)
VARIABLES	**log(PAT_5yr)**	**log(CIT_5yr)**	**log(PAT_5yr)**	**log(CIT_5yr)**
move (dummy)	-0.100**	-0.144**	-0.040	-0.072
	[0.041]	[0.069]	[0.057]	[0.096]
post (dummy)	0.303***	0.061	0.315***	0.216**
	[0.044]	[0.073]	[0.058]	[0.090]
move * post	0.089	0.216**	-0.066	-0.023
	[0.061]	[0.100]	[0.086]	[0.134]
Constant	1.406***	1.720***	1.374***	1.418***
	[0.031]	[0.051]	[0.038]	[0.064]
Observations	2,220	2,220	1,088	1,088
R-squared	0.058	0.008	0.042	0.010
F test	47.98	6.050	15.88	3.659

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Table 6 (con't): Mobility–productivity-relationship (Difference-in-Differences Estimation); by environment (voluntary moves)

	voluntary moves science based		technology based	
	(Model M11)	(Model M12)	(Model M13)	(Model M14)
VARIABLES	**log(PAT_5yr)**	**log(CIT_5yr)**	**log(PAT_5yr)**	**log(CIT_5yr)**
move (dummy)	-0.113**	-0.185**	-0.030	-0.054
	[0.049]	[0.083]	[0.067]	[0.113]
post (dummy)	0.289***	0.015	0.346***	0.242**
	[0.054]	[0.089]	[0.067]	[0.107]
move * post	0.136*	0.322***	-0.083	-0.017
	[0.073]	[0.120]	[0.102]	[0.160]
Constant	1.395***	1.711***	1.352***	1.401***
	[0.038]	[0.063]	[0.044]	[0.075]
Observations	1,534	1,534	782	782
R-squared	0.062	0.011	0.048	0.012
F test	35.61	5.935	13.22	3.084

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Table 6 (con't): Mobility–productivity-relationship (Difference-in-Differences Estimation); by environment (involuntary moves)

	involuntary moves science based		technology based	
	(Model M15)	(Model M16)	(Model M17)	(Model M18)
VARIABLES	**log(PAT_5yr)**	**log(CIT_5yr)**	**log(PAT_5yr)**	**log(CIT_5yr)**
move (dummy)	-0.071	-0.054	-0.062	-0.115
	[0.073]	[0.122]	[0.110]	[0.180]
post (dummy)	0.337***	0.162	0.238**	0.151
	[0.078]	[0.127]	[0.112]	[0.167]
move * post	-0.017	-0.021	-0.024	-0.039
	[0.109]	[0.178]	[0.161]	[0.248]
Constant	1.431***	1.738***	1.429***	1.460***
	[0.054]	[0.088]	[0.077]	[0.121]
Observations	686	686	306	306
R-squared	0.053	0.005	0.028	0.008
F test	13.34	1.168	2.966	0.785

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Table 7 investigates our intuition that the effect of knowledge fit is more important in science-based fields as opposed to technology-based fields. Model 3 presents the result of an OLS regression model with an interaction term for inventors working in science-based fields. The main knowledge fit effect (representative of technology-based fields) is not significantly different from zero and the knowledge fit effect for science-based fields is -0.688 and significantly different from zero at the 1 percent probability threshold. In other words, the results suggest that a loss of knowledge does not affect post-move productivity in technology-based fields, presumably because inventors are able to make up for it easily. By contrast, a loss of knowledge in science-based fields has lasting effects on productivity.

Models (4a) and (4b) adopt a split-sample approach to estimating field-specific effects. Each covariate is interacted with the science-based dummy in Model (4a) and the technology-based dummy in Model (4b), and the interaction dummy is added to the regression models. This approach is useful to keep the sample size to its maximum and to ensure comparability of coefficients across regression models, i.e. across fields. Previous results are largely comforted: the effect of a lack of knowledge fit is -0.989 and significantly different from zero at the 1 percent probability threshold for science-based fields. The effect for technology-based fields is again not significantly different from zero at the 10 percent level. The results also hold when the knowledge fit variable is instrumented (Models 5a and 5b), although identification in the technology-based field regression model is weak.

