How General is Human Capital? A Task-Based Approach

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Abstract

This paper studies how portable skill accumulated in the labor market are. Using rich data on tasks performed in occupations, we propose the concept of task-specific human capital to measure the transferability of skills empirically. Our results on occupational mobility and wages show that labor market skills are more portable than previously considered. We find that individuals move to occupations with similar task requirements and that the distance of moves declines with time in the labor market. We also show that task-specific human capital is an important source of individual wage growth, in particular for university graduates. For them, at least 40 percent of overall wage growth over a ten year period can be attributed to task-specific human capital. For the low- and medium-skilled, task-specific human capital accounts for at least 35 and 25 percent of overall wage growth respectively.

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1 Introduction

Human capital theory (Becker, 1964; Mincer, 1974) and job search models (e.g. Jovanovic, 1979a; 1979b) are central building blocks for economic models of the labor market. Both are widely used to study job mobility behavior, wage determination and their aggregate implications for wage inequality, unemployment and economic growth.

A crucial decision in these models is how to characterize labor market skills. Human capital and job search theories typically distinguish between general skills like education and experience and specific skills, i.e. skills that are not portable across jobs. Recent contributions have focused on the importance of specific skills to explain phenomena like the growth differences between continental Europe and the United States (e.g. Wasmer, 2004), the rise of unemployment in continental Europe (e.g. Ljungqvist and Sargent, 2005) and the surge in wage inequality over the past decades (e.g. Violante, 2002; Kambourov and Manovskii, 2007a). The basic idea is that job reallocation, job displacement and unemployment are more costly for the individual worker and the economy if skills are not transferable across jobs.

However, we know little about how portable skills accumulated in the labor market actually are. In this article, we propose the concept of 'task-human capital' to measure the specificity of labor market skills empirically.[1] We then use this concept to show that human capital is more portable than previously considered.

The basic idea of our approach is straightforward. Suppose there are two types of tasks performed in the labor market, for example analytical and manual tasks. Both tasks are general in the sense that they are productive in many occupations. Occupations combine these two tasks in different ways. For example, one occupation (e.g. accounting) relies heavily on analytical tasks, a second one (e.g. bakers) more on manual tasks, and a third combines the two in equal proportion (e.g. musicians).

Skills accumulated in an occupation are then 'specific' because they are only productive in occupations which place a similar value on combinations of tasks (see also Lazear, 2003). This type of

[1] Our concept of task human capital is closely related to the ideas proposed in Gibbons and Waldman (2004; 2006). However, they apply the idea to internal promotions and job design while we use it to study occupational mobility and wage growth.

task-specific human capital differs from general skills because it is valuable only in occupations that require skills similar to the current one. It differs from occupation-specific skills in that it does not fully depreciate if an individual leaves his occupation. Compare, for instance, a carpenter who decides to become a cabinet maker with a carpenter who decides to become a baker. In our approach, the former can transfer more skills to his new occupation than the latter.

Our data is uniquely suited to analyze the transferability of skills empirically. It combines information on tasks performed in different occupations with a high-quality panel on complete job histories and wages. The first data is a large panel that follows individual labor market careers from 1975 to 2001. The data, derived from a two percent sample of all social security records in Germany, provides a complete picture of job mobility and wages for more than a 100,000 workers. It has several distinct advantages over the data used in the previous literature on occupational mobility. First, the administrative nature of our data ensures that there is little measurement error in wages and occupational coding. Both are serious problems in data sets like the PSID or NLSY used previously. Furthermore, we have much larger samples available than in typical household surveys.

The third advantage of our data is that we can measure what tasks are performed in different occupations. This information comes from a large survey of 30,000 employees at four separate points in time. Exploiting the variation in task usage across occupations and time, we construct a continuous measure of skill distance between occupations. Based on the task data, the skill requirements of a baker and a cook are very similar. In contrast, switching from a banker to an unskilled construction worker would be the most distant move observable in our data. We then use this skill distance measure together with the panel on job mobility to construct an individual's task-human capital.

We find that individuals are much more likely to move to similar occupations than suggested by search and turnover models in which the source occupation has no impact on the choice of future occupations. The distance of actual moves like the propensity to switch occupations declines sharply with labor market experience. These results are consistent with the idea that task-specific human capital is an important determinant of occupational mobility.

If human capital is largely task-specific and therefore transferable to similar occupations, this should also be reflected in individuals' wages. Our framework can explain why tenure in the pre-displacement job has been found to have a positive effect on the post-displacement wage, especially in high-skilled occupations (Kletzer, 1989). We also show that wages and tenure in the last occupation have a stronger effect on wages in the new occupation if the two occupations require similar skills.

We then show that task-specific human capital is an important determinant of individual wage growth compared to other general and specific skills, using a control function approach. Occupation-specific skills and general experience become less important for wage growth once we include task specific human capital. For university graduates, at least 40 percent of wage growth due to human capital accumulation can be attributed to task-specific skills. For the medium-skilled (low-skilled), at least 25 (35) percent of individual wage growth is due to task-specific human capital.

Our results have important implications for the costs of job reallocation and hence welfare in an economy. We illustrate this by calculating the costs of job displacement for the individual worker. Workers who are able to find employment in occupations with similar skill requirements lose 12 percent of their wages; wage losses are almost three times as high if they have to move to very distant occupations instead. Hence, reallocation costs in an economy will depend crucially on the thickness of the labor market.

The article makes several contributions to the literature. First, we introduce a novel way to define how occupations are related to each other in terms of their skill requirements. In particular, we use data on actual tasks performed in occupations to characterize the distance between occupations along a continuous scale. Previous empirical papers on the transferability of skills across occupations (Shaw, 1984; 1987) have used the frequency of occupational switches to define similar occupations (i.e. occupations that often exchange workers are assumed to have similar skill requirements).

Second, using our distance measure, we document novel patterns in mobility that are consistent with our view that specific labor market skills are more portable than previously considered. A key implication of our framework, which we confirm with our data, is that the source occupation has a strong influence on the choice of one's future occupation. The literature on firm and occupational mobility in contrast focuses on the determinants of switching firms (Flinn, 1986; Topel and Ward, 1992) or both firms and occupations (McCall, 1990; Miller, 1984; Neal, 1998; Pavan, 2005), but has not studied the type and direction of a move.[2]

Our third contribution is to quantify the contribution of task-specific human capital to individual wage growth and compare it to other forms of human capital like experience and occupational tenure. While a large number of studies have estimated the contribution of firm-specific human capital to individual wage growth (Abraham and Farber, 1987; Altonji and Shakotko, 1987; Altonji and Williams, 2005; Topel, 1991; Kletzer, 1989)[3], recent evidence suggests that specific skills might be more tied to an occupation than to a particular firm (Gibbons et al., 2006; Kambourov and Manovskii, 2007b; Parent, 2000; Neal, 1999). We show in contrast that specific human capital is not fully lost if an individual leaves an occupation. Poletaev and Robinson (2008) report a similar result using information from the Dictionary of Occupational Titles (DOT). In addition, we are able to quantify the role of task-specific skills for wage growth over the life-cycle.

Finally, our paper provides the first attempt to integrate the recent literature using task data (Autor et al., 2003; Spitz-Öner, 2006; Borghans et al., 2006) with human capital models of the labor market.[4] Our paper employs data on tasks to propose a new measure of the specificity of skills. In contrast to the literature on task usage, we abstract from which particular task (analytical, manual etc.) matters for mobility and wages. Instead, we explore the implications of task-specific human capital for occupational mobility, the direction of the occupational move, and the transferability of human capital.

The paper proceeds as follows. The next section outlines our concept of task human capital and how it relates to the previous literature on labor market skills. Section 3 introduces the two data sources

[2] In a paper complementary to ours, Malamud (2005) analyzes how the type of university education affects occupational choice and mobility.

[3] See Farber (1999) for a comprehensive survey of this literature.

[4] Autor et al. (2003) for the United States and Spitz-Öner (2006) for West Germany study how technological change has affected the usage of tasks, while Borghans et al. (2006) show how the increased importance of interactive skills has improved the labor market outcomes of under-represented groups. Similarly, Ingram and Neumann (2006) argue that changes in the returns to tasks performed on the job are an important determinant of wage differentials across education groups.

and explains how we measure the distance between occupations in terms of their task requirements. Descriptive evidence on the similarity of occupational moves and its implications for wages across occupations are presented in Section 4. Section 5 quantifies the importance of task-specific human capital for individual wage growth and calculates wage costs of job displacement. Finally, Section 6 concludes.

2 Conceptual Framework

2.1 Task-Specific Human Capital

This section defines how occupations are related to each other and introduces our concept of task-specific human capital. Suppose that output in an occupation is produced by combining multiple tasks, for example negotiating, teaching or managing personnel. These tasks are general in the sense that they are productive in different occupations. Occupations differ in which tasks they require and in the relative importance of each task for production. An individual's productivity is then 'specific' to that occupation because occupations place different values on combinations of skills.

More specifically, consider the case of two tasks, denoted by $j = A, M$. We think of them as manual and analytical tasks. Workers are endowed with a productivity in each task, which we denote by $T^j_{it}, j = A, M$. Occupations combine the two tasks in different ways. For example, one occupation might rely heavily on analytical tasks, a second more on manual tasks, and a third combines the two in equal proportion. Let β_o $(0 \leq \beta_o \leq 1)$ be the relative weight on the analytical task, and $(1 - \beta_o)$ be the relative weight on the manual task. We specify worker i's productivity (measured in log units) in occupation o as

$$\ln S_{it} = \beta_o T^A_{it} + (1 - \beta_o) T^M_{it}.$$

For example, if in an occupation analytical tasks are more important than manual tasks, $\beta_o > 0.5$. In another occupation, only the manual task might be performed, so $\beta_o = 0$. By restricting the weights on the tasks to sum to one, we focus on the relative importance of each task, not on the task intensity of an occupation. We impose this restriction for illustrative purposes only. None of our empirical results below require this restriction.

In this approach, we can define the relation between occupations in a straightforward way. Two occupations o and o' are similar if they employ analytical and manual tasks in similar proportions, i.e. β_o is close to $\beta_{o'}$. We can then measure the distance between the two occupations as the absolute difference between the weight given to the analytic task in each occupation, i.e. $|\beta_o - \beta_{o'}|$. The maximum distance of one is between an occupation that fully specializes in the analytical task ($\beta_o = 1$) and the one that fully specializes in the manual task ($\beta_o = 0$).

We further assume that log-productivity can be decomposed into a time-varying component that captures human capital accumulation, $X_{iot}\gamma_o$, and a time-invariant component that captures the quality of the occupational match, $\beta_o T_i^A + (1 - \beta_o)T_i^M$:[5]

$$\ln S_{iot} = \underbrace{\gamma_o X_{iot}}_{\text{Human Capital}} + \underbrace{\beta_o T_i^A + (1 - \beta_o)T_i^M}_{\text{Match Quality}}$$

We now describe each component in turn.

Human Capital Accumulation With time in the labor market, individuals become more productive in each task through learning-by-doing. In particular, we assume that X_{iot} contains three types of human capital: general human capital (Exp_{it}), purely occupation-specific human capital (OT_{it}), and what we call task-specific human capital (TT_{it}). The vector $\gamma_o = [\gamma_{1o}\ \gamma_{2o}\ \gamma_{3o}]$ denotes the returns to the three types of human capital, which vary across occupations. This specification takes seriously the existing empirical evidence that returns to labor market skills differ across occupations (for example, Gibbons et al, 2005; Heckman and Sedlacek, 1985).

General human capital is valuable in all occupations, while occupation-specific human capital is fully lost once a worker leaves the occupation. Task-specific human capital in contrast is transferable to

[5]For simplifaction, we do not incorporate the search for a firm match here. We discuss the implications of matching across firms in Section 5.4 below.

occupations with similar skill requirements. More specifically, we assume that the transferability of skills between the source and destination occupation depends on the distance between the two occupations: Workers can transfer a fraction $1 - |\beta_o - \beta_{o'}|$ of their human capital if they switch from occupation o to o'. For example, if workers move from an occupation that fully specializes in the analytical task ($\beta_o = 1$) to an occupation that fully specializes in the manual task ($\beta_{o'} = 0$), none of the acquired skills can be transferred. If, in contrast, workers move from an occupation that mostly uses the analytical task (e.g. $\beta_o = 0.75$) to an occupation that employs both tasks in equal proportions (e.g. $\beta_{o'} = 0.5$), they are able to transfer 75 percent of their acquired skills. Hence, task-specific human capital is neither fully general nor purely specific, but partially transferable across occupations.

Using these assumptions, we can collapse the accumulation of skills in *multiple* tasks into a *one-dimensional observable* measure of task-specific human capital, TT_{it}. We calculate task human capital from occupation tenure in all previous occupations, inversely weighted by the distance between the current and previous occupations. We therefore abstract from estimating human capital accumulation separately in each task, and instead focus on the portability of skills from one occupation to another. One advantage of this approach is that we can compare the importance of task-specific human capital to other, more standard measures of human capital like experience or occupational tenure.

Match Quality The occupation-specific match component is specified as a weighted average of the individual's productivity in each task, $\beta_o T_i^A + (1 - \beta_o) T_i^M$. Hence, match qualities are correlated across occupations in our specification if the two occupations rely on similar tasks. Existing models of occupational choice (for example, Neal (1999) and Pavan (2005)) in contrast assume that the occupational match is uncorrelated across occupations.

