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# Matching Skills of Individuals and Firms along the Career Path

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Abstract

This paper presents an analytical setup that makes predictions for the relationships between firm- and occupation-specific human capital and job switches. The predictions are then tested using the task-based approach. The results, based on data for Germany, show that the degree to which firm knowledge is portable depends on skill similarities between the firms. In the case of job switches, less experienced workers travel longer skill distances between firms than more experienced workers. Firm and occupational skill distances, that is firm- and occupation-specific knowledge, both are negatively related to wages in a new job, although the relative importance differs by qualification level. The share of workers in the same occupational group within the firm, occupational intensity, can reflect switching motivations of workers. Occupational intensity decreases with experience and is negatively associated with wages.

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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 emphasis 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. A similar approach is implemented by Gathmann and Schönberg (G&S, 2010) for occupation-specific knowledge. These authors show that the amount of specific knowledge, and, thus, the number of portable skills, varies between occupations. 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.

To date, there has been no investigation of the degree to which firm knowledge is portable across establishments. Specifically, in the case of firm switches, it is not known (1) if the distance of a move varies along the career path or (2) how it relates to wages. For joint occupational and firm switches, it is unknown whether the loss of occupation- or firm-specific knowledge is more costly for workers. Therefore, the aim of this paper is to discover if firm knowledge is transferable, in addition to occupational knowledge, and how that affects individuals who switch jobs. In addition to calculating a new measure for firm-specific knowledge, this analysis sheds more light on how individuals and firms are matched along the career path. 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. The analysis also aids in 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.

This paper investigates job switches by calculating different knowledge measures for occupations and firms that capture human capital on a task level. To this end, I begin by formally modeling the relationship between specific knowledge and labor mobility. A combination of the approaches of Lazear and G&S allows developing one that accounts for firm and occupational knowledge. 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). In this context, the approach is used to identify the amount of occupation- and firm-specific as well as general knowledge. Calculated differences in the task portfolios of firms, or respectively occupations, show their distance from each other. Additionally, firm and occupational task tenure are determined, as suggested by G&S, to capture transferable and, thereby, general knowledge. This study then investigates the relationships between human capital (distances, task tenures), experience, and wages. In addition, it looks at how occupational peers relate to switching and wages of workers. This follows the idea that certain task compositions in the firm are of more advantage early in the career when workers still have much to learn. Later, they benefit from having knowledge that is more unique in the firm.

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 are provided by the BIBB/BAuA Employment Survey 2006. The results reveal the following patterns of how employees and firms are matched along the career path. In general, the less knowledge can be transferred to a new firm, the more costly and less likely is a firm switch. Long distance firm switches occur more often early in the career than later on. Which type of knowledge can be transferred and to what extent depends on the qualification level of workers. Firm and occupational knowledge both matter for wages. While no clear order of importance emerges for low-skilled workers, for higher qualified employees, occupational knowledge is more important. A high correlation between standard experience variables and the measure for task tenure of firms and occupations suggests that standard experience or firm and occupation tenure variables that are applied in the literature should be sufficient to measure general knowledge. The role of occupational groups is analyzed to identify possible switching motivations. It can be shown that individuals start work in firms that have a relatively high share of employees in the same occupational group, that means, a high occupational intensity, and that this share decreases with increasing work experience. A lower occupational intensity is associated with higher wages. This result supports the notion that, after learning how to carry out tasks, workers move to where they primarily apply their knowledge.

The remainder of this paper is organized as follows. Section 2 presents the skill-weights approach and the analytical setup. In Section 3, the data set and empirical methods are introduced. Section 4 contains the results and a discussion of their implications. Section 5 concludes.

# 2 Conceptual Framework

## 2.1 Labor Mobility and the Skill-Weights Approach

How people move across jobs as part of a career strategy has been studied in details for the case of intraorganizational careers (cf., among others, Doeringer and Piore, 1971; Gaertner, 1980). However, workers also build careers *across* firms and their motivations for leaving one company for another vary along the career path (Bidwell and Briscoe, 2010). It is still not completely understood how workers combine jobs in different organizations into one career in the contemporary labor market. One influential factor is likely to be the amount of transportable knowledge because specific knowledge is lost when changing jobs and, therefore, doing so becomes a costly investment for workers.

In human capital theory, human capital is defined as worker knowledge that is acquired through education and experience (Becker, 1964; Mincer, 1974). Under this theory, specific human capital, in contrast to general human capital, which is understood as knowledge that can be reapplied after a job switch, is defined as knowledge that can be used by only a single employer or occupation. Human capital theory has been enormously enlightening, but certain questions remain. For example, the theory focuses on the supply side and lacks a detailed analysis of the demand side. Granovetter (1986) provides a comparison of sociological and economic approaches to labor mobility and job matching. He stresses the importance of the embeddedness of workers in their firms and encourages taking into account the demand side in the form of firm characteristics. Another shortcoming of human capital theory is that education is often used as a proxy for skill, but such does not easily capture within variation due to the high aggregation. More recently, skill-oriented and task-based approaches to human capital (Autor, Levy, and Murnane, 2003; Gibbons and Waldman, 2004; Spitz-Oener, 2006) have been used to measure human capital with regard to job or occupational content. Task data allow moving away from a generic classification of specific or general skills and measuring instead the degree of similarities (general) or differences (specific) between portfolios (cf. G&S, 2010; Poletaev and Robinson, 2008). This paper takes as its foundation human capital theory, but also takes into consideration those more recent ideas.

Research on the dynamics of job mobility is built on the assumptions of human capital theory, particularly on the distinction between general skills and skills that are specific to a firm or an occupation. Workers may be selected into jobs through mechanisms of screening and signaling (Stiglitz, 1975; Spence, 1973) or through a matching process of workers to jobs (Jovanovic, 1979a, b). Here, I focus on job matching. Jovanovic develops job search models to explain turnover and wage determination. In the model focusing on job matching, he finds that the likelihood of separation is a decreasing function of job tenure (Jovanovic, 1979b). Workers remain in jobs in which their productivity is relatively high and leave when their productivity is relatively low. Another of Jovanovic's (1979a) models focuses on the relationship between firm-specific human capital and the likelihood of job separation. The better the job match, the less likely is job separation. In both models the results are to a large extent driven by the potential loss of firm-specific knowledge in the case of job separation. The higher age and tenure are, the more firm-specific knowledge has been accumulated, and the more costly becomes a job separation because no better match can be achieved.

The skill-weights approach of Lazear (2009) allows taking into account the different dimensions discussed above. In his model, firms attach weights to skills for each job. Lazear 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. Instead, they are defined endogenously with observable market parameters. In Lazear's model, a worker uses two skills (A, B) that determine the output $y_i$ at firm *i* *(*$y_i = \lambda_i A + (1 - \lambda_i)B$*;* $\lambda_i \in [0,1]$*).* There are two periods; investments are made in the first period and payoffs are received in the second. After the first period, a worker can decide whether to switch to a different firm or stay with the current employer. This decision depends on external factors such as the unemployment rate or—and the focus of this analysis—the difference between the skill weights of the current firm *i* and the possible future firm *j*. The skill weights are also determined by the probability of separation and the distribution of outside opportunities. The worker stays when the output, that is, the wage, at the initial firm is higher than the outside offer. The greater the extent to which skills will be rendered redundant by a job switch, the less attractive switching becomes. The skill-weights model is a particular matching model where workers choose jobs that best fit their strongest skills.

