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How General Is Human Capital? A Task-Based Approach

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This article studies how portable skills 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 empirically the transferability of skills across occupations. 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 experience. We also show that task-specific human capital is an important source of individual wage growth, accounting for up to 52% of overall wage growth.

I. Introduction

Human capital theory (Becker 1964; Mincer 1974) and job search models (e.g., Jovanovic 1979a, 1979b) are central building blocks for studying job mobility and the evolution of wages. A crucial decision in these models is how to characterize labor market skills. Both types of models typically

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distinguish between general skills, such as education and experience, and specific skills, that is, skills that are not portable across jobs. Specific skills, for example, have recently played an important role in models explaining 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 1998), and the surge in wage inequality over the past decades (e.g., Violante 2002; Kambourov and Manovskii 2009a). The basic idea is that job reallocation, job displacement, and unemployment are more costly for both the individual worker and the economy as a whole if skills are not transferable across jobs.

Empirically, however, we know little about how specific skills accumulated in the labor market actually are. In this article, we propose the concept of "task-specific human capital" to measure the transferability of labor market skills.[1] The basic idea of our approach is straightforward. Suppose that there are two types of tasks performed in the labor market, for example, analytical tasks and manual tasks. Both types of 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) relies 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 where similar tasks are performed. This type of 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.[2]

To measure the transferability of skills empirically, we combine a high-quality panel on complete job histories and wages with information on tasks performed in occupations. The data on job histories and wages are derived from a 2% sample of all social security records in Germany, and

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

[2] In a recent paper, Lazear (2009) 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 approach assumes instead that workers are endowed with a productivity in each task and then choose the occupation.

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they provide a complete picture of job mobility and wages for more than 100,000 workers from 1975 to 2001. This 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 used previously, such as the Panel Study of Income Dynamics (PSID) or the National Longitudinal Survey of Youth (NLSY). Furthermore, we have much larger samples available than in typical household surveys.

The information on task usage in different occupations 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 this measure, the skill requirements of a baker and a cook are very similar. In contrast, switching from working as a banker to working as an unskilled construction worker would be the most distant move observable in our data. We then combine the task usage together with the panel on job mobility to construct a measure of the individual's task-specific human capital.

We find that human capital is more portable across occupations than previously considered. Specifically, we show that individuals move to occupations having skill requirements similar to those of their previous occupation. In addition, the distance of actual moves, as well as the propensity to switch occupations, declines sharply with labor market experience. Our framework can also explain why tenure in the predisplacement job has a positive effect on the postdisplacement wage (see also Kletzer 1989). Furthermore, we provide evidence 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. These results are consistent with the idea that human capital is partially transferable across occupations.

We then show, using a control function approach, that our empirical measure of task-specific human capital is an important determinant of individual wage growth. In contrast, the importance of occupation-specific skills and general experience declines once we account for task-specific human capital. Overall, task-specific human capital accounts for from 22% to 52% of overall wage growth.

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 have to move to a very distant occupation after displacement suffer a 10 percentage point larger wage loss than workers who are able to find employment in occupations with similar skill requirements. Hence, reallocation costs in an economy will depend crucially on the thickness of the labor market.

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The article makes several contributions to the literature. First, we introduce a continuous measure to define how occupations are related to each other in terms of their skill requirements. Previous empirical papers on the transferability of skills across occupations (Shaw 1984, 1987) have used the frequency of interoccupational switches to define similar occupations (i.e., occupations that often exchange workers are assumed to have similar skill requirements).

Using our distance measure, we then analyze the type and direction of occupational moves. The literature on firm and occupational mobility has focused on the determinants of switching firms (Flinn 1986; Topel and Ward 1992) or both firms and occupations (Miller 1984; McCall 1990; Neal 1999; Pavan 2005) but could not study how the source occupation affects the choice of the new occupation.[3]

Our article also contributes to the literature on the importance of general and specific human capital. While many studies have estimated the contribution of firm-specific human capital to individual wage growth (Abraham and Farber 1987; Altonji and Shakotko 1987; Kletzer 1989; Topel 1991; Altonji and Williams 2005),[4] recent evidence suggests that specific skills might be more tied to an occupation than to a particular firm (Neal 1999; Parent 2000; Gibbons et al. 2005; Kambourov and Manovskii 2009b). We show in contrast that specific human capital is not fully lost if an individual leaves an occupation (see Poletaev and Robinson [2008] for a similar result), and we quantify its contribution to wage growth.

Finally, our article provides the first attempt to integrate the recent literature using task data (Autor, Levy, and Murnane 2003; Spitz-Öner 2006; Borghans, Weel, and Weinberg 2009) with human capital models of the labor market.[5] 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 and the transferability of human capital in the labor market.

The article proceeds as follows. Section II outlines our concept of task-specific human capital and its implications for occupational mobility and wages. Section III introduces the two data sources and explains how we measure the distance between occupations in terms of their task require-

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

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

[5] 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. (2009) show how the increased importance of interactive skills has improved the labor market outcomes of underrepresented 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.

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ments. Descriptive evidence on the similarity of occupational moves and its implications for wages across occupations is presented in Section IV. Section V quantifies the importance of task-specific human capital for individual wage growth and calculates wage costs of job displacement. Finally, Section VI concludes.

II. Conceptual Framework

A. Task-Specific Human Capital

Suppose that output in an occupation is produced by combining multiple tasks, for example, negotiating, teaching, and 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.

More specifically, consider the case of two tasks, denoted by $j = A, M$. We think of them as analytical tasks and manual tasks. Workers (denoted by the subscript i) have a productivity in each task, which we allow to vary by occupations (denoted by the subscript o) and time in the labor market (denoted by the subscript t): t^j_{iot}. 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 combine the two in equal proportion. Let β_o ($0 \le \beta_o \le 1$) be the relative weight on the analytical task and $(1 - \beta_o)$ be the relative weight on the manual task. Worker i's task productivity S (measured in log units) in occupation o at time t is then

$$\ln S_{iot} = \beta_o t^A_{iot} + (1 - \beta_o) t^M_{iot}. \tag{1}$$

If analytical tasks are more important than manual tasks in an occupation, $\beta_o > 0.5$. 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 in an occupation, not its task intensity.[6] The weight β_o can then be interpreted as the share of time a worker spends on average in the analytical task in occupation o.

We can now 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, that is, β_o is close to $\beta_{o'}$.

[6] Restricting the weights to sum to one abstracts from occupational mobility along a job ladder (see Jovanovic and Nyarko 1997; Gibbons et al. 2005; Yamaguchi 2008). Within our framework, job ladders can easily be incorporated. 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. Our estimation approach in Sec. V is, however, consistent even in the presence of career mobility because the validity of our instruments does not rely on the assumption that the occupation-specific weights add up to one.

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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, that is, $|\beta_o - \beta_{o'}|$. 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 ($\beta_o = 0$).

Worker productivity t^j_{iot} is determined by a person's initial endowment in each task ("ability") and the human capital accumulated in the labor market. More specifically, the productivity in each task evolves according to

$$t^j_{iot} = t^j_i + \gamma_o H^j_{it} \qquad (j = A, M), \tag{2}$$

where t^j_i is worker i's initial skill endowment in task j and H^j_{it} is the human capital accumulated in task j until time period t. With time in the labor market, individuals become more productive in each task through passive learning-by-doing. In particular, we assume that the amount of learning in each task depends on how important the task is in that occupation. For example, a worker accumulates more of the analytical skill if he works in an occupation in which analytical skills are very important (i.e., β_o is large). In contrast, he will not learn anything in tasks that he does not use in his occupation. Human capital H^j_{it} in each task is then accumulated as follows:

$$\begin{aligned} H^A_{it} &= \beta_{o'} O_{io't}, \\ H^M_{it} &= (1 - \beta_{o'}) O_{io't,} \end{aligned} \tag{3}$$

where $O_{io't}$ denotes the tenure in each prior occupation. Plugging (2) and (3) back into (1), we get

$$\begin{aligned} \ln S_{iot} = {} & \underbrace{\gamma_o[\beta_o H^A_{it} + (1 - \beta_o) H^M_{it}]}_{T_{iot}} \\ & + \underbrace{\beta_o t^A_i + (1 - \beta_o) t^M_i}_{m_{io}}, \end{aligned} \tag{4}$$

where T_{iot} is our observable measure of task-specific human capital and m_{io} is the unobservable task match, that is, how well an individual is matched to his occupation given his endowment. Our parameter of interest is γ_o, the return to task-specific human capital, which varies across occupations.

Note that, unlike standard search models (e.g., Jovanovic 1979a, 1979b), task match qualities m_{io} in (4) are correlated across occupations, where this correlation is stronger if the occupations rely on similar tasks (i.e., β_o is close to $\beta_{o'}$). Our setup is therefore closely related to the Roy model of occupational sorting (Roy 1951; Heckman and Sedlacek 1985). How-

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ever, we impose the restriction that the correlation in unobservable match quality has a linear factor structure ($\beta_o t_i^A + (1 - \beta_o)t_i^M$). This restriction allows us to quantify task similarity across occupations and to analyze its impact on occupational mobility and wage growth for a large number of occupations.

Furthermore, the assumptions in (2) and (3) allow us to collapse the accumulation of skills in multiple tasks into a one-dimensional observable measure of task-specific human capital. We therefore abstract from estimating human capital accumulation separately in each task and focus instead on the similarity of skill sets across occupations and their transferability from one occupation to another.

Note that the weights occupations place on analytical and manual tasks (β_o, $1 - \beta_o$) enter the calculation of task-specific human capital twice. First, they determine how much of a task is learned in an occupation (see [3]). Workers in occupations with a high weight on analytical skills (e.g., $\beta_o > 0.5$) learn more in that task than workers in occupations with a low weight on analytical tasks. Second, β_o also governs the weight each task is given when calculating a worker's overall productivity (see [1]).

As an illustration of our concept of task-specific human capital, consider the following examples. Suppose that a worker was employed for 1 year in an occupation that fully specializes in analytical skills ($\beta_{o'} = 1$). Using (3), this worker accumulates one unit of analytical skills and zero units of manual skills. If he stays in the occupation, his task tenure is 1 (($1 \times 1) + (0 \times 0$)) unit (according to the first term in [4]). If he moves to an occupation with equal weight on both skills ($\beta_o = 0.5$), his task-specific human capital declines to 0.5 (($0.5 \times 1) + (0.5 \times 0$)) units, whereas he cannot transfer any human capital if he moves to an occupation that fully specializes in manual tasks ($\beta_o = 0$). Hence, the transferability of task-specific human capital declines in the distance (i.e., $|\beta_{o'} - \beta_o|$) of the occupational move.