2.2 Wage Determination and Occupational Mobility

Wages in occupation o and time t are equal to worker i's productivity, S_{iot}, multiplied with the occupation-specific skill price, P_o, i.e. $w_{iot} = P_o S_{iot}$. Hence, log wages satisfy:

$$\begin{aligned} \ln w_{iot} &= p_o + \ln S_{iot} + \varepsilon_{iot} = p_o + \gamma_o X_{iot} + \beta_o T_i^A + (1-\beta_o) T_i^M + \varepsilon_{iot} \\ &= \underbrace{p_o + \gamma_{1o} Exp_{it} + \gamma_{2o} OT_{iot} + \gamma_{3o} TT_{it}}_{\text{observed}} + \underbrace{\beta_o T_i^A + (1-\beta_o) T_i^M + \varepsilon_{iot}}_{\text{unobserved}}, \end{aligned} \quad (1)$$

where $p_o = \ln P_o$. We have added an iid error term ε_{iot} is assumed to be uncorrelated with the regressors and reflects for instance measurement error in wages. We observe general (Exp_{it}), occupation-specific (OT_{iot}), and task-specific skills (TT_{it}). We do not observe the quality of the match, $\beta_o T_i^A + (1-\beta_o) T_i^M$. Since the concept of task-specific human capital is novel, we next clarify the interpretation of the return to task-specific human capital, γ_{2o}. Consider a worker who has worked for his occupation o for one year. Suppose he is exogenously displaced from his occupation and then randomly assigned to a new occupation. A worker who moves to the most similar occupation loses γ_{2o} (i.e. the purely occupation-specific skills). In contrast, a worker who moves to the most distant occupation loses $\gamma_{2o} + \gamma_{3o}$, while a worker who moves to an occupation where he can transfer fifty percent of his skills loses $\gamma_{2o} + 0.5\gamma_{3o}$.

Of course, workers are not randomly allocated into occupations. We assume that workers search over occupations to maximize earnings.[6] The decision to switch occupations is determined by three factors: the potential loss in occupation- and task-specific human capital (OT_{iot}, TT_{it}), the task match ($\beta_o T_i^A + (1-\beta_o) T_i^M$) and the occupation-specific returns to human capital (γ_{1o}, γ_{2o}, γ_{3o} and p_o).

If returns to skills are the same across occupations, workers would switch occupations only if the gain in match quality compensates for the loss in occupation- and task-specific human capital. This decision rule is the same irrespective of whether the search process is completely undirected or partially directed. In the case of undirected search, workers would search for the best match across all occupations regardless

[6] For example, Fitzenberger and Kunze (2006) and Fitzenberger and Spitz-Öner (2004) argue that search is the most important source of occupational switches in Germany.

of the worker's true productivity in each task. In the case of partially directed search, workers would only apply to occupations that promise a better match. Occupational mobility results either because workers are at labor market entry not fully informed about which occupation provides the best match at labor market entry, or there is a rationing of jobs in the worker's most preferred occupation.

If, in contrast, the returns to human capital accumulation in the prospective occupation exceed those in the current occupation, workers may voluntarily switch occupations even if they lose specific human capital *and* are worse matched in the new occupation. This may occur because the new occupation promises higher wage growth in the future than the old one. This result again holds in the case of random or partially directed search.

Our framework produces a number of novel empirical implications. It implies that, everything else equal, workers are more likely to move to occupations in which they can perform similar tasks as in their previous occupation. The reason is that task-specific human capital is more valuable in similar than in distant occupations. We also expect that distant moves occur early, rather than late, in the labor market career for two reasons. First, the accumulation of task-specific human capital makes distant occupational switches increasingly costly. Second, with time in the labor market, workers gradually locate better and better occupational matches. It therefore becomes less and less likely that they accept offers from very distant occupations. Since both the transferability of task-specific human capital and the correlation of match qualities across occupations declines in the occupational distance, we also expect that wages at the source occupation are a better predictor for wages at the target occupation if the two occupations require similar tasks.

2.3 Comparison with Alternative Approaches

Our setup is closely related to the Roy model of occupational sorting (Roy, 1951; Heckman and Sedlacek, 1985). Just like in the Roy model, individuals in our framework sort themselves into occupations according to comparative advantage. While the original Roy model allows skills to be arbitrarily correlated across occupations, we impose a linear factor structure with two factors $(\beta_o T_{it}^A + (1-\beta_o) T_{it}^M)$. This restriction allows us to define how similar occupations are in their skill requirements in a straightforward way.

Our framework is also related to search and matching models of the labor market (Jovanovic, 1979a; 1979b). As in search or matching models, we include a match component that (partially) determines mobility decisions. In contrast to existing search and matching models however, our setup incorporates that specific skills are partially transferable and match qualities correlated across occupations. These extensions provide new insights into the direction of occupational mobility and allow us to quantify the importance of task-specific human capital for individual wage growth relative to other forms of human capital.

In a recent paper, Lazear (2003) also sets up a model in which firms use general skills in different combinations with firm-specific weights attached to them. In this model, workers are exogenously assigned to a firm (in our application: occupation) and then choose how much to invest in each skill. Our - in our opinion more intuitive - approach assumes instead that workers are endowed with a productivity in each task, and then choose the occupation. Furthermore, unlike Lazear (2003), our empirical analysis focus on the transferability of skills across occupations and its implications for occupational mobility and individual wage growth.

3 Data Sources and Descriptive Evidence

To study the transferability of skills empirically, we combine two different data sources from Germany. Further details on the definition of variables and sample construction can be found in Appendix A.

3.1 Data on Tasks Performed in Occupations

Our first data set contains detailed information on tasks performed in occupations, which we use to characterize how similar occupations are in their skill requirements. The data come from the repeated cross-section *German Qualification and Career Survey,* which is conducted jointly by the Federal Institute for Vocational Education and Training (BIBB) and the Institute for Employment (IAB) to track skill requirements of occupations. The survey, previously used for example by DiNardo and Pischke (1997) and Borghans et al. (2006), is available for four different years: 1979, 1985, 1991/92 and 1998/99. Each wave contains information from 30,000 employees between the ages of 16 and 65. In what follows, we restrict our analysis to men since men and women differ significantly in their work attachments and occupational choices.

In the survey, individuals are asked whether they perform any of nineteen different tasks in their job. Tasks vary from repairing and cleaning to buying and selling, teaching, and planning. For each respondent, we know whether he performs a certain task in his job and whether this is his main activity. Table 1 lists the fraction of workers performing each of the nineteen different tasks. Following Autor et al. (2003) and Spitz-Öner (2006), we combine the 19 tasks into three aggregate groups: analytical tasks, manual tasks and interactive tasks. On average, 55 percent report performing analytic tasks, 72 percent manual tasks, and 49 percent interactive tasks. The picture for the main task used is similar: 32 percent report analytical tasks, 57 percent manual tasks and 28 percent interactive tasks as their main activity on the job.

The last two columns in table 1 show the distribution of tasks performed on the job for two popular occupations: teacher and baker. According to our task data, a teacher primarily performs interactive tasks (95.3 percent) with teaching and training others being by far the most important one (91.4 percent). Two other important tasks are correcting texts or data (39.6 percent) and organizing, coordinating and managing personnel (39.4 percent). A baker in contrast is a primarily manual occupation (96.4 percent) with manufacturing, producing, installing as the most important task (87.9 percent) followed by teaching and training others (34.3 percent) as well as organizing, coordinating and managing personnel (29.9 percent).

To see how task usage varies across the 64 occupations contained in our data, table A1 lists the fraction of workers performing manual, analytical, and interactive tasks for all 64 occupations. The table shows that there is a lot of variation in task usage across occupations. For example, while the average use of analytical tasks is 56.3 percent, the mean varies from 16.7 percent as an unskilled construction worker to 92.4 percent for an accountant. We found little evidence that tasks performed in the same occupation vary across industries, which suggest that industries matter less for measuring human capital once we control for the skill set of an occupation, and justifies our focus on occupations.

3.2 Measuring the Distance between Occupations

According to our framework, two occupations have similar skill requirements if they put similar weights on tasks, i.e. individuals perform the same set of tasks. With two tasks, the maximum distance between two occupations occurs if occupation o only uses task A ($\beta_o = 1$), and occupation $o\prime$ only task M ($\beta_{o'} = 0$). The basic idea extends naturally to the case with more than two tasks. Though we cannot observe these weights directly, our task data provide us with a closely related measure of the skill content of each occupation.

In particular, the task data described in the previous section tell us the set of skills employed in each occupation. We can then characterize the skill content of each occupation by a 19-dimensional vector $q_o = (q_{o1}, ..., q_{oJ})$ where q_{oj} denotes the fraction of workers in an occupation performing task j. We can think of this vector as describing a position in the task space. In equilibrium, an occupation with a high weight β_{oj} for a particular task will also employ this task extensively, i.e. have a high q_{oj}. To measure the distance between occupations in the task space, we use the angular separation or uncentered correlation of the vectors q_o and $q_{o'}$:

$$AngSep_{oo'} = \frac{\sum_{j=1}^{J} q_{jo} * q_{jo'}}{\left[(\sum_{j=1}^{J} q_{jo}^2) * \left(\sum_{k=1}^{J} q_{ko'}^2 \right) \right]^{1/2}}$$

where q_{jo} is the fraction of workers using task j in occupation o and $q_{jo'}$ is defined analogously. This measure defines the distance between two occupations as the cosine angle between their positions in vector space. The measure has been used extensively in the innovation literature to characterize the proximity of firms' technologies (Jaffe, 1986).[7]

[7] Unlike the Euclidean distance, the angular separation measure is not sensitive to the length of the vector, i.e. whether an occupation only uses some tasks but not others. For example, two occupations using all tasks moderately (and thus have a position close to the origin of the coordinate system) will be similar according to the angular separation measure

We use a slightly modified version of the above, namely $Dis_{oo'} = 1 - AngSep_{oo'}$ as our distance measure. The measure varies between zero and one. It is zero for occupations that use identical skill sets and unity if two occupations use completely different skills sets. The measure will be closer to zero the more two occupations overlap in their skill requirements. To account for changes in task usage over time, we calculated the distance measures separately for each wave. For the years 1975-1982, we use the measures from the 1979 cross-section, for 1983-1988 the task measures from the 1985 wave; for the years 1989-1994, we use the measures based on the 1991/2 wave; and the 1997/8 wave for the years 1995-2001. Our results are robust to assigning different time windows to the measures.[8]

The mean distance between occupations in our data is 0.24 with a standard deviation of 0.22 (see Table 2). The most similar occupational move is between paper and pulp processing and a printer or typesetter with a distance of 0.002. The most distant move is between a banker and an unskilled construction worker. Table 2 also shows at the bottom the distance measure for the three most common occupational switches separately by education group. The most popular move for low-skilled worker is between a truck driver and a warehouse keeper, while for the high skilled, it is between an engineering occupation and a chemist or physicist.[9]

3.3 The German Employee Panel

Our second data set is a two percent sample of administrative social security records in Germany from 1975 to 2001 with complete job histories and wage information for more than 100,000 employees. The data has at least three advantages over household surveys commonly used in the literature to study mobility in the United States. First, its administrative nature ensures that we observe the exact date of a job change and the wage associated with each job. Second, occupational titles are consistent across

even if their task vectors are orthogonal, and therefore distant according to the Euclidean distance measure. If all vectors have the same length (i.e. if all tasks are used by at least some workers in all occupations), our measure is proportional to the Euclidean distance measure.

[8] While there have been changes over time in the distance measures, they are with 0.7 highly correlated.

[9] Our distance measure treats all tasks symmetrically. It may, however, be argued that some tasks are more similar than others. For instance, the task 'equipping machines' may be more similar to 'repairing' than to 'teaching'. In order to account for this, we also defined the angular separation measure using information on the 3 aggregate task groups (analytical, manual and interactive tasks). The results based on this alternative distance measures are qualitatively very similar to the ones reported in the paper.

firms as they form the basis for wage bargaining between unions and employers. Finally, measurement error in earnings and occupational titles are much less of a problem than in typical survey data as misreporting is subject to severe penalties.

The data is representative of all individuals covered by the social security system, roughly 80 percent of the German workforce. It excludes the self-employed, civil servants, and individuals currently doing their compulsory military service. As in many administrative data sets, our data is right-censored at the highest level of earnings that are subject to social security contributions. Top-coding is negligible for unskilled workers and those with an apprenticeship, but reaches almost 25 percent for university graduates. For the high-skilled, we use tobit or semiparametric methods to account for censoring.

Since the level and structure of wages differs substantially between East and West Germany, we drop from our sample all workers who were ever employed in East Germany. We also drop all those working in agriculture. In addition, we restrict the sample to men who entered the labor market in or after 1975. This allows us to construct precise measures of actual experience, firm, task, and occupation tenure from labor market entry onwards. Labor market experience and our tenure variables are all measured in years and exclude periods of unemployment and apprenticeship training.

Since the concept is novel, we now explain how we calculate our measure of task human capital. Each individual starts with zero task tenure at the beginning of his career. Task tenure increases by the duration of the spell if a worker remains in the same occupation. If he switches occupations, we calculate task tenure in the new occupation as the weighted sum of time spent in all previous occupations where the weights are the distance between the current and all past occupations.[10]

As an example, consider a person who starts out in occupation A, then switches to occupation B after one year, and switches to occupation C again after one year. Suppose the distance between occupation A and B is 0.5, between occupation A and C 0.2 and 0.8 between occupation B and C. Before moving to occupation B, he has accumulated 1 unit of task tenure. Since he can only transfer 50

[10] In principle, our separation measure takes values between 0 and 1. However, the maximum distance observed in our data (across all occupation pairs) is 0.93. In our calculation, we assume that a worker cannot transfer any skills if he makes the most distant occupation switch, and define the *relative* distance between two occupations A and B as the difference between the maximum distance in our data and the distance between occupations A and B, divided by the maximum distance. Our results do not change if we use the actual distance instead of this relative distance measure.

percent of his task human capital to occupation B, his task tenure declines to 0.5. After working one year in occupation B, he accumulates another unit of task human capital, so task tenure increases to 1.5 ($0.5 * 1 + 1$). Switching to occupation C after the second year, the worker can transfer 20 percent of his task human capital he accumulated in occupation A in the first period and 80 percent of the human capital accumulated in occupation B in the second period. His task tenure variables is thus $1 = 0.2 * 1 + 0.8 * 1$.

Table 3 reports summary statistics for the main variables. In our sample, about 16 percent are low-skilled workers with no vocational degree. The largest fraction (68.3 percent) are medium-skilled workers with a vocational degree (apprenticeship). The remaining 15.4 percent are high-skilled workers with a tertiary degree from a technical college or university. Wages are measured per day and deflated to 1995 German Marks. Mean task tenure in our sample is between 4.6 years for the low-skilled and 4.8 years for the medium-skilled. Total labor market experience is on average a year higher (since the general skills captured by time spent in the labor market do not depreciate) and about one year lower for occupation tenure (since this measure assumes that these skills fully depreciate with an occupational switch).

