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Matching Skills of Individuals and Firms along the Career Path

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Abstract: Research since Gary Becker equated specific human capital with firm-specific human capital. This paper divides firm human capital into a specific and a general component to investigate the relationships between firm- and occupation-specific human capital and job switches. Applying the task-based approach, the results show that the degree to which firm knowledge is portable depends on tasks similarities between the firms. In the case of switches, less experienced workers travel longer tasks distances between firms than more experienced workers. Firm- and occupation-specific knowledge are negatively related to wages in a new job but achieving a good occupational, instead of firm, match is most important for employees. The amount of specific knowledge on the firm level, called occupational intensity, decreases with experience and leads to higher wages for higher qualification levels. In addition, the positive effect of occupational intensity on wages can outweigh the negative consequences of covering long tasks distances.

Keywords: skill-weights, task-based approach, specific human capital, labor mobility
JEL classification: J24, J62

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1 Introduction

It is well established that firm-specific knowledge increases with firm tenure and that it is lost when employees switch employers (Becker, 1964). Many studies use firm tenure as proxy for accumulated firm-specific knowledge. The question remains, however, as to what exactly this knowledge is and whether all firm knowledge is specific and, thus, not transferable. The skill-weights approach (Lazear, 2009) takes an alternative method to modeling firm-specific knowledge by letting firms place different weights on general skills. The weights generate firm-specific skill portfolios that can be compared to each other. This assumes that a certain amount of all knowledge is transferable across firms. Gathmann and Schönberg (G&S, 2010) test this approach for occupation-specific knowledge by investigating the relationship between occupational knowledge and wages. Following Lazear's theoretical arguments, G&S show empirically that the amount of specific knowledge, and, thus, the number of portable skills, varies between occupations and along the career path. Accordingly, individuals move more often between similar occupations because it is less costly. The distance of moves declines with the time spent in the labor market, reflecting that the value and amount of accumulated knowledge is likely to change along the career path. However, occupational switches continue to persist despite the associated costs.

To date, there has been no investigation of the degree to which firm knowledge is portable across establishments. Therefore, the aim of this paper is to discover how the firm distance of moves varies along the career path and how it relates to wages. In addition, the relative importance of firm and of occupational knowledge for wages is determined, providing an indication for switchers whether it is more important to find a good firm or a good occupational match. Regarding the incentives to switch, the analysis considers a new variable for the specific knowledge structure of firms by measuring the share of occupational peers on the firm level (occupational intensity). This allows determining to what degree knowledge that is specific to firms can benefit workers who switch jobs.

I begin by formally modeling the relationship between specific, non-transferable knowledge and labor mobility. A combination of the approaches of Lazear (2009) and G&S (2010) allows developing one that accounts for firm and occupational knowledge as well as occupational intensity. The predictions for firm knowledge are that, first, the amount of lost human capital decreases with increasing task similarity of firms. Thus, more switches should be observed between similar firms. Second, inexperienced workers are predicted to cover the longest distances between firms, for instance, because they are still looking for their best possible match. Third, when two jobs require similar tasks, then wages at the source firm are expected to help predict wages in the target firm because they reflect how a larger number of transferable skills reduces the tasks distance. The fourth prediction states that both occupation- and firm-specific knowledge are expected to matter but in the case of joint switches their relative importance is unclear and hence depends on the estimated parameter values of the model. Last, occupational intensity affects wages either negatively, in the spirit of learning opportunities (investment in learning is costly and does not pay off immediately), or positively, when it reflects the value of an occupation to the firm (learning starts to pay off)—again depending on the parameter values.

The predictions are empirically tested with the task-based approach that analyzes which tasks are performed on the job (cf. Autor, Levy, and Murnane, 2003; Poletaev and Robinson, 2008; Gathmann and Schönberg, 2010). The data used for the empirical analyses are from three sources. The Sample of Integrated Labour Market Biographies (SIAB) covers a representative sample of the working population in Germany and allows tracking workers' employment histories. Information about firms is drawn from the Establishment History Panel (BHP). Details on occupational skill sets and tasks are provided by the BIBB/BAuA Employment Survey 2006. The task-based approach is used to identify the amount of occupation- and, for the first time, firm-specific knowledge. As a preparatory step, a factor analysis is applied to categorize tasks into groups. The task composition of firms is determined via the occupational composition of the workforce. The relative task importance is calculated from the share that a selected task makes up against all tasks of all employees, regardless of their occupation. The task distance between firms is calculated using the angular separation, following G&S.

The results are in line with the predictions. The descriptive results confirm that long distance firm switches occur more often early in the career than later on. A switch becomes more costly and less likely the lesser knowledge can be transferred to a new firm. Which type of knowledge can be transferred and to what extent depends on the qualification level of workers. In the case of joint firm and occupation switches, firm- and occupation-specific knowledge both matter for wages. The present evidence indicates that firm-specific knowledge matters less than occupation-specific knowledge. Interestingly, it can further be shown that individuals start work in firms that have a relatively higher share of employees in the same occupational group, that means, a high occupational intensity, and that this share decreases with increasing work experience. Taking this a step further in the OLS estimations reveals that a lower occupational intensity is associated with higher wages. However, workers might strategically select into firms with a certain occupational diversity. To control for this selection problem, occupational intensity is instrumented with occupational diversity on the industry level. Contrary to the OLS results, occupational intensity now shows a positive effect on wages for medium- and high-skilled workers and becomes insignificant for low-skilled employees. Surprisingly, the sizes of the coefficients, which are calculated using standardized variables, suggest that the benefits of occupational intensity can clearly outweigh the costs of both distance measures. This effect supports the notion that a high occupational intensity shows on average a higher demand for an occupational tasks set which is reflected in higher wages. The overall results generally hold for both men and women. They are further robust to various control variables and alternative model specifications.

The paper is embedded into the emerging literature on skill-weights and on the task-based approach. Lazear (2009) suggests that all human capital is general; it becomes specific through weights that are firm specific. His approach is novel because, compared to earlier work (cf. Becker, 1962), there is no longer a clear, exogenously given distinction between general and specific human capital. As done in the empirical analysis of this paper, they are defined endogenously with observable market parameters. First empirical tests of Lazear's model have analyzed if and to what extent a firm's investments in human capital (training) depend on the specificity of the firm's skill combination, the breadth of the skill bundle, the thickness of the external labor market, and the probability of separation (Backes-Gellner and Mure, 2005). Also, Geel, Mure, and Backes-Gellner (2010) have investigated why firms invest in apprenticeship training, which is considered to be general human capital. In both cases, the predictions of the model are borne out by the data, making the model a worthwhile basis for the present analysis. The approach of this paper also relates to Neal (1999) who stresses the prevalence of complex job switches, involving a higher degree of career changes as measured by simultaneous firm and industrial moves, early on the career. To date, to estimate which types of switches are more costly, scholars analyze whether specific knowledge is more tied to occupations, firms, or industries. For instance, some scholars are more in favor of industry-specific human capital (Neal, 1995; Parent, 2000) while others prefer the idea of occupation-specific human capital (Kambourov and Manovskii, 2009; Poletaev and Robinson, 2008). Parent (2000) acknowledges that industry-specific human capital might measure something similar to occupation-specific human capital. Pavan (2011) criticizes that the importance of firm-specific human capital is regularly underestimated. With the exception of Poletaev and Robinson (2008), all studies mentioned above use tenure variables for industries, firms, and occupations, which prevents that knowledge can be divided into a sticky and a portable component. The advantage of tasks data is that they allow moving away from such a generic classification of specific or general skills and measuring instead the degree of similarities (general) or differences (specific) between portfolios. Gathmann and Schönberg (2010) are first to make use of this approach by combining task-specific human capital and a skill-weights approach to investigate job mobility. However, the present paper is the first to conduct an analysis of specific versus general human capital on the firm level using the skill-weights approach. In this context it provides a new measure for firm knowledge using tasks data.

While specific human capital on the individual level is regarded as costly in the case of a job change, a specific knowledge structure on the firm level could motivate workers to cover long distances. Keeping in mind the transferability of knowledge, the question arises as to what degree careers might be structured to minimize the loss of knowledge and, simultaneously, optimize learning potential and wages. Although well equipped to start working after going through school, vocational training or university, the majority of workers receives additional on-the-job training (Mincer, 1962, for an overview, 1989). Studies have estimated varying incidences of on-the-job training but there is clear evidence for the importance of formal and also informal training (for an overview, Barron, Berger, and Black, 1997). Naturally, what can be learnt depends on the job chosen and the workforce composition at the firm as shown in organization research (e.g., Baron, 1984; Hannan, 1988) which has long emphasized that organizations shape jobs, e.g. through their size, growth, demography, technology, and unionization. Occupational intensity can be interpreted as a signal sent by the firm that shows either how large the firm's market power and hence bargaining power is (reflected in lower wages) or how much a firm values an occupational group (as reflected in higher wages). In more details, from a supply side perspective it can be argued that being around a larger peer group might be costly—because it reduces the uniqueness of own knowledge—but important at the beginning of an occupational career to develop own skills. Learning processes are time-consuming and hence costly as individuals and firms cannot immediately reap the benefits of the investments (for instance, as indicated by the relationship between experience and wages). This is reflected by a negative relationship between occupational intensity and wages. After some years, the importance of workers in the same group will decrease and potentially turn zero because individuals have accumulated more knowledge, in sum providing fewer incentives to accept costs associated with a high occupational intensity and potentially encouraging switches to firms with lower occupational intensities. Occupational intensity should therefore decrease along the career path and wages should increase as the occupational intensity decreases. Opposite to this but in line with Bidwell and Briscoe (2010), a demand side perspective suggests that organizations with a higher demand for a bundle of occupational skills also have a higher occupational intensity. By providing more complex, challenging task combinations and being willing to also pay higher wages the firms become very attractive for workers. Effectively, these firms value selected occupations already very highly as they are and do not reduce wages due to learning investments. Assuming that with increasing experience, workers become even more attractive to firms would imply that occupational intensity increases with experience. It further follows that wages increase as occupational intensity increases. Theoretically it appears plausible that both the supply and the demand effect are at work but which one dominates is an empirical question. Hence, the present paper contributes to the literature on (motivations for) job switches by directly capturing the knowledge environment in the firm not only as a type of knowledge that can be lost, thereby discouraging switches, but also a type of knowledge that can facilitate learning or help to maximize earnings, thereby encouraging switches.

