How General is Specific Human Capital? Using Mobility Patterns to Study Skill Transferability in the Labor Market

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Abstract

Previous studies assume that labor market skills are either fully general or specific to the firm. This paper uses patterns in mobility and a wages to analyze the transferability of specific skills across occupations. The empirical analysis combines information on tasks performed in different occupations with a large panel on complete working histories and wages. Our results demonstrate that labor market skills are partially transferable across occupations. We find that individuals move to occupations with similar task requirements and that the distance of moves declines with time in the labor market. Further, tenure in the last occupation affects current wages, and the effect is stronger if the two occupations are similar. We calculate that task-specific human capital is an important source of wage growth, especially for university graduates.

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1 Introduction

The distinction between general and specific human capital is a central concept in labor economics (Becker, 1964). Specific human capital, defined as skills that are productive only in a particular firm or with a certain technology, plays an important role for answering several economic questions. For example, reallocation costs of worker displacement and the speed of adjustment to technological change depend crucially on how transferable specific skills are across jobs.[1]

The empirical literature has followed two approaches to isolate the value of specific skills: first, a number of studies have estimated the effects of firm tenure on wages (Abraham and Farber, 1987; Altonji and Shakotko, 1987; Altonji and Williams, 2005; Topel, 1991). The second approach infers the value of specific skills from wage losses of displaced workers (Jacobson et al, 1993; Kletzer, 1989). While the first approach finds conflicting estimates of the returns to firm tenure, the latter reports substantial wage losses from displacement.

Firm tenure might however be a poor measure of specific skills. For example, firms and workers could split the costs and returns of investment in specific skills in such a way that firms pay for the training and workers do not receive any wage compensation. In this case, the coefficient on tenure in a wage regression would be zero despite investment in specific skills (Farber, 1999).

Recent evidence also suggests that specific skills are more general than previously considered. Several studies using US data have shown that the coefficient on firm tenure in a wage regression is no longer statistically different from zero once controls for occupational or industry tenure are included (Gibbons et al, 2005; Kambourov and Manovskii, 2002; Parent, 2000). Similarly, evidence from displaced workers shows that wage losses are much lower for workers returning to the sector of their pre-displacement job (Neal, 1999). This suggests that specific skills might be tied more to an occupation than to a particular firm.

This paper analyzes how general or specific human capital accumulated in the labor market is. Our strategy to answer the question differs from previous research in three important ways: first,

[1] Recent macroeconomic models have argued that the specificity of skills with respect to the current technology plays a crucial role in explaining the divergent growth experience of the United States and Europe (Krueger and Kumar, 2004; Wasmer, 2005) and the rise in wage inequality over the past two decades (Violante, 2002).

the existing literature assumes that skills are either general or fully depreciate when workers leave a firm or occupation.[2] We in contrast ask whether human capital is specific to an occupation or more generally transferable across occupations. Second, our analysis uses for the first time patterns in occupational mobility together with information on wages to demonstrate that skills are partially transferable across occupations. Finally, our empirical strategy combines two unusually rich data sources: a large survey on tasks performed in occupations and a panel of individual labor market careers spanning almost three decades.

The economic intuition behind our approach is that individual's occupational choices also involve the choice of a particular set of skills. Suppose there are two types of skills in the labor market, for example analytical and manual skills. Both skills are general in the sense that they are productive in different jobs. Occupations combine the two skills in different ways. For example, one occupation might rely heavily on analytical skills, a second more on manual skills, and a third might combine the two in equal proportion. Human capital accumulated while working in an occupation is then "specific" to that occupation to the extent that occupations place different values on combinations of skills (see also Lazear, 2004).

This setup would predict that individuals are more likely to move to an occupation with skill requirements similar to the occupation of origin.[3] Mobility costs arise naturally in our framework from the limited transferability of skills across occupations. These costs of mobility are rising in the distance between the skill requirements of the current and potential future jobs. Furthermore, wages after a move should be higher in a similar occupation because more of the skills from the last occupation are valuable in the new occupation.

To analyze the transferability of human capital across occupations empirically, we require high-quality panel data on worker mobility as well as information on the skill requirements in different occupations. In the absence of reliable data for the United States, we combine information from

[2] There are two exceptions to this. Keane and Wolpin (1997) provide evidence that human capital in blue-collar occupations is rewarded in white-collar occupations and vice versa. Their dynamic discrete choice setup however constrains them to two occupational choices. Shaw (1987) in contrast constructs a measure of occupational distance based on actual worker flows. She also provides evidence that skills are partially transferable across occupations.

[3] Job ladder models in contrast assume that there is only one type of skill in the labor market or have little to say about whether skills are transferable across rungs of the ladder (Galor and Sicherman, 1990; Gibbons and Waldman, 2006).

two different data sources in Germany. The first data set is a large survey that provides detailed information on 19 different tasks performed in occupations at four separate points in time. The data allows us to characterize whether two occupations require similar or very different skills.[4] Using this variation in skill requirements across occupations, we construct measures of 'distance' between occupations. Based on the task data, the skill requirements of a baker and a cook are very similar. In contrast, switching from a banker to an unskilled construction worker would be the most distant move observable in our data.

Our second data source is a large panel that follows individual labor market careers fom 1975 to 2001. The data, derived from a two percent sample of all social security records in Germany, provides a complete picture of job mobility and wages in each job with more than one million observations. Its administrative nature ensures that there is little measurement error in wages and occupational coding. Both are serious problems in datasets like the PSID or NLSY used in the previous literature on occupational mobility. In addition, we have much larger samples available than in typical household surveys.

Matching the information on tasks and distance between occupations to the individual panel data on mobility and wages, we can link observable patterns in mobility and wages to the transferability of skills in an innovative way.

Our results suggest that task human capital is partially transferable across occupations, but is not a general skill like labor market experience. More specifically, we show that individuals are much more likely to move to similar occupations than we would expect if mobility was random. The result stands in stark contrast to the standard turnover models, which assume that worker productivity is unrelated across jobs (Jovanovic, 1979a; 1979b; Flinn, 1986; Topel and Ward, 1992).[5] This suggests that there is much more mobility between occupations than switches in tasks performed on the job.

If individuals move to a distant occupation, this switch occurs very early in their career, mostly

[4] Note that the data do not allow us to analyze specialization and the accumulation of specific skills within a given occupation, for example the type of law practiced by a lawyer.

[5] More recently, models consider both occupational and firm mobility (Miller, 1984; Neal, 1998; Pavan, 2005). These models assume however that all specific skills are lost when an individual switches occupations.

within five years of labor market entry. Both the distance of actual moves and the propensity to switch occupations declines sharply with labor market experience. This is consistent with the idea that the accumulation of task-specific human capital makes occupational mobility increasingly costly.

If human capital is task specific and therefore in part transferable across occupations, this should also be reflected in individuals' wages. Our framework can explain why tenure in the pre-displacement job has been found to have a positive effect on the post-displacement wage (Kletzer, 1989). We also show that for movers the correlation of wages in old and new occupations is much higher if the two occupations require similar skills.

Using a nonlinear instrumental variable approach, we show that task-specific human capital is an important source of wage growth, in particular for the high-skilled. @All our empirical results are much stronger for university graduates than for the other two education groups. We interpret this as evidence that the high-skilled have a comparative advantage in learning tasks.

In contrast, skills specific to the firm and occupation are most important for the low-skilled. These differences by education are consistent with previous evidence on the returns to firm tenure and experience from Germany (Dustmann and Meghir, 2005).

The structure of the paper is as follows. The next section outlines a model of task human capital and occupational choice. Section 3 introduces the two data sources and how we relate occupations to each other in terms of their skill requirements. The empirical results on the similarity of occupational moves and its implications for wages across occupations are presented in Section 4. Section 5 estimates the importance of task human capital for wage growth. Finally, Section 6 discusses future extensions and concludes.

2 Specific Skills, Mobility and Wages

Our goal is to analyze the nature of specific skills that individuals accumulate over their labor market career. To this end, we outline a simple framework of occupational choice with task-specific human capital that highlights how skill requirements of occupations are related to each other. We start out with a one-period occupational choice model. We then extend it to a dynamic setting to allow for human capital accumulation.

2.1 Static Occupational Choice Model

The labor market consists of N different occupations. Output in an occupation is produced by combining different tasks, for example negotiating, writing or calculating. Occupations differ in the tasks they require and in the relative importance of each task for production. To simplify notation, we consider the case of two tasks, denoted by $j = A, M$. We think of them as manual and analytical tasks.

There is a continuum of risk-neutral workers indexed by i. Workers are endowed with productivities in each task. Let T_i^A and T_i^M denote worker i's productivity in task A and M. These productivities are drawn from a joint normal distribution with mean $\overline{T}^A, \overline{T}^M$, variance σ_A^2, σ_M^2, and correlation ρ.

Wages of individuals working in occupation o are given by

$$W_{io} = P_o S_{io},$$

where P_o is the occupation-specific price for skill S_{io}.[6] We specify S_{io} to be log-linear in task-specific productivity, i.e.

$$S_{io} = e^{\beta_o T_i^A + (1-\beta_o) T_i^B}.$$

Here, $0 \leq \beta_o \leq 1$ is the relative weight on the analytical task. For example, if in an occupation analytical tasks are more important than manual tasks, $\beta_o > 0.5$. In another occupation, only the manual task might be performed, so $\beta_o = 0$. By restricting the weights on the tasks to sum to one, we focus on the relative importance of each task in an occupation, not on their intensity.[7] Two

[6] Skill prices are determined endogenously in equilibrium. Let L_o denote the labor input in occupation o (L_o aggregates the skill units S_{io} over workers employed in occupation o). Each occupation's output is a concave function of its labor input: $y_o = F_o(L_o)$. Let Π_o denote occupation product prices. Firms behave competitively in both the product and labor market, and tak product prices Π_o and skill prices P_o as given. Competition implies that $P_o = \Pi_o F_o'(L_o)$.

[7] Our setup is a restricted version of the classic Roy model. In that model, each sector has its own task, and productivity can be arbitrarily correlated across occupations. However, this setup becomes quickly untractable as the

occupations o and o' are similar if they employ analytical and manual tasks in similar proportions, i.e. β_o is close to $\beta_{o'}$. The occupation that fully specializes in the analytical task ($\beta_o = 1$) and the occupation that fully specializes in the manual task ($\beta_o = 0$) are the two most distant occupations.

Workers choose where to work by comparing wages across occupations. They prefer occupation o over occupation o' if

$$\ln P_o + \beta_o T_i^A + (1 - \beta_o)T_i^B > \ln P_{o'} + \beta_{o'} T_i^A + (1 - \beta_{o'})T_i^B.$$

Assuming $\beta_o > \beta_{o'}$,

$$T_i^A > \frac{\ln P_{o'} - \ln P_o}{\beta_o - \beta_{o'}} + T_i^B$$

Figure 1 illustrates occupational choice when there are four occupations with $\beta_1 > \beta_2 > \beta_3 > \beta_4$. Occupation 1 mostly requires the analytical task, while occupation 4 primarily relies on the manual task. Occupation 2 and 3 put a more equal weight on both tasks.

Workers with a high productivity in the analytical task relative to the manual task sort into occupation 1 that puts a high value on the analytical task. Similarly, workers with a high productivity in the manual task relative to the analytical task choose occupation 4. Workers with more similar relative endowments will be found in occupations 2 and 3. Note that occupations 2 and 3 will have positive employment in equilibrium only if they pay higher skill prices (P_o) than the occupations 1 and 4 that focus on only one task.

2.2 Dynamic Model with Mobility and Human Capital Accumulation

We now extend the model to a dynamic setting with two periods. Individuals accumulate human capital in their occupation through learning-by-doing. To keep the model tractable, we assume in

number of occupations increases. We reduce the dimensionality by restricting occupational output to be a weighted function of a number of tasks strictly smaller than the number of occupations N. Assuming that productivities in analytical and manual tasks are uncorrelated, the population variance of productivities in the log-linear setup is given by $Var(\ln y_o) = (\beta_o)^2 \sigma^A + (1 - \beta_o)^2 \sigma^M$. The population covariance of productivities between occupation o and $o\prime$ is

$$Cov(\ln y_o, \ln y_{o'}) = (\beta_o \beta_{o'}) \sigma_1 + ((1 - \beta_o)(1 - \beta_{o'}) \sigma_2 + (\beta_o(1 - \beta_{o'}) + (1 - \beta_o)\beta_{o'})\sigma_{12}$$

Instead of allowing for an arbitrary covariance between the productivities, our model imposes a linear factor structure, where the factors are the population variances and covariance of the two tasks and the factor loadings are a function of the occupation-specific weights on the skills.

addition that each individual accumulates the same amount of task human capital in each task and occupation. This implies that the learning rate does not depend on the occupational choice in the first period (as in Rosen, 1983; Murphy, 1986) or an individual's initial endowment (as in Ben-Porath, 1967). These restrictions allows us to focus our analysis on the types of move we observe and the relative importance of task human capital relative to general or more specific skills (see Section 5).

If a worker switches occupation, the similarity of the source and target occupation determines how much of the task human capital can be transferred to the new job. In particular, we assume that workers can transfer a fraction $1 - |\beta_o - \beta_{o'}|$ of their human capital if they switch from occupation o to o'. For example, if workers move from an occupation that fully specializes in the analytical task ($\beta_o = 1$) to an occupation that fully specializes in the manual task ($\beta_{o'} = 0$), none of the acquired skills can be transferred. In contrast, if workers move from an occupation that mostly uses the analytical task (e.g. $\beta_o = 0.75$) to an occupation that employs both tasks in equal proportions (i.e. $\beta_{o'} = 0.5$), they are able to transfer around 75 percent of their acquired skills.[8]

Since task-specific human capital has the highest value in workers' current occupation, no worker would ever switch occupations between period 1 and 2 in the absence of uncertainty. We formalize uncertainty as individual-specific shocks to task-specific productivities, and denote these shocks by u_i^j, $j = A, M$. Task shocks occur with probability p, and are revealed only after the first period.[9] Thus, task-specific productivity in the second period equals

$$T_{2i}^j = T_i^j + D_i^j u_i^j, \qquad j = A, M.$$

Here, D_i^j is an indicator function equal to 1 if worker i experienced a shock at task j, and 0 otherwise.

