Wage Growth Due to Human Capital Accumulation and Job Search: A Comparison between the United States and Germany

Uta Schönberg[*]

[*]University of Rochester,

Wage Growth Due to Human Capital Accumulation and Job Search: A Comparison between the United States and Germany

Uta Schönberg

Abstract

This paper compares the sources of wage growth of young male workers in two countries with very different labor market institutions, the United States and Germany. The author first develops a simple method for decomposing wage growth into components due to general human capital accumulation, firm-specific human capital accumulation, and job search. The empirical analysis uses data from administrative records (Germany) and the National Longitudinal Survey of Youth (United States) for cohorts entering the labor market in the late 1970s and early 1980s. Although the two countries differed substantially in mobility rates, they were similar in the sources of wage growth, with general human capital accumulation being the most important single source and job search accounting for an additional 25% or more of total wage growth. There is no evidence that returns to firm-specific human capital accumulation were higher for German apprentices than for U.S. high school dropouts or graduates.

KEYWORDS: wage growth, human capital accumulation, job search

WAGE GROWTH DUE TO HUMAN CAPITAL ACCUMULATION AND JOB SEARCH: A COMPARISON BETWEEN THE UNITED STATES AND GERMANY

UTA SCHÖNBERG*

This paper compares the sources of wage growth of young male workers in two countries with very different labor market institutions, the United States and Germany. The author first develops a simple method for decomposing wage growth into components due to general human capital accumulation, firm-specific human capital accumulation, and job search. The empirical analysis uses data from administrative records (Germany) and the National Longitudinal Survey of Youth (United States) for cohorts entering the labor market in the late 1970s and early 1980s. Although the two countries differed substantially in mobility rates, they were similar in the sources of wage growth, with general human capital accumulation being the most important single source and job search accounting for an additional 25% or more of total wage growth. There is no evidence that returns to firm-specific human capital accumulation were higher for German apprentices than for U.S. high school dropouts or graduates.

In their early phases, labor market careers are characterized by many job switches and rapid wage growth. According to Topel and Ward (1992), workers in the United States typically switch firms about six times during their first ten years in the labor market, and over that period their wages grow by an average of roughly 66%. An important question is how much of total wage growth can be attributed to optimal job search.

In this paper I first propose a simple method for decomposing total wage growth into three components: general human capital accumulation, firm-specific human capital accumulation, and job search. I then compare the sources of wage growth of young men in two countries with very different labor market institutions, the United States and Germany. The U.S. labor market is typically considered to be one of the most flexible labor markets in the advanced world. The German labor market, in contrast, is often viewed as the prototype of a heavily regulated labor market, characterized by severe firing restrictions, centralized wage-setting institutions, and generous unemployment insurance coverage.

I focus on the following questions. First, does wage growth due to firm-specific human capital accumulation play a more important role in Germany than in the United States? One reason this might be the case is that German workers expect to stay with their employer longer than U.S. workers do, and thus have a stronger incentive to invest in (specific) human capital (see, for

example, Harhoff and Kane 1997; Acemoglu and Pischke 1998). Second, does the lower firm mobility in Germany result in lower job-search-related wage gains for German workers than for U.S. workers?

The empirical analysis is based on a survey data set, the National Longitudinal Survey of Youth, for the United States, and an administrative data set, the IAB-Beschäftig-tenstichprobe, for Germany. Both data sets cover cohorts that entered the labor market in the late 1970s and early 1980s. They are well suited for the analysis of job mobility and wage growth, as they allow observation of workers' entire work history from labor market entry onward, including all job-to-job and job-to-unemployment transitions.

A Framework to Identify Wage Growth Due to Job Search and Human Capital

The framework I employ for identifying wage growth due to job search and human capital accumulation is in the spirit of search models with on-the-job search developed by Burdett (1978), Jovanovic (1979a, 1984), and Mortensen (1988). Workers either work or are unemployed. Their wages differ both within and across firms. Some of the variation may be due to match-specific productivity: two workers with the same ability in the same firm, for example, may earn different wages because one is better matched with the firm—and thus more productive—than the other. Alternatively, the variation may reflect inter-firm variation in productivity. Finally, as shown by the growing literature on equilibrium search models, similar workers may be paid different wages even if firms are homogeneous, due to search frictions (for example, Burdett and Mortensen 1998). In this paper I make no attempt to distinguish among these cases. The model I employ assumes that workers do not know the location of the firm where they are most productive, and that they are continually searching for a good match, both on- and off-the-job. Unemployed workers accept a job offer if the value of the job exceeds the value of unemployment. Employed workers accept an outside offer if the value of the new job exceeds the value of the old job. On-the-job

search thus leads to endogenous job-to-job transitions and allows workers to achieve better matches over time.

I allow workers' wages to be subject to shocks. Such shocks may occur as a result of new information workers and their employers glean about the quality of the match while workers "experience" the job, as in Jovanovic's (1979a) model. Alternatively, wages may be affected by productivity shocks that are firm-wide in nature. The presence of productivity shocks leads to endogenous job-to-unemployment transitions: the arrival of disappointing news about a job match may reverse the worker's perception of the job as preferable to unemployment.

In such a framework, how wages are determined is still in question, as firms do not need to pay wages equal to productivity in order to attract workers. Rather than add to the literature on that question, I simply assume that log-wages linearly depend on firm-specific human capital as well as on match quality.[1] Suppose that the log-wage of worker i in firm j at calendar time t can be written as

$$(1) \qquad \ln w_{ijt} = \alpha(e_{it}) + \beta(\tau_{ijt}) + \gamma_t + u_{ijt}.$$

Here e and τ denote actual experience and firm tenure, respectively. General and firm-specific human capital accumulation are represented by $\alpha(e)$ and $\beta(\tau)$. Alternatively, $\beta(\tau)$ may reflect wage growth by tenure due to deferred compensation, as in Lazear (1979) or Salop and Salop (1976). Note that all workers accumulate the same amount of general and firm-specific human capital.[2] The time effect γ_t captures aggregate wage growth. Suppose the error term u_{ijt} can be

---

[1]Some justification for this approach is provided by Woodcock (2003), who showed that in a model with learning about match quality and Nash bargaining, but without on-the-job search, equilibrium wages are linear in a person-specific component, a firm-specific component, and the posterior mean of beliefs about match quality.

[2]Also note that firm-specific human capital accumulation does not depend on the quality of the match. Jovanovic (1979b) presented a model in which workers invest more in firm-specific human capital accumulation the better their match.

decomposed as

(2) $u_{ijt} = f_i + m_{ij}(\tau_{ijt}) + \varepsilon_{ijt}.$

Here f_i is a fixed worker effect, representing workers' time-invariant ability that is equally valued at all firms; $m_{ij}(\tau)$ denotes the (expected) quality of the match and is allowed to vary with tenure at the same firm; and ε_{ijt} is an i.i.d. wage shock, representing, for instance, measurement error. In addition to aggregate wage growth, three distinct sources of wage growth are implied by the two equations: general human capital accumulation, $\alpha(e)$; firm-specific human capital accumulation or deferred compensation, $\beta(\tau)$; and on-the-job search—whereby workers achieve better matches with time in the labor market—captured by the term $m_{ij}(\tau)$.

Defining Wage Growth Due to Job Search and Firm-Specific Human Capital Accumulation

It is useful to start with a comparison of the wage growth of stayers, job-to-job movers, and job-to-unemployment movers. Taking first differences of equation (1), for those who stay with the firm, yields

$$\Delta \ln w_{ijt} = \Delta\alpha(e_{it}) + \Delta\gamma_t + \Delta\beta(\tau_{ijt}) + \Delta m_{ij}(\tau_{ijt}) + \Delta\varepsilon_{ij}.$$

Clearly, the fixed worker effect drops out of the first-difference equation. Suppose that transitory wage shocks do not affect workers' decision to move. This is the case if the shocks purely reflect measurement error. It is also a reasonable assumption if workers are not credit-constrained, and thus are able to insure against transitory income shocks. Under this assumption, the average wage growth of stayers with tenure τ equals

$$E[\Delta \ln w \mid \text{stay}] = \Delta\alpha(e) + \Delta\gamma_t + E[\Delta m(\tau) + \Delta\beta(\tau) \mid \text{stay}].$$

Similarly, the average wage growth of workers with tenure $\tau - 1$ in the last period who move from job-to-job (*jtj*) and job-to-unemployment (*jtu*) equals

$$E[\Delta \ln w \mid jtj] = \Delta\alpha(e) + \Delta\gamma_t + E[m_{ij'}(0) - (m_{ij}(\tau - 1) - \beta(\tau - 1)) \mid jtj]$$

and

$$E[\Delta \ln w \mid jtu] = \Delta\alpha(e) + \Delta\gamma_t + E[m_{ij'}(0) - (m_{ij}(\tau - 1) - \beta(\tau - 1)) \mid jtu].$$

For all three groups under consideration—stayers, job-to-job movers, and job-to-unemployment movers—average wage growth has two common components: wage growth due to general human capital, $\Delta\alpha(e)$, and aggregate wage growth, $\Delta\gamma_t$. Wage growth for stayers additionally reflects wage growth due to firm-specific human capital accumulation or deferred compensation, $\Delta\beta(\tau)$, and the change in the quality of the match, $E[\Delta m_{ij}(\tau) \mid \text{stay}]$. I expect the latter term to be positive, as workers who receive a higher wage shock are more likely to stay. According to most search models, job-to-job movers lose their firm-specific human capital, but improve the quality of their match. Job-to-unemployment movers, in contrast, not only lose their firm-specific human capital, but may also become less well matched at the new job.

How can one define wage growth due to job search alone? For a worker with tenure $\tau - 1$ at the old job, a natural way to do so is as follows:

Wage growth search =
$$\Pr(\text{stay})E[\Delta m_{ij}(\tau) \mid \text{stay}]$$
$$+ \Pr(jtj)E[m_{ij'}(0) - m_{ij}(\tau - 1) \mid jtj]$$
$$+ \Pr(jtu)E[m_{ij'}(0) - m_{ij}(\tau - 1) \mid jtu].$$

In order to obtain wage growth due to search by actual experience, unconditional on tenure, one has to average over the tenure distribution by experience.