Occupational mobility is important in our sample: 19 percent of the low-skilled switch occupations each year and with 11 percent somewhat lower for the high skilled. To see how occupational mobility varies over the career, figure 1 plots quarterly mobility rates over the first ten years in the labor market, separately by education group. Occupational mobility rates are very high in the first year (particularly in the first quarter) of a career, and highest for the low-skilled. Ten years into the labor market, quarterly mobility rates drop to 2 percent. The next section uses our distance measure to analyze in more detail the type of occupational mobility we observe in the data.

4 Patterns in Occupational Mobility and Wages

We now use the sample of occupational movers to provide descriptive evidence that skills are partially transferable across occupations. While the patterns shown below are not a rigorous test, they are all consistent with our task-based approach. Section 4.1 studies mobility behavior, while Section 4.2 analyzes wages before and after an occupational move.

4.1 Occupational Moves are Similar

Our framework predicts that workers are more likely to move to occupations with similar tasks requirements. In contrast, if skills are either fully general or fully specific to an occupation, they do not influence the direction of occupational mobility: in the first case, human capital can be equally transferred to all occupations, while in the second case, human capital fully depreciates irrespective of the target occupation.

To test this hypothesis, we compare the distance of observed moves to the distribution of occupational moves we would observe if the direction of occupational moves was random. In particular, we assume that under random mobility the decision to move to a particular occupation is solely determined by its relative size. For example, if occupation A employs twice as many workers as occupation B, the probability that a worker joins occupation A would then be twice as high as the probability that he joins occupation B. The way we calculate random mobility ensures that we account for shifts in the occupational structure over time, i.e. the fact that employment shares may be increasing or decreasing for some occupations.[11]

Figure 2 plots the density of the distance measure under observed and random mobility. The horizontal axis is the distance measure where larger values are associated with movements to more distant occupations. The distribution under both random and observed mobility is bimodal, with many occupation switches concentrated at the distance measure of about 0.1 and 0.65. The peak at the distance measure of 0.1 is considerably lower, while the share of distant occupation switches is considerably higher under random than under observed mobility. The two distributions are statistically different at the 1 percent level based on a Kolmogoroff-Smirnov test. To allow a more detailed comparison, table

[11] Observed moves are calculated as the percentage of moves for each value of the distance measure. To compare this to expected distance under random mobility, we calculate the fraction of individuals leaving an occupation that would end up in any of the 63 occupations in proportion to their relative size. Each random source-target occupation combination is then multiplied with the appropriate distance measure.

4 compares selected moments of the distribution of our distance measure under observed and random mobility. The observed mean and the 10th, 25th, 50th, 75th and 90th percentile of the distance distribution are much lower than what we would observe under random mobility. Figure 2 and table 4 both show that empirically observed moves are much more similar than we would expect if occupational mobility was determined by relative size alone.

Our framework also predicts that distant moves occur early in the labor market career and moves become increasingly similar with time in the labor market. One reason is that the accumulation of task-specific skills makes distant occupational switches increasingly costly. A second reason is that with time in the labor market, workers gradually locate better and better occupational matches. It therefore becomes less and less likely that they accept offers from very distant occupations.

Table 5 provides empirical support for these predictions. It shows the results from a linear regression where the dependent variable is the distance of an observed move separately by education group. Column (1) controls for experience and experience squared and year and occupation dummies. For all education groups, the distance of an occupational move declines with time spent in the labor market though at a decreasing rate. The declining effect is strongest for the high-skilled, who also make more similar moves on average (see last row). For the high-skilled, 10 years in the labor market decrease the distance of a move by 0.16 or about 70 percent of the standard deviation. For the medium-skilled, the decline is only about 0.03 or 14 percent of a standard deviation.

Furthermore, more time spent in the previous occupation decreases the distance of an occupational move in addition to labor market experience (column (2)). Column (3) reports the results from an fixed-effects estimator to control for heterogeneity in mobility behavior across individuals. The within estimator shows that occupational moves become more similar even for the same individual over time. If anything, the pattern of declining distance is more pronounced in the fixed effects estimation.

Table 5 imposed a quadratic relationship between actual labor market experience and the distance of moves. In figure 3, we relax this restriction. The figure displays the average distance of a move by actual experience, separately for the three education groups. The average distance is obtained from a least-squares regression of the distance on dummies for actual experience as well as occupation and year dummies, similar to Column (1) in table 5. The figure shows that occupational moves become more similar with time in the labor market for all education groups, but particularly so for the high-skilled in the first 5 years in the labor market. The decline in distance between the first and 15th year of actual labor market experience is statistically significant at the 1 percent level for all education groups.

In sum, individuals are more likely to move to occupations in which similar tasks are performed as in their source occupation, particularly so later in their career. These patterns are consistent with our view that human capital is task-specific and hence, more transferable between occupations with similar skill requirements.

4.2 Wages in Current Occupation Depend on Distance of Move

If skills are task-specific and hence partially transferable across occupations, this should also be reflected in the wages of occupational movers. Specifically, we expect that wages in the new occupation are more highly correlated with wages in the source occupation if the two require similar skills. The reason is that the wage in the previous occupation in part reflects task-specific human capital, which is valuable in the new occupation. In our data, we only observe occupational moves for workers who chose to move a nearby or distant occupation, and the correlation between wages in the source and target occupation is likely to be different for these workers than for workers who are forced to move to a nearby or distant occupation. We wish to stress, however, that despite the endogenous selection of workers into occupations, a decline in the correlation with the distance of the move is consistent with our task-based approach.

Table 6 investigates whether the correlation of wages before and after an occupational move indeed declines with the distance of a move. It reports estimates from a wage regression where the dependent variable is the log daily wage. All specifications include experience and experience squared as well as year and occupation dummies. Compared to the benchmark of occupational stayers (column (1)), the correlation of wages is much lower for our sample of occupational movers (column (2)).

The third specification (column (3)) adds the distance of the move as well as the distance interacted with the wage at the source occupation as additional regressors. As expected, wages in the source occupation are a better predictor for wages in the new occupation if the occupations require similar skills. For the high-skilled, our estimates imply that the correlation of the wage at the source occupation and the wage at the target occupation is 0.35 for the most similar move, 0.31 for the median move ($0.351 - 0.103 \times 0.354$), and approaches 0 for the most distant move ($0.352 - 0.939 \times 0.354$).

If skills are partially transferable across occupations, time spent in the last occupation should also matter for wages in the new occupation, especially if the two occupations require similar skills. In Column (1) of table 7, we regress wages at the new occupation on occupational tenure at the previous occupation and the same controls as before. Past occupational tenure positively affects wages at the new occupation.

Column (2) adds the distance measure interacted with past occupational tenure as controls. As expected, the predictive power of past occupational tenure is stronger if source and target occupations are similar, especially for university graduates. For the high-skilled, the impact of past occupational tenure on wages is 2.3 percent for the most similar move, but only 1 percent ($0.023 - 0.103\times 0.072 = 0.010$) for the median move.

Figure 4a relaxes the assumption that the correlation between wages across occupations declines linearly with the distance. The x-axis shows the distance with one being the most similar occupational moves and 10 the most distant ones, while the y-axis reports the coefficient on the wage in the source occupation for each of the 10 categories.[12] Figure 4b provides a similar analysis for past occupational tenure. The y-axis are now the coefficients on the 9 distance measure dummies from a tobit regression that also controls for actual experience, actual experience squared and year dummies.

Two things are noteworthy: first, the figures highlight that the source occupation has a stronger explanatory power for the wage at the target occupation if the source and the target occupation have

[12] The coefficient is obtained form a OLS regression (tobit regression for the high-skilled) that controls for actual experience, actual experience squared, year dummies, the wage at the source occupation, 9 dummies for the distance of the move and the 9 dummies interacted with the wage at the source occupation (see column (3) in table 6).

similar skill requirements. Second and in line with our results on mobility and wages, the decline is strongest for the high-skilled. For this education group, the partial correlation coefficient between wages in the source and target occupation drops from 37 percent for the 10 percent most similar moves to around 15 percent for the 10 percent most distant moves. The drop is statistically significant at a one percent level for all education groups.

We have performed a number of robustness checks. First, results for alternative distance measures are very similar. Second, our sample of movers contains both occupational switches between firms as well as within the same firm. The latter account for roughly 10 percent of all occupational movers. If some skills are tied to a firm, internal movers would have more portable skills than firm switchers. We therefore reestimated our specifications in table 5 to 7 using only external movers. The results exhibit the same patterns in mobility and wages which we observe for the whole sample of movers. Finally, our original sample of movers contains everybody switching occupations irrespective of the duration of intermediate un- or nonemployment spells. To account for potential heterogeneity between those remaining out of employment for an extended period of time and job-to-job movers, we reestimated the results only for the sample of workers with intermediate un- or nonemployment spells of less than a year. Again, this does not change the patterns on mobility and wages.

4.3 Can these Patterns be Explained by Unobserved Heterogeneity?

The strong patterns in mobility and wages reported in the last section support our view that human capital accumulated in the labor market is portable across occupations, and the more so the more similar are the occupations. This section discusses whether our findings could be rationalized by individual unobserved heterogeneity.

Note first that all results presented above are based on a sample of occupational movers. The patterns in mobility and wages can therefore not be accounted for by a simple mover-stayer model, where movers have a higher probability of leaving a job and therefore lower productivity because of less investment in specific skills. To the extent that movers differ from stayers in terms of observable and unobservable characteristics, this sample restriction reduces selection bias.

However, other sources of unobserved heterogeneity could bias our results. First, suppose that high ability workers are less likely to switch occupations. This could account for the fact that the time spent in the last occupation has a positive effect on wages in the current occupation, as past occupational tenure would act as a proxy for unobserved ability in the wage regression (see table 7). However, unobserved ability per se cannot explain why the effect of past occupational tenure should vary with the distance of the move or why individuals move to similar occupations at all.

First, one might argue that similar moves in the data are voluntary transitions, while distant movers are "lemons" that are laid from their previous job and cannot find jobs in similar occupations. The distinction between quits and layoffs could explain why wages are more highly correlated across similar occupations or why past occupational tenure has a higher return in a similar occupation. However, the distinction between voluntary and involuntary movers cannot explain why voluntary movers choose similar occupations in the first place.

We checked whether our results differ between job-to-job movers, which are more likely to be voluntary, and job-to-unemployment transitions, which are more likely to be involuntary. While the distance of moves is lower for job-to-job transitions, we find similar patterns for mobility and wages for the two types of movers. Hence, differences between voluntary and involuntary occupational movers cannot account for our findings.

Finally, suppose that the sample of movers differs in their taste for particular tasks. Some individuals prefer research over negotiating, while other prefer negotiating over managing personnel etc. Taste heterogeneity can explain why we see similar moves in the data. If individuals choose their occupations based on earnings and preferences for tasks, individuals would want to move to occupations with similar task requirements. However, a story based on taste heterogeneity alone cannot explain why wages are more strongly correlated between similar occupations. If there are compensating wage differentials, we would actually expect the opposite result: individuals would be willing to accept lower wages in an occupation with their preferred task requirements.

This discussion highlights that a simple story of unobserved heterogeneity cannot account for all of the results presented above. The next section outlines an estimation approach to quantify the importance of task-specific human capital for individual wage growth that takes into account workers' decision whether to switch occupations, and whether to move to a close or distant occupation.

5 Task-Specific Human Capital and Individual Wage Growth

To estimate the contribution of task-specific human capital to individual wage growth, we start from the log-wage regression (equation (1) in Section 2) augmented by control variables $\widetilde{X}_{iot}$:

$$\begin{aligned} \ln w_{iot} &= \gamma_{1o} Exp_{it} + \gamma_{2o} OT_{iot} + \gamma_{3o} TT_{iot} + \eta' \widetilde{X}_{iot} + u_{iot}, \\ u_{iot} &= \beta_o T_i^A + (1-\beta_o) T_i^M + \varepsilon_{iot}. \end{aligned} \tag{2}$$

Here Exp_{it} denotes actual experience, OT_{iot} occupation tenure, and TT_{iot} task tenure, capturing general, occupation- and task-specific human capital accumulation respectively. γ_{1o}, γ_{2o}, γ_{3o} denote the occupation-specific return to the three types of human capital. $\widetilde{X}_{iot}$ captures other control variables (year, occupation and region dummies) with the common return η. The unobserved (for the econometrician) error term u_{iot} consists of the task-specific match in an occupation ($\beta_o T_i^A + (1-\beta_o) T_i^M$) and an *iid* error term (ε_{iot}).

Our goal here is to identify the *average* return to the three types of human capital across occupations, $\overline{\gamma}_{ko} = E_o[\gamma_{ko}], k = 1, 2, 3$. Rewriting equation (2) as a random coefficient model:

$$\begin{aligned} \ln w_{iot} &= \overline{\gamma}_1 Exp_{it} + \overline{\gamma}_2 OT_{iot} + \overline{\gamma}_3 TT_{iot} + \eta' \widetilde{X}_{iot} + \widetilde{u}_{iot}, \\ \widetilde{u}_{iot} &= (\gamma_{1o} - \overline{\gamma}_1) Exp_{it} + (\gamma_{2o} - \overline{\gamma}_2) OT_{it} + (\gamma_{3o} - \overline{\gamma}_3) TT_{it} + \beta_o T_i^A + (1-\beta_o) T_i^M + \varepsilon_{iot}. \end{aligned} \tag{3}$$

The unobserved error term $\widetilde{u}_{iot}$ now contains an additional term capturing the occupational heterogeneity in the return to the three types of human capital accumulation.

The next section presents our benchmark least squares results. We then discuss how to get consistent estimates of (3) in the presence of endogenous selection into occupations: first, we use a sample of displaced workers and second, we outline a control function approach to model endogenous selection. Section 5.3. shows the economic significance of our results, while Section 5.4 discusses the robustness to alternative specifications.