[8] A more general model of occupational choice and human capital accumulation would allow workers to invest separately in task-specific skills A and M. For instance, learning could depend on the usage of a task in an occupation. If a worker chooses an occupation that mainly specializes in task A, he would mainly accumulate skills in task A. This ties the skill investment decision to the choice of an occupation. See Murphy (1986) or Rosen (1983) models along these lines. The more general model would however not lead to an empirical specification we could estimate with the data available to us. Our more restricted setting allows us estimate the importance of task-specific human capital relative to purely general or occupation-specific human capital.

[9] This type of shocks has the advantage that they induce mobility both from occupation o to o' and vice versa. This is consistent with the empirical observation that gross mobility is much more important than net mobility.

The productivity shocks are assumed to be independent of each other, and are drawn from a joint normal distribution with mean $\overline{u}^A = \overline{u}^M = 0$ and variance $\sigma^2_{u_A} = \sigma^2_{u_B}$. One interpretation of the shocks is that the productivity of an individual is only revealed through performing that task. Our setup says that task-specific shocks do *not* depend on occupational choice in the first period; in particular, they are independent of the relative usage of a task in the occupation.

Our assumptions on human capital accumulation and productivity shocks imply that log-wages in the first period can be written as

$$\ln w_{io1} = \ln P_o + \beta_o T_i^A + (1-\beta_o) T_i^B \tag{1}$$

while in the second period, wages are given as

$$\begin{aligned}\ln w_{io2} &= \ln P_o + \beta_o (T_i^A + D_i^j u_i^A) + (1-\beta_o)(T_i^B + D_i^j u_i^B) + H \cdot TS_i \qquad (2)\\ &= \ln w_{io1} + \beta_o D_i^j u_i^A + (1-\beta_o) D_i^j u_i^B + H \cdot TS_i.\end{aligned}$$

In (2),TS_i denotes worker i's 'task-specific tenure', and H is the return to task-specific human capital or tenure. TS_i is equal to 1 if the worker does not switch occupations; it is equal to $1 - |\beta_o - \beta_{o'}|$ if he moves from occupation o to o'. This specification can easily be extended to incorporate purely general human capital accumulation that is fully transferable across all occupations, and purely occupation-specific human capital accumulation that fully depreciates if a worker leaves the occupation. Note that task-specific human capital is more specific than general human capital - since skills can only be partly transferred across occupations -, but more general than occupation-specific human capital - since skills do not fully decpreciate when a worker switches occupations.

Workers choose occupations by maximizing expected life-time income. In the second period, occupational choice is like in the static model. Given their accumulated task human capital, occupation-specific skill prices P_o and realizations of the productivity shocks u^A and u^M, individuals choose the occupation that pays them the highest wage.

In the first period, in contrast, choosing the occupation that offers the highest wage may no longer be optimal. This is because occupational choice in the first period affects the applicability of skills in the second period, and thus also occupational choice in the second period[10]. Formerly, in the first period workers maximize

$$\max_{o} \qquad EW_{io1} + \frac{1}{1+r} E \max_{l} \left[W_{il2} | o \right],$$

where r is a common interest rate, and o and l denote the optimal occupational choice in the first and second period, respectively. Occupational mobility between period 1 and 2 is purely driven by the task-specific shocks u^A and u^M. A worker will not move unless the productivity shocks offset the loss in task human capital from switching to a different occupation.

2.3 An Illustration of the Effect of Task-Specific Human Capital on Mobility and Wages using Simulations

Since there is no analytical solution to the model, we illustrate the equilibrium choices using simulations. Our model economy consists of 15000 workers and four symmetric occupations; $\beta_1 = 1, \beta_2 = \frac{2}{3}, \beta_3 = \frac{1}{3}$, and $\beta_4 = 0$. Hence, occupation 1 and 4 are specialized occupations that use only one task, while occupations 2 and 3 are general occupations that use both tasks.

Task-specific productivity is independently jointly normally distributed with means $\overline{T}_A = \overline{T}_M = 1$ and variances $\sigma^2_A = \sigma^2_M = 1$. Productivity shocks occur with probability $p = 0.25$, and the variance of the productivity shocks is $\sigma^2_{u_A} = \sigma^2_{u_B} = 0.2$. Task-specific human capital is accumulated at rate $H = 0.1$. Occupation- specific skill prices are set at $P_1 = P_4 = 2$ and $P_2 = P_3 = 2.1$.[11][12] These parameter values replicate wage growth and occupational mobility in our data during the early years in the labor market. Table 1a shows the transition matrix from

[10] $\sigma^2_{u_A} \neq \sigma^2_{u_B}$ would also make occupational choice in the first period dynamic.

[11] In a future version of the paper, we plan to endogenously derive aggregate skill prices .

[12] The chosen parameter values imply that the four occupations are symmetric, i.e. average wages and mobility will be similar in occupations 1 and 4 as well as in occupations 2 and 3. Suppose instead that $\sigma^2_A > \sigma^2_M$. In this case, occupations can be ordered with respect to the relative usage of task A. Similar to the standard Roy model, average wages in an occupation will be the higher the more heavily task A is used. Suppose further that $\sigma^2_{u_A} > \sigma^2_{u_B}$. In this case, occupations with a higher relative usage of task A face more uncertainty and thus a higher option value. Since the focus of this paper is the transferability of skills across jobs, we abstract from these asymmetries.

Table 1: Occupational Choice in Period 1 and 2

period 1\period 2	1	2	3	4	Fraction
1	89.54 %	6.22 %	2.73 %	1.51 %	25.18 %
	–	59.46 %	26.10 %	14.43 %	
2	13.01 %	73.85 %	7.58 %	5.56 %	24.71 %
	49.74 %	–	29.00 %	21.26 %	
3	5.72 %	8.03 %	73.02 %	13.23 %	24.49 %
	21.19 %	29.77 %	–	49.04 %	
4	1.38 %	3.12 %	5.98 %	89.51 %	25.62 %
	13.15	29.78	57.07	–	
Fraction	27.52 %	22.58 %	21.97 %	27.93 %	

N=15000 (workers), simulated data. The first entry shows the fraction of workers employed in occupation 1-4 in the second period, conditional on occupational choice in the first period. The second entry shows the fraction of workers employed in occupation 1-4 in the second period, conditional on switching occupations.

the simulated data. Rows refer to occupational choice in the first period, while columns refer to occupational choice in the second period. The first entry in each cell reports the fraction of workers who are employed in occupations 1 to 4 in the second period, conditional on occupational choice in the first period. The second entry in each cell shows the fraction of workers who are employed in occupations 1 to 4 in the second period conditional on switching occupations.

Two things are noteworthy in Table 1a. First, occupational mobility is substantially higher in occupations 2 and 3 than in occupations 1 and 4, which focus on only one task. This is because occupations 2 and 3 have two neighboring occupations where 2/3 of the acquired human capital can be transferred, while occupations 1 and 4 only have one such neighboring occupation.

Second, workers are more likely to move to similar occupations. For instance, among workers who chose occupation 1 in the first period and move to another occupation in the second period, 59.46 % move to the closest occupation and 14.43 % to the most distant occupation. This is so for two reasons. First, the amount of human capital that can be transferred from one occupation to another is higher if the worker moves to a similar occupation. Second, it is unlikely that a worker who preferred a certain occupation in period 1 receives so high productivity shocks that in period 2 a distant occupation becomes optimal. Table 1b shows the correlation between first and second period wages by the distance of the move under observed mobility, and compares it with the

Table 2: Correlation of Wages in Period 1 and 2 under Observed and Random Mobility

		observed mobility	random mobility
occupational stayers		0.8773	0.8229
occupational movers:	close	0.5705	0.6434
	medium	0.4765	0.3038
	distant	0.3507	0

N=15000 (workers), simulated data. Column 1: Correlation of wages in period 1 and 2 under observed mobility. Column 2: Correlation of wages in period 1 and 2 under random mobility. Close occupational movers: Movers from 1 to 2 and vice versa, 2 to 3 and vice versa, 3 to 4 and vice versa. Medium occupational movers: Movers from 1 to 3 and vice versa, movers from 2 to 4 and vice versa. Distant occupational movers: Movers from 1 to 4 and vice versa.

correlation we would observe if workers were randomly assigned to occupations. Not surprisingly, the correlation is highest for workers who do not switch occupations. More interestingly, first and second period wages are more strongly correlated for workers who move to similar occupations - since productivity is more strongly correlated across similar occupations.

Also note that differences by the distance of the occupational move are lower under observed mobility than under random mobility. This is because it is workers at the edge of an occupation who are most likely to leave the occupation, and for these workers, productivity is more strongly correlated across occupations. Table 1c reports results from Mincer-type wage regressions from

Table 3: Returns to General, Occupational, and Task-Specific Tenure

	1	2	3	4	5
general experience	0.1237	0.0980	0.0389	0.0523	0.0859
	(0.0033)	(0.0058)	(0.0177)	(0.0118)	(0.0211)
occupational tenure		0.0314	-0.0145		
		(0.0059)	(0.0143)		
task-specific tenure			0.1050	0.0776	0.1050
			(0.0296)	(0.0123)	(0.0341)

N=15000 (workers). General experience: 0 in period 1, 1 in period 2. Occupational tenure: 0 for occupation movers, 1 for occupation stayers. Task-specific tenure: 1 for occupation stayers, 1- for occupation movers.

the simulated data. In the first column, we regress log-wages on experience only. Overall wage growth in our model economy is about 13 %, and thus higher than the rate of (task-specific) human capital accumulation. This is because of selection; since workers have the option to switch occupations, they are partially insured against low realizations of productivity shocks. The second column adds occupational tenure. Although there is no true general or occupation-specific human capital in our model, both coefficients are positive and significant.

The third column additionaly includes task-specific tenure. This greatly reduces the coefficient on experience and occupational tenure; the coefficient on occupational tenure even becomes negative. The coefficient on task-specific tenure is close to the true rate of human capital accumulation of 10 %. The next column excludes occupational tenure. This increases the return to general experience, and decreases the return to task-specific tenure. The final column restricts the analysis to workers who switch occupations. The return to task-specific tenure is again close to the true return of 10 %.

We now turn to the data to demonstrate that mobility behavior and wages are consistent with the predictions of our task-specific human capital model.

3 Data Sources and Descriptive Evidence

To study patterns in mobility and wages across occupations, we combine two different data sources from Germany. We describe each of them in turn.[13]

3.1 Data on Tasks Performed in Occupations

Our first data set contains detailed information on tasks performed in different occupations, which we use to construct a measure of how similar or distant occupations are in their skill requirements. The data come from the repeated cross-section *German Qualification and Career Survey,* which is conducted jointly by the Federal Institute for Vocational Education and Training (BiBB) and the Institute for Employment (IAB) to track skill requirements of occupations. The survey, previously used for example by DiNardo and Pischke (1997), 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

[13] Further details on the definition of variables and sample construction can be found in Appendix A and B.

in their work attachment and occupational distribution.

In the survey, individuals are asked whether they perform any of nineteen different tasks in their job. Tasks vary from repairing and cleaning to buying and selling, teaching, and planning. For each respondent, we know whether he performs a certain task in his job and whether this is his main activity. Table A1 lists the fraction of workers performing each of the nineteen different tasks.[14] Following Autor et al. (2003), we combine the 19 tasks into three aggregate groups: analytical tasks, manual tasks and interactive tasks. On average, 55 percent report performing analytic tasks, 72 percent manual tasks, and 49 percent interactive tasks. The picture for the main task used is similar: 32 percent analytical, 57 percent report manual tasks and 28 percent interactive tasks as their main activity on the job.

The last two columns in Table A1 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 organize, coordinate, manage personnel (39.4%). A baker in contrast is a primarily manual occupation (96.4%) with manufacturing, producing, installing as 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 occupations, Table A2 lists the fraction of workers performing manual, analytical, and interactive tasks for all 64 occupations. The table shows that there is a lot of variation in task usage across occupations. For example, while the average use of analytical tasks is 48 percent, the mean varies from 10 percent as an unskilled construction worker to 68 percent for a banker. The variation is similar if we focus on the main activity performed in occupations instead.

We next explain how we use information on task usage to characterize the distance between occupations in terms of their skill requirements.

[14] The survey does not report how much time workers spend on each task. Our task data and derived measures thus use variation in task requirements *across* occupations and over time. They will not reflect changes over time in the task itself like for example, computing skills. Also, the data does not allow us to analyze individual specialization within tasks (for example, what type of law or medicine is practiced).

3.2 Measuring the Distance between Occupations

In our model, two occupations have similar skill requirements if they put similar weights on tasks, i.e. individuals perform the same set of tasks. With two tasks, the maximum distance between two occupations occurs if one only uses task T^A ($\beta = 1$), and the other only task T^M ($\beta = 0$). The framework extends naturally to our case with more than two tasks.

As our empirical measure of distance between occupation o and occupation o', we use the differences in reported usage summed over all the ninenteen tasks. More formally, the distance measure is

$$Dis_{oo'} = \sum_{j=1}^{J} \left| \frac{q_{jo}}{q_o} - \frac{q_{jo'}}{q_{o'}} \right| \tag{3}$$

where $\frac{q_{jo}}{q_o}$ denotes the fraction of workers in occupation o who perform task j.[15]

Our primary distance measure is thus the sum of the difference in average task usage between occupations over all the 19 tasks. Theoretically, the maximum distance between occupations is given if two occupations use complementary skill sets. For example, if all workers in occupation A use task 1-10 and none of the others, while in occupation B all workers perform only tasks 11-19.

We normalized the measure to vary between 0 and 1 by dividing by the total number of tasks. The mean observed distance between occupations in the data is 0.052 with a standard deviation of 0.025. To account for changes in skill requirements over time, we calculated the distance measures separately for each wave. For the years 1975-1982, we use the measures from the 1979 cross-section, for 1983-1988 the task measures from the 1985 wave; for the years 1989-1994, we use the measures based on the 1991/2 wave; and the 1997/8 wave for the years 1995-2001. While there have been changes over time in the distance measures, the four measures are with 0.7 highly correlated. Our results are robust to assigning different time windows to the measures.[16]

[15] Alternatively, q_{jo} in (3) can be computed as follows. Let D_{ji} be a dummy variable which is equal to 1 if individual i performs task j. We weigh each observation by the number of tasks reported by the individual, i.e.$q_{jo} = \sum_{i \in o} \frac{D_{ji}}{\left(\sum_{j=1}^{J} D_{ji}\right)}$. The correlation between these two measures is over 0.95, and both measures lead to very similar results.