Wage growth due to job search thus consists of three parts. First, the expected match quality of stayers may improve since matches that turn out to be a disappointment are destroyed.[3] Second, the expected match quality

---

[3]In Postel-Vinay and Robin (2002), wage growth due to job search also shows up partly as within-job wage growth, although productivity does not change over time. Postel-Vinay and Robin (2002) allowed firms to respond to outside offers. Hence, if a worker encounters a firm that is willing to pay a higher wage than her current wage, but her productivity is lower at the outside firm than at her current firm, she stays with the current employer and receives a wage increase.

of job-to-job movers typically increases, since a move occurs only if the value of the new job exceeds the value of the old job, taking into account the loss in firm-specific human capital. Third, job-to-unemployment movers may lose search capital in addition to firm-specific human capital.

Turning to wage growth due to firm-specific human capital accumulation over the lifecycle, a natural way to define this source of wage growth, for a worker with tenure τ, is

$$\text{wage-growth–specific human capital} =$$
$$\text{Pr(stay)}\Delta\beta(\tau) - \text{Pr(move)}\beta(\tau - 1).$$

Again, in order to obtain wage growth due solely to firm-specific human capital accumulation by actual experience, unconditional on tenure, one has to average over the tenure distribution by experience.

Wage growth due to firm-specific human capital accumulation consists of two parts. First, wages of stayers grow by $\Delta\beta(\tau)$ due to firm-specific human capital accumulation. Wages of movers, in contrast, decline by $\beta(\tau - 1)$, as these workers lose the stock of firm-specific human capital when switching employers. Note that this definition differs from the concept of the return to tenure. While the return to tenure measures how much a worker can expect his wage to grow with tenure at the same firm, relative to his outside option, I estimate how much a labor market entrant can expect his wage to grow due to firm-specific human capital accumulation with time in the labor market.

Estimation of Wage Growth Due to Job Search and Firm-Specific Human Capital Accumulation

How can one estimate wage growth solely due to job search, using these definitions? Suppose we have estimates for aggregate wage growth and wage growth due to general human capital. Estimating wage growth due to job search then boils down to disentangling wage growth due to firm-specific human capital accumulation and learning about match quality, for workers who stay with their employer. In this paper I make no attempt to distinguish between these alternative sources of within-job wage growth. Instead, I first

assume that all within-job wage growth (on top of wage growth due to general human capital accumulation and aggregate time effects) is due to firm-specific human capital accumulation. In other words, I assume that there is no learning about match quality, so that all wage growth due to job search shows up in the wage growth of movers. This provides a lower bound for wage growth due to job search, as long as $E[\Delta m_{ij}(\tau)|\text{stay}] > 0$ and $\beta(\tau -1) > 0$. I compute this lower bound as follows. For each wage observation, I first subtract estimates for the return to general human capital, $\hat\alpha(e)$, and aggregate wage growth, $\hat\gamma$:

$$\ln w_{ijt} - \hat\gamma_t - \hat\alpha(e) := \ln \tilde{w}_{ijt} = \beta(\tau) + f_i + m_{ij}(\tau) + \tilde\varepsilon_{ijt},$$

where $\tilde\varepsilon_{ijt} = \varepsilon_{ijt} + (\gamma_t - \hat\gamma_t) + (\alpha(e) - \hat\alpha(e))$.

I then compute

(3)   wage growth search, lower bound =
$$\sum_{e=1}^{E} \text{Pr(move)}_e E_e[\Delta \ln \tilde{w}_{ijt}|\text{move}].$$

I provide an alternative estimate for wage growth due to job search by assuming that there is no firm-specific human capital accumulation, so that all wage growth for stayers—in addition to aggregate wage growth and general human capital accumulation—reflects learning about match quality. This provides an upper bound of wage growth due to job search as long as $\Delta\beta(\tau) > 0$. This upper bound is equal to total wage growth minus aggregate wage growth and general human capital, and results in $\sum_{e=1}^{E} E_e[\Delta \ln \tilde{w}_{ijt}]$. This estimate can be interpreted as what a worker would lose if his job ended for purely exogenous reasons and he had to search from scratch. Such a worker loses not only his firm-specific human capital, but also his search capital.

Wage growth due to firm-specific human capital accumulation can be estimated in a similar way. First, I compute average wage growth of stayers, adjusted for aggregate wage growth and wage growth due to general human capital accumulation:

$$E[\Delta \ln \tilde{w}_{ijt}|\text{stay}] = \Delta\beta(\tau) + E[\Delta m_{ij}(\tau)|\text{stay}].$$

I then obtain the cumulative log-wage growth due to firm-specific human capital accumulation as

(4)   wage-growth–specific human capital =
$$\sum_{e=1}^{E} \Pr(\text{stay})_e E_e[\Delta \ln \widetilde{w}_{ijt} | \text{stay}].$$

This provides an upper bound for wage growth due to firm-specific human capital, for two reasons. First, wage growth of stayers—net of aggregate wage growth and general human capital accumulation—reflects not only firm-specific human capital accumulation, $\Delta\beta(\tau)$, but also wage growth due to learning about match quality, $E[\Delta m_{ij}(\tau)|\text{stay}]$. Second, it does not take into account the loss in firm-specific human capital for workers who switch jobs.

Identifying Returns to General Human Capital Accumulation, $\alpha(e)$

Estimating (1) by OLS, controlling for firm tenure and aggregate wage growth, is likely to yield an upward estimate of $\alpha(e)$ for at least two reasons. First, $Cov(e, m_{ij}(\tau)|\tau, \gamma_t) > 0$: workers achieve better job matches with time in the labor market. Second, $Cov(e, f_i|\tau, \gamma_t) > 0$: more able workers may become unemployed less often and thus have more actual experience. I follow Dustmann and Meghir (2005) and use involuntary firm switchers to identify returns to general human capital accumulation. The idea is that these workers lose their search capital and have to search from scratch, thus mitigating the problem of a positive correlation between experience and match quality. I proxy an involuntary job loss with a job-to-unemployment transition.

There are several problems with this strategy. First, it may not be true that job-to-unemployment movers lose all search capital if that group includes voluntary job switchers. Such may be the case, for instance, because workers who enter unemployment have a job lined up already.[4]

Second, the search problem may be different for more experienced workers, for instance because young workers accumulate general and firm-specific human capital at a faster rate than do older workers. Third, job-to-unemployment movers may be less able, on average, than randomly selected workers.[5] This is a serious problem particularly if the return to human capital accumulation is heterogeneous, that is, if more able workers accumulate more general human capital.[6] Even with homogeneous returns to human capital accumulation, the selection of workers into unemployment is problematic if it changes over the life-cycle.

I acknowledge that I cannot fully deal with these problems. In order to get some idea of how severe the bias might be, I check the robustness of my results with respect to (a) alternative definitions of a job-to-unemployment transition and (b) the inclusion of proxies for workers' ability.

I also acknowledge that some skills may be neither purely general nor purely firm-specific, but partially transferable across firms. In particular, firm switchers can retain industry- or occupation-specific skills if they find employment in their previous industry or occupation. I leave the comparison between the returns to industry and occupation tenure in the U.S. and Germany for future research.

In line with much of the literature on the returns to human capital accumulation,[7] my approach does not allow for the depreciation of general human capital. If workers lose

---

[4]Also note that unemployed job search may be more efficient than on-the-job search (for example, Kahn and Low 1982).

[5]One reason for the negative selection of (job-to-unemployment) movers is asymmetric information between incumbent and outside firms (Gibbons and Katz 1991). Neal (1998) presented a model in which more able workers are less likely to switch jobs because they invest more in specific human capital.

[6]Heterogeneous human capital accumulation implies that past wage growth predicts future wage growth. Hence, residuals from a wage growth regression should be positively correlated, at least at higher lags. Consistent with results reported in the literature (for example, McCurdy 1982; Abowd and Card 1989; Topel 1991; Topel and Ward 1992; Meghir and Pestaferri 2004), I find no evidence for a positive correlation, suggesting that heterogeneity in the rate of human capital accumulation is not a serious problem.

[7]See, for example, Altonji and Williams (2005), Topel (1991), and Dustmann and Meghir (2005).

labor market skills while not working, any wage loss of job-to-unemployment movers reflects not only the loss of search capital and firm-specific human capital, but also the depreciation of general human capital. In a similar vein, I perform the decomposition of total wage growth by actual experience as opposed to potential experience. While I make no attempt to estimate the depreciation rate of general human capital due to unemployment, I do compare U.S. and German workers in terms of actual experience, as well as in terms of the average duration of the unemployment spell. I also check to see how the wage growth of job-to-unemployment movers and the return to general human capital change if I control for the duration of the employment gap.

Data Description and Variables

This section briefly describes the two data sets used in the empirical analysis. Details on the definition of variables and sample construction can be found in Appendix A (German data) and Appendix B (U.S. data).

German Data

The data from Germany are a 2% sample of administrative social security records. The data are principally available for the years 1975–2001. However, in order to make the data as comparable as possible to the U.S. data, I discard information for years after 1994. Furthermore, since the U.S. data include individuals born between 1957 and 1964 only, from the German dataset I drop all individuals born before 1957 or after 1964.

The data are well suited for an analysis of the job search process. First, their administrative nature ensures that wages, unemployment, and employment are measured accurately. Second, wages can always be matched to a particular employer, and are never averaged across jobs—which is necessary to identify wage growth due to job search.

The data are representative of all individuals covered by the social security system, roughly 80% of the German work force. They exclude the self-employed, civil servants, and individuals currently fulfilling their compulsory military service. As in many administra-

tive data sets, the data are right-censored at the highest level of earnings that are subject to social security contributions. Top-coding is about 1% for the low- and medium-skilled, but reaches close to 25% for university graduates. For this reason, the empirical analysis focuses on the low- and medium-skilled.

I restrict the sample to men who entered the labor market in or after 1975. This allows me to construct precise measures of actual experience and firm tenure. Since East and West Germany differ substantially in the level and structure of wages, I drop all workers who were employed at least once in East Germany.

I then organize the data in two ways. I use quarterly data to analyze firm mobility. Since for firm stayers wages are available only once per year, I use yearly data to study wage growth. I discard part-time work from my sample.

U.S. Data

The U.S. data, covering the years 1979–94, come from the 1979 National Longitudinal Survey of Youth (NLSY79). I drop information for years after 1994 because valid wage information was typically available only every two years after that date, due to the NLSY's switch to a biannual interview schedule in 1994. The NLSY has several advantages over other commonly used data sets in the United States, such as the Panel Study of Income Dynamics (PSID) and Current Population Survey (CPS). Most important, the NLSY focuses on young workers. As in the German data, I observe the respondent's complete work history—including job-to-job and job-to-unemployment switches—from labor market entry onward. Moreover, unlike in the PSID, in the NLSY wages are never averaged across jobs.

