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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 through which knowledge is diffused is the job-to-job mobility of workers. The research question addressed in this study is an empirical exploration of the industry-specific factors that influence the level of job-to-job mobility of highly qualified workers (HQWs) within three-digit industrial sectors. To this end, we use panel data based on the social security records of the German Federal Employment Agency. We find that HQW job-to-job mobility is dependent on technology-specific and an 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 degree of voluntary and overall HQW mobility. The intra-industry mobility of this group is also affected by establishment-size effects, the inflow of HQWs from other industries, and the type of industry (service or manufacturing).

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Keywords: mobility, highly qualified workers, technological change, knowledge transmission

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1. Introduction

In the last two decades, the literature on knowledge spillovers (Griliches, 1979) has become more precise about channels of knowledge transmission. While earlier contributions (to this literature) considered knowledge as something that is immeasurable, hence not tractable (e.g., Krugman, 1991, p. 53), later works gave an empirical dimension to the theory (e.g., Jaffe et al., 1993, Jaffe et al., 2000) and, therefore, facilitated identification of channels for knowledge diffusion. Knowledge exchange comes about either through contact between people (informal communication, cooperation, training, and its acquisition by people or groups of people) or 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, which, unlike information, is often remarkably difficult to convey without direct and repeated communication, the direct means of knowledge transmission have gained increasing attention in the theory of innovation.

The remarkable intra-industry job-to-job mobility of engineers and other HQWs 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 these 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 the 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, HQW job-to-job mobility has not been sufficiently emphasized in this literature. Only recently–as notably relevant for the economics of innovation–a number of formal models have clarified the implications of labor mobility as a knowledge carrier (Cooper, 2000; Franco and Filson, 2000; Fosfuri and Rønde, 2003; Fallick et al., 2006; Combes and Duranton, 2006). Empirical evidence of knowledge transmission through inventors' mobility has been established

[1] They focused on issues such as unemployment, wages, and investment in education and training.

by the analysis of 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 clear that the pool of workers having access to innovation-relevant knowledge in a firm is limited. For this reason, our study focuses on the broader group of HQWs[2] as carriers of innovation-relevant knowledge.

To justify a separate study on HQW mobility, the first step was to investigate whether the mobility behavior of HQWs significantly differed from that of non-HQWs. Previous studies discriminating between different educational and skill groups have yielded differing results.[3] As we found significant differences between the intra-industry mobility of HQWs and non-HQWs in terms of their voluntary and involuntary mobility patterns, we proceeded with our research by focusing on HQWs only.

The purpose of this study is to highlight the impact of industrial turbulence and technological regimes on the level of HQW job-to-job mobility. The basic idea is that the role of job-to-job mobility, as a channel of knowledge diffusion, differs depending on the evolutionary stage of an industry. In more turbulent and more entrepreneurial industries, job-to-job mobility should be a more active channel of knowledge transmission than in mainly routinized industries.

It should be noted that this study is not aimed at measuring knowledge diffusion across firms. 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), namely that a more flexible labor force increases the overall potential for knowledge transmission through this channel. Hence, we argue that sectors with higher HQW job-to-job mobility can rely on this channel of knowledge transmission more than sectors with lower job-to-job mobility.

We find that, in the five-year period under investigation, on the level of economy, between 13.9% and 16.9%, on average, of HQWs in Germany changed their job, continuing at another firm. At

[2] See section III for an operational definition of highly qualified workers.

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

the industry level, on average, between 3.6% and 4.4% of HQWs changed their job without changing the industry. Further, we find that HQW job-to-job mobility is dependent on technology-specific and an industry's evolution-specific factors. We also find a significant and positive effect of the technological regime and the degree of job destruction on the level of voluntary and overall HQW mobility. The intra-industry mobility of this group is also affected by establishment-size effects, the inflow of HQWs from other industries, and the type of industry (service or manufacturing).

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

2. 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 the former are, to a large extent, inspection goods (Hirshleifer, 1973) as well, in the sense that learning about the other side of the match happens before the "purchase." This assumption is not unrealistic when taking into consideration the contemporary selection processes, where the applicants extensively demonstrate their past experience, skills, knowledge, and qualifications in the job application stage. On the other side, job applicants actively collect information about the firm and the job position before they apply and accept a job. Acknowledging job matches as an inspection good implies that both employer and employee become aware of the potential knowledge exchange that may take place in case of a successful match. According to 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 such a match results in higher productivity, this may well be due to the higher complementarity of

[4] A 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.

knowledge and competence of both sides. We find empirical evidence that support this assumption, namely direct job-to-job transitions, where employees earn at least the same as at the previous job, are associated with a higher utilization of professional knowledge than job-to-job transitions to worse paid jobs (see Appendix D). 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 employee's knowledge, or, in other words, higher knowledge transmission.

Another implication for the theory and measurement of knowledge transmission is derived from the human capital theory (Becker, 1962, 1964). Involuntarily mobile workers (at least in our definition)[5] are often those who have experienced unemployment between employment spells. A break in employment may lead to significant human capital losses. In highly dynamic industries, a break of several months may essentially separate 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 to employment after having experienced an unemployment spell. Thus, matches made between an employer and a worker who was temporarily unemployed are very likely not formed with the intention to access updated knowledge from the worker's previous firm. Such matches are made nevertheless because, aside from updated knowledge, the worker's skills and abilities have a value of their own for the employer. We also find empirical evidence of worse utilization of professional human capital for job-unemployment-job transitions compared to direct job-to-job transitions (see Appendix D).