5.1 Least Squares Results

This section discusses our benchmark least squares results; for university graduates, we estimated censored regression models to account for topcoded wages. Table 8 reports results for the whole sample and the sample of firm switchers. The first specification (odd columns) displays results from a wage regression that ignores task-specific human capital, while even columns includes task tenure as an additional regressor.

The results (columns (1) to (4)) reveal several interesting patterns. Returns to task tenure are sizeable and exceed those of occupational tenure for all education groups. A second interesting result is that the returns to more specific and general human capital decline once we account for task-specific human capital. More specifically, returns to occupational tenure decline by about 33 percent, while returns to experience go down by 30 percent for high-skilled workers with 10 years of experience. This result is consistent with our view that human capital is partially transferable across occupations.

While these patterns are suggestive, least squares estimates of (3) suffer from two biases. First, individuals select into a new occupation based on the value of their task match, $\beta_o T_i^A + (1 - \beta_o) T_i^M$. The second source of bias is that individuals select into occupations based on the returns to their skills $(\gamma_{1o}, \gamma_{2o}, \gamma_{3o})$.[13]

[13] We expect the average return to experience, $\overline{\gamma}_1$, to be upward biased because worker locate better matches with time in the labor market through on-the-job search. Hence, the return to experience does not only reflect accumulation of general human capital, but also wage growth due to job search (see also Topel, 1991; Dustmann and Meghir, 2005). In contrast, the return to occupation- and task-specific human capital, $\overline{\gamma}_2$ and $\overline{\gamma}_3$, may be upward or downward biased. Workers with a good match are less likely to switch occupations, which produces a positive (partial) correlation between occupation and task tenure and the match quality. However, workers may have switched to a new occupation or moved to a distant occupation *because* they found a particularly good match with the new occupation, which implies a downward bias in the return to occupation- and task-specific human capital. Finally, workers may also move to a new and/or a distant occupation because of a higher return to human capital, which provides another reason why the (partial) bias in the return to occupation and task tenure cannot be signed.

Our first step towards eliminating these biases is to use a sample of workers who were exogenously displaced from their job due to plant closure (see Gibbons and Katz, 1991; Neal, 1995 and Dustmann and Meghir, 2005 for a similar strategy).[14] Displaced workers differ from voluntary firm switchers because they are willing to accept a new job offer if its value exceeds the value of unemployment, as opposed to the value of the old job. Hence, displaced workers lose some of their 'search capital', which reduces the first source of bias from improved matches.

The last two columns in table 8 shows that task tenure remains an important source of individual wage growth for the sample of displaced workers. The results for the low- and medium-skilled remain very stable. For the high-skilled, the return to experience declines in the displaced sample, which suggests that improvements in match quality (due to job search) are important for this group. Restricting the sample to displaced workers does, however, not solve the problem of endogenous selection into new occupations. We now outline a control function approach to get consistent estimates of the wage equation.

5.2 Control Function Estimates

To account for endogenous selection into occupations, we need to explicitly model the conditional mean of the error term in (3) (Heckman and Vytlacil, 1998). More specifically, we require that the following exclusion restriction holds:

$$E[\widetilde{u}_{iot}|X_{iot}, Z_{iot}] = 0,$$

where $X'_{iot} = [Exp_{it}\ OTen_{iot}\ TTen_{iot}\ \widetilde{X}_{iot}]$ is the vector of regressors and Z_{iot} denotes a vector of instruments. The above conditions is equivalent to

$$E[\beta_o T_i^A + (1-\beta_o) T_i^M | X_{iot}, Z_{iot}] = 0, \quad \text{and} \tag{4}$$

$$E[\gamma_{1o} - \overline{\gamma}_1 | X_{iot}, Z_{iot}] = E[\gamma_{2o} - \overline{\gamma}_2 | X_{iot}, Z_{it}] = E[\gamma_{3o} - \overline{\gamma}_3 | X_{iot}, Z_{it}] = 0. \tag{5}$$

[14] Dustmann and Meghir (2005) provide evidence that the assumption of plant closure as an exogenous job loss is reasonable in the German context.

The first exclusion restriction in (4) accounts for selection based on the task match, while the second one in (5) addresses the selection into occupations based on the occupation-specific returns to human capital.

As instruments, we require variables that affect the worker's mobility decision (i.e. whether to move to a new occupation and whether to move to a similar or distant occupation), but not his wage offer conditional on all regressors. Our main instruments for experience are age and age squared. To instrument for occupation tenure, we follow Altonji and Shakotko (1987) and Parent (2000) and use the deviation of occupation tenure from its occupation-specific mean as an instrument. This instrument is uncorrelated with the time-invariant task match, $\beta_o T_i^A + (1-\beta_o)T_i^M$, by construction.

For task tenure, we use local labor market conditions, in particular the size of occupation and the average distance to other occupations in the same local labor market, as well as both variables interacted with age, as instruments.[15] The basic idea is that workers who have more employment opportunities in their original occupation or similar occupations will be less likely to switch occupations or move to a distant occupation. Since all our specifications include occupation, region and time dummies, the variation we exploit is changes in the occupational structure over time within the same region. These changes will not affect wages if factor prices are equalized across local labor markets. Hence, our assumption requires that wages are set in a national labor market (see Adda et al., 2006 for a similar argument).

To implement the estimator, we estimate in a first step the reduced forms for experience, occupational tenure and task tenure to predict the residuals. The results are shown in Table A2 for the low- and medium-skilled and Table A3 for the high-skilled. In the second step, we estimate the log wage equation in (3) including the estimated residuals as well as their interaction with the endogenous regressors. For the high-skilled, we use the semiparametric estimator proposed by Blundell and Powell (2004) to account for censoring in addition to endogenous regressors. We describe this estimator in detail in Appendix

[15] The average distance, AD_{rt}, to other occupations is computed separately for each local labor market r and time period t as follows: $AD_{rt} = \sum_{o' \neq o}^{64} \text{Prop}_{rto'} \cdot \text{Distance}_{oo'}$). We define a region as the individual's county (*Kreis*) of residence as well as all the neighboring counties, corresponding roughly to a 50 mile radius from the individual's home.

B. To correct for generated regressor bias, we bootstrap standard errors with 100 replications using the individual as the sampling unit.

Table 9 reports the results of our control function estimates, for a sample of firm switchers (columns (1) and (2)) and a sample of displaced workers (columns (3) and (4)).[16] For the sample of firm switchers, the control function estimates yield similar returns to experience than the OLS results. The return to occupation tenure, however, decreases and even becomes negative for the low- and high-skilled. In contrast, the return to task tenure, however, increases considerably when the control function estimator is used. One explanation for this finding is that workers move to distant occupations because they are well matched with that occupation, implying a negative correlation between task tenure and the task match.

Results for the sample of displaced workers (columns (3) and (4)) are considerably more noisy. This result is not too surprising given that identification relies on workers who lose their job due to plant closure more than once.[17] Nevertheless, we find similar estimates for the low-skilled though only the return to experience is statistically significant. The effect of task tenure is considerably stronger for the medium-skilled but weaker for the small sample of high-skilled displaced workers.

Across all specifications, we find that task-human capital is an important source of individual wage growth. Furthermore, returns to general and more specific human capital decline substantially once we account for task human capital.

5.3 Economic Interpretation

How important then is task-specific human capital for individual wage growth over the life-cycle? The least squares results for the displaced sample imply that a high-skilled worker can expect his wages to grow by 36% due to human capital accumulation over the first ten years in the labor market (table 8, column (6)). Task-specific human capital contributes 40 percent (0.023*6.19/0.36) to this wage growth,

[16] The coefficients on the residuals and their interaction with the main regressors can be found in Table A4. Both the residuals and the residuals interacted with the regressors enter the wage equation significantly, indicating that selection into occupations based on the task match and occupation-specific returns is important.

[17] The reason is that for workers who experienced only one plant closure our instrument for occupation tenure, i.e. the deviation from its occupation-specific mean, is zero.

experience 46 percent ((0.037*6.81-0.002*6.81^2)//0.36) and occupation-specific human capital only 14 percent (0.01*4.95/0.36).[18] A similar calculation for the medium- and low-skilled implies that task-specific human capital accounts for at least 35 and 25 percent of overall wage growth, respectively. These calculations demonstrate that task-human capital is an important source of wage growth over the labor market career.

More generally, our results suggest that most human capital is quite portable and at least partially transferable across occupations. This result is important for evaluating the costs of job displacement, for example following technological change or economic restructuring more generally.

As an illustration, consider again a high-skilled worker who is displaced after 10 years in his occupation. If the worker can find employment in an occupation with similar skill requirements (e.g. in the 10th percentile of the distribution of moves), his overall wage loss would be 12.3 percent. Most of this decline is due to the loss of occupation-specific skills while few task-specific human capital is lost. However, if the worker cannot find employment in a similar occupation (e.g. in the 90th percentile of the distribution of moves), his wage would decline by 30.1 percent.[19] The basic pattern holds for all education and experience groups.

These calculations highlight that wage losses of job displacement strongly depend on the thickness of labor markets. In particular, wage losses are higher in occupations with skill requirements that are very different from other occupations. Costs of job displacement will also be higher in an economy where information about the task content of alternative occupations is limited. In contrast, job reallocation is less costly if similar occupations and information about close substitute occupations are widely available.

[18] This calculation takes into account that after 10 years in the labor market, a high-skilled worker has accumulated 6.81 years of actual experience, 4.95 years of occupation tenure, and 6.19 years of task tenure. When we base the calculation on the control function estimates for the sample of firm switchers, task-specific human capital becomes the main source of wage growth from human capital accumulation.

[19] We again base our calculation on the least squares estimates for the displaced sample (table 8, column (6)). Note that since our calculation excludes the loss in task match quality, our wage losses are a lower bound for the true wage loss of job displacement.

5.4 Further Robustness Checks

This section discusses three extensions to our framework: worker ability, firm matches and job ladders. We address each of them in turn.

Suppose workers differ in their general ability so that the error term in wage regression (2) does not only consist of the task match, but also of a fixed worker effect. If workers who switch to distant occupations are of lower ability ('lemons'), then this could potentially explain our positive return to task-human capital in the OLS regressions. Note, however, that our control function estimates account for this bias. An alternative way to eliminate this type bias is by first differencing. As a further robustness check, we report first difference estimates for the sample of firm switchers in table 9, columns (5) and (6). Since we cannot estimate first differences for university graduates, we use Honoré's trimming estimator (1992) for censoring (Type 1 tobit model) with fixed effects instead.[20] While the first difference estimates for occupation- and task tenure are somewhat smaller than the OLS and control function estimates, task tenure remains a significant source of individual wage growth even after accounting for general worker ability.[21]

Our wage specification (3) does not incorporate job search over *firm* matches which has been shown to be an additional source of wage growth (e.g. Topel and Ward, 1991; Pavan, 2005; Yamaguchi, 2007b). How would firm matches affect our findings? Neal (1999) proposes a model in which workers search over both firm and occupation matches. He shows that it is optimal for workers to first search for a good occupation match, and then for a good firm match. For a sample of young workers like ours, he then provides empirical support for such a search strategy. Under the two-stage search strategy, our estimates will be little affected by search over firm matches. The reason is that the majority of young workers in our sample has been in the labor market for less than 8 years so their decision whether to switch occupations and to which occupation to move should be predominantly driven by the task match,

[20] Since the estimator is semiparametric, no functional form assumption on the error term is required. However, we do require pairwise exchangeability of the error terms conditional on the included regressors (see Honoré 1992 for details).

[21] Note that due to differences in the econometric model, the results for the low- and medium-skilled cannot be directly compared to those of the high-skilled. Also note that in the first difference regression, the coefficient on (the change in) experience should not be interpreted as returns to general human capital accumulation, as they additionally reflect the change in the firm and task match quality.

and not by the firm match.

What if the worker's search strategy does not follow this two-stage rule? Then firm matches provide another reason why in an OLS regression the return to task tenure may be *downward* biased because some workers may have moved to a distant occupation because of a high *firm* match, despite a low *task* match.

In addition to firm matches, we have also abstracted from occupational mobility along a job ladder (see Gibbons et al., 2005; Jovanovic and Yarkow, 1997; Yamaguchi, 2007a). Within our framework, job ladders can be modeled by relaxing the restriction that the occupation-specific weights add up to one. We would expect occupations that have a higher analytic and manual weight to be higher up the job ladder, and workers should move along the ladder as they become more experienced. While we do not explicitly analyze hierarchical occupation mobility in this paper, our control function estimates is consistent even in the presence of career mobility. This is because the validity our instruments, in particular the deviation of occupation tenure from its occupation-specific mean, does not rely on the assumption that the occupation-specific weights add up to one.

6 Conclusion

How general is human capital? The evidence in this article demonstrates that specific skills are more portable than previously considered. We show that workers are much more likely to move to occupations that require similar skills and that the distance of occupational moves declines over the life-cycle. Furthermore, wages and occupation tenure at the source occupation have a stronger impact on current wages if workers switch to a similar occupation.

The evidence also suggests that task-specific human capital is an important source of individual wage growth, in particular for university graduates. For them, at least 40 percent of wage growth due to human capital accumulation can be attributed to task-specific human capital, while occupation-specific skills and experience account for 14 and 47 percent respectively. For the medium-skilled (low-skilled), at least 25 (35) percent of individual wage growth is due to task-specific human capital. We also provide evidence that the costs of displacement and job reallocation depend on the employment opportunities after displacement: Wage losses are lower if individuals are able to find employment in an occupation with similar skill requirements.

Our findings on both mobility patterns and wage effects are strongest for the high-skilled, suggesting that task-specific skills are especially important for this education group. One explanation for this pattern is that formal education and task-specific human capital are complements in production. Complementarity implies that high-skilled workers accumulate more task human capital on the job which would account for the sharp decline in the distance of moves over the life cycle. It would also explain why wages in the previous occupation are less valuable in the new occupation and why returns to task human capital are higher than for the two other education groups.