For each respondent I construct the labor market history from the work-history file, which contains week-by-week longitudinal work records. From this file, I select the respondent's labor force status and job number at the beginning of each quarter. To this data set I match the educational histories of respondents (enrollment status as well as highest grade completed).

Table 1. Correlation between a Transition into Non-Employment and a Layoff.

	Job-to-Job	*Job-to-Non-Employment*	*Total*
Quit	4,990	4,004	8,994
	77.96% (55.48%)	56.38% (44.52%)	66.61%
Layoff	1,411	3,098	4,509
	22.04% (31.29%)	43.62% (68.71%)	33.39%
Total	6,401	7,102	13,503
	47.40%	47.40%	100%

Notes: The table shows the cross-tabulation between a job-to-job/job-to-nonemployment transition, based on the time between two jobs, and a quit/layoff, based on workers' response when asked why they left the job. The latter variable is missing in 27.84% of the cases. Percentages refer to the relative frequency of the cell within its column (within its row). A chi-squared test rejects the hypothesis that the two variables are independent at the 1% level (p-value = 0.000).

A major problem in using the NLSY concerns the type of employment status that should be included in the analysis. In the German data set, I only observe "regular" employment status, covered by the social security system. In the NLSY, in contrast, all kinds of employment positions are reported, regardless of whether the respondent was enrolled in school, or for how long and how many hours per week he worked at each job.

Hence, counting all jobs reported in the NLSY is likely to overstate mobility in the United States compared to Germany. In order to avoid this problem, I consider only those jobs that are held after completion of a transition from non-work to work. My main definition follows Farber and Gibbons (1996). According to this definition, a transition from non-work to work takes place when the worker was not working for at least one year, followed by at least two consecutive years in which he was working. A worker is classified as working when he has worked a minimum of 30 hours per week during each of at least 26 weeks in a calendar year.

It may be argued that working part-time jobs while at school is more common in the United States than in Germany, for (at least) two reasons. First, the German apprenticeship program is often credited with institutionalizing—and thus smoothing—the transition from school to work (for example, Ryan 1999). Second, more generous unemployment benefits in Germany may reduce workers' incentive to accept part-time jobs. Hence, the restriction above may discard too many jobs in the United States, and thus bias

the comparison between the United States and Germany. For this reason, I repeat the empirical analysis using a less stringent definition of labor market entry. According to this definition, a transition from non-work to work takes place when the worker was not working for at least one year, followed by only one year in which he was working. As an additional robustness check, I also determine how my results change when part-time jobs are not dropped.

My sample is then constructed as follows. There are 6,398 men in the NLSY79. I discard respondents belonging to the military sample. Since my empirical analysis distinguishes between education groups, I keep the supplementary samples of poor whites, blacks, and Hispanics. This leaves me with 5,579 individuals. Of those, 374 (194) have never entered the labor market, based on the first (second) definition of labor market entry. My final sample consists of 3,807 or 4,014 men, based on the first and second definitions of a labor market entry, respectively.

As with the German data, I use quarterly data to study firm mobility, and yearly data to study wage growth.

Variable Definitions

In both the German and U.S. data, workers sometimes leave their current employer, and return to the employer a couple of weeks later. I consider these workers stayers; movers are those who have permanently left their employer.

I classify a transition as a job-to-unemploy-

Table 2a. Means and Standard Deviations of Selected Variables: Germany.
(Annual Data)

Variable	Low	Medium	High
No. Workers	13,715	57,810	10,241
Fraction	16.77%	70.70%	12.52%
No. Observations	80,288	340,851	44,453
Age at Labor Market Entry	18.334	20.737	24.915
	(1.935)	(1.814)	(3.588)
Foreign	34.20%	4.76%	5.20%
Potential Experience	5.743	4.885	5.607
	(4.267)	(3.431)	(4.180)
Actual Experience	4.795	4.239	3.449
	(3.802)	(3.134)	(2.900)
Tenure	2.948	2.864	2.299
	(2.988)	(2.557)	(2.101)
Total Wage Growth	0.090	0.058	0.085
	(0.239)	(0.165)	(0.196)
Wage Growth, Stayers	0.062	0.042	0.058
	(0.158)	(0.110)	(0.125)
Wage Growth, Movers	0.169	0.111	0.179
	(0.372)	(0.270)	(0.325)

ment transition if the worker started the new job at least four weeks after his old job ended. I thus do not distinguish between unemployment and out of the labor force. It is important to stress that not all of these workers are looking for work; some have gone back to school, and others are in the military. Moreover, in the German data set, some of these workers may actually be self-employed or working as civil servants.

In both data sets, it is in principle possible to distinguish between unemployment and out of the labor force. In the NLSY, I observe whether an individual is looking for work on a weekly basis. In the German data set, I observe whether a worker receives unemployment benefits. While I do some robustness checks using this alternative definition, I prefer to base the definition of a job-to-unemployment transition on the time away from work, because the alternative definition is likely to measure different things in the two data sets.

It may also be argued that (involuntary) layoffs and (voluntary) quits proxy better for whether a worker loses or gains search capital than do job-to-job and job-to-unemployment transitions, and should thus be preferred.

In the NLSY, individuals are asked why they left a job. Table 1 shows that the two variables are correlated, but far from perfectly: among workers with a job-to-job transition, about 78% say they quit the job, compared to 56% of workers with a job-to-unemployment transition. Note that information on the reason a worker has left the job is missing in 27% of the cases, casting some doubt on the validity of this variable. No similar variable is available for the German data set.

I distinguish three education groups, which I label low, medium, and high. For the United States, low-skilled workers are high school dropouts with less than 12 years of schooling; medium-skilled workers are high school graduates with at least 12 years of schooling, but less than 16; and high-skilled workers are university graduates with more than 16 years of schooling. For Germany, I distinguish among workers who enter the labor market without postsecondary qualification (low-skilled), workers who completed an apprenticeship (medium-skilled), and university graduates (high-skilled). It is important to stress that the education groups may not be directly comparable across countries; for instance, the skills brought to

Table 2b. Means and Standard Deviations of Selected Variables: United States.
(Annual Data)

Variable	Main Definition of Labor Market Entry			Alternative Definition of Labor Market Entry		
	Low	Medium	High	Low	Medium	High
No. Workers	530	2,353	911	588	2,476	931
Fraction (unweighted)	13.97%	62.02%	24.01%	14.72%	61.98%	23.30%
Fraction (weighted)	9.70%	58.44%	31.87%	10.10%	58.75%	31.14%
No. Observations	4,101	19,846	7,092	4,347	20,671	7,376
Age at Labor Market Entry	20.294	20.074	22.452	19.423	19.267	21.396
	(3.164)	(3.166)	(2.881)	(2.887)	(2.782)	(3.012)
White	70.78%	75.37%	89.96%	69.47%	74.74%	89.76%
Potential Experience	6.351	6.744	6.111	6.696	7.141	6.759
	(4.064)	(4.137)	(3.789)	(4.184)	(4.230)	(4.031)
Actual Experience	5.331	5.591	5.046	5.308	5.603	5.107
	(3.554)	(3.633)	(3.264)	(3.573)	(3.649)	(3.299)
Tenure	2.505	2.854	2.956	2.423	2.788	2.887
	(2.589)	(2.731)	(2.571)	(2.567)	(2.716)	(2.559)
Total Wage Growth	0.037	0.052	0.081	0.034	0.053	0.092
	(0.390)	(0.401)	(0.400)	(0.396)	(0.403)	(0.412)
Wage Growth, Stayers	0.017	0.038	0.058	0.016	0.039	0.056
	(0.341)	(0.314)	(0.326)	(0.340)	(0.310)	(0.327)
Wage Growth, Job-to-Job	0.063	0.077	0.137	0.055	0.076	0.167
	(0.447)	(0.521)	(0.534)	(0.454)	(0.520)	(0.542)

Notes: By the main definition, a transition from non-work to work takes place if the respondent was not working for at least one year, followed by at least two consecutive years of working. By the alternative definition, a transition from non-work to work takes place if the respondent was not working for at least one year, followed by only one year of working.

the labor market by apprentices in Germany are likely to differ from those brought to the labor market by high school graduates in the United States.

Actual experience and tenure are measured in years, and exclude part-time work. For apprentices, I measure experience and tenure from apprenticeship completion onward. I thus treat apprenticeship training the same way as university education.

In the German data set, wages refer to daily wages; in the U.S. data, I use hourly wages. Wages are deflated by the Consumer Price Index, using 1980 as the base year.

Tables 2a and 2b report the means and standard deviations of the main variables used in the empirical analysis. For the United States, I distinguish between the two definitions of a labor market entry. Not surprisingly, workers are younger at labor market entry—and thus have more potential experience—when the second, less stringent, definition of a labor

market entry is used. Means of the other variables are similar for the two definitions.

Results

Unless otherwise stated, results for the United States are based on the main definition of a labor market entry. I discuss differences in the results between the two definitions at the end of this section. Since I include the supplementary samples of poor whites, blacks, and Hispanics in the NLSY, all results are weighted using the sampling weight provided by the NLSY.

Actual versus Potential Experience

I begin by comparing U.S. and German workers in terms of actual experience by time in the labor market. Table 3 reports the average actual experience by potential experience and education. For the United States, I distinguish between the two defini-

Table 3. Potential versus Actual Experience.
(Standard Deviations in Parentheses)

	Germany			United States					
				Main Definition of Labor Market Entry			Alternative Definition of Labor Market Entry		
	Low	*Medium*	*High*	*Low*	*Medium*	*High*	*Low*	*Medium*	*High*
1	0.682	0.820	0.722	0.836	0.749	0.757	0.784	0.699	0.708
	(0.369)	(0.294)	(0.385)	(0.243)	(0.322)	(0.325)	(0.258)	(0.326)	(0.328)
3	1.835	2.253	1.932	2.447	2.410	2.456	2.131	2.102	2.117
	(1.099)	(0.845)	(1.172)	(0.515)	(0.584)	(0.679)	(0.709)	(0.758)	(0.848)
5	2.965	3.788	3.052	3.992	4.021	4.150	3.568	3.595	3.597
	(1.792)	(1.337)	(1.898)	(0.907)	(0.930)	(1.028)	(1.175)	(1.208)	(1.363)
10	5.884	7.729	5.677	8.039	8.178	8.338	7.460	7.577	7.539
	(3.609)	(2.589)	(3.238)	(1.833)	(1.759)	(1.769)	(2.209)	(2.193)	(2.156)

Notes: The table reports average actual experience by potential experience. Quarterly data. For the United States, entries are weighted using the sampling weights in the NLSY. By the main definition, a transition from non-work to work takes place if the respondent was not working for at least one year, followed by at least two consecutive years of working. By the alternative definition, a transition from non-work to work takes place if the respondent was not working for at least one year, followed by only one year of working.

tions of labor market entry. Not surprisingly, workers accumulate more actual experience according to the first, more stringent definition. Regardless of the definition of labor market entry, workers with low and high levels of education have less actual experience in Germany than in the United States throughout the life-cycle. This result has to be interpreted with some caution, for several reasons. First, many workers in Germany satisfy their compulsory military service after they enter the labor market. Second, workers who previously were covered by the social security system may now be self-employed or work as civil servants. Both show up as an employment gap in my data. With this in mind, it is not surprising that the median non-employment spell duration is substantially larger in Germany than in the United States (for example, 47 weeks for German apprentices and 13 weeks [first definition] or 15 weeks [second definition] for U.S. high school graduates).