3. 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 evolutionary stage. These differences affect labor dynamics, and, to the extent they influence the mobility-related behavior of HQWs, they may determine the level of knowledge diffusion as well. Our research question resembles the questions of labor economists who ask how industry dynamics influence the movement of workers more and

[5] See section III for the operational definition of voluntary and involuntary mobility.

the questions of scholars in the industry dynamics literature less. Therefore, much of this section has its roots in an earlier tradition. At the center of our analysis are factors of HQW mobility that are important from an innovation perspective, namely technological change and technological regimes.

3.1. Technological regimes

Based on the work of Joseph Schumpeter (1912, 1942), it was Nelson and Winter (e.g., 1982b) and later Malerba and Orsenigo (e.g., 1993 and 1997) who prepared the ground for what, in evolutionary economics, is known as technological regimes. The term '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 regime, 'creative destruction' is the major innovation mode while, in the routinized regime, 'creative accumulation' underlies the innovative processes. According to the work of Nelson and Winter (1982a, 1982b) and 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, a lack of appropriability, and a low degree of cumulativeness. The knowledge base is such that much knowledge has not yet been codified and has probably not been systematically connected to its full potential due to its newness. Such conditions result in a low concentration of innovative activities, a large number of innovators, and high rates of entry (Malerba and Orsenigo, 1997, p. 100). 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 an innovation advantage, whereas under the routinized regime, the innovation edge is in the hands of incumbents.

We argue that the technological regime of an industry has an impact on the level of HQW intra-industry mobility. The economic outcomes of the entrepreneurial regime (low concentration of innovative activities, large number of innovators, and high rates of entry) create conditions facilitating labor mobility, both voluntary and involuntary. A low concentration of innovative activities means that numerous firms possess some novel knowledge. This creates an environment in which the incentives for knowledge exchange among firms are high, as multiple firms have innovation-relevant knowledge with a high potential for useful combinations if connected. A large number of innovators indicate possibilities for the workers to move among the firms in search of better matches. High entry rates point to new jobs being created and, therefore, new opportunities for movement from incumbents to newcomers. Hence, we expect a positive relationship between the level of mobility, both voluntary and overall, and the degree to which an industry is entrepreneurial. This leads us to our first set of hypotheses:

H1a. The more entrepreneurial the character of an industry, the higher the level of HQW voluntary mobility.
H1b. The more entrepreneurial the character of an industry, the higher the level of HQW overall mobility.

3.2. Turbulence

As industries evolve, the entrepreneurial entry of firms, as well as their exit, expansion, and contraction, show different dynamics. These are often termed ‘industrial turbulence’ (e.g., Acs and Audretsch, 1990). In our approach, turbulence is closely related to the notions of job creation and job destruction common in the labor economics literature. Instead of having a single measure of turbulence, we estimate rates of job creation and destruction, which, in our view, do more to explain the forces of mobility. Here the term ‘job’ is defined as an employment position filled by a worker. Job creation refers to the job openings filled by start-ups and expanding firms, while job destruction consists of the job closures by firms’ exits and contractions (see section III and Davis et al., 1996 p. 299, for a detailed description of these measures).

Both the industrial dynamics and the labor economics literature agree that a major force behind industrial turbulence is technological and organizational change (e.g., Aghion and Howitt, 1992; Klepper, 1996; Mortensen and Pissarides, 1998; Bauer and Bender, 2004). Mainly due to technological and organizational change as well as demand shifts, jobs are reallocated from contracting firms or firm exits to expanding firms or firm entries. The relationships between technological change and job creation and destruction are complex (Mortensen and Pissarides, 1998), as are those between organizational change and job creation and destruction (Askenazy and Moreno-Galbis, 2007). Explaining these relationships is not the focus of this study, but it is worth emphasizing previous findings, namely that the fluctuations of workers between different employment states (including job-to-job transitions) are not primarily driven by short-term fluctuations in the labor demand, but mainly by long-term adjustments in the labor demand of firms facing changes in technology and organizational structure (Davis and Haltiwanger, 1992; Bauer and Bender, 2004). Further findings reflect a simultaneous existence of high rates of job creation and destruction within narrowly defined sectors of the economy,[6] theoretically allowing for considerable of workers within the same sectors. A high correlation between the rates of job creation and destruction is evident in our data (see Table A4, Appendix A). This provides additional support for the claim that both phenomena are most likely caused by a common factor, as stated by many scholars, namely technological and organizational change (see, e.g., Bauer and Bender, 2004).

The empirical investigations conducted in the last decades agree on the presence of skill-biased technological change (see, e.g., Berman et al., 1998, Hujer et al., 2002), suggesting that, in general, the new jobs created favor the employment of skilled labor, while the jobs destroyed mainly affect the employment of unskilled labor. The dynamics behind this general picture are by no means that clear-cut. Particularly when organizational change enters the analysis, it becomes evident that it is not only the stability of low-skilled labor that is being questioned, but also the job stability of those with high qualifications. For example, Bauer and Bender (2004) find that the reduction of hierarchy levels at establishments significantly and positively affects the job destruction rates of professionals and engineers in Germany (p. 283-4). Askenazy and Moreno-

[6] See Davis and Halitiwanger, 1992 and 2006, for the U.S. Our findings are not much different than those of the U.S economy with a median rate of job creation of 7.5% and a median rate of job destruction of 8.4%.