Table 7: Determinants of productivity change following a move in science-based vs. technology-based environments

	Model (3)	Model (4a)	Model (4b)	Model (5a)	Model (5b)
Fields:		science based	technology based	science based	technology based
Econometric method:	OLS	OLS	OLS	2SLS	2SLS
inter-firm effect ($\Delta\bar{q}_{j^1j^0}$)	1.090***	1.156***	1.063***	1.180***	1.066***
	[0.030]	[0.063]	[0.033]	[0.070]	[0.033]
knowledge fit (log)	-0.107	-0.989***	0.045	-2.893**	-0.293
	[0.163]	[0.267]	[0.182]	[1.162]	[1.200]
knowledge fit = 0 (D)	-0.087	-0.743**	0.290	-2.857**	-0.061
	[0.226]	[0.326]	[0.297]	[1.272]	[1.262]
Knowledge fit (log) * science based (D)	-0.581***				
	[0.219]				
age at move (log)	-0.474*	-0.485	-0.475	-1.083	-0.568
	[0.259]	[0.501]	[0.298]	[0.675]	[0.449]
doctoral degree (D)	0.093	-0.274	0.235*	-0.315	0.232*
	[0.116]	[0.239]	[0.130]	[0.261]	[0.131]
number of moves	0.056	0.259	-0.086	0.200	-0.072
	[0.128]	[0.195]	[0.163]	[0.224]	[0.170]
interaction dummy	0.478**	2.393	1.328	6.793**	2.006
	[0.219]	[1.852]	[1.175]	[3.454]	[2.693]
Constant	1.393	-0.270**	-0.001	-0.270**	-0.001
	[0.999]	[0.110]	[0.164]	[0.109]	[0.164]
Observations	869	869	869	869	869
R-squared	0.647	0.207	0.447	0.183	0.446
F test	171.3	59.62	165.1	45.91	169.75
p-value	0.000	0.000	0.000	0.000	0.000
F test 1st-stage	-	-	-	3.73 (p=0.005)	*n.a.*
Hansen J statistic	-	-	-	6.094 (p=0.11)	0.837 (p=0.841)
Instruments	-	-	-	no. applicants (log), ctryUS (D), ctryGB (D), combine family and work (log)	

Notes:
Dependent variable is productivity change ($\Delta q_{ij^1j^0}$).
'D' stands for dummy variable.

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

Models (3), (4a), and (5a): *interaction dummy* = science-based environment
Models (4b), and (5b): *interaction dummy* = technology-based environment

6 Discussion

6.1 Contributions to the literature

The contribution to the literature is threefold. The main contribution is to provide novel insights into the causality between inventor mobility and inventor productivity as well as an explanation for the productivity gains that mobile inventors enjoy. We know from previous studies that mobility of scientists is positively associated with productivity (Trajtenberg 2006, Franzoni et al. 2012, Hussinger 2012) and that this relationship is, at least partly, causal (Hoisl 2007). However, existing research has not been able to explain the mechanism underlying these possible productivity gains. This paper connects the strategic management literature and the theoretical labor economics literature and hypothesizes that mobility productivity gains are explained by match effects between inventor and employer. This hypothesis is formally tested and validated using a sample of mobile inventors and a measure of match quality related to what we call ‘knowledge fit’.

Second, the paper contributes to the more specific literature on search and knowledge recombination. It provides a novel insight into the conditions under which individuals successfully transfer their knowledge to, and combine it with, the existing knowledge base of the new employer. As mentioned earlier, employee mobility is an important source of knowledge acquisition (Rosenkopf and Almeida 2003, Franco and Filson 2006, Paloremas and Melero 2010) but individuals need the link their knowledge to the existing knowledge base of the new employer (Cohen and Levinthal 1990, Fleming 2001).

Finally, the paper also contributes to the labor economics literature. It provides direct evidence that match effects explain productivity gains from mobility in the context of knowledge workers. There are three noticeable features to our study. First, while match effects are central to the understanding of the labor market, there exists little direct evidence of their existence. The literature has traditionally inferred match quality from data rather than directly observed it (e.g., Song et al. 2003), so that the mechanisms through which match effects occur have hitherto been treated as a black box. This paper provides a direct measure of match quality allowing a richer understanding of the match effect. Second, we are able to observe output directly, in the form of patents. This is in sharp contrast with most existing studies, which rely on indirect inference using wage data. As explained in Jackson (2013), wage is an imperfect measure of productivity, and wage equations are particularly prone to misspecification and omitted variable bias. Third, our focus on ‘knowledge fit’ as one dimension of match quality is particularly relevant given that knowledge is an archetypal example of an experience good.