The results in this paper are difficult to reconcile with a standard human capital model with fully general or firm- (or occupation-) specific skills. Our findings also contradict search models where the current occupation has no effect on future occupational choices, and skills are not transferable across occupations. The findings however support a task-based approach to modeling labor market skills in which workers can transfer specific human capital across occupations.

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A Data Sources

A.1 Data on Occupational Tasks (1979-1999)

We use four cross-sections of the *German Qualification and Career Survey* conducted in 1979, 1985, 1991/92 and 1998/99 by the Federal Institute of Vocational Training (BIBB) and the Institute for Labor Market Research (IAB). The data with a sample size of 30,000 covers individuals between 16 and 65, who are employed at the time of the survey. We restrict our sample to men employed in West Germany and exclude the self-employed, civil servants and those working in agriculture. We also exclude those without German nationality since they were not included in each wave. We use the same 64 occupations based on a classification system by the Federal Employment Office, which is standardized over time. The aggregation at the 2-digit level decreases well-known measurement error problems of occupational classifications in survey data and allows us to match the data to our main data set on job histories.

For each respondent, we know whether the worker performs certain tasks in his job and whether this is his main activity on the job. Unlike the Dictionary of Occupational Titles (DOT) in the United States, we do not know how intensively a particular task is used beyond the distinction of main activity, task performed and not performed. Overall, we have information on 19 different tasks workers perform in their jobs. Following Autor et al. (2003), we group the 19 tasks into three groups of tasks: analytical tasks, manual tasks and interactive tasks. The assignment of tasks is as follows: manual tasks (equip or operate machines, repair, reconstruct or renovate, cultivate, manufacture, cleaning, serve or accommodate, construct or install, pack or ship or transport, secure, nurse or treat others), analytical tasks (research or evaluate or measure, design or plan or sketch, correct texts or data, bookkeeping or calculate, program, execute laws or interpret rules) and interactive tasks (sell or buy or advertise, teach or train others, publish or present or entertain, employ or manage personnel or organize or coordinate).

A.2 Employee Sample (1975-2001)

Our main data set is a two percent sample of all German social security records administered by the Institute for Employment Research. By law, employers are required to report the exact beginning and end of any employment relation of new hires and employees leaving the firm which are subject to social security contributions. In addition, employers provide information about all their employees at the end of each year. We therefore know the exact date of employer changes and movements into and out of paid employment. Another advantage is that the data contain an unusually in-depth set of background information for each individual, including his age, education, gender, nationality, plant of work and occupation. We distinguish three education levels: low-, medium-, and high-skilled. We define a worker to be high-skilled if at least one spell classifies him as a graduate from a university or technical college. (*Fachhochschule*). A worker is medium-skilled if he spent at least 450 days in apprenticeship training, and no spell classifies him as a college graduate. A worker is low-skilled if he spent less than 450 days in apprenticeship training and did not attend a technical college or university. The occupational categories of employees and apprentices in the social security records are highly accurate as the classification forms the basis of wage agreements between unions and employers' association. To make the 130 different occupations we observe in our sample comparable to the BIBB data, we aggregated them into 64 occupations at the 2-digit level using a code provided to us by the Institute for Employment Research. All experience and tenure variables refer to the beginning of each spell. Time out of the labor force and time in unemployment as well time in apprenticeship training is not counted. If an employee returns to his occupation, we count the time spent in the earlier spell towards his occupational tenure. The same holds in the unlikely event that a worker returns to a firm he has worked for previously. Our results on occupational movers exclude these return movers, but the estimates are similar if they are included.

In addition to the sample restrictions mentioned in the text, we dropped all spells in vocational training and those job spells that started prior to an apprenticeship or tertiary education. In addition, we excluded observations that were still in vocational training at the end of the sample period in 2001 or pursued more than one apprenticeship, that is were employed as an apprentice for more than 7 years. We also require a person to be below a certain age when we first observe them. This ensures that we can follow them from day one of their entry into the labor market. The age restriction is 19 if the individual has no high school degree (*Abitur*), 22 if the individual has a high school degree, but no higher degree, 28 if the individual graduated from a community college (*Fachhochschule*), and 30 if he graduated from university. Finally, we drop all observations we observe less than a year, with missing education or nationality, and observations with no valid wage or a daily (real) wage below 20 DM during an employment spell. To estimate the returns to different types of human capital in Section 5, we use a sample of displaced workers. A worker is displaced from his firm due to plant closure if he left the firm in the year or one year before the firm closed down. As a robustness check, we have repeated the analysis restricting the sample to workers who have left the firm in the year or *one or two* year before the firm closed down. The first definition has the advantage that it includes less workers who have left the firm voluntarily, for reasons other than plant closure. It has the disadvantage that it may exclude workers that leave the firm prior to plant closure, anticipating that the firm may shut down in the future. Both definitions give very similar results.

B Blundell and Powell (2004) Control Variable Estimator

For the high-skilled, the control variable estimates in Table 9, columns (1) to (4) are based on the semiparametric estimator proposed by Blundell and Powell (2004). This estimator accounts for censoring in addition to endogenous regressors. It does so however at the price of imposing common returns on the observable human capital variables. For simplicity, we drop the subscript o. The model is

$$\ln W_{it} = min\{X_{it}\beta + u_{it}, c_t\}$$

where X_{it} are the endogenous regressors, u_{it} is the scalar error term and c_t is the time-dependent censoring point. For notational convenience, we suppress all exogenous regressors here. The reduced form links the instruments Z_{it} to the endogenous regressors:

$$X_{it} = Z_{it}\gamma + v_{it}$$

where v_{it} is a scalar error term and γ the unknown coefficient vector with suitable dimensions. Instead of imposing independence between (u_{it}, v_{it}) and Z_{it}, the estimator imposes a weaker conditional quantile exclusion restriction

$$F_u(q|X_{it}, Z_{it}) \equiv Pr\{u_{it} \leq q|X_{it}, Z_{it}\} = Pr\{u_{it} \leq q|v_{it}\} = F_u(q|v_{it}) \qquad q \in R$$

This assumption implies that the dependence of the regressors X_{iot} and the error term u_{it} is driven by the residuals v_{it} (control variable). To consistently estimate the reduced-form above, we also require that $E[v_{it}|Z_{it}] = 0$. The estimation then proceeds as follows: first, we predict $\widehat{v_{it}}$ from regressions of the endogenous regressors on the instruments and other control variables. Then, we estimate a quantile regression of the dependent variables on both the endogenous regressors and the instruments as well as the control variables to obtain the fitted values $\widehat{\ln W_{it}}$. The second step is to estimate a weighted least squares regression of all pairwise differences of the predicted dependent variable $\widehat{\ln W_{it}}$ on the endogenous regressors X_{it}. The weights are the pairwise differences of the residuals $\widehat{v_{it}}$, which are used as inputs into a multivariate kernel function. Formally, the second-stage estimator is defined as

$$\begin{aligned} \widehat{\beta} \;=\; & \left[\sum_{s<t}\sum_{i<j} K_v\left(\frac{\widehat{v_{is}} - \widehat{v_{jt}}}{h_n}\right)\widehat{t_{is}}\widehat{t_{jt}}(X_{is} - X_{jt})'(X_{is} - X_{jt})\right]^{-1} \times \\ & \left[\sum_{s<t}\sum_{i<j} K_v\left(\frac{\widehat{v_{is}} - \widehat{v_{jt}}}{h_n}\right)\widehat{t_{is}}\widehat{t_{jt}}(X_{is} - X_{jt})'(\widehat{\ln W}_{is} - \widehat{\ln W}_{jt})\right] \end{aligned}$$

where $K_v(\cdot)$ is the kernel function and h_n is a sequence of scalar bandwidth terms. $\widehat{t_{is}}$ is a "trimming" term, constructed so that $\widehat{t_{is}} = 0$ unless the estimated quantiles $\widehat{\ln W}_{is} > 0$ and X_{is} and v_{is} fall in some compact set S. We used the product epanechnikov kernel and a separate bandwidth h_n for each endogenous variable. Standard errors are bootstrapped using 100 replications.

Table 1: Summary Statistics of Task Data

	Mean	Std.Dev	Example: Teacher	Example: Baker
Analytical Tasks	55.02	49.75	63.73%	32.42%
Research, evaluate or measure	25.11	43.37	34.02%	13.56%
Design, plan or sketch	10.21	30.28	17.62%	3.60%
Correct texts or data	23.85	42.62	39.64%	6.36%
Calculate or bookkeeping	26.02	43.87	11.34%	22.46%
Program	8.35	27.66	8.43%	0.42%
Execute laws or interpret rules	7.85	26.89	17.24%	0.85%
Analytical is Main Task	31.56	46.48	15.93%	13.14%
Manual Tasks	72.42	44.69	25.59%	96.40%
Equip or operate machines	19.98	39.99	7.03%	27.12%
Repair, renovate or reconstruct	31.38	46.40	8.15%	10.38%
Cultivate	1.77	13.19	2.25%	1.91%
Manufacture, install or construct	11.97	32.46	1.97%	87.92%
Cleaning	3.50	18.38	1.78%	6.14%
Serve or accommodate	1.21	10.92	0.28%	3.60%
Pack, ship or transport	18.76	39.04	2.72%	15.25%
Secure	15.72	36.40	7.22%	18.01%
Nurse or treat others	9.76	29.67	11.53%	7.84%
Manual is Main Task	57.46	49.44	10.50%	88.77%
Interactive Tasks	48.48	49.98	95.31%	44.07%
Sell, buy or advertise	29.21	45.48	12.00%	16.53%
Teach or train others	17.15	37.69	91.38%	34.32%
Publish, present or entertain others	9.58	29.43	26.24%	3.81%
Employ, manage personnel, organize, coord	37.09	48.31	39.36%	29.87%
Interactive is Main Task	27.55	44.68	85.94%	14.83%
Observations	52,718		1,067	472

Notes : The table reports the percentage of individuals in the career survey that report performing the type of task in their job. We grouped the 19 different tasks into three task groups (analytical, manual and interactive skills) following Autor et al. (2003) and Spitz (2006). The fraction for main tasks sum to more than 100 percent as around 10 percent reported performing more than one main task. The last two columns show the distribution of task usage for two common occupations: teachers (which exclude university or technical college professors) and baker.

Source : Qualification and Career Survey: 1979, 1985, 1991/2, 1997/8

Table 2: Measuring Distances between Occupations

Distance Measure (Angular separation)		
Occupation 1	Occupation 2	Distance
Mean		0.244
Standard Deviation		0.221
Most Similar (all Education Groups)		
Paper and Pulp Processing	Printer, Typesetter	0.002
Wood Processing	Metal Polisher	0.003
Chemical Processing	Plastics Processing	0.004
Most Distant (all Education Groups)		
Banker	Unskilled Construction Worker	0.939
Banker	Miner, Stone-Breakers	0.935
Publicists, Journalist	Unskilled Construction Worker	0.933
Most Common Occupational Moves (Low-Skilled)		
Truck Driver, Conductor	Store or Warehouse Keeper	0.029
Unskilled Worker	Store or Warehouse Keeper	0.267
Assembler	Store or Warehouse Keeper	0.372
Most Common Occupational Moves (Medium-Skilled)		
Chemist, Physicist	Electricians, Electrical Installation	0.171
Sales Personnel	Office Clerk	0.077
Truck Driver, Conductor	Store or Warehouse Keeper	0.028
Most Common Occupational Moves (High-Skilled)		
Engineers	Chemist, Physicist	0.037
Entrepreneurs	Office Clerk	0.048
Accountant	Office Clerk	0.080

Notes : The table shows at the top summary statistics of the distance measure as well as the three most similar and distant occupations and their corresponding distance. The distance measure is the angular separation using the 19 different tasks (see Table B1 for a list of tasks) and normalized to vary between 0 and 1. The bottom part of the table shows the three most commonly observed moves in the data by education group and the corresponding distance measure.

Table 3: Summary Statistics of West German Employee Panel

	Low Skill	Medium Skill	High Skill
Percentage in Sample	16.27%	68.30%	15.43%
Age (in Years)	25.82	27.47	31.85
	(6.26)	(5.24)	(5.60)
Not German Citizen	0.32	0.052	0.047
	(0.47)	(0.22)	(0.21)
Median Daily Wage	114.39	135.32	204.23
	(45.44)	(43.52)	(61.43)
Log Daily Wage	4.66	4.89	5.19
	(0.45)	(0.33)	(0.43)
Percentage censored	0.01	0.02	0.24
	(0.10)	(0.14)	(0.43)
Actual Experience (in Years)	5.76	5.59	5.25
	(5.40)	(4.76)	(4.81)
Occupational Tenure (in Years)	3.28	3.87	3.62
	(4.27)	(4.12)	(4.07)
Firm Tenure (in Years)	2.47	2.79	2.46
	(3.87)	(3.66)	(3.33)
Task Tenure (in Years)	4.58	4.81	4.66
	(4.65)	(4.28)	(4.38)
Occupational Mobility	0.186	0.114	0.109
	(0.389)	(0.317)	(0.311)
Distance of Move	0.054	0.0525	0.0441
	(0.025)	(0.025)	(0.024)
Firm Mobility	0.236	0.18	0.18
	(0.425)	(0.384)	(0.384)
Most Common Occupations	Warehouse Keeper (10%)	Electrical Installation (7%)	Engineer (25%)
	Assembler (7%)	Locksmith (8%)	Technician (12%)
	Conductor (6%)	Mechanic, Machinist (6%)	Accountant (9%)
	Unskilled Worker (4%)	Office Clerk (7%)	Office Clerk (8%)
	Office Clerk (4%)	Conductor (5%)	Researcher, Clergymen (5%)
Number of Observations	223,399	1,000,934	197,420
Number of Individuals	18,604	78,101	17,648

Notes : The table reports summary statistics for the administrative panel data on individual labor market histories and wages from 1975 to 2001. Low skilled workers are those without a vocational degree, medium skilled have either a high school or vocational degree and the high skilled have an advanced degree from a technical college or university. Experience, occupation, task and firm tenure are measured from actual spells and exclude periods of unemployment or out of the labor force. The wage is measured in German Marks at 1995 prices and is subject to right censoring.