Galbis (2007) also find that delegation of responsibilities to lower hierarchical levels decreases the job stability of managers, while team work decreases the job stability of both, managers and intermediate professionals, in France (p. 14).

Based on the foregoing, it is useful to note that, although high levels of turbulence are generally associated with the early stages of industry development (see, e.g., Malerba and Orsenigo, 1997, and the high positive correlation between the entrepreneurial regime and both measures of turbulence in Table A4, Appendix A), one should by no means underestimate the level of turbulence present in mature industries. The advantage of using job creation and destruction as measures of turbulence is that they do not only capture the turbulence in terms of entries and exits of firms (which is more prevalent in the early stages of industrial development), but also, to a certain extent, in terms of internal technological and organizational restructuring of firms (which should be of higher importance for mature firms).

When workers expect elimination of their current job position, they increase their on-the-job search, with a higher probability of a new employee-employer match formation. The search will either result in a non-worse match (non-decreasing earnings), a worse one (lower earnings), or, if unsuccessful, in transition to unemployment. Therefore, we expect that job destruction increases both the voluntary and involuntary HQW mobility (and thus the overall HQW mobility). This reasoning leads us to our second set of hypotheses:

H2a. The higher the level of job destruction, the higher the level of voluntary mobility.
H2b. The higher the level of job destruction, the higher the level of overall mobility.

Job creation is an indicator of job opportunities. The level of job creation affects voluntary mobility, as it creates more scope for employees to choose among jobs. It also positively affects the level of involuntary mobility, as it generates opportunities for those who have lost their jobs to return to the same industry. The claim that technological change is skill biased further supports our belief that job creation, in particular, should affect the behavior of workers with high qualifications. This reasoning leads us to our third set of hypotheses:

H3a. The higher the level of job creation, the higher the level of voluntary mobility.

H3b. The higher the level of job creation, the higher the level of overall mobility.

Finally, in concluding this section, it is worth noting that, while any findings on how the levels of job creation and job destruction influence the level of HQW mobility are valuable on their own, our aim is to corroborate empirically our belief that the mobility of the main carriers of knowledge, and therefore the flow of knowledge itself, is to a certain degree determined by employment opportunities and the constraints generated by organizational and technological change.

4. Empirical strategy

4.1 Data and methodology

As primary data sources, we used the IAB Employment Sample (IABS), available for the period 1975-2004, and the IAB Establishment History Panel (BHP), available for the period 1975-2005.[7] From the available cross sections, we only utilized the period 2000-2004.[8] The IABS contains information about the employment history of 2% of the German population subject to social security. This means that civil servants, as well as the 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 in 1999, including those with at least one marginally employed subject). We had access to a 50% sample of the BHP population, stratified by industries.

Three-digit industries provided the most appropriate observational level for our purpose. On the one hand, they are, on average, large enough to allow for a meaningful level of HQW mobility within the industry, and, on the other, firms in the same three-digit sector are closely related technologically, allowing 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 employees,

[7] 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 a detailed description of these datasets, see Drews (2007) and Spengler (2007).

[8] 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.

some data issues had to be taken into account. Particularly in some very small industries, the number of employees was not sufficient to compute meaningful intra-industry mobility rates. Therefore, small industries were merged in order to achieve a sample size large enough to derive reliable mobility rates. The merging of industries was carried out by maintaining the closest distance with respect to the underlying labor inputs.

We define HQWs as being employed in the observed industry, having at least university degree[9], whose average earnings in each consecutive year are at least as high as the average earnings in Eastern or Western Germany, depending on their place of work. The earnings limitation is to eliminate the group of highly educated HQWs who are underemployed. This group, employed in positions where they are less exposed to strategic information and knowledge is less likely to contribute to knowledge transmission.

After selecting employees with a university degree and only full-time employment spells, our sample summed to 104,285, or an average of 20,857 workers per year. Among these HQWs, we observed a total of 13,648 mobility counts or, on average, 2,730 job-to-job transitions annually. HQW voluntary mobility accounted for between 52% and 70% of overall HQW mobility on the level of economy. HQW intra-industry voluntary mobility accounted for between 58% and 72% of overall HQW intra-industry mobility. The descriptive statistics of individuals and their mobility, both HQWs and non-HQWs, are presented in Table A3, Appendix A.

While the IABS is the only sample of the German population large enough to allow for a reliable observation of the mobility level of the HQW population within relatively small sectors of the economy, it also has its drawbacks. Namely, if an establishment for different reasons changes its identification number, it is automatically registered as a new establishment in the database. This overestimates our measure of mobility as well as the measures of job creation due to entry of establishments and job destruction due to exits. We still do not have a clear indication of how severe this overestimation might be.

[9] Here we include both, employees with university degree and those with degree obtained from a university of applied sciences.