Consider next a worker who was employed in an occupation that places a high weight on analytical tasks (e.g., $\beta_{o'} = 0.75$). This worker accumulates 0.75 units of analytical skills and 0.25 units of manual skills. If he stays in the occupation after 1 year, his task tenure is 0.625 (($0.75 \times 0.75) + (0.25 \times 0.25$)) units. If he moves to an occupation that fully specializes in analytical tasks (i.e., $\beta_o = 1$), his task tenure increases to 0.75. The economic logic is that the worker has accumulated more human capital in analytical tasks than in manual tasks and that the target occupation rewards this type of human capital more than the source occupation. If the worker instead moves to an occupation that places less weight on analytical tasks than the source occupation (e.g., $\beta_o < 0.75$), task tenure declines with the distance of the move. For example, if he moves to an occupation that uses analytical tasks and manual tasks in equal proportions ($\beta_o = 0.5$), his task tenure declines to 0.5 units (($0.5 \times 0.75) + (0.5 \times 0.25$)). Generally, if

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$\beta_{o'} > 0.5$, task tenure increases if workers switch to occupations with $\beta_o > \beta_{o'}$ and decreases if they switch to occupations with $\beta_o < \beta_{o'}$; if $\beta_{o'} < 0.5$, the opposite holds.

Finally, consider a worker who was employed in a "general" occupation that that uses analytical tasks and manual tasks in equal proportions (i.e., $\beta_{o'} = 0.5$). This worker accumulates 0.5 units of task tenure and can transfer the full amount, regardless of which occupation he moves to $((\beta_o \times 0.5) + [(1 - \beta_o) \times 0.5] = 0.5)$.

These examples demonstrate that the transferability of task-specific human capital is governed by two factors: first, it depends on the degree of "specialization" in the source occupation. Workers accumulate more portable human capital in specialized occupations where $\beta_{o'}$ is close to one or zero than in general occupations where $\beta_{o'}$ is close to 0.5. At the same time, however, workers in general occupations can transfer more human capital if they switch occupations than workers in specialized occupations. Second, and most importantly in our context, the transferability of human capital depends on whether two occupations employ analytical tasks and manual tasks in similar proportions. We next turn to a description of the wage equation and its implications for job mobility.

B. Wages and Occupational Mobility

Wages in occupation o and time t equal the worker i's productivity multiplied with the occupation-specific skill price, P_o. Hence, log wages satisfy

$$\ln w_{iot} = p_o + \gamma_o T_{iot} + m_{io}, \tag{5}$$

where $p_o = \ln P_o$. We observe task-specific skills (T_{iot}) but do not observe the quality of the match, $m_{io} = \beta_o t_i^A + (1 - \beta_o) t_i^M$.[7]

Workers search over occupations to maximize earnings.[8] The decision to switch occupations is determined by three factors: the transferability of task-specific human capital (T_{iot}), the task match (m_{io}), and the occupation-specific return to human capital (γ_o).

The basic intuition can be developed in a simple two-period setup. Consider the decision problem of a worker employed in occupation o' in the first period. For simplicity, suppose that he is more skilled in analytical tasks than manual tasks (so, $H_{it}^A \geq H_{it}^M$, $t_i^A \geq t_i^M$). Then, this

[7] In the empirical model in Sec. V, we augment this wage regression to allow for other forms of human capital, such as experience, occupational tenure, and firm tenure. This will allow us to estimate and compare the contributions of the different types of human capital to individual wage growth. We will additionally allow for search over firm matches.

[8] For example, Fitzenberger and Spitz-Öner (2004) and Fitzenberger and Kunze (2005) argue that search is the most important source of occupational switches in Germany.

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worker will move to occupation o in the second period if the wage in that occupation exceeds the wage in his current occupation, that is, if

$$(p_o - p_{o'}) + (\gamma_o - \gamma_{o'})T_{io't} + (m_{io} - m_{io'}) > \gamma_o[(\beta_o - \beta_{o'})(H_{it}^A - H_{it}^M)]. \tag{6}$$

Consider, first, the case where skill price and returns to human capital are constant across occupations ($p_o = p$ and $\gamma_o = \gamma$ for all o). Then, workers are only willing to switch occupations if the improvement in the task match $(m_{io} - m_{io'})$ exceeds the potential loss in task-specific human capital $(\beta_o - \beta_{o'})(H_{it}^A - H_{it}^M)$.

If returns differ across occupations, workers also switch occupations because of higher future wage growth ($\gamma_o > \gamma_{o'}$) or a higher skill price ($p_o > p_{o'}$) in the new occupation. Hence, with heterogeneous returns, workers may voluntarily switch occupations even if they lose task-specific human capital and are worse matched in the new occupation.

Note that the decision rule in (6) 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 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 not fully informed about which occupation provides the best match at labor market entry or because there is a rationing of jobs in the worker's most preferred occupation.

C. Empirical Predictions

Our framework produces a number of novel empirical implications. It predicts that, everything else equal, individuals are more likely to make distant moves earlier, rather than later, in their careers for two reasons. First, as workers accumulate more and more task-specific human capital as they age, a distant occupational switch tends to become 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 workers will find a match that exceeds their current match quality; that is, the probability that the left-hand side of (6) is greater than zero decreases with age. Another implication of the framework is that, on average, workers are more likely to move to occupations in which they can perform tasks similar to those in their previous occupation. The reason is that the loss with task-specific human capital tends to be smaller if a person moves to an occupation with similar skill requirements.

Since both the transferability of task-specific human capital and the correlation of match qualities across occupations tend to decline in the occupational distance, we also expect that wages at the source occupation

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are a better predictor for wages at the target occupation if the two occupations require similar tasks. Finally, tenure in the last occupation is valuable in a new occupation, and the value should be higher the more similar the two occupations are in their task requirements. The reason for this is that more of the task-specific human capital that was accumulated through learning in previous occupations is transferable to occupations with similar task requirements.

III. Data Sources

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.

A. 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, which has been previously used, for example, by DiNardo and Pischke (1997) and Borghans et al. (2009), 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 19 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 different tasks. To simplify the exposition, we follow Autor et al. (2003) and Spitz-Öner (2006) and categorize the 19 tasks into three aggregate groups: analytical tasks, manual tasks, and interactive tasks. On average, 55% report performing analytic tasks, 72% manual tasks, and 49% interactive tasks. The picture for the main task used is similar: 32% report analytical tasks, 57% manual tasks, and 28% 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%), with teaching and training others being by far the most important one (91.4%). Two other important tasks are correcting texts or data (39.6%) and or-

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Table 1
Summary Statistics of Task Data

	Mean	Standard Deviation	Example Teacher (%)	Example Baker (%)
Analytical tasks:	55.02	49.75	63.7	32.4
Research, evaluate, or measure	25.11	43.37	34.0	13.6
Design, plan, or sketch	10.21	30.28	17.6	3.6
Correct texts or data	23.85	42.62	39.6	6.4
Calculate or do bookkeeping	26.02	43.87	11.3	22.5
Program	8.35	27.66	8.4	.4
Execute laws or interpret rules	7.85	26.89	17.2	.8
Analytical is main task	31.56	46.48	15.9	13.1
Manual tasks:	72.42	44.69	25.6	96.4
Equip or operate machines	19.98	39.99	7.0	27.1
Repair, renovate, or reconstruct	31.38	46.40	8.2	10.4
Cultivate	1.77	13.19	2.2	1.9
Manufacture, install, or construct	11.97	32.46	2.0	87.9
Cleaning	3.50	18.38	1.8	6.1
Serve or accommodate	1.21	10.92	.3	3.6
Pack, ship, or transport	18.76	39.04	2.7	15.3
Secure	15.72	36.40	7.2	18.0
Nurse or treat others	9.76	29.67	11.5	7.8
Manual is main task	57.46	49.44	10.5	88.8
Interactive tasks:	48.48	49.98	95.3	44.1
Sell, buy, or advertise	29.21	45.48	12.0	16.5
Teach or train others	17.15	37.69	91.4	34.3
Publish, present, or entertain others	9.58	29.43	26.2	3.8
Employ, manage personnel, organize, coordinate	37.09	48.31	39.4	29.9
Interactive is main task	27.55	44.68	85.9	14.8
No. observations	52,718		1,067	472

Source.—Qualification and Career Surveys, 1979, 1985, 1991/92, 1997/98.
Note.—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-Öner (2006). The fractions for main tasks sum to more than 100% as around 10% reported performing more than one main task. The last two columns show the distribution of task usage for two common occupations: teacher (which excludes university or technical college professors) and baker.

ganizing, coordinating, and managing personnel (39.4%). A baker, in contrast, is a primarily manual occupation (96.4%), with manufacturing, producing, or installing being the most important task (87.9%), followed by teaching and training others (34.3%), as well as organizing, coordinating, and managing personnel (29.9%).

To see how task usage varies across the 64 occupations contained in our data, table A1 in appendix A lists the fraction of workers performing manual, analytical, and interactive tasks for all 64 occupations. The table shows that there is a great deal of variation in task usage across occu-

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pations. For example, while the average use of analytical tasks is 56.3%, the mean varies from 16.7% as an unskilled construction worker to 92.4% for an accountant. We found little evidence that tasks performed in the same occupation vary across industries, which suggests that industries matter less for measuring human capital once we control for the skill set of an occupation; this justifies our focus on occupations.

B. Measuring the Distance between Occupations

According to our framework, two occupations have similar skill requirements if they put similar weights on tasks, that is, individuals perform the same set of tasks. With two tasks, we can measure the distance between two occupations o and o' as the absolute difference between the weight each occupation places on the first task, that is, as $|\beta_o - \beta_{o'}|$. The basic idea extends naturally to the case with more than two tasks.

From the task data described in the previous section, we know the set of skills employed in each occupation. The skill content of each occupation can then be characterized by a 19-dimensional vector, $q_o = (q_{o1}, \ldots, q_{oJ})$, 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. Occupations with a high weight in a particular task β_{oj} will also employ this task extensively, that is, 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 observable vectors q_o and $q_{o'}$:

$$\mathrm{AngSep}_{oo'} = \frac{\sum_{j=1}^{J}(q_{jo} \times q_{jo'})}{[(\sum_{j=1}^{J} q_{jo}^2) \times (\sum_{k=1}^{J} q_{ko'}^2)]^{1/2}},$$

where q_{jo} ($q_{jo'}$) is the fraction of workers using task j in occupation o (o'). 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).[9]

We use a slightly modified version of the above, namely, $\mathrm{Dis}_{oo'} = 1 - \mathrm{AngSep}_{oo'}$, 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

[9] 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 having a position close to the origin of the coordinate system) will be similar according to the angular separation measure 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.