[16] Since our data cover nearly three decades, it is not surprising that there are shifts in the composition of tasks used in occupations. In particular, we observe that the requirement for analytical and to a lesser extent interactive skills has increased in the 1990s. Similar results have been documented by Autor et al. (2003) for the United States and Spitz (2006) for West Germany using the same task data. Two-thirds of the overall increase in the demand for analytical skills occurs within occupations and only one-third between (i.e. occupations with a higher demand for analytical skills grow relative to others). As a result, the average distance between occupations declined somewhat

Table 2 lists at the top the three most similar and most distant pairs of occupations. The most distant move observed in the data is between a banker and a metal processor, unskilled worker or assembler. The occupations most similar in their task requirements are carpenter, a bricklayer or mason and a joiner or cabinet maker.

The bottom panel in Table 2 shows the three most common occupational moves observed in the data for each education group. For the low-skilled, the most occupational moves are observed in and out of the occupation as a store and warehouse keeper. For individuals with a vocational degree, popular moves are from an office clerk to being employed as sales personnel or from working as an electrician to being a chemist or physicist. For the high-skilled, we observe many moves into and out of entrepreneurship and in and out of engineering.

The distance measure just described is one way of combining the information on task usage into a one-dimensional index. We also construct two alternative distance measures to check the robustness of our results. Our second measure is the angular separation or uncentered correlation between two vectors. This distance measure has been used extensively in industrial organization to calculate potential spillover effects from R&D between firms with similar technologies (see for example, Jaffe, 1986).[17] The measure also varies from 0 to 1. The more two occupations overlap in their skill requirements, the closer the measure is to 0. The mean distance with this measure in our data is 0.48 with a standard deviation of 0.21. The most similar occupational moves for this measure are between occupations in wood processing (carpenter, lumber and timber processing) as was the case for our main measure.

The third measure we calculate uses the average difference in task usage across occupations, but accounts for the fact that some of the nineteen tasks are more similar than others.[18] To calculate it, we use the three aggregate task categories, analytical, manual, and interactive, and normalize it

in the late 1990s making occupations more similar.

[17] The measure is calculated as

$$AngSep_{oo'} = F_o F_{o'}' / \left[(F_o F_{o'}) \, (F_{oo'}) \right]^{1/2}$$

where F_o contains the fraction of workers using a task in occupation o and $F_{o'}$ is defined analogously. The measure varies from 0 to 1. In order to make it comparable to our main distance measure, we rescaled it such that the two most distant occupations have a value of 1 (their vectors of skill requirements are orthogonal).

[18] Our main measure treats all tasks symmetrically and thus ignores that some tasks are more similar than others. To see this, suppose that workers in occupation A mostly clean, while workers in occupation B mostly repair machines. Workers in occupation C predominantly teach. It may be argued that the two tasks 'cleaning' and 'repairing' are more similar than the two tasks 'cleaning' (or 'repairing') and 'teaching'.

to lie between zero and one. The most distant moves for this third measure are between a banker and an unskilled worker and an unskilled construction worker, while the most similar occupations are between a bricklayer or mason and a lumber or wood processor.

The correlation between our three measures is with 0.5 reasonably high, and the three measures yield very similar results as we demonstrate below.[19] The results we present in the following sections are based on our main measure using all nineteen tasks.

3.3 The German Employee Panel

Our second data set is a two percent sample of administrative social security records in Germany from 1975 to 2001 with more than two million observations. The data has at least three advantages over household surveys commonly used in the US literature to study mobility. First, its administrative nature ensures that we observe the exact date of a job change and the wage associated with each job. Second, measurement error in earnings and occupational titles are much less of a problem than in typical survey data as misreporting is subject to severe penalties. Finally, occupational titles are consistent across firms as they form the basis for wage bargaining between unions and employers.

The data is representative of all individuals covered by the social security system, roughly 80 percent of the German workforce. It excludes the self-employed, civil servants, and individuals currently doing their compulsory military service. As in many administrative data sets, our data is right-censored at the highest level of earnings that are subject to social security contributions. Top-coding is below one percent for unskilled workers and those with an apprenticeship, but can reach almost 10 percent for university graduates.

We restrict our sample to men who entered the labor market in or after 1975. This allows us to construct precise measures of actual experience, firm and occupation tenure. Since the level and structure of wages differs substantially between East and West Germany, we drop all workers who

[19] While different distance measures yield the same results, they might still be biased if occupations that are similar with respect to observed tasks differ with respect to tasks we do not observe. Since the goal of the survey is to track changes in skill requirements in occupations, it seems unlikely that major tasks were omitted. One way we can assess the magnitude of this problem is through a Monte Carlo analysis, which omits an observed tasks and tests how sensitive our distance measures are to this omission.

were employed at least once in East Germany. Finally, we exclude all those working in agriculture.

Table 3 reports summary statistics of the main variables. In our sample, about 16 percent are low-skilled workers with no vocational degree. The largest fraction (68.5 percent) are medium-skilled workers with a vocational degree (apprenticeship). The remaining 15.4 percent are high-skilled workers with a tertiary degree from a technical college or university.

Wages are measured per day and deflated to 1995 German Marks. For medium-skilled workers, the median daily wage in our sample is 141 DM or $86 at 1995 prices. Median wages are about 10 percent lower for the low-skilled and 53 percent higher for the high skilled.

Our experience and tenure variables are measured in years, and exclude periods of unemployment and apprenticeship training. Actual experience is highest for low-skilled workers as they enter the labor market at a younger age (7.9 years vs 7.05 and 6.7 years for medium- and high skilled workers respectively). The average time a medium skilled worker spends in the same occupation is 5.32 years, while the average tenure in a firm is with 4.28 years about one year lower.

3.4 Occupational Mobility

Occupational mobility is an important feature of labor market careers in Germany. On average, annual mobility rates are 15 percent for our 64 two-digit occupations compared to 21 percent of job changers between firms. As Table 3 shows, occupational mobility is higher for the low-skilled (20.3%) and lowest for the high-skilled (10.9%). The same is true for firm mobility (26% and 18% for the low- and high-skilled respectively).

To see how mobility changes with time in the labor market, the top panel of Figure 3 plots annual mobility rates over the first twenty years of labor market experience, separately by education group. Occupational mobility rates are very high in the first five years of the labor market career and highest for the low-skilled.

For comparison, the bottom panel shows mobility across firms. While firm mobility is somewhat higher throughout, it exhibits a very similar decline with time in the labor market. For example, in the first year after labor market entry, 26 percent of all low-skilled switch their occupation, while 29 percent switch firms. Ten years into the labor market, 8 percent of the low-skilled switch occupations and 10 percent switch firms. The numbers for the high-skilled are 5 percent (occupations) and 8 percent (firms).[20]

The type of popular occupational moves however changes very little over the life-cycle for all education groups. The three most popular moves within the first 5 years after labor market entry are the same we observe for individuals with 15 or more years of labor market experience.

We merged our distance measures, which varies across the four time periods and by occupation, to our panel of labor market careers and wages. The next section provides evidence that there are strong patterns in mobility and wages across occupations with respect to our distance measures.

4 Patterns in Occupational Mobility and Wages

This section uses the sample of occupational movers to demonstrate that skills are partially transferable across occupations. We first study mobility behavior, while the second section analyzes wages before and after an occupational move.

4.1 Occupational Moves are Similar

Our model predicts that workers are more likely to move to occupations, in which they can perform similar tasks as in their previous occupation. In contrast, standard job search models (Kambourov and Manovskii, 2004; Neal, 1999; Pavan, 2005) or human capital models with firm-specific and general skills (Topel, 1991; Farber, 1999) assume that workers' current occupation does not affect the direction of occupational mobility.

We first show that individuals switching occupations are much more likely to go to an occupation that requires similar skills. In particular, we compare the distance of observed moves to the distribution of occupational moves we would observe if mobility was purely random. We compute

[20] Figure 2 shows average mobility rates. However, some workers switch occupations multiple times. On average, medium-skilled workers have worked in 2.5 occupations and in 3.5 firms after 10 years of potential experience. 40 percent of medium-skilled workers have never switched occupations, while 25 percent never switched firms. In contrast, about 10 percent have switched occupations and 26 percent switched firms at least five times. Low-skilled workers are considerably more likely, while high skilled workers are considerably less likely to switch both occupations and firms multiple times.

the distribution under random mobility by assuming that the decision to move to a particular occupation is solely determined by its relative size. For example, if occupation A employes 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.[21]

Figure 4 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 of the distance measure under observed mobility is more skewed to the right than the distribution under random mobility. Therefore, observed moves are more similar than we would expect under random mobility. The two distributions are statistically different at the 1 percent level based on a Kolmogoroff-Smirnov test.

To allow a more detailed comparison, Table 4 compares selected moments of the distribution of our distance measure under observed and random mobility. The observed mean is much lower than what we would expect under random mobility. The same is true for the 10th, 25th, 50th, 75th and 90th percentile of the distance distribution. The results are qualitatively the same for our alternative distance measure and even more for our distance measure based on the three task groups.

Both Table 4 and Figure 4 demonstrate that individuals are more likely to move to similar occupations in their career. This speaks against the assumption of standard search models that workers' past occupation has no impact on the type of occupation chosen.

If individuals accumulate task-specific human capital over time, we would also expect that distant moves occur early in the labor market career, while moves become increasingly similar with time in the labor market. Table 5 provides empirical support for both implications. It shows the results from a linear regression where the dependent variable is the distance of an observed move separately by education group. Column (1) contains experience and experience squared as well as year and occupation dummies, while column (2) adds regional and sector dummies to control for

[21] 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. The way we calculate random mobility ensures that we account for shifts in the occupational structure, i.e. the fact that some occupations have increasing or decreasing employment shares.

differences in local labor markets and across industries. For all education groups, the distance of an occupational move declines with time spent in the labor market, though at a declining rate.

The declining effect is strongest for the high-skilled, who also make more similar moves on average (see last row). For the high-skilled, 10 years in the labor market decrease the distance of a move by 0.018 or three-quarter of the standard deviation. For the medium-skilled, the decline is only about 0.008 or one-third of the standard deviation.

Column (3) adds the time spent in the last occupation, while column (4) reports the results from a fixed-effects estimator to account for heterogeneity in mobility behavior across individuals. More time spent in the previous occupation decreases the distance of an occupational move in addition to labor market experience. The within estimator shows that occupational moves become more similar for the same individual. The results are therefore not driven differences between low- and high experience workers. The decline in the distance becomes even more pronounced for the high-skilled in the fixed effects estimation.

The finding that occupational moves become increasingly similar over the labor market career is very robust across alternative measures of distance. For specification 1 and 2, differences between education groups are weaker when the second measure is used. However, if we condition on occupational tenure or fixed worker effects (specification 3 and 4), both measures give very similar results (see Table A4, column (1) and (2) for each education group).

Table 4 imposed a quadratic relationship between actual labor market experience and the distance of moves. In Figure 5, we relax this restriction. The figure displays the average distance of a move by actual experience, separately for the three education groups. The average distance is obtained from a least-squares regression of the distance on dummies for actual experience as well as year dummies. The figure shows that occupational moves become more similar at all experience levels and for all education groups. The decline between the first and 15th year of actual labor market experience is statistically significant at the 1 percent level.

Since the overall propensity to move declines sharply over the career, movers become a smaller and more selected sample with time spent in the labor market. To adjust for that, the bottom panel shows the average distance of moves by experience for the whole sample, where occupational stayers are assigned a distance of zero. The decline in distance is now even more pronounced for all education groups. As before, the decline is statistically significant at the 1 percent level.

Among movers (top panel), high-skilled workers move to more distant occupations than medium or low-skilled workers early in their career. However, later in the career, occupational moves of high-skilled workers are much more similar than those of low- and medium-skilled workers. If we include stayers in the sample (bottom panel), the high-skilled have actually a lower decline than the low skilled, in particular early in their labor market career. This is because the propensity to switch occupations is smaller for the high-skilled at all stages of the labor market career (see Figure 3).

In sum, individuals are more likely to move to occupations in which similar tasks are performed as in their source occupation. Our model in Section 2 proposes a simple explanation for this pattern. The basic mechanism is that human capital is more transferable between occupations with similar skill requirements.

4.2 Wages in the Current Job depend on the Distance of Move

If individuals move to more similar occupations because skills are more transferable, we would expect the wage at the source occupation to be a better predictor for the wage at the target occupation. Table 5 reports estimates from a wage regression, where the dependent variable is the log daily wage. To account for censoring, we estimate tobit models. All results are reported separately by education. As a benchmark for comparison, the first specification (column (1)) estimates the correlation of wages for stayers. Wages in the same job are highly correlated over time with the correlation being highest for university graduates. All specifications include experience and experience squared, an indicator for right censoring, year and occupation dummies as well as state and sector dummies.

In the next specification, we restrict the sample to movers who start out with zero occupational tenure. We split the sample into movers from similar occupations (column (2)) and those from distant occupations (column (3)) where the median observed distance is used to split the sample. For all education groups, the wage at the source occupation is positively correlated with the wage at the target occupation. Moreover, the predictive power of the wage at the source occupation is larger for movers from similar occupations. Interestingly, the difference in the correlation is strongest for the high-skilled workers, the group that is also most likely to move to similar occupations.[22]

As a second test of skill transferability, we estimate whether tenure in the last occupation matters for wages in the new occupation. Table 6 reports results from wage regressions as a function of past occupational tenure and the same controls as in Table 5. To allow for differences by distance, we estimated a linear spline function of past occupational tenure on wages where the switching point is the median distance.

Past occupational tenure is positively correlated with wages in the target occupation, and the correlation is stronger if source and target occupations are similar. In line with our previous results, the impact of past occupational tenure declines more sharply with distance for university graduates. Our results are consistent with previous evidence that post-displacement wages depend positively on tenure in the pre-displacement job (Kletzer, 1989).

The analysis thus far has restricted the effect across occupations to be linear. Figure 6a provides a nonparametric analysis of the correlation of wages across occupations as a function of their distance. The x-axis shows the distance with one being the most similar occupational moves and 10 the most distant ones, while the y-axis reports the coefficient on the wage in the source occupation for each of the 10 categories. The coefficient is obtained form a tobit regression that controls for actual experience, actual experience squared, year dummies, the wage at the source occupation, 9 dummies for the distance of the move and the 9 dummies interacted with the wage at the source occupation (see column (1) in Table 6).