The skill-weights approach is in line with Jovanovic's matching models (1979a, b) with regard to firm choice in the second period, where workers switch only if doing so will result in higher wages. The approach is different from traditional matching models, however, in that the job switch depends on the worker's unbalanced investment strategy (i.e., higher investment in skill A than in skill B). This is an artifact of the technology employed in the first job the worker held because, in this model, workers cannot choose their first employer. Further, Lazear suggests that the skill weight $\lambda$ is not only firm but also job and maybe even industry specific. When $\lambda$ is, for instance, occupation specific, task-specific human capital provides a useful measure for a detailed analysis. According to Gibbons and Waldman (2004), jobs in a firm are heterogeneous as regards the type of task-specific human capital that they require. Job switching is then used to find a better match and avoid underutilization of task-specific human capital. As pointed out by Lazear (2009), similarities arise to picking a job in the second period that better matches skills acquired in the first period.

Some implications of Lazear's model have been empirically tested. One approach investigates 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). These implications are confirmed with the data, which, however, is cross-sectional. The firm's specificity is measured in terms of the workers' specificity, that is, with the number of previous jobs changes, and with a survey question about replaceability at the current job. The measure, thus, tries to capture the specificity of a certain job but does not look at the firm's complete skill set. In contrast with classic studies such as work by Jovanovic (1979b), who finds that the lower the probability of separation, the larger the investment in human capital, Lazear predicts and Backes-Gellner and Mure (2005) confirm that even in the case of a large probability of separation, there continues to be substantial investment in human capital. A study by Geel, Mure, and Backes-Gellner (2010) investigates why firms invest in apprenticeship training, which is considered to be general human capital. They find that the more specific an occupational skill set is compared to the general labor market, the higher are the firm's net costs for apprenticeship training in the respective occupations. They conclude from their findings that apprenticeship training, which is normally regarded as general training, is very heterogeneous in its degree of specificity, meaning that for certain occupations it is indeed specific. This paper now combines specific and general human capital of firms and occupations to develop an analytical setup for switching behavior.

## 2.2 Modeling Firm and Occupational Knowledge

To estimate which types of switches are more costly, scholars analyze whether specific knowledge is more tied to occupations, firms, or industries. This discussion can be traced back to Becker's suggestions on the specificity of human capital. 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) indeed acknowledges that industry-specific human capital might measure something similar to occupation-specific human capital. Most studies contrast occupation- or industry-specific human capital with firm-specific human capital. Often, firm-specific human capital plays a minor or no significant role in the empirical estimations. Pavan (2011) criticizes that the importance of firm-specific human capital is regularly underestimated. In a novel approach that accounts for two-stage search process, it matters in addition to career-specific human capital while it does not when using previously applied estimation techniques.

With the exception of Poletaev and Robinson (2008), all studies use tenure variables for industries, firms, and occupations to measure specificity of knowledge. This prevents that knowledge can be divided in a sticky and a portable component. For instance, Gathmann and Schönberg (2010) build on Gibbons and Waldman (2004) and show that human capital is task specific and therefore portable across occupations. They combine task-specific human capital and a skill-weights approach to investigate job mobility. How much knowledge can be transferred ultimately depends on the tasks carried out in occupations. They find that the distance and propensity of job moves decline with time in the labor market because workers are better able to locate occupational matches over time and, additionally, changing jobs becomes more costly. Further, they show that wage growth is determined by up to 52% by task-specific human capital. Nedelkoska and Neffke (2010) account for asymmetries in the skill transferability between occupations and still find that occupational human capital is transferable. Still, it is not known how much specific human capital is acquired in firms or to what degree firm knowledge can be transferred to new firms. Hence, in this analysis I investigate the degree to which firm knowledge is specific.

Although Lazear's title suggests otherwise, his model leaves open whether, in an empirical analysis, weights should be determined at the occupation, firm, or industry level (or a combination of all of them) (Lazear 2009, p. 929). In practice, it is difficult to look at knowledge specificity without being specific as to the level of analysis. According to G&S estimations, there is little evidence that occupational skill sets vary across industries. As discussed earlier, it likely that both measure similar knowledge dimensions. This leaves the comparison of occupation-specific and firm-specific human capital which, following Pavan (2011), should both contribute to wages. Therefore, I investigate occupational and firm knowledge separately to see if and under what conditions they influence labor mobility and wages. It is argued that task-specific human capital is not sufficiently captured by the occupational level but needs to be extended by including the firm level. This means that G&S's analytical setup is expanded to include variables that capture task importance at the firm level. A detailed description of the conceptual framework, as well as some numerical examples, can be found in the paper by G&S. To facilitate the comparison between that work and the present paper, similar equations have the same numbers. In what follows, the focus is on changes of the framework that were implemented to incorporate firm knowledge.

The following needs to be noted. 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 further in line with the methodology chosen in the empirical section.

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 $\beta$ $(0 \leq \beta \leq 1)$ 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

$$(1)\ ln\, S_{ifot} = \underbrace{[\beta_o t^A_{iot} + (1-\beta_o) t^M_{iot}]}_{\substack{task-specific\ HC\ of\ occupation \\ ln\, S_{iot}}} + \underbrace{[\beta_f t^A_{ift} + (1-\beta_f) t^M_{ift}]}_{\substack{task-specific\ HC\ of\ firm \\ ln\, S_{ift}}}.$$

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 at the 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.

Next, the worker's task productivity in an occupation and in a firm $t^j_{igt}$ (with g= occupation, firm) needs to be determined with

$$(2)\ t^j_{igt} = t^j_i + \gamma_g H^j_{igt}\ (j = A, M)$$

where $t^j_i$ describes the ability of worker *i* in a certain task *j* (initial endowment). $H^j_{igt}$ 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 $\beta_g$ and thus time spent on a task. This can be written as

$$H^A_{igt} = \beta_{g'} F_{ig't}$$

$$(3)\ H^M_{igt} = (1-\beta_{g'}) F_{ig't}$$

where $F_{ig't}$ is the experience of worker *i* in previous firms or occupations. Combining the equations above gives

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

$$+\underbrace{\gamma_f \underbrace{\left[\beta_f H_{ift}^A + (1-\beta_f) H_{ift}^M\right]}_{T_{ift}} + \underbrace{\beta_f t_i^A + (1-\beta_f) t_i^M}_{m_{if}}}_{firm}$$

where $\gamma_f$ ($\gamma_o$) 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.

To investigate labor mobility, wages in different jobs need to be compared. These are determined by multiplying productivity with the skill prices of firms $P_f$ (occupations $P_o$). The log wages then are

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

where $p_f = lnP_f$ ($p_o = lnP_o$ ). 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

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

This equation can be rearranged as follows

$$(6)\ \ (p_f - p_{f'}) + (m_{if} - m_{if'}) + \gamma_f T_{ift} > \gamma_{f'} T_{if't}$$

which shows that what is paid for task-specific human capital in the previous occupation must be exceeded by the sum of the returns to task-specific human capital in the new occupation, and the difference of skill prices and of the task match. To illustrate the influence of the $\beta$s the equation can be rewritten as

$$(7)\ \ \underbrace{(p_f - p_{f'}) + (\gamma_f - \gamma_{f'}) T_{if't}}_{wage\ growth\ in\ firm} + \underbrace{(m_{if} - m_{if'})}_{task\ match} >$$
$$-\underbrace{\gamma_f \left[(\beta_f - \beta_{f'})(H_{ift}^A - H_{ift}^M)\right]}_{\substack{-\gamma_f (T_{ift} - T_{if't})\\ loss\ in\ human\ capital}}.$$

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 $\beta$s. 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 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

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

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

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

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, which are tested for the case of occupational human capital by G&S, but, according to my argument, should also 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. This is summarized in the following hypotheses.