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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 1975–82, we use the measures from the 1979 cross section; for the years 1983–88, the measures from the 1985 wave; for the years 1989–94, the measures from the 1991/92 wave; and for the years 1995–2001, the measures from the 1997/98 wave. Our results are robust to assigning different time windows to the measures.[10]

The mean distance between occupations in our data is 0.24, with a standard deviation of 0.22 (see table 2). The closest possible occupational move is between a paper and pulp processing worker and a printer or typesetter, with a distance of 0.002. The most distant possible move is between a banker and an unskilled construction worker. Table 2 also shows the distance measure for the three most common occupational switches separately by education group. The most popular move for low-skill workers is between being a truck driver and a warehouse keeper, while for high-skill workers, it is between being in an engineering occupation and working as a chemist or physicist.[11]

C. The German Employee Panel

Our second data set is a 2% 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. These data have at least three advantages over household surveys commonly used in the literature to study mobility in the United States. First, their 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 firms as they form the basis for wage bargaining between unions and employers. Finally, measurement error in earnings and occupational titles is much less of a problem than in typical survey data as misreporting is subject to severe penalties.

These data are representative of all individuals covered by the social security system, roughly 80% of the German workforce. It excludes the self-employed, civil servants, and individuals currently performing their compulsory military service. As in many administrative data sets, our data

[10] While there have been changes over time in the distance measures, they are highly correlated, with a correlation coefficient of 0.7.

[11] 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 three 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 this article.

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Table 2
Distance Measures between Occupations (Angular Separation)

	Occupation 1	Occupation 2	Distance
Mean			.243
Standard deviation			.221
Most similar (all education groups)	Paper and Pulp Processing	Printer, Typesetter	.002
	Wood Processing	Metal Polisher	.003
	Chemical Processing	Plastics Processing	.004
Most distant (all education groups)	Banker	Unskilled Construction Worker	.939
	Banker	Miner, Stone-Breaker	.936
	Publicist, Journalist	Unskilled Construction Worker	.935
Most common occupational moves (low-skilled)	Truck Driver, Conductor	Store or Warehouse Keeper	.029
	Unskilled Worker	Store or Warehouse Keeper	.269
	Assembler	Store or Warehouse Keeper	.369
Most common occupational moves (medium-skilled)	Chemist, Physicist	Electrician, Electrical Installation	.171
	Sales Personnel	Office Clerk	.076
	Truck Driver, Conductor	Store or Warehouse Keeper	.028
Most common occupational moves (high-skilled)	Engineer	Chemist, Physicist	.034
	Entrepreneur	Office Clerk	.047
	Accountant	Office Clerk	.080

Note.—The top of the table provides summary statistics of occupations and their corresponding distance. The distance measure is the angular separation using the 19 different tasks (see table 1 for a list of tasks), and it is normalized to vary between 0 and 1. The middle part of the table shows pairs of occupational moves with the least and greatest differences of distance. The bottom part of the table shows the three most commonly observed moves in the data by education group and the corresponding distance measure.

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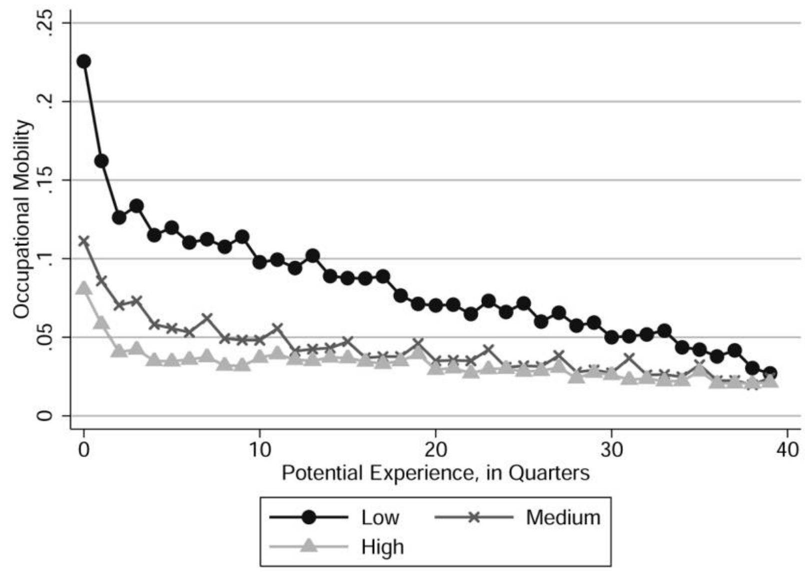

FIG. 1.—Quarterly occupation mobility rates by time in the labor market. The figure shows the quarterly occupation mobility rate by education and time in the labor market (potential experience). Mobility rates are defined over the sample of workers who are employed at the beginning of the quarter.

are 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 it reaches 30% 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 and firm, task, and occupation tenure from labor market entry onward. Labor market experience and our tenure variables are all measured in years and exclude periods of unemployment and apprenticeship training.

Occupational mobility is important in our sample: 19% of the low-skilled switch occupations each year as compared to 10% of the high-skilled. To see how occupational mobility varies over the career, figure 1 plots quarterly mobility rates over the first 10 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 they are

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highest for the low-skilled. Ten years into the labor market, quarterly mobility rates drop to 2%.

D. Measuring Task-Specific Human Capital

Since the concept is novel, we now explain how we calculate our measure of task-specific human capital, which we term "task tenure." Task tenure crucially depends on the weights occupations place on tasks, β_{oj}. We measure these occupation-specific weights as follows. First, we calculate the share of time workers spend in each of the 19 tasks, assuming that they spend the same amount of time in each task they perform. We then average over all workers in the occupation. This ensures that the occupation-specific weights add up to one.

We compute task tenure following equations (3) and (4) in Section II.B with one modification. The reason we do this is that (3) and (4) imply that task tenure would increase by less than one unit for workers who remain in the same occupation and therefore by less than occupational tenure. To see this, consider again the case with two tasks and a worker who is currently employed in an occupation with $\beta_o = 0.75$. After 1 year, this worker has accumulated 0.75 units in analytical tasks and 0.25 units in manual tasks. His task tenure would increase by only 0.625 $((0.75 \times 0.75) + (0.25 \times 0.25))$, while occupational tenure increases by one unit. Our goal, however, is to compare the return to task-specific human capital with that to general experience and the less portable occupation-specific skills. To ensure this comparability, we normalize the accumulation of task tenure for occupational stayers to be one in each occupation. We do this by dividing the task tenure accumulated in the current period by the sum of squared weights in that occupation. This normalization also ensures that task tenure always increases more for occupational stayers than for occupational movers.

As an illustration, consider a worker in occupation A with equal weights on analytical and manual tasks ($\beta_o = 0.5$). After 1 year, he has accumulated 0.5 units of analytical skills and 0.5 units of manual skills (i.e., $H_{i1}^{A} = 0.5$ and $H_{i1}^{M} = 0.5$). His normalized measure of task-specific human capital is then one unit $([(0.5 \times 0.5) + (0.5 \times 0.5)]/[(0.5 \times 0.5) + (0.5 \times 0.5)])$. If instead he switches to occupation B with weights 0.3 on the analytical task and 0.7 on the manual task, his task tenure after the move declines to 0.5 units $((0.3 \times 0.5) + (0.7 \times 0.5))$. After a year in occupation B, his analytical and manual skills increase to ${H^{A}}_{i2} = 0.5 + 0.3 = 0.8$ and ${H^{M}}_{i2} = 0.5 + 0.7 = 1.2$ units. His overall task tenure is then 1.5 units $(\{[(0.3 \times 0.5) + (0.3 \times 0.3)]/[(0.3 \times 0.3) + (0.7 \times 0.7)]\} + \{[(0.7 \times 0.5) + (0.7 \times 0.7)]/[(0.3 \times 0.3) + (0.7 \times 0.7)]\})$. The first (second) term in curly brackets denotes the contribution of analytical (manual) skills in occupation A and B to total task tenure. This normalization ensures that task tenure is at least as large as occupational tenure (since occupation-

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Table 3
Summary Statistics of West German Employee Panel

	Low-Skilled	Medium-Skilled	High-Skilled
Percentage in sample (%)	17.82	67.87	14.31
Age (in years)	25.81	27.47	31.88
	(6.03)	(5.23)	(5.27)
Not German citizen (%)	34.42	5.29	5.19
Median daily wage	113.78	135.32	206.74
	(44.97)	(43.33)	(60.23)
Log daily wage	4.66	4.89	5.20
	(.45)	(.33)	(.42)
Percentage censored	1.17	2.39	30.00
Actual experience (in years)	5.67	5.58	4.96
	(5.34)	(4.75)	(4.58)
Occupational tenure (in years)	2.93	3.61	3.34
	(4.09)	(4.04)	(3.88)
Firm tenure (in years)	2.44	2.80	2.43
	(3.84)	(3.66)	(3.25)
Task tenure (in years)	3.23	3.57	3.90
	(3.02)	(2.92)	(3.44)
Occupational mobility	.19	.11	.10
Distance of move	.28	.24	.16
	(.23)	(.22)	(.18)
Firm mobility	.24	.18	.17
Most common occupations	Warehouse Keeper	Electrical Installation	Engineer
	Assembler	Locksmith	Technician
	Conductor	Mechanic, Machinist	Accountant
	Unskilled Worker	Office Clerk	Office Clerk
	Office Clerk	Conductor	Scientist, Clergyman
No. observations	244,759	1,003,823	172,930
No. individuals	20,846	79,396	16,735

Source.—Employee Sample (Institute for Labor Market Research [IAB]), 1975–2001.
Note.—The table reports means and standard deviations (in parentheses) for the administrative panel data on individual labor market histories and wages from 1975 to 2001. Low-skilled are those without a vocational degree, medium-skilled have either a high school or vocational degree, and high-skilled have an advanced degree from a technical college or university. Experience, occupational tenure, and task and firm tenure are measured from actual spells and exclude periods of unemployment or being out of the labor force. The wage is measured in German marks at 1995 prices and is subject to right-censoring.

specific skills fully depreciate with an occupational switch) and no larger than experience (since general skills do not depreciate).[12]

Table 3 reports summary statistics for the main variables. In our sample, about 18% are low-skill workers with no vocational degree. The largest fraction (67.9%) is medium-skill workers with a vocational degree (apprenticeship). The remaining 14.3% are high-skill workers with a tertiary degree from a technical college or university. Wages are measured per day and are deflated to 1995 German marks. Mean task tenure in our sample is between 3.23 years for the low-skilled and 3.9 years for the high-skilled. Total labor market experience is, on average, 1–2 years higher, while tenure in an occupation is, with the exception of the medium-skilled, somewhat lower.

[12] This is true as long as the occupation-specific weights do not change over time. We account for changes in task usage over time by calculating the weights separately for four cross sections (see Sec. III.B). Hence, task tenure may be lower than occupational tenure in our sample.

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IV. 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 IV.A studies mobility behavior, while Section IV.B analyzes wages before and after an occupational move.