Three things are noteworthy: first, the figure highlights that the wage at the source occupation has a stronger explanatory power for the wage at the target occupation if the source and the target occupation are similar. Second and in line with our results on mobility and wages, the decline is

[22]We also estimated a regression with an interaction effect between distance of move and wage in the source occupation for movers instead of a switching regression model. The results were similar. Since the coefficients from the switching regression model can be interpreted more easily, we prefer the specification reported in Table 5.

strongest for the high-skilled. The partial correlation coefficient between wages in the old and new occupation drops from 40 percent for the most similar move to around 23 percent for the most distant move is statistically significant. Third, the largest decline occurs from the first category (very similar moves) up to the fifth category (the median move). The correlation of wages does not decline further for moves more distant than the median. This pattern holds for all education groups.

Figure 6b provides a similar analysis for past occupational tenure. The y-axis are now the coefficients on the 9 distance measure dummies from a tobit regression that also controls for actual experience, actual experience squared and year dummies. The correlation between past occupational tenure and wages in the new occupations is declining roughly linearly with the distance of the move. The overall decline is statistically significant for all education group at the 1 percent level. As before, the declining pattern is strongest for the high-skilled, particularly for very distant occupational moves.

We also performed several additional tests to check the robustness of our results to alternative sample definitions and measures of distance. First, our sample of movers contains both occupational switches between firms as well as within the same firm. The latter account for roughly 10 percent of all occupational movers. If some skills are tied to a firm, internal movers would have more portable skills than firm switchers. We therefore reestimated our specifications in Table 4 to 6 using only external movers to test whether any of our results are sensitive to this sample definition. The results shown in the top panel of Table A3 show that movers switching occupations *and* firms exhibit the same patterns in mobility and wages we observe for the whole sample of movers.

Second, our original sample of movers contains everybody switching occupations irrespective of the duration of intermediate un- or nonemployment spells. To the extent that those remaining out of employment for an extended period of time are different from for example job-to-job movers, our results might again not be valid for those with high attachments to the labor market. To account for this, we reestimated the results only for the sample of workers with intermediate un- or nonemployment spells of less than a year. As the bottom panel in Table A3 shows, this again does not change our results on mobility and wages.

As a final robustness test, we reestimated the specifications in Table 4 to Table 6 for our two alternative distance measures, the uncentered correlation and the one based on the three task groups. As shown in Table A4 in the appendix, the results are remarkably similar to the ones we presented here. Occupational mobility becomes increasingly similar over the life-cycle and productivity (as measured by wages) in two different occupations is more highly correlated if the two occupations are similar.

4.3 Can these Patterns be Explained by Unobserved Heterogeneity?

The empirical analysis presented above deliberately imposed very little structure on the data. The strong patterns we find for both mobility and wages are consistent with our theoretical model, in which individuals accumulate task-specific human capital that is partially transferable across occupations. This section discusses whether our findings could possibly be rationalized by pure unobserved heterogeneity between workers.

Note first that all results presented in the last section are based on the sample of occupational movers. The patterns in mobility and wages can therefore not be accounted for by a simple mover-stayer model, where movers have a higher probability of leaving a job and thus possibly lower productivity because of lower investments in specific skills. To the extent that movers differ from stayers in terms of observable and unobservable characteristics, this sample restriction reduces selection bias.[23]

While focusing on the sample of movers reduces the selection problem, there are still possible sources of unobserved heterogeneity that might drive our results. We discuss each of them in turn. Suppose first that the sample of movers differs in their taste for particular tasks. Some individuals prefer research over negotiating, while other prefer negotiating over managing personnel etc. Taste heterogeneity can explain why we see similar moves in the data. If individuals choose

[23] It is indeed the case that movers are on average negatively selected. We estimated a censored wage regression of log wages in the current occupation on an indicator whether a person moves in the next period on the whole sample of workers and a set of controls (experience, experience squared, occupational tenure as well as year and occupation dummies). The coefficient on the indicator is negative for all education groups and specifications implying that movers earn on average 10.7 (low-skilled), 11.3 (medium-skilled) and 20.5 percent (high-skilled) lower wages than stayers. This implies that occupational movers are on average negatively selected in their source occupations.

their occupations by the combination of earnings and preferences for tasks, individuals would want to move to occupations with similar task requirements.

However, a story based on taste heterogeneity alone cannot explain the observed patterns in wages. Suppose all individuals make their occupational choices optimally at the beginning of their career. If there are compensating wage differentials for preferences over tasks, moves to more distant occupations (which use different tasks and are therefore not preferred to the current one) would carry a higher wage to compensate for the move away from the preferred task set. Thus, wages of more distant moves should be more highly correlated or the wage growth of a move should be *increasing* with distance just the opposite of what we find in the data.

Alternatively, one might argue that the similar moves in the data are voluntary job-to-job transitions, while the distant moves are by workers laid off from their previous job. The data does not allow us to distinguish between the two reasons for observed occupational changes. If the type of job change is correlated with a worker's productivity on the job, this would explain why wages are more highly correlated between similar occupations and also why past occupational tenure has a higher return in a similar occupation. However, the distinction between voluntary and involuntary movers does not explain why voluntary movers move to similar occupations in the first place.[24]

Finally, assume that individuals differ in their unobserved ability, which is equally valued in all sectors, for example by increasing one's productivity in each task. Individuals with high unobserved ability are then the high-wage workers in all 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. This is because past occupational tenure would act as a proxy for unobserved ability in the wage regression (Table 6). However, unobserved ability per se cannot explain why the effect of past occupational tenure should vary with the distance of the move or why we see the patterns in mobility to similar occupations.

[24] It is however the distant movers have lower wages in their source occupation than those moving to more similar occupations. To get at this result, we again estimated a censored wage regression of log wages in the current occupation on an indicator whether a person moves in the next period on the sample of movers and a set of controls (experience, experience squared, occupational tenure as well as year and occupation dummies). The coefficient on the indicator is negative for all education groups implying that distant occupational movers are on average negatively selected in their source occupations.

The above discussion makes clear that a simple story based on unobserved heterogeneity cannot explain the results on movers we presented in the last section. In order to generate the patterns in mobility and wages, we would require not only that unobserved ability has a different value in occupations, but also that its return is similar in similar occupations. In the next section, we turn to an analysis of specific skills and wage growth that incorporates unobserved heterogeneity within an econometric framework.

5 Skill Tenure and Wage Growth over the Life-Cycle

An important conclusion emerging from the observed patterns in mobility and wages is that accumulated skills are partially transferable across occupations. However, skills accumulated in the labor market are not universally transferable as suggested by the low task distance of observed moves and the fact that occupational mobility declines sharply with experience. This section provides a quantitative assessment of the importance of skill tenure for wage growth relative to other commonly used measures of specific skills.

5.1 Empirical Specification

Our empirical model of wages needs to incorporate observable characteristics and specify the structure of unobservables. Assume that wages depend on observables and task human capital as follows

$$\ln W_{iot} = P_o + \gamma' X_{it} + \left\{ \beta_o T_{it}^A + (1 - \beta_o)\, T_{it}^M + \varepsilon_{it} \right\} \tag{4}$$

where ε_{it} denotes any remaining measurement error in wages and $X_{it} = [Exp_{it} \quad SkillTenure_{it} \quad OccTenure_{it}]'$.where $T_{it}^j = T_{it-1}^j + u_{it}^j$, i.e. task human capital is subject to productivity shocks that do not depend on occupational choice. $\beta_o T_{it}^A + (1 - \beta_o)\, T_{it}^M$ may be viewed as an unobserved individual-occupation-specific match that varies over time. ε_{it} is an iid error term reflecting for instance measurement error.

Note that this specification allows for sorting into occupations on the basis of the initial endowment in task human capital and the productivity shocks. To keep the framework empirically tractable, we abstract for now from sorting with respect to returns in observable skills (like experience, occupational tenure).

It is clear that both OLS and first-differenced estimates will be biased. For OLS, the unobserved task human capital is correlated with occupational choice, which in turn determines the value of the regressors.[25] While first-differencing would eliminate the initial task endowment for those remaining in the occupation, it does not so for occupational movers. To estimate (4), we therefore use a nonlinear instrumental variable approach similar to Lemieux (1998) and Gibbons et al. (2005). The details of the estimation approach are provided in Appendix C.

5.2 Estimation Results

We first report the OLS estimates from a censored regression of the log daily wage on our measures of specific human capital. The first column in Table 8 includes only occupation-specific and general human capital, while the second column also adds our measure of task human capital. All specifications include occupation dummies to absorb the occupation-specific constant. In addition, year, state and sector dummies are included to control for aggregate, local labor market and industry-specific shocks respectively.

The first panel (Panel A) uses the whole sample. There are several noteworthy patterns. First, returns to general experience are higher than returns to occupational tenure for all education groups. Second, returns to skill tenure are sizeable, especially for university graduates. Third, including skill tenure results in a decline in the return to experience by ten percent for the low- and medium-skilled, but by 50 percent for the high-skilled. Finally, returns to occupational tenure decline by 30 percent for the two lower educated groups. For the high-skilled in contrast, the return to occupational human capital is no longer statistically different from zero once we include our measure of skill tenure.

Panel B focuses on the sample of occupational movers to reduce a possible selection bias. This

[25] Since elements of the specific skill vector X are highly correlated, it is difficult to sign the bias of OLS estimates. See Altonji and Williams (2005) for a closely related discussion on the bias of firm tenure and experience in a wage regression.

decreases the return to general experience and increases the return to occupational tenure, but has little impact on the return to skill tenure.

In Panel C, we restrict the sample to occupational movers who exerience an intermediate unemployment spell. Note that the distance of an occupational move is much higher after an unemployment spell (3x for low-skilled, 10 times for high-skilled). The return to experience and occupational tenure are now lower than for the sample that includes job-to-job switchers (Panel B), while the return to skill tenure remains again unchanged. One explanation for this finding is that after an involuntary job loss and unemployment spell, workers start their search for a good match from the full distribution of job offers. Voluntary job-to-job movers, in contrast, only accept job offers that strictly dominate the current job offer. Hence, returns to experience are likely to be upward biased in a sample that includes voluntary job-to-job movers, but not necessarily in a sample that excludes them.

These results suggest that task-specific human capital that is partially transferable across occupations is an important source of wage growth for all education groups. For the low- and medium-skilled, truely general skills seem to play the most important role; and task-specific skills are of similar importance as truely occupation-specific skills. For the high-skilled in contrast task-specific human capital is the dominating source of wage growth. This is also the education group that experienced a steeper decline in the distance of occupational moves over their career. Further, the relationship between the distance of the occupational move and the correlation of wages at the old and new occupation as well as the effect of past occupational tenure on current wages is much stronger among the high-skilled.

6 Conclusion

Most studies of the labor market assume that skills are either fully general (like education and experience) or specific (for example, tied to a particular firm). Recent studies however suggest that specific skills might be more general than previously considered. Following the evidence on the importance of occupational skills, this paper analyzes whether skills are specific to an occupation or more generally transferable across occupations.

Our main innovation is to use patterns in occupational mobility together with information on wages to analyze the specificity of skills. The empirical analysis combines data from a large administrative panel on individual labor market careers with detailed information on tasks performed in different occupations. Using the task data, we construct new measures of how similar occupation are in terms of their skill requirements. This allows us to characterize the relationship between occupations in much more detail than the previous literature.

We find strong evidence that labor market skills are at least partially transferable across occupations. The transferability however declines rapidly if individuals move to occupations that require very different skills. Second, our result show that task specific human capital is especially important for the high-skilled. We interpret this result as evidence that university graduates have a comparative advantage in learning new skills in the labor market. In contrast, wage growth for the low-skilled is largely driven by firm-specific and to some extent occupation-specific human capital.

The evidence we presented is difficult to reconcile with a standard human capital model with either fully general or firm-specific skills. The results also contradict undirected search models of turnover, where the current occupation has no effect on future choices, and skills are not transferable across occupations (e.g. Kambourov and Manovskii, 2003; Neal, 1999; Pavan, 2005).

We think that the importance of task human capital in Germany is likely to be a lower bound for the United States. First, firm-specific human capital is relatively more important in Germany than in the United States even controlling for occupational and task-specific human capital. Second, Germany's system of vocational training focuses much more on specific skills than for example a college education. The assumption of more general skills in the United States has been the basis for several recent models of the productivity differential between the US and Europe (Krueger and Kumar, 2004; Wasmer,2005). This assumption is in principle empirically testable provided reliable data on task usage and labor market mobility were available for the United States.

The framework and results of this paper suggest at least two other avenues for future research.

First, our results imply that reallocation costs, after a job loss, crucially depend on the probability of finding a job in an occupation with similar skill requirements. Reallocation costs might be lower or higher for more educated individuals: on the one hand, we find that the high-skilled have accumulated more task human capital and therefore more to lose. On the other hand, they can learn new skills faster, which would reduce the costs of an unemployment spell. Estimating the size and distribution of reallocation costs would have important implications for how training and other active labor market programs should be targeted.[26]

Second, our framework and data can be used to analyze how technological change and changes in the organization of production affected skill requirements. Have specific skills become more or less transferable over time? Our task data provides a unique opportunity to address this question as it not only contains data on tasks, but also detailed information on the type of technology and machines used in an occupation.

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A Data Sources

A.1 Employee Sample (1975-2001)

Our main dataset is the Employee Sample, a 2 percent sample of all German social security records administered by the Institute for Employment Research from 1975 to 2001. The data contains an unusually in-depth set of background information for each individual, including age, education, gender, nationality, occupation, etc.

By law, employers are required to report the exact beginning and end of any employment relation of all new hires and employees leaving the firm which are subject to social security contributions. In addition, employers provide information about all their employees at the end of each year. We therefore know the exact date of employer changes and movements into and out of paid employment. The dataset does not distinguish between voluntary quits and layoffs, though the quality of this distinction in survey data has been questioned.

The occupational categories of employees and apprentices in the social security records are highly accurate as the classification forms the basis of wage agreements between unions and employers' association. In the 2% sample, we have 130 occupations available. To make this classification comparable to the tasks performed in occupations from the BIBB data, we aggregated them further into 64 occupations at the 2-digit level.

