Industry Dynamics and Highly Qualified Labor Mobility

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Abstract

The literature on knowledge spillovers offers substantial evidence that workers, as main carriers of knowledge, play a role in the diffusion of knowledge among firms. One of the channels though which knowledge is being diffused is the job-to-job mobility of workers. The purpose of this study is to zoom in this channel and to empirically explore the industry-specific factors that influence the level of job-to-job mobility of highly qualified workers (HQW) within three-digit industrial sectors. We use panel data on individuals and establishments from the German social security notifications to investigate our question. We find that, in the five-year period under investigation, on average, on the level of economy, between 13.9 and 16.9 percent of the highly qualified workers in Germany changed their job from one establishment to another. At the three-digit industry level, on average between 3.6 and 4.4 percent of the HQW changed their employer without changing the industry. We further find that the HQW job-to-job mobility is dependent on technology- and industry's evolution-specific factors. The results show a significant and positive effect of the technological regime and the level of job destruction on the level of voluntary and overall highly qualified workers' mobility. The intra-industry mobility of this group is also affected by establishment-size effects, the inflow of highly qualified workers form other industries and the type of industry (service or manufacturing).

JEL Classification Numbers: D83, J44, J62, O33.
Keywords: job-to-job mobility of highly qualified workers, technological and organizational change, knowledge transmission

Introduction

The literature on knowledge spillovers (Griliches, 1979) became more precise about the channels of knowledge transmission in the last two decades. While earlier contributions to this literature considered knowledge as something that is immeasurable, hence not tractable (e. g. Krugman 1991, p. 53), later work gave an empirical dimension to the theory (e. g. Jaffe et al. 1993), and therefore opened a way for identification of the channels for knowledge diffusion. Knowledge exchange comes about either through direct contact of people (informal communication, cooperation, training, acquiring of people or groups of people) or through analysis of product-embedded knowledge (publications, licenses, patents and final products). Malerba and Orsenigo (1997) name the earlier direct and the latter indirect means of knowledge transmission (p. 96). After acknowledging the distinct character of knowledge that unlike information is often remarkably difficult to convey without direct and repeated communication, the direct means of knowledge transmission gained an increasing attention in the theory of innovation.

The purpose of this study is to zoom-in one of these channels - the job-to-job mobility of highly qualified workers. Remarkable intra-industry job-to-job mobility of engineers and other highly qualified workers has been observed in several empirical studies, primarily case studies focusing on dynamic, innovative regions (Saxenian, 1994; Keeble et al. 1998;) and clusters (Henry and Pinch, 2000). These studies acknowledge the merits of the workers' mobility for the growth of these regions and clusters. Other studies associate the growth of industries with the high mobility of technical personnel (Cooper, 2000; Franco and Filson, 2000; Klepper, 2002; Klepper and Sleeper, 2005).

The phenomenon of job-to-job mobility of workers in general has been extensively explored both theoretically and empirically within the human capital framework and within the search and matching theories. However, their focus has not been on knowledge dissemination[1] and therefore the job-to-job mobility of HQW has been insufficiently emphasized within this literature. Only recently, as notably relevant for the economics of innovation, a number of formal models

[1] In the focus of these theories have been issues such as unemployment, wages and investment in education and training.

elaborated the implications of labor mobility as knowledge carrier (Cooper, 2000; Franco and Filson, 2000; Fosfuri and Rønde, 2003; Fallick et al., 2004; Combes and Duranton, 2005). Empirical evidence of the knowledge transmission through mobility of inventors has been established by analysis of the patent citations (Jaffe et al., 1993; Almeida and Kogut 1999; Balconi et al. 2004). While it is clear that not only inventors are responsible for innovation-relevant knowledge transmission, it is also explicit that the pool of workers who have an access to innovation-relevant knowledge in a firm is limited. This is why our study focuses on the broader group of highly qualified workers (HQW)[2] as carriers of innovation-relevant knowledge.

To justify a separate study on mobility of highly qualified workers the first step was to investigate whether the mobility behavior of HQW significantly differs from the one of non-HQW. Previous studies discriminating between different educational and skill groups yield differing results[3]. As we find significant differences between the intra-industry mobility of HQW and non-HQW in terms of their voluntary and involuntary mobility patterns, we proceed the research by focusing on HQW only.

What the reader has to have in mind when reading this study is that it is not aimed at measuring the knowledge diffusion across firms. For such an ambition this is not the appropriate design. Our research rather looks at the mobility dynamics of the group of HQW, who in the previous literature are indicated as the major carrier of knowledge (see e.g. OECD, 1995). The study also focuses on only one channel through which knowledge is being transmitted among firms and therefore it is not informative when it comes to the overall potential of knowledge transmission within industries. We do not claim that each job-to-job transition results in innovation-relevant knowledge exchange, but we do start from a justified assumption (see e. g. Saxenian, 1995; Henry and Pinch, 2001) that a more flexible labor force increases the overall potential for knowledge

[2] Operationally we define HQW as workers employed in the observed industry with at least technical college degree (Fachhochschule Abschluss) whose average earnings in each consecutive year are at least as high as the average earnings for the economy. The earnings limitation is an attempt to eliminate that group of highly educated people who are underemployed. This group of workers due to working at positions where workers are less exposed to strategic information and knowledge is less likely to contribute to the knowledge transmission. We also only consider the employment spells where the employee is full-time employed.

[3] Many studies found higher mobility levels of people with higher qualifications (e.g. Weißhuhn, 1987; Velling and Bender, 1994) while other find no difference in the mobility levels for different educational categories (Mühleisen and Zimmermann 1994, Zimmermann 1998)

transmission through this channel. Therefore we argue the sectors with higher job-to-job mobility of HQW can rely more on this channel of knowledge transmission than sectors with lower mobility.

We find that, in the five-year period under investigation, on average, on the level of economy, between 13.9 and 16.9 percent of the highly qualified workers in Germany changed their job from one establishment to another. At the industry level, on average between 3.6 and 4.4 percent of the HQW changed their job without changing the industry. We further find that the HQW job-to-job mobility is dependent on technology- and industry's evolution-specific factors. We find a significant and positive effect of the technological regime and the level of job destruction on the level of voluntary and overall highly qualified workers' mobility. The intra-industry mobility of this group is also affected by establishment-size effects, the inflow of highly qualified workers form other industries and the type of industry (service or manufacturing).