A. Occupational Moves Are Similar

Our framework predicts that workers are more likely to move to occupations with similar task 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 were 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, that is, the fact that employment shares may be increasing or decreasing for some occupations.[13]

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% level based on a Kolmogoroff-Smirnov test. To allow a more detailed comparison, table 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 percentiles of

[13] 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.

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FIG. 2.—Observed mobility is more similar than random mobility. 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 is angular separation, based on 19 tasks.

the distance distribution are much lower than what we would observe under random mobility.

Our framework also predicts that distant moves occur early in the labor market career and that moves become increasingly similar with time in the labor market. 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. We include experience and experience squared as well as year and occupation fixed effects as controls. Occupation dummies control for the occupation-specific skill price (p_o) in the occupation, which might be correlated with experience or directly with the distance measure.[14] Year fixed effects account for aggregate shocks to the economy.

For all education groups, the distance of an occupational move declines with time spent in the labor market, although it does so at a decreasing

[14] We find that workers in occupations that pay higher wages (i.e., employ a higher average skill level) also have higher task tenure and move to more similar occupations. The occupation dummies control for these correlations and hence avoid overestimating the relationship between experience and distance of move or distance and wages in the next section.

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Table 4
Observed Moves Are More Similar than under Random Mobility

	Random Mobility	Observed Mobility
Mean	.466	.406
Percentile:		
10th	.083	.047
25th	.267	.122
50th	.507	.381
75th	.668	.597
90th	.776	.679

NOTE.—The table reports 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 a similar occupation.

rate. After 10 years in the labor market, the distance of an occupational move declines by 0.03 for the low-skilled and medium-skilled and by as much as 0.10 for the high-skilled. Given the coefficients in specification 1 of table 5, actual labor market experience can account for up to two-thirds of this decline.

Time spent in the previous occupation also decreases the distance of an occupational move in addition to labor market experience (col. 2). Column 3 reports the results from a fixed effects estimator, which is used in order 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.

The specification reported in 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, separately for the three education groups, the average distance of a move by actual experience. 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 that is particularly so for the high-skilled in the first 5 years in the labor market. The decline in distance between the first and fifteenth year of actual labor market experience is statistically significant at the 1% level for all education groups.

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

	Low-Skilled			Medium-Skilled			High-Skilled		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Experience	−.006***	−.005***	−.005***	−.003***	−.002***	−.004***	−.011***	−.009***	−.008***
	(.001)	(.001)	(.002)	(.001)	(.001)	(.001)	(.001)	(.001)	(.003)
$(\text{Experience})^2$	.000***	.000***	.000***	.000***	.000***	.000***	.001***	.001***	.001***
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Occupation tenure		−.003***	−.002***		−.002***	−.000		−.003***	−.001
		(.000)	(.001)		(.000)	(.000)		(.001)	(.001)
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
No. observations	45,124	45,124	45,124	99,390	99,390	99,390	13,680	13,680	13,680
Mean distance of move	.279	.279	.279	.246	.246	.246	.158	.158	.158

Note.—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 current occupation dummies. Robust standard errors clustered at the individual level are reported in parentheses.
*** $p < .01$.

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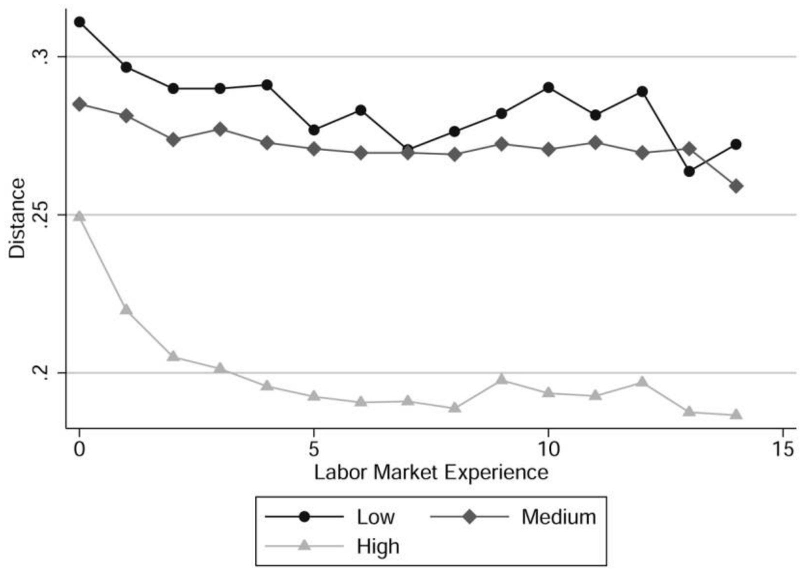

FIG. 3.—Distance of occupational moves declines over career. The figure plots the average distance of the occupational move by actual experience. Regressions control for 15 experience dummies, occupation dummies, and time dummies. The decline in the average distance by experience is significant at a 1% level for all education groups. Distance measure is angular separation, based on 19 tasks.

B. Wages in Current Occupation Depend on Distance of Move

If skills are task-specific, and hence partially transferable across occupations, 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 for this is that the wage in the previous occupation partly reflects task-specific human capital, which is also valuable in the new occupation.

Table 6 reports estimates from a wage regression in which 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 firm movers (col. 1), the correlation of wages between source and target occupation is much lower for our sample of workers who switch both occupations and firms (col. 2). Hence, workers that switch occupations lose more of their skills than workers that only switch employers.

The third specification (col. 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 of wages in the new occupation if the occupations require

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Table 6
Similar Moves and the Correlation of Wages across Jobs

	Low-Skilled			Medium-Skilled			High-Skilled		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Wage last period	.261***	.168***	.202***	.363***	.258***	.312***	.413***	.270***	.318***
	(.006)	(.006)	(.009)	(.004)	(.005)	(.006)	(.009)	(.013)	(.017)
Wage last period ×									
Distance			−.133***			−.243***			−.383***
			(.020)			(.016)			(.055)
Distance of move			.518***			1.020***			1.500***
			(.090)			(.075)			(.262)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. observations	64,674	45,124	45,124	190,962	99,390	99,390	27,150	11,848	11,848

NOTE.—The table reports results from wage regressions where the dependent variable is the log daily wages at the target occupation after switching both employers and occupations. Results are reported separately by education group. Column 1 uses the sample of firm movers as a benchmark for comparison. Column 2 repeats the analysis for the sample of joint occupational and firm movers. Column 3 adds the distance measure as well as the distance measure interacted with the wage in the last period. The distance measure is the angular separation, based on all 19 tasks. All specifications include the log daily wage in the last period, actual experience, actual experience squared, and year and current occupation dummies. For the low-skilled and the 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 200 replications to allow for clustering at the individual level.

*** $p < .01$.

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Table 7
Past Occupational Tenure Matters for Wages

	Low-Skilled		Medium-Skilled		High-Skilled	
	(1)	(2)	(1)	(2)	(1)	(2)
Past occupational tenure	.014***	.015***	.013***	.014***	.024***	.026***
	(.001)	(.001)	(.001)	(.001)	(.002)	(.003)
Past tenure × Distance		−.007*		−.006***		−.037***
		(.004)		(.002)		(.011)
Distance of move		−.086***		−.133***		−.358***
		(.010)		(.007)		(.030)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Occupational dummies	Yes	Yes	Yes	Yes	Yes	Yes
No. observations	45,124	45,124	99,390	99,390	13,680	13,680

NOTE.—The table reports wage regressions where the dependent variable is the log wages in the target occupation after switching both employers and occupations. Column 1 in each specification controls for past tenure in the source occupation, experience, experience squared, and year and current occupation dummies. Column 2 additionally includes the distance measure and its interaction with past occupational tenure. The distance measure used is the angular separation, based on all 19 tasks. For the low-skilled and the 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 200 replications to account for clustering at the individual level.
* $p < .10$.
*** $p < .01$.

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 0.26 for the mean move (0.318 − (0.383 × 0.158)) but only 0.12 for a distant (90th percentile) move (0.318 − (0.383 × 0.507)).

If skills are partially transferable across occupations, then 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 this education group, the impact of past occupational tenure on wages is 2.6% for the most similar move and around 2% (0.026 − (0.037 × 0.158)) for the mean distance move.

The specification in figure 4*a* relaxes the assumption that the correlation between wages across occupations declines linearly with the distance. The *x*-axis shows the distance, with 1 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.[15]

[15] The coefficient is obtained form an OLS regression (tobit regression for the high-skilled) that controls for actual experience, actual experience squared, year dummies, the wage at the source occupation, nine dummies for the distance of the

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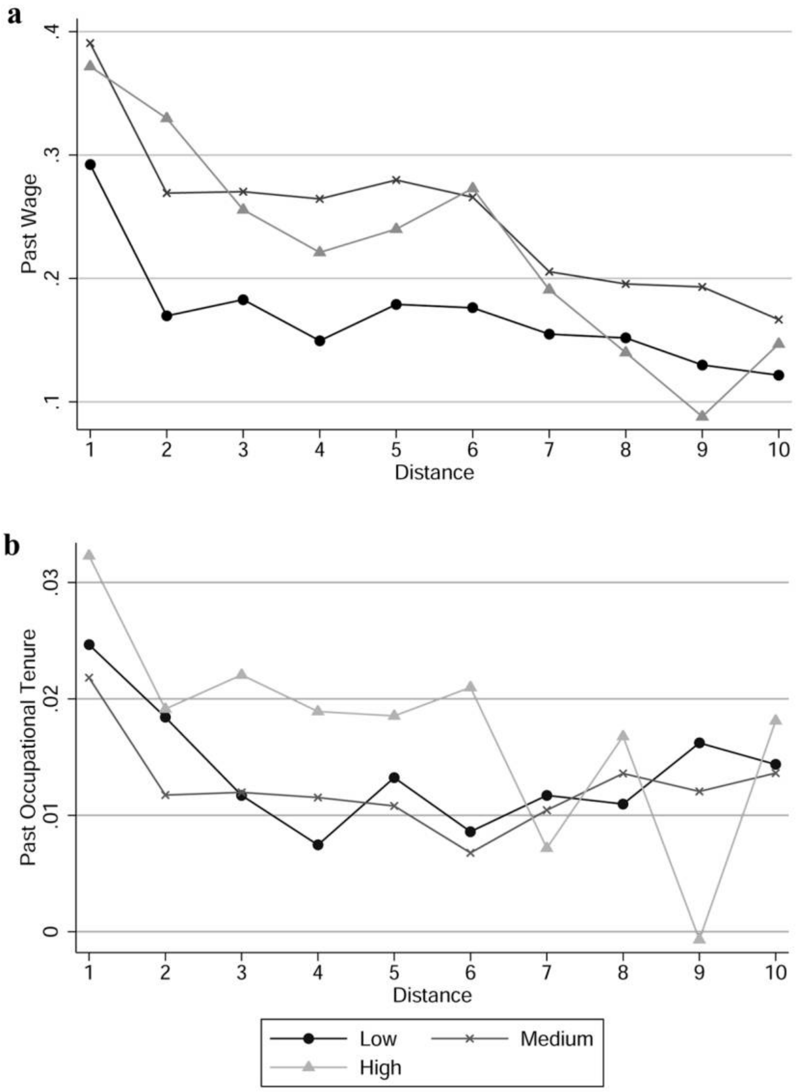

FIG. 4.—*a*, Correlation of wages by distance of move; *b*, impact of past occupational tenure by distance of move. The upper panel plots the impact of the past wage on the current wage by the distance of the occupational move. Regressions control for occupation and time dummies, past wages, 10 distance 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 10 distance dummies.