Employers are not required to notify an occupational switch if the employee remains with the same firm, but we do know the employee's occupation at the end of each year. This leads us to underestimate occupational mobility. To see this, consider first a worker who switches firms on April 1st. For this worker, we observe two spells: the first from January 1st to March 31st and the second from April 1st to December 31st. Suppose that the individual works in occupation A in the first spell, and B in the second spell. For this worker, and firm switchers in general, it is reasonable to assume that he worked on January 1st at occupation A, and April at occupation B. He may have switched occupations once more between January and April, and between April and December. Next, consider a worker who stayed with the same employer for at least two years. For this worker, we observe two spells, both from January 1st to December 31st. Suppose that the first spell classifies the worker as in occupation A, while this spell classifies him as in occupation B. For this worker, it is reasonable to assume that on January 1st he was working in occupation A, and on January first one year later in occupation B. He may have switched occupations more than once. Since most of our analysis focuses on switches of both occupations and employer, this is of minor concern.

In addition to the sample restrictions mentioned in the text, we also dropped all spells in vocational training and those job spells that started prior to an apprenticeship or tertiary education. In addition, we excluded observations that were still in vocational training at the end of the sample period in 2001 or pursued more than one apprenticeship, that is where employed as an apprentice for more than 7 years. We also require a person to be below a certain age when we first observe them. This ensures that we can follow them from day one of their entry into the labor market. The age restriction is 19 if unskilled (no vocational degree), 21 if medium-skilled (vocational or highschool degree) and 29 if high-skilled (university or equivalent degree). Finally, we drop all observations we observe less than a year, with missing education or nationality, and observations with no valid wage during an employment spell.

We converted the dataset into two datasets: annual observations and quarterly data. In both cases, all tenure variables are measured at the beginning of each spell. If a worker returns to an occupation with at least one year lag in between, we assume that his occupational experience has depreciated and set occupational tenure to zero. As in many administrative datasets, observations on wages are censored if they exceed the upper limit for social security contributions. In our sample, around 4 percent of the observations have right-censored wages. Censoring is less than 1 percent for the low and medium skilled, but almost 10 percent among the high-skilled. Among the high-skilled with more than 10 years of labor market experiences, almost 23 percent of the wage observations are top-coded. To account for right-censoring in wages, we estimate tobit models whenever appropriate. After 1984, firms have to report wages inclusive of fringe benefits, which affects mostly the wages of high-skilled workers. To control for that and other aggregate shocks, we always include year effects in the estimation.

A.2 Data on Occupational Tasks (1979-1999)

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

For each respondent of the survey, we know whether he performs certain tasks in his job and whether this is his main activity on the job. Unlike the Dictionary of Occupational Titles (DOT) in the United States, we do not know how intensively a particular task is used beyond the distinction of main activity, task performed and not performed. Overall, we have information on 19 different tasks workers perform in their jobs. Following Autor et al (2003), we also group the 20 tasks into three groups of tasks: analytical tasks, manual tasks and interactive tasks. The assignment of tasks is as follows: manual tasks (equip or operate machines, repair, reconstruct or renovate, cultivate, manufacture, cleaning, serve or accomodate, construct or install, pack or ship or transport, secure, nurse or treat others), analytical tasks (research or evaluate or measure, design or plan or sketch, correct texts or data, bookkeeping or calculate, program, execute laws or interpret rules) and interactive tasks (sell or buy or advertise, teach or train others, publish or present or entertain, employ or manage personnel or organize or coordinate).

A.3 Nonlinear Instrumental Variable Estimation

As dicussed in Section 5, least-squares estimates of log wages on our skill measures are biased. This appendix shows that we can use a nonlinear instrumental variables estimator (similar to Gibbons et al.,2005; Holtz-Eakin et al, 1988; Lemieux, 1998) to determine the contribution of skill tenure to wage growth over the life-cycle. The setup is the same as in the main text with wages given as

$$\ln W_{iot} = P_o + \gamma' X_{it} + \left\{\beta_o T^A_{it} + (1-\beta_o)\, T^M_{it} + \varepsilon_{it}\right\} \tag{5}$$

First, define the task human capital differential (which is a sufficient statistic for sectoral choice) $\widetilde{T_{it}}$ as

$$\widetilde{T_{it}} = \left(T^A_i - T^M_i\right) + \left(\varepsilon^A_{it} - \varepsilon^M_{it}\right) \tag{6}$$

Second, write log wages in each sector as

$$\ln W_{it} = \sum_{o=1}^{O} D_{iot} P_o + \gamma' X_{it} + \sum_{o=1}^{O} D_{iot} \beta_o \widetilde{T_{it}} + T^M_i + \varepsilon^M_{it} + u_{it} \tag{7}$$

where $D_{iot} = 1$ if individual i works in occupation o in time t and zero otherwise.

Third, solve the above equation for $\widetilde{T_{it}}$

$$\widetilde{T_{it}} = \frac{\ln W_{it} - \sum_{o=1}^{O} D_{iot} P_o - \gamma' X_{it} - \left[T_i^M + \varepsilon_{it}^M + u_{it}\right]}{\sum_{o=1}^{O} D_{iot} \beta_o}$$

Fourth, use wages in the past period to solve for the task endowment differential $\left(T_i^A - T_i^M\right)$

$$T_i^A - T_i^M = \frac{\ln W_{it-1} - \sum_{o'=1}^{O} D_{io't-1} P_{o'} - \gamma' X_{it-1} - \left[T_i^M + \varepsilon_{it-1}^M + u_{it-1}\right]}{\sum_{o'=1}^{O} D_{io't-1} \beta_{o'}}$$

where $D_{iot} = 1$ if individual i works in occupation o' in time t and zero otherwise. Plugging the two previous equations into the definition of the task human capital differential (6) yields

$$\frac{\ln W_{it}}{\sum_{o=1}^{O} D_{iot} \beta_o} = \frac{\ln W_{it-1}}{\sum_{o'=1}^{O} D_{io't-1} \beta_{o'}} + \frac{\sum_{o=1}^{O} D_{iot} P_o + \gamma' X_{it}}{\sum_{o=1}^{O} D_{iot} \beta_o} - \frac{\sum_{o'=1}^{O} D_{io't-1} P_{o'} - \gamma' X_{it-1}}{\sum_{o'=1}^{O} D_{io't-1} \beta_{o'}} + e_{it}$$

where the error term is

$$e_{it} = \left(\varepsilon_{it}^A - \varepsilon_{it}^M\right) + \frac{\left[T_i^M + \varepsilon_{it}^M + u_{it}\right]}{\sum_{o=1}^{O} D_{iot} \beta_o} - \frac{\left[T_i^M + \varepsilon_{it-1}^M + u_{it-1}\right]}{\sum_{o'=1}^{O} D_{io't-1} \beta_{o'}}$$

Current sector affiliation and our skill variables are correlated with the error term. However, the twice or more lagged variables and any interactions are uncorrelated since neither D_{iot-s} and X_{it-s} for $s \geq 2$ help to predict ε_{it}^M or ε_{it-1}^M; likewise, future *realizations* of productivity shocks do not influence current sectoral choices (and thus skill tenure and occupational tenure). Denote a set of valid instruments for time period t by Z_{it}.

Stacking the error terms e_{it} into a large vector e and likewise the set of instruments into Z, the orthogonality condition becomes

$$\frac{1}{N}\left(e'Z\right) = 0 \tag{8}$$

The nonlinear instrumental variable estimator finds the parameter vector (P_o, γ) by minimizing

$$\frac{1}{N}\left(e'Z\right) WM \left(e'Z\right)'$$

where WM is the weighting matrix. If error term is homoscedastic, use inverse of variance of $\left(Z'Z\right)^{-1}$. If heteroscedastic, we can use two-step procedure to get the robust variance-covariance matrix (efficient GMM). The latter might be harder to estimate/get convergence.

Table 2: Measuring Distance between Occupations

Distance Measure (19 Tasks)		
Occupation 1	Occupation 2	Distance
Mean		0.0523
Standard Deviation		0.0245
Most Similar (all Education Groups)		
Carpenter	Bricklayer, Mason	0.0061
Joiner, Cabinet Maker	Bricklayer, Mason	0.0065
Joiner, Cabinet Maker	Carpenter	0.0078
Most Distant (all Education Groups)		
Banker	Assembler	0.1611
Banker	Unskilled Worker	0.1633
Banker	Metal Presser and Moulder	0.1635
Most Common Occupational Moves (Low-Skilled)		
Conductor	Store or Warehouse Keeper	0.0228
Unskilled Worker	Store or Warehouse Keeper	0.0632
Assembler	Store or Warehouse Keeper	0.0695
Most Common Occupational Moves (Medium-Skilled)		
Chemist, Physicist	Electricians, Electrical Installation	0.0464
Sales Personnel	Office Clerk	0.0259
Conductor	Store or Warehouse Keeper	0.0235
Most Common Occupational Moves (High-Skilled)		
Engineers	Chemist, Physicist	0.0230
Entrepreneurs	Office Clerk	0.0257
Entrepreneurs	Engineers	0.0270

Notes : The table shows at the top summary statistics of the distance measure as well as the three most similar and distant occupations and their corresponding distance. The distance measure is based on the relative differences in using the 19 different tasks (see Table A1 for a list of tasks) and normalized to vary between 0 and 1. The bottom part of the table shows the three most commonly observed moves in the data by education group and the corresponding distance measure.

Table 3: Summary Statistics of West German Employee Panel

	Low Skill	Medium Skill	High Skill
Percentage in Sample	16.10%	68.48%	15.41%
Age (in Years)	27.07	28.07	32.61
	(5.96)	(5.14)	(5.35)
Not German Citizen	0.31	0.05	0.05
	(0.46)	(0.21)	(0.21)
Median Daily Wage	126.3	141.03	216.29
	(56.905)	(51.708)	(53.259)
Log Daily Wage	4.659	4.973	5.364
	(0.635)	(0.438)	(0.367)
Actual Experience (in Years)	7.9	7.05	6.7
	(5.56)	(4.81)	(4.88)
Occupational Tenure (in Years)	5.21	5.32	5.02
	(4.64)	(4.25)	(4.22)
Firm Tenure (in Years)	4.37	4.28	3.82
	(4.36)	(3.88)	(3.55)
Occupational Mobility	0.203	0.12	0.109
	(0.403)	(0.325)	(0.311)
Similarity of Move	0.0556	0.0536	0.045
	(0.024)	(0.025)	(0.024)
Firm Mobility	0.26	0.191	0.179
	(0.439)	(0.393)	(0.383)
Most Common Occupations	Warehouse Keeper (10%)	Electrical Installation (7%)	Engineer (25%)
	Assembler (7%)	Locksmith (8%)	Technician (12%)
	Conductor (6%)	Mechanic, Machinist (6%)	Accountant (9%)
	Unskilled Worker (4%)	Office Clerk (7%)	Office Clerk (8%)
	Office Clerk (4%)	Conductor (5%)	Researcher, Clergymen (5%)
Number of Observations	225,900	1,005,802	198,229
Number of Individuals in Sample	18,414	78,315	17,627

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

Source : Employee Sample (IAB), 1975-2001

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

	Main Distance Measure (19 Tasks)		Distance (3 Groups)	
	Random Mobility	Observed Mobility	Random Mobility	Observed Mobility
Mean	0.061	0.058	0.286	0.198
10th Percentile	0.027	0.021	0.052	0.043
25th Percentile	0.049	0.034	0.105	0.074
50th Percentile	0.065	0.058	0.246	0.127
75th Percentile	0.077	0.071	0.466	0.241
90th Percentile	0.083	0.078	0.573	0.425

Notes : The table reports selected moments of the distribution of observed occupational moves in terms of their distance ("Observed Mobility"). Observed moves are compared 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 results in the first 2 columns are based on the weighted average over all 19 tasks and one the distance based on 3 task groups in the last 2 columns. Since all moments of the observed distribution are below those under random mobility, individuals are much more likely to move to similar occupation.

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

	Low-Skilled				Medium-Skilled				High-Skilled			
Distance (19 Tasks)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Experience	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	0.000	-0.001	-0.002	-0.002	-0.002	-0.004
	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.001)**
Experience Squared	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**
Occupational Tenure			-0.001				0.000				-0.001	
			(0.000)**				(0.000)				(0.000)**	
Constant	0.057	0.059	0.058	0.054	0.055	0.055	0.055	0.048	0.061	0.060	0.061	0.041
	(0.003)**	(0.003)**	(0.003)**	(0.003)**	(0.004)**	(0.004)**	(0.004)**	(0.003)**	(0.005)**	(0.005)**	(0.005)**	(0.007)**
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region Dummies	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Industry Dummies	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Individual Fixed Effects	No	No	No	Yes	No	No	No	Yes	No	No	No	Yes
Observations	43,051	43,051	43,051	43,051	118,169	118,169	118,169	118,169	20,709	20,709	20,709	20,709
R Squared	0.15	0.15	0.15	0.09	0.12	0.12	0.12	0.07	0.16	0.17	0.17	0.1
Mean Distance of Move	0.0556	0.0556	0.0556	0.0556	0.0536	0.0536	0.0536	0.0536	0.045	0.045	0.045	0.045
	(0.024)	(0.024)	(0.024)	(0.024)	(0.025)	(0.025)	(0.025)	(0.025)	(0.024)	(0.024)	(0.024)	(0.024)

Notes: The table reports results from a regression where the dependent variable is the distance between two occupations based on the 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 state and industry dummies, while Column (3) adds actual tenure in the current occupation. Finally, Column (4) includes fixed effects to control for individual unobserved heterogeneity. All specifications include year and occupation dummies. Robust standard errors are reported in parentheses. Coefficients with * are statistically significant at the 5 percent level, those with ** at the 1 percent level.

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

Y: Log Daily Wage	Low-Skilled			Medium-Skilled			High-Skilled		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Wage Last Period	0.775	0.204	0.15	0.743	0.297	0.222	0.822	0.353	0.233
	(0.002)**	(0.006)**	(0.006)**	(0.001)**	(0.004)**	(0.004)**	(0.001)**	(0.009)**	(0.010)**
Actual Experience	0.011	0.037	0.038	0.01	0.034	0.039	0.009	0.038	0.047
	(0.000)**	(0.002)**	(0.002)**	(0.000)**	(0.001)**	(0.001)**	(0.000)**	(0.003)**	(0.003)**
Actual Experience Squared	0	-0.001	-0.001	0	-0.001	-0.001	0	-0.001	-0.002
	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**
Constant	1.084	3.589	3.854	1.234	3.266	3.605	0.895	3.048	3.687
	(0.014)**	(0.043)**	(0.047)**	(0.009)**	(0.030)**	(0.031)**	(0.023)**	(0.084)**	(0.077)**
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Dummies	Yes	Yes	No	Yes	No	Yes	Yes	Yes	Yes
Sector Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Indicator for Wage Censoring	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	154,506	21,226	21,222	801,117	58,897	58,863	156,278	10,269	10,022

Notes: The table reports censored wage regressions where the dependent variable is the log daily wages. Results are reported separately by education group. All specifications include the log daily wage in the last period, actual experience, actual experience squared, year and occupation dummies as well as sector and state dummies as controls. Column (1) uses the sample of stayers as a benchmark for comparison. The next two columns split the sample of movers into those that move from a similar occupation (column (2)) and those moving from a distant occupation (column (3)) where the split point is the median distance of an observed move. Standard errors in parentheses are bootstrapped with replacement and 50 replications to allow for clustering at the occupation and period level. The distance measure used is based on all 19 tasks. We report results from the two alternative distance measures in Table A4. Coefficients with * are statistically significant at the 5 percent level, those with ** at the 1 percent level.