All in all, this analysis sheds more light on how individuals and firms are matched along the career path and presents a new measure for specific firm knowledge and, thereby, a new application for tasks data. The comparison of occupational and firm knowledge further provides an indication for switchers whether it is more important to find a good firm or a good occupational match while accounting for a potential switching motivation via occupational intensity. The analysis also contributes to a better understanding which individuals will travel longer distances between firms and thereby, due to this greater flexibility, might be easier to match to new jobs. Finally, it takes into account potential (dis-) advantages resulting from switches by looking at the role of a specific firm environment.

The remainder of this paper is organized as follows. Section 2 presents the conceptual framework. In Section 3, the data set and variables are introduced. Section 4 contains the results and a discussion of their implications. Section 5 concludes.

2 Conceptual Framework

To investigate the relationship between specific human capital and wages, I take as a starting point the conceptual framework by G&S (2010). Both firm and occupational knowledge are divided into a specific and a general component. In the following paragraphs, the focus is on changes to the framework of G&S that were implemented to incorporate firm knowledge. To facilitate the comparison between that work and the present paper, similar equations have the same numbers. As regards the terminology, Acemoglu and Autor (2011) suggest distinguishing skills from tasks because "a skill is a worker's endowment of capabilities for performing various tasks" (Acemoglu and Autor, 2011, p. 1045). They cannot, necessarily, be taken to be equivalent. Now, Lazear refers to *skill* weights which in G&S approach are labeled *task* weights. Nonetheless, in light of the similarity of both approaches, it appears reasonable to assume that the idea behind both models is the same and, thus, does not change with labels. The description of the following analytical set-up sticks to the wording by G&S because my equations are based on theirs. Thus, preference is given to tasks because this is also in line with the methodology chosen in the empirical section.

It is also acknowledged that the individual has one knowledge base and will not necessarily distinguish between occupational or firm knowledge although they may be of different value. However, individuals in the same occupation differ as regards the overall accumulated human capital because of different work experiences at different firms, introducing additional variation across individuals within the same occupation. From a firm's perspective it is of interest what the individual has learnt through experience in another firm as regards organizational practices when recruiting personnel. It is hence assumed that firm knowledge can enter in a wage equation separately. In the end, there will be one price but two components contribute separately to it. To illustrate the basic idea, the two knowledge types will be handled separately in the following framework.

Suppose that the output in a job is determined by fulfilling a variety of general tasks that become specific by the relative importance attached to them in an occupation and in a firm. Following Lazear and G&S, my approach uses two tasks *j*, which can be interpreted as analytical and manual tasks (=*A, M*). The productivity (*S*) of a worker (*i*) varies by occupation (*o*), by firm (*f*), and by the time spent in the labor market (*t*). The relative weight β $(0 \leq \beta \leq 1)$ shows the importance of tasks in an occupation *o* or firm *f*. G&S suggest that the importance corresponds to the time spent on that task. Worker *i*'s productivity (measured in log units) in occupation *o* at firm *f* and at time *t* is

$$(1)\quad ln\, S_{ifot} = \underbrace{[\beta_o t_{iot}^A + (1-\beta_o) t_{iot}^M]}_{\substack{task-specific\ HC\ of\ occupation \\ ln\, S_{iot}}}$$

$$+\underbrace{\left[\beta_f t_{ift}^A+(1-\beta_f)t_{ift}^M\right]}_{\substack{task-specific\ HC\ of\ firm\\ ln\ S_{ift}}}+\underbrace{\alpha_{fo}X_{fot}}_{\substack{occupational\\ intensity}}.$$

G&S's equation ($ln\ S_{iot}$) is augmented with the second term ($ln\ S_{ift}$), which measures the importance of task-specific human capital (HC) at the firm level. The tasks composition on the firm level results from the occupational structure of the workforce, reflecting an interaction between the occupational and firm level. It is now possible to calculate the absolute distances between current and previous firms (occupations) by comparing their task weights, $|\beta_f-\beta_{f'}|$ ($|\beta_o-\beta_{o'}|$). The more similar firms (occupations) are, the smaller is the absolute difference. Although the empirical analyses consider multiple tasks, it is sufficient to consider only two at the moment to illustrate the logic behind the analytical setup. Furthermore, occupational intensity X_{fot} reflects that the productivity of workers also depends on the tasks to which they are assigned in the firm. These tasks are the result of the firm's structure or of who else works at the firm. X_{fot} is measured as the share of workers in the same occupational group in a firm ($\frac{n_{fo}}{N_f}$). As outlined above, the group size of occupational peers at the current firm can but does not need to be of advantage; the direction of the relationship is determined by the parameter α_{fo}. X_{fot} also influences the previously accumulated human capital, as outlined below in equation (3).

Next, the worker's task productivity in an occupation and in a firm t_{igt}^j (with g= occupation, firm) needs to be determined with

(2) $t_{igt}^j = t_i^j+\gamma_g H_{igt}^j\ (j=A,M)$

where t_i^j describes the ability of worker *i* in a certain task *j* (initial endowment). H_{igt}^j includes all previously accumulated human capital of worker *i* in task *j* in different firms f or occupations *o.* In contrast to G&S, I allow this variable to vary on the firm level and, correspondingly, on the occupation level which is necessary if I want to investigate the difference between firm- and occupation-specific human capital. The equation incorporates the idea that workers gain more knowledge on the job. The degree to which this can be achieved in a certain task t depends on the importance of β_g which is assumed to be captured with the time spent on a task. The more experienced workers are, however, the lesser they can learn. This can be written as

$$H_{igt}^A=\beta_{g'}F_{ig't}$$

(3) $H_{igt}^M=(1-\beta_{g'})\underbrace{F_{ig't}}_{\substack{experience\\ in\ prior\\ occupations/\\ firms}}$ with $F_{ig't}=f(X_{fot})$

where $F_{ig't}$ is the experience of worker *i* in previous firms or occupations. In addition to G&S, the type of accumulated human capital is a function of the firm structure as measured by X_{fot}. This follows the idea that what you learn on the firm and occupational level is determined by the environment, in this case your coworkers.

Combining the equations above gives

$$(4)\ \ln S_{ifot} = \underbrace{\gamma_o \underbrace{[\beta_o H^A_{iot} + (1-\beta_o)H^M_{iot}]}_{T_{iot}} + \underbrace{\beta_o t^A_i + (1-\beta_o)t^M_i}_{m_{io}}}_{occupation}$$

$$+ \underbrace{\gamma_f \underbrace{[\beta_f H^A_{ift} + (1-\beta_f)H^M_{ift}]}_{T_{ift}} + \underbrace{\beta_f t^A_i + (1-\beta_f)t^M_i}_{m_{if}}}_{firm} + \underbrace{\alpha_{fo} X_{fot}}_{occupation\,\&firm}$$

where γ_f (γ_o) measures the returns to task-specific human capital of firms (occupations). T_{ift} (T_{iot}) can be observed as a time-variant measure of task-specific human capital; m_{if} (m_{io}) is the unobservable match to the firm (occupation) that does not vary over time. The equation further includes X_{of} which represents occupational intensity.

To investigate labor mobility, wages in different jobs need to be compared. These are determined by multiplying productivity with the skill or tasks prices of firms P_f (occupations P_o), that is $w_{iot} = P_o * S_{iot}$. Next, the equation is logarithmized and yields the following expression

$$(5)\ \ln w_{ifot} = \left(\underbrace{p_o}_{\substack{skill\ price \\ occupation}} + \underbrace{\gamma_o T_{iot} + m_{io}}_{\ln S_{iot}} \right) + \left(\underbrace{p_f}_{\substack{skill\ price \\ firm}} + \underbrace{\gamma_f T_{ift} + m_{if}}_{\ln S_{ift}} \right) + \underbrace{\ln\alpha_{fo} X_{fot}}_{\substack{occupational \\ intensity}}$$

where $p_f = \ln P_f$ ($p_o = \ln P_o$). Equation (5) can be used to investigate labor mobility of workers. Like Lazear, G&S suggest a two-period setup where the worker has to decide whether to stay or to switch jobs in the second period. A firm switch occurs when

$$\underbrace{\ln w_{ifot}}_{\substack{wages\ in\ \textbf{new} \\ firm}} > \underbrace{\ln w_{if'ot}}_{\substack{wage\ in\ \textbf{previous} \\ firm}}$$

This equation can be rearranged as follows

$$(6)\ (p_f - p_{f'}) + (m_{if} - m_{if'}) + (\ln\alpha_{fo} X_{fot} - \ln\alpha_{f'o'} X_{f'o't}) + \gamma_f T_{ift} > \gamma_{f'} T_{if't}$$

which shows that what is paid for task-specific human capital in the previous firm must be exceeded by the sum of the returns to task-specific human capital in the new firm, the difference of skill prices, of the task match, and the improved task environment as indicated by occupational intensity. To illustrate the influence of the βs the equation can be rewritten as

$$(7)\quad \underbrace{(p_f - p_{f'}) + (\gamma_f - \gamma_{f'})T_{if't}}_{wage\ growth\ in\ firm} + \underbrace{(m_{if} - m_{if'})}_{task\ match} + \underbrace{(ln\alpha_{fo}X_{ft} - ln\alpha_{f'}X_{f't})}_{changes\ in\ task\ environment} >$$

$$-\underbrace{\gamma_f\left[(\beta_f - \beta_{f'})(H^A_{ift} - H^M_{ift})\right]}_{\substack{-\gamma_f(T_{ift} - T_{if't}) \\ loss\ in\ human\ capital}}.$$

The right-hand-side term in Equation (7) shows the loss in task-specific human capital where one can again see the influence of the difference between the βs. The left-hand side is the sum of the difference of the firm task match, the wage growth attributable to an increase in skill prices, and the returns to previously acquired task-specific human capital. In addition, it shows the advantages resulting from a good match in terms of the task environment.