4.1.1. Dependent variables

In order to calculate the yearly mobility rates, we included only the employment spells that cover the June 30th in each year, and calculated the number of intra-industry job changes between two consecutive time points. Our dependent variable is this number divided by the total employment in the industry in the second time point. We distinguished between voluntary and involuntary mobility, based on two criteria: the existence of unemployment or marginal employment spells between two full-time employments and the earnings levels. Involuntarily mobile workers are those who have experienced unemployment spells and/or earn less at the new job than at the previous one. In our definition, each of these two criteria alone is sufficient to categorize a job move as involuntary. We used nominal wages due to the phenomenon of the real wages decrease in Germany during the period under review.[10]

There are two important aspects to keep in mind with respect to our definition of voluntary and involuntary transitions. First, voluntary mobility, as we define it, may not always reflect the true intention of the worker to transit to another job voluntarily. More explicitly, a job move is categorized as voluntary as long as the two above-described criteria are fulfilled, although the true reason for the transition may be a layoff or the elimination of a job. Similarly, a job quit is categorized as involuntary if a worker voluntarily transits to a lower paid job. Although this confuses the conventional understanding of voluntary and involuntary mobility in terms 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 knowledge the employee brings to his or her new workplace are compatible with those needed by the new employer, and the absence of unemployment spells guarantees that knowledge is not outdated. We keep the terms voluntary and involuntary because our observations of these two types of job transitions largely coincide with the true intentions of 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 HQWs are

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

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

affected by it, and no imputation method can replicate the true earnings of this group accurately enough. This creates doubt as to whether our sample of HQWs adequately reflects the mobility behavior of the group of HQWs with the highest earnings. To the extent possible, we explored the mobility behavior of the group with earnings above the censoring point. This group was significantly less involuntarily mobile ($t = 8.4$, $p<.01$) than the other group of HQWs observed whose earnings were not above the censoring point, but who did not significantly differ in terms of voluntary mobility. Here, as a criterion for voluntary/involuntary mobility, we used the presence of unemployment/marginal employment spells between two consecutive employments. Therefore, at least in terms of the voluntary mobility of "high earners," we find no evidence for behavioral differences between these two income groups.

4.1.2. Independent variables

As our first independent variable, we used a rough indicator of the degree to which an industry is entrepreneurial to capture the most indicative feature of the two regimes. Following Audretsch (2008), our indicator of the degree to which an industry is entrepreneurial is the share of employees pursuing careers in occupations mainly requiring a university degree in natural sciences or engineering, working in small firms (with 50 or fewer employees). The higher this share, the more entrepreneurial an industry is considered to be. It is thus a continuous variable. As mentioned above, the crucial difference between these two regimes is that in the entrepreneurial one, small and young firms have an innovation advantage, while in the routinized one, large incumbents are more innovative. This innovation advantage is well reflected in the R&D intensity indicators of small and large firms, which is what our indicator is supposed to capture. Winter (1984) as well as Malerba and Orsenigo (e.g., 1997) show that the entrepreneurial regime is associated with higher entry rates and lower firm size. Correspondingly (see Table A4, Appendix A), our measure of entrepreneurial regime is correlated positively with the indicators of job creation due to start-ups and expansions, and negatively with the median establishment size.

Our second independent variable is turbulence. As we argued in the theory part in section II, turbulence is considered to be a consequence mainly of technological change. We measured the level of turbulence by estimating the rates of job creation (*JC*) and job destruction (*JD*). We obtained the sum of the changes in the number of fully employed workers (x) in all establishments e in a sector between time $t-1$ and t and divided it by the size of the sector (the number of fully employed workers in all establishments) at time t. Positive change in the number of fully employed workers entered the measure of job creation. This measure also included employment in establishments that appear in the database for the first time, indicating job creation as a result of start-ups. As all establishments in Germany with at least one marginally employed employee have been obliged to report data to the social security administration 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]

A negative change in the number of fully employed workers between two consecutive periods is associated with job destruction. This measure also encompasses the job closures in establishments that leave the database (our indicator of firm exits).

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

4.1.3. Controls

We controlled for industry agglomeration effects, firm size, inflow of HQWs from other sectors, business cycle effects, and temporary shortages of HQWs (mismatch of supply and demand in the labor market). To indicate the degree to which an industry is geographically agglomerated, we applied the Gini measure of inequality as used by Krugman (1991). In order to control for establishment size-related factors, the median establishment size was included. We avoided using the average establishment size, as is often done in the literature, because we observed right-skewed establishment size distributions within the industries. We also created a time-invariant variable (the average over the five-year period we observed), measuring the flows of HQWs from

[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.

the other three-digit industries within the same one-digit sector toward the relevant three-digit sector. The idea was that industries that can satisfy their demand for HQWs through the inflow of workers from technologically related sectors should have lower intra-industry mobility. The possible effects of the business cycle were controlled for by using time dummies. To construct an indicator of the HQW shortage, we used data on the average time it takes to fill a position opening in a given industry (vacancy time), as reported by the German Federal Employment Agency (Bundesagentur für Arbeit 2008). We used the vacancy time of new job openings as an indicator of the mismatch between the demand and supply of labor as proposed in the literature (see, e.g., Abraham, 1987). A longer vacancy time of new job openings should indicate a more severe shortage of HQWs. Higher shortages of qualified personnel should increase HQW mobility because this, in turn, increases the incentives of employers to poach already employed workers. The analysis results reported in this study are based on the vacancy time of all position openings. We also obtained the average industry vacancy time based on occupations that generally require a university degree. The results remained unchanged.