Table 7: Past Occupational Tenure Matters for Wages

	Low-Skilled		Medium-Skilled		High-Skilled	
Y: Log Daily Wage after Move	(1)	(2)	(1)	(2)	(1)	(2)
Past Occupational Tenure	0.009		0.006		0.011	
	(0.001)**		(0.000)**		(0.001)**	
Past Tenure * Similar Move		0.111		0.055		0.108
		(0.016)**		(0.009)**		(0.030)**
Past Tenure * Distant Move		-0.011		0.027		-0.232
		(0.092)		(0.040)		(0.173)
Distance		-1.107		-1.389		-2.644
		(0.087)**		(0.049)**		(0.140)**
Experience	0.0440	0.044	0.043	0.044	0.0814	0.071
	(0.001)**	(0.001)**	(0.001)**	(0.001)**	(0.002)	(0.002)**
Experience Squared	-0.0010	-0.001	-0.001	-0.001	-0.0031	-0.002
	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)	(0.000)**
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Occupational Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Sector Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Region Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	42,478	42,478	117,760	117,760	20,291	20,291

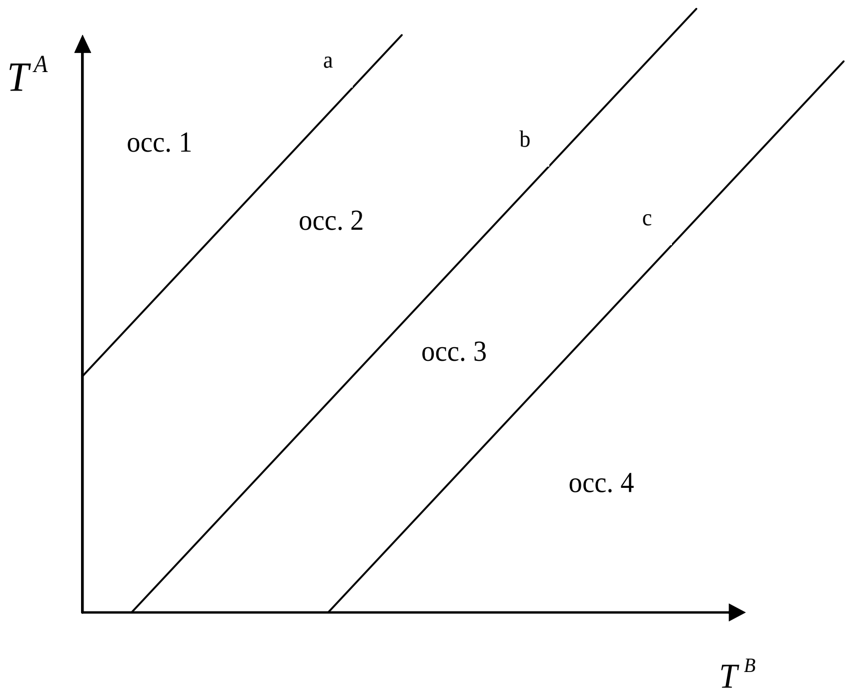
Notes: The table reports censored wage regressions where the dependent variable is the log wages in the target occupation after an occupational move. Estimates are reported for each education group separately. Column (1) in each specification controls for past tenure in the source occupation, experience, experience squared, as well as year and occupation dummies. Column (2) allows the coefficient on past occupational tenure to differ for similar and distant moves, where the mediam move is used as the breakpoint. The distance measure used is based on all 19 tasks (see Table A4 for results from other distance measures). Standard errors in parentheses are bootstrapped with replacement and 50 replications to allow for clustering by occupation and time period. Coefficients with * are statistically significant at the 5 percent level, those with ** at the 1 percent level.

Table 8: The Importance of Skill Tenure for Wage Growth

	Low-Skilled		Medium-Skilled		High-Skilled	
Y: Log Daily Wage in t	(1)	(2)	(3)	(4)	(1)	(2)
A: Whole Sample						
Skill Tenure		0.01		0.011		0.063
		(0.001)**		(0.000)**		(0.002)**
Actual Experience	0.069	0.063	0.043	0.036	0.08	0.039
	(0.001)**	(0.001)**	(0.000)**	(0.000)**	(0.001)**	(0.001)**
Experience Squared	-0.002	-0.002	-0.001	-0.001	-0.003	-0.003
	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**
Occupational Tenure	0.013	0.009	0.011	0.007	0.013	-0.007
	(0.000)**	(0.001)**	(0.000)**	(0.000)**	(0.000)**	(0.001)**
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Occupation Dummies	Yes	Yes	Yes	Yes	Yes	Yes
State Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Sector Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	225,007	225,007	1,001,459	1,001,459	194,756	194,756
B: Sample of Movers						
Skill Tenure		0.008		0.014		0.082
		(0.003)**		(0.002)**		(0.006)**
Actual Experience	0.052	0.048	0.038	0.03	0.091	0.042
	(0.001)**	(0.002)**	(0.001)**	(0.001)**	(0.003)**	(0.004)**
Experience Squared	-0.002	-0.002	-0.002	-0.002	-0.004	-0.004
	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**
Occupational Tenure	0.02	0.017	0.025	0.02	0.028	-0.001
	(0.001)**	(0.002)**	(0.001)**	(0.001)**	(0.002)**	(0.003)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Occupation Dummies	Yes	Yes	Yes	Yes	Yes	Yes
State Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Sector Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	41,006	41,006	100,653	100,653	16,976	16,976
C. Movers with Intermediate Unemployment Spell						
Skill Tenure		0.006		0.01		0.06
		(0.006)		(0.005)*		(0.017)**
Actual Experience	0.027	0.023	0.025	0.02	0.052	0.016
	(0.003)**	(0.005)**	(0.003)**	(0.004)**	(0.010)**	(0.014)
Experience Squared	-0.001	-0.001	-0.001	-0.001	-0.002	-0.002
	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.001)**	(0.001)**
Occupational Tenure	0.013	0.01	0.014	0.01	0.02	-0.005
	(0.003)**	(0.004)*	(0.002)**	(0.003)**	(0.009)*	(0.011)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Occupation Dummies	Yes	Yes	Yes	Yes	Yes	Yes
State Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Sector Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,156	7,156	14,611	14,611	1,365	1,365

Notes : The table reports results from a censored regression of the log daily wage on measures of general human capital (experience, experience squared), occupation-specific tenure and skill tenure (see Section 2 for how we calculate the skill tenure measure). All specifications also include year and occupation dummies as well as state and sector dummies. The results are reported for three different samples and separately by education group. Panel A estimates the wage regression on the whole sample (job stayers and movers). Panel B restricts the sample to those moving occupations; finally, Panel C uses only those that are both occupational movers and an intermediate unemployment spell. Standard errors are reported in parentheses. Coefficients with * are significant at the 5 percent level, those with ** at the 1 percent level.

Figure 1: Occupational Choice in the Static Model



$$a: \quad T^{A} = \frac{\ln P_2 - \ln P_1}{b_2 - b_{1'}} + T^{B}$$

$$b: \quad T^{A} = \frac{\ln P_3 - \ln P_2}{b_3 - b_2} + T^{B}$$

$$c: \quad T^{A} = \frac{\ln P_4 - \ln P_3}{b_4 - b_3} + T^{B}$$

Figure 2: Histogram of Distance Measure

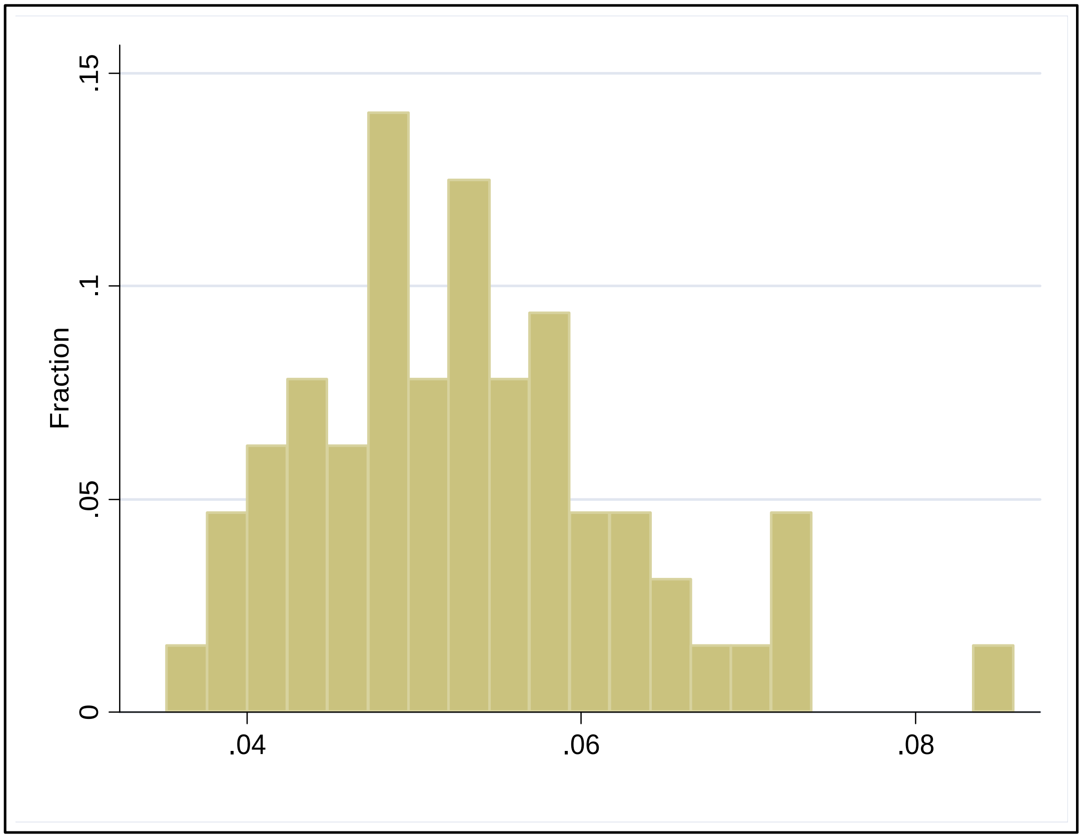
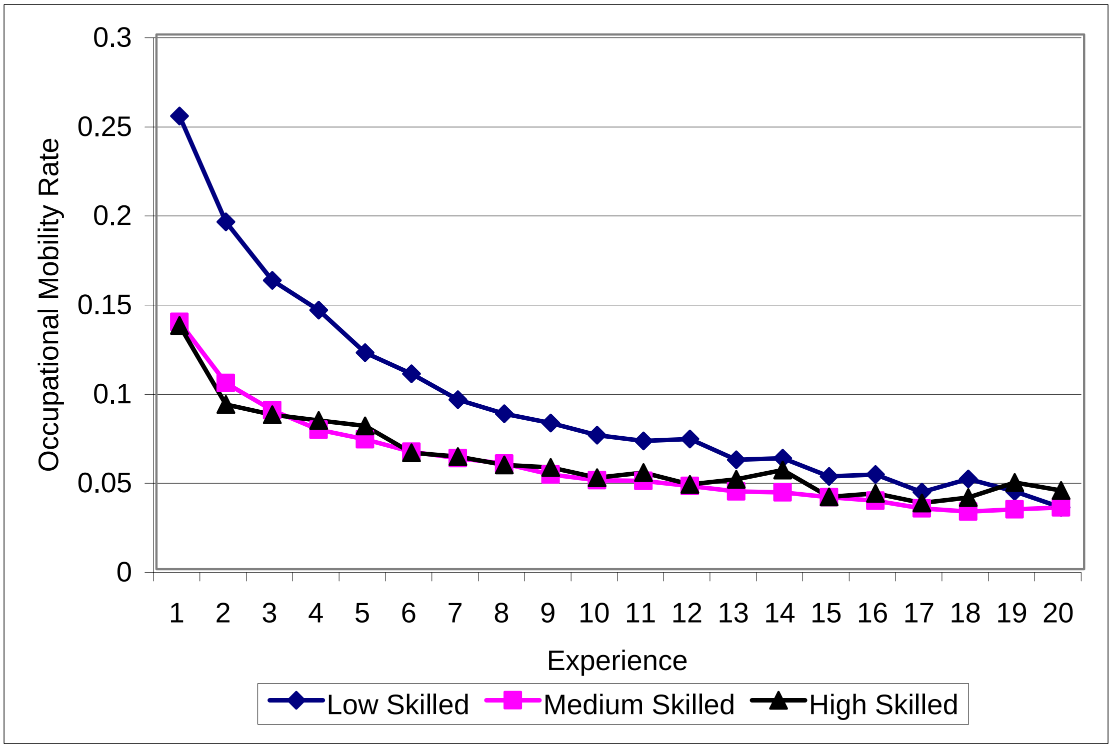
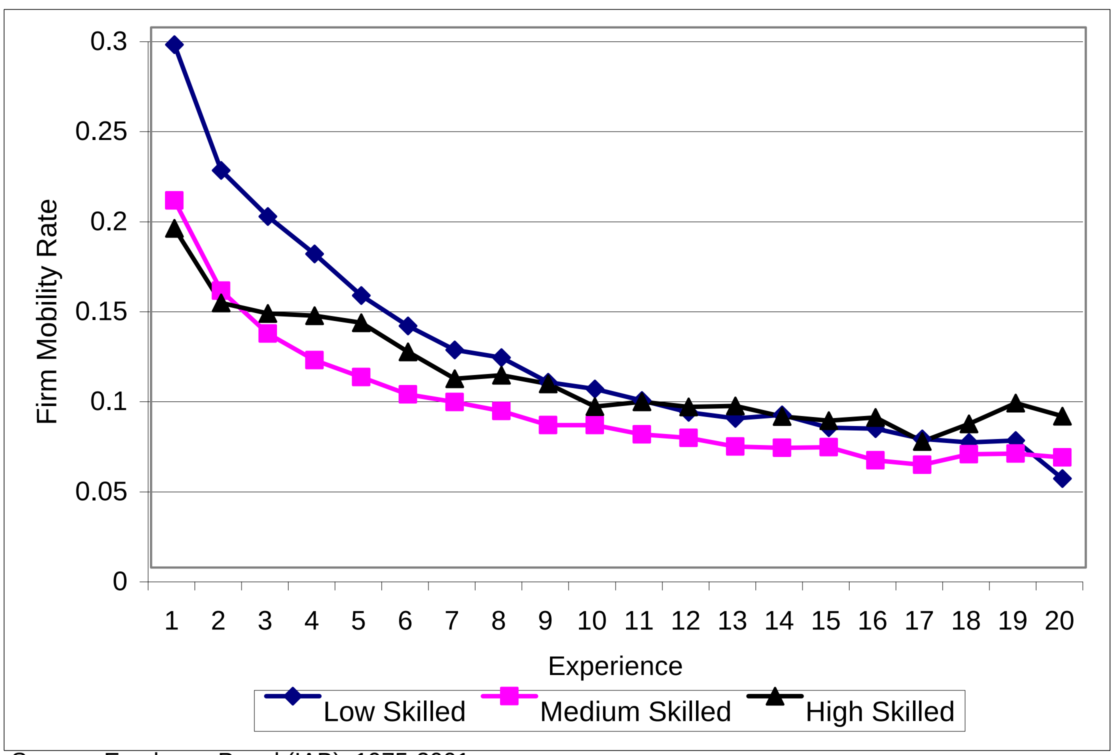