Source : Employee Sample (IAB), 1975-2001

Table 4: Observed Moves are More Similar than under Random Mobility

	Random Mobility	Observed Mobility
Mean	0.466	0.409
10th Percentile	0.083	0.047
25th Percentile	0.267	0.122
50th Percentile	0.507	0.381
75th Percentile	0.668	0.595
90th Percentile	0.776	0.682

Notes: The table repports selected moments of the distribution of observed occupational moves ("Observed Mobility") and compares it against what we would expect to observe under random mobility ("Random Mobility"). We calculate random mobility as follows: for each mover, we assume that the probability of going to any other occupation in the data is solely determined by the relative size of the target occupation. We then multiply this "random move" with its distance to get the distribution of the distance measure under random mobility. The distance measure is the angular separation, based on 19 tasks. Since all moments of the observed distribution are below those under random mobility, individuals are much more likely to move to similar occupation.

Table 5: Distance of Move Declines with Time in the Labor Market

	Low-Skilled			Medium-Skilled			High-Skilled		
Y: Distance of Move	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Experience	-0.005	-0.005	-0.004	-0.003	-0.003	-0.003	-0.016	-0.015	-0.017
	(0.001)**	(0.001)**	(0.002)**	(0.000)**	(0.000)**	(0.001)**	(0.001)**	(0.001)**	(0.003)**
Experience Squared	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.001	0.001
	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**
Occupation Tenure		-0.003	-0.002		0.000	0.002		-0.003	0.000
		(0.001)**	(0.001)*		0.000	(0.000)**		(0.001)**	-0.001
Constant	0.382	0.385	0.377	0.391	0.391	0.346	0.397	0.399	0.258
	(0.012)**	(0.012)**	(0.018)**	(0.015)**	(0.015)**	(0.022)**	(0.046)**	(0.045)**	(0.062)**
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual Fixed Effects	No	No	Yes	No	No	Yes	No	No	Yes
Observations	44,149	44,149	44,149	117,206	117,206	117,206	20,947	20,947	20,947
Mean Distance of Move	0.2757	0.276	0.276	0.243	0.243	0.243	0.185	0.185	0.185
	(0.2255)	(0.226)	(0.226)	(0.220)	(0.220)	(0.220)	(0.202)	(0.202)	(0.202)

Notes: The table reports results from a regression where the dependent variable is the distance between two occupations. The distance measure is the angular separation, based on 19 tasks. The sample consists of all occupational movers and results are reported separately by education group. Column (1) only includes experience and experience squared. Column (2) adds occupation tenure. Column (3) includes fixed worker effects to control for individual unobserved heterogeneity. All specifications include year and occupation dummies. Robust standard errors clustered at the individual level are reported in parentheses. Coefficients with * are statistically significant at the 5 percent level, those with ** at the 1 percent level.

Table 6: Similar Moves and the Correlation of Wages Across Jobs

	Low-Skilled			Medium-Skilled			High-Skilled		
Y: Log Daily Wage after Move	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Wage Last Period	0.783	0.220	0.252	0.787	0.328	0.381	0.890	0.296	0.351
	(0.004)**	(0.007)**	(0.010)**	(0.002)**	(0.004)**	(0.006)**	(0.005)**	(0.010)**	(0.011)**
Wage Last Period*Distance			-0.127			-0.243			-0.354
			(0.023)**			(0.015)**			(0.032)**
Distance of Move			0.495			1.040			1.481
			(0.101)**			(0.069)**			(0.152)**
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	158,808	44,137	44,137	802,197	117,204	117,204	158,416	18,285	18,285

Notes : The table reports results from wage regressions where the dependent variable is the log daily wages at the target occupation after an occupational move. Results are reported separately by education group. For the low- and medium-skilled, we estimate OLS models. Standard errors in parentheses allow for clustering at the individual level. For the high-skilled, we estimate tobit models, and exclude censored observations at the previous occupation. Standard errors in parentheses are bootstrapped with 100 replications to allow for clustering at the individual level. All specifications include the log daily wage in the last period, actual experience, actual experience squared, year and occupation dummies. Column (1) uses the sample of occupational stayers as a benchmark for comparison. Column (2) repeats the analysis for occupational movers, while Column (3) adds the distance measure as well as the distance measure interacted with the wage last period. The distance measure used is the angular separation based on all 19 tasks. Coefficients with * are statistically significant at the 5 percent level, those with ** at the 1 percent level.

Table 7: Past Occupational Tenure Matters for Wages

	Low-Skilled		Medium-Skilled		High-Skilled	
Y: Log Daily Wage after Move	(1)	(2)	(1)	(2)	(1)	(2)
Past Occupational Tenure	0.015	0.018	0.013	0.016	0.015	0.023
	(0.001)**	(0.001)**	(0.0005)**	(0.0006)**	(0.002)**	(0.002)**
Past Tenure *Distance		-0.018		-0.022		-0.072
		(0.003)**		(0.002)**		(0.006)**
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Occupational Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	44,149	44,149	117,206	117,206	20,947	20,947

Notes: The table reports wage regressions where the dependent variable is the log wages in the target occupation after an occupational move. Estimates are reported for each education group separately. For the low- and medium-skilled, we report results from OLS regressions. Standard errors in parentheses allow for clustering at the individual level. For the high-skilled, we estimate tobit models. Here, standard errors in parentheses are bootstrapped with 100 replications to account for clustering at the individual level. Column (1) in each specification controls for past tenure in the source occupation, experience, experience squared, as well as year and occupation dummies. Column (2) additionally includes the distance measure interacted with past occupational tenure. The distance measure used is the angular separation based on all 19 tasks. Coefficients with * are statistically significant at the 5 percent level, those with ** at the 1 percent level.

Table 8: Returns to Labor Market Skills: Least Squares

	Whole Sample		Firm Switchers		Displaced Workers	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Low-Skilled						
Task Tenure		0.012		0.024		0.020
		(0.001)***		(0.001)***		(0.003)***
Occupational Tenure	0.009	0.007	0.021	0.020	0.016	0.014
	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.002)***	(0.002)***
Experience	0.062	0.054	0.047	0.032	0.044	0.031
	(0.001)***	(0.001)***	(0.001)***	(0.002)***	(0.004)***	(0.004)***
Experience Squared	-0.002	-0.002	-0.002	-0.002	-0.001	-0.001
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Firm Tenure	0.008	0.007				
	(0.001)***	(0.001)***				
Observations	202,327	202,327	56,831	56,831	5,891	5,891
R Squared	0.370	0.370	0.250	0.250	0.300	0.310
Panel B: Medium-Skilled						
Task Tenure		0.009		0.018		0.012
		(0.0005)***		(0.001)***		(0.002)***
Occupational Tenure	0.007	0.005	0.016	0.014	0.015	0.013
	(0.000)***	(0.0003)***	(0.000)***	(0.000)***	(0.001)***	(0.001)***
Experience	0.040	0.034	0.038	0.026	0.036	0.028
	(0.000)***	(0.0006)***	(0.001)***	(0.001)***	(0.002)***	(0.002)***
Experience Squared	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.000)***	(0.0000)***	(0.000)***	(0.000)***	(0.001)***	(0.001)***
Firm Tenure	0.008	0.007				
	(0.000)***	(0.0002)***				
Observations	918,366	918,366	188,383	188,383	21,286	21,286
R Squared	0.350	0.350	0.260	0.260	0.270	0.270
Panel C: High-Skilled						
Task Tenure		0.021		0.025		0.023
		(0.001)***		(0.001)***		(0.005)***
Occupational Tenure	0.006	0.004	0.012	0.010	0.012	0.010
	(0.000)***	(0.000)***	(0.001)***	(0.001)***	(0.003)***	(0.003)***
Experience	0.082	0.065	0.066	0.047	0.054	0.037
	(0.001)***	(0.001)***	(0.001)***	(0.002)***	(0.005)***	(0.006)***
Experience Squared	-0.003	-0.003	-0.003	-0.002	-0.002	-0.002
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Firm Tenure	0.009	0.007				
	(0.000)***	(0.000)***				
Observations	196,900	196,900	35,072	35,072	3,533	3,533
Log-Likelihood	-93460.3	-93134.0	-14300.1	-14152.7	-933.6	-921.6

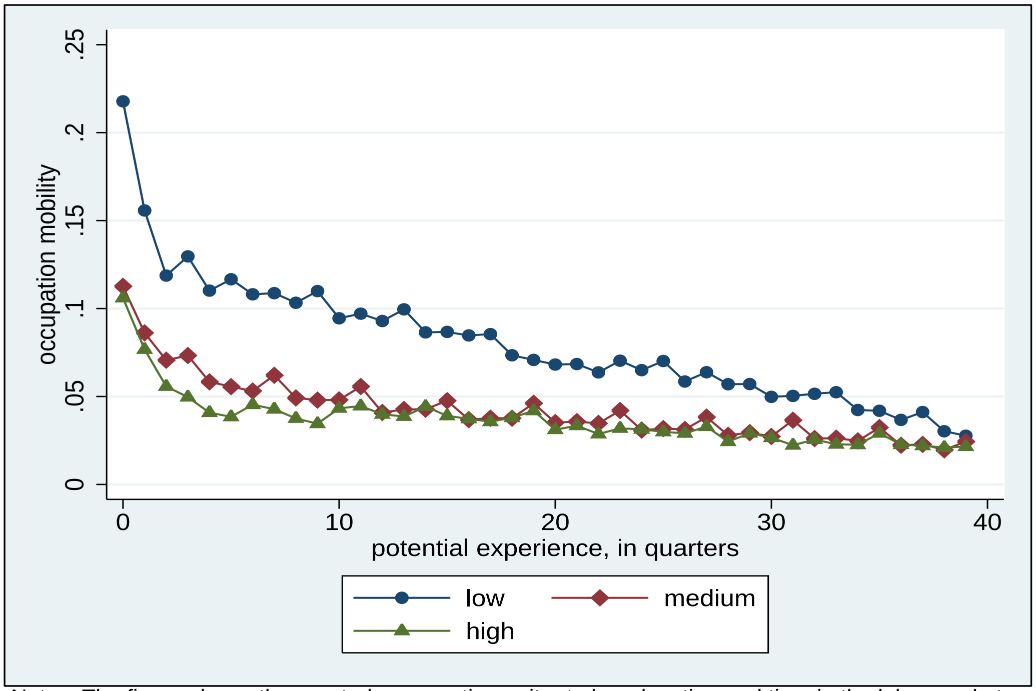
Notes: The table reports results from a regression of the log daily wage on general human capital (experience, experience squared), firm tenure, occupation and task tenure. All specifications include year, region and occupation dummies. Panel C estimates tobit models to account for censoring. Specifications in columns (2), (4) and (6) add our measure of task tenure to the specification in columns (1), (3) and (5). Columns (1)-(2) are estimated for the whole sample, columns (3)-(4) on those who have switched firms and columns (5)-(6) on our sample of displaced workers. Standard errors allow for clustering at the individual level. For Panel C, standard errors are bootstrapped with 100 replications to account for clustering at the individual level. Coefficients with ***, **, * are significant at the 1, 5 and 10 percent level respectively.

Table 9: Returns to Labor Market Skills: Control Function

	Control Function Firm Switchers		Control Function Displaced Sample		FD/FE Firm Switchers	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Low-Skilled						
Task Tenure		0.035		0.032		0.007
		(0.015)**		(0.0340)		(0.002)***
Occupational Tenure	-0.001	-0.016	0.008	-0.007	0.009	0.010
	(0.0030)	(0.005)**	(0.004)*	(0.0140)	(0.001)***	(0.001)***
Experience	0.061	0.044	0.049	0.035	0.079	0.072
	(0.002)***	(0.018)**	(0.003)***	(0.019)*	(0.009)***	(0.009)***
Experience Squared	-0.002	-0.002	-0.002	-0.002	-0.006	-0.006
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Observations	56,943	56,943	7,976	7,976	56,814	56,814
R Squared	0.31	0.32	0.35	0.36	0.060	0.060
Panel B: Medium-Skilled						
Task Tenure		0.027		0.081		0.007
		(0.007)***		(0.018)***		(0.001)***
Occupational Tenure	0.011	-0.002	0.006	-0.027	0.008	0.009
	(0.001)***	(0.0030)	(0.001)***	(0.009)***	(0.000)***	(0.000)***
Experience	0.04	0.029	0.04	0.02	-0.010	-0.018
	(0.001)***	(0.003)***	(0.001)***	(0.009)*	(0.003)***	(0.003)***
Experience Squared	-0.001	-0.001	-0.001	-0.001	-0.002	-0.002
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Observations	189,435	189,435	28,137	28,137	188,381	188,381
R Squared	0.31	0.32	0.32	0.32	0.040	0.040
Panel C: High-Skilled						
Task Tenure		0.068		0.009		0.053
		(0.029)***		(0.0100)		(0.003)***
Occupational Tenure	-0.014	-0.037	-0.004	-0.010	0.006	-0.006
	(0.002)***	(0.010)***	(0.001)***	(0.028)	(0.000)**	(0.001)***
Experience	0.127	0.091	0.109	0.126	0.082	0.033
	(0.002)***	(0.022)***	(0.003)***	(0.017)***	(0.001)**	(0.002)***
Experience Squared	-0.007	-0.008	-0.006	-0.008	-0.003	-0.003
	(0.000)***	(0.000)***	(0.000)***	(0.001)***	(0.000)**	(0.000)***
Observations	30,376	30,376	3,065	3,065	35,072	35,072