The structure of the paper is as follows. In section I we explain why we focus on particular job-to-job transitions which we name voluntary. Section II presents the theory and the hypotheses. Section III explicates our empirical strategy and the results of the analysis. Section IV concludes.

I. Voluntary and involuntary mobility

Voluntary mobility is led by the search for better employer-employee matches (e. g. Jovanovic, 1979) and therefore generates better-quality matches with higher probability when compared to involuntary mobility. Without contradicting the common understanding that job matches are experience goods, we believe that job matches are to large extent inspection goods (Hirshleifer, 1973) as well. This means that the learning about the other side of the match happens before the "purchase". This assumption is not unrealistic taking into consideration the contemporary selection processes where the applicants extensively evidence their past experience, skills, knowledge and qualifications at the job application stage. On the other side, job applicants actively collect information about the firm and the job position before they apply and agree on a job. Acknowledging job matches as an inspection good has the implication that both the employer and the employee become aware of the potential knowledge exchange that may take place in case of a successful match. In the search and matching theory a better-quality match often translates into higher earnings for the employee (Burdett 1978) and higher productivity for the firm[4]. If a better-quality match results in higher productivity this may well be due to the higher complementarity of knowledge and competence of the both sides. Therefore we generalize that matches resulting in higher (or at least non-decreasing) earnings for the employee are more likely to result in a higher utilization of the knowledge possessed by the worker, or in other words, higher knowledge transmission.

Another implication for the theory and the measurement of knowledge transmission is derived from the human capital theory (Becker, 1962, 1964). Involuntary mobile (at least in our definition)[5] are often people who have experienced unemployment spells between two employment spells. Break in the employment may lead to significant human capital losses. In highly dynamic industries a break of several months may substantially depart the worker from updated information and knowledge about the ongoing processes in the former firm. Under the assumption that job matches are inspection goods, the new employer should expect fewer spillovers from employees who return into employment after having experienced unemployment spell. Therefore, matches that are created between an employer and a worker that was unemployed for a while are very likely not formed with the intention to access updated knowledge from the firm where the employee previously worked. Such matches still form because aside from the updated knowledge, the skills and the abilities of the worker bring a value on its own to the employer.

II. Technologies, technological change and mobility

It is well known in the industrial dynamics literature that industries vary in many respects, both due to the differences in their technology and due to the evolutionary stage they are experiencing.

[4] Better match does not exclusively translate into better pay for the worker. Better working conditions, location, fringe benefits and other non-pecuniary incentives may also initiate a voluntary movement.
[5] Please see section III for the operational definition of voluntary and involuntary mobility.

These differences affect the labor dynamics, and to the extent they influence the mobility-related behavior of the highly qualified workers, they may be determining the level of knowledge diffusion as well. Our question resembles more the questions of the labor economists that ask how the industry dynamics influence the movement of workers, and less the questions of the scholars in the industry dynamics literature. Therefore, much of what the following section offers has its roots in the earlier tradition. In the center of the analysis are factors of HQW mobility that are interesting from an innovation perspective, namely the technological change and the technological regimes.

Technological regimes

Based on the work of Joseph Schumpeter (1912, 1942), Nelson and Winter (e. g. 1982b), and later Malerba and Orsenigo (e. g. 1993, 1997) elaborated the grounds of what in the evolutionary economics is known as technological regimes. Technological regime refers to the underlying factors and elements that mandate the pattern of innovative activities. It relates to the "technicians' belief of what is feasible or at least worth attempting" in problem-solving (Nelson and Winter 1982b, p. 259). Two regimes have been theoretically and empirically observed: Schumpeter Mark I (entrepreneurial regime) and Schumpeter Mark II (routinized regime).

In the entrepreneurial one, 'creative destruction' is the major innovation mode, while in the routinized one, the 'creative accumulation' underlies the innovative processes. According to the work of Nelson and Winter (1982a, 1982b), and later Malerba and Orsenigo (1990, 1993, and 1997), these two regimes differ along four major technology-related features: the opportunity conditions, appropriability conditions, the degree of cumulativeness, and the knowledge base. The entrepreneurial regime is characterized by high opportunities, lack of appropriability, and low degree of cumulativeness. The knowledge base is such that much knowledge is not yet codified and probably not systematically connected to its full potential due to its newness. Such conditions result in low concentration of innovative activities, large number of innovators, and high rates of entry (Malerba and Orsenigo, 1997, p. 100). The opposite conditions and outcomes prevail in the routinized regime. The major implication of these differing conditions is that under the entrepreneurial regime new and small firms have the innovative advantage, where under the routinized one the innovative edge is in the hands of incumbents.

We argue that the technological regime of an industry has impact on the level of intra-industry mobility of highly qualified workers. The economic outcomes of the entrepreneurial regime: low concentration of innovation, large number of innovators and high rates of entry create conditions for much mobility of workers, both voluntary and involuntary. Low concentration of innovative activities means that numerous firms possess pieces of novel knowledge. Such situation creates an environment in which the incentives for knowledge exchange among firms are high, as multiple firms own innovation-relevant knowledge with high potential to result in useful combinations if connected. The large number of innovators indicates possibilities for the workers to move among the firms in search for better matches. High entry rates speak about new jobs being created and therefore new opportunities for movement from incumbents to newcomers. Therefore, we expect positive relationship between the level of mobility, both voluntary and overall, and the degree to which an industry is entrepreneurial.

H1. The more entrepreneurial the character of an industry is, the higher level of voluntary mobility of highly qualified workers

Turbulence

As industries evolve, the entrepreneurial entry of firms, their exit, expansion, and contraction show different dynamics. Both, the industrial dynamics and the labor economics literature agree that the major force behind this development is technological and organizational change (e. g. Aghion and Howitt 1992; Klepper 1996; Mortensen and Pissarides 1998; Bauer and Bender 2004). The entrepreneurial, rather than the innovative turbulence of firms (although both highly related) more directly affects the transitions of workers among different employment states and therefore we are more interested in the entrepreneurial turbulence. Additionally, labor markets spread over multi-product and multi-service industries and mobility around a single product/service may not reflect the natural borders of workers' mobility. Therefore we are focusing on multi-product/service industries.