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

4.2 Model specification

The most prominent way to deal with time-invariant unobserved heterogeneity across industries is a "fixed effects" (FE) model. The Hausman test rejected the null hypothesis of the absence of systematic differences between the RE and FE models. Therefore, we proceeded with the analysis, using models that allowed 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 (cf. Parent, 2000), industry-specific capital, labor, knowledge demands, and other factors. 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 rarely change over time, a number of problems occur when unit fixed effects are present. Industry-specific effects, such as geographic 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 for the estimation of time-invariant variables at all. One possibility for dealing with rarely changing variables in an FE setting is an FE vector decomposition (FEVD) model (Plümper and Troeger, 2007). The procedure is as follows: First, an FE model is estimated with all our variables of interest that are time-variant or rarely time-variant; second, the unit fixed effects of this model are decomposed into one part that can be explained by the time-invariant and rarely changing variables and another that cannot be explained by these variables using pooled OLS. Third, the initial model is reestimated, using OLS and including the part of the unit fixed effects 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 showed 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 an industry i who work at $t=0$ in firm j and at t-1 in another firm, divided by the total employment in industry i. X is a vector of industry-specific variables considered time-variant, and Z is a vector of variables considered time-invariant. Since almost all independent variables are skewed, we used log-transformations.

Plümper and Troeger (2007) suggest a criterion for deciding when a variable should be treated as time-variant or time-invariant, namely by looking at the ratio of the between and within variance of the variable of interest. Although a ratio above 1.7 is already sufficient for a variable to be considered as time-invariant in cases of zero correlation between the variable and the unit effects, as the correlation between the variable of interest and the unit effects is unobservable and positively influences the bias in the estimators, the authors suggest a threshold of at least 2.8 in the between/within ratio (p. 136). Based on this criterion, our variables *geographic concentration* and *median establishment size*, with the respective between/within variance ratios of 16.7 and 9.7, were treated as time-invariant, while *entrepreneurial regime,* with a between/within variance ratio of 1.7, was treated as time-variant.

4.3 Results

4.3.1. Descriptive Statistics

HQWs are significantly more voluntarily mobile than non-HQWs within industries ($t = 3.31$, $p<.01$). They are also significantly less involuntarily mobile than non-HQWs 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 was reshuffled annually across the whole economy in the period 2000-2004. When it comes to the HQW mobility within three-digit industries, the average annual mobility rates shift between 3.6% and 4.4%. Looking at the voluntary HQW mobility rates within industries, between 2.4% and 3.2% of all HQWs change their jobs annually within three-digit industries.

With respect to HQW mobility, we find that the largest share of general HQW mobility can be traced 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 Table A4, Appendix A, 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 instructive to observe the change of the mean mobility rates over time. Figures 1 and 2 show respectively the average HQW mobility levels for the general economy and within the industries. It seems that HQW voluntary mobility is pro-cyclical and involuntary mobility counter-cyclical, as is usually argued in the labor economics literature. Some of the industries with the highest voluntary HQW mobility in the service sector are railways, telecommunications, pharmacies, central banks and financial institutions, and advertising. Industries with the highest voluntary mobility in manufacturing are electricity, gas, steam, water supply, civil engineering, publishing, the manufacturing of electronic valves and tubes, and the 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.

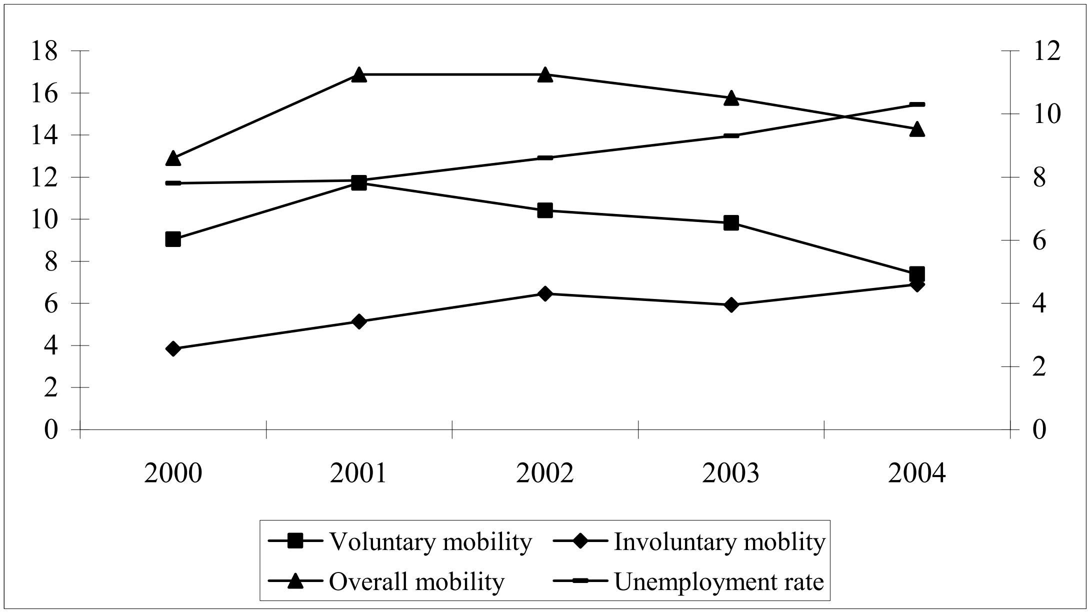

Figure 1. General HQW job-to-job mobility and the unemployment rate
Source: IAB Employment Sample (1975-2004), own calculations
Note: Unemployment rate on the right-hand axis