In addition to pure firm switches, it is necessary to look at joint occupation and firm switches because this allows comparing the influence of task-specific human capital on the occupational and firm level. Accordingly, a joint switch can be observed when

$$\underbrace{ln\, w_{ifot}}_{\substack{wages\ in\ \boldsymbol{new} \\ occupation\ and \\ firm}} > \underbrace{ln\, w_{if'o't}}_{\substack{wage\ in\ \boldsymbol{previous} \\ occupation\ and \\ firm}}$$

$$(8)\quad [(p_o - p_{o'}) + (\gamma_o - \gamma_{o'})T_{io't} + (m_{io} - m_{io'})] + \left[(p_f - p_{f'}) + (\gamma_f - \gamma_{f'})T_{if't} + (m_{if} - m_{if'})\right] + (ln\alpha_{fo}X_{fot} - ln\alpha_{f'o'}X_{f'o't}) >$$

$$-\gamma_o\left[(\beta_o - \beta_{o'})(H^A_{iot} - H^M_{iot})\right] - \gamma_f\left[(\beta_f - \beta_{f'})(H^A_{ift} - H^M_{ift})\right].$$

In this case, the worker has to evaluate both the occupational and the firm level before deciding to switch. The analytical setup yields the following intuitive results, part of which were tested for the case of occupational human capital by G&S, but, according to my argument, should simultaneously matter for human capital at the firm level. First, less task-specific human capital is lost when the switch takes place between firms that are more similar with regard to their task composition. Therefore, switches occur more often between similar firms. Second, the distance covered in a switch will be the highest early in the career. Specifically, during early years of employment, workers are still looking for their best possible match, which might include a certain amount of trial and error. After having spent a longer time in the labor market, people are less likely to travel long distances because, possibly, they have already found a good match. Third, wages at the source firm are expected to be a better predictor of wages in the target firm if both positions require similar tasks. This follows from the idea that with a higher number of transferable skills a better match is achieved because distances are shorter. Fourth, both occupation and firm knowledge matter for wages. When investigating joint switches, I thus take into account both knowledge types to compare their relative importance. Finally, occupational intensity negatively affects wages because of a time investment in learning by the employee. The theoretical counter-argument suggests a positive relationship, showing that a set of occupational skills is more highly valued by firms. The direction of the effect depends on the parameter values from the empirical analysis. The analysis carried out in this paper is innovative in its methodological measurement of firm knowledge, providing a direct empirical measure for firm specific knowledge, and it incorporates a unique test of potential (dis-)advantages arising from occupational composition of firms.

3 Data

3.1 Data Sources

Three data sources are accessed for the analysis. The first data set is the weakly anonymous Sample of Integrated Labour Market Biographies (SIAB). Data access was provided via on-site use at the Research Data Centre of the German Federal Employment Agency at the Institute for Employment Research and subsequently remote data access. The SIAB contains a very long observation period (1975–2008) and information on labor market histories of 1.5 million individuals in Germany (Dorner et al., 2010). It is the most comprehensive administrative micro-level data set on employment histories currently available for Germany. In addition, it is possible to link the establishment information of the Establishment History Panel (BHP) to the SIAB. This combination of individual labor market histories (SIAB) and firm employment structure (BHP) makes the data perfectly suited for this analysis. The SIAB provides information on wages and occupations of individuals and the BHP has information on the occupational categories of all employees in a firm.

A detailed description of the data set is included in the Annex. In short, I restrict the analysis to men, employees with an average daily wage of at least 10 Euros and to voluntary switches. To identify and later exclude involuntary switches, I start with job switches where simultaneously structural changes occurred in the firm, for instance, a change of ownership or the firm's exit from the market. This group is augmented with other involuntary switchers who are identified by receiving unemployment benefits immediately after leaving the firm. Note that in Germany, workers who give notice, in contrast to being given notice, may not receive unemployment benefits for three months.

The classification of individuals and firms according to their task sets requires, of course, information on tasks. The BIBB/BAuA Employment Survey 2006 (Hall and Tiemann, 2006; Rohrbach-Schmidt, 2009), which was undertaken in 2005 and 2006 by the Federal Institute for Vocational Education and Training (BIBB) and the Federal Institute for Occupational Safety and Health (BAuA) provides all necessary information. This wave consists of a random sample of 20,000 people who are active in the labor force in Germany. In addition to individual-specific data, the survey includes information on the tasks requirements of occupations. For further examples using this data base see Spitz-Oener (2006, 2008) and Borghans, ter Weel, and Weinberg (2014). The BIBB/BAuA data are merged by occupation (SIAB) or occupational groups (BHP).

3.2 Variables

The dependent variable is the logarithm of wage, as proposed in the analytical setup. Wage is measured as gross daily income of employees and reported in Euros. Occupational intensity—the share of occupational peers—is calculated by dividing the number of workers in the same occupational group, using Blossfeld categories, by the total number of workers in the firm. The Blossfeld classification, which is the only available unit for occupations on the firm level in the BHP, is based on the three-digit occupation of an individual as specified by the employer in the notification to the social security agencies. Blossfeld first distinguishes between three upper-level groups, namely, production, service, and administration, and secondly ranks occupations according to the type of required skills. Accordingly, blue-collar workers who perform simple manual tasks and white-collar workers who provide simple services are regarded as unskilled; blue-collar workers engaged in complicated tasks, white-collar workers performing qualified tasks, and semi-professionals are regarded as skilled workers. The third and most highly qualified group includes engineers, technicians, professionals, and managers. The Blossfeld classification thus assigns upper-level group and then ranks individuals according to their skill requirements. To address a potential bias in the estimation, I further calculate the degree of occupational diversity on an industry level (28 industries) to create a Herfindahl index and use this variable as an instrument for occupational intensity. The idea is that firms located in diverse industries will exhibit lower shares of occupational intensity. There is, however, no empirical evidence that occupational diversity on the industry level has an effect on wages. A detailed description of the instrument variable Herfindahl Blossfeld can be found in Section 4.3.

To measure general work experience, I calculate the number of years someone has worked since labor market entry by using information on the exact number of working days, excluding periods of unemployment. It is common practice in wage regressions to include a squared term for work experience because a concave relationship is in line with changes that occur later along the career path. This specification is more restrictive than suggested by the analytical setup but still in line with the general idea. I distinguish three levels of education in the regressions. Low-skilled workers are defined as those who did not pass the Abitur (German university entrance qualification) and have not completed apprenticeship training. This also includes unskilled workers. Medium-skilled workers passed the Abitur and have completed nothing above an apprenticeship. High-skilled workers hold a degree from a university or university of applied sciences. Incentives to switch firms can be driven by regional characteristics and, therefore, controls for region types are introduced. Additional controls include, as dummies, years, industry, occupational groups, and the logarithm of establishment size. The summary statistics as well as correlations for the most important variables can be found in Table A 2 and Table A 3 in the annex.

The analyses of employment biographies are carried out separately for men and women because the two groups are known to show significant differences in terms of wages and employment careers. Note that I only report the results for men, leaving the results for women to the discussion at the end. The measures for tasks distance between occupations, using the BIBB/BAuA data, include both men and women (see Section 4.1). In the regressions all variables are standardized.

4 Analysis

4.1 A Task-Based Measure for Specific Human Capital of Firms

The main variable of interest is a measure of the firm- and occupation-specific human capital. G&S group tasks manually into three categories: analytical, manual, and interactive. This categorization makes it possible to combine tasks from different years. As they show, the task content of occupations changes only slightly. In contrast, this paper lets the data structure determine the task groups, which has the advantage of allowing me to take into account more tasks because they do not have to be included in every survey wave. The disadvantage is that this procedure cannot be carried out with every survey because tasks do, and therefore factors would, vary. Thus, I rely on G&S's result that, over time, task variation in occupations is low and I instead use a factor analysis. Here, a principal factor analysis shows whether certain tasks need to be clustered on the occupational level in latent variables. The first advantage of this procedure is an easier interpretation of the data due to condensed information and orthogonal factors. In addition, since task level is determined by executing a task regularly or by the degree of expert knowledge required, it takes more than a high value in one task to end up with a high value in a factor. Thus, the factor reflects the task level in a certain domain and the level can change through adjustments of different tasks. Indeed, using exploratory factor analysis on high-dimensional tasks data is in line with Green (2012) who also discusses the risks associated with classifying tasks by hand. In addition, my analysis does not need to reproduce existing categorizations nor interpret the results in the framework of routine versus non-routines tasks, as done by Autor, Levy, and Murnane (2003). Although using tasks data from different survey waves can be of advantage, it is ultimately a trade-off between (1) exogenously determined tasks categories to which survey questions from different years are assigned and (2) endogenously determined tasks categories from one observation period. In the current context, applying factor analysis (option (2)) is considered to be the more appropriate procedure.

A selection of 31 survey questions from the BIBB/BAuA Employment Survey 2006 gives information about tasks applied in the employee's current job. The closest approximation to tasks of individuals in this context is achieved on the occupational level. The survey question asks respondents to assess the task level that they use in their current position. The calculations of the factor analysis return seven factor variables that explain around 91% of the total variation in 248 occupations (see Table 1, for an overview, and Annex A, for details on the data and computations).

>> Table 1 about here <<

The factors are then labeled according to their content, which is the combination of certain tasks, placing most emphasis on the variables that load the highest. This is similar to what Poletaev and Robinson (2008) and Nedelkoska and Neffke (2011) do. The factor labels are: intellectual, technological, health, commercial, instruction, production, and protection. To make the occupational classification more transparent, Table 2 reports the occupations with the highest and lowest values in each factor. The example occupations set out in the table make intuitive sense, thus confirming the plausibility of the principal factor analysis. For instance, the technological factor has a strong focus on the application of technological and manual knowledge, both of which are characteristics of occupations such as aircraft engine mechanic or optometrist. The health factor is most important for various types of medical practitioners and other occupations in the health care system. More routine tasks like producing and manufacturing goods, measuring, testing, and operating machines load highest in the production factor, which is where occupations such as machine operators for dairy and paper products are found.