Due to technological and organizational change, as well as demand shifts jobs get reallocated from less to more productive firms, and from declining to growing industries. Productive firms also destroy jobs in order to further improve their performance. New, different jobs may be created by these same or other firms. Novel technology makes existing one obsolete resulting in both, closure of jobs developed around the old technology and creation of jobs emanating from the new one. Worker flows happen as a consequence; workers transit from employment to unemployment or out of the labor force, from unemployment or out of labor force into employment and from one job to another (within or across industries). Such job-, and consequently, worker-flows are largely induced by the changes in the desired establishment size (Davis and Haltiwanger 1992) and organization (Bauer and Bender 2004). As such, these changes act as exogenous factors that partially drive the workers' movement from one job to another by creating opportunities and restrictions to voluntary mobility on one hand and pressure for involuntary mobility on the other[6].

In our approach turbulence is closely related to the notions of job creation and job destruction common in the labor economics literature.[7] Instead of having a single measure of turbulence, we estimate the job creation and destruction rates, which we find more enlightening in explaining the forces of mobility. Definition of these variables is given in section III. Our analysis shows that the bulk of job creation in the German economy in the observed period (2000-2004) stems from expansions of existing firms (88.5%), while startups account for only (11.5%) of the job creation. Contractions of firms account for 76% of the job destruction, while firm exits account for the rest 24% of job destruction.

Mainly based on the longitudinal research of the American economy, labor economists find that at any moment of time there is a high degree of both, job creation and job destruction (Davis and

[6] For the German economy, Bauer and Bender (2004) find that investments in IT positively and significantly affect the hiring rate of professionals and engineers without having an influence of the job creation rate of this group, while the reduction of the hierarchy level significantly and positively affects the job destruction and separation rates of professionals and engineers (p. 283-4).
[7] For a comprehensive explanation of these phenomena see Davis and Haltiwanger (1992) or Boeri and Cramer (1992).

Haltiwanger 1992, 1999). Sectors that undergo a vivid technological and organizational change are characterized by simultaneous coexistence of high level of the above mentioned phenomena. In line with these results, we also find comparatively high levels of job creation and destruction in the German economy. The median rate of job creation within industries is 7.5 %, while the median industry rate of job destruction is 8.4% for the five-year period under observation. The rates of job creation and destruction are highly correlated ($r = .59$, $p<.05$), bringing additional support for the claim that job creation and job destruction most likely are caused by the same factor – many scholars claim it to be technological change (see Bauer and Bender (2004) for further evidence).

We expect positive relationship between the level of job creation and the level of voluntary mobility. We also expect positive relationship between the level of job destruction and the level of voluntary mobility. The same relationships we expect for the overall mobility of HQW. Job creation is an indicator for job opportunities. The level of job creation affects the voluntary mobility as it creates more room for employees to choose among jobs. It also affects positively the level of involuntary mobility as it generates opportunities for those who have lost their jobs to return back to the same industry. The claim that technological change is skill-biased further supports the belief that the job creation should in particular affect the behavior of workers with high qualifications. Job destruction may force workers to search for other jobs in expectation of losing the current job and may either result in better or worse match than the current one. Therefore, it may positively affect both, the voluntary and the involuntary movement of workers in our definition.

H2. The higher the level of job creation, the higher the level of voluntary mobility

H3. The higher the level of job destruction, the higher the level of voluntary mobility

III. Empirical Strategy

A. Data and methodology

As primary data sources we use the IAB Employment Sample (IABS), available for the period 1975 - 2004 and the IAB Establishment History Panel (BHP), available for the period 1975 –

2005[8]. From the available cross sections we only utilize the period 2000-2004[9]. The IABS contains information about the employment history of 2% of the German population liable to social security. This means that civil servants, as well as self-employed are not part of the sample. The BHP contains information about all establishments in Germany with at least one employee subject to social security, (starting 1999 also those with at least one marginally employed). We had an access to a 50% sample of BHP population stratified by industries.

Three digit industries are the most appropriate observational level for our purpose because of two reasons: on one hand, on average they are large enough to allow for meaningful level of mobility of HQW within the industry, and on the other, firms within the same three digit sector are closely technologically-related, which allows for reciprocal interest in the mutual knowledge supply. However, since the size of industries differs to a large degree in terms of both, the number of firms and the number of employees, some data issues had to be taken into account. Especially for some very small industries the number of employees was not sufficient to compute meaningful intra-industry mobility rates. Therefore, small industries have been merged in order to achieve a large enough sample size that allows deriving trustable mobility rates. Collapsing industries was carried out by preserving the closest distance with respect to the underlying labor inputs.

After selecting only those employees with a tertiary degree of education and only full-time employment spells, our sample sums to 104 285, or an average of 20 857 workers per year. Among these HQW, we observe a total of 13 648 mobility counts, or on average 2 730 job-to-job transitions annually. Voluntary HQW mobility accounts for between 52% and 70% of the overall HQW mobility on the level of the economy. The intra-industry voluntary mobility of HQW accounts for between 58% and 72% of the overall HQW intra-industry mobility. The descriptive statistics of individuals and their mobility, both HQW and non/HQW are stated in Table A5 in the appendix.

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8 Both datasets were accessed on-site at the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB). For detailed description of these datasets see Drews (2007) and Spengler (2007).

9 Utilizing the data prior to 1999 necessitates conversion of the NACE 93 and 03 codes to WZ 73 which, we suspect, will result in substantial inconsistencies.

Dependent variables

Since the IABS reports the notifications to the social security on continuous (daily) bases, one can observe more than one change of the employment position in a given year. However, in order to calculate the yearly mobility rates we took one point in time (June 30th) each year and ignored those spells of relatively short character that do not cover the chosen time point. Therefore, it becomes important whether a person changed a job in a given year as compared to the previous one and not how many times we see an occurrence of individual's job changes in a given year. Our dependent variable is then the count of intra-industry job-switchers between two years divided by the total employment in the industry in the second year. We distinguish between voluntary and involuntary mobility based on two criteria: the existence of unemployment or marginal employment spell between two full-time employments, and the earnings levels. Involuntary mobile are those workers who have experienced unemployment spell and/or earn less at the new job than at the previous one. Each of these two criteria alone is sufficient to categorize a job move as involuntary in our definition. We use nominal wages due to the phenomenon of real wages decrease in Germany exactly in the time-period we are interested in[10].