Job-to-Job and Job-to-Unemployment Mobility

Next, I turn to differences in mobility rates between the two countries. Figure 1a plots quarterly mobility rates, that is, the probability that a worker who is employed at the beginning of the quarter permanently leaves his current employer by the end of the quarter. During the first six months following labor market entry, mobility rates tend to be similar in the two countries. However, later on, firm mobility is substantially higher in the United States for all education groups. For instance, during the 5th year in the labor market, the quarterly mobility rates of those with low, medium, and high education are, respectively, 16.89%, 13.09%, and 9.02% in the United States, but only 8.62%, 5.77%, and 5.85% in Germany. In both countries, better-educated workers are less likely to switch firms.

These differences in mobility rates imply that after 10 years in the labor market, workers with low, medium, and high education have on average worked for, respectively, 5.82, 5.38, and 4.46 firms in the United States, compared to 3.52, 3.25, and 2.94 firms in Germany.

Figures 1b and 1c distinguish between job-to-job and job-to-unemployment transitions. In both countries, job-to-unemployment transitions—defined as a gap of at least four weeks between the end of the old job and start of the new job—are more common than job-to-job transitions for all education

Figure 1a. Quarterly Firm Mobility Rates by Potential Experience and
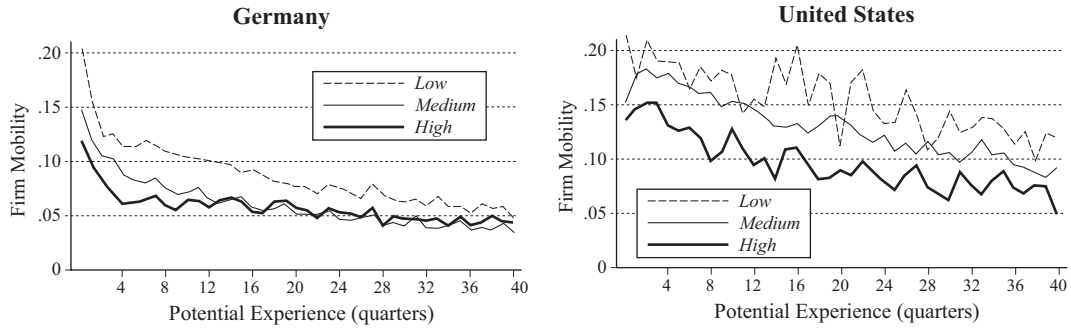Education: Germany versus the United States.

Figure 1b. Quarterly Job-to-Job Mobility Rates by Potential Experience and
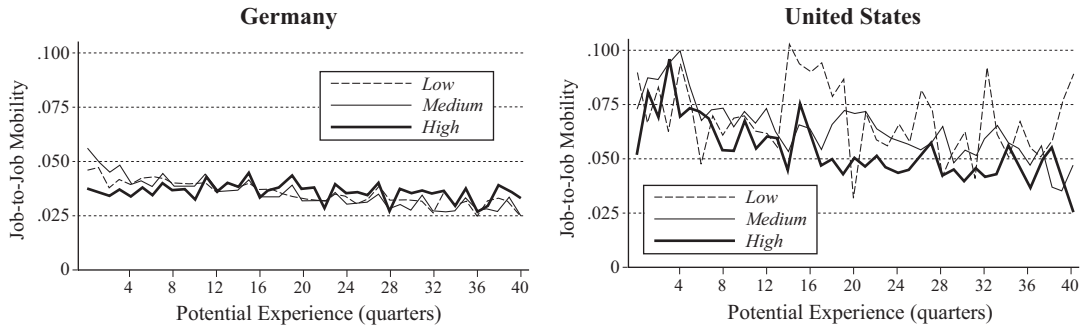Education: Germany versus the United States.

Figure 1c. Quarterly Job-to-Unemployment Mobility Rates by Potential
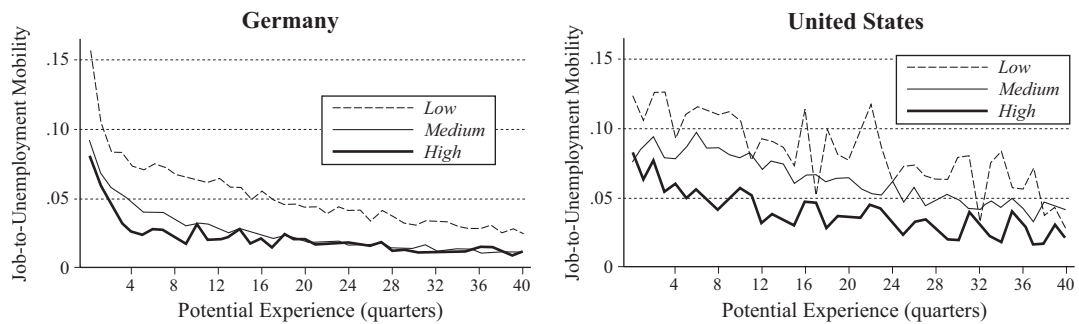Experience and Education: Germany versus the United States.

Table 4a. Wage Growth by Actual Experience: Germany.
(Standard Errors in Parentheses)

	Low			Medium			High	
	Cross-Section		FD	Cross-Section		FD	Cross-Section	
	N= 80,288		N = 67,537	N = 340,851		N = 248,786	N = 44,453	
	No Year Dummies	*Year Dummies*		*No Year Dummies*	*Year Dummies*		*No Year Dummies*	*Year Dummies*
1	0.168 (0.004)***	0.144 (0.004)***	0.160 (0.004)***	0.108 (0.001)***	0.096 (0.001)***	0.088 (0.001)***	0.184 (0.004)***	0.144 (0.004)***
3	0.441 (0.005)***	0.382 (0.005)***	0.389 (0.006)***	0.230 (0.001)***	0.194 (0.001)***	0.174 (0.002)***	0.366 (0.005)***	0.276 (0.005)***
5	0.563 (0.005)***	0.479 (0.005)***	0.472 (0.007)***	0.314 (0.002)***	0.256 (0.002)***	0.231 (0.002)***	0.468 (0.006)***	0.345 (0.007)***
10	0.714 (0.005)***	0.570 (0.008)***	0.550 (0.010)***	0.457 (0.003)***	0.358 (0.004)***	0.344 (0.004)***	0.533 (0.013)***	0.363 (0.014)***

Notes: There are separate regressions for each education group. Censored regression for university graduates. For each education group, the first column controls for foreign status and actual experience dummies only. The second column additionally includes calendar year dummies. Standard errors allow for clustering at the individual level. Column (3) reports estimates from a first difference regression in which time effects have been pre-estimated from a wage level regression. Here, the reported standard error is the standard deviation of the block bootstrap, treating each individual as a sampling unit. 50 repetitions are used.

*Statistically significant at the .10 level; **at 0.05 level; ***at the .01 level.

groups, particularly at low experience levels. Except during the first six months in the labor market, German workers are less likely than their U.S. counterparts not only to move from job to job, but also to move from job to unemployment. For instance, during the fifth year in the labor market, the quarterly job-to-unemployment transition rate of the low-, medium-, and high-skilled is 9.83%, 6.87%, and 4.10% in the United States, compared to 4.97%, 2.19%, and 1.99% in Germany. Interestingly, in both countries, across education groups the differences in job-to-unemployment mobility rates are much larger than the differences in job-to-job mobility rates.

Overall Wage Growth

Estimates of wage growth by actual experience in Germany and the United States are reported in Tables 4a and 4b. The results in the first set of columns do not condition on calendar year effects. Overall wage growth is roughly similar for German apprentices and American high school graduates. Both groups experience wage growth of about 50% in ten years.

The second set of columns additionally control for calendar year effects. In Germany, year effects are positive and of similar magnitude for all education groups. As a result, returns to experience decline for all education groups when year dummies are included in the wage regression. In the United States, in contrast, year effects are negative for high school dropouts and graduates, and positive for university graduates. This is consistent with the well-documented increase of returns to education in the United States in the 1980s. When year dummies are included in the wage regression, wage growth by experience for high school graduates and dropouts rises, while for university graduates it falls. Conditional on year dummies, wage growth is considerably higher for American high school graduates than for German apprentices. Workers with low education experience higher wage growth in Germany than in the United States in their early years in the labor market, but not later. The same holds for university graduates.

To make sure that wage growth by actual experience is not biased because more able workers accumulate more actual experience, the third set of columns in Table 4a and 4b report results from a first difference regression. This cancels out the fixed worker effect.

Table 4b. Wage Growth by Actual Experience: United States.
(Standard Errors in Parentheses)

	Low			*Medium*			*High*		
	Cross-Section		*FD*	*Cross-Section*		*FD*	*Cross-Section*		*FD*
	N = 4,101		*N = 3,571*	*N = 19,846*		*N = 17,494*	*N = 7,092*		*N = 6,181*
	No Year Dummies	*Year Dummies*		*No Year Dummies*	*Year Dummies*		*No Year Dummies*	*Year Dummies*	
1	0.029 (0.031)	0.036 (0.034)	0.085 (0.023)***	0.089 (0.012)***	0.103 (0.014)***	0.117 (0.009)***	0.132 (0.019)***	0.099 (0.020)***	0.125 (0.015)***
3	0.190 (0.038)***	0.239 (0.047)***	0.263 (0.034)***	0.268 (0.014)***	0.288 (0.018)***	0.291 (0.016)***	0.344 (0.022)***	0.264 (0.029)***	0.291 (0.025)***
5	0.247 (0.038)***	0.323 (0.051)***	0.379 (0.042)***	0.367 (0.016)***	0.385 (0.024)***	0.392 (0.020)***	0.477 (0.027)***	0.375 (0.039)***	0.412 (0.037)***
10	0.371 (0.046)***	0.545 (0.070)***	0.546 (0.057)***	0.529 (0.022)***	0.587 (0.036)***	0.552 (0.029)***	0.704 (0.036)***	0.595 (0.065)***	0.596 (0.059)***

Notes: Separate regressions for each education group. For each education group, the first column controls for race and actual experience dummies only. The second column additionally includes calendar year dummies. Standard errors allow for clustering at the individual level. Column (3) reports estimates from a first difference regression where time effects have been pre-estimated from a wage level regression. Here, the reported standard error is the standard deviation of the block bootstrap, treating each individual as a sampling unit. 50 repetitions are used. Entries are weighted using the sampling weight provided in the NLSY.