>>Table 2 about here <<

The task composition of the workforce is determined with information on the 12 occupational groups by Blossfeld (1985, see Table A 1). This classification does not allow seeing whether the firm employs workers in the same three-digit occupation as held by the switcher. From an employee perspective, however, it is unlikely that they have detailed information as to all the occupations of prospective co-workers. Thus, the Blossfeld classification appears to be an adequate indicator of one aspect that is driving a voluntary job switcher's decision. Task factors for each Blossfeld group are calculated as follows. First, the average factor value of each task is determined for all occupations that belong to one Blossfeld group (t_b). These task factors are then weighted by multiplying them with the corresponding number of workers in a firm in that Blossfeld group (n_{fb}). Since the focus is the structure of the workforce, this value is divided with the sum of all weighted task factors to calculate the relative importance of a task factor in a firm. The idea behind this procedure is that a firm's task composition represents firm knowledge. The more similar firms are with regard to the task composition, the more firm knowledge can be reapplied by the worker after a switch. Job switchers are, thus, also included because they are part of the firm's task structure. This procedure returns the *relative* importance of tasks in a firm to avoid that firm size drives differences.

$$Task\ importance\ in\ firms = \frac{t_b * n_{fb}}{\sum_{b=1}^{n} t_b * n_{fb}}$$

Next, the distance of firms/occupations is determined by using the angular separation or uncentered correlation of two vectors representing two firms/occupations (for details on the computational method, see Gathmann and Schönberg, 2010; Jaffe, 1986). The equation is

$$AngSep_{gg'} = 1 - \frac{\sum_{j=1}^{J} q_{jg} * q_{jg'}}{\left[\left(\sum_{j=1}^{J} q_{jg}^2\right) * \left(\sum_{k=1}^{J} q_{kg'}^2\right)\right]^{1/2}}$$

$$Distance_{gg'} = 1 - AngSep_{gg'}$$

where q is the vector of all tasks in a firm/occupation. The measure is slightly adjusted so that a value of 1 (0) means that the firms/occupations are completely different (identical). This distance measure reflects the differences between firms or occupations with regard to their task-specific human capital. The measure for occupations is calculated on the basis of the original factors of occupations from the factor analysis (see Table 1). For firms, the relative tasks importance is compared between origin and target firm.

4.2 Transferability of Firm and Occupational Knowledge

In what follows, the analysis always distinguishes between qualification levels of employees. This is important because the amount of human capital and, thereby, general and specific knowledge can be expected to differ between groups. First, the share of switches by different firm distance intervals is calculated. The results in Figure 1 show that the majority of switches involves low firm distances. The largest share of joint occupational and firm switches occurs in the lowest firm distance interval, confirming that switches occur more often between similar firms. Firm distance appears to decrease when qualification level increases. Possibly, workers with higher qualification levels can be more selective in choosing a suitable target firm or low-skilled employees are to a smaller degree affected by firm distance. The figure also reveals, as a control analysis, that the distribution differs for layoffs which cover slightly longer distances than voluntary switchers. As announced, layoffs are thus excluded from the following analysis.

>>Figure 1 about here <<

In Figure 2, I investigate the relationship between average firm distance and different years of work experience for all male employees. The more experienced workers are, the smaller firm distance becomes. An exception is an increase in firm distance between the second and fourth year. Across qualification groups the negative trend turns out to be very similar. Low-skilled employees exhibit smaller values than the other groups until the third year. From then on, low-skilled have the highest average firm distance values, followed by medium- and high-skilled workers. The results could be interpreted as evidence that workers accumulate more specific knowledge or achieve a better match along the career path, providing less incentive to cover larger distances and pay associated costs.

>>Figure 2 about here <<

Following, the relationships between task-specific human capital at the occupational as well as firm level and wages are investigated. The analysis focuses on switchers and builds on the analytical framework by estimating the following equation

$$lnw_{ifot} = \gamma_o D_{ot} + \gamma_f D_{ft} + \alpha X_{oft} + \beta \mathbf{Z}_{ifot} + \varepsilon_{ifot}$$

where the dependent variable is the logarithm of wage (lnw_{ifot}), D is the distance on the firm or occupational level, X_{oft} is occupational intensity, Z_{ifot} is a vector of control variables, and ϵ is the error term. The equation is first estimated using ordinary least squares in the baseline and in the next section using two stage least squares. All regressions report coefficients based on standardized variables which are needed to compare the relative contribution of occupational and firm knowledge in explaining the variation of the model.[1] Past wages are included as a control measure for the reservation wage and, in addition, interactions between past wages and task distance follow the idea that wages at the source firm are expected to be a better predictor of wages in the target firm if both positions require similar tasks. The estimations further include work experience, work experience squared, firm size, as well as dummies for occupational groups, regions, industry, and years. It is acknowledged—for instance by not claiming causal relationships—that the estimation procedure cannot account for endogeneity in the decision to switch jobs, leading to a potential bias in the estimations. Hence, to at least increase homogeneity in the group, the focus remains on voluntary switchers. Nonetheless, the results continue to provide information on the relative importance of firm and occupational knowledge which is the goal of this exercise and the preparation for the analysis of (dis)advantages of firm knowledge in the following section.

Table 3 reports the OLS results by qualification level, following a stepwise inclusion of the variables. The baseline specification in Column A shows that previous wage and previous firm size contribute positively to the current wage. Work experience has a positive relation with the current wage but the coefficient decreases over time. Occupational distance shows a negative sign. I continue by replicating the results by G&S, using only occupational distance (Column B-C).[2] Across qualification groups, most variables have the expected signs. Occupational distance decreases the current wage. Expect for high-skilled workers (Column 13), previous wage correlates positively with the current wage but the coefficient decreases with increasing task distance. Column D and E complement the previous estimations by including the firm distance variables. With one exception for low-skilled workers (Column 4), firm distance matters in addition to occupational distance. With the exception of high-skilled employees, the interactions between the distance measures and previous wages are significant (Column 15). Whenever both firm and occupational distance measures are significant, the coefficient of occupational distance is roughly twice as large as the one of

[1] Note that the standardization of interaction terms changes the null hypothesis and, thereby, complicates the interpretation of the results. Comparison between models is, thus, not possible. It can further lead to coefficients and significance levels that differ from those of an unstandardized model. Nonetheless, the goal of testing the contribution of firm and occupational human capital justifies this approach. Also note that clustered standard errors are not suitable for standardized variables because variables are standardized using the population mean. Standard errors would instead be clustered on the individual level. Thus, the models are estimated with robust standard errors instead. Control regressions with standard errors clustered on the individual level using standardized variables confirm the reported relationships (results available upon request).

[2] G&S did not include occupational intensity and firm size but leaving these variables out does not alter the results. Results are available upon request.

firm distance, reflecting that a good occupational match is relatively more important. So far, the results confirm that the newly constructed measure for firm knowledge plays a significant role in explaining wages in target firms. In all specifications, occupational intensity contributes negatively to wage but further evidence is needed to corroborate this finding. From this I can conclude that the skill-weights approach as implemented by G&S, whose results are replicated in the regressions, can and should be extended to firm knowledge. However, instead of proceeding the same way as G&S did, the focus will now shift to a more in-depth investigation of firm knowledge in terms of occupational intensity.

>>Table 3 about here <<

4.3 (Dis-)Advantages of Occupational Intensity in Firms

The descriptive evidence documents the importance of learning in firms. The BIBB/BAuA survey (N=15,796 with sample restrictions as defined above) shows that 78.2 % of the workers need on the job either a longer training or instruction to carry out their current activities and 60 % declare to need special courses or trainings. 78.3 % often receive support from colleagues and 58.3 % from supervisors. In addition, 23.8 % have acquired their skills primarily and 37.3 % secondarily through experience. In the latter case, this is the answer that was most often chosen among all options. These results confirm that, for the majority of workers, their previously acquired knowledge did not match perfectly the job that they were carrying out. Instead, additional effort was required to learn while working on the job, for instance, from colleagues. Figure 3 shows the relationship between work experience and average occupational intensity for all male employees. Low- and medium-skilled employees start work in firms where the own occupational group accounts for around 55 % of the workforce and after 30 years for around 40 %. High-skilled workers start at around 35 % and move to around 28 %. In both cases this implies a drop of 20 percentage points.

>>Figure 3 about here <<

To address the relationship between wages and occupational intensity in more details, I estimate two stage least square regressions. Across all qualification levels, the OLS results suggest that occupational intensity and wages correlate negatively. As instrument for occupational intensity I use the Herfindahl Blossfeld index to measure occupational diversity on an industry level, as opposed to the standard procedure of measuring industrial diversity on a regional level. A heterogeneous occupational composition of industries should relate to the occupational composition of firms because industrial and firm labor demand should be highly correlated. In the data the newly created Herfindahl Blossfeld index is significantly positively but moderately related to occupational intensity (r=0.2943, see Table A 3). To my knowledge there is no evidence that being in an occupationally diverse industry has a direct impact on wages. The Herfindahl Blossfeld index shows indeed negligible correlations with all the other variables in the analysis, most importantly with wages (r=0.0436). Technically, an indirect relationship could exist since workers' wages can be understood as a function of industry productivity which in turn is determined by firm size and the type of workers needed. The calculations show, however, that the correlation between firm size and the Herfindahl Blossfeld index is very low (r=-0.0295, see Table A 3). Indeed, the Herfindahl Blossfeld index is calculated as a percentage measure and should be independent of the number of workers. There is also no evidence for an important correlation between workers' qualification levels and the Herfindahl Blossfeld index. In any case, the regressions are carried out separately for qualification level. To avoid that the final results are driven by unobserved, indirect connections or that the Herfindahl Blossfeld index picks up other industrial or firm characteristics, control dummies for the 28 industries of the Herfindahl Blossfeld index, for firm size and for occupational groups (as a measure for type of worker) are included.

Table 4 reports the 2SLS results. The odd numbered columns (also Column A and C) show the first, the even numbered columns (also Column B and D) the second stage regressions. The specifications are the same as the final regressions in Column D and E of Table 3, including all variables of interest.[3] The Herfindahl Blossfeld index relates positively to wages in the first regression in all estimations. The F-statistic on the excluded instrument is always clearly above the threshold of 10. The results for occupational intensity in the second stage clearly differ from the OLS regressions. Occupational intensity becomes insignificant for low-skilled but positively significant for medium- and high-skilled workers. The pattern and signs of the other variables reflect closely the OLS results in Table 3. One important difference is that the coefficients of firm distance increase substantially for medium- and high-skilled employees but are insignificant for low-skilled employees. Nonetheless, occupational distance continues to show larger coefficients than firm distance.

The reduced form estimates for this analysis are also in line with the expectations, showing significant, positive coefficients of the Herfindahl Blossfeld index for medium- and high-skilled employees but insignificant coefficients for low-skilled employees in the wage regressions (results are available upon request). Comparing the size of the distance variables and occupational intensity shows that the sum of the negative distance coefficients never amounts to the size of the positive coefficient for occupational intensity. In other words, although individual might cover costly distances, these costs are outweighed by the benefits of working in an occupationally intensive firm.