Two things are important to bear in mind when thinking about our definitions of voluntary and involuntary transitions. First, voluntary mobility the way we define it may not always reflect the true intention of the worker to transit to another job on his/her own initiative. More explicitly, a move will be categorized as voluntary as long as the above described two criteria are fulfilled, although the true reason for transition may be a lay-off or abolishment of a job. Similarly, a quit will be categorized as involuntary if a person voluntarily transits to a job with lower pay. Although this confuses the conventional understanding of voluntary and involuntary move in sense of intentions, it does not contradict our argumentation about the different potential of knowledge transmission through voluntary and involuntary transitions. Non-decreasing earnings in general signal that the skills and the knowledge the employee brings to the new workplace are compatible with those of the new employer and the absence of unemployment spell guarantees that the knowledge is not outdated. We keep the terms voluntary and involuntary because our observations

[10] Close inspection of the earnings' behaviour of workers who retained a job within a firm in consecutive time-periods showed that between 26.6% and 40.2% of the working population was affected by real wages decrease in the observed time-frame.

of these two types of job transitions to a large extent overlap with the true intentions of the workers as reported by the German Socio Economic Panel[11]. Second, the IABS earnings' data is censored at an arbitrarily given censoring point. Around 12% of all observations of HQW are affected by this censoring and no imputation method can replicate the true earnings of this group accurately enough. This creates a doubt whether our sample of HQW reflects adequately the mobility behavior of the group of HQW with highest earnings. To the extent possible we explored the mobility behavior of the group of observations with earnings above the censoring point. This group was significantly less involuntary mobile ($t = 8.4$, $p<.01$) than the group of HQW observations who does not earn over the censoring point, but was not significantly different in terms of voluntary mobility. Here as a criterion for voluntary/involuntary movement we used the presence of unemployment/marginal employment spell between two employments. Therefore, at least in terms of voluntary mobility of "high-earners" we do not find evidence for behavioral differences between these two income groups.

Independent variables

We use a rough indicator of the degree to which one industry is entrepreneurial, but we believe that this measure captures the most indicative feature of the regimes. Our indicator of the degree to which one industry is entrepreneurial is the share of workers with careers in occupations mainly requiring a tertiary degree in natural sciences or engineering in small firms (with fifty or less employees). The higher this share, the more entrepreneurial the industry is considered to be. As mentioned above, the crucial difference between these two regimes is that in the entrepreneurial one small and young firms have the innovative advantage, while in the routinized one large incumbents are more innovative. This innovative advantage is well reflected in the R&D intensity indicators of small and large firms and the employment of personnel in natural sciences and engineering occupations is one such indicator. We our indicator of technological regime "entrepreneurial regime" in order to allow for easy interpretation-the higher its value the more entrepreneurial the character of an industry is considered to be.

[11] The results of the comparison between the mobility transitions in the IABS and the SOEP is available from the authors on request.

Our second independent variable is turbulence. As we argued in the theory part, turbulence is considered to be mainly a consequence of technological change. We measure the level of turbulence through estimating the rates of job creation (*JC*) and job destruction (*JD*). We obtain the sum of the change in the number of fully-employed workers (*x*) in all establishments *e* in a sector between time *t-1* and *t* and divide it by the size of the sector (number of fully employed workers at all establishments) at time *t*. Positive change in the number of fully employed workers enters the measure of job creation. In this measure we also include the employment in establishments that appear in the database for a first time. This indicates the job creation that is a result of start-ups. As all establishments in Germany with at least one marginally employed employee are obliged to report to the social security since 1999, the BHP data should be a reliable basis for identifying start-ups.

$$JC = \frac{\sum_{e=1}^{n} \Delta x_e}{\sum_{e=1}^{n} x_{et}}; \; if \;\; \Delta x_e > 0 .$$[12]

Negative change in the number of fully employed workers between two time periods (years) is associated with job destruction. This measure also encompasses the job closings of establishments that leave the database (our indication for firm exits).

$$JD = \frac{\sum_{e=1}^{n} |\, \Delta x_e \,|}{\sum_{e=1}^{n} x_{et}}; \; if \;\; \Delta x_e < 0 .$$

Controls

We control for industry agglomeration effects, firm size, inflow of HQW from other sectors, business cycle effects and temporary shortages of HQW (mismatch of the supply and demand on the labor markets). To indicate the degree to which an industry is geographically agglomerated, we apply the gini measure of inequality, as used by Krugman (1991). In order to control for establishment size-related factors the median establishment size is included. We avoid using the

[12] We also tried a different approach for measuring job creation by looking at the annual total number of new job openings for positions requiring high qualifications. The data was provided by the Federal Employment Agency. The results however remained unchanged.

average establishment size, as often used in the literature, because we observe right skewed establishment size distributions within the industries. We also created a time-invariant variable (average over the five-year period we observe) that measures the flows of HQW from the rest 3-digit industries within the same 1-digit sector towards the relevant 3-digit sector. The idea is that industries that can satisfy their demand for HQW through inflow of workers form technologically-related sectors should have lower intra-industry mobility. The possible effects of the business cycle are controlled for by using time dummies. To construct an indicator of the HQW shortage we use data on the average time it takes to fill up a position opening in given industry (vacancy time) as reported by the German Federal Employment Office (BA). We use the vacancy time of new job openings as an indicator of the mismatch between the demand and the supply of labor, as proposed in the literature (see e. g. Holt and David, 1966; Abraham, 1987). Longer vacancy time of new job openings should indicate a more severe shortage of HQW. Higher shortages of qualified personal should increase the mobility of HQW because this increases the incentives of employers to poach already employed workers. The reported analysis results in this paper are based on the vacancy time for all position openings. We also obtained the average industry vacancy time based on occupations that in general require a tertiary educational degree. The results remained unchanged.

The summary statistics of the variables as well as their definitions are provided in Tables A1 and A2 in the appendix.