*Statistically significant at the .10 level; **at 0.05 level; ***at the .01 level.

Due to wage censoring, I do not report results for university graduates in Germany. In order to control for aggregated wage growth, I pre-estimate time effects from a wage-level regression. I then regress wage growth, adjusted for aggregate wage growth, on the differenced actual experience dummies.[8] In both countries, the results are similar to and not statistically different from those based on wage levels.

Wage Growth of Stayers, Job-to-Job Movers, and Job-to-Unemployment Movers

How much of the overall wage growth is due to general and firm-specific human capital accumulation, and how much is due to job search? For a first pass, I compare the wage growth of stayers, job-to-job movers, and job-to-unemployment movers. I regress wage growth, measured as the difference between the log-wage in two periods, on a constant and the difference in experience squared, separately for the three groups of workers. Table 5 reports the results.

I find the same pattern in both countries. Stayers experience lower wage growth than job-to-job and job-to-unemployment movers during their early years in the labor market. Wage growth declines with experience for all education groups. The decline is stronger for movers than for stayers, and particularly strong for job-to-unemployment movers. This is in line with findings by Mincer (1986) and Perticara (2002). The most important difference between the two countries is that the wage growth of job-to-unemployment movers relative to that of stayers is higher in Germany than in the United States. These patterns are robust with respect to the inclusion of the duration of the employment gap (last panel of Table 5) as well as to alternative definitions of a job-to-unemployment transition (not reported).

Wage Growth Due to General Human Capital

In estimating wage growth due to general

[8]I have tried estimating time and experience effects jointly in a first differenced regression. Due to the high correlation between experience and time in both data sets, the estimates for time and experience effects are very noisy. Standard errors are smaller when a functional form for time and experience effects is assumed. Predictions for total wage growth based on these estimates are quantitatively similar to the ones reported here. I prefer, however, not to impose a functional form on time and experience.

Table 5. Wage Growth of Stayers, Job-to-Job Movers, and Job-to-Unemployment Movers.
(Standard Errors in Parentheses)

	Germany		United States		
	Low	*Medium*	*Low*	*Medium*	*High*
Stayers	N = 48,957	N = 216,226	N = 2,024	N = 10,996	N = 4,286
Constant	0.120	0.065	0.042	0.071	0.103
	(0.002)***	(0.000)***	(0.017)**	(0.006)***	(0.009)***
$\Delta\exp^2$	−0.006	−0.003	−0.002	−0.003	−0.004
	(0.000)***	(0.000)***	(0.001)**	(0.000)***	(0.001)***
Job-to-Job	N = 11,444	N = 54,065	N = 513	N = 2,675	N = 995
Constant	0.251	0.147	0.174	0.164	0.231
	(0.006)***	(0.002)***	(0.035)***	(0.021)***	(0.032)***
$\Delta\exp^2$	−0.012	−0.006	−0.008	−0.006	−0.007
	(0.000)***	(0.000)***	(0.003)**	(0.002)***	(0.003)***
Job-to-Unemployment (JTU)	N = 6,172	N = 12,794	N = 1,034	N = 3,823	N = 900
Constant	0.284	0.182	0.106	0.139	0.223
	(0.007)***	(0.004)***	(0.033)***	(0.015)***	(0.033)***
$\Delta\exp^2$	−0.018	−0.014	−0.007	−0.010	−0.016
	(0.001)***	(0.001)***	(0.003)**	(0.002)***	(0.004)***
JTU + Unemployment Duration	N = 6,217	N = 12,750	N = 1,034	N = 3,823	N = 900
Constant	0.242	0.145	0.156	0.149	0.214
	(0.009)***	(0.005)***	(0.035)***	(0.016)***	(0.036)***
$\Delta\exp^2$	−0.017	−0.012	−0.007	−0.010	−0.016
	(0.001)***	(0.001)***	(0.003)**	(0.002)***	(0.004)***

Notes: Separate regressions for each education group. Standard errors are clustered at the individual level.
*Statistically significant at the .10 level; **at 0.05 level; ***at the .01 level.

human capital accumulation, I specify the latter as a polynomial of order 2, but results are similar if a different functional form is used. As discussed early in the paper (in the "Framework" section), I use wages of job-to-unemployment movers to identify returns to general human capital accumulation.

Tables 6a and 6b report the results. The first set of columns control for calendar year effects, citizenship (Germany), and race (United States) in addition to actual experience and actual experience squared. In Germany, the return to general human capital accumulation is somewhat lower for apprentices than for university graduates and workers without post-secondary education. For instance, an apprentice can expect his wage to grow due to general human capital accumulation by about 18% in 5 years and 24% in 10 years, compared to 25% and 30% for a university graduate. With the exception of university graduates, the return to general

human capital accumulation is higher in the United States than in Germany. For instance, for high school graduates in the United States, wage growth due to general human capital accumulation is 26% in 5 years and 39% in 10 years.

These estimates may suffer from an "ability bias," as more able workers may be less likely to become unemployed. To investigate that possibility, I next include in the wage regression the number of prior job-to-job and job-to-unemployment switches as a proxy for workers' ability. The second set of columns in Tables 6a and 6b report the results. In Germany, the number of prior job-to-unemployment switches negatively affects starting wages of job-to-unemployment movers, and the negative selection increases with education. The inclusion of job-to-job and job-to-unemployment transitions leads to higher returns to general human capital accumulation for all education groups, but

Table 6a. Returns to General Human Capital Accumulation: Germany.
(Standard Errors in Parentheses)

	Low			*Medium*			*High*		
	JTU	*Controls*	*All*	*JTU*	*Controls*	*All*	*JTU*	*Controls*	*All*
	N = 12,694	N = 12,694	N = 37,609	N = 20,041	N = 20,041	N = 115,868	N = 3,019	N = 3,019	N = 12,466
Experience	0.060	0.070	0.075	0.045	0.064	0.071	0.073	0.097	0.111
	(0.004)***	(0.004)***	(0.002)***	(0.003)***	(0.003)***	(0.001)***	(0.009)***	(0.009)***	(0.003)***
Experience^2	–0.003	–0.004	–0.003	–0.002	–0.003	–0.003	–0.004	–0.005	–0.006
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.001)***	(0.001)***	(0.000)***
No. Prior JTJ		0.002	0.002		–0.009	–0.009		–0.034	–0.024
		(0.003)	(0.001)*		(0.001)**	(0.001)***		(0.006)***	(0.002)***
No. Prior JTU		–0.017	–0.024		–0.032	–0.041		–0.040	–0.061
		(0.002)***	(0.001)***		(0.002)***	(0.001)***		(0.007)***	(0.003)***
Predictions									
1	0.056	0.066	0.071	0.043	0.061	0.067	0.067	0.091	0.1065
	(0.004)***	(0.004)***	(0.002)***	(0.003)***	(0.003)***	(0.001)***	(0.008)***	(0.008)***	(0.003)***
3	0.149	0.172	0.194	0.116	0.162	0.184	0.176	0.242	0.279
	(0.009)***	(0.010)***	(0.005)***	(0.007)***	(0.007)***	(0.003)***	(0.019)***	(0.019)***	(0.007)***
5	0.216	0.245	0.288	0.172	0.237	0.276	0.250	0.351	0.403
	(0.012)**	(0.013)***	(0.008)***	(0.009)***	(0.010)***	(0.004)***	(0.024)***	(0.025)***	(0.010)***
10	0.266	0.283	0.403	0.239	0.305	0.399	0.281	0.440	0.498
	(0.017)**	(0.019)***	(0.011)***	(0.014)***	(0.014)***	(0.005)***	(0.039)***	(0.043)***	(0.013)***

Notes: Separate regressions for each education group. Censored regressions for university graduates. For each education group, regressions in the first (JTU) and second (Controls) columns use wages following a job-to-unemployment transition. Regressions in the third column (All) use wages following a job-to-job as well as a job-to-unemployment transition. Column (1) controls for foreign status, actual experience, actual experience squared, and calendar year dummies. Columns (2) and (3) additionally control for the number of prior job-to-job and job-to-unemployment transitions. Standard errors allow for clustering at the individual level.

*Statistically significant at the .10 level; **at 0.05 level; ***at the .01 level.

particularly so for university graduates. In the United States, in contrast, there is evidence for a negative selection of job-to-unemployment movers only among university graduates, and the inclusion of prior job switches increases the return to general human capital only for this education group.[9]

For comparison, the third set of columns in Tables 6a and 6b report estimates using all new jobs, that is, jobs following both job-to-job and job-to-unemployment transitions. As argued by Topel (1991), this is likely to lead to an upward bias in the return to general human capital accumulation, as job-to-job movers may accept new offers because of a higher wage. With the exception of U.S. high school graduates, estimates using all new jobs exceed those using only jobs following a job-

to-unemployment transition. I interpret this as evidence that job search plays an important role in both countries.

These results are robust with respect to controlling for the duration of the non-employment gap. They are similar if I define a job-to-unemployment transition based on whether a worker is looking for work (United States) or receiving unemployment benefits (Germany).

Wage Growth Due to Job Search and Firm-Specific Human Capital Accumulation

To analyze the wage growth contribution of job search and firm-specific human capital accumulation, I begin by computing a lower bound for wage growth due to job search, defined by equation (3). The empirical implementation is as follows. My dependent variable is equal to the worker's wage growth, adjusted for aggregate wage growth and general human capital accumulation, if

---

[9]However, due to the large standard errors, the difference is not statistically significant at conventional levels.

Table 6b. Returns to General Human Capital Accumulation: United States.