*H1a: Switches occur more often between similar firms.*

*H1b: The distance covered in a firm switch decreases with experience.*

The focus now shifts to the relationship between job switches, task-specific human capital, and wages. Another explanation for a high number of switches with shorter firm distances can be the accumulation of task-specific human capital over time. This makes later switches more costly because workers have acquired more knowledge that they can potentially lose. Further, 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 a higher number of transferable skills and, thereby, a better match is achieved when distances are shorter. Lastly, both occupation and firm knowledge matter for wages. Experience from previous firms continues to be valuable after a switch because not all firm knowledge is specific. However, specific knowledge has a negative association with wages. When investigating joint switches, I thus take into account both knowledge types to compare their relative importance. This will further show whether one dimension outweighs the other. The hypotheses are, thus, as follows.

> *H2a: Switches with larger distances between firms are negatively associated with wages.*
>
> *H2b: Wages at the source firm are a better predictor of wages in the target firm if both positions require similar tasks.*
>
> *H2c: Both firm and occupational knowledge matter for future wages in case of joint switches.*

### 2.3 Job Sequencing along the Career Path

Gibbons and Waldman (2004) suggest that task-specific human capital plays a decisive role in how jobs are sequenced from the standpoint of a job ladder. Using the example of firm promotions, they argue that promotions are structured in a way that ensures that as much human capital as possible can be applied in the new position. In more general terms, this means that if individuals switch jobs, they want to avoid the underutilization of human capital. Bidwell and Briscoe (2010) then suggest that mobility takes place along interorganizational career ladders. According to their approach, investigating job switches across organizations reveals further insight into how workers exploit organizational diversity. They find consistent evidence that workers are more likely to work in large firms at the beginning of their careers and in smaller firms later on. The dynamics behind these results are that in the data set, large firms provide more learning possibilities, whereas small firms have high demands for previously acquired skills.

Both approaches come to the same conclusion that workers choose jobs where they can transfer and apply what they have previously learned. In line with Bidwell and Briscoe, I believe that workers start their careers in organizations that provide more learning opportunities and then later move to organizations where previously acquired skills can be applied. However, it appears important to avoid that this relation is confounded with firm size. At least in Germany, this procession does not necessarily have to do with firm size but it is instead the learning opportunities at the first firm that are important, learning opportunities that are to some degree dependent on the knowledge of co-workers. The main reason the German case may be somewhat unique is the country's demonstrated employment stability in large firms where workers with higher tenure enjoy high job security and additional benefits. This makes it less likely that large firm employees will leave their jobs. Although, according to Gibbons and Waldman and others, the overall distance between jobs should be small, it appears reasonable to cover a certain distance when moving to jobs where own knowledge constitutes a unique advantage. These advantages outweigh the disadvantage of losing specific knowledge through a switch. Therefore, this paper focuses on the role of those task bundles that represent the own occupation.

In what follows, I investigate the role of interaction with people in the same occupational group. To this end, I look at occupational intensity, that is, the number of people in the same occupational group at the firm. It is argued that, due to learning, this peer group is more important at the beginning of an occupational career than later on. After some years, workers are expected to learn more from other occupational groups than their own and, therefore, the importance of workers in the same group will decrease. It should, indeed, constitute an advantage for more experienced workers to move to firms where their knowledge is more unique because it makes them more valuable to the firm. Wages should, therefore, increase as the occupational intensity decreases. This yields the following hypotheses.

*H3a: Occupational intensity shows a negative relationship with experience.*

*H3b: Wages are negatively associated with occupational intensity.*

# 3 Data and Methodology

## 3.1 Data Structure

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.

In what follows, I restrict the analysis to employees with an average daily wage of at least 10 Euros and to voluntary switches.[1] To identify and later exclude involuntary switches, I start with job switches where simultaneously structural changes

[1] In addition, I follow G&S's suggestion to exclude spells in vocational training or individuals who never entered the labor force after vocational training. I further impose a minimum age for the first observation that is in accordance with the educational degree to ensure that I observe individuals from the day they enter the labor market.

occurred in the firm, for instance, a new owner or the firm's exit from the market. This group is augmented with other involuntary switches that 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. Involuntary switches are only used for comparison.

The classification of individuals and firms according to their skill sets requires, of course, information on skills. 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. The data sets are merged by occupation (SIAB) or occupational groups (BHP).

## 3.2 A Task-Based Measure for Specific and General Human Capital of Firms and Occupations

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 cannot be done for every survey because tasks do, and therefore factors would, vary. Thus, I build on G&S's result that, over time, task variation in occupations is low.

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. First, 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. The calculations 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. As most previous work has classified tasks following the suggestions by Autor, Levy, and Murnane (2003), I add labels that describe the character of the task factor and, thereby, make the factors more comparable with previous research. Compared to non-routine tasks, routine tasks are codifiable and, therefore, are more likely to be replaced by computers. The factor labels are: intellectual (non-routine analytical), technological (non-routine manual and cognitive), health (non-routine interactive), commercial (non-routine cognitive and interactive), instruction (non-routine interactive), production (routine manual and cognitive), and protection (non-routine interactive). Except for the production factor, all these factors are more likely to use computers more as complementary than as replacive tools. It is important to note that the task description of the Employment Survey is broader than the one used by Autor, Levy, and Murnane (2003) and includes fewer tasks that qualify as non-routine tasks. Therefore, the fact that out of seven factors there is only one routine factor cannot be interpreted as evidence that routine tasks make up only around 14% of all tasks.

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 characteristic 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. Standard 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 of Blossfeld (1985, see Table A 1). 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 skills required. 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. 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 determined as follows. First, the average factor value of each task for all occupations that belong to one Blossfeld group ($t_b$) is calculated. 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.

$$Task\ composition\ of\ firms = \frac{\sum_{b=1}^{n} t_b * n_{fb}}{\sum_{t=1}^{n} \sum_{b=1}^{n} t_b * n_{fb}}$$

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

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

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

where $q$ is the vector of all tasks in a firm. The measure is slightly adjusted so that a value of 1 (0) means that the firms are completely different (identical). This distance measure reflects the differences between firms with regard to their task-specific human capital. The same calculations are carried out to determine occupational distance.

Finally, a measure for accumulated human capital is constructed by following the computational method of G&S. All tasks are combined into a variable called task tenure, which is calculated as

$$task\ tenure_{ift} = \frac{\sum_{t=1}^{n}\left(\beta_f * H_{ift}^{A}\right) + \sum_{t=1}^{n}((1-\beta_f)H_{ift}^{M})}{\left(\beta_f\right)^2 + (1-\beta_f)^2}$$

where the sum of all accumulated human capital is multiplied with current weights $\beta$ and then normalized by dividing it by the squared $\beta$s. This is done separately for occupations and firms. The idea is that accumulated knowledge, that is, task tenure, represents general human capital, which can be transferred across firms and occupations. The distance measure looks instead at differences and, thus, measures specific human capital. In case of a job switch, workers knowledge at the new firm can be measured with task tenure, which represents all transferable human capital. The distance measure shows how much of the prior knowledge is lost.