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Figure 4*b* presents results from a similar analysis for past occupational tenure. The *y*-axis now shows, for each of the 10 distance categories, the coefficients on occupational tenure in the source occupation from a (tobit) wage regression that also controls for actual experience, actual experience squared, and year dummies.

Two things are noteworthy. First, the figures highlight that wages in the source occupation are more strongly related to wages at the target occupation if the source and the target occupation have similar skill requirements. Second, and in line with our results on mobility and wages, the decline in the relationship is strongest for the high-skilled. For this education group, the partial correlation coefficient between wages in the source and target occupation drops from 38% for the 10% most similar moves to around 14% for the 10% most distant moves. The drop is statistically significant at a 1% level for all education groups.

We performed a number of robustness checks. First, results for alternative distance measures are very similar. Furthermore, our original sample of movers contains everybody switching occupations irrespective of the duration of intermediate unemployment 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 unemployment or nonemployment spells of less than a year. Again, this does not change the observed patterns in mobility and wages.

C. Can These Patterns Be Explained by Unobserved Heterogeneity?

This section discusses whether the patterns in mobility and wages found in the last section are consistent with other forms of unobserved heterogeneity. Note, first, that all results presented above are based on a sample of occupational movers. Hence, the observed patterns cannot 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.

Other sources of unobserved heterogeneity could, however, 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

move, and the nine dummies interacted with the wage at the source occupation (see col. 3 in table 6).

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why the effect of past occupational tenure should vary with the distance of the move or why individuals move to similar occupations at all.

Second, one might argue that similar moves in the data are voluntary transitions, while distant movers are "lemons" who are laid off 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, who are more likely to be moving 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 even for the two types of movers.

Finally, suppose that the sample of movers differs in their taste for particular tasks. Some individuals prefer research over negotiating, while others favor negotiating over managing personnel, and so forth. Taste heterogeneity can explain why we see similar moves in the data. 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 mix.

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' decisions of whether to switch occupations and whether to move to a close or distant occupation.

V. Task-Specific Human Capital and Individual Wage Growth

A. Econometric Model

To estimate the contribution of task-specific human capital to individual wage growth, we start from the log-wage regression (eq. [5]) in Section II, augmented by other forms of human capital:

$$\ln w_{ioft} = \alpha_o \mathrm{Exp}_{it} + \gamma_o T_{iot} + \delta_o O_{iot} + \lambda_o F_{ift} + \varepsilon_{ioft}, \tag{7}$$

where Exp_{it} denotes actual experience and T_{iot} task tenure, with their respective returns α_o and γ_o. As specific human capital, we include occupation tenure O_{iot} and firm tenure F_{ift}, with returns δ_o and λ_o, respectively. Note that we allow the return to all forms of human capital accumulation to be occupation-specific. This specification takes seriously the existing empirical evidence that returns to labor market skills differ

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across occupations (e.g., Heckman and Sedlacek 1985; Gibbons et al. 2005).

The unobserved (for the econometrician) error term ε_{ioft} has the following components:

$$\varepsilon_{ioft} = \theta_i + \beta_o t_i^A + (1 - \beta_o)t_i^M + m_{if} + u_{ioft}. \tag{8}$$

The first term represents individual ability that is equally valued across all occupations, $\beta_o t_i^A + (1 - \beta_o)t_i^M$ is the task-specific match in an occupation, and m_{if} denotes the firm match between worker i and employer f. Finally, u_{ioft} is an independent and identically distributed error term capturing, for example, measurement error in wages.

Our goal is to estimate the average returns of the different forms of human capital and to compare their relative contributions to individual wage growth. To understand the selection issues involved in the estimation, we can rewrite equations (7) and (8) as a random coefficient model:

$$\begin{aligned} \ln w_{ioft} &= \bar{\alpha}\mathrm{Exp}_{it} + \bar{\gamma} T_{iot} + \bar{\delta} O_{iot} + \bar{\lambda} F_{ift} + e_{ioft}, \\ e_{ioft} &= \pi_o' X_{ioft} + \theta_i + [\beta_o t_i^A + (1 - \beta_o)t_i^M] + m_{if} + u_{ioft}, \end{aligned} \tag{9}$$

where $X_{ioft}' = [\mathrm{Exp}_{it}\ \ T_{iot}\ \ O_{iot}\ \ F_{ift}]$ and $\pi_o' = [(\alpha_o - \bar{\alpha})\ \ (\gamma_o - \bar{\gamma})\ \ (\delta_o - \bar{\delta})\ \ (\lambda_o - \bar{\lambda})]$. The unobserved error term e_{ioft} now contains an additional term capturing the occupational heterogeneity in the returns to human capital.

Suppose, first, that returns to observable human capital are constant across occupations. Then, $\pi_o' X_{ioft}$ equals zero, which rules out that workers sort into occupations based on the returns to human capital. Estimating equation (9) without the $\pi_o' X_{ioft}$ term by least squares results in three biases due to unobserved ability (θ_i), occupational matches ($\beta_o t_i^A + (1 - \beta_o)t_i^M$), and firm matches ($m_{if}$). We would expect the return to experience, α, to be upward biased because workers locate better occupational and firm matches with time in the labor market through on-the-job search. The return to experience therefore reflects not only accumulation of general human capital but also wage growth due to job search. Similarly, workers with higher ability (higher θ_i) are typically more attached to the labor market, which creates an additional upward bias. In contrast, the returns to occupation-specific and task-specific human capital, γ and δ, may be upward or downward biased. On the one hand, workers with a good occupation or firm match are typically less likely to switch occupations, which produces a positive (partial) correlation between occupation and task tenure and the match terms. On the other hand, workers may have switched to a new occupation or moved to a distant occupation because they found a particularly good occupation or firm match, which implies a downward bias in the return to occupation-specific and task-specific human capital. Moreover, high-ability workers may be less likely to switch occupations in general, or to switch to distant

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occupations, creating an additional upward bias in the return to occupational and task tenure.

In the more general case with heterogeneous returns ($\pi_o' X_{ioft} \neq 0$), we will have an additional source of bias because workers sort themselves into occupations based on the returns to human capital. Sorting according to comparative advantage is another reason why the (partial) bias in the return to occupation and task tenure cannot be signed. We next outline our estimation approach to address these selection issues.

B. Estimation Approach

Our first step to get consistent estimates of the average returns to human capital 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). Exogenously displaced workers lost their current firm match and need to start searching for a new employer from scratch. Such workers are willing to accept a new job offer if its value exceeds the value of unemployment. In contrast, voluntary job switchers are only observed because the value of the new job exceeds that of the old job. Hence, using the sample of exogenously displaced workers eliminates the upward bias in the returns to general human capital from improved firm matches (m_{if}) because their firm match after reemployment is a random sample of the working population conditional on the observable characteristics.[16] Note that this condition only holds for the first period after the displaced worker has been reemployed. Therefore, our sample of displaced workers is based on this first period alone. Since firm tenure is zero in this sample, we cannot estimate the return to firm tenure, and we therefore drop the term $\lambda_o F_{ift}$ from the wage equation (9).[17]

The returns to experience, occupational tenure, and task tenure are then primarily identified from the cross-sectional comparison of displaced workers with different years of accumulated human capital. Estimating wage equation (9) with fixed effects for the displaced sample (and hence exploiting that some workers were displaced more than once) will absorb the individual ability term θ_i. This approach reduces the possible upward bias in the returns to experience, occupation tenure, and task tenure due to a positive (partial) correlation between these variables and ability. However, the fixed effect approach does not solve the problem of endogenous

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

[17] The same restriction applies to our sample of voluntary firm switchers. That sample also has a firm tenure of zero, and we therefore cannot estimate the return to firm tenure for this group.

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selection into occupations based on the task match and heterogeneous returns to observable human capital.

To address these selection issues, we rely on a control function approach. The basic idea is to explicitly model the conditional mean of the error term in (9) and then include its empirical counterpart as a control variable in the estimation of the wage equation (see Heckman and Vytlacil [1998] for the general setup).[18] For consistent estimates, the control function approach requires the following assumptions. First, the instruments need to satisfy a rank condition. Economically, this implies that the instruments affect the worker's mobility decision, that is, whether to move to a new occupation and whether to move to a similar or distant occupation conditional on the observables and other exogenous controls. Second, the instruments Z_{iot} must be uncorrelated with the error term in the wage equation conditional on our exogenous control variables (time, occupation, and region dummies that we include in all specifications below). Formally, the exclusion restrictions are

$$E[\{\theta_i + \beta_o t_i^A + (1 - \beta_o)t_i^M\} + m_{if} + u_{ioft} | \tilde{X}_{iot}, Z_{iot}] = 0,$$

$$E[(\alpha_o - \bar{\alpha}) | \tilde{X}_{iot}, Z_{iot}] = E[(\gamma_o - \bar{\gamma}) | \tilde{X}_{iot}, Z_{iot}]$$

$$= E[(\delta_o - \bar{\delta}) | \tilde{X}_{iot}, Z_{iot}] = 0,$$

where $\tilde{X}_{iot}$ denotes the set of exogenous controls (and hence does not include our potentially endogenous human capital variables X_{iot}). 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 individual occupation tenure from its occupation-specific mean as an instrument. This instrument is uncorrelated with ability, θ_i, and the time-invariant task match, $\beta_o t_i^A + (1 - \beta_o)t_i^M$, by construction.[19]

[18] Note that a linear instrumental variable strategy will not identify the average return to human capital in this case except in very special circumstances. In particular, we would need to assume that the instruments are uncorrelated with the occupation-specific deviations from the average return and also are uncorrelated with the individual task match conditional on our observable human capital variables and other exogenous controls.

[19] Note that the deviation of occupation tenure from its occupation-specific mean does not eliminate a possible correlation with the firm-specific match component. This is likely to lead to a downward bias in the returns to occupation as workers may switch occupations and lose occupation-specific human capital because they secured a particularly good firm match. It is also likely to lead to a downward bias in the return to task-specific human capital as, among occupation switchers, workers may switch to a distant occupation and lose more task-specific human capital because of a good firm match. The sample restriction to consider only exogenously displaced workers should weaken this trade-off between specific human capital and a good firm match, but it may not completely eliminate it. A second reason why we expect

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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.[20] The basic idea is that workers who have more employment opportunities in their original occupation, or similar such occupations, will be less likely to switch occupations or move to a distant occupation. Conditional on 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 occupation-specific factor prices are equalized across local labor markets. Hence, our assumption requires that occupation-specific wages be set in a national labor market (see Adda et al. [2006] for a similar argument).