	Low			Medium			High		
	JTU	*Controls*	*All*	*JTU*	*Controls*	*All*	*JTU*	*Controls*	*All*
	N = 1,349	N = 1,349	N = 2,265	N = 4,852	N = 4,852	N = 9,085	N = 1,035	N = 1,035	N = 2,352
Experience	0.028 (0.026)	0.021 (0.026)	0.054 (0.021)**	0.066 (0.012)***	0.066 (0.013)***	0.058 (0.010)***	0.039 (0.029)	0.061 (0.030)**	0.092 (0.020)***
Experience^2	0.002 (0.002)	0.002 (0.002)	0.000 (0.001)	−0.003 (0.001)***	−0.003 (0.001)***	−0.002 (0.001)**	−0.002 (0.002)	−0.003 (0.002)	−0.004 (0.002)**
No. Prior JTJ		0.020 (0.015)	0.012 (0.014)		0.002 (0.009)	0.013 (0.007)*		−0.011 (0.025)	−0.010 (0.016)
No. Prior JTU		0.001 (0.009)	−0.006 (0.009)		−0.004 (0.006)	−0.011 (0.005)*		−0.082 (0.016)***	−0.102 (0.012)***
Predictions									
1	0.030 (0.024)	0.023 (0.025)	0.053 (0.020)**	0.063 (0.012)***	0.063 (0.012)***	0.056 (0.009)***	0.037 (0.027)	0.060 (0.028)**	0.087 (0.019)***
3	0.103 (0.063)*	0.083 (0.063)	0.159 (0.051)***	0.173 (0.030)***	0.173 (0.031)***	0.157 (0.025)***	0.098 (0.068)	0.162 (0.071)**	0.237 (0.049)***
5	0.192 (0.088)**	0.162 (0.088)*	0.262 (0.073)***	0.263 (0.042)***	0.262 (0.045)***	0.246 (0.036)***	0.145 (0.092)	0.238 (0.097)***	0.353 (0.069)***
10	0.489 (0.103)***	0.440 (0.106)***	0.509 (0.096)***	0.393 (0.059)***	0.392 (0.062)***	0.409 (0.052)***	0.192 (0.114)*	0.317 (0.120)***	0.495 (0.090)***

Note: Separate regressions for each education group. For each education group, regressions in the first (JTU) and second (Controls) columns use wages following a job-to-unemployment transition only. Regressions in the third column (All) use wages following both a job-to-job and a job-to-unemployment transition. Column (1) controls for race, actual experience, actual experience squared, and calendar year dummies. Columns (2) and (3) additionally control for the number of prior job-to-job and job-to-unemployment transitions. Standard errors allow for clustering at the individual level. Entries are weighted using the sampling weight provided by the NLSY.
*Statistically significant at the .10 level; **at 0.05 level; ***at the .01 level.

he switches employers, and zero otherwise. I regress this variable on the differenced experience dummies. To account for the fact that aggregate wage growth and general human capital accumulation are estimated at an earlier stage, I bootstrap standard errors, allowing for clustering at the individual level.

I then compute wage growth due to firm-specific human capital and learning about match quality, defined by equation (4). Here, my dependent variable is equal to the adjusted wage growth if the worker stays with his employer, and 0 otherwise.

Tables 7a and 7b report the results. The first and second columns of the tables show total wage growth, using estimates from the third set of columns in Tables 4a and 4b, and wage growth due to general human capital accumulation, using estimates from the first set of columns in Tables 6a and 6b. The third column reports the lower bound for wage growth due to job search, while the fourth column displays wage growth due to

firm-specific human capital accumulation. The upper bound of wage growth due to job search can be obtained by adding up wage growth due to job switching and firm-specific human capital accumulation.

Job search is an important contributor to wage growth for all education groups in both countries. It is most important during the first year in the labor market, explaining roughly one-third of the overall wage growth for that year. Interestingly, search capital hardly increases from the fifth to the tenth year in the labor market for any education group.

In Germany wage growth due to job switching is most important for those with low skills, while in the United States it is most important for those with high skills. Note that these are the two groups for whom the returns to general human capital are most sensitive to the choice to use all new jobs in the estimation, as opposed to new jobs following a job-to-unemployment transition (see Table 6a and 6b). Possibly most surprisingly, wage

Table 7a. Sources of Wage Growth: Germany.
(Standard Errors in Parentheses)

Actual Experience	Total Wage Growth	General HC	Search: Movers	Firm-Specific HC
Low				
1	0.160 (0.003)***	0.056 (0.004)***	0.071 (0.003)***	0.033 (0.003)***
3	0.389 (0.005)***	0.149 (0.009)***	0.155 (0.005)***	0.086 (0.007)***
5	0.472 (0.006)***	0.216 (0.012)**	0.176 (0.006)***	0.082 (0.009)***
10	0.550 (0.008)***	0.266 (0.017)**	0.201 (0.007)***	0.083 (0.014)***
Medium				
1	0.088 (0.001)***	0.043 (0.003)***	0.039 (0.001)***	0.010 (0.002)***
3	0.174 (0.002)***	0.116 (0.007)***	0.063 (0.002)***	0.005 (0.004)
5	0.231 (0.002)***	0.172 (0.009)***	0.074 (0.003)***	−0.005 (0.005)
10	0.344 (0.004)***	0.239 (0.014)***	0.094 (0.003)***	−0.004 (0.012)

Note: For each education group, the first column displays first difference estimates for the total wage growth by actual experience (Table 4a). The second column reports estimates for wage growth due to general human capital accumulation (Table 6a). Column (3) reports wage growth due to job switching, computed as the product of the probability of job switching and wage growth of job switchers, adjusted for aggregate wage growth and wage growth due to general human capital. Column (4) shows wage growth due to firm-specific human capital accumulation, computed as the product of the probability of staying and adjusted wage growth of job stayers. Reported standard errors are the standard deviation of the block bootstrap, treating each individual as a sampling unit. 50 Repetitions are used.

*Statistically significant at the .10 level; **at 0.05 level; ***at the .01 level.

growth due to job switching is only slightly lower for German apprentices than for U.S. high school graduates.

Within-wage growth, adjusted for aggregate wage growth and general human capital accumulation, in contrast, plays an important role only for low-skilled workers in Germany and university graduates in the United States. For all other education groups, its influence is negligible. Is this because my estimates for general human capital accumulation are upwardly biased? This seems unlikely, as the results in Table 7a and 7b are based on my lowest estimates for general human capital accumulation; in Tables 6a and 6b, estimates tend to be higher if the number of prior job switches as a proxy for workers' ability is included in the regression.

Finally, wage growth due to general human capital accumulation is the most important source of overall wage growth for all education groups, particularly during the later years in the labor market.

Robustness Checks

A disadvantage of my approach to estimating wage growth due to job search is that it relies on estimates for aggregate wage growth and returns to general human capital accumulation. As a robustness check, I provide an alternative estimate for wage growth due to job search that does not require reliance on such estimates. This estimate is based on comparison of the wage growth of movers and stayers, and is computed as follows:

wage growth job search =

$$\sum_{e=1}^{E} \Pr(\text{move})_e \{E_e[\Delta \ln w_{ijt}|\text{move}] -$$

Table 7b. Sources of Wage Growth: United States.
(Standard Errors in Parentheses)

Actual Experience	Total Wage Growth	General HC	Search: Movers	Firm-Specific HC
Low				
1	0.085 (0.023)***	0.030 (0.024)	0.065 (0.020)***	−0.010 (0.011)
3	0.263 (0.034)***	0.103 (0.063)*	0.151 (0.035)***	0.009 (0.025)
5	0.379 (0.042)***	0.192 (0.088)**	0.177 (0.039)***	0.010 (0.034)
10	0.546 (0.066)***	0.489 (0.103)***	0.166 (0.052)***	−0.109 (0.040)*
Medium				
1	0.117 (0.009)***	0.063 (0.012)***	0.049 (0.009)***	0.005 (0.006)
3	0.291 (0.016)***	0.173 (0.030)***	0.113 (0.016)***	0.004 (0.013)
5	0.392 (0.020)***	0.263 (0.042)***	0.123 (0.020)***	0.007 (0.018)
10	0.552 (0.029)***	0.393 (0.059)***	0.125 (0.024)***	0.034 (0.025)
High				
1	0.125 (0.015)***	0.037 (0.027)	0.058 (0.014)***	0.030 (0.016)*
3	0.291 (0.025)***	0.098 (0.068)	0.130 (0.030)***	0.063 (0.037)*
5	0.412 (0.037)***	0.145 (0.092)	0.195 (0.037)***	0.087 (0.052)
10	0.596 (0.059)***	0.192 (0.114)*	0.235 (0.047)***	0.168 (0.079)**

Notes: For each education group, the first column displays first difference estimates for the total wage growth by actual experience (see Table 4b). The second column reports estimates for wage growth due to general human capital accumulation (see Table 6b). Column (3) reports wage growth due to job switching, computed as the product of the probability of job switching and wage growth of job switchers, adjusted for aggregate wage growth and wage growth due to general human capital. Column (4) shows wage growth due to firm-specific human capital accumulation, computed as the product of the probability of staying and adjusted wage growth of job stayers. Reported standard errors are the standard deviation of the block bootstrap, treating each individual as a sampling unit. 50 Repetitions are used. Entries are weighted using the sampling weight provided by the NLSY.

*Statistically significant at the .10 level; **at 0.05 level; ***at the .01 level.

$$E_e[\Delta \ln w_{ijt}|\text{stay}]\}$$
$$= \sum_{e=1}^{E} E_e[\Delta \ln w_{ijt}] - E_e[\Delta \ln w_{ijt}|\text{stay}].$$

Estimates based on this measure are similar to those from the lower bound for wage growth due to job search reported in Tables 7a and 7b. For instance, according to this measure, wage growth due to job search is 8.32% and 10.51% for U.S. high school graduates, and 8.33% and 10.41% for German apprentices,

after 5 and 10 years in the labor market. Hence, the finding that wage growth due to job search is similar for these two groups is robust with respect to this alternative computational approach.

It may also be argued that my definition of a labor market entry in the United States is too stringent, and discards too many jobs. I check the robustness of my results to the alternative definition of labor market entry. This less stringent definition leads to some-

what higher total estimated wage growth for all education groups. For instance, for high school graduates wage growth due to 10 years of actual experience is 63% according to the second definition, but only 55% according to the first definition. However, the relative contributions of general and firm-specific human capital accumulation and job search tend to be similar. My overall conclusions are thus unchanged.

Finally, I repeat the empirical analysis in which I discard part-time jobs with less than 10 hours per week, as opposed to part-time jobs with less than 30 hours per week. By and large, this does not affect my conclusions. Results are available on request.

