Economics Working Papers

2012-02

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Return to Experience and Initial Wage Level: Do Low Wage Workers Catch Up?*

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January 3, 2012

This paper estimates the relationship between initial wage and return to experience. We use a Mincer-like wage model to nonparametrically estimate this relationship allowing for an unobservable individual permanent effect in wages and unobservable individual return to experience. The relationship between return to experience and unobservable individual ability is negative when conditioning on educational attainment while the relationship between return to experience and educational attainment is positive. We link our finding to two main theories of wage growth, namely search and human capital. We are able to test if search frictions are the main driver of the negative relationship, but we find this is not the case.

Keywords: Wage growth, initial wage, return to experience, nonparametric estimation

JEL codes: J3, J24

*We thank Michael Svarer, Christopher Taber, Greg Veramendi, participants at the DGPE conference 2010, the Xiamen-Aarhus Labor workshop, Xiamen 2010, CEF 2011, San Fransisco, BI-LMDG annual meeting, 2011, Brownbag lunch seminar Aarhus University 2011 and at the annual workshop of the NBER group on micro and macro perspectives, 2011. We would like to thank The Cycles, Adjustment, and Policy research unit, CAP, Department of Economics and Business, Aarhus University, for support and for making the data available. Vejlin greatly acknowledges financial support from the Danish Social Sciences Research Council (grant no. FSE 09-066745).

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1. Introduction

Since Mincer (1958, 1974) it has been commonly acknowledged that earnings rise with the accumulation of experience. Furthermore, one of the most established facts in the literature is that wage profiles can be ranked by education. The wage-experience profile for workers with a higher educational level dominates that of workers with a lower educational level. E.g. Sørensen and Vejlin (2009) show that the return to experience depends on observable measures of permanent ability such as education, while Bagger, Fontaine, Postel-Vinay, and Robin (2011) show the same in a structural search model with experience accumulation.

It is also widely recognized that workers have permanent abilities that go beyond for instance education. Thus, including only education in wage regressions might bias the estimates, and therefore the inclusion of an individual worker fixed effect in wage regressions is by now standard. Using for instance the Abowd, Kramarz, and Margolis (1999) decomposition, which decomposes wages into observed and unobserved fixed effects for workers and firms, one usually finds that observable measures for skills such as detailed educational information only explain a smaller part of the variation in the estimated worker fixed effect, see e.g. Sørensen and Vejlin (2009) and Woodcock (2011).

Combining these two empirical regularities, we might suspect that the return to experience also change with unobservable skills. However, the relationship between unobserved individual permanent ability and the individual experience profile is greatly understudied in the literature.

One of the contributions of this paper is to nonparametrically estimate the relationship between an individual permanent component of wages and an individual return to experience. We thus extend the identification argument developed by Gladden and Taber (2009), who show that the covariance between the permanent component of wages and a random coefficient on experience can be estimated from initial wages and later wage growth. We extend this argument in order to nonparametrically estimate this relationship. Like Gladden and Taber (2009) we find that workers with high permanent abilities have low individual returns to experience for all educational groups.

Gladden and Taber (2009) use a sample of the NLSY79 data set to estimate the covariance between initial wages and later wage growth for low skilled workers. They estimate the relationship using observations that are sufficiently far apart in time such that they avoid potential problems with autocorrelation in the error term, which would generate a negative bias in the estimate. They find only a small and insignificant effect between initial wages (interpreted as skill level) and future wage growth. Specifically they find that a one standard deviation increase in permanent skill level reduces future wage growth (interpreted as return to experience) by 0.87 per cent. Gladden and Taber (2009) conduct their analysis using mainly covariances because of lack of data. Almost all their estimates are only borderline significant, which is a problem since the limited amount of observations only allows them to estimate a covariance giving them an estimate of the slope between wage growth and initial wages. Although not the focus of his paper, Baker (1997) also estimates a similar model and finds a negative covariance between wage growth and wage level in the PSID data. However, Baker does not emphasize the potential problem with autocorrelation in the error term.