### 3.3 Variables

The dependent variables are wages and the skill distance between firms. Wage is measured as gross daily income of employees and reported in Euros. For the calculations, the natural logarithm is used, as proposed in the analytical setup. I also include the following control variables. 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, only adjusted to account for later life developments of individuals. Following the same principle, occupational (firm) tenure is the number of consecutive years someone has spent in an occupation (firm). 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 an 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 included. Additional controls are introduced for years and occupational groups.

### 3.4 Summary Statistics

Table A 2 and Table A 3 set out summary statistics and correlation for the variables. The average wage increases with qualification level. The share of women is lowest for high-skilled and shows similar values for medium- and low-skilled workers. The task tenure variables are on average higher than the standard tenure variables which reflects the idea that knowledge is transferred in case of switches. The majority of workers are medium-skilled, showing evidence of the important role of vocational training in Germany. These workers also show the longest experience and tenure in all variable specifications when compared to other qualification groups. High-skilled workers show the shortest tenure in all variable specifications. Low-skilled workers are located in between the other two groups.

The average number of firm switches increases with qualification levels; the highest number is found for high-skilled workers. Joint occupational and firm switches occur to a higher extent for low- and high-skilled than for medium-skilled workers. The average values of firm distance are much lower than those of occupational distance. The distance measures show that low-skilled workers travel the longest distances between occupations and between firms. Medium- and high-skilled workers show lower but similar values. One possible reason for more distant moves by low-skilled workers may be that they, in general, engage in fewer tasks and therefore their overlap with other occupations or firms will be lower. The relatively high differences between the mean distance of a move in G&S and in my analysis might stem from a different task categorization. G&S aggregate their occupations to 64 occupations and use 19 tasks; I use 248 occupations and 31 tasks. This means that the data includes more occupational changes but that it picks up smaller occupational changes which correspond with a shorter skill distance.

The correlations reveal that firm and occupational tenure are highly correlated with the firm and occupational *task* tenure measure, and, even more so, with experience. This can cause multicollinearity problems in the regression analyses. Therefore, I will use these variables only in the case of joint occupational and firm switches when the other tenure variables are zero and, thus, are not included in the standard models.

# 4 Analysis

## 4.1 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. Slightly above 90 percent of all firm switches are located in the lowest interval. Differences across qualification levels appear negligible. Joint switches also show the largest percentage in the lowest interval; however, the share is lower than that of firm switches. It appears reasonable that switching occupation and firm is accompanied by larger changes in the firm environment. Differences between qualification groups become more pronounced. The distribution in the lowest interval reveals that as qualification levels increase, so does the percentage of switches with low distances. The results confirm hypothesis H1a which states that switches occur more often between similar firms. The figure also reveals that the distribution differs for layoffs which cover slightly larger distances than voluntary switchers. Layoffs are thus excluded from the following analysis.

*>>Figure 1 about here <<*

In the next step, the relationship between firm distance and work experience is investigated for different qualification levels. Figure 2 reports the estimated coefficients of work experience from fixed effects regressions with firm distance as dependent variable for workers who switch the firm or both, the occupation and the firm.[2] Additional controls are firm tenure, occupational distance, type of switch, region, year, and occupational field. The coefficients of work experience are jointly significant and negative. The more experienced workers are, the larger the negative relationship of work experience and firm distance. One outlier are workers with low qualification levels and experience of 27 years who suddenly show a positive relationship which becomes negative soon afterwards. In all other cases and across qualification groups the negative relationship turns out to be very similar. This is in line with hypothesis H1b in which it says that the firm distance covered in a switch decreases with experience.

*>>Figure 2 about here <<*

Following, the relationships between task-specific human capital at the occupational as well as firm level and wages are investigated. All OLS regressions report standardized coefficients which are needed to compare the relative contribution of occupational and firm knowledge in explaining the variation of the model.[3] The estimations include work experience, work experience squared, occupational tenure (for firm switchers), as well as dummies for occupational groups, regions, and years. Across all qualification groups, women earn significantly less than men and previous wage is positively correlated with current wage. Column A and B of Table 3 show results for firm switchers. Firm distance is negatively associated with wages for medium- and high-skilled worker but it is not significant for low-skilled workers (Column A). This provides only partial support for hypothesis H2a because differences persist across qualification levels. When including an interaction term between firm distance and previous wage, the results confirm that, for medium- and low-skilled workers, wages in the source firm are a better predictor of wages in the new firm if the firms are more similar (Column B). For

[2] The detailed results of the fixed effect regressions are available from the author upon request.

[3] 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. In a separate specification of the model with unstandardized variables (not reported here), the results pattern are identical with those by Gathmann and Schönberg (2010) who also report unstandardized coefficients. Significance levels remain the same in both specifications. Also note that clustered standard errors are not suitable for standardized variables and, thus, the models are estimated with robust standard errors instead.

high-skilled individuals, the interaction term is also significant and negative but firm distance becomes insignificant. This might be a hint that distance operates via wages. In sum, hypothesis H2b, thus, holds and, this time, it does for all qualification groups.

The focus now shifts to workers who switch firm and occupation. This allows comparing the relative importance of firm- and occupation-specific knowledge for wages in case of joint switches. Column C of Table 3 reveals that, for low-skilled employees, firm and occupational distance contribute negatively to wages but firm distance does so to a greater extent. This changes for medium- and high-skilled employees where occupational distance is more important than firm distance. Column D confirms the negative influence of an interaction term between previous wage and distance. Occupational distance decreases the predictive power of previous wage on future wages to a larger extent than firm distance. This holds for all qualification groups. However, the difference between the interaction terms becomes smaller with increasing qualification levels. In general, whenever the interaction term is included, the coefficients of the respective distance variables increase.

*>>Table 3 about here <<*

Lastly, I compare the importance of task tenure of firms and occupations. The goal is to see whether firm task tenure matters in addition to occupational task tenure. Only workers who switch both firm and occupation are included. In light of high correlations between experience and tenure variables, this has the advantage that standard variables for occupational and firm tenure become zero and need not to be included in the analysis.  The results in Table 4, with standardized variables, show again a positive relationship of previous and future wages and a negative association between female workers and wages. They further confirm a positive relationship between wages and both occupational and firm task tenure. Distances show a negative correlation, with the exception of occupational distance for low-skilled workers which is insignificant. However, work experience now shows a negative coefficient, which is most likely due to a high correlation between these variables. The differences between the two distance measures, if significant, are very small. For low-skilled employees, firm task tenure contributes to a larger extent, than occupational tenure, to wages after a job switch. The reverse order holds for high- and medium-skilled employees. In sum, this confirms that, for higher qualification levels, experience from previous firms and occupations continue to be valuable after a switch and that occupation- and firm-specific knowledge are negatively related to future wages (Hypothesis H2c). The only exception are low-skilled workers the patterns are not as pronounced and robust as for the other qualification groups.