>>Table 4 about here <<

In sum, instrumenting occupational intensity confirms that the OLS results are biased and that for medium- and high-skilled employees wages in target firms increase with occupational intensity. Thus, in terms of wages, the 2SLS estimates for these groups confirm the demand side hypothesis by Bidwell and Briscoe, according to which occupationally intensive firms are of advantage to workers. The decreasing share of occupational peers with

[3] The 2SLS for columns A-C of Table 3 are also in line with the results in Table 4. Results are available upon request.

experience is in line with the supply side hypothesis. Taking into account that distance and occupational intensity decrease with increasing experience suggests that, when distances are shorter, there is less need to choose occupationally intensive firms as a compensation mechanism. However, this cannot be causally interpreted. Low-skilled workers are not affected by firm knowledge, neither by firm distance nor by occupational intensity—an even stronger result than in the previous models. This again might explain why they cover on average longer firm distances.

To verify the robustness of the 2SLS estimations, the same equations were estimated using limited information maximum likelihood (LIML) and generalized method of moments (GMM). The results stay virtually the same. Including the squared term of occupational intensity provides no robust evidence for a non-linear relationship between occupational intensity and wages. All of the previous regressions focus on men. Additional analyses for women show the same patterns. In fact, the positive relationship between occupational intensity and wages can also be confirmed for low-skilled women. All results are available upon request.

5 Conclusions

Recent work in the field of labor mobility that uses task-based measures to determine job content has helped address several puzzles of labor economists, such as, for instance, skill-biased technological change (Autor, Levy, and Murnane, 2003). Other work with tasks data has addressed the question of human capital specificity, that is, knowledge that cannot be transferred in the case of job switches. As regards occupational specificity, it has been shown that the distance of occupational switches determines how much knowledge is lost and how much is still reusable (Gathmann and Schönberg, 2010; Nedelkoska and Neffke, 2011). This paper is located in the theoretical fields of the skills-weights model (Lazear, 2009) and the task-based approach (Gathmann and Schönberg, 2010). It splits occupational and firm knowledge both in two, a specific and a general component. This is done by determining how transferable knowledge between two firms or two occupations is. In addition, it takes into account the role of working in an occupationally intensive firm, that is, a firm with a large amount of specific knowledge.

The results reveal the following patterns with regard to how individuals are matched along the career path. First, the majority of switchers travel only small distances between firms. Furthermore, long distance switches between firms become less likely with increasing work experience, indicating that workers might find better work matches as they move along their career path. Firm and occupational distances—measures for specific knowledge—show a negative relationship with wages with the exception of low-skilled workers where firm distance is not always insignificant. Occupational knowledge is of higher importance than firm knowledge. In early career stages, individuals work with a higher share of colleagues in the same occupational group, called occupational intensity, than is the case later on in their employment history. In 2SLS it can be shown that occupational intensity positively affects wages for higher qualification levels, supporting the idea of higher wages in firms with a higher demand for an occupation. In addition, the sum of the negative coefficients from increasing both occupational and firm distance by one standard deviation is smaller than the positive coefficient of increasing occupational intensity by one standard deviation. This indicates that long distance switches can still be rewarding in terms of the awaiting environment at the target firm.

In sum, this paper contributes to the literature by showing that the specificity of knowledge on the occupational *and* firm level is determined by context. All knowledge can, thus, become either specific or general. In addition, the results suggest that both firm and occupational knowledge matter for wages after switches. The paper can hence not only confirm previous work by G&S but also show that Lazear's skill-weights approach holds for firm knowledge. Human capital theory predicts that costs of general on-the-job training should be borne by the worker while in reality specific training costs seem to be covered partly by workers and partly by firms. If the specificity depends on where workers move next, then this might explain why the empirical studies differ from the theoretical predictions (e.g., Barron and Berger, 1999; Parent, 1999). Further, in a task-based analysis averaging across occupations (which is the standard procedure) and thereby disregarding firm knowledge implies a loss of information. The paper has, so far, not directly tested how industrial and occupational knowledge relate to each other. In addition, only the general relationships between specific human capital, that is distances, and wages but not the direction of the relation was determined. It implies that sorting into firms could only be addressed with regard to occupational intensity. These issues have to be left to future research.