6.2 Limitations

There are a number of limitations to our study, which we briefly discuss. Although we have emphasized the benefits of using patent data to answer our research question – in particularly if combined with survey data – the disadvantages of using patent data apply. As mentioned earlier not all inventions are patentable or patented (Griliches 1990). In case an inventor did not patent his inventions this affects our productivity measures. In case we did not observe any patents during the 5 years prior or after the move, the inventor would have been dropped from our sample. Furthermore, even though quality adjusted patent counts are a common measure for inventor productivity (Lanjouw and Schankerman 2004), other unobservable measures like ‘percentage of goals achieved’ may be even more appropriate to capture the productivity of inventors. Furthermore, we surveyed only one inventor per invention; in cases where the invention was made by an inventor team, other team members (movers or non-movers) also have contributed to the invention. Even though it is common practice in the literature to assign the outcomes to the surveyed inventor (e.g. Hoisl 2007) and even though the inventors in our survey were selected at random among the inventors listed on the patent application, we cannot fully rule out that the results would have been different in case we had surveyed different inventors. Apart from these patent data-inherent limitations two additional limitations of our explanatory variable are discussed below.

First, we are not able to assess the long-term impact of match effects due to data truncation and due to the fact that longer periods would result in additional moves, which could blur our results. As such, we should be careful in our interpretation of the results. For instance, while we observe that inventors with a poor fit have lower productivity in a 5-year time window following a move, they could come up with more radical innovations in the longer term once they have assimilated the new knowledge and are able to combine it with their past inventive experience.

Second, although we have put the spotlight on an issue which we believe is important, we do not claim that knowledge fit is the only relevant dimension of match quality, nor do we claim that match quality is the only factor affecting productivity gains from mobility. The paper raises more questions than it answers, and we hope that future research will contribute to improving our understanding of mobility productivity gains.

6.3 Implications

Our findings lend themselves to implications for policymakers, firms and inventors. The mobility of inventors is a topic of great policy interest. Economists see lack of mobility as a market friction that prevents the realization of efficiency gains arising from the optimal allocation of resources. As a result, policymakers in the developed world have sought to facilitate mobility e.g. by making the free movement of people a fundamental right in the European Union or by facilitating access to business entry visa for skilled migrants. Our results show that mobility alone is not sufficient to fully realize efficiency gains. We have put the focus on one barrier to such gains, and shown that it is more prevalent in science-based fields. This is particularly unfortunate since science-based fields have the most opportunities for radical innovations (Fleming and Sorenson 2004; Gruber et al. 2013).

The paper also comes with practical implications for R&D and human resource managers by shedding light on the determinants of productivity-enhancing hires. The person-organization fit paradigm has long been an important area of psychology and organizational behavior research (Tom 1971; Schneider 1987; Chatman 1989), and prospective employers routinely assess the extent to which job candidates fit their organization. This paper has described, and shown the importance of a new dimension of fit in the specific context of knowledge workers, namely knowledge fit. The findings suggest that recruiters should pay attention to knowledge fit as it directly affects recruitment success.

Finally, we can derive implication for inventors. Psychological studies show that most individuals are overconfident about their own abilities (Weinstein 1980; Taylor and Brown 1988) and inventors are no exception to the rule. Our results suggest that inventors should take adaptation cost seriously as their productivity, and hence their carrier, may be durably affected by accepting a job in which they poorly fit.

References

Agarwal R., Ohyama A. 2013. Industry or academia, basic or applied? Career choices and earnings trajectories of scientists. Management Science. Accepted.

Allen, J., Van der Velden, R. 2002. When do skills become obsolete, and when does it matter?. Research in Labor Economics 21: 27-50.

Almeida P., Kogut B. 1999. Localization of knowledge and the mobility of engineers in regional networks. Management Science 45: 905–917.

Altonji J., Shakotko R. 1987. Do wages rise with job seniority? Review of Economic Studies 54(3): 437–459.

Argote, L. McEvily, B., Reagans, R. 2003 Managing Knowledge in Organizations: An Integrative Framework and Review of Emerging Themes. Management Science 49(4): 571-582.

Becker, G. 1973. A theory of marriage: part I. Journal of Political Economy 81(4): 813–846.

Beveridge, B.W.H.B. 1930. Unemployment: A problem of industry. London: Longmans, Green & Company.

Boschma, R., Eriksson, R. , Lindgren U. 2009. How does labour mobility affect the performance of plants? The importance of relatedness and geographical proximity. Journal of Economic Geography 9: 169-190.

Card, D., Krueger, A.B. 1994. Minimum Wages and Employment: A Case Study of the Fast Food Industry in New Jersey and Pennsylvania, American Economic Review 84: 772-793.

Carrington, W.J. 1993. Wage losses for displaced workers: is it really the firm that matters?. Journal of Human Resources 28: 435-462.

Chatman, J. 1989. Improving Interactional Organizational Research: A Model of Person-Organization Fit. Academy of Management Review 14(3): 333–349.

Cohen, W., Levinthal, D. 1990. Absorptive capacity: A new perspective on learning and innovation. Administrative Science Quarterly 35: 128–152.