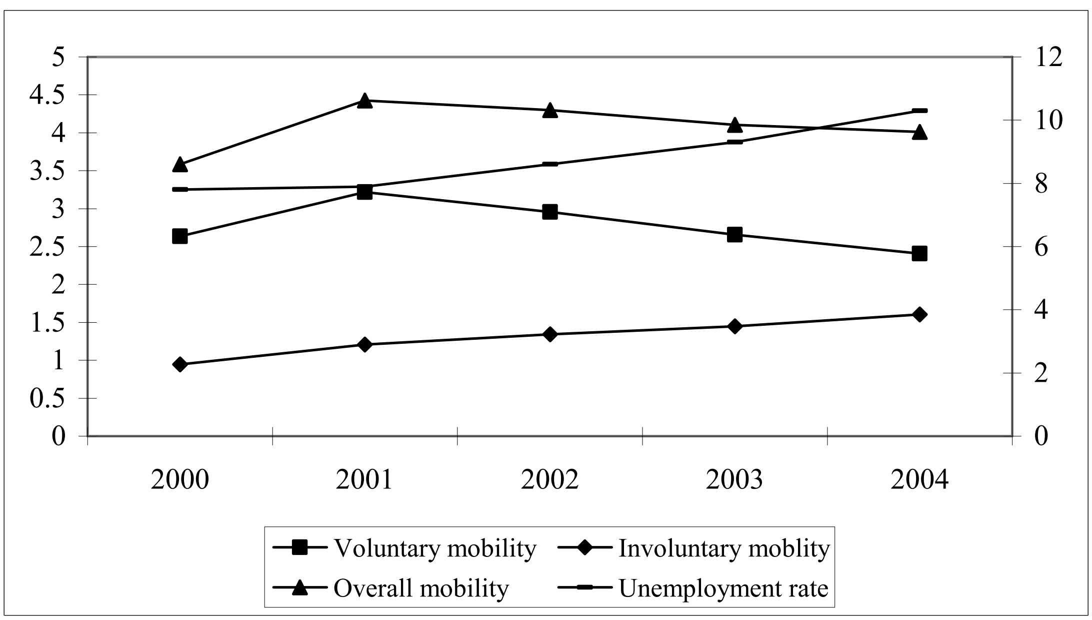

Figure 2. HQW intra-industry job-to-job mobility and the unemployment rate
Source: IAB Employment Sample (1975-2004), own calculations
Note: Unemployment rate on the right-hand axis

4.3.2. Regression results

Table 1 presents the regression results for HQW overall and voluntary intra-industry mobility, 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 job destruction on voluntary mobility, we need to bear in mind our definition of voluntary mobility. It is certainly possible that job destruction increases voluntary mobility as defined in our case, because as long as workers whose jobs have been destroyed encounter job opportunities that do not compromise their earnings and protect them from unemployment, their job moves will enter our group of voluntary movement. Job creation has no significant impact on mobility at the 5% significance level. The insignificant coefficient of job creation was puzzling to us. The common understanding that technological change is skill biased leads us to believe that the group of HQWs should be the one benefiting most from the creation of new jobs. Therefore, the incentives to switch jobs should be high. One possible explanation 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 primarily affect the demand for fresh technical college and university graduates and HQW intra-firm mobility while leaving the inter-firm mobility unaffected. Obviously, this issue merits further investigation of labor mobility within the firm. The entrepreneurial regime, which captures the importance of small firms for the industries' innovative activities, has a significantly positive impact on HQW voluntary and overall mobility.

Turning to the control variables, our measure of geographic concentration is only significant at the 10% significance level for voluntary mobility. It has the expected positive sign; in industries that are more geographically concentrated, employees generally experience less search and adjustment costs, and job switching should therefore be less costly than in geographically less concentrated

[13] As job creation and destruction are highly correlated, we were concerned about a 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 to the set of models presented in Table 1. These estimations are available from the authors on request.

industries. Our measure of shortage does not show any significant impact on mobility at the 5% significance level in the models.

Table 1. Determinants of HQW job-to-job mobility

	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)
Geographic 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 other industries within 1-digit sector	-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.

It might be the case that those establishments that employ highly demanded workers are able to keep them, although the shortage of labor supply shifts bargaining power to them (e.g., by providing better wages and working conditions and various fringe benefits). Median establishment size is significant and positive for both voluntary and overall mobility, which can be explained by the stronger ties that HQWs develop when working in small firms. These firms find it more difficult to recruit skilled personnel, and, therefore, it is costlier for them to let go of such personnel voluntarily. The interaction term shows that the positive effect of median establishment size decreases with the increase in this variable. There are different theoretical explanations for this, one being that large firms create internal labor markets in which workers move through promotions. Intra-firm movements through promotions are likely to happen owing to inter-firm movements. The inflow of HQWs from other three-digit sectors within the same one-digit sector is significant and negative, suggesting that, on average, sectors with higher HQW inflows from outside the sector experience lower mobility inside the sector. The year dummies controlling for business cycle effects are jointly significant in both models. Finally, a service sector, in particular, has a positive and significant impact on mobility. This is a well-established finding in the earlier literature.