Connolly and Gottschalk (2006) analyzes whether returns to education and experience are lower for the less educated using the 1986-1993 panels of the Survey of Income and Program Participation (SIPP) which are comparable to the PSID although its time frame is considerably shorter than that of the PSID. SIPP's advantage lies in more frequent interviews and thus more precise information on income and employer tenure. Connolly and Gottschalk argue that the number of former successful job matches is more important for job match quality than the number of former draws from the wage distribution. They analyze all age groups, both women and men, and find that higher educated do have higher returns to both experience and tenure. French, Mazumder, and Taber (2006) also use the SIPP, but confine themselves to using workers between the ages of 18-28, in order to analyze the dependence of early career wage growth from accumulated work experience and job match quality for three different groups of education levels. Formally, they would like to test whether labor market policies encouraging job market experience help low educated workers out of poverty. They find that simple experience accumulation is important for early career wage growth whereas they on average do not find support for the importance of job changes in wage growth.

Since we use a much larger data set than both Baker (1997) and Gladden and Taber (2009) we are able to divide our sample into finer educational groups. For all educational subgroups (primary/high school, vocational, bachelor, and master) there seems to be a negative relationship between initial wage and later wage growth. The negative relationship is most pronounced for those with a vocational education.

Both Baker (1997) and Gladden and Taber (2009) only estimate the covariance. A potential problem is that the relationship between wage growth and wage level is non-linear. This paper thus takes the analysis one step further and nonparametrically estimates the return to experience given permanent skills. We find that the relationship is non-linear for those with only a primary/high school education and those with a master degree and thus the covariance might not be a particular good measure to describe the distribution. Using our rich data set we explore some of the theoretical channels of the negative relationship.

One explanation is provided by human capital theory. Human capital theory is based on the seminal work of Becker (1962), Mincer (1962), and Ben-Porath (1967) and emphasizes the role of human capital acquirement in school and on the job. While on the job workers face a trade-off between earning wages and investing in their human capital in order to earn higher wages in the future. Thus, human capital theory will predict a negative relationship between initial wages and return to experience.

The second explanation is one of frictions. Standard search models like Burdett and Mortensen (1998) or Postel-Vinay and Robin (2002) also predict a negative relationship. In a wage posting model like Burdett and Mortensen workers will gradually move up the wage ladder. This implies that those who are initially lucky and find a firm with a high wage will later have lower wage growth, simply because there are fewer firms which are offering higher wages. Postel-Vinay and Robin (2002) use Bertrand competition among firms to determine wages. This mechanism actually enhances the negative relationship, since high productivity firms will be able to pressure workers to start out with a very low wage in order to later have the potential of very high wage growth as they find outside offers to pressure the incumbent firm. Like in the human capital theory this will generate a negative relationship between initial wages and later wage growth. A comparison of the human capital and search explanation is given in Rubinstein and Weiss (2006).

Using the fact that unemployment acts as a resetting device in search models we are able to test if the search model is driving the result. We find that this is not the case. Finally, we investigate if the negative relationship between permanent ability and return to experience is driven by any specific group. We look closer at occupations, industries, time of labor market entry and finally labor market transitions. We find that none of these observable features explain the negative relationship.

The rest of this paper is organized as follows. Section 2 goes through our wage model and the nonparametric estimation approach. In section 3 we discuss the data used for the estimation and sections 4 and 5 present results and robustness checks. Finally, in section 6, we conclude.

2. Econometric Approach

We use a correlated random effects model inspired by Baker (1997) and Gladden and Taber (2009). Our goal is to analyze the relationship between initial wages and future wage growth within the first ten years of a worker's labor market life. This relationship holds important information on wage profiles for workers with different skill levels. We assume that the wage structure is a linear function of worker specific permanent ability and human capital, measured as experience. Wages have been detrended by a simple OLS regression of year dummies on log wages such that all year specific effects have been removed. Let detrended log wages be defined as

$$w_{it} = \theta_i + \gamma_i E_{it} + \varepsilon_{it}, \tag{1}$$

where θ_i and γ_i are worker specific random effects, E_{it} is the experience of worker i at time t and ε_{it} is an error term. The linear relationship in (1) necessitates us to be very restrictive with how many years to include in the sample. The typical experience-wage profile is concave on its full support, but will be very nearly linear during the first 10 years on the labor market.[1] We thus include observations up until $t = 9$ only (labor market entry at $t = 0$ makes it 10 years).