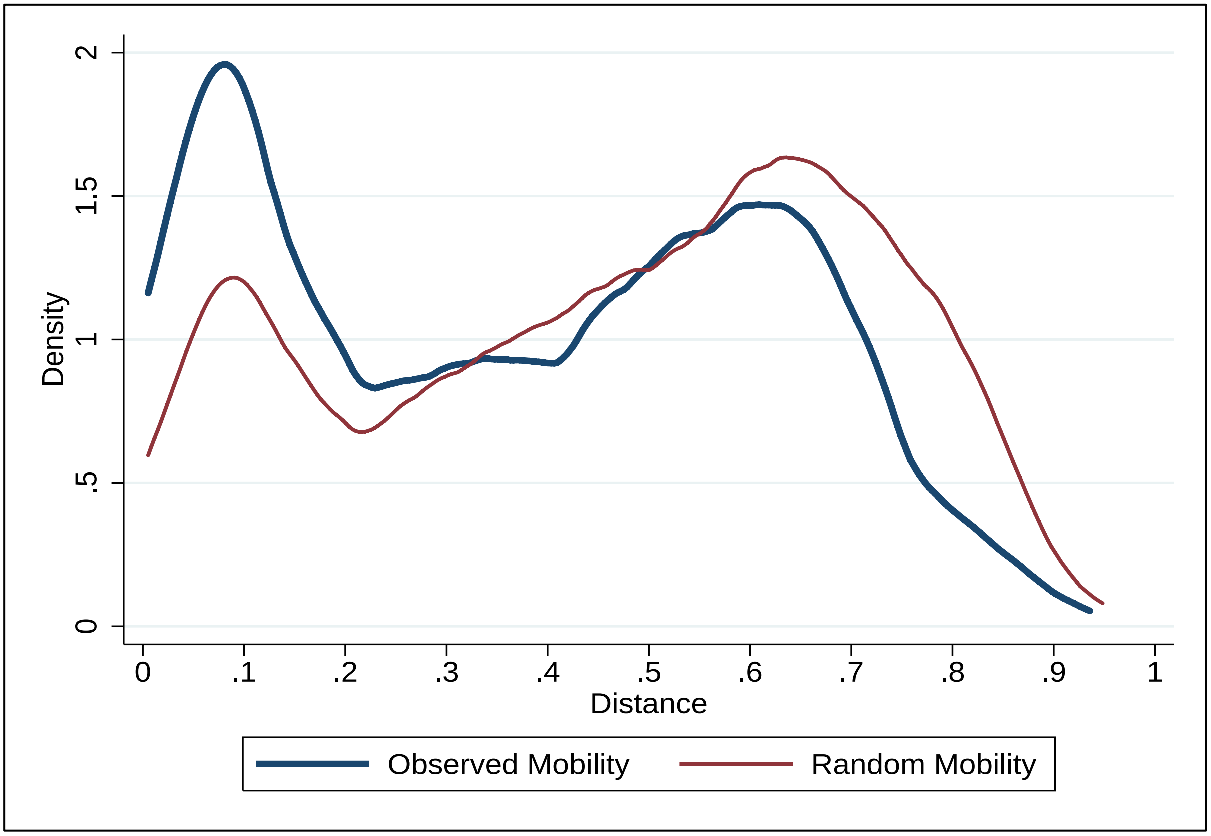
Note: For the medium- and low-skilled (Panel A and B), columns (1) to (4) report the control function estimates for those who have switched firms (columns (1) and (2)) and our sample of displaced workers (columns (3) and (4)). Columns (5) and (6) report first difference estimates using the sample of firm switchers. For the high-skilled (Panel C), columns (1) to (4) report a semiparametric estimator proposed by Blundell and Powell (2004) to account for censoring in addition to endogenous regressors. Columns (5) and (6) show fixed effects estimates using Honore's semiparametric trimming procedure for tobit models. In all specifications, standard errors are bootstrapped with 100 replications and allow for clustering at the individual level. All specifications include year, region and occupation dummies. Note that due to differences in the econometric model, results of the high-skilled are not directly comparable to those of the other two education groups. Coefficients with ***, **, * are significant at the 1, 5 and 10 percent level.

Figure 1: Quarterly Occupation Quit Rate by Time in the Labor Market



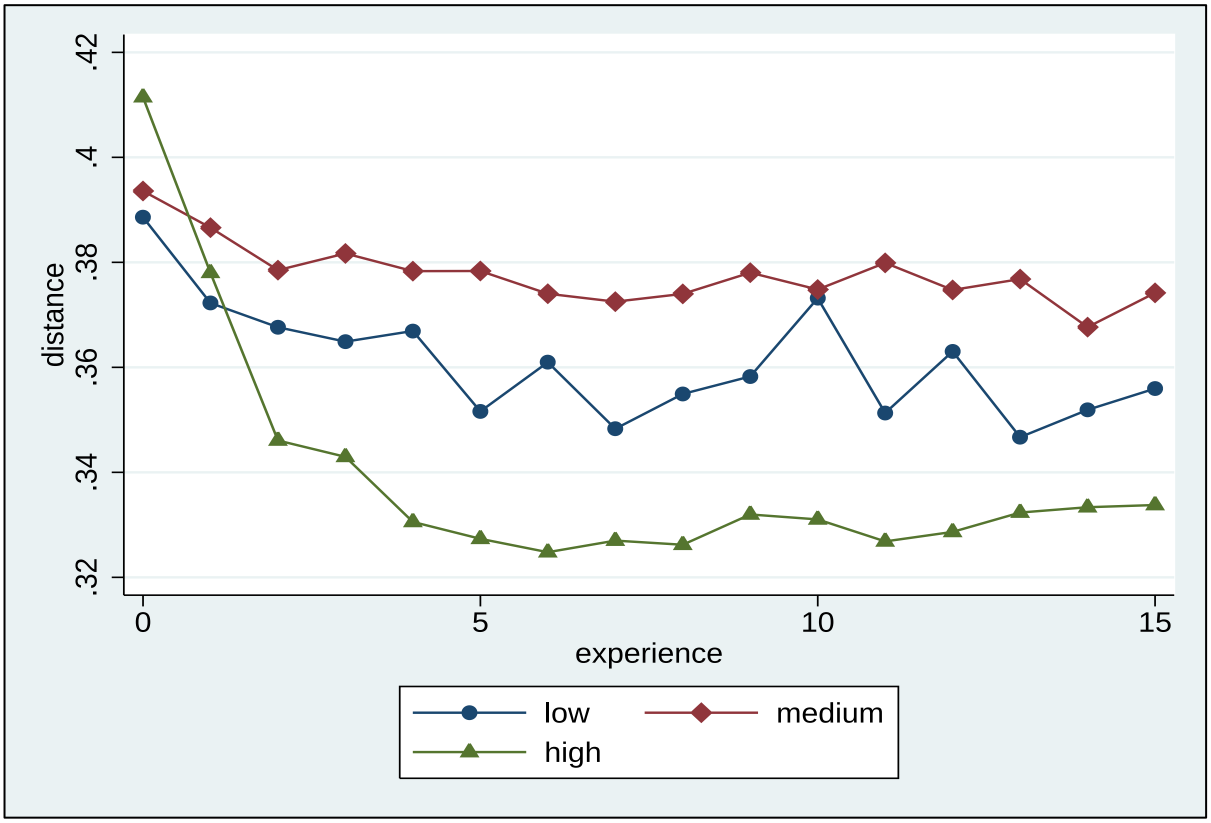
Notes: The figure shows the quarterly occupation quit rate by education and time in the labor market (potential experience). Quit rates are defined over the sample of workers who are employed at the beginning of the quarter.

Figure 2: Observed Mobility is More Similar Than Random Mobility



Notes: The figure plots the density of the distance measure under observed and random mobility. We calculate random mobility as follows: for each mover, we assume that the probability of going to any other occupation in the data is solely determined by the relative size of the target occupation. We then multiply this "random move" with its distance to get the distribution of the distance measure under random mobility. Distance measure: angular separation, 19 tasks.

Figure 3: Distance of Occupational Moves Declines over Career



Notes: The figure plots the average distance of the occupational move by actual experience. Regressions control for 15 experience dummies, occupation dummies, and time dummies. The decline in the average distance by experience is significant at a 1 % level for all education groups. Distance measure: angular separation based on 19 tasks.

Figure 4a: Correlation of Wages by Distance of Move

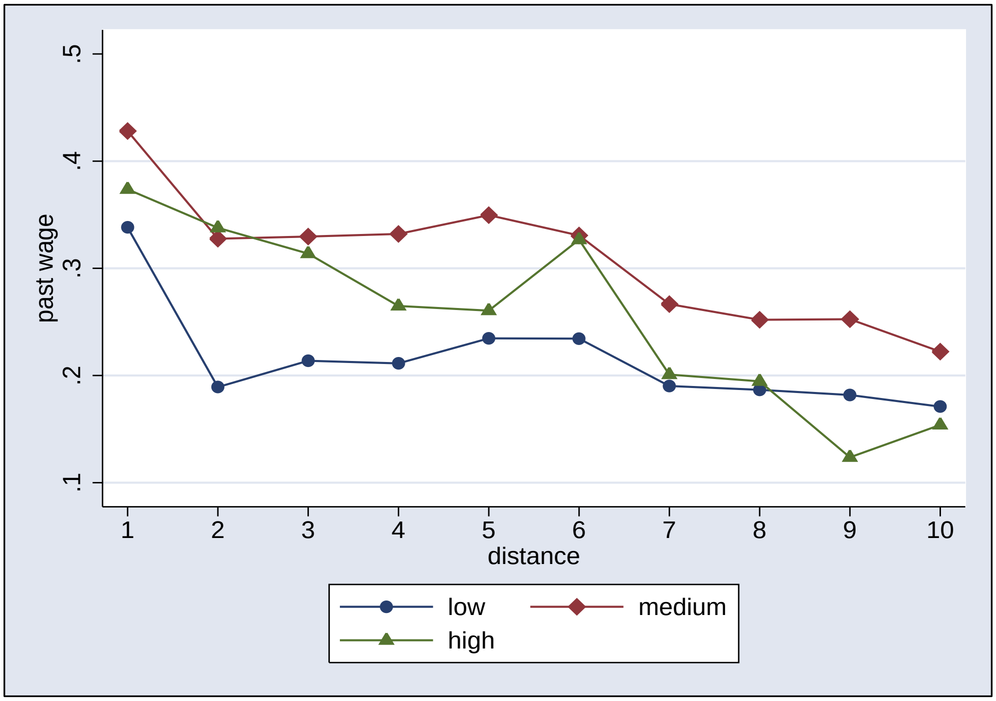
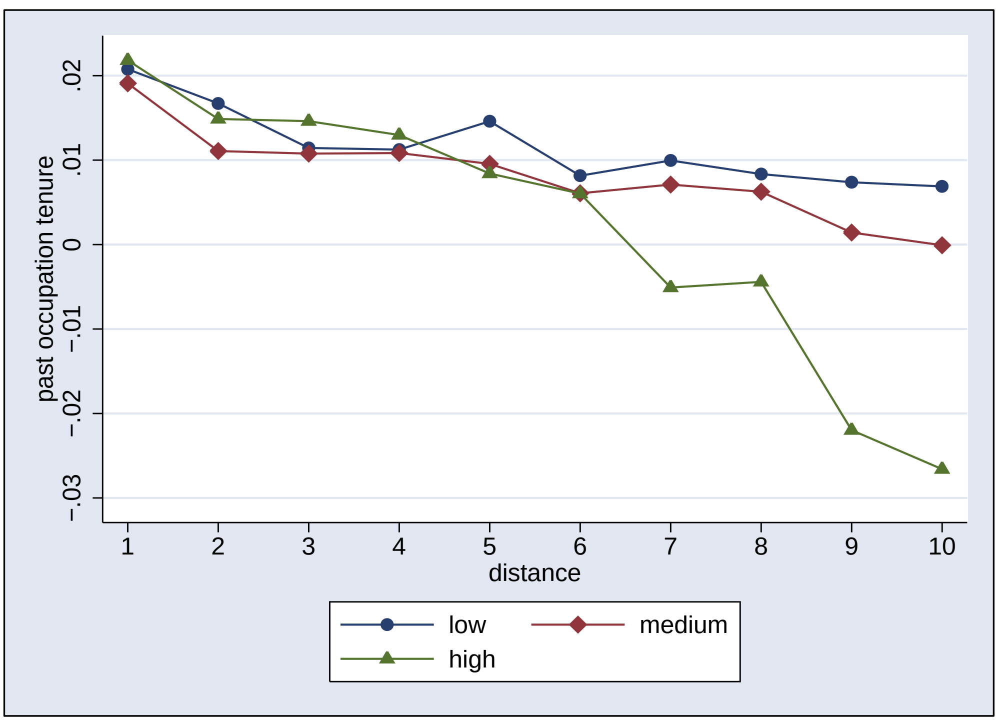


Figure 4b: Impact of Past Occupational Tenure by Distance of Move



Notes: The upper panel plots the impact of the past wage on the current wage by the distance of the occupational move. Regressions control for occupation and time dummies, past wages, ten distance dummies as well as the past wage interacted with the 10 distance dummies. The lower panel plots the impact of past occupation tenure on current wages by the distance of the occupational move. Regressions control for occupation and time dummies, past occupation tenure and past occupation tenure interacted with ten distance dummies.