Finally, the following control function assumptions need to hold:

$$\begin{aligned} E[(\alpha_o - \bar{\alpha})|\tilde{X}_{iot}, X_{iot}, Z_{iot}] &= f(v^{Exp}, v^T, v^O), \\ E[(\gamma_o - \bar{\gamma})|\tilde{X}_{iot}, X_{iot}, Z_{iot}] &= g(v^{Exp}, v^T, v^O), \qquad (10) \\ E[(\delta_o - \bar{\delta})|\tilde{X}_{iot}, X_{iot}, Z_{iot}] &= h(v^{Exp}, v^T, v^O), \end{aligned}$$

and

$$E[\{\theta_i + \beta_o t_i^A + (1 - \beta_o) t_i^M\} + m_{ift} + u_{ioft}|X_{iot}, Z_{iot}] = k(v^{Exp}, v^T, v^O), \quad (11)$$

where $v^{\text{Exp}} = \text{Exp}_{it} - E[\text{Exp}_{it}|X_{iot}, Z_{iot}]$, $v^T = T_{iot} - E[T_{iot}|X_{iot}, Z_{iot}]$, and $v^O = O_{iot} - E[O_{iot}|X_{iot}, Z_{iot}]$ are the residuals from the respective reduced forms and $f(\cdot)$, $g(\cdot)$, $h(\cdot)$, and $k(\cdot)$ are linear in their arguments.[21] The first set of conditions (see [10]) accounts for sorting based on the occupation-specific returns to human capital, while the last assumption (see [11]) accounts for selection into occupations based on task match quality.

To implement the control function estimator, we first estimate the reduced forms for experience, occupational tenure, and task tenure and predict the residuals. The results are shown in table A2 in appendix A

this bias to be small is that the majority of young workers in our sample have been in the labor market for less than 8 years, so their decisions whether to switch occupations and to which occupation to move should be predominantly driven by the task match and not by the firm match (Neal 1999).

[20] The average distance, AD_{rt}, to other occupations is computed separately for each local labor market r and time period t as follows: $\text{AD}_{rt} = \sum_{o' \neq o}^{64} \text{Prop}_{rto'} \times \text{Distance}_{oo'}$. The first term denotes the proportion of workers in occupation o' in year t and regional labor market r; the second term describes the distance between occupations o and o'. 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.

[21] Note that the identification of the control function approach does not hinge on these linearity assumptions. See Florens et al. (2008) for a discussion of nonparametric identification of the control function estimator.

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for the low-skilled and medium-skilled and in table A3 (also in app. A) for the high-skilled. In the second step, we estimate the log wage equation in (9) including the estimated residuals as well as their interaction with the endogenous regressors. The latter controls for selection based on heterogeneous returns to human capital. 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 B. Since this estimator identifies the slope of the conditional quantile function and imposes common returns on the observable human capital variables, the estimates are not directly comparable to those of the other education groups or the least squares estimates in table 8. We bootstrap standard errors with 200 replications using the individual as the sampling unit in order to correct for generated regressor bias.

C. Empirical Results

We first report our benchmark least squares results; for university graduates, we estimated censored regression models to account for top-coded wages. Table 8 reports results first for the whole sample and then for the sample of firm switchers and displaced workers. The odd columns display results from a wage regression that ignores task-specific human capital, while the results presented in the even columns are from a specification that includes task tenure as an additional regressor.

The results in columns 1–6 reveal several interesting patterns. Returns to task tenure are sizable and exceed those of occupational tenure for all education groups. A second interesting result is that the returns to occupation-specific and general human capital decline once we account for task-specific human capital. For example, for the high-skilled who were displaced from their firm (cols. 5 and 6), returns to occupational tenure decline from 1.7% to 0.6% and returns to experience become negligible.

Since least squares estimates are biased, we now turn to two alternative estimators of the wage equation in table 9. We first show the fixed effects estimates for the displaced sample (cols. 1 and 2). This specification eliminates an upward bias in the return to experience from search over firm matches as well as from unobserved ability that is equally valued across occupations. For university graduates, we use the trimming estimator for censoring (Type 1 tobit model) with fixed effects proposed by Honoré (1992).[22] For the low-skilled and the medium-skilled, results are similar to the OLS estimates for the same sample. For the high-skilled, estimates are very noisy, so no firm conclusion can be drawn.

[22] 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).

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Table 8
Returns to Labor Market Skills: Least Squares Estimates

	Whole Sample		Firm Switchers		Displaced Workers	
	(1)	(2)	(3)	(4)	(5)	(6)
A. Low-skilled:						
Task tenure		.011***		.020***		.019***
		(.001)		(.002)		(.003)
Occupational tenure	.011***	.009***	.025***	.020***	.020***	.016***
	(.001)	(.001)	(.001)	(.001)	(.002)	(.002)
Experience	.072***	.065***	.049***	.037***	.046***	.034***
	(.001)	(.001)	(.001)	(.002)	(.003)	(.004)
$(\text{Experience})^2$	−.003***	−.002***	−.002***	−.001***	−.001***	−.001***
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Firm tenure	.007***	.007***				
	(.001)	(.001)				
No. observations	244,759	244,759	64,674	64,674	9,275	9,275
B. Medium-skilled:						
Task tenure		.020***		.032***		.029***
		(.001)		(.001)		(.002)
Occupational tenure	.007**	.004***	.018***	.012***	.015***	.010***
	(.000)	(.000)	(.000)	(.000)	(.001)	(.001)
Experience	.044***	.030***	.039***	.018***	.037***	.019***
	(.000)	(.001)	(.001)	(.001)	(.002)	(.002)
$(\text{Experience})^2$	−.002***	−.001***	−.001***	−.001***	−.001***	−.001***
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Firm tenure	.007***	.007***				
	(.000)	(.000)				
No. observations	1,003,823	1,003,823	190,962	190,962	28,441	28,441
C. High-skilled:						
Task tenure		.068***		.089***		.070***
		(.003)		(.004)		(.009)
Occupational tenure	.006***	−.003**	.017***	.004**	.017***	.006**
	(.001)	(.001)	(.002)	(.002)	(.003)	(.003)
Experience	.095***	.044***	.082***	.016***	.061***	.010
	(.002)	(.003)	(.002)	(.004)	(.006)	(.009)
$(\text{Experience})^2$	−.003***	−.003***	−.003***	−.002***	−.002***	−.001***
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Firm tenure	.005***	.005***				
	(.001)	(.001)				
No. observations	172,930	172,930	28,982	28,982	2,919	2,919

NOTE.—The table reports results from a regression of the log daily wage on general human capital (experience, experience squared), firm tenure, occupation tenure, and task tenure. All specifications include year, region, and occupation dummies. Panel C estimates tobit models to account for censoring. Specifications in cols. 2, 4, and 6 add our measure of task tenure to the specification in cols. 1, 3, and 5. Columns 1 and 2 are estimated for the whole sample, cols. 3 and 4 are estimated for those who have switched firms, and cols. 5 and 6 are estimated for our sample of displaced workers. Standard errors (in parentheses) allow for clustering at the individual level. For panel C, standard errors are bootstrapped with 200 replications to account for clustering at the individual level.

** $p < .05$.

*** $p < .01$.

With heterogeneous returns to human capital, the control function approach will also account for the fact that individuals select into a new occupation based on their task match $(\beta_o t_i^A + (1 - \beta_o) t_i^M)$ and the returns to their skills $(\alpha_o, \gamma_o, \delta_o, \lambda_o)$. Since our estimates on the displaced sample are identified from workers who are displaced from their job more than once, we also estimate the control function for the larger sample of firm switchers. Results for the sample of firm switchers are reported in columns 3 and 4 of table 9; those for the sample of displaced workers are shown

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Table 9
Returns to Labor Market Skills: Control Function Estimates

	Fixed Effects		Control Function			
	Displaced Sample		Firm Switchers		Displaced Sample	
	(1)	(2)	(3)	(4)	(5)	(6)
A. Low-skilled:						
Task tenure		.016***		.029***		.030***
		(.005)		(.006)		(.010)
Occupational tenure	.009***	.006**	.002	−.010***	.008**	−.004
	(.003)	(.003)	(.002)	(.003)	(.003)	(.004)
Experience	.062***	.047***	.063***	.050***	.056***	.043***
	(.008)	(.009)	(.002)	(.004)	(.003)	(.006)
$(\text{Experience})^2$	−.002***	−.001***	−.002***	−.002***	−.002***	−.002***
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
No. observations	9,275	9,275	64,674	64,674	9,275	9,275
B. Medium-skilled:						
Task tenure		.024***		.051***		.031***
		(.003)		(.004)		(.007)
Occupational tenure	.008***	.004***	.012***	−.002*	.010***	.001
	(.002)	(.001)	(.001)	(.001)	(.002)	(.002)
Experience	.050***	.027***	.043***	.015***	.042***	.026***
	(.005)	(.006)	(.001)	(.003)	(.002)	(.004)
$(\text{Experience})^2$	−.001***	−.001***	−.001***	−.001***	−.001***	−.001***
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
No. observations	28,441	28,441	190,962	190,962	28,441	28,441
C. High-skilled:						
Task tenure		.010		.022**		.022
		(.028)		(.010)		(.027)
Occupational tenure	.003	.002	−.024***	−.019***	−.004***	−.019**
	(.009)	(.008)	(.002)	(.005)	(.001)	(.005)
Experience	.057**	.044	.136***	.011***	.117***	.110***
	(.031)	(.056)	(.003)	(.022)	(.003)	(.022)
$(\text{Experience})^2$	−.001	−.001	−.008***	−.007***	−.007***	−.007***
	(.001)	(.002)	(.000)	(.001)	(.000)	(.001)
No. observations	2,919	2,919	28,982	28,982	2,919	2,919

Note.—For the medium-skilled and the low-skilled (panels A and B), cols. 1 and 2 report fixed effects estimates using the sample of displaced workers. Columns 3–6 report the control function estimates for those who have switched firms (cols. 3 and 4) and our sample of displaced workers (cols. 5 and 6). For the high-skilled (panel C), cols. 1 and 2 show fixed effects estimates using Honore's semiparametric trimming estimator for tobit models. Columns 3–6 report a semiparametric estimator proposed by Blundell and Powell (2004) to account for censoring in addition to endogenous regressors. In all specifications, standard errors are bootstrapped with 200 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, the results of the high-skilled are not directly comparable to those of the other two education groups.
* $p < .10$.
** $p < .05$.
*** $p < .01$.

in columns 5 and 6.[23] In both samples, the return to occupation tenure is considerably smaller than the return to task tenure, and it even becomes negative in some cases. The return to task tenure remains sizable for all

[23] 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.