Cook, T.D., Campbell, D.T. 1979. Quasi-Experimentation – Design & Analysis Issues for Field Settings, Houghton Mifflin Company.

Dane, E. 2010. Reconsidering the Trade-Off Between Expertise and Flexibility: A Cognitive Entrenchment Perspective, Academy of Management Review 35(4): 579-603.

De Grip, A., Van Loo, J. 2002. The economics of skills obsolescence: a review. Research in Labor Economics 21: 1-26.

Ferreira P., Taylor, M. 2011. Measuring match quality using subjective data. Economics Letters 113(3): 304–306.

Fleming, L. 2001. Recombinant uncertainty in technological search. Management Science 47 117-132.

Fleming L., Mingo S., Chen, D. 2007. Collaborative brokerage, generative creativity, and creative success. Administrative Science Quarterly 52: 443–475.

Fleming, L., O. Sorenson 2004. Science as a map in technological search. Strat. Mgmt. J. 25: 909-928.

Franco, A., Filson, D. 2006. Spin-outs: knowledge diffusion through employee mobility. The RAND Journal of Economics 37(4): 841–860.

Franzoni, C., Scellato, G., Stephan, P. 2012. The mover's advantage: scientific performance of mobile academics. NBER Working Paper 18577.

Gambardella, A., Giuri, P., Harhoff, D., Hoisl, K., Mariani, M., Torrisi, S. 2014. Inventive Process and Economic Use of EPO Patents: Summary Evidence from the PatVal Surveys, Working Paper.

Gibbons, M., R. Johnston 1974. The roles of science in technological innovation. Research Policy 3: 220-242.

Griliches Z. 1990. Patent statistics as economic indicators: A survey. Journal of Economic Literature 28(4): 1661–1717.

Gruber, M., Harhoff, D., Hoisl, K. 2013. Knowledge Recombination across Technological Boundaries: Scientists versus Engineers, Management Science 59(4): 837-851

Hamermesh, D.S. 1987. The costs of worker displacement. The Quarterly Journal of Economics 102(1): 51-75.

Harhoff, D. 2011. Patent Citation Project; EQUIVALENTS_042011.dta, see http://www.inno-tec.bwl.uni-muenchen.de/forschung/forschungsprojekte/patent_cit_project/index.html, accessed January 10, 2013.

Hoisl K. 2007. Tracing Mobile Inventors – The Causality between Inventor Mobility and Inventor Productivity. Research Policy 36(5): 619–636.

Hussinger, K. 2012. Absorptive capacity and post-acquisition inventor productivity. The Journal of Technology Transfer, 37(4): 490-507.

Jackson C. 2013. Match quality, worker productivity, and worker mobility: Direct evidence from teachers. Review of Economics and Statistics 95(4): 1096–1116.

Johnson W. 1978. A theory of job shopping. Quarterly Journal of Economics 92(2): 261–278.

Jovanovic, B. 1979. Job Matching and the Theory of Turnover, Journal of Political Economy 87(5): 972–990.

Kapoor, R., & Lim, K. 2007. The impact of acquisitions on the productivity of inventors at semiconductor firms: A synthesis of knowledge-based and incentive-based perspectives. Academy of Management Journal 50(5): 1133-1155.

Krueger, A.B. 1990. Workers' Compensation Insurance and the Duration of Workplace Injuries, NBER Working Paper No. 3253, Cambridge, Mass.Lanjouw, J. O., Schankerman, M. 2004. Patent quality and research productivity: Measuring innovation with multiple indicators. The Economic Journal 114(495): 441-465.

Lee, D.M., Allen, T.J. 1982. Integrating new technical staff: Implications for acquiring new technology. Management Science 28(12): 1405-1420.

Marx, M., D. Strumsky, L. Fleming 2009. Mobility, skills, and the Michigan Non-Compete Experiment. Management Science 55: 875-889.

Meyer, B.D. 1995. Natural and Quasi-Experiments in Economics, Journal of Business & Economic Statistics 13(2): 151-162.Mortensen, D. 1986. Job search and labor market analysis, in Ashenfelter, O. and R. Layard (ed.), Handbook of Labor Economics, Vol. 2, Ch. 15., North-Holland.

Müller K., Peters B. 2010. Churning of R&D personnel and innovation. ZEW Discussion Paper 10-032, Mannheim.

Nakajima R., Tamura R., Hanaki N. 2010. The effect of collaboration network on inventors' job match, productivity and tenure. Labour Economics 17(4): 723–734.

Nelson P. 1970. Information and consumer behaviour. Journal of Political Economy 78(2): 311–329.