Discussion

Comparison with Existing Literature

How do my results compare with those in the existing literature? For the United States, studies that estimate returns to experience include Topel (1991) and Altonji and Williams (2005). Both found that the cumulative log-wage return to experience is around 40% after ten years. This is in line with my estimates for high school dropouts and graduates. Turning to Germany, Dustmann and Meghir (2005) reported similar returns to general human capital accumulation for low-skilled workers, but somewhat higher returns for apprentices. In line with my findings, Dustmann and Perreira (2005) concluded that returns to experience for the low- and high-skilled are higher than for apprentices.

The magnitude of returns to tenure is still very much in dispute. For the United States, Topel (1991) and Beffy et al. (2005) reported substantial returns to tenure. Altonji and Shakatko (1987), Abraham and Farber (1987), and Altonji and Williams (2005), in contrast, found much smaller returns to tenure. My finding that aggregate wage growth and general human capital accumulation account for most of the within-job wage growth for U.S. high school dropouts and graduates is consistent with results reported by Connolly and Gottschalk (2006) and Barlevy (2003). In line with my findings for Germany, Dustmann

and Meghir (2006) found larger returns to tenure for low-skilled workers than for apprentices; Dustmann and Pereirra (2005) also concluded that returns to tenure are close to zero for apprentices.

Turning to wage growth due to job search, my findings for the United States are in accord with Topel and Ward's (1992) original finding that job search accounts for one-third of overall wage growth. My finding that university graduates accumulate more search capital than high school graduates or dropouts is further corroborated by Connolly and Gottschalk (2006), who showed that wage gains due to job switching are larger for university graduates. My findings for Germany are consistent with von Wachter and Bender (2006), who concluded, among other things, that voluntary job mobility is important for German apprentices.

While a few papers have attempted to directly estimate wage growth due to job search, there is a larger literature on displacement effects that asks a closely related question: what is the wage loss a worker suffers if he loses his job for largely exogenous reasons? Such a worker loses not only his firm-specific human capital, but also his search capital. According to the most recent and comprehensive study by Hildreth et al. (2006) for the United States, the "true" cost of job loss lies between 12% and 16% of the pre-displacement wage.[10] This fits well with my estimates for wage growth due to job search. My finding that wage growth due to firm-specific human capital accumulation plays only a limited role for high school graduates and dropouts further suggests that most of this loss reflects the loss of search capital, as opposed to firm-specific human capital. Turning to Germany, Burda and Mertens (2001) found that, on average, a job loss is associated with a wage loss of 2–6%, although it is much larger for workers in the three upper quartiles of the earnings distribution. Bender et al. (1999) also found only small losses due to displacement, defined as a job loss due to plant closure or due to a reduction in firm size of

---

[10]They are, however, only 1–2% for a job loss due to plant closure.

at least 40%. These estimates are considerably exceeded by estimates for the United States and by my estimates for wage growth due to job search. Generous unemployment benefits that shelter workers from large wage losses due to unemployment might account for these disparate results.

Interpretation

One of the main findings of this study is that for the low- and medium-skilled, returns to general human capital accumulation after 10 years in the labor market are about 10 percentage points larger in the United States than in Germany. A possible explanation for this finding is that collective bargaining institutions in Germany compress wages of young workers, relative to old workers. Consistent with this hypothesis is Dustmann and Schönberg's (2005) finding that returns to experience are higher in unionized than in non-unionized firms.

Second, I find no evidence supporting the hypothesis that wage growth due to firm-specific human capital accumulation is a more important contributor to overall wage growth for German apprentices than for U.S. high school dropouts and graduates (as hypothesized by, for example, Harhoff and Kane 1997). Theoretically, the impact of mobility rates on returns to tenure is ambiguous. On the one hand, workers have a stronger incentive to invest in firm-specific human capital when they expect to stay with the firm longer. On the other hand, as Beffy et al. (2005) argued based on a model by Burdett and Coles (2003), firms may offer higher rewards to seniority in a high-mobility country as an incentive.

Third, wage growth due to job search is of similar magnitude for German apprentices and U.S. high school graduates, and larger for German low-skilled workers. This is somewhat surprising, for two reasons. First, collective bargaining institutions in Germany are likely to compress wages, implying lower gains due to job search. Second, higher unemployment benefits in Germany mean that German workers turn down matches that U.S. workers accept, also resulting in lower gains due to job search. So why is wage growth due to job

search not lower in Germany? The answer is that German workers experience higher gains from switching firms, for two reasons: they are less likely than their U.S. counterparts to become unemployed, and thus less likely to have to search from scratch (see Figure 1c); and they lose less than U.S. workers when they become unemployed (see Table 5). The reduced probability of unemployment may be linked to higher firing costs and a longer advance notice period in Germany. The longer advance notice period also may be partly responsible for the lower average losses when workers become unemployed, since it gives them more time to search for a good match, possibly reducing the wage loss due to a layoff. Alternatively, more generous unemployment benefits in Germany may shelter workers from suffering larger losses due to an involuntary job loss.

Conclusion

The contribution of this paper is twofold. First, I have proposed a simple method for decomposing total wage growth into wage growth due to general human capital accumulation, firm-specific human capital accumulation, and job search. Second, I have compared the sources of wage growth in two countries with very different labor market institutions, the United States and Germany.

My main findings can be summarized as follows. In both countries and for all education groups, general human capital accumulation is the most important source of wage growth. Wage growth due to firm-specific human capital accumulation and deferred compensation is considerable for workers with low education in Germany and for workers with high education in the United States, but negligible for all other groups. Job search plays an important role for all education groups in both countries. Despite much lower mobility rates in Germany than in the United States, wage growth due to job switching is roughly similar for German apprentices and U.S. high school graduates. My preferred explanation for this is that, due to higher firing costs and higher unemployment benefits in Germany, German workers are less likely than U.S.

workers to become unemployed, and when they do become unemployed they tend to suffer smaller losses.

I conclude by pointing out possible extensions for future work. First, I have ignored occupation- and industry-specific skills, as well as mobility across occupations and industries. The importance of industry-specific human capital in the United States has been stressed by, for instance, Neal (1995) and Parent (2000).[11] Kambourov and Manovskii (2002) argued that skills are mainly occupation-specific. Moreover, many firm switches may in fact involve occupation or industry switches. An interesting question is thus how much of the wage growth attributable to search is due to workers finding a firm with which they are better matched, as opposed to an occupation for which they are better suited. Second, my decomposition of overall wage growth into wage growth due to general human capital, firm-specific human capital, and job search is done by actual experience, and not by potential experience. Future work may take into account the time German and U.S. workers spend in unemployment and out of the labor force. Third, a natural next step is the structural estimation of a search model, which would enable researchers to address questions I could not. For example, how much worse off would workers be if they did not have the option to search on-the-job? And do offer arrival probabilities differ for German and U.S. workers or across education groups?

---

[11]Results found by Dustmann and Meghir (2005), in contrast, suggest that industry-specific skills are only of minor importance in Germany.

Appendix A
German Data

Sample. The sample consists of all workers born between 1957 and 1964 who entered the labor market after 1975. Workers who worked at least once in East Germany are dropped, as are apprentices who completed more than one apprenticeship. In order to ensure that I observe workers from labor market entry onward, I impose the following age restrictions:

- Workers without A-levels (Abitur) at labor market entry are included in the sample if they were not older than 15 in 1975 and at most 19 at labor market entry.

- Workers with A-levels at labor market entry are included in the sample if they were not older than 19 in 1975 and at most 21 at labor market entry.

- Workers with a college degree (Fachhochschule) at labor market entry are included in the sample if they were not older than 23 in 1975 and at most 28 at labor market entry.

- Workers with a university degree (Universität) at labor market entry are included in the sample if they were not older than 23 in 1975 and at most 30 at labor market entry.

For workers who worked before they started an apprenticeship or entered a university, I only consider those spells after they completed apprenticeship training or graduated from university.

Table A.1. Which Wages Are Dropped in the Yearly Data Set? (Germany)

Actual Experience (End of Spell)	Number of Firms	Spells Kept
0.24	1	Keep
0.32	2	Drop
0.40	3	Drop
1.40	3	Keep, Move
2.39	3	Keep, Stay

Note: First employment spells of worker 284.

Creation of the quarterly and yearly data set. I organize the data in quarterly and yearly formats. In the quarterly data, the employment status refers to the beginning of the quarter. Workers on leave are considered to be out of the labor force. I use this data set to study mobility.

For firm stayers, new wage information is available only once per year. I therefore transform the data into a yearly data set when analyzing wage growth. Here, my goal is to use wage observations one year apart in terms of actual experience. I drop all part-time spells and spells that indicate that a worker is on leave. Table A.1 lists the number of firms the worker with identification number 284 worked for during the first year in the labor market. This particular worker changed jobs many times, and for each job, I observe the average daily wage he earned. I keep only three wage spells: the first spell at labor market entry, and the spells at which the worker's actual experience exceeded 1 and 2 years for the first time. Table A.2 shows the number of valid wage observations in the original (spell) data and in the yearly data, separately by education group.

Variable Definitions

Education. A worker is classified as an apprentice if he worked as a trainee for at least 450 days, regardless of whether the education variable classifies him as a worker with or without a finished apprenticeship. I classify a worker as a university graduate if he held at least one job that classified him as a university or college graduate. Low-skilled workers are workers who are classified neither as apprentices nor as university graduates.

Experience and tenure (yearly data). Actual experience is measured as weeks (divided by 52) spent in full-time employment. Part-time employment, time spent unemployed, time as an apprentice, and time spent out of the labor force are not counted. Actual tenure is measured as weeks (divided by 52) spent in full-time employment with the same employer. I assume that both experience and tenure refer to the end of the employment spell. This has little impact on the results. For apprentices, experience and tenure are counted from apprenticeship completion onward. For workers who stay with their training firm after apprenticeship completion, I do not observe the exact date the apprenticeship ended. For these workers, I observe an average of the last apprenticeship wage and the current wage. For this reason, I start counting experience and tenure from January 1 following the year in which the apprenticeship ended.

Wages. The wage variable is the daily average wage, deflated by the Consumer Price Index, using 1995 as the base year.

Table A.2. Number of Observations in the Original Data and the Yearly Data.

	Low	Medium	High
Germany			
Spell Data	132,065	514,179	65,835
Yearly Data	80,834	341,108	44,576
United States			
Spell Data	5,723	26,367	8,797
Yearly Data	4,102	19,847	7,093

Note: Observations refer to the first definition of a labor market entry.