The models presented in Table 1 explain 52% of the variance of the overall mobility and 40% of the variance of the voluntary mobility. The presented adjusted R-squared also encompasses 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 shares of HQWs. The results are presented in Table 2. For the sample of all industries, the within variance explained by the four time-variant variables, including year dummies, is 13% for the overall mobility and 7% for the voluntary mobility model, whereas for the sample of industries with above-median shares of HQWs the explained variance is 27% and 19%, respectively. The overall R-squared for the models that include all industries is 7% for the overall and 5% for the voluntary mobility model, while the respective R-squared for the sample that only includes industries with above-median shares of HQWs is 14% and 10%. It is therefore evident that the fit of our models is much better when we explain the variance in HQW mobility for the industries with above-median shares of HQWs.

Table 2. Determinants of HQW job-to-job mobility

	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.

4.4 Robustness Checks

In order to check the stability of our results, we used a number of different regression techniques. The coefficients of our variables of interest remain almost unchanged, independently of the choice between using the FE vector decomposition model or the usual FE model. We prefer to report the FEVD model primarily 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 when we limit our analysis to the industries with above-median shares of HQWs. 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 alter much. The results of these estimations are presented in Table A5, Appendix B.

5. Conclusions

This study combines existing knowledge in a way that provides a novel approach to the empirical investigation of labor mobility as relevant for knowledge transmission. We propose and evidence that the distinction between voluntary and involuntary mobility is of importance because voluntary transitions guarantee a transfer of updated knowledge and do not signal a mismatch of the competencies between employee and employer through lower wages.

Our main findings suggests that job-to-job mobility as a channel of knowledge transmission may play a more active role in knowledge diffusion in the earlier stages of an industry's development. Namely, we find that the level of turbulence as measured in terms of job destruction positively influences both HQW voluntary and overall mobility. Additionally, HQWs are more mobile (both voluntarily and overall) in more entrepreneurial industries. As both, the level of industry turbulence and the degree to which an industry is entrepreneurial depend on the stage of the industry's evolution, our findings seem to be in line with the theoretical reasoning that the direct channels of knowledge transmission are more important in the early developmental stages of industries.

Nevertheless, this study offers only an initial insight into how the technological regime may affect the level of labor mobility. It will be left to future research to examine how the different conditions of the technological regimes (opportunity, appropriability, knowledge base, and cumulativeness) affect the way knowledge is being diffused within industries. An additional weakness of this study is that it does not use a direct measure of knowledge spillovers; we have examined factors that influence one channel of knowledge transmission, but not how much knowledge is being diffused/ transmitted via this channel.

More direct policy suggestions in terms of institutional arrangements that allow for higher labor force flexibility cannot be offered, based on this or any similar study that focuses on a single country because institutions are often constant within sectors of one country. Repeating the design of mobility measurement of this study by using the social security data available in different

European countries may allow for a comparative institutional research study with direct policy implications. However, before such an analysis is of any use one has to answer how does the current level of job-to-job mobility of HQW compare to the optimum mobility in the observed sectors or economies.

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Appendix A

Table A1. Description of variables

Overall mobility	Count of HQWs changing establishments between two consecutive periods (years) divided by the total employment in the industry in the second period
Voluntary mobility	Same as *Mobility*, only that a person earns at least the salary of the last period and has not experienced an unemployment spell
Involuntary mobility	Same as *Mobility*, but a person earns less than in the last period and/or 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 in an industry to fill 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 fewer employees) (log values)
Geographic concentration	The standard Gini coefficient adjusted to measure the geographic concentration of industries (log values)
Median establishment size	Median establishment size of the industry (log values)
Median establishment size squared	Square term of the median establishment size
HQW Inflow rate from other industries within one-digit sector	Count of HQWs that enter a three-digit sector, but originate from another three-digit sector within the same one-digit sector, divided by the total number of HQWs in the three-digit sector of entry
Service	Dummy variable; equals one if a sector is a service sector

Table A2. Summary statistics of the variables

Variable	Mean	Median	Std. dev.			Skewness	Kurtosis	Observations
			Overall	Between	Within			
Overall mobility	4.31	3.33	3.36	2.77	2.38	1.6	6.96	512
Voluntary mobility	2.77	2.17	2.93	2.07	2.08	1.84	8.59	512
Job creation	-2.65	-2.6	0.56	0.43	0.36	-0.69	4.36	512
Job destruction	-2.57	-2.49	0.53	0.41	0.34	-1.08	5.06	512
Shortage	52.1	49.48	18.51	13.9	12.28	3.76	34.54	512
Entrepreneurial regime	-1.89	-1.7	1.6	1.39	0.81	-2.56	11.98	512
Median establishment size	1.74	1.79	0.7	0.7	0.07	-0.03	3.01	512
Geographic concentration	-1.38	-1.27	0.55	0.55	0.03	-0.69	3.02	512
HQW Inflow from other industries within the same one-digit sector	1.27	1.63	1.27	1.28	0	1.02	4.33	512
Service	0.41	0	0.49	0.5	0	0.35	1.12	512

Table A3. Selected statistics about HQWs and non-HQWs 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-HQWs	HQWs	All individuals	Non-HQWs	HQWs	Non-HQWs	HQWs				
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						