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Figures & Tables

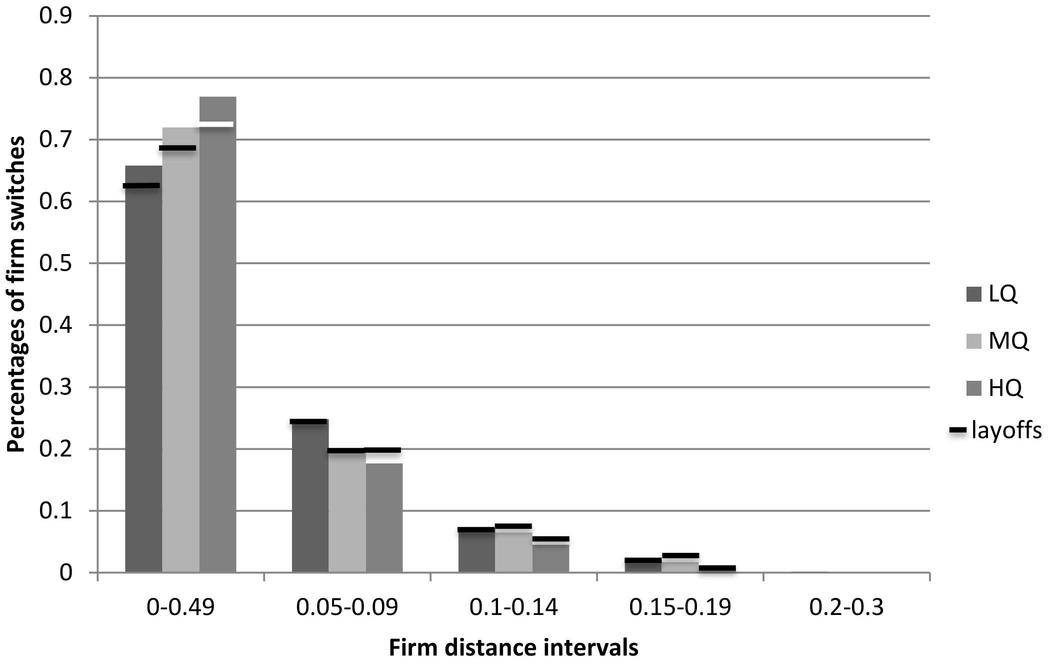

Figure 1: Distribution of joint switches across firm distance intervals

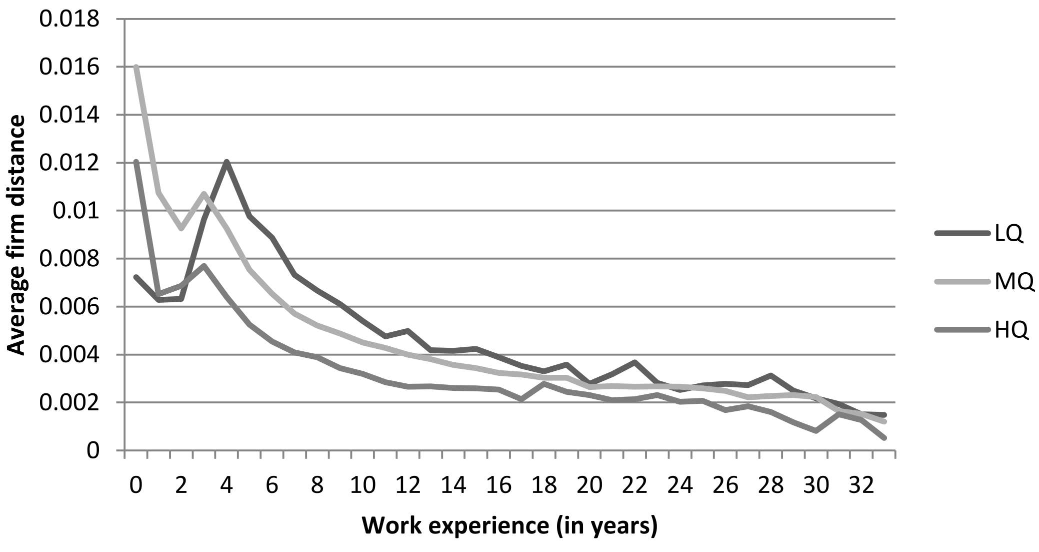

Figure 2: The relationship between work experience and firm distance

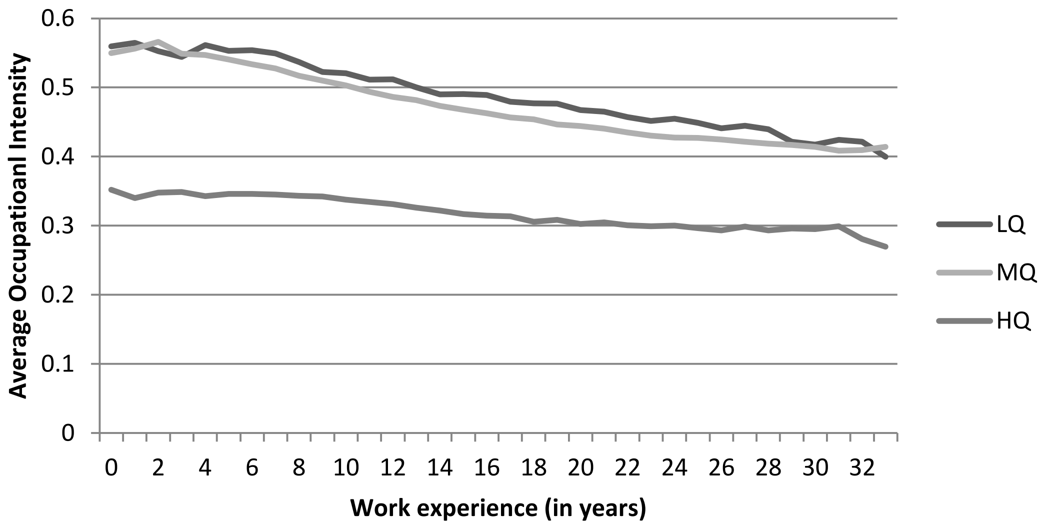

Figure 3: The relationship between work experience and occupational intensity

Table 1: Results of principal factor analysis with 31 tasks*

Question	Task Description	Factor1 *intellectual*	Factor2 *techno-logical*	Factor3 *health*	Factor4 *commercial*	Factor5 *instruction*	Factor6 *production*	Factor 7 *protection*	**Unique-ness**
F301	Managerial responsibility	0.25	0.2174	0.006	0.0866	0.3279	0.0911	0.201	0.4023
F303	Producing, manufacturing goods	-0.3112	0.3289	-0.1539	-0.1697	-0.1025	0.6615	-0.1331	0.2687
F304	Measuring, testing, quality control	-0.0856	0.6327	0.035	-0.0455	-0.0074	0.5842	0.0493	0.1946
F305	Operating, monitoring machines	-0.2069	0.4936	-0.0162	-0.2875	-0.1788	0.4962	0.3177	0.1971
F306	Repairing (machines)	-0.3278	0.8038	-0.0146	-0.0319	0.0163	0.0993	0.0855	0.2023
F307	Purchase, procure, selling	0.111	-0.037	0.2128	0.8109	0.0662	-0.062	-0.0033	0.2469
F308	Transport, stock, shipping	-0.4143	0.2281	0.0046	0.1763	-0.1611	0.1323	0.3534	0.5265
F309	Advertising, marketing, PR	0.4036	-0.2785	0.1343	0.4437	0.337	-0.1456	-0.0023	0.2565
F310	Organization, planning other people's work processes	0.4199	0.1245	0.1575	0.2282	0.3508	-0.0182	0.0216	0.3061
F311	Develop, research, design	0.5607	0.2936	0.0514	-0.0593	0.2352	0.051	-0.2722	0.2323
F312	Teaching, educating	0.3278	0.0845	0.3216	0.0858	0.7425	-0.0213	0.0354	0.1803
F313	Collecting information, investigating, documenting	0.8005	-0.0911	0.2242	0.1252	0.2473	-0.1568	0.1118	0.1402
F314	Advising, informing, consulting	0.5367	-0.0277	0.2671	0.5106	0.3419	-0.2214	-0.0153	0.1716
F315	Serving, accommodating, meals preparation, entertaining	-0.185	-0.2718	0.253	0.3179	0.2033	0.0774	0.0729	0.4656
F316	Caring, curing, healing	-0.0376	-0.0974	0.8777	0.0726	0.2301	-0.0087	0.0689	0.1457
F317	Protecting, guarding, observing , controlling traffic	-0.0563	0.3099	0.2696	-0.0892	0.07	-0.0547	0.6386	0.3744
F318	Working with computer (frequency)	0.8651	-0.1556	0.0268	0.0507	0.0244	0.0825	0.0702	0.1778
F319A	Cleaning, waste disposal, recycling	-0.7009	0.2131	0.1667	0.0907	-0.0661	0.3365	0.1477	0.2098
F403_01	Natural science knowledge	0.4284	0.3209	0.4545	0.1275	0.0827	-0.0081	0.0337	0.2364

F403_02	Manual (artisan) knowledge	-0.3498	0.8558	-0.0464	-0.025	0.0312	0.0858	-0.034	0.1264
F403_03	Pedagogical knowledge	0.2743	-0.0758	0.4517	0.135	0.714	-0.137	-0.0468	0.1302
F403_04	Law knowledge	0.4988	-0.1251	0.253	0.1774	0.2469	-0.3443	0.2094	0.1837
F403_05	Project management knowledge	0.7342	0.029	0.0124	0.228	0.2231	-0.1476	-0.0968	0.1322
F403_06	Medical, care-related knowledge	0.0683	-0.0231	0.8686	0.1232	0.1315	-0.0435	0.044	0.1959
F403_07	Layout, design, visualization knowledge	0.5843	-0.0203	-0.0475	0.1878	0.2881	-0.0862	-0.293	0.2337
F403_08	Math, advanced calculus, statistics knowledge	0.4414	0.5029	-0.0874	0.3	0.1337	0.0533	-0.0536	0.2603
F403_09	German language, writing, grammar knowledge	0.7215	-0.1639	0.1303	0.1888	0.2796	-0.1437	-0.0848	0.2077
F403_10	Computer knowledge in application software (level)	0.7559	0.0136	-0.1016	0.1217	0.041	-0.0946	-0.0856	0.3181
F403_11	Technological knowledge	0.2118	0.8796	-0.0548	-0.1084	-0.0413	0.0728	0.0996	0.1184
F403_12	Business and commercial knowledge	0.5554	-0.2138	-0.0064	0.6151	0.0737	-0.1313	-0.0862	0.1552
F403_13	Foreign languages knowledge	0.742	-0.1193	0.099	0.1487	0.1442	-0.0685	-0.019	0.2546
	Variance (after orthogonal variance rotation)	7.17492	3.91560	2.55826	2.19369	2.16042	1.52732	1.00752	
		non-routine analytical	*non-routine manual & cognitive*	*non-routine interactive*	*non-routine cognitive & interactive*	*non-routine interactive*	*routine manual & cognitive*	*non-routine interactive*	

*Source: Own calculations with BIBB/BAuA Employment Survey 2006. Calculations are based on 248 occupations (N = 15,603).

Table 2: Ranking of occupations for seven factors*

Occupations with highest score	Occupations with lowest score
FACTOR 1: Intellectual (non-routine analytical)	
Other production engineers	Helpers and cleaners in offices, hotels and other establishments
Mechanical engineers	Building structure cleaners
Computer assistants	Domestic helpers
Mining engineers, metallurgists, and related professionals	Upholsterers and related workers
Electronics engineers	Roofers
FACTOR 2: Technological (non-routine manual & cognitive)	
Aircraft engine mechanics and fitters	Meat-processing-machine operators
Industrial machinery mechanics and fitters	Judges
Shoe makers and related workers	Data entry operators
Structural metal preparers and erectors	Real estate agents and administrators
Optometrists and opticians	Personal care and related workers not elsewhere classified
FACTOR 3: Health (non-routine interactive)	
Dentists	Real estate agents and administrators
Medical doctors	Accounting and bookkeeping clerks
Veterinarians	Home loan bank clerks
Nursing associate professionals	Bookkeepers
Physiotherapists and related associate professionals	Banking experts
FACTOR 4: Commercial (non-routine cognitive)	
Shop salespersons and demonstrators	Judges
Optometrists and opticians	Plant security officers, detectives
Personal care and related workers not elsewhere classified	Data entry operators

Filling station attendant	Metal finishing-, plating- and coating-machine operators
Druggist	Mineral-ore- and stone-processing-plant operators
FACTOR 5: Instruction (non-routine interactive)	
Secondary education teaching professionals** (“Fachschul-, Berufsschul-, Werklehrer”)	Personal care and related workers not elsewhere classified
Secondary education teaching professionals** (“Real-, Volks-, Sonderschullehrer”)	Farmhands and laborers
Pastor	Translators and interpreters
Secondary education teaching professionals** (“Gymnasiallehrer”)	Other beverage machine-operators
Secondary education teaching professionals** (“Lehrer für musische Fächer”)	Judges
FACTOR 6: Production (routine manual & cognitive)	
Dairy-products-machine operators	Legal and related business associate professionals
Paper-products-machine operators	Crane operators
Mineral-ore- and stone-processing-plant operators	Building frame workers
Fiber-preparing-, spinning- and winding-machine operators	Judges
Rolling-mill operators	Building construction laborers
FACTOR 7: Protection (non-routine interactive)	
Locomotive engine drivers	Florist
Safety inspectors	Jewelry and precious metal workers
Dairy-products-machine operators	Upholsterers and related workers
Ships' deck officers	Tailors and dressmakers
Plant security officers, detectives	Draftspersons

*Source: Own calculations with BIBB/BAuA Employment Survey 2006. The translations correspond in the majority of cases to the ISCO88 labels.
**The German classification includes a very detailed classification of teachers because of the diversified German school system for secondary education. While the age of students will be roughly the same in all school types, the intellectual requirements and the educational focus differ.

Table 3: Specific knowledge—Distance of switches and the correlation of wages (OLS)

DEPVAR: current wage (log)	**A**	**B**	**C**	**D**	**E**
LOW QUALIFICATION	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
PREVIOUS WAGE (LOG)	0.111***	0.110***	0.155***	0.109***	0.167***
	(0.004)	(0.004)	(0.006)	(0.004)	(0.007)
OCC INTENSITY	-0.009**	-0.009**	-0.008**	-0.009**	-0.008**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
FIRM DISTANCE				-0.001	-0.009***
				(0.002)	(0.002)
FIRM DIST * PREVIOUS WAGE					-0.013***
					(0.002)
OCC DISTANCE		-0.006***	-0.017***	-0.006***	-0.015***
		(0.002)	(0.002)	(0.002)	(0.002)
OCC DISTANCE * PREVIOUS WAGE			-0.020***		-0.017***
			(0.002)		(0.002)
PREVIOUS FIRM SIZE (LOG)	0.095***	0.095***	0.094***	0.094***	0.093***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
WORK EXPERIENCE	0.800***	0.799***	0.794***	0.804***	0.796***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
WORK EXPERIENCE^2	-0.600***	-0.600***	-0.598***	-0.602***	-0.597***
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
Constant	-0.014	-0.003	0.032	-0.220***	-0.179***
	(0.082)	(0.081)	(0.082)	(0.063)	(0.063)
Observations	32,306	32,306	32,306	31,516	31,516
R-squared	0.324	0.324	0.326	0.326	0.329
MEDIUM QUALIFICATION	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
PREVIOUS WAGE (LOG)	0.176***	0.167***	0.233***	0.163***	0.242***
	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)
OCC INTENSITY	-0.032***	-0.031***	-0.030***	-0.028***	-0.027***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
FIRM DISTANCE				-0.014***	-0.015***
				(0.001)	(0.001)
FIRM DIST * PREVIOUS WAGE					-0.013***
					(0.001)
OCC DISTANCE		-0.033***	-0.038***	-0.029***	-0.033***
		(0.001)	(0.001)	(0.001)	(0.001)
OCC DISTANCE * PREVIOUS WAGE			-0.033***		-0.029***
			(0.002)		(0.002)
PREVIOUS FIRM SIZE (LOG)	0.068***	0.068***	0.067***	0.065***	0.063***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
WORK EXPERIENCE	0.476***	0.464***	0.455***	0.467***	0.456***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
WORK EXPERIENCE^2	-0.292***	-0.282***	-0.278***	-0.285***	-0.281***
	(0.009)	(0.009)	(0.008)	(0.009)	(0.009)
Constant	-0.112	-0.064	-0.029	-0.345***	-0.292***
	(0.073)	(0.073)	(0.074)	(0.036)	(0.036)