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education groups. For the low-skilled and the medium-skilled, our control function estimates for the return to task tenure actually exceed the OLS estimates in table 8. One explanation for this finding is that workers move to distant occupations because they find a good match with that occupation, implying a negative correlation between task tenure and the task match.

How important then is task-specific human capital for individual wage growth over the life cycle? The wage of a medium-skill worker increases on average by 35% during the first 10 years in the labor market. Based on the control function results for the displaced sample (table 9, col. 6), task-specific human capital contributes 53% $((0.031 \times 5.81)/0.34)$ to this wage growth and experience contributes 43% $([(0.026 \times 8.19) - (0.001 \times 8.19^2)]/0.34)$, whereas occupation-specific tenure hardly contributes to the overall wage growth $((0.001 \times 5.63)/0.34 = 1.7\%)$.[24] A similar calculation for the low-skilled and the high-skilled implies that task-specific human capital accounts for 28% and 22% of overall wage growth, respectively. These calculations demonstrate that task-specific human capital is an important source of wage growth over the career.

The transferability of human capital is important for evaluating the costs of job displacement, for example, following technological change or economic restructuring more generally. As an illustration, consider a medium-skill worker who is displaced after 10 years in a specialized occupation. We take the example of goods transportation drivers. This occupation places a high weight on the task "packaging" ($\beta_{oj} = 0.73$) and relatively low weights on the other tasks ($\beta_{o-j} < 0.05$). Assuming that the returns to human capital in this occupation equal the average returns across occupations, wage losses will be 10 percentage points larger for workers reemployed in a very distant occupation, that is, as a bank or insurance clerk, than for workers who can find employment in an occupation with similar skill requirements, for example, as a warehouse keeper.[25] The basic pattern holds for all education and experience groups.

These calculations highlight the fact that wage losses due to job displacement strongly depend on the thickness of labor markets. In partic-

[24] This calculation takes into account that, after 10 years in the labor market, a high-skill worker has accumulated 5.81 years of task tenure, 8.19 years of actual experience, and 5.63 years of occupational tenure.

[25] We calculate the task tenure in the two alternative occupations as the product of the weight in the displaced occupation and the new occupation summed over all tasks. The loss of task-specific human capital is defined by 10 years minus the task-specific human capital that the worker can transfer to the new occupation. The worker who moves to the similar occupation can transfer 2.9 more units of task-specific human capital to his new occupation than the worker who moves to the distant occupation. The extra wage loss of distant movers is then computed as the return to task-specific human capital, 0.031 (see table 9, col. 6), times the extra task-specific human capital lost, 2.9.

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ular, 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.

VI. Conclusion

How general is human capital? In this article, we propose a new approach to measure the transferability of skills accumulated in the labor market. Our framework provides a parsimonious way to summarize the skill similarity between many occupations. Based on our approach, we document new patterns in occupational mobility and wages that are consistent with the idea that skills are partially transferable across occupations.

We then show that task-specific human capital is an important source of individual wage growth, explaining more than half of the overall wage growth for the medium-skilled and around one-quarter for the low-skilled and the high-skilled. We also provide evidence that the costs of displacement and job reallocation depend on the employment opportunities after displacement: wage losses are much 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 typically 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-skill workers accumulate more task-specific 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 for this education group the correlation between wages in the source occupation and the target occupation declines more strongly with the distance of the move and why returns to task-specific human capital are higher than for the two other education groups.

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

Appendix A

Data Sources

1. Data on Occupational Tasks (1979–99)

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

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of Vocational Training (BIBB) and the Institute for Labor Market Research (IAB). The data, with a sample size of 30,000, cover individuals between the ages of 16 and 65 who are employed at the time of the survey. We restrict our sample to men employed in West Germany, and we 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 two-digit level decreases well-known measurement error problems of occupational classifications in survey data and allows us to match the task 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 task not performed. Overall, we have information on 19 different tasks workers perform in their jobs. For expositional purposes, we also group the 19 tasks into three groups of tasks, following Autor et al. (2003): analytical tasks, manual tasks, and interactive tasks. The assignment of tasks is as follows: *analytical tasks* (research, evaluate, or measure; design, plan, or sketch; correct texts or data; calculate or do bookkeeping; program; execute laws or interpret rules), *manual tasks* (equip or operate machines; repair, renovate, or reconstruct; cultivate; manufacture, construct, or install; cleaning; serve or accommodate; pack, ship, or transport; secure; nurse or treat others), and *interactive tasks* (sell, buy, or advertise; teach or train others; publish, present, or entertain others; employ, manage personnel or organize or coordinate).

2. Employee Sample (1975–2001)

Our main data set is a 2% 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 relationship that is 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-skilled, medium-skilled, 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

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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' associations. To make the 130 different occupations we observe in our sample comparable to the BIBB data, we aggregated them into 64 occupations at the two-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 start his occupational tenure from zero. The same holds in the unlikely event that a worker returns to a firm for which he has worked 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 individuals who were still in vocational training at the end of the sample period in 2001 or who pursued more than one apprenticeship, that is, those who 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 1 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 for less than a year, those with missing education or nationality, and observations with no valid wage or a daily (real) wage below 20 DM (10 euros) during an employment spell.

While most employees are covered by collective bargaining agreements between unions and employers (84% in the late 1990s), the bargained wages only set a wage floor. There is substantial variation in wages above this floor. We estimated a regression of log wages on industry and state dummies, a full set of interaction terms, individual demographics, and year and occupation dummies. We find that the controls for wage bargaining (industry and state dummies plus their interaction) only explain an additional 4% of the wage variation for the low-skilled and the medium-skilled, for which unions are most important. For additional information on unions and wages, see Fitzenberger and Kohn (2005) and Dustmann and Schönberg (2009) and the references therein.

Our sample of displaced workers used in Section V is defined as follows. A worker is displaced from his firm due to plant closure if he left the firm in the year or 1 year before the firm closed down. As a robustness

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check, we have repeated the analysis restricting the sample to workers who have left the firm in the year or 1 or 2 years before the firm closed down. The first definition has the advantage that it includes fewer workers who have left the firm voluntarily for reasons other than plant closure. It has the disadvantage that it may exclude workers who leave the firm prior to plant closure because they anticipate that the firm may shut down in the future. Both definitions give similar results.

Table A1
List of Occupations and Task Usage

Title of Occupation	Employed (%)	Manual Tasks	Analytic Tasks	Interactive Tasks
Miners, Stone-breaker, Mineral Processing	.96	.975	.257	.281
Concrete and Cement Finisher, Stone Processing	.37	.995	.364	.365
Potter, Ceramicist, Gaffer	.37	.957	.484	.321
Chemical Processing	1.69	.965	.576	.397
Plastics and Polymer Processing	1.17	.973	.463	.396
Paper and Pulp Processing	.70	.961	.557	.494
Printer, Typesetter, Typographer	.83	.912	.589	.461
Wood, Lumber, and Timber Processing	.47	.866	.344	.230
Metal and Iron Manufacturer	.42	.973	.361	.280
Molding, Shaping	.40	.928	.369	.225
Metal Presser and Molder	.56	.998	.392	.231
Metal Polisher, Sander, Buffer, Lathe Operator	2.31	.988	.485	.321
Welder, Brazing, Soldering	.53	.952	.332	.218
Blacksmith, Farrier, Forger, Plumber, and Pipe Fitter	3.27	.977	.527	.500
Locksmith	6.28	.977	.454	.363
Mechanic, Machinist, Repairmen	4.29	.971	.568	.471
Tool and Dye Maker, Instrument Mechanic	1.28	.980	.573	.448
Metal Craftsman	.35	.959	.701	.570
Electrician, Electrical Installation	5.45	.966	.642	.520
Assembler	2.81	.904	.349	.241
Weaver, Spinner, Knitter, Wool Trade	.14	.974	.329	.345
Tailor, Textile Worker	.19	.911	.346	.270
Shoemaker	.23	.906	.315	.483
Baker	1.02	.963	.399	.502
Butcher	1.04	.895	.351	.470
Cook	1.31	.918	.450	.648
Beverage Production, Milk Production, Grease Processing	.48	.916	.563	.463
Bricklayer, Mason	2.54	.932	.338	.376
Carpenter	1.62	.957	.390	.420
Road Builder	.83	.915	.292	.309
Unskilled Construction Worker	1.31	.893	.167	.168
Plasterer	1.11	.935	.404	.408
Interior Decorator, Interior Designer	.32	.943	.471	.532
Joiner, Cabinet Maker	2.86	.972	.503	.442
Painter	2.24	.909	.329	.414
Product Tester	1.73	.697	.576	.394
Unskilled Worker	1.78	.903	.305	.199
Crane Driver, Crane Operator, Skinner, Machine Operator	.94	.982	.466	.367
Engineer	3.24	.533	.935	.865

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Table A1 (*Continued*)

Title of Occupation	Employed (%)	Manual Tasks	Analytic Tasks	Interactive Tasks
Chemist, Physicist	4.27	.721	.886	.813
Technical Service Personnel	1.00	.550	.919	.568
Sales Personnel	4.89	.573	.696	.958
Banker	2.91	.429	.844	.932
Traders, Trading Personnel	.78	.517	.792	.892
Truck Driver, Conductor	4.09	.851	.230	.352
Sailor, Seaman, Navigator, Mariner	.15	.851	.525	.642
Mail Carrier and Handler, Postal Clerk	.48	.781	.404	.402
Storekeeper, Warehouse Keeper	4.74	.822	.354	.389
Entrepreneur	1.56	.513	.885	.973
Politician, Member of Parliament	.26	.453	.924	.908
Accountant, Bookkeeper	2.13	.541	.924	.804
Office Clerk	6.14	.434	.822	.789
Guard, Watchman, Police, Security Personnel	1.11	.809	.575	.621
Publicist, Journalist, Author	.17	.404	.842	.866
Musician	.41	.628	.682	.739
Physician	.51	.850	.642	.708
Nurse, Dietitian, Physical Therapist	.77	.964	.627	.691
Social Worker	.52	.764	.696	.936
Teacher (except university)	.89	.476	.698	.964
Scientist, Clergyman	.82	.417	.849	.898
Personal Hygiene Technician	.12	.897	.392	.755
Waiter, Barkeeper, Innkeeper	.71	.919	.352	.735
Janitor, Home Economics, Housekeeper	.03	.615	.650	.804
Cleaning Service Worker	1.12	.848	.244	.248
Mean		.8028	.5628	.5464

Source.—IAB Employee sample, matched with qualification and career.

Note.—The table shows the titles of the 64 occupations, the percentage of individuals employed in the occupations, and the fraction of individuals who 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 1.