Oettl A., Agrawal A. 2008. International Labor Mobility and Knowledge Flow Externalities. Journal of International Business Studies 39(8): 1242-1260.

Palomeras, N., Melero, E. 2010. Markets for Inventors: Learning-by-Hiring as a Driver of Mobility. Management Science 56(5): 881–895.

Pellizzari M. 2011. Employers' search and the efficiency of matching. British Journal of Industrial Relations 49(1): 25–53.

Perrucci, R., Rothman R.A. 1969. Obsolescence of knowledge and the professional career." Pp. 247-275 in Robert Perrucci and Joel Gerstl (eds.), The Engineers and the Social System. New York: Wiley.

Podsakoff, P., MacKenzie, S., Lee, J.-Y., Podsakoff, N. 2003. Common method biases in behavioral research: a critical review of the literature and recommended remedies. The Journal of applied psychology 88(5): 879–903.

Rosen, S. 1975. Measuring the obsolescence of knowledge. In Education, income, and human behavior (pp. 199-232). NBER.

Rosenkopf L., Almeida, P. 2003. Overcoming local search through alliances and mobility. Management Science 49: 751-766.

Rothman R.A., Perrucci, R. 1971. Vulnerability to Knowledge Obsolescence among Professionals, The Sociological Quarterly 12(2): 147-158.

Schmoch, U., 2008. Concept of a Technology Classification for Country Comparisons, Final Report to the World Intellectual Property Organisation (WIPO), Fraunhofer Institute for Systems and Innovation Research, Karlsruhe, Germany.

Schneider, B. 1987. The People Make the Place. Personnel Psychology 40(3): 437–453.

Shalem, R., Trajtenberg, M. 2009. Software Patents, Inventors and Mobility. SSRN Working Paper. http://dx.doi.org/10.2139/ssrn.1547276.

Solon, G. 1985. Work Incentive Effects of Taxing Unemployment Benefits, Econometrica 53: 295-306.

Singh J., Agrawal A. 2011. Recruiting Ideas: How firms exploit the prior inventions of new hires. Management Science 57: 129–150.

Song J., Almeida P., Wu G. 2003. Learning-by-hiring: When is mobility more likely to facilitate interfirm knowledge transfer? Management Science 49: 351–365.

Sørensen T., Vejlin R. 2012. The importance of worker, firm and match effects in the formation of wages. Empirical Economics, Accepted.

Spence, M., 1973. Job market signalling. The Quarterly Journal of Economics 87(3): 355–374

Stoyanov, A., Zubanov, N. 2012. Productivity Spillovers across Firms through Worker Mobility, American Economic Journal: Applied Economics, American Economic Association 4(2): 168-98.

Szulanski, G. 1996. Exploring internal stickiness: Impediments to the transfer of best practice within the firm. Strategic Management J. 17: 27–43.

Taylor, S. E., & Brown, J. D. (1988). Illusion and well-being: a social psychological perspective on mental health. Psychological Bulletin 103(2): 193–210.

Tom, V. 1971. The role of personality and organizational images in the recruiting process. Organizational Behavior and Human Performance 6: 573–592.

Topel R.H., Ward P.W. 1992. Job Mobility and the Careers of Young Men, The Quarterly Journal of Economics 107(2): 439–479.

Trajtenberg, M. 2006. The "names game": Harnessing inventors' patent data for economic research. NBERWorking Paper 12479, National Bureau of Economic Research, Cambridge, MA.

Weinstein, N. D. (1980). Unrealistic optimism about future life events. Journal of Personality and Social Psychology 39(5): 806–820.

Woodcock S. 2008. Wage differentials in the presence of unobserved worker, firm, and match heterogeneity. Labour Economics 15(3): 772–794.

Wooldridge, J.M. 1999. Introductory Econometrics – A Modern Approach, New York et al.

Yamaguchi S. 2010. The effect of match quality and specific experience on career decisions and wage growth. Labour Economics 17(2): 407–423.

Younge, K. A., Tong, T. W., Fleming, L. 2011. How anticipated employee mobility affects acquisition likelihood: Evidence from a natural experiment. Working Paper, University of Colorado at Boulder and Harvard Business School.

Zahra S.A., George G. 2002. Absorptive capacity: A review, reconceptualization, and extension. Academy of Management Review 27: 185–203.

Zander, U., B. Kogut. 1995. Knowledge and the speed of the transfer and imitation of organizational capabilities: An empirical test. Organ. Sci. 6 76–92.

Zollo M, Singh H. 1997. Learning to acquire: knowledge codification, process routinization and post-acquisition integration strategies. Working paper of the Wharton Financial Institution Center.