Observations	100,935	100,935	100,935	98,363	98,363
R-squared	0.406	0.413	0.418	0.415	0.421
HIGH QUALIFICATION	**(11)**	**(12)**	**(13)**	**(14)**	**(15)**
PREVIOUS WAGE (LOG)	0.155***	0.145***	0.152***	0.142***	0.151***
	(0.005)	(0.005)	(0.007)	(0.005)	(0.008)
OCC INTENSITY	-0.022***	-0.024***	-0.024***	-0.022***	-0.022***
	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)
FIRM DISTANCE				-0.012***	-0.011***
				(0.002)	(0.002)
FIRM DIST * PREVIOUS WAGE					-0.003
					(0.003)
OCC DISTANCE		-0.035***	-0.035***	-0.033***	-0.034***
		(0.003)	(0.003)	(0.003)	(0.003)
OCC DISTANCE * PREVIOUS WAGE			-0.004		-0.003
			(0.003)		(0.003)
PREVIOUS FIRM SIZE (LOG)	0.075***	0.075***	0.075***	0.072***	0.072***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
WORK EXPERIENCE	0.333***	0.306***	0.304***	0.308***	0.306***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
WORK EXPERIENCE^2	-0.223***	-0.201***	-0.200***	-0.205***	-0.203***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Constant	-0.610**	-0.522*	-0.523*	-0.209	-0.209
	(0.289)	(0.282)	(0.282)	(0.138)	(0.139)
Observations	21,669	21,669	21,669	21,381	21,381
R-squared	0.437	0.444	0.444	0.445	0.445

Notes: The dependent variable is the logarithm of the wage in the current job after a joint switch for male employees. The calculations show coefficients for standardized variables of OLS regressions. Robust standard errors are in parentheses (see footnote 1 for details). All models include controls for occupational field, region, industry and year. Columns (1)–(5) are workers with low, (6)–(10) with medium, (11)–(15) are high qualification levels.

*** p<0.01, ** p<0.05, * p<0.1

Table 4: The (dis)advantages of occupational intensity (2SLS)

	First stage		*First stage*	
DEPVAR: current wage (log)	**A**	**B**	**C**	**D**
LOW QUALIFICATION	**(1)**	**(2)**	**(3)**	**(4)**
OCC INTENSITY		-0.063		-0.063
		(0.069)		(0.069)
HERFINDAHL BLOSSFELD	0.132***		0.132***	
	(0.014)		(0.014)	
OCC DISTANCE	-0.019***	-0.007***	-0.011***	-0.016***
	(0.003)	(0.002)	(0.004)	(0.002)
OCC DISTANCE * PREVIOUS WAGE			0.014***	-0.016***
			(0.004)	(0.003)
FIRM DISTANCE	0.055***	0.002	0.055***	-0.006
	(0.003)	(0.004)	(0.004)	(0.004)
FIRM DIST * PREVIOUS WAGE			0	-0.013***
			(0.004)	(0.002)
PREVIOUS WAGE (LOG)	-0.002	0.109***	-0.032***	0.165***
	(0.006)	(0.004)	(0.010)	(0.007)
PREVIOUS FIRM SIZE (LOG)	-0.231***	0.081***	-0.230***	0.080***
	(0.007)	(0.016)	(0.007)	(0.016)
WORK EXPERIENCE	0.096***	0.809***	0.099***	0.801***
	(0.022)	(0.017)	(0.022)	(0.017)
WORK EXPERIENCE^2	-0.104***	-0.608***	-0.106***	-0.603***
	(0.028)	(0.023)	(0.028)	(0.023)
Constant	-0.672***	-0.163***	-0.695***	-0.129***
	(0.096)	(0.038)	(0.096)	(0.038)
Observations	31,516	31,516	31,516	31,516
R-squared	0.208	0.321	0.209	0.324
F-statistic	87.044***		86.772***	
MEDIUM QUALIFICATION	**(5)**	**(6)**	**(7)**	**(8)**
OCC INTENSITY		0.096***		0.079***
		(0.020)		(0.020)
HERFINDAHL BLOSSFELD	0.223***		0.223***	
	(0.007)		(0.007)	
OCC DISTANCE	-0.001	-0.029***	0.002	-0.034***
	(0.002)	(0.001)	(0.002)	(0.001)
OCC DISTANCE * PREVIOUS WAGE			0.018***	-0.030***
			(0.002)	(0.002)
FIRM DISTANCE	0.051***	-0.020***	0.050***	-0.021***
	(0.002)	(0.001)	(0.002)	(0.001)
FIRM DIST * PREVIOUS WAGE			-0.007***	-0.012***
			(0.002)	(0.001)
PREVIOUS WAGE (LOG)	-0.028***	0.167***	-0.053***	0.247***
	(0.004)	(0.003)	(0.006)	(0.005)
PREVIOUS FIRM SIZE (LOG)	-0.249***	0.096***	-0.249***	0.089***
	(0.004)	(0.005)	(0.004)	(0.005)

WORK EXPERIENCE	-0.088***	0.478***	-0.084***	0.466***
	(0.013)	(0.009)	(0.013)	(0.009)
WORK EXPERIENCE^2	0.031**	-0.289***	0.029**	-0.284***
	(0.013)	(0.009)	(0.013)	(0.009)
Constant	0.374***	0.059**	0.359***	0.065***
	(0.067)	(0.023)	(0.068)	(0.023)
Observations	98,363	98,363	98,363	98,363
R-squared	0.194	0.386	0.194	0.399
F-statistic	966.873***		972.649***	
HIGH QUALIFICATION	**(9)**	**(10)**	**(11)**	**(12)**
OCC INTENSITY		0.127***		0.128***
		(0.034)		(0.034)
HERFINDAHL BLOSSFELD	0.215***		0.213***	
	(0.014)		(0.014)	
OCC DISTANCE	-0.030***	-0.029***	-0.031***	-0.029***
	(0.004)	(0.003)	(0.004)	(0.003)
OCC DISTANCE * PREVIOUS WAGE			0.012***	-0.005
			(0.004)	(0.004)
FIRM DISTANCE	0.061***	-0.021***	0.063***	-0.021***
	(0.004)	(0.003)	(0.004)	(0.003)
FIRM DIST * PREVIOUS WAGE			-0.021***	0.001
			(0.004)	(0.003)
PREVIOUS WAGE (LOG)	-0.006	0.143***	-0.001	0.150***
	(0.006)	(0.005)	(0.010)	(0.008)
PREVIOUS FIRM SIZE (LOG)	-0.149***	0.094***	-0.149***	0.094***
	(0.007)	(0.007)	(0.007)	(0.007)
WORK EXPERIENCE	-0.076***	0.319***	-0.078***	0.317***
	(0.025)	(0.018)	(0.025)	(0.018)
WORK EXPERIENCE^2	-0.02	-0.200***	-0.018	-0.199***
	(0.027)	(0.019)	(0.027)	(0.019)
Constant	-0.371	-0.002	-0.383	-0.004
	(0.292)	(0.111)	(0.290)	(0.111)
Observations	21,381	21,381	21,381	21,381
R-squared	0.316	0.409	0.317	0.409
F-statistic	234.185***		231.983***	

Notes: The dependent variable is the logarithm of the wage in the current job after a joint switch for male employees. The calculations show coefficients for standardized variables of two stage least squares regressions. The odd numbered columns (also, A and C) show the first stage results. Robust standard errors are in parentheses (see footnote 1 for details). All models include controls for occupational field, region, industry and year. Columns (1)–(4) are workers with low, (5)–(8) with medium, (9)–(12) are high qualification levels. *** p<0.01, ** p<0.05, * p<0.1

Annex

Occupational Tasks

To determine the task sets of occupations, I choose a set of questions from the BIBB/BAuA Employment Survey 2006 that encompasses 31 tasks (for details on questionnaire, see Rohrbach-Schmidt, 2009). These tasks are taken from the categories main job tasks and skill requirements in different subject areas. I consider only those respondents who are dependently employed because in earlier analyses the self-employed showed significant differences regarding their job requirements when using the same survey question (Bublitz and Noseleit, 2014).

The first part consists of 17 job tasks (questions F303–F319) and respondents are asked: "Please remember your current job as a <…>. I will name some selected job tasks. Would you please tell me how frequent these tasks appear in your job?" (Rohrbach-Schmidt, 2009) Answers are given on a frequency scale, with (1) never, (2) sometimes, (3) frequently. Another included task is taken from question F301, which asks about the respondent's managerial responsibility, with the answers being coded as none, responsibility for 10 or less employees, or responsibility for more than 10 employees. The second part includes 13 specific subject areas (questions F403_1–F403_13). Respondents are asked: "I will now read several skills in specific subject areas (German: *Kenntnisgebiete*) to you. Please tell me for each of these skills whether you require them in your current job as a <…>, and, if yes, whether you require basic or "expert"/specialized skills (German: *Fachkenntnisse*)? In the case that you require "expert" skills only for a sub domain within a specific subject area, nevertheless please state that you need "expert" skills." This question is followed by an item battery that requests the respondent to answer by using the following rating scale: (1) no such skills required, (2) basic, (3) expert/specialized. Please note that the German word here can be translated as either skills or tasks. In addition, the context of the question asks for those skills that are actually applied in the current job and that therefore can be taken to be equivalent to tasks. In the following analysis, I weigh subject areas according to the level to which they are required (0 = none, 1 = medium, 2 = large) because it will help distinguish between occupations with similar subject areas but different education levels (e.g., medicine for doctors and nurses).