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

	A. Low-Skilled						B. Medium-Skilled					
	Starting New Job			Displaced Sample			Starting New Job			Displaced Sample		
	Actual Experience (1)	Occupation Tenure (2)	Task Tenure (3)	Actual Experience (4)	Occupation Tenure (5)	Task Tenure (6)	Actual Experience (1)	Occupation Tenure (2)	Task Tenure (3)	Actual Experience (4)	Occupation Tenure (5)	Task Tenure (6)
Age	.016	.533***	.011	.152***	.124***	.638***	−.055***	.137***	.562***	.044	.252***	.678***
	(.018)	(.013)	(.014)	(.051)	(.043)	(.037)	(.011)	(.011)	(.009)	(.030)	(.033)	(.023)
(Age)^2	.013***	.000*	.003***	.009***	.001	.000	.013***	.002***	.001***	.011***	.000	.000
	(.000)	(.000)	(.000)	(.001)	(.001)	(.001)	(.000)	(.000)	(.000)	(.001)	(.000)	(.001)
Mean distance to other occupations	1.501***	10.082***	1.950***	−1.451	2.212***	12.041***	−.784***	1.010***	9.209***	(.667)	1.067	12.940***
	(.392)	(.270)	(.291)	(1.032)	(.857)	(.735)	(.234)	(.243)	(.183)	(.603)	(.665)	(.470)
Age × Mean distance	−.063***	−.413***	−.095***	.050	−.071**	−.496***	.019**	−.057***	−.384***	.025	−.033	−.512***
	(.015)	(.011)	(.011)	(.040)	(.033)	(.029)	(.009)	(.009)	(.007)	(.022)	(.025)	(.017)
Size of occupation	−3.275	−10.846***	−2.865*	−.304	−3.142	−15.460***	−9.751***	.091	−24.081***	−14.971***	−9.673***	−26.540***
	(2.283)	(1.573)	(1.692)	(6.466)	(5.370)	(4.605)	(1.230)	(1.276)	(.964)	(3.300)	(3.636)	(2.573)
Age × Size of occupation	.147*	.507***	.204***	−.063	.253	.654***	.409***	.104**	1.077***	.602***	.432***	1.152***
	(.089)	(.061)	(.066)	(.244)	(.203)	(.174)	(.045)	(.046)	(.035)	(.118)	(.130)	(.092)
Deviation from occupation tenure	.157***	.158***	.625***	.265***	.888***	.247***	.192***	.763***	.218***	.261***	.917***	.263***
	(.006)	(.004)	(.004)	(.016)	(.013)	(.011)	(.002)	(.003)	(.002)	(.006)	(.007)	(.005)
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
No. observations	64,674	64,674	64,674	9,275	9,275	9,275	190,962	190,962	190,962	28,441	28,441	28,441

Note.—The table reports the regression results of the reduced forms for experience, occupational tenure, and task tenure that are used to construct the control function in table 9, for the low-skilled and the medium-skilled. All specifications are estimated on the sample of firm switchers in cols. 1–3 and on the sample of displaced workers in cols. 4–6. For each education group, the dependent variable is experience (cols. 1 and 4), occupational tenure (cols. 2 and 5), and task tenure (cols. 3 and 6), respectively. All specifications include occupation, year, and region dummies. Robust standard errors are reported in parentheses. See also note to table 9.

* $p < .10$.
** $p < .05$.
*** $p < .01$.

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

	C. High-Skilled									
	Starting New Job					Displaced Sample				
	Actual Experience (1)	(Experience)² (2)	Occupation Tenure (3)	Task Tenure (4)	Log Wage (5)	Actual Experience (6)	(Experience)² (7)	Occupation Tenure (8)	Task Tenure (9)	Log Wage (10)
Age	−.502***	−29.821***	−.439***	−.258***	.101***	−.184	−26.754***	−.283***	−.179*	.114***
	(.035)	(.569)	(.027)	(.029)	(.001)	(.123)	(2.281)	(.092)	(.105)	(.000)
(Age)²	.017***	.586***	.012***	.006***	−.001***	.014***	.578***	.010***	.006***	−.001***
	(.000)	(.008)	(.000)	(.000)	(.000)	(.002)	(.031)	(.001)	(.001)	(.000)
Mean distance to other occupations	.525	40.772***	−6.422***	−3.850***	.460***	5.292**	81.816*	−2.136	.842	.901***
	(.727)	(11.776)	(.552)	(.607)	(.011)	(2.460)	(45.447)	(1.840)	(2.099)	(.000)
Age × Mean distance	−.069***	−1.443***	.174***	.146***	−.016***	−.177**	−2.908**	.107*	.047	−.033***
	(.022)	(.360)	(.017)	(.019)	(.000)	(.076)	(1.402)	(.057)	(.065)	(.000)
Size of occupation	−13.684***	−583.161***	−13.296***	1.594	.745***	10.534	111.336	−12.086	−9.332	1.485***
	(3.864)	(62.549)	(2.930)	(3.224)	(.057)	(13.753)	(254.034)	(10.285)	(11.735)	(.000)
Age × Size of occupation	.606***	20.524***	.582***	.020	−.016***	−.357	−4.613	.457	.303	−.027***
	(.120)	(1.943)	(.091)	(.100)	(.002)	(.419)	(7.738)	(.313)	(.357)	(.000)
Deviation from occupation tenure	.310***	4.514***	.309***	.967***	−.013***	.325***	4.510***	.384***	.999***	−.008***
	(.008)	(.123)	(.006)	(.006)	(.000)	(.025)	(.463)	(.019)	(.021)	(.000)
Experience					.002***					.002***
					(.000)					(.000)
(Experience)²					−.001***					−.001***
					(.000)					(.000)
Occupational tenure					.007***					.005***
					(.000)					(.000)
Task tenure					.039***					.036***
					(.000)					(.000)
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
No. observations	28,982	28,982	28,982	28,982	28,982	2,919	2,919	2,919	2,919	2,919

Note.—For the high-skilled, the table reports the regression of experience, occupational regression of the log wage on the instruments, and endogenous controls. All specifications include year, occupation, and region dummies. See also note to table 9 and the appendix.

* $p<.10$.

** $p<.05$.

*** $p<.01$.

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Table A4
The Impact of the Residuals in the Wage Equation (Table 9)

	A. Low-Skilled				B. Medium-Skilled			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Residual experience	−.025***	−.024***	−.014***	−.012	−.011***	−.006**	−.007***	−.009
	(.002)	(.004)	(.005)	(.008)	(.002)	(.003)	(.003)	(.005)
Exp. res. × Experience	.002***	.004***	.001**	.005***	.003***	.006***	.002***	.005***
	(.000)	(.001)***	(.001)	(.002)	(.000)	(.001)	(.001)	(.001)
Exp. res. × (Experience)^2	.000	.000***	.000	.000	.000**	.000***	.000	.000*
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Exp. res. × Task tenure		−.005***		−.007***		−.006***		−.006***
		(.000)		(.002)		(.000)		(.001)
Exp. res. × Occupation tenure	−.002***	−.001	.000	.001	−.002***	0**	0***	−.002
	(.000)	(.001)	(.001)	(.001)	(.000)	(.000)	(.001)	(.001)
Residual occupation tenure	.066***	.069***	.040***	.040***	.036***	.038***	.029***	.027***
	(.002)	(.003)	(.004)	(.005)	(.001)	(.001)	(.002)	(.002)
Occ. res. × Experience	−.002***	.000	−.002**	.003**	−.001***	.002***	.000	.002***
	(.001)***	(.001)	(.001)	(.002)	(.000)***	(.000)***	(.001)	(.001)***
Occ. res. × (Experience)^2	.000***	.000*	.000*	.000	.000***	.000***	.000***	.000**
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Occ. res. × Task tenure		−.002***		−.003***		−.002***		−.001
		(.000)		(.001)		(.000)		(.001)
Occ. res. × Occupation tenure	−.003***	−.002***	−.003***	−.002**	−.004***	−.003***	−.004***	−.003***
	(.000)	(.000)	(.001)	(.001)	(.000)	(.000)	(.000)	(.000)

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Table A4 (*Continued*)

	A. Low-Skilled				B. Medium-Skilled			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Residual task tenure		−.006		−.006		−.011***		−.004
		−.007		(.014)		(.004)		(.009)
Task res. × Experience		.001		.000		−.001		.001
		(.001)		(.003)		(.001)		(.002)
Task res. × (Experience)^2		.000**		.000*		.000***		.000
		(.000)		(.000)		(.000)		(.000)
Task res. × Task tenure		−.003**		−.002*		−.001**		−.001
		(.001)		(.001)		(.000)		(.001)
Task res. × Occupation tenure		.002**		−.001		0***		−.002**
		(.001)		(.001)		(.000)		(.001)
p-value for joint significance (%)	.00	.00	.00	.00	.00	.00	.00	.00

Note.—The table reports the coefficients on the residuals and their interaction with the main regressors to control for selection in table 9. The column numbers in this table correspond to cols. 1–4 in table 9. Standard errors (in parentheses) 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 the note to table 9.

* $p < .10$.
** $p < .05$.
*** $p < .01$.

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Appendix B

Blundell and Powell (2004) Control Variable Estimator

For the high-skilled, the control variable estimates in table 9, columns 3–6, 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 is 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:

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

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 estimate the control variable $\hat{v}_{it}$ from regressions of the endogenous regressors on the instruments and other control variables. Then, we predict the conditional quantile of $\ln \hat{W}_{it}$ from a quantile regression of log wages on the endogenous regressors, instruments and other control variables. The final step involves a weighted least squares regression of all pairwise differences of the predicted dependent variable $\ln \hat{W}_{it}$ on the endogenous regressors X_{it}. The weights are determined by a multivariate

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kernel function that is declining in the distance between the residuals $\hat{v}_{it}$ and $\hat{v}_{it}$. Formally, the second-stage estimator is defined as

$$\hat{\beta} = \left[\sum_{s<t}\sum_{i<j} K_v\left(\frac{\hat{v}_{is} - \hat{v}_{jt}}{h_n}\right)\hat{t}_{is}\hat{t}_{jt}(X_{is} - X_{jt})'(X_{is} - X_{jt})\right]^{-1} \times$$

$$\left[\sum_{s<t}\sum_{i<j} K_v\left(\frac{\hat{v}_{is} - \hat{v}_{jt}}{h_n}\right)\hat{t}_{is}\hat{t}(X_{is} - X_{jt})'(\ln \hat{W}_{is} - \ln \hat{W}_{jt})\right],$$

where $K_v(\cdot)$ is the kernel function and h_n is a sequence of scalar bandwidth terms; $\hat{t}_{is}$ is a "trimming" term, constructed so that $\hat{t}_{is} = 0$ unless the estimated quantiles $\ln \hat{W}_{is} > 0$ 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 200 replications.

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