*>>Table 4 about here <<*

## 4.2 Learning Opportunities in Firms

In light of the above results, it would be interesting to find out whether certain task combinations are of more advantage to workers than others. Task bundles are here represented by occupations. Even if long distance switches become less likely with increasing work experience, certain changes in the occupational composition can still be of advantage. After all, even in the case of voluntary switches, workers travel some distance between firms, in particular early in the career. For this reason it becomes necessary to look at the relationship between the size of the occupational group to which the worker belongs, experience, and wages. This investigation includes all workers and not only switchers.

*>>Figure 3 about here <<*

Figure 3 shows the estimated coefficients of work experience from a fixed effects regression with occupational intensity as dependent variable for different qualification levels.[4] Additional controls are a dummy marker for non-switchers, and variables for region, year, and occupational field. Early in the career, the coefficients of work experience, which are all highly jointly significant, are positive but then quickly become negative. This trend is particularly steep for low-skilled workers. Medium- and high-skilled workers appear to be as well, but to a lesser degree, affected by occupational intensity. These results support hypothesis H3a which states that occupational intensity shows a negative relationship with experience.

Next, Table 5 reports results from an OLS regression for the relationship between wages and occupational intensity. Controls for occupational groups, regions, and years are included. A gender dummy, experience, and experience squared show the expected signs. Non-switchers have a higher wage than switchers. Most importantly, it can be shown that having more colleagues in the same occupational group decreases the wage of a worker for all qualification levels.

*>>Table 5 about here<<*

## 4.3 Which Type of Human Capital is Transferable?

I turn now to a discussion of the differences between occupational and firm knowledge. It is not my intent to find out whether firm or occupational human capital is specific, but to instead determine to what extent both types of human capital can be specific, thus transferable. I extend G&S's concept to include task-specific knowledge of firms. Indeed, this type of knowledge plays a significant role in addition to task-specific human capital of occupations. It appears that the distance measure for specific human capital delivers more robust results than the task tenure measure for general human capital. This can most likely be explained by the high correlation between the different tenure and experience measures. The

[4] The detailed results of the fixed effect regressions are available from the author upon request.

good news is that measuring knowledge with standard tenure variables appears to be sufficient. The bad news is that doing so fails to capture switching costs that arise due to a loss of specific knowledge**,** which could be taken into account by including distance measures for occupations or firms.

There could be several reasons for the finding that less experienced workers travel longer distances between firms. Perhaps these workers are simply more flexible. Or, and more plausibly, they could still be looking for an appropriate learning environment and, in line with the analytical setup, their best match. In other words, more experienced workers have already achieved a good match and, therefore, prefer similar firms. The learning argument is further supported by the results for occupational intensity, which reveal that a decreasing share of workers in the own occupational group increases wages. One could also interpret this as evidence that with increasing work experience, more knowledge is embodied in an individual, thus rendering colleagues with similar skills redundant for the individual. The value of occupational knowledge increases, the fewer there are who hold the same or similar occupations.

Across the different estimations it becomes obvious that medium- and high-skilled workers are quite similar while low-skilled workers differ from them in several regards.  In case of firm switches, firm distance does not directly affect future wages of low-skilled workers. Once an interaction with previous wage is included firm distance turns out to be significant. When investigating joint switches, firm distance appears to matter more than occupational distance. The opposite holds true when including an interaction where occupational distance matters more again. For medium- and high-skilled workers, occupational distance is always more important than firm distance. As regards general knowledge, firm task tenure contributes more to explaining wages than occupational task tenure for low-skilled workers. The opposite relationship is found for high-skilled workers while the importance of the two tasks tenures is similar for medium-skilled workers. A possible interpretation for these findings is that low-skilled workers acquire more knowledge on-the-job by carrying out firm-specific tasks than workers with higher qualification. This is supported by the description of these occupations as helpers in different environments (e.g., care of elderly, hotel industry, metal construction; see Bundesagentur für Arbeit, 2013) who acquire their skills at the workplace instead of completing vocational training. Thus, in this case, what is accumulated on the job in the firm matters more for wages. However, as this group remains low qualified, this still reflects little knowledge overall. With regard to distance measures, the relationships are less robust. With increasing qualification levels, more knowledge is fitted in occupations, which makes the order of importance of the knowledge dimensions more stable. In general, the results for low-skilled workers appear to be in line with the finding that they switch less often between firms than the other groups. If they do switch however, most likely the occupation changes as well since their knowledge is more related to firms than occupations. Also, the negative relationship between occupational intensity and experience later in the career is much more pronounced for low-skilled workers. The reasoning behind occupational intensity was that having unique knowledge constitutes an advantage for workers. The results seem to indicate that, along the career path, the value of occupational knowledge of low-skilled workers diminishes more quickly and they can be more easily replaced. The opposite holds true for higher qualification levels.

## 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 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.

The results reveal the following patterns with regard to how individuals are matched along the career path. First, the majority of firm switchers travel only small distances between firms. Furthermore, long distance switches between firms become less likely with increasing work experience, indicating that workers find better work matches as they move along their career path. Firm and occupational distances—measures for specific knowledge—show in most cases a negative relationship with wages. Firm and occupational task tenure—measures for general knowledge—contribute positively to future wage but are highly correlated with experience and other tenure variables, suggesting that general knowledge is already captured by the standard variables. The relative importance of occupational and firm knowledge for wages differs with qualification levels. Occupational knowledge is of more importance for workers with higher qualification levels while for low-skilled workers it changes in different model specifications. Finally, early on the career path, individuals prefer to 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. It can be shown that occupational intensity is negatively associated with wages, supporting the idea of different learning environments and their advantages for workers.

Future work could now address the following topics. The newly developed firm distance measure appears promising and, thus, could be extended to analyses of cognitive proximity of firms (see, Boschma, 2005; Nooteboom et al., 2007). Further research could also investigate the effect of other task tenure variables in more detail as doing so is an alternative way of capturing accumulated knowledge. In sum, this paper contributes to the literature by showing that the specificity of knowledge is determined by context. All knowledge can, thus, become either specific or general. In addition, it suggests that both firm and occupational knowledge matter both on the general and specific dimension. It has, however, not directly tested how industrial and occupational knowledge relate to each other. This also has to be left to future research.