B. Model specification

The most prominent way to deal with time-invariant unobserved heterogeneity across industries is a "fixed effects" (FE) model. Hausman test rejected the null hypothesis of absence of systematic differences between the RE and the FE models. Therefore we proceeded with the analysis by using models that allow for correlation between the regressors and the unit fixed effects. Time invariant industry specific effects of mobility are in our example caused by industry specific human capital (compare Parent, 2000), industry specific capital, labor, knowledge demands, and other factors. Still one major drawback of FE models is that only the within variance is used while the between variance is not taken into account. Since several industry characteristics that are important for explaining labor mobility are rarely changing over time, a number of problems occur when unit fixed effects are present. Industry specific effects like geographical concentration, industry concentration and median establishment size show very little variation over time so that the FE model performs poorly in estimating the effect of these variables. Furthermore, a basic FE model does not allow estimating time-invariant variables at all. One possibility to deal with rarely changing variables in a fixed effects setting is a fixed effects vector decomposition (FEVD) model (Plümper and Troeger, 2007). The procedure is as follows: first a fixed effects model is estimated with all our variables of interest; second, the unit fixed effects of this model are decomposed into a part that can be explained by the time-invariant and rarely changing variables and a part that cannot be explained by these variables by using pooled OLS; and third, the initial model is re-estimated by using OLS and by including the part of the unit fixed effect that cannot be explained by the time-invariant and rarely changing variables (the residual of the second step). Based on Monte Carlo simulations, Plümper and Troeger show that the vector decomposition method performs more efficiently than the FE model, especially for those independent variables where the ratio of within and between variance is large (Plümper and Troeger, 2007).

The estimated model has the following form

$$mobility_{i,t} = \frac{\sum employees_{i,j_{t-1} \neq j_{t=0}}}{\sum employment_{i,t=0}} = \beta_0 + \beta_a X_{i,t} + \beta_b Z_{i,t} + \upsilon_i + \varepsilon_{i,t} \,,$$

where $mobility_{i,t}$ is the mobility rate, defined as the number of employees in industry *i* that work in *t=0* in firm *j* and in *t-1* in another firm divided by the total employment in industry *i*. *X* is a vector of industry specific variables considered as time variant and *Z* is a vector of variables considered as rather time invariant. Since almost all independent variables are skewed we use log-transformations. For our control variables *geographical concentration* and *Median establishment size* it was straightforward that they have to be treated as time-invariant in the FEVD model (the between/within variance ratios of these variables are respectively 16.7 and 9.7). Our variable measuring the entrepreneurial character of an industry shows between/within variance ratio of 1.7.

For such cases, Plümper and Troeger advice that one should rather include the variable in the time variant group of regressors (p. 136).

C. Results

Descriptive Statistics

Highly qualified workers are significantly more voluntary mobile than non-HQW within industries, ($t = 3.31$, $p<.01$). They are also significantly less involuntary mobile than the non-HQW within industries, ($t = -4.11$, $p<.01$). Both findings are in line with our expectations. Between 12.9% and 16.9% of the HQW population in Germany is being reshuffled annually across the whole economy in the period 2000-2004. When it comes to the HQW mobility within 3-digit industries, the average annual mobility rates move between 3.6% and 4.4%. Looking at the voluntary mobility rates of HQW within industries, between 2.4% and 3.2% of all HQW change their jobs annually within 3-digit industries.

With respect to mobility of HQW we find that the largest share of general mobility of HQW can be tracked back to voluntary mobility during the period of investigation. This is true for overall job-to job mobility as well as for intra-industry mobility. As the correlation table in the appendix shows, general and voluntary intra-industry mobility are correlated to a higher degree, ($r = .89$, $p<.01$), than overall and involuntary intra-industry mobility, ($r = .65$, $p<.01$). The observed correlation between voluntary and involuntary mobility is about 0.23 ($p<.01$). It may also be interesting to glance at the change of the mean mobility rates over time. Figure 1 and Figure 2 show respectively the average mobility levels of HQW for the general economy and within the industries. It seems that the voluntary HQW mobility is pro-cyclical and involuntary counter-cyclical, as usually argued in the labor economics literature. Some of the industries with highest voluntary mobility of HQW in services are Railways, Telecommunications, Pharmacies, Central banks and financial institutes, and Advertising. Industries with highest voluntary mobility in manufacturing are Electricity, gas, steam, and water supply, Civil engineering, Publishing, Manufacturing of electronic valves and tubes and Manufacturing of office machinery and computers. It is noticeable that several of these industries (Railways, Telecommunications and Electricity) have been subject to deregulation in Germany during the last decade.

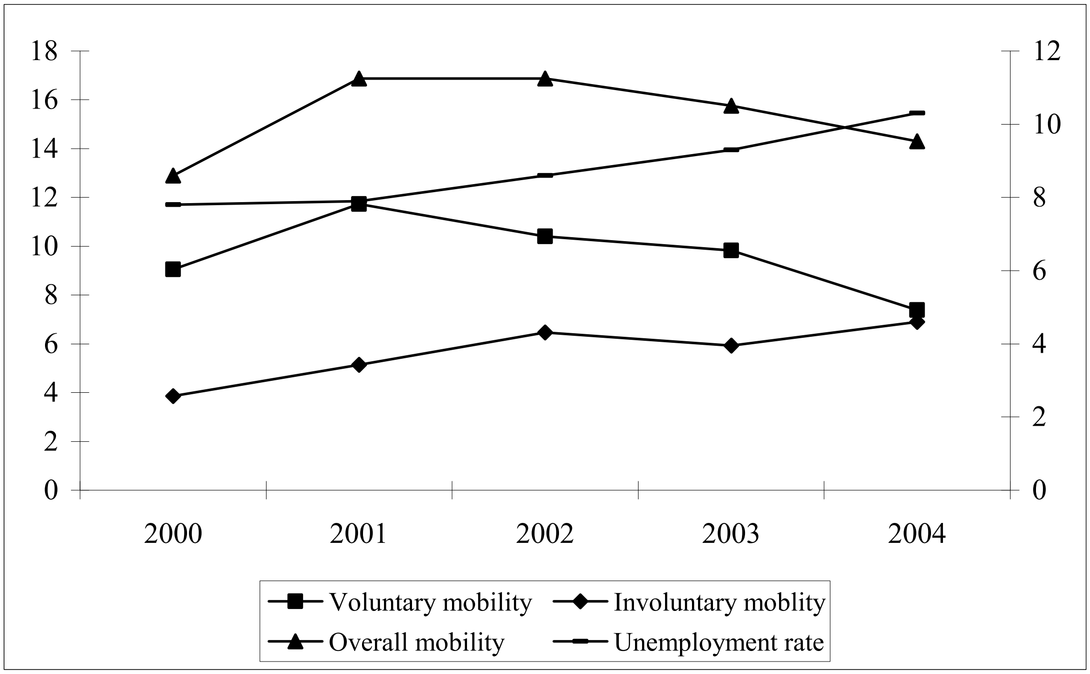

Figure 1. Overall job-to-job mobility of highly qualified workers and the unemployment rate