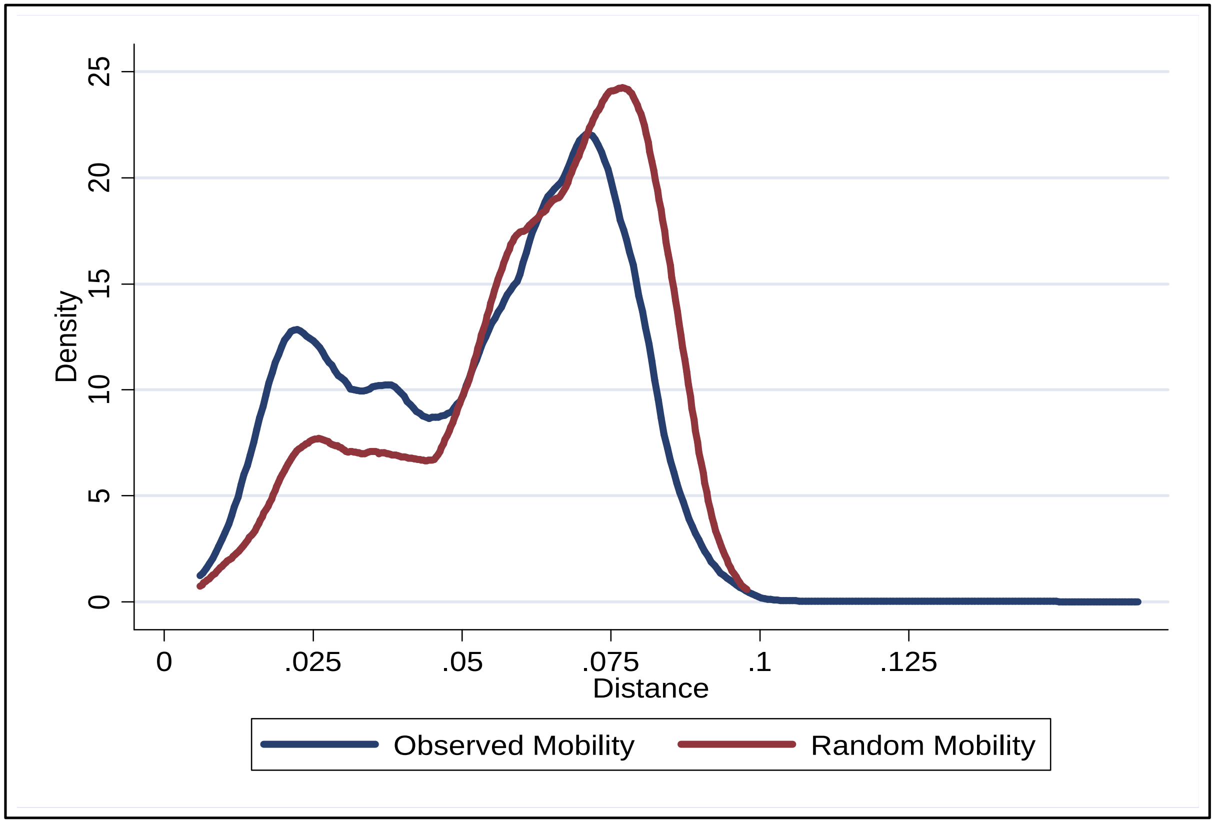
Figure 3: Occupational and Firm Mobility Over the Life-Cycle





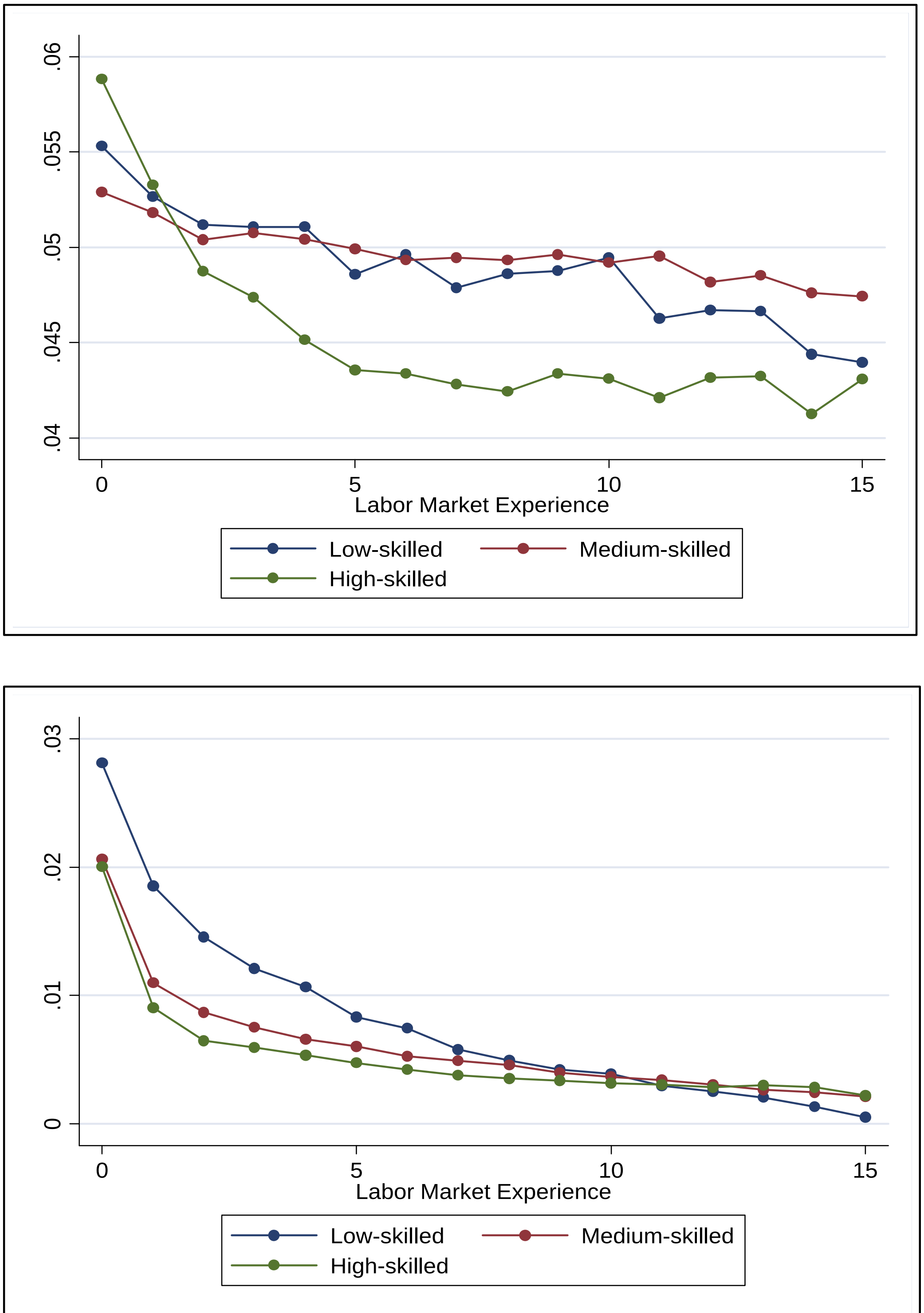
Source : Employee Panel (IAB), 1975-2001

Figure 4: Observed Mobility is More Similar than Random Mobility



Source: Employee Panel (IAB), 1975-2001

Figure 5: Distance of Occupational Moves Declines over Career



Notes : The figure shows the distance of occupational moves by labor market experience for movers (top panel) and for all individuals in the labor market (bottom panel) where stayers are assigned a distance of zero. All results are reported separately for the three education groups: no vocational degree (low), vocational degree (medium) and university degree (high). The values are coefficients from a regression that controls for each year of actual labor market experience as well as year dummies.

Source : Employee Panel (IAB), 1975-2001

Figure 6a: Correlation of Wages Decreases with Distance of Move

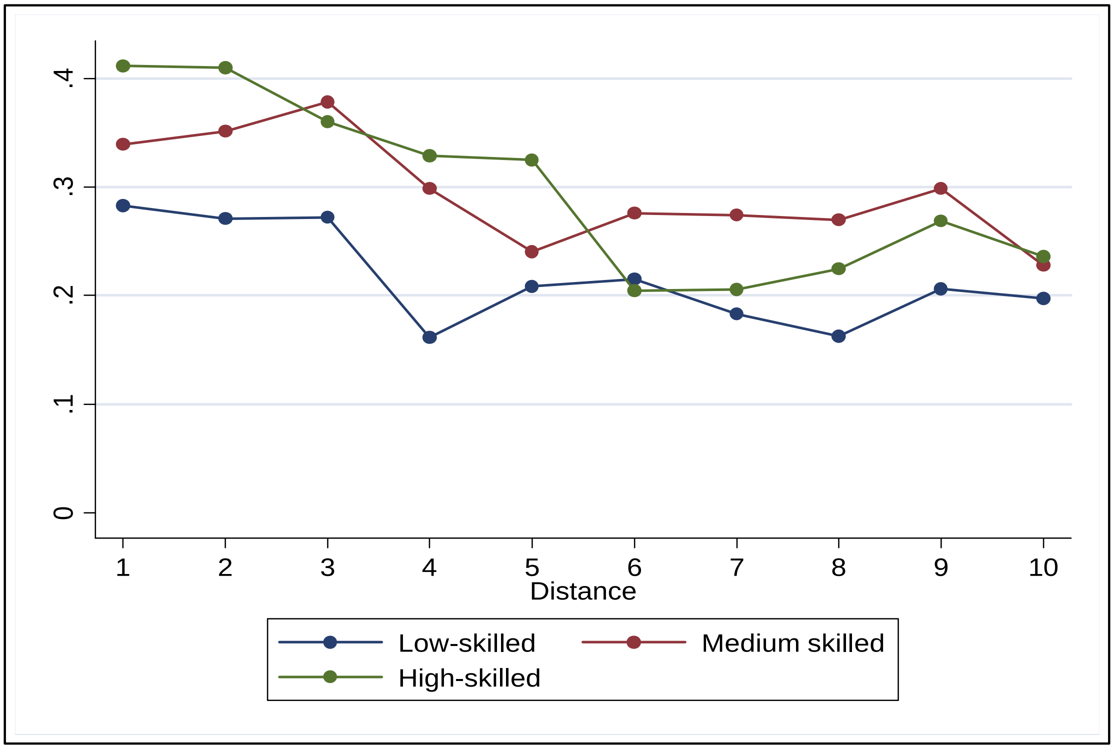
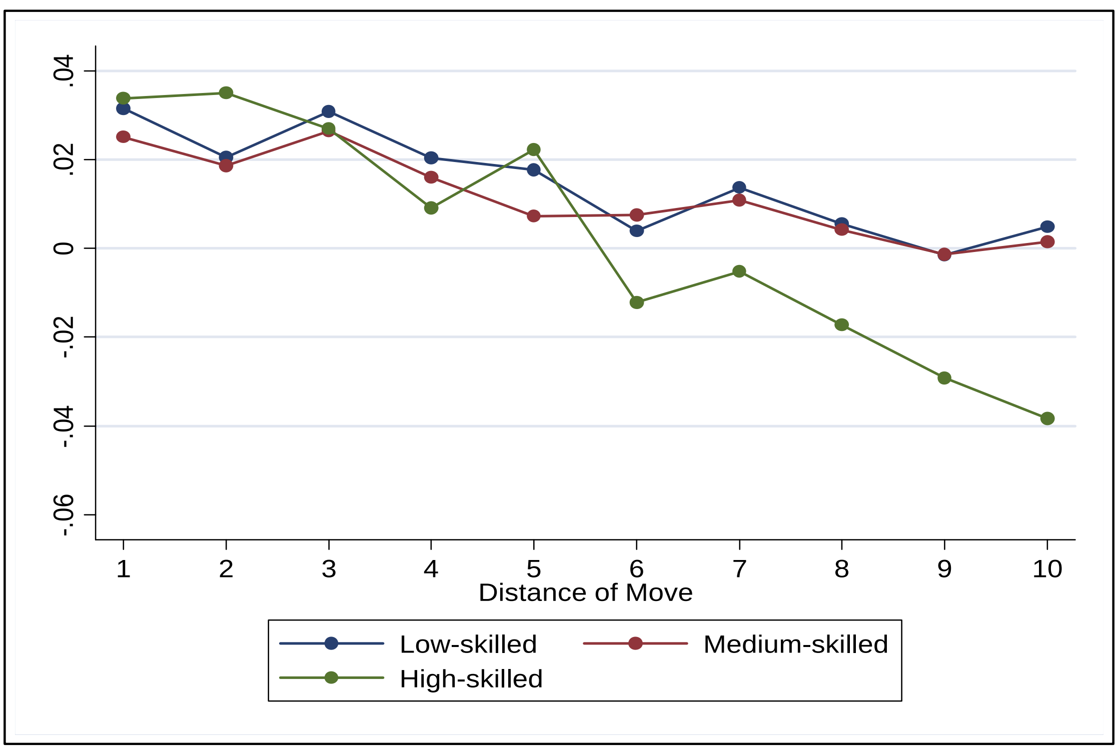