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## Figures & Tables

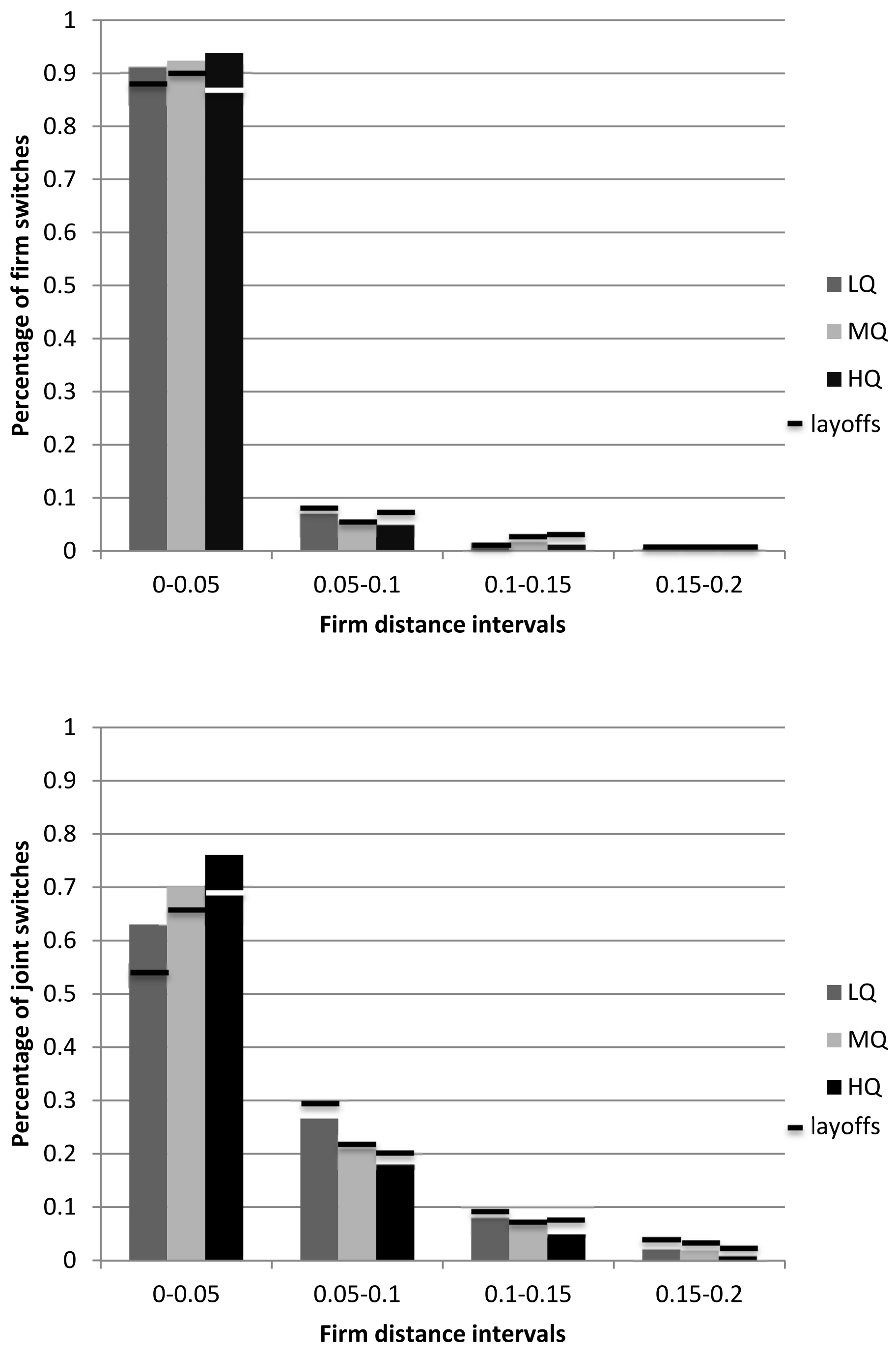
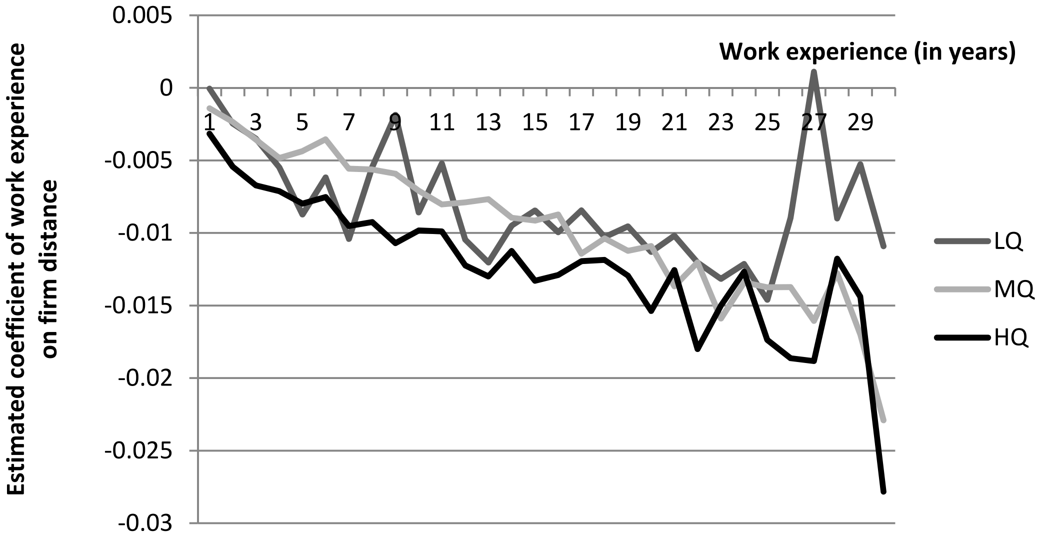


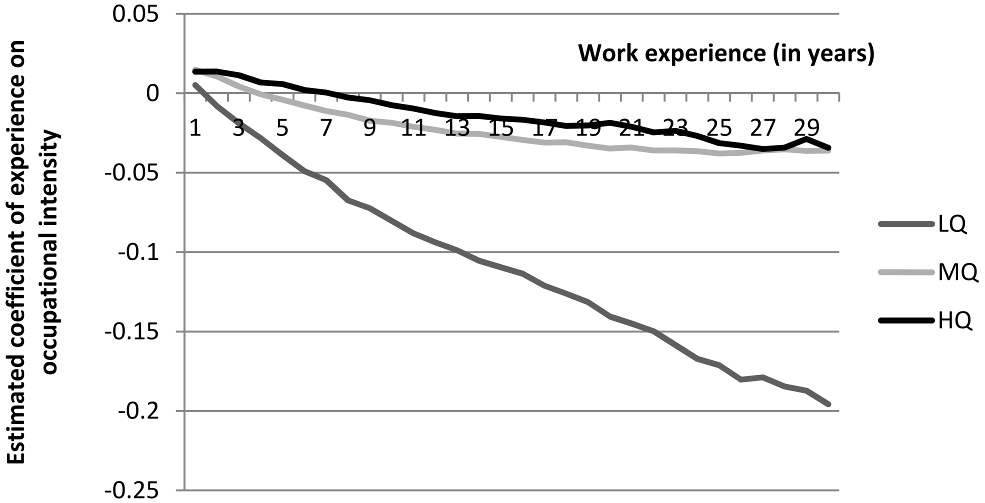

**Figure 1: Distribution of switches across firm distance intervals (upper graph: firm switches; lower graph: joint switches)**




| | LQ | MQ | HQ |
|---|---|---|---|
| No. observations | 16,820 | 129,458 | 34,170 |
| No. individuals | 11,152 | 63,912 | 17,779 |
| R-squared | 0.1772 | 0.1388 | 0.1248 |
| Joint significance of work experience | * | *** | *** |

Notes: The coefficients of work experience are estimated in fixed effect regression with firm distance as dependent variable. The sample includes workers who experienced a firm or joint switch. All coefficients are significant at the 1% level. It is additionally controlled for firm tenure, occupational distance, type of switch, region, year, and occupational field. Robust standard errors are clustered on the individual level.

**Figure 2: The relationship between work experience and firm distance**




| | LQ | MQ | HQ |
|---|---|---|---|
| No. observations | 166,322 | 1,347,547 | 259,381 |
| No. individuals | 25,459 | 109,832 | 27,489 |
| R-squared | 0.0429 | 0.0376 | 0.0193 |
| Joint significance of work experience | *** | *** | *** |

Notes: The coefficients of work experience are estimated in fixed effect regression with occupational intensity as dependent variable. It is additionally controlled for non-switcher, region, year, and occupational field. Robust standard errors are clustered on the individual level.