Appendix B
U.S. Data

Sample. The sample consists of men, excluding those in the military, who have made a transition from non-work to work and who entered the labor market after 1978. My main definition follows Farber and Gibbons (1996). According to this definition, a transition from non-work to work takes place when the worker was not working for at least one year, followed by at least two consecutive years in which he was working. A worker is classified as working when he has worked at least 26 weeks, and during these weeks at least 30 hours per week, in a calendar year. As a robustness check, I employ an alternative, less stringent definition. According to this definition, a transition from non-work to work takes place when the worker was not working for at least one year, followed by only one year in which he was working.

Creation of the quarterly and yearly data sets. I construct the quarterly data set from the Work-History file, which contains week-by-week longitudinal work records. From this file, I select the respondent's labor force status and job number at the beginning of each quarter. To those data I match the educational histories of the respondents, that is, enrollment status as well as highest grade completed.

I then transform the quarterly data into a yearly format. First I transform the quarterly data set into a spell data set. To do so, I drop all non-employment spells, and keep one valid observation per job and interview year. I drop observations for the 6th job and higher in an interview year, since the NLSY collects information only on up to 5 jobs between two interviews. It sometimes happens that the worker's secondary job becomes his main job. In this case the job number in the quarterly data changes although the worker has not switched employers. If the (previously) secondary job started after and ended before the main job, I ignore it. It can also happen that the "new" job in the quarterly data started before the previous job, or the previous job ends after the "new" job. When jobs overlap in this way, I only consider the job on which the worker worked the most hours. I then drop part-time jobs (< 30 hours per week), jobs without pay, jobs of the self-employed, and

jobs in the agricultural sector. I also drop observations in which the wage is smaller than $1 or greater than $500. As a robustness check, I repeat the empirical analysis deleting only jobs with less than 10 hours per week (as opposed to the 30-hour cut-off).

Since wage information is available only once per year for firm stayers, I do not use all available observations, but only those observations separated by approximately one year of actual experience. Here, I follow the same rule as for the German data set. Table B.1 lists the number of wage observations in the spell data and in the yearly data, separately by education group.

Variable Definitions

Education. High school dropouts are workers who in 1994 had less than 12 years of education. High school graduates are workers who in 1994 had at least 12, but less than 16 years of education. Hence, high school graduates include college dropouts. College graduates are workers who in 1994 had at least 16 years of education. There are some inconsistencies in the education variable. For instance, it sometimes happens that in a period of three years, the education variable first increases from the first to the second year, then decreases from the second to the third year. In these cases, I use the lower value in the first and third year.

Experience and tenure. Actual experience is measured as weeks (divided by 52) spent in full-time employment after the transition from non-work to work. Part-time employment, time spent as self-employed or working without pay, time spent unemployed, and time spent out of the labor force are not counted. Actual tenure is measured as weeks (divided by 52) spent in full-time employment with the same employer. I assume that experience and tenure refer to the end of each wage spell.

Wages. The wage variable is the hourly wage rate computed by the Bureau of Labor Statistics, deflated by the Consumer Price Index with 1995 as the base year. I drop unreasonable wage information (smaller than $1 or greater than $500).

REFERENCES

Abowd, John M., and David Card. 1989. "On the Co-variance Structure of Earnings and Hours Changes." *Econometrica,* Vol. 57, No. 2 (March), pp. 411–45.

Abraham, Katharine G., and Henry S. Farber. 1987. "Job Duration, Seniority, and Earnings." *American Economic Review,* Vol. 77, No. 3 (June), pp. 278–97.

Acemoglu, Daron, and Jörn-Steffen Pischke. 1998. "Why Do Firms Train? Theory and Evidence." *Quarterly Journal of Economics,* Vol. 113, No. 2 (February), pp. 79–119.

Altonji, Joseph G., and Robert A. Shakotko. 1987. "Do Wages Rise with Job Seniority?" *Review of Economic Studies,* Vol. 54, No. 3 (July), pp. 437–59.

Altonji, Joseph G., and Nicolas Williams. 2005. "Do Wages Rise with Seniority? A Reassessment." *Industrial and Labor Relations Review,* Vol. 58, No. 3 (April), pp. 370–97.

Barlevy, Gadi. 2003. "Estimating Models of On-the-Job Search Using Record Statistics." Federal Reserve Bank of Chicago Working Paper No. 18.

Beffy, Magali, Moshe Buchinsky, Denis Fougère, Thierry Kamionka, and Francis Kramarz. 2004. "The Returns to Seniority in France (and Why Are They Lower in the United States?)." Unpublished paper, CREST-INSEE.

Bender, Stefan, Christian Dustmann, David Margolis, and Costas Meghir. 2002. "Worker Displacement in France and Germany." In Peter Kuhn, ed., *Losing Work: International Perspectives on Job Displacement,* pp. 375–347. Kalamazoo, Mich.: W. E. Upjohn Institute for Employment Research.

Burda, Michael C., and Antje Mertens. 2001. "Estimating Wage Losses of Displaced Workers in Germany." *Labour Economics,* Vol. 8, No. 1 (January), pp. 15–41.

Burdett, Kenneth. 1978. "A Theory of Employee Job Search and Quit Rates." *American Economic Review,* Vol. 68, No. 1 (March), pp. 212–20.

Burdett, Kenneth, and Melvyn G. Coles. 2003. "Equilibrium Wage-Tenure Contracts." *Econometrica,* Vol. 71, No. 5 (December), pp. 1377–1404.

Burdett, Kenneth, and Dale T. Mortensen. 1998. "Wage Differentials, Employer Size, and Unemployment." *International Economic Review,* Vol. 39, No. 2 (May), pp. 257–73.

Connolly, Helen, and Peter Gottschalk. 2006. "Difference in Wage Growth by Education Level: Do Less-Educated Workers Gain Less from Work Experience?" IZA Discussion Paper No. 2331.

Dustmann, Christian, and Costas Meghir. 2005. "Wages, Experience, and Seniority." *Review of Economic Studies,* Vol. 72, No. 1 (January), pp. 77–108.

Dustmann, Christian, and Sonia Perreira. 2005. "Wage Growth and Job Mobility in the U.K. and Germany." IZA Discussion Paper No. 1586.

Farber, Henry S., and Robert Gibbons. 1996. "Learning and Wage Dynamics." *Quarterly Journal of Economics,* Vol. 111, No. 4 (November), pp. 1007–47.

Gibbons, Robert, and Lawrence F. Katz. 1991. "Layoffs and Lemons." *Journal of labor Economics,* Vol. 9, No. 4 (October), pp. 351–80.

Harhoff, Dietmar, and Thomas J. Kane. 1997. "Is the German Apprenticeship System a Panacea for the U.S. Labor Market?" *Journal of Population Economics,* Vol. 10, No. 4–5 (December), pp. 171–96.

Hildreth, Andrew K. G., Till M. von Wachter, and Elizabeth Weber Handwerker. 2005. "Estimating the 'True' Cost of Job Loss: Evidence Using Matched Data from California, 1990–2001." Unpublished paper, Columbia University.

Jovanovic, Boyan. 1979a. "Job Matching and the Theory of Turnover." *Journal of Political Economy,* Vol. 87, No. 5 (October), pp. 972–90.

____. 1979b. "Firm-Specific Human Capital and Turnover." *Journal of Political Economy,* Vol. 87, No. 6 (December), pp. 1246–60.

____. 1984. "Matching, Turnover, and Unemployment." *Journal of Political Economy,* Vol. 92, No. 1 (February), pp. 108–22.

Kahn, Lawrence M., and Stuart A. Low. 1982. "The Relative Effects of Employed and Unemployed Job Search." *Review of Economics and Statistics,* Vol. 64, No. 2 (May), pp. 234–41.

Kambourov, Gueorgui, and Iourii Manovskii. 2005. "Occupational Specificity of Human Capital." Unpublished paper, University of Pennsylvania.

Lazear, Edward P. 1979. "Why Is There Mandatory Retirement?" *Journal of Political Economy,* Vol. 87, No. 6 (December), pp. 1261–84.

MaCurdy, Thomas E. 1982. "The Use of Time Series Processes to Model the Error Structure of Earnings in a Longitudinal Data Analysis." *Journal of Econometrics,* Vol. 18, No. 1 (January), pp. 83–114.

Meghir, Costas, and Luigi Pistaferri. 2004. "Income Variance Dynamics and Heterogeneity." *Econometrica,* Vol. 72, No. 1 (January), pp. 1–32.

Mincer, Jacob. 1986. "Wage Changes in Job Changes." *Research in Labor Economics,* Vol. 8, Part A, pp. 171–97.

Mortensen, Dale T. 1988. "Wages, Separations, and Job Tenure: On-the-Job Specific Training or Matching?" *Journal of Labor Economics,* Vol. 6, No. 4 (October), pp. 445–71.

Neal, Derek. 1995. "Industry-Specific Human Capital: Evidence from Displaced Workers." *Journal of Labor Economics,* Vol. 13, No. 4 (October), pp. 653–77.

____. 1998. "The Link between Ability and Specialization." *Journal of Human Resources,* Vol. 33 (Winter), pp. 173–200.

Parent, Daniel. 2000. "Industry-Specific Capital and the Wage Profile: Evidence from the National Longitudinal Survey of Youth and the Panel Study of Income Dynamics." *Journal of Labor Economics,* Vol. 18, No. 2 (April), pp. 306–23.

Perticara, Marcela C. 2002. "Wage Mobility through Job Mobility." Unpublished paper, Georgetown University.

Postel-Vinay, Fabien, and Jean-Marc Robin. 2002. "Equilibrium Wage Dispersion with Worker and Employer Heterogeneity." *Econometrica,* Vol. 70, No. 6 (November), pp. 2295–2350.

Salop, Joanne, and Steven Salop. 1976. "Self-Selection and Turnover in the Labor Market." *Quarterly Journal of Economics,* Vol. 90, No. 4 (November), pp. 619–27.

Topel, Robert H. 1991. "Specific Capital, Mobility, and Wages: Wages Rise with Seniority." *Journal of Political Economy,* Vol. 99, No. 1 (February), pp. 145–76.

Topel, Robert H., and Michael P. Ward. 1992. "Job Mobility and the Careers of Young Men." *Quarterly Journal of Economics,* Vol. 107, No. 2 (May), pp. 439–79.

von Wachter, Till, and Stefan Bender. 2006. "In the Right Place at the Wrong Time: The Role of Firms and Luck in Young Workers' Careers." *American Economic Review,* Vol. 96, No. 5 (December), pp. 1679–1705.

Woodcock, Simon D. 2003. "Heterogeneity and Learning in Labor Markets." Unpublished paper, Simon Fraser University.