Figure 6b: Return to Past Occupational Tenure by Distance



Source : Employee Panel (IAB), 1975-2001

Table A1: Summary Statistics of Task Data

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

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

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

Table A2: List of Occupations and Task Usage

Title of Occupation	Employed (%)	Manual Tasks	Analytic Tasks	Interactive Tasks
Miners, Stone-Breaker, Mineral Processing	0.56	0.724	0.166	0.255
Concrete and Cement Finishers, Stone Processing	0.22	0.851	0.203	0.287
Potter, Ceramicist, Gaffer	0.27	0.845	0.276	0.257
Chemical Processing	1.01	0.839	0.329	0.291
Plastics and Polymer Processing	0.19	0.854	0.270	0.304
Paper and Pulp Processing	0.24	0.865	0.305	0.429
Printer, Typesetter, Typographer	1.02	0.781	0.338	0.357
Wood, Lumber and Timber Processing	0.16	0.836	0.218	0.180
Metal and Iron Manufacturer	0.31	0.857	0.192	0.199
Moulding, Shaping	0.24	0.899	0.179	0.169
Metal Presser and Moulder	0.24	0.899	0.225	0.191
Metal Polisher, Sanders, Buffers, Lathe Operators	1.51	0.912	0.261	0.223
Welder, Brazing, Soldering	0.53	0.818	0.183	0.155
Blacksmith, Farrier, Forger, Plumber and Pipe Fitters	2.42	0.754	0.300	0.374
Locksmith	5.47	0.735	0.246	0.256
Mechanic, Machinist, Repairmen	3.83	0.591	0.321	0.362
Tool and Dye Maker, Instrument Mechanic	0.96	0.863	0.283	0.313
Metal Craftsmen	0.47	0.772	0.367	0.476
Electricians, Electrical Installation	5.06	0.650	0.362	0.398
Assembler	0.79	0.855	0.194	0.179
Weaver, Spinner, Knitters, Wool Trade	0.18	0.913	0.291	0.338
Tailor, Textile Worker	0.24	0.802	0.270	0.284
Shoemaker	0.24	0.754	0.241	0.473
Baker	0.90	0.947	0.279	0.458
Butcher	0.65	0.845	0.268	0.438
Cook	0.62	0.799	0.339	0.565
Beverage Production, Milk Production, Grease Processing	0.27	0.870	0.332	0.426
Bricklayer, Mason	2.72	0.765	0.213	0.292
Carpenter	1.09	0.748	0.226	0.316
Road Builder	0.68	0.697	0.193	0.248
Unskilled Construction Worker	1.00	0.746	0.109	0.124
Plasterer	0.93	0.710	0.254	0.312
Interior Decorator, Interior Designer	0.26	0.755	0.289	0.474
Joiner, Cabinet Maker	2.01	0.879	0.272	0.333
Painters	1.72	0.529	0.189	0.324
Product Tester	0.92	0.536	0.330	0.297
Unskilled Worker	2.20	0.799	0.164	0.131
Crane Driver, Crane Operator, Skinner, Machine Operator	2.00	0.836	0.238	0.245
Engineers	3.68	0.263	0.596	0.758
Chemist, Physicist,	6.19	0.439	0.540	0.661
Technical Service Personel	1.09	0.267	0.474	0.371
Sales Personnel	5.34	0.316	0.573	0.928
Banker	3.15	0.127	0.679	0.833
Traders, Trading Personnel	1.18	0.299	0.594	0.826
Conductor	5.24	0.690	0.170	0.260
Sailor, Seaman, Navigator, Mariner	0.31	0.590	0.337	0.576
Mail Carrier and Handlers, Postal Clerks	0.58	0.662	0.326	0.318
Storekeeper, Warehouse Keeper	2.77	0.685	0.271	0.333
Entrepreneurs	3.14	0.206	0.654	0.917
Politicians, Member of Parliament	1.28	0.113	0.633	0.812
Accountant, Book Keeper	2.35	0.279	0.622	0.582
Office Clerk	8.55	0.196	0.671	0.652
Guards, Watchmen, Police, Security Personnel	3.07	0.287	0.456	0.499
Publicist, Journalist, Authors	0.36	0.193	0.606	0.810
Musicians	0.66	0.434	0.291	0.649
Physicians	0.51	0.155	0.498	0.728
Nurses, Dietitians, Physical Therapists	1.04	0.191	0.430	0.512
Social Worker	0.93	0.197	0.497	0.917
Teacher (except university)	2.02	0.148	0.426	0.945
Scientist, Clergymen	0.94	0.149	0.553	0.822
Personal Hygiene Technician	0.22	0.112	0.267	0.729
Waiter, Barkeeper, Innkeeper	0.66	0.241	0.333	0.655
Janitor, Home Economics, Housekeeper	0.06	0.360	0.392	0.765
Cleaning Service Workers	0.58	0.353	0.152	0.182
Mean		0.803	0.481	0.449

Notes : The table shows the title of the 64 occupations, the percentage of individuals employed in it and the fraction of individuals that report performing analytical, manual and interactive tasks on their job following the classification of Autor et al (2003). For a description of the tasks underlying the three aggregate task groups, see Table A2.

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

Table A3: Alternative Sample Definitions: Restriction to External Movers and Job-to-Job Transitions

	Low -Skilled					Medium -Skilled					High -Skilled				
	distance	distance	wages	wages	tenure	distance	distance	wages	wages	tenure	distance	distance	wages	wages	tenure
A. Occupational Movers that Also Switch Firms															
Experience (Years)	-0.001	-0.001				-0.001	-0.001				-0.002	-0.004			
	(0.000)**	(0.000)**				(0.000)**	(0.000)**				(0.000)**	(0.001)**			
Experience Squared	0	0				0	0				0	0			
	(0.000)**	(0.000)**				(0.000)**	(0.000)**				(0.000)**	(0.000)**			
Wage Last Occupation			0.164	0.118				0.23	0.181				0.303	0.177	
			(0.006)**	(0.007)**				(0.004)**	(0.004)**				(0.009)**	(0.010)**	
Past Tenure * Similar Move					0.009					0.005					0.01
					(0.001)**					(0.001)**					(0.002)**
Past Tenure * Distant Move					0.008					0.005					0.004
					(0.001)**					(0.001)**					(0.002)*
Mean Distance	0.0553	0.0553			0.0535	0.0535				0.0453	0.0453				
	(0.024)	(0.024)			(0.024)	(0.024)				(0.023)	(0.023)				
Year Dummies	Yes	Yes	Yes	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	Yes	Yes	Yes
State Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	No	Yes	No	No	No	No	Yes	No	No	No	No	Yes	No	No	No
Observations	38,412	38,439	18,692	18,831	37,523	105,370	105,476	51,627	51,916	103,543	18,388	18,399	8,896	8,625	17,521
B. Occupational Moves with Intermediate Un- or Nonemployment of less than a Year															
Experience (Years)	-0.001	-0.002				0	-0.001				-0.002	-0.004			
	(0.000)**	(0.000)**				(0.000)**	(0.000)**				(0.000)**	(0.001)**			
Experience Squared	0	0				0	0				0	0			
	(0.000)**	(0.000)**				(0.000)**	(0.000)**				(0.000)**	(0.000)**			
Wage Last Occupation			0.188	0.146				0.255	0.202				0.33	0.221	
			(0.006)**	(0.007)**				(0.004)**	(0.004)**				(0.009)**	(0.009)**	
Past Tenure * Similar Move					0.012					0.006					0.013
					(0.001)**					(0.001)**					(0.002)**
Past Tenure * Distant Move					0.011					0.008					0.009
					(0.001)**					(0.001)**					(0.002)**
Mean Distance	0.0557	0.0557			0.0536	0.0536				0.0446	0.0446				
	(0.025)	(0.025)			(0.025)	(0.025)				(0.023)	(0.023)				
Year Dummies	Yes	Yes	Yes	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	Yes	Yes	Yes
State Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	No	Yes	No	No	No	No	Yes	No	No	No	No	Yes	No	No	No
Observations	39,651	39,680	19,080	18,796	37,904	113,486	113,599	55,269	55,234	110,614	19,994	20,006	9,702	8,894	18,607

Notes : The table reports estimation results for two alternative sample definitions of movers in Section 4. Panel A uses only those occupational movers that also switch firms in order to get rid of any firm effects. Panel B restricts the sample of movers to those that get reemployed in a new occupation within a year of leaving the old oneThe first two specifications are replicated from Table 4 (columns "distance") using a fixed effects estimator in the second column. The third and fourth column ("wages") replicate results from the correlation of wages for similar and distant movers (column (2) and (3) in Table 5). Finally, the last column "tenure" replicates the spline regression from Table 6 (column (2)). See notes to the previous tables for the other controls included and the treatment of censoring and standard errors. Bootstrapped standard errors are reported in parentheses.

Table A4: Results from Alternative Distance Measures

	Low -Skilled					Medium -Skilled					High -Skilled				
	distance	distance	wages	wages	tenure	distance	distance	wages	wages	tenure	distance	distance	wages	wages	tenure
A. Uncentered Correlation															
Experience (Years)	-0.005	-0.006				-0.005	-0.007				-0.022	-0.021			
	(0.001)**	(0.002)**				(0.001)**	(0.002)**				(0.003)**	(0.004)**			
Experience Squared	0	0				0	0				0.001	0.001			
	(0.000)**	(0.000)**				(0.000)**	(0.000)**				(0.000)**	(0.000)**			
Wage Last Occupation			0.211	0.15				0.306	0.214				0.279	0.307	
			(0.006)**	(0.006)**				(0.004)**	(0.004)**				(0.009)**	(0.010)**	
Past Tenure * Similar Move					0.024					0.018					0.033
					(0.003)**					(0.001)**					(0.004)**
Past Tenure * Distant Move					-0.016					-0.029					-0.089
					(0.006)**					(0.003)**					(0.012)**
Mean Distance	0.541	0.541				0.533	0.533				0.404	0.404			
	(0.219)	(0.219)				(0.206)	(0.206)				(0.194)	(0.194)			
Year Dummies	Yes	Yes	Yes	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	Yes	Yes	Yes
State Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	No	Yes	No	No	No	No	Yes	No	No	No	No	Yes	No	No	No
Observations	43,021	43,021	21,056	21,392	42,448	118,054	118,054	58,819	58,941	117,760	20,697	20,697	10,158	10,133	20,291
B. 3 Task Groups															
Experience (Years)	-0.002	-0.001				-0.001	-0.003				-0.014	-0.025			
	(0.001)**	(0.001)				(0.001)*	(0.001)*				(0.003)**	(0.005)**			
Experience Squared	0	0				0	0				0.001	0.001			
	(0.000)**	(0.000)				(0.000)	(0.000)				(0.000)**	(0.000)**			
Wage Last Occupation			0.194	0.164				0.291	0.228				0.335	0.243	
			(0.006)**	(0.006)**				(0.004)**	(0.004)**				(0.009)**	(0.010)**	
Past Tenure * Similar Move					0.03					0.007					0.062
					(0.005)**					(0.002)**					(0.010)**
Past Tenure * Distant Move					-0.042					0.019					-0.154
					(0.023)					(0.011)					(0.061)*
Mean Distance	0.1681	0.1681				0.1821	0.1821				0.1818	0.1818			
	(0.135)	(0.135)				(0.151)	(0.151)				(0.157)	(0.157)			
Year Dummies	Yes	Yes	Yes	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	Yes	Yes	Yes
State Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	No	Yes	No	No	No	No	Yes	No	No	No	No	Yes	No	No	No
Observations	43,021	43,021	21,201	21,247	42,448	118,054	118,054	58,747	59,013	117,760	20,697	20,697	10,245	10,046	20,303

Notes : The table reports estimation results using two alternative distance measures separately by education group. Panel A uses the uncentered correlation known from innovation studies in industrial organization (see for example, Jaffe, 1986). Panel B uses a distance measure that accounts for the fact that some of the 19 tasks are more similar than others. The first two specifications are replicated from Table 4 (columns "distance") using a fixed effects estimator in the second column. The third and fourth column ("wages") replicate results from the correlation of wages for similar and distant movers (column (2) and (3) in Table 5). Finally, the last column "tenure" replicates the spline regression from Table 6 (column (2)). See notes to the previous tables for the other controls included and the treatment of censoring and standard errors. Bootstrapped standard errors are reported in parentheses. Coefficients with * are statistically significant at the 5 percent level, those with ** at the 1 percent level.

Table A: Selection of Distant and Similar Occupational Movers

	Low-Skilled		Medium-Skilled		High-Skilled	
Y: Log Daily Wage in t	(1)	(2)	(3)	(4)	(1)	(2)
Distance to Target in t+1	-1.869	-0.891	-0.325	-0.161	-0.754	-0.249
	(0.086)**	(0.086)**	(0.009)**	(0.009)**	(0.033)**	(0.035)**
Actual Experience	0.058	0.053	0.03	0.028	0.109	0.088
	(0.002)**	(0.002)**	(0.001)**	(0.001)**	(0.003)**	(0.003)**
Experience Squared	-0.002	-0.002	0.000	0.000	-0.004	-0.003
	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**
Occupational Tenure	0.04	0.039	0.064	0.06	0.055	0.054
	(0.002)**	(0.002)**	(0.001)**	(0.001)**	(0.004)**	(0.004)**
Tenure Squared	-0.001	-0.001	-0.003	-0.003	-0.003	-0.003
	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Occupation Dummies	No	Yes	No	Yes	No	Yes
Observations	42,478	42,478	117,875	117,875	20,303	20,303

Notes : The table reports censored regression estimates where the dependent variable is the log daily wage in the current job. We compare wages earned in the current job for movers that go to a similar occupation relative to those that move to a distant occupation in the next period. Results are reported separately by education group. Robust standard errors that are boostrapped with replacement and 50 replications to allow for clustering by occupation and time period are in parentheses.