**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**

| DEPVAR: current wage (log) | (A) | (B) | (C) | (D) |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| LOW QUALIFICATION | FIRMSW | FIRMSW | BOTHSW | BOTHSW |
| FEMALE (1=YES) | -0.215*** | -0.215*** | -0.402*** | -0.400*** |
| | (0.017) | (0.017) | (0.016) | (0.016) |
| PREVIOUS WAGE (LOG) | 0.495*** | 0.511*** | 0.074*** | 0.194*** |
| | (0.020) | (0.023) | (0.008) | (0.014) |
| FIRM DISTANCE | -0.001 | -0.015** | -0.020*** | -0.033*** |
| | (0.005) | (0.006) | (0.003) | (0.005) |
| FIRM DIST * PREVIOUS Wage | | -0.032*** | | -0.019*** |
| | | (0.010) | | (0.005) |
| OCC DISTANCE | | | -0.014*** | -0.046*** |
| | | | (0.003) | (0.005) |
| OCC DISTANCE * PREVIOUS WAGE | | | | -0.044*** |
| | | | | (0.005) |
| Constant | -0.109* | -0.106* | -0.661*** | -0.498*** |
| | (0.058) | (0.057) | (0.094) | (0.094) |
| Observations | 6,022 | 6,022 | 10,793 | 10,793 |
| R-squared | 0.686 | 0.687 | 0.326 | 0.337 |
| | (5) | (6) | (7) | (8) |
| MEDIUM QUALIFICATION | FIRMSW | FIRMSW | BOTHSW | BOTHSW |
| FEMALE (1=YES) | -0.267*** | -0.266*** | -0.486*** | -0.481*** |
| | (0.005) | (0.005) | (0.008) | (0.008) |
| PREVIOUS WAGE (LOG) | 0.484*** | 0.504*** | 0.121*** | 0.265*** |
| | (0.006) | (0.007) | (0.004) | (0.006) |
| FIRM DISTANCE | -0.013*** | -0.019*** | -0.026*** | -0.043*** |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| FIRM DIST * PREVIOUS Wage | | -0.042*** | | -0.036*** |
| | | (0.004) | | (0.002) |
| OCC DISTANCE | | | -0.045*** | -0.072*** |
| | | | (0.002) | (0.002) |
| OCC DISTANCE * PREVIOUS WAGE | | | | -0.053*** |
| | | | | (0.003) |
| Constant | -0.389*** | -0.377*** | -0.592*** | -0.434*** |
| | (0.035) | (0.034) | (0.045) | (0.044) |
| Observations | 74,606 | 74,606 | 54,917 | 54,917 |
| R-squared | 0.598 | 0.601 | 0.297 | 0.315 |

| HIGH QUALIFICATION | (9)<br>FIRMSW | (10)<br>FIRMSW | (11)<br>BOTHSW | (12)<br>BOTHSW |
|---|---|---|---|---|
| FEMALE (1=YES) | -0.212*** | -0.211*** | -0.332*** | -0.332*** |
| | (0.010) | (0.010) | (0.014) | (0.014) |
| PREVIOUS WAGE (LOG) | 0.373*** | 0.384*** | 0.118*** | 0.187*** |
| | (0.015) | (0.017) | (0.007) | (0.010) |
| FIRM DISTANCE | -0.014*** | -0.007 | -0.019*** | -0.025*** |
| | (0.003) | (0.005) | (0.003) | (0.003) |
| FIRM DIST * PREVIOUS Wage | | -0.024** | | -0.021*** |
| | | (0.010) | | (0.004) |
| OCC DISTANCE | | | -0.028*** | -0.039*** |
| | | | (0.004) | (0.004) |
| OCC DISTANCE * PREVIOUS WAGE | | | | -0.028*** |
| | | | | (0.005) |
| Constant | -0.078 | -0.081 | -0.492** | -0.470** |
| | (0.117) | (0.116) | (0.198) | (0.194) |
| Observations | 18,229 | 18,229 | 15,948 | 15,948 |
| R-squared | 0.579 | 0.58 | 0.319 | 0.324 |

Notes: The dependent variable is the wage in the current job. The calculations show standardized coefficients of a OLS regression. Robust standard errors are in parentheses. In the interest of brevity, results for work experience, work experience squared, and occupational tenure (only column A and B) are not reported. All models include controls for occupational groups, regions, and years. Columns (1)–(4) are workers with low, (5)–(8) with medium, (9)–(12) are high qualification levels. Column A and B report results for firm switchers, Column C and D for joint switchers.

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

**Table 4: General knowledge—Task tenure and wages**

| DEPVAR: Wage after switch (log) | (1)<br>LQ | (2)<br>MQ | (3)<br>HQ |
|---|---|---|---|
| FEMALE (1=YES) | -0.400*** | -0.495*** | -0.330*** |
| | (0.015) | (0.008) | (0.014) |
| PREVIOUS WAGE (LOG) | 0.096*** | 0.148*** | 0.122*** |
| | (0.008) | (0.004) | (0.007) |
| FIRM DISTANCE | -0.010*** | -0.017*** | -0.017*** |
| | (0.003) | (0.002) | (0.003) |
| OCC DISTANCE | 0.004 | -0.014*** | -0.016*** |
| | (0.003) | (0.002) | (0.004) |
| FIRM TASK TENURE | 1.630*** | 1.097*** | 0.405*** |
| | (0.283) | (0.090) | (0.148) |
| OCC TASK TENURE | 0.924*** | 1.146*** | 0.698*** |
| | (0.074) | (0.036) | (0.094) |
| WORK EXPERIENCE | -2.026*** | -1.840*** | -0.669*** |
| | (0.258) | (0.085) | (0.159) |
| WORK EXPERIENCE^2 | -0.180*** | -0.130*** | -0.346*** |
| | (0.043) | (0.018) | (0.038) |
| Constant | -0.542*** | -0.500*** | -0.471** |
| | (0.091) | (0.043) | (0.198) |
| Observations | 10,793 | 54,917 | 15,948 |
| R-squared | 0.354 | 0.327 | 0.324 |

Notes: The dependent variable is the wage in the current job after a joint switch. Standardized coefficients are reported. Controls for occupational groups, regions, and years are included. All columns report OLS regressions. Robust standard errors are in parentheses. Column (1) are worker with low, (2) with medium, (3) with qualification levels.
*** p<0.01, ** p<0.05, * p<0.1

**Table 5: The role of occupational intensity at the firm for employee wages**

| | (1) | (2) | (3) |
|---|---|---|---|
| DEPVAR: Wage (log) | LQ | MQ | HQ |
| FEMALE (1=YES) | -0.300*** | -0.358*** | -0.258*** |
| | (0.007) | (0.003) | (0.006) |
| OCC INTENSITY | -0.191*** | -0.156*** | -0.168*** |
| | (0.011) | (0.004) | (0.007) |
| NON-SWITCHER (1=YES) | 0.094*** | 0.083*** | 0.016*** |
| | (0.005) | (0.002) | (0.003) |
| WORK EXPERIENCE | 0.062*** | 0.037*** | 0.055*** |
| | (0.001) | (0.000) | (0.001) |
| WORK EXPERIENCE^2 | -0.001*** | -0.001*** | -0.001*** |
| | (0.000) | (0.000) | (0.000) |
| Constant | 3.005*** | 2.760*** | 3.381*** |
| | (0.027) | (0.013) | (0.092) |
| Observations | 165,986 | 1,345,798 | 259,070 |
| R-squared | 0.476 | 0.416 | 0.462 |

Notes: The dependent variable is the wage logarithm. Controls for occupational groups, regions, and years are included. All columns report OLS regressions. Robust standard errors in parentheses are clustered on the individual level. Column (1) are workers with low, (2) with medium, (3) with high qualification levels.
*** p<0.01, ** p<0.05, * p<0.1

## Annex

### Occupational Tasks

To calculate the task set 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, 2011).