Source: IAB Employment Sample (1975-2004), own calculations

Note: Unemployment rate on the right-hand axis

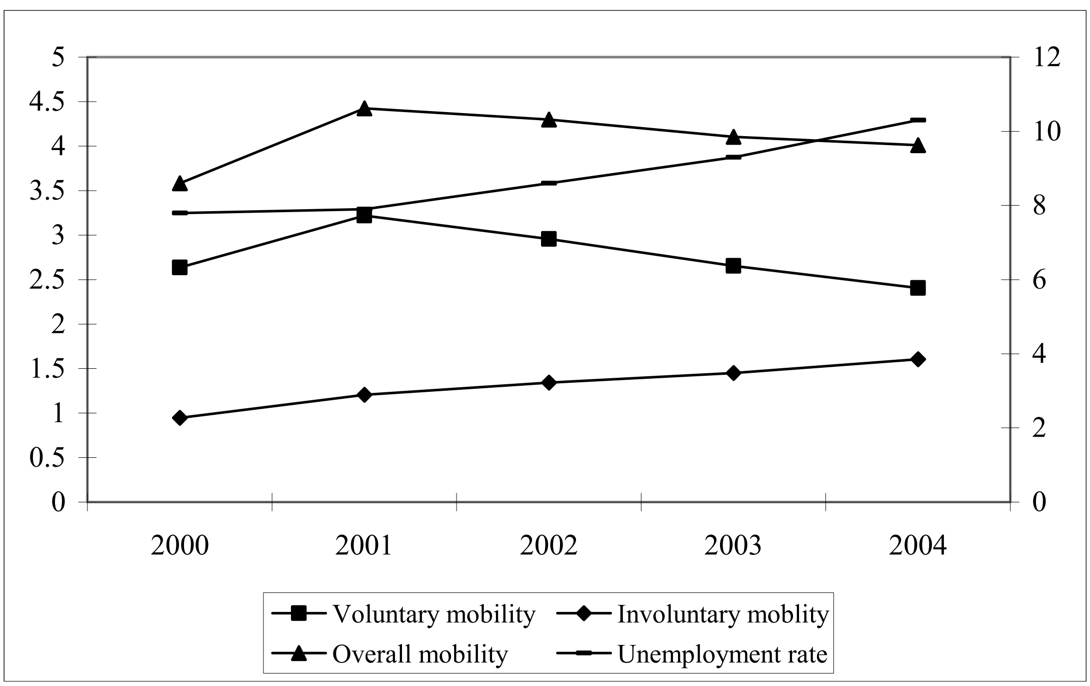

Figure 2. Intra-industry job-to-job mobility of highly qualified workers and the unemployment rate

Source: IAB Employment Sample (1975-2004), own calculations

Note: Unemployment rate on the right-hand axis

Regression results

Table 1 presents the regression results for overall and voluntary intra-industry mobility of HQW using FEVD models[13]. The regression results indicate that job destruction – often interpreted as a consequence of technological and organizational change – increases both the voluntary and the overall intra-industry mobility. In order to interpret the positive effect of the job destruction on voluntary mobility we need to think back of our definition of voluntary mobility. As we argued above, it is certainly possible that job destruction increases the voluntary mobility as defined in our case because as long as workers whose jobs have been destroyed encounter job opportunities which do not compromise their earnings and prevent workers from going into unemployment, these moves will enter our group of voluntary movement. Job creation has no significant impact on mobility at five percent significance level. The insignificant coefficient of job creation was puzzling to us. The common understanding that technological change is skill-biased suggests us to believe that the group of HQW should be the one benefiting most from the creation of new jobs and therefore the incentives to switch jobs should be high. One possible explanation for this is that when firms expand, the new job openings for junior positions are filled by first-time labor market entrants, while the senior positions are filled through internal promotions. As a result firm expansions affect mostly the demand for fresh technical college and university graduates as well as the intra-firm mobility of HQW, while leaving the inter-firm mobility unaffected. Obviously, this issue deserves further attention through investigation of the mobility of workers within the firm. Entrepreneurial regime, which captures the importance of small businesses for the industries' innovative activities, has a significantly positive impact on voluntary and overall HQW mobility.

Turning to the control variables, our measure of geographical concentration was only significant at ten percent significance level for the voluntary mobility. It has the expected positive sign; in industries that are more geographically concentrated employees in general experience less search and adjustment costs and therefore job switching should be less costly than in geographically less concentrated industries. Our measure of shortage did not show any significant impact on mobility

[13] As job creation and job destruction are highly correlated, we suspected potential collinearity problem and therefore estimated models that include only one of our turbulence measures. The set of models including only job destruction is nearly identical with the set of models presented in Table 2. These estimations are available from the authors on request.

Table 1. Determinants of job-to-job mobility of highly qualified workers

	Model I	Model II
	Overall mobility	Voluntary mobility
Job creation	0.605^{+}	0.255
	(0.33)	(0.26)
Job destruction	2.505**	1.317**
	(0.45)	(0.28)
Entrepreneurial regime	0.281**	0.279**
	(0.06)	(0.08)
Geographical concentration	0.281	0.192^{+}
	(0.27)	(0.10)
Shortage	0.432	0.377
	(0.54)	(0.31)
Median establishment size	2.805**	2.711**
	(0.72)	(0.53)
Median establishment size squared	-0.336**	-0.485**
	(0.17)	(0.12)
HQW Inflow rate from the rest industries within 1-digit	-0.498**	-0.192*
	(0.09)	(0.08)
Service	1.447**	1.278**
	(0.09)	(0.16)
Year dummy	yes	*yes*
Constant	7.930**	2.764**
	(0.09)	(0.70)
Adjusted R-squared	0.52	0.40
Observations	512	512

Panel fixed effects regression with vector decomposition.
Panel corrected standard errors in parentheses. Significant at $^{+}$ 10%, * 5%, **1%.
All independent variables except for "HQW inflow from 1-digit sector" are in log form

at significance level of five percent in the models. It might be the case that those businesses that employ the workers are able to keep their employees although the shortage of labor supply shifts bargaining power to the employees (e.g. by increasing wages, better working conditions and various fringe benefits). Medium establishment size is significant and positive for both voluntary and overall mobility which can be explained by stronger ties that HQW have when they work in small firms. Small firms find it more difficult to recruit skilled personnel and therefore it is costlier for them to separate from such personnel voluntary. The interaction term shows that the positive effect of median establishment size decreases with the increase in this variable. The inflow of

HQW from other 3-digit sectors within the same 1-digit sector is significant and negative meaning that on average sectors who have higher inflow of HQW from outside the sector have lower mobility inside the sector. The year dummies that control for business cycle effects are jointly significant therein both models. Finally, being a service sector has positive and significant impact on mobility. This is a well-established finding in the earlier literature.