Table A1: List of Occupations and Task Usage

Title of Occupation	Employed (%)	Manual Tasks	Analytic Tasks	Interactive Tasks
Miners, Stone-Breaker, Mineral Processing	0.91	0.975	0.256	0.280
Concrete and Cement Finishers, Stone Processing	0.36	0.995	0.363	0.365
Potter, Ceramicist, Gaffer	0.36	0.957	0.481	0.319
Chemical Processing	1.65	0.965	0.575	0.397
Plastics and Polymer Processing	1.14	0.972	0.462	0.395
Paper and Pulp Processing	0.68	0.961	0.556	0.493
Printer, Typesetter, Typographer	0.83	0.911	0.587	0.458
Wood, Lumber and Timber Processing	0.46	0.866	0.343	0.230
Metal and Iron Manufacturer	0.41	0.974	0.364	0.281
Moulding, Shaping	0.38	0.928	0.366	0.224
Metal Presser and Moulder	0.54	0.998	0.391	0.230
Metal Polisher, Sanders, Buffers, Lathe Operators	2.26	0.988	0.483	0.319
Welder, Brazing, Soldering	0.51	0.952	0.331	0.217
Blacksmith, Farrier, Forger, Plumber and Pipe Fitters	3.24	0.977	0.525	0.498
Locksmith	6.23	0.977	0.452	0.361
Mechanic, Machinist, Repairmen	4.26	0.971	0.566	0.469
Tool and Dye Maker, Instrument Mechanic	1.29	0.980	0.569	0.443
Metal Craftsmen	0.34	0.959	0.698	0.568
Electricians, Electrical Installation	5.49	0.965	0.639	0.516
Assembler	2.75	0.904	0.348	0.240
Weaver, Spinner, Knitters, Wool Trade	0.13	0.974	0.326	0.343
Tailor, Textile Worker	0.19	0.911	0.346	0.270
Shoemaker	0.22	0.906	0.316	0.483
Baker	1.00	0.963	0.396	0.500
Butcher	1.02	0.895	0.351	0.470
Cook	1.21	0.918	0.449	0.648
Beverage Production, Milk Production, Grease Processing	0.47	0.916	0.563	0.462
Bricklayer, Mason	2.52	0.933	0.335	0.373
Carpenter	1.61	0.957	0.387	0.417
Road Builder	0.79	0.915	0.292	0.309
Unskilled Construction Worker	1.24	0.893	0.167	0.168
Plasterer	1.09	0.935	0.403	0.407
Interior Decorator, Interior Designer	0.31	0.943	0.471	0.532
Joiner, Cabinet Maker	2.85	0.972	0.501	0.440
Painters	2.20	0.909	0.327	0.412
Product Tester	1.70	0.697	0.575	0.392
Unskilled Worker	1.69	0.903	0.303	0.198
Crane Driver, Crane Operator, Skinner, Machine Operator	0.91	0.982	0.466	0.366
Engineers	3.64	0.526	0.934	0.859
Chemist, Physicist,	4.46	0.717	0.883	0.807
Technical Service Personel	1.05	0.538	0.920	0.551
Sales Personnel	4.90	0.572	0.695	0.958
Banker	2.97	0.425	0.844	0.930
Traders, Trading Personnel	0.77	0.516	0.791	0.891
Truck Driver, Conductor	3.99	0.852	0.230	0.351
Sailor, Seaman, Navigator, Mariner	0.12	0.849	0.528	0.659
Mail Carrier and Handlers, Postal Clerks	0.47	0.784	0.406	0.395
Storekeeper, Warehouse Keeper	4.57	0.823	0.354	0.388
Entrepreneurs	1.64	0.510	0.885	0.973
Politicians, Member of Parliament	0.26	0.452	0.924	0.908
Accountant, Book Keeper	2.23	0.536	0.924	0.797
Office Clerk	6.21	0.432	0.823	0.785
Guards, Watchmen, Police, Security Personnel	1.08	0.809	0.575	0.620
Publicist, Journalist, Authors	0.17	0.403	0.841	0.866
Musicians	0.41	0.625	0.680	0.735
Physicians	0.51	0.850	0.642	0.708
Nurses, Dietitians, Physical Therapists	0.76	0.964	0.624	0.687
Social Worker	0.58	0.754	0.693	0.934
Teacher (except university)	0.91	0.474	0.697	0.964
Scientist, Clergymen	0.84	0.414	0.848	0.897
Personal Hygiene Technician	0.12	0.898	0.388	0.750
Waiter, Barkeeper, Innkeeper	0.64	0.919	0.352	0.737
Janitor, Home Economics, Housekeeper	0.03	0.616	0.649	0.804
Cleaning Service Workers	1.04	0.848	0.243	0.247
Mean		0.8028	0.5628	0.5464

Notes : The table shows the title of the 64 occupations, the percentage of individuals employed in it and the fraction of individuals that report performing analytical, manual and interactive tasks on their job following the classification of Autor et al (2003). For a description of the tasks underlying the three aggregate task groups, see Table B2.

Source : IAB Employee Sample, matched with Qualification and Career Survey: 1979, 1985, 1991/2, 1997/8.

Table A2: Estimates of Reduced Forms for Control Function Estimator (Table 9)

	Panel A: Low Skilled						Panel B: Medium Skilled					
	Starting New Job			Displaced Sample			Starting New Job			Displaced Sample		
	Actual Experience	Occupation Tenure	Task Tenure	Actual Experience	Occupation Tenure	Task Tenure	Actual Experience	Occupation Tenure	Task Tenure	Actual Experience	Occupation Tenure	Task Tenure
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
Age	0.047	0.099	-0.069	0.296	0.258	0.168	0.005	0.125	0.050	0.114	0.200	0.186
	(0.025)*	(0.022)***	(0.021)***	(0.072)***	(0.066)***	(0.066)**	-0.014	(0.014)***	(0.015)***	(0.037)***	(0.037)***	(0.042)***
Age Squared	0.011	0.007	0.004	0.008	0.005	0.001	0.013	0.008	0.004	0.011	0.006	0.002
	(0.000)***	(0.000)***	(0.000)***	(0.001)***	(0.001)***	(0.001)	(0.000)***	(0.000)***	(0.000)***	(0.001)***	(0.001)***	(0.001)***
Mean Distance to Other Occupations	-0.627	3.596	-1.596	2.090	4.744	-1.881	1.180	5.447	-0.606	1.028	3.882	-0.670
	(0.433)	(0.386)***	(0.364)***	(1.171)*	(1.073)***	(1.075)*	(0.235)***	(0.237)***	(0.258)**	(0.608)*	(0.622)***	(0.691)
Age*Mean Distance	0.026	-0.166	0.077	-0.083	-0.209	0.059	-0.035	-0.218	0.062	-0.037	-0.174	0.039
	(0.017)	(0.015)***	(0.014)***	(0.045)*	(0.041)***	(0.041)	(0.009)***	(0.009)***	(0.010)***	(0.023)*	(0.023)***	(0.026)
Size of Occupation	2.035	4.513	0.970	8.427	6.041	-0.317	-9.828	-6.870	2.948	-12.458	-13.680	-1.813
	(2.456)	(2.187)**	(2.065)	(7.122)	(6.524)	(6.538)	(1.238)***	(1.246)***	(1.356)**	(3.324)***	(3.399)***	(3.781)
Age*Size of Occupation	-0.079	-0.168	0.048	-0.468	-0.252	0.072	0.414	0.361	0.005	0.498	0.574	0.145
	(0.094)	(0.084)**	(0.079)	(0.267)*	(0.244)	(0.245)	(0.045)***	(0.045)***	-0.049	(0.119)***	(0.121)***	(0.135)
Deviation from Occupation Tenure	0.160	0.306	0.570	0.258	0.455	0.800	0.193	0.381	0.656	0.263	0.485	0.791
	(0.006)***	(0.006)***	(0.005)***	(0.017)***	(0.016)***	(0.016)***	(0.002)***	(0.002)***	(0.003)***	(0.006)***	(0.006)***	(0.007)***
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	56,943	56,943	56,943	7,976	7,976	7,976	189,435	189,435	189,435	28,137	28,137	28,137
R Squared	0.65	0.58	0.36	0.69	0.63	0.47	0.75	0.66	0.50	0.76	0.69	0.58

Notes: The table reports the regression results of the reduced forms for experience, occupational tenure and task tenure used to construct the control function in Table 9, for the low- and medium-skilled. All specifications are estimated on the sample of firm switchers in columns (1) to (3) and on the sample of displaced workers in columns (4) to (6). For each education group, the dependent variable is experience (columns (1) and (4)), occupational tenure (columns (2) and (5)) and task tenure (columns (3) and (6)) respectively. All specifications include occupation, year and region dummies. Coefficients with ***, **, * are significant at the 1, 5 and 10 percent level respectively. See also notes to Table 9.

Table A3: First- and Second-Stage Regression of Control Variable Estimator for Models with Censoring

	Panel C: High Skilled									
	Starting New Job					Displaced Sample				
	Actual Experience (1)	Experience Squared (2)	Occupation Tenure (3)	Task Tenure (4)	Log Wage (5)	Actual Experience (6)	Experience Squared (7)	Occupation Tenure (8)	Task Tenure (9)	Log Wage (10)
Age	-0.435	-29.961	-0.422	-0.336	0.082	-0.184	-26.754	-0.179	-0.181	0.0742
	(0.034)***	(0.577)***	(0.031)***	(0.030)***	(0.0064)***	-0.123	(2.281)***	(0.105)*	-0.111	(0.0000)***
Age Squared	0.017	0.606	0.014	0.009	-0.001	0.014	0.578	0.006	0.012	-0.0009
	(0.000)***	(0.008)***	(0.000)***	(0.000)***	(0.0001)***	(0.002)***	(0.031)***	(0.001)***	(0.002)***	(0.0000)***
Mean Distance to Other Occupations	2.120	63.892	2.339	-1.861	0.139	5.292	81.816	0.842	6.882	0.2156
	(0.675)***	(11.611)***	(0.620)***	(0.610)***	(0.119)	(2.460)**	(45.447)*	-2.099	(2.217)***	(0.0000)***
Age*Mean Distance	-0.111	-2.244	-0.094	0.101	-0.004	-0.177	-2.908	0.047	-0.202	-0.0136
	(0.021)***	(0.361)***	(0.019)***	(0.019)***	(0.004)	(0.076)**	(1.402)**	-0.065	(0.068)***	(0.0000)***
Size of Occupation	-8.088	-485.684	-8.408	5.456	0.259	10.534	111.336	-9.332	17.506	0.3309
	(3.499)**	(60.167)***	(3.211)***	(3.163)*	(0.618)	-13.753	-254.034	-11.735	-12.393	(0.0000)***
Age*Size of Occupation	0.440	17.425	0.431	-0.090	-0.002	-0.357	-4.613	0.303	-0.545	-0.0024
	(0.109)***	(1.871)***	(0.100)***	-0.098	(0.019)	-0.419	-7.738	-0.357	-0.377	(0.0000)***
Deviation from Occupation Tenure	0.284	4.109	0.443	0.819	-0.014	0.325	4.51	0.999	0.528	-0.0072
	(0.007)***	(0.118)***	(0.006)***	(0.006)***	(0.0016)***	(0.025)***	(0.463)***	(0.021)***	(0.023)***	(0.0000)***
Experience					0.0197					0.0235
					(0.0024)***					(0.0000)***
Experience Squared					-0.0014					-0.0015
					(0.0001)***					(0.0000)***
Occupational Tenure					0.01					0.0073
					(0.0011)***					(0.0000)***
Task Tenure					0.0172					0.0151
					(0.0019)***					(0.0000)***
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	34,794	34,794	34,794	34,794	34,794	3533	3533	3533	3533	3533
R Squared	0.68	0.65	0.66	0.57		0.68	0.63	0.62	0.68	

Notes : For the high-skilled, the table reports the regression of experience, occupational tenure and task tenure on the instruments in columns (7)-(9). In column (10), it reports the results of a quantile regression of the log wage on the instruments and endogenous controls. All specifications include year, occupation and region dummies. See also notes to Table 9 and the Appendix.

Table A4: Impact of Residuals on Wage Equation (Table 9)

	Panel A: Low Skilled				Panel B: Medium Skilled			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Residual Experience	-0.031	-0.044	-0.018	-0.019	-0.015	-0.031	-0.01	0.015
	(0.002)***	(0.009)***	(0.006)***	(0.035)	(0.002)***	(0.004)***	(0.002)***	(0.011)
Exp. Res.* Experience	0.003	0.008	0.004	0.005	0.004	0.007	0.003	0.005
	(0.001)***	(0.001)***	(0.001)***	(0.002)**	(0.000)***	(0.001)***	(0.001)***	(0.001)***
Exp. Res.* Experience Squared	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.005)	(0.000)	(0.000)	(0.000)**	(0.000)**	0.000	0.000
Exp. Res.* Task Tenure		(0.001)***		-0.004		-0.004		-0.004
		(0.001)***		(0.002)*		(0.001)***		(0.001)***
Exp. Res.* Occupation Tenure	-0.001	0.001	-0.001	0.002	-0.002	0.000	-0.002	0.000
	(0.001)	(0.001)	(0.001)	(0.002)	(0.000)***	(0.000)	(0.001)***	-0.001
Residual Occupation Tenure	0.066	0.063	0.039	0.041	0.039	0.024	0.032	0.054
	(0.003)***	(0.006)***	(0.005)***	(0.013)***	(0.001)***	(0.007)***	(0.003)***	(0.009)***
Occ. Res.* Experience	-0.004	-0.004	-0.002	-0.002	-0.002	0.000	-0.001	0.001
	(0.001)***	(0.001)***	(0.001)*	(0.002)	(0.000)***	(0.000)	-0.001	(0.001)
Occ. Res.* Experience Squared	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)***	(0.000)***	(0.000)**	(0.000)	(0.000)***	(0.000)	(0.000)***	0.000
Occ. Res.* Task Tenure		0.005		0.004		0.002		0.001
		(0.001)***		(0.002)**		(0.000)***		(0.001)
Occ. Res.* Occupation Tenure	-0.002	-0.003	-0.002	-0.003	-0.003	-0.004	-0.004	-0.004
	(0.000)***	(0.000)***	(0.001)***	(0.001)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Residual Task Tenure		0.018		0.000		0.032		-0.05
		(0.006)***		(0.035)		(0.003)***		(0.020)**
Task Res.* Experience		-0.003		0.001		-0.003		0.001
		(0.001)**		(0.002)		(0.001)***		(0.001)
Task Res.* Experience Squared		0.000		0.000		0.0001		0.000
		(0.000)***		(0.000)		(0.000)***		(0.000)
Task Res.* Task Tenure		0.001		-0.001		0.000		0.000
		(0.001)*		(0.001)		(0.001)		(0.001)
Task Res.* Occupation Tenure		-0.004		-0.004		-0.003		-0.002
		(0.001)***		(0.002)**		(0.000)***		(0.001)**
P value for Joint Significance	0%	0%	0%	0%	0%	0%	0%	0%

Notes: The table reports the coefficients on the residuals and their interaction with the main regressors to control for selection in Table 9. The column number in this table correspond to the column numbers (1) to (4) in Table 9. Standard errors are bootstrapped with 100 replications. The last column reports the p-value of the test for joint significance of the residuals and the interaction terms. See also notes to Table 9.