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 on a frequency scale, with (1) never, (2) sometimes, (3) frequently. One additionally included task is in 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 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, typist, 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. |

**Table A 2: Summary statistics**

| Variable | LQ | MQ | HQ | All |
|---|---|---|---|---|
| Percentage in sample (%) | 9.4 % | 76.0 % | 14.6 % | |
| Female | 0.462 | 0.490 | 0.301 | 0.460 |
| | (0.498) | (0.500) | (0.459) | (0.498) |
| Wage | 55,234 | 72.061 | 107.477 | 75.661 |
| | (31.322) | (36.288) | (44.847) | (39.799) |
| Work experience (in years) | 8.696 | 9.296 | 8.195 | 9.079 |
| | (7.599) | (7.067) | (6.731) | (7.082) |
| Firm tenure (in years) | 6.106 | 6.096 | 4.979 | 5.930 |
| (FIRM TENURE) | (6.401) | (5.839) | (5.250) | (5.826) |
| Occupational tenure (in years) | 6.378 | 7.214 | 6.246 | 6.994 |
| (OCC TENURE) | (6.486) | (6.337) | (6.020) | (6.318) |
| Firm task tenure (in years) | 8.615 | 9.200 | 8.095 | 8.983 |
| (FIRM TASK TENURE) | (7.537) | (6.992) | (6.645) | (7.007) |
| Occupational task tenure (in years) | 8.360 | 9.070 | 8.024 | 8.850 |
| (OCC TASK TENURE) | (7.352) | (6.902) | (6.615) | (6.916) |
| Firm distance | 0.005 | 0.003 | 0.004 | 0.004 |
| (FIRM DIST) | (0.018) | (0.014) | (0.014) | (0.015) |
| Occupational distance | 0.019 | 0.009 | 0.011 | 0.010 |
| (OCC DIST) | (0.070) | (0.045) | (0.047) | (0.048) |
| Firm switches | 0.040 | 0.060 | 0.074 | 0.060 |
| | (0.196) | (0.238) | (0.261) | (0.238) |
| Joint switches | 0.069 | 0.043 | 0.063 | 0.048 |
| | (0.253) | (0.202) | (0.244) | (0.214) |
| Occupational intensity | 0.484 | 0.504 | 0.352 | 0.480 |
| (OCC INT) | (0.298) | (0.308) | (0.302) | (0.311) |
| No. observations | 167,283 | 1,353,608 | 260,587 | 1,781,478 |

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

| ALL QUALIFICATION LEVELS | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Female | 1781478 | 0.460 | 0.498 | 0 | 1 |
| Wage | 1781478 | 75.661 | 39.799 | 10 | 4121.01 |
| Work experience (in years) | 1781478 | 9.079 | 7.082 | 0 | 30 |
| Firm tenure (in years) | 1781478 | 5.930 | 5.826 | 0 | 30 |
| Occupational Tenure (in years) | 1781478 | 6.994 | 6.318 | 0 | 30 |
| Firm task tenure (in years) | 1781478 | 8.983 | 7.007 | 0 | 31.119 |
| Occupational task tenure (in years) | 1781478 | 8.850 | 6.916 | 0 | 34.234 |
| Firm distance | 1581473 | 0.004 | 0.015 | 0 | 0.274 |
| Occupational distance | 1650897 | 0.010 | 0.048 | 0 | 0.879 |
| Firm switch | 1781478 | 0.060 | 0.238 | 0 | 1 |
| Joint switch | 1781478 | 0.048 | 0.214 | 0 | 1 |
| Layoffs | 1781478 | 0.005 | 0.070 | 0 | 1 |
| Occupational intensity | 1781478 | 0.480 | 0.311 | 0 | 1 |

Sources: Own calculations with SIAB, BHP and BiBB/BAuA Employment Survey.

**Table A 3: Correlations**

| | Correlations | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Female | 1 | | | | | | | | | | | | | | |
| 2 | Wage | -0.337* | 1 | | | | | | | | | | | | | |
| 3 | Experience | -0.085* | 0.450* | 1 | | | | | | | | | | | | |
| 4 | Firm tenure | -0.060* | 0.292* | 0.714* | 1 | | | | | | | | | | | |
| 5 | Occupational tenure | -0.024* | 0.351* | 0.816* | 0.728* | 1 | | | | | | | | | | |
| 6 | Firm task tenure | -0.085* | 0.450* | 0.999* | 0.723* | 0.820* | 1 | | | | | | | | | |
| 7 | Occupational task tenure | -0.078* | 0.451* | 0.995* | 0.725* | 0.844* | 0.996* | 1 | | | | | | | | |
| 8 | Firm distance | 0.023* | -0.103* | -0.113* | -0.204* | -0.177* | -0.122* | -0.124* | 1 | | | | | | | |
| 9 | Occupational distance | -0.016* | -0.102* | -0.120* | -0.167* | -0.235* | -0.124* | -0.144* | 0.489* | 1 | | | | | | |
| 10 | Firm switches | 0.020* | 0.010* | -0.043* | -0.227* | -0.030* | -0.046* | -0.042* | 0.177* | -0.056* | 1 | | | | | |
| 11 | Joint switches | -0.005* | -0.077* | -0.114* | -0.207* | -0.228* | -0.118* | -0.128* | 0.563* | 0.688* | -0.056* | 1 | | | | |
| 12 | Layoff | 0.004* | -0.015* | -0.020* | -0.058* | -0.032* | -0.021* | -0.022* | 0.099* | 0.060* | 0.133* | 0.087* | 1 | | | |
| 13 | Occupational intensity | 0.129* | -0.177* | -0.093* | -0.085* | -0.006* | -0.097* | -0.084 | 0.012* | -0.027* | 0.036* | -0.009* | 0.015* | 1 | | |
| 14 | Low-skilled | 0.001 | -0.165* | -0.017* | 0.010* | -0.031* | -0.017* | -0.023* | 0.028* | 0.058* | -0.028* | 0.031* | 0.006* | 0.004* | 1 | |
| 15 | Medium-skilled | 0.109* | -0.161* | 0.055* | 0.049* | 0.062* | 0.055* | 0.057* | -0.024* | -0.047* | -0.000 | -0.045* | -0.001 | 0.138* | -0.573* | 1 |
| 16 | High-skilled | -0.132* | 0.331* | -0.052* | -0.068* | -0.049* | -0.053* | -0.050* | 0.006* | 0.009* | 0.023* | 0.029* | -0.003* | -0.171* | -0.133* | -0.736* |

Notes: * indicates that the correlation is significant at the 1% level.