The models presented in Table 1 explain 52 percent of the variance of overall, and 40 percent of the variance of voluntary mobility. The presented adjusted R-squared also encompass the part of the variance explained by the unit fixed effects. To see what part of the variance is explained by our variables of interest we estimated panel fixed effects models for the complete population and for the population of industries with above-median share of HQW. The results are presented in Table 2. It is evident from the table that the fit of our models is much better when we try to explain the variance in the mobility of HQW for the industries with above-median share of HQW.

Table 2. Determinants of job-to-job mobility of highly qualified workers

	Model I	Model II	Model III	Model IV
	Overall mobility	Voluntary mobility	Overall mobility	Voluntary mobility
Job creation	0.562	0.230	0.546	0.243
	(0.39)	(0.30)	(0.55)	(0.47)
Job destruction	2.508**	1.351**	2.847**	1.906**
	(0.49)	(0.47)	(0.58)	(0.57)
Entrepreneurial regime	0.289*	0.274*	0.556**	0.384*
	(0.12)	(0.11)	(0.12)	(0.15)
Shortage	0.456	0.376	0.586	0.446
	(0.65)	(0.59)	(0.89)	(0.73)
Year dummies	*yes*	*yes*	*yes*	*yes*
Constant	10.732**	5.708^{+}	12.175**	7.610*
	(3.24)	(2.95)	(3.94)	(3.44)
Within R-sq	0.13	0.07	0.27	0.19
Between R-sq	0.05	0.04	0.09	0.07
Overall R-sq	0.07	0.05	0.14	0.10
Observations	512	512	254	254

Panel fixed effects regression.
Robust standard errors in parentheses. Significant at $^{+}$ 10%, * 5%, **1%. All independent variables in log form

D. Robustness Checks

In order to check the stability of our results we used few different regression techniques. As already mentioned, the results concerning our variables of interest remain unchanged independently of the choice whether to use the fixed effects vector decomposition model, or the usual fixed effects model. We prefer to primarily report the first one because it allows for efficient estimation of our time-invariant and almost time-invariant control variables. It is also evident from the regressions in Table 2 that the pattern remains stable if we limit our analysis to the industries with above median share of highly qualified workers. Additionally, we estimated count models, namely unconditional negative binomial models with industry dummies as proposed by Allison and Waterman (2002). The general picture did not change significantly. The results of these estimations are presented in Table A4 in the appendix. hh

IV. Conclusion

This study combines existing knowledge in a way which provides a different approach in the empirical investigation of workers' mobility relevant for knowledge transmission. We propose that the distinction between voluntary and involuntary mobility may be of importance because voluntary transitions guarantee a transfer of updated knowledge and do not signal a misfit of the competencies between the employee and the employer through lower wages.

We find that the level of turbulence measured through job destruction positively influences both the voluntary and the overall mobility of HQW. Additionally, highly qualified workers are more mobile (both voluntary and overall) in more entrepreneurial industries. Both, the level of industry turbulence and the degree to which an industry is entrepreneurial are associated with the stage of the industry evolution. This means that job-to-job mobility as a channel of knowledge transmission may play a more active role in knowledge diffusion in earlier stages of industry development. Our results suggest that sectors in a routinized regime should not rely much on mobility as a channel of knowledge diffusion. Rather than this, firms in such sectors should focus on nurturing or establishing other ways of communicating knowledge, as for example open research environments and different forms of R&D cooperation. This study offers only an initial insight of how the technological regime may affect the level of knowledge transmission through labor mobility. Further research may look at how the different conditions of the technological regimes: opportunity, appropriability, knowledge base, and cumulativeness affect the way knowledge is being diffused within industries.

More direct policy implications in terms of institutional arrangements cannot be concluded based on this or any similar study that focuses on a single country because institutions are often constant within sectors of one country. However, repeating the design of mobility measurement of this study by using the social security data available in different European countries may enable a comparative institutional research with direct policy implications.

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Appendix

Table A1. Description of variables

Overall Mobility	Count of highly qualified workers changing establishment between two consecutive periods (years) divided by the total employment in the industry in the second period.
Voluntary mobility	Same as *Mobility*, only the person earns at least the salary of the last period and has not experienced an unemployment spell.
Involuntary mobility	Same as *Mobility*, but the person earns less than in the last period or/and has experienced an unemployment spell.
Job creation	Sum of the positive changes in employment between two years and the employment due to start-ups divided by the total employment in the second period, (log values).
Job destruction	Sum of the negative changes in employment between two years including those due to exits divided by the employment in the last period, (log values).
Shortage	Average waiting time within an industry to fill up a position opening, (log values).
Entrepreneurial regime	Share of workers with positions requiring a degree in natural sciences or engineering in small establishments (with 50 or less employees), (log values).
Geographical concentration	The standard Gini coefficient adjusted to measure geographical concentration of industries, (log values).
Median establishment size	Firm size of half the industries' population of establishments, (log values).
Median establishment size squared	Square term of the firm size of half the industries' population of establishments, (log values).
HQW Inflow rate from other industries within 1-digit sector	Count of highly qualified workers switching the establishment from one 3-digit industry (within one 1-digit industry) towards the relevant 3-digit sector between two time periods, divided by the total number of highly qualified workers in the relevant sector in the second period.
Service	Dummy variable; equals one if a sector is a service sector