HQWs - highly qualified workers
NA - not available

Table A4. Correlation matrix

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*	*(11)*
Overall mobility (1)	1										
Voluntary mobility (2)	0.75*	1									
Job creation (3)	0.17*	0.18*	1								
Job destruction (4)	0.22*	0.19*	0.58*	1							
Entrepreneurial regime (5)	0.18*	0.13*	0.42*	0.48*	1						
Geographic concentration (6)	-0.14*	-0.14*	-0.44*	-0.42*	-0.49*	1					
Median establishment size (7)	0.00	-0.04	-0.49*	-0.44*	-0.48*	0.48*	1				
HQW Inflow rate from other industries within 1-digit sector (8)	-0.14*	-0.06	0.2*	0.10*	0.09*	-0.08	-0.18*	1			
Shortage (9)	0.10*	0.14*	-0.01	0.02	-0.05	0.14*	0.06	0.11*	1		
Service (10)	0.18*	0.20*	0.52*	0.33*	0.38*	-0.50*	-0.54*	0.22*	0.10*	1	
Industrial concentration (11)	-0.12*	-0.08	-0.48*	-0.52*	-0.60*	0.75*	0.52*	0.06	0.23*	-0.41*	1

*Significant at 5%

All variables except (1), (2), (9) and (10) are in log form.

Appendix B

Table A5. Determinants of HQW job-to-job mobility

	Overall mobility	Voluntary mobility
Job creation	0.233**	0.124
	(06)	(0.10)
Job destruction	0.462**	0.277**
	(0.06)	(0.09)
Entrepreneurial regime	0.088*	0.195*
	(0.04)	(0.08)
Shortage	0.361**	0.468*
	(0.12)	(0.19)
Median establishment size	-0.297	-0.823
	(0.44)	(0.66)
Median establishment size squared	0.097	0.227
	(0.12)	(0.20)
Geographic concentration	-0.098	-0.537
	(0.68)	(0.94)
Number of Highly Qualified Workers	0.001**	0.002**
	(0.00)	(0.00)
Industry dummies	*yes*	*yes*
Year dummies	*yes*	*yes*
Constant	0.207	4.839
	(1.99)	(8.48)
Wald χ^2	10611	5366.79
Log likelihood	-1218.01	-843.02
Observations	512	512

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

Appendix C

The role of HQWs in knowledge spillovers

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

Table A6. Determinants of HQW and non-HQW voluntary job-to-job mobility

	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)
Geographic 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 one-digit	-0.192*	-1.107**
	(8.50)	(0.08)
Service	1.278**	1.687**
	(0.16)	(0.12)
Year dummies	*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 one-digit sector" are in log form.

Appendix D

Comparison between self-reported voluntary mobility and voluntary mobility defined on the bases of earnings differentials and unemployment spells, using the SOEP

Based on assumptions in section I, we claim that voluntary mobility, as defined by the absence of an unemployment spell between two employments and by non-decreasing earnings at the new job, results in higher utilization of a worker's knowledge and higher knowledge transmission. In order to test whether this claim is justified, we use the German Socio-Economic Panel (SOEP) for the same period of observation. We compare our measure of voluntary mobility with the self-reported voluntary mobility of full-time white-collar workers in the SOEP sample.

A general question that could be asked is to what extent is it justified to identify our measure of voluntary mobility with one based on intentions? Although, as we argue in sections I and III, we are not interested in intentions, it seems necessary nevertheless to justify the use of the term 'voluntary.' Between 78% and 88.9% of all self-reported voluntary movements are related to non-decreasing earnings. This supports our approach to associate intention-based movements with our measure of voluntary mobility. In addition, we find that 84% of self-reported movements overlap with the reporting of voluntary movements based on earnings' comparison and unemployment spell presence. However, it should be noted that our definition of voluntary movements overstates the number and share of voluntary moves (46% of movements are self-reported as voluntary, while our measure states 67% as voluntary). The reason is that some workers, who had to search for a new position, managed to find one without compromising their earnings and experiencing unemployment.

A more important question is whether higher earnings at the new job are associated with a better use of professional knowledge and generally of human capital. Based on the SOEP analysis of the population of white-collar workers, we find that 90.4% of self-reported voluntary job movers reported an about equal or higher use of their professional knowledge at the new job. Concerning the absence of unemployment and non-decreasing earnings to define voluntary mobility in the SOEP data, 93 % reported an equal or higher use of professional knowledge at the new job. Although our definition has led to a somewhat higher share of an equal or higher use of knowledge, the mean difference between the two groups is not statistically significant, indicating that both selection criteria, self-reported voluntary mobility and the absence of unemployment plus non-decreasing earnings, are suited to indicate a better use of professional knowledge at the new job.

Finally, we have examined whether there is a difference in the level of professional knowledge use between the groups of voluntary and involuntary job movers. The Mann Whitney (Wilcoxon) test shows a significant difference in favor of the voluntarily mobile group ($z=2.825$, $p<.01$). This group, as defined by us, report a significantly higher use of professional knowledge at the new job than the involuntarily mobile group. Interestingly, we do not find a significant difference in the use of professional knowledge between the groups of self-reported voluntary and involuntary job movers. This supports our claim that earnings differences and the presence of unemployment spells, rather than the self-reporting of voluntary and involuntary moves, better reflect the knowledge compatibility in the new job.