The data consists of 15,603 observations, which correspond to 248 occupations. To reduce the dimensions of the information a principal factor analysis is run. The uniqueness of the variables is relatively low and the Kaiser-Meyer-Olkin measure shows relatively high values; thus, both measures confirm that it is appropriate and necessary to combine the variables into factors. According to the Kaiser criterion, the principal factors analysis suggests retaining seven factors, which account for around 91% of total variance (compared to 77% in the principal component analysis).

Table A 1: The 12 occupational groups by Blossfeld (Source: author following Blossfeld, 1985)

	Blossfeld "Occupational Groups"			Composition of the occupational groups according to the German occupational classification (1970)	Examples
	Abbr.	Full Name	Description		
Production					
1	AGR	agricultural occupations	occupations with a dominant agricultural orientation	011-022, 041-051, 053-062	farmers, agricultural workers, gardeners, workers in the forest economy, fishermen, etc.
2	EMB	unskilled manual occupations	all manual occupations that showed at least 60% unskilled workers in 1970	071-133, 135-141, 143, 151-162,164, 176-193, 203-213, 222-244,252, 263, 301, 313, 321-323, 332-346, 352.371, 373, 375-377, 402-403, 412, 423-433, 442, 452-463,465-472, 482, 486, 504, 512-531,543-549	miners, rock breakers, paper makers, wood industry occupations, printing industry occupations, welders, riveters, unskilled workers, road and railroad construction workers, etc.
3	QMB	skilled manual occupations	all manual occupations that showed at most 40% unskilled workers in 1970	134, 142, 144, 163, 171-175, 201-202, 221, 251, 261-262, 270-291, 302, 305-312, 314-315, 331, 351, 372, 374, 378-401, 411, 421-422, 441, 451, 464, 481, 483-485, 491-503, 511, 541-542	glassblowers, bookbinders, typesetters, locksmiths, precision instrument makers, electrical mechanics, coopers, brewers, carpenters, etc.
4	TEC	Technicians	all technically trained specialists	303, 304, 621-635, 721-722, 733, 857	machinery technicians, electrical technicians, construction technicians, mining technicians, etc.
5	ING	Engineers	highly trained specialists who solve technical and natural science problems	032, 052, 601-612, 726, 883	construction engineers, electrical engineers, production designers, chemical engineers, physicists, mathematicians, etc.

Service					
6	EDB	unskilled services	all unskilled personal services	685-686, 688, 706, 713-716, 723-725, 741-744, 791-794, 805, 838, 911-913, 923-937	cleaner, waiters, servers, etc.
7	QDB	skilled services	essentially order and security occupations as well as skilled service occupations	684, 704-705, 711-712, 801-804,812, 814, 831, 837, 851-852, 854-856, 892-902, 921-922	policemen, firemen, locomotive engineers, photographers, hairdressers, etc.
8	SEMI	semiprofessions	service positions characterized by professional specialization	821-823, 853, 861-864, 873-877	nurses, educators, elementary school teachers, kindergarten teachers, etc.
9	PROF	professions	all liberal professions and service positions that require a university degree	811, 813, 841-844, 871-872, 881-882, 891	dentists, doctors, pharmacists, judges, secondary education teachers, university professors, etc.
Administration					
10	EVB	unskilled commercial and administrational occupations	relatively unskilled office and commerce occupations	682, 687, 731-732, 734, 782-784, 773	postal occupations, shop assistants, typists, etc.
11	QVB	skilled commercial and administrational occupations	occupations with medium and higher administrative and distributive functions	031, 681, 683, 691-703, 771-772, 774-781	credit and financial assistants, foreign trade assistants, data processing operators, bookkeepers, goods traffic assistants, etc.
12	MAN	managers	occupations that control factors of production as well as functionaries of organizations	751-763	managers, business administrators, deputies, ministers, social organization leaders, etc.

Description of Data Set

The data come from see separate sources: (1) Sample of Integrated Labour Market Biographies (SIAB), (2) the establishment information of the Establishment History Panel (BHP) and (3) BIBB/BAuA Employment Survey 2006. Data sets (1) and (2) are both from the Research Data Centre of the German Federal Employment Agency at the Institute for Employment Research (IAB), data set (3) is provided by the Federal Institute for Vocational Education and Training (BIBB) and the Federal Institute for Occupational Safety and Health (BAuA). While (1) and (2) can be merged using establishments identifiers and years, (3) has to be merged by occupation to (1) or occupational group to (2). The data cover employment histories of individuals during the observation period 1975 to 2008. Information on tasks is taken from a cross-sectional survey and therefore only calculated once.

The goal is to make the SIAB comparable to the IABS which is used by G&S. All these data come from the German social security records, they represent a 2 % random sample but they cover different time periods. I therefore further follow G&S's suggestion to exclude spells in vocational training or individuals who never entered the labor force after vocational training. In addition, individuals who took longer than seven years to complete an apprenticeship are dropped. I further impose the same minimum age as G&S for the first observation which is in accordance with the educational degree to ensure that I observe individuals from the day they enter the labor market. Individual working in agriculture are also excluded. As regards income, employees are only included if they earn an average daily wage of at least 10 Euros. Also, it is important to note that the administrative data from the IAB suffers from topcoding in the income variable.

To distinguish between voluntary and involuntary switchers, I take advantage of administrative processes. Workers who give notice themselves are banned from receiving unemployment benefits for three months after their contract ended. In comparison, workers who were laid off have immediate access to unemployment benefits. In addition, a unique variable in the data set allows identifying firms where structural changes occurred, for instance, a change of ownership or the firm's exit from the market. Structural changes can be assumed to induce involuntary switches.

The analyses in the tables only report results for men. In separate regressions, not included in the paper, the analyses were also carried out for women. Individuals have to be at least 16 years old to enter the sample. The group further includes all individuals regardless of their working hours or their place of residence or of work. As regards the latter, the regressions include control variables for the region (degree of agglomeration). Naturally, anyone with missing values in these variables is excluded. As regards the number of switches over the complete time span and observations, medium-skilled individuals switch on average most often (0.076), followed by low-skilled individuals (0.066) and high-skilled individuals (0.031).

Variables are standardized in the regressions to allow for a comparison of their importance. The standardization process conflicts with clustered standard errors (see footnote 1).

However, the results remain unchanged when robust standard errors are replaced with clustered standard errors.

Table A 2: Summary statistics

Variable (not standardized)	**LQ**	**MQ**	**HQ**	**ALL**
Percentage in sample (%)	18.7%	68.7%	12.6%	
Wage	38.854	75.118	112.364	73.011
	(29.809)	(36.292)	(43.945)	(41.602)
Age	24.195	30.829	36.214	30.264
	(7.897)	(8.105)	(7.678)	(8.706)
Work experience (in years)	5.816	11.488	9.910	10.226
	(6.755)	(7.543)	(7.258)	(7.682)
Firm distance (FIRM DISTANCE)	0.007	0.005	0.004	0.006
	(0.021)	(0.019)	(0.016)	(0.019)
Occupational distance (OCC DISTANCE)	0.024	0.016	0.013	0.017
	(0.075)	(0.061)	(0.050)	(0.062)
Number of joint switches	0.287	0.246	0.191	0.246
	(1.270)	(1.096)	(0.881)	(1.107)
Occupational intensity (OCC INTENSITY)	0.523	0.500	0.332	0.483
	(0.292)	(0.305)	(0.293)	(0.306)
Firm size (log)	4.578	4.515	5.743	4.682
	(2.213)	(2.249)	(2.259)	(2.280)
Herfindahl Blossfeld	0.240	0.253	0.233	0.248
	(0.078)	(0.118)	(0.128)	(0.114)

Notes: Own calculations with Sample of Integrated Labour Market Biographies (SIAB), establishment history panel (BHP) and BiBB/BAuA Employment Survey 2006 for male employees. The table reports means and standard deviations (in parentheses) for low, medium, and high qualification levels.

ALL QUALIFCATION LEVELS	Obs	Mean	Std. Dev.	Min	Max
Wage	2751134	73.011	41.602	10	3838.780
Wage (log)	2751134	4.099	0.675	2.303	8.253
Previous wage (log)	2662157	4.032	0.755	-4.605	8.253
Age	2751134	30.264	8.706	16	73
Work experience	2751134	10.226	7.682	0	33.932
Firm distance	2389484	0.006	0.019	0	0.274
Occupational distance	2662157	0.017	0.062	0	0.879
Number of joint switches	2751134	0.246	1.107	0	47
Occupational intensity	2751134	0.483	0.306	0	1
Firm size (log)	2751134	4.682	2.280	0	11.077
Herfindahl Blossfeld	2751134	0.248	0.114	0.122	0.828

Notes: Own calculations with SIAB, BHP, and BiBB/BAuA Employment Survey 2006 for male employees. Variables are not yet standardized.

Table A 3: Correlations

		1	2	3	4	5	6	7	8	9	10	11	12
1	Current wage (log)	1											
2	Previous wage (log)	0.8747*	1										
3	Work experience	0.6155*	0.6046*	1									
4	Firm distance	-0.1165*	-0.1587*	-0.1322*	1								
5	Occupational distance	-0.1249*	-0.1774*	-0.1457*	0.5353*	1							
6	Number of joint switches	-0.0542*	-0.1010*	-0.0587*	0.4284*	0.5479*	1						
7	Occupational intensity	-0.1839*	-0.1733*	-0.1194*	0.0275*	-0.0069*	0.0114*	1					
8	Firm size (log)	0.2229*	0.2073*	0.1057*	-0.1393*	-0.0353*	-0.0589*	-0.4147*	1				
9	Herfindahl Blossfeld	0.0436*	0.0424*	0.0134*	-0.0169*	-0.0273*	-0.0174*	0.2943*	-0.0295*	1			
10	Low-skilled	-0.4955*	-0.4138*	-0.2757*	0.0252*	0.0480*	0.0175*	0.0635*	-0.0219*	-0.0339*	1		
11	Medium-skilled	0.2078*	0.1497*	0.2431*	-0.0040*	-0.0211*	-0.0011	0.0803*	-0.1080*	0.0647*	-0.7110*	1	
12	High-skilled	0.2923*	0.2661*	-0.0156*	-0.0230*	-0.0258*	-0.0191*	-0.1871*	0.1767*	-0.0506*	-0.1822*	-0.5619*	1

Notes: * indicates that the correlation is significant at the 1% level. Own calculations with SIAB, BHP, and BiBB/BAuA Employment Survey 2006 for male employees.

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