Table A2. Summary Statistics of the Variables

Variable	Mean	Std. Dev.	Median	Skewness	Kurtosis	Obs.
Overall mobility	4.3	3.6	3.3	1.6	6.96	512
Voluntary mobility	2.8	2.9	2.2	1.85	8.58	512
Involuntary mobility	1.3	1.8	0.7	2.14	9.67	512
Job creation	-2.64	0.56	-2.58	-0.63	4.47	530
Job destruction	-2.56	0.54	-2.48	-0.76	5.54	530
Shortage	3.95	2.92	3.9	0.62	5.06	512
Entrepreneurial regime	-1.89	1.61	-1.7	-2.6	12	512
Median establishment size	1.74	0.7	1.79	0.03	3.01	512
Geographical concentration	-1.38	0.55	-1.27	-0.69	3.02	512
HQW Inflow from other industries within the same 1-digit sector	1.8	1.3	1.6	1.02	4.33	512
Service	N/A	N/A	N/A	N/A	N/A	512

Table A3. Correlation matrix

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*	*(11)*
Overall mobility (1)	1										
Voluntary mobility (2)	0.76*	1									
Involuntary mobility (3)	0.53*	0.23*	1								
Job creation (4)	0.19*	0.20*	0.10*	1							
Job destruction (5)	0.23*	0.22*	0.15*	0.59*	1						
Shortage (6)	0.10*	0.17*	-0.02	0.02	0.04	1					
Entrepreneurial regime (7)	0.16*	0.13*	0.17*	0.42*	0.48*	-0.06	1				
Geographical concentration (8)	-0.16*	-0.16*	-0.19*	-0.43*	-0.40*	0.11*	-0.48*	1			
Median establishment size (9)	0.00	-0.04	-0.11*	-0.49*	-0.43*	0.06	-0.49*	0.46*	1		
HQW Inflow rate from other industries within 1-digit sector (10)	-0.17*	-0.09*	-0.10*	0.17*	0.07	0.17*	0.09*	-0.07	-0.17*	1	
Service(11)	0.17*	0.19*	0.17*	0.52*	0.35*	0.11*	0.39*	-0.47*	-0.55*	0.22*	1

*Significant at 5%

All variables except (1), (2), (3) and (10) are in log-form

Table A4 Determinants of job-to-job mobility of highly qualified workers

	Model I	Model II
	Overall mobility	Voluntary mobility
Job creation	0.193**	0.07
	(0.06)	(0.1)
Job destruction	0.482**	0.305**
	(0.06)	(0.09)
Entrepreneurial regime	0.074^{+}	0.174*
	(0.04)	(0.08)
Shortage	0.214^{+}	0.255
	(0.12)	(0.18)
Industry dummies	*Yes*	*Yes*
Year dummies	*Yes*	*Yes*
Constant	2.531**	5.133
	(0.75)	(5.67)
Wald χ^2	10043.07**	5314.41**
Observations	512	512

Unconditional negative binomial model.
Standard errors in parentheses. Significant at $^{+}$ 10%, * 5%, **1%. All independent variables in log form

Table A5. Selected Statistics about highly qualified and non-highly qualified workers in the sample

	Observations			Overall mobility counts			Voluntary mobility share		Voluntary intra-industry non-HQW mobility share	Voluntary intra-industry HQW mobility share	Involuntary intra-industry non-HQW mobility share	Involuntary intra-industry HQW mobility share
Year	All individuals	Non-HQW	HQW	All individuals	Non-HQW	HQW	Non-HQW	HQW				
1999	412.146	396.887	15.259	NA	NA	NA	NA	NA	NA	NA	NA	NA
2000	428.818	412.356	16.462	46.036	43.912	2.124	49,5%	70,2%	55.3%	71,1%	44.7%	28,9%
2001	425.514	408.674	16.840	62.195	59.354	2.841	45,5%	70,0%	52.6%	72,3%	47.4%	27,7%
2002	414.718	398.096	16.622	61.320	58.515	2.805	40,1%	61,7%	50.2%	64,0%	49.8%	36,0%
2003	408.744	389.074	19.670	58.479	55.379	3.100	34,2%	62,4%	43.4%	67,6%	56.6%	32,4%
2004	410.563	391.131	19.432	63.569	60.791	2.778	30,7%	51,7%	41.0%	58,3%	58.3%	41,7%
Sum	2.500.503	2.396.218	104.285	291.599	277.951	13.648						

HQW- highly qualified workers
NA-not available

A Note on the Role of HQW in Knowledge Spillovers

One feasible interpretation that industry differences in technology and evolutionary stage result in different intra-industry mobility patterns for HQW is based on the assumption of differences in the underlying spillovers that may occur through job switches. As we assume that mobility of highly qualified workers matters for knowledge to spill over but cannot be measured directly (Griliches, 1992), the indication of existence from the above empirical assessment has to be further investigated. Comparing mobility of HQW to that of non-HQW is a straightforward way to collect further details if underlying spillover differences can account for different mobility patterns. We concentrate on the entrepreneurial regime variable since this is the only variable where we can make theory guided assumptions about differences in the impact on HQW and non-HQW. However the only possible conclusion that can be drawn from this exercise would be that externalities might be more important in entrepreneurial industries (see Table A6).

Table A6. Determinants of voluntary job-to-job mobility of highly qualified workers and non-highly qualified workers

	Model I	Model II
	HQW Voluntary mobility	Non-HQW Voluntary mobility
Job creation	0.255	0.743**
	(0.26)	(0.11)
Job destruction	1.317**	1.113**
	(0.28)	(0.1)
Entrepreneurial regime	0.279**	-0.023
	(0.08)	(0.03)
Geographical concentration	0.192[+]	0.218*
	(0.10)	(0.09)
Shortage	0.377	-0.037
	(0.31)	(0.16)
Median establishment size	2.711**	2.239**
	(0.53)	(0.2)
Median establishment size squared	-0.485**	-0.371**
	(0.12)	(0.05)
HQW Inflow rate from the rest industries within 1-digit	-0.192*	-1.107**
	(8.50)	(0.08)
Service	1.278**	1.687**
	(0.16)	(0.12)

Year dummy	*yes*	*Yes*
Constant	2.764**	5.599**
	(0.70)	(0.68)
Adjusted R-squared	0.40	0.73
Observations	512	512

Panel fixed effects regression with vector decomposition.
Panel corrected standard errors in parentheses. Significant at + 10%, * 5%, **1%.
All independent variables except for "HQW inflow from 1-digit sector" are in log form