θ_i and γ_i represent unobserved individual permanent abilities and the unobserved individual ability to make use of experience interpreted as the return to experience. The overall goal of this paper is to gain insights in the relationship between θ_i and γ_i from model (1).

We allow workers into our sample only after they have completed their highest education. The identifying assumption is that no worker has any experience when entering the labor market or that the experience that he has is not useful, i.e. $E_{i0} = 0$. This assumption is crucial for the identification of the random effects. With the wage specification (1) the initial wage is

$$w_{i0} = \theta_i + \varepsilon_{i0}, \tag{2}$$

and the wage growth from period $t - \tau$ to t becomes

$$\Delta_\tau w_{it} = \gamma_i \Delta_\tau E_{it} + \Delta_\tau \varepsilon_{it}, \tag{3}$$

where $\Delta_\tau x_{it} = x_{it} - x_{it-\tau}$. A simple transformation of (3) gives the more convenient representation of wage growth normalized by the growth in experience as a function of the unobservable individual return to experience

[1] Gladden and Taber (2009) also use a linear model in experience. They justify this by referring to experience profiles in Gladden and Taber (2000), which are very close to linear. Sørensen and Vejlin (2011) estimate experience profiles using the same Danish data as used in this paper and find that the experience profiles are also close to linear.

and an altered error term

$$\frac{\Delta_\tau w_{it}}{\Delta_\tau E_{it}} = \gamma_i + \frac{\Delta_\tau \varepsilon_{it}}{\Delta_\tau E_{it}}. \tag{4}$$

As intuition would suggest equations (2) and (4) tell us that the initial wage might be a good estimate of unobserved permanent ability, while wage growth might be a good estimate for unobserved ability to learn. However, loosely speaking we need the error terms in equations (2) and (4) to be uncorrelated. Baker (1997) estimates a model very close to ours and fits the error term by an ARMA(1,2) process. Gladden and Taber (2009) use Baker's estimates to show that the covariance between the error term in equations (2) and (4) is tiny compared to the estimate and thus the potential bias is very small. Using the data in this paper we have estimated a corresponding model.[2] The results confirm the previous findings by Gladden and Taber (2009) and Baker (1997) in that the potential bias is negligible compared to the estimates.

For simplicity we set up the system in matrix form as

$$\boldsymbol{W_{it}} = \begin{pmatrix} w_{i0} \\ \frac{\Delta_\tau w_{it}}{\Delta_\tau E_{it}} \end{pmatrix}, \quad \boldsymbol{\beta_i} = \begin{pmatrix} \theta_i \\ \gamma_i \end{pmatrix}, \quad \boldsymbol{\epsilon_{it}} = \begin{pmatrix} \varepsilon_{i0} \\ \frac{\Delta_\tau \varepsilon_{it}}{\Delta_\tau E_{it}} \end{pmatrix}.$$

So

$$\boldsymbol{W_{it}} = \boldsymbol{\beta_i} + \boldsymbol{\epsilon_{it}}, \tag{5}$$

for $i = 1, \ldots, N$ and $t = T_L, \ldots, T_U$ with T_L being the lower limit, where the assumption of independence is justified, and T_U our upper limit of early labor market life. If we let $N \to \infty$ the distribution of $\boldsymbol{W_{it}}$ will in probability be proportional to the distribution of $\boldsymbol{\beta_i}$ up to a constant independent of $\boldsymbol{\beta_i}$. To see this, note that $\boldsymbol{\beta_i}$ is a two-variate, absolutely continuously random variable with unknown joint density $f_{\boldsymbol{\beta_i}}(\boldsymbol{\beta_i})$. Since $\boldsymbol{W_{it}} = \boldsymbol{A\beta_i} + \boldsymbol{\epsilon_{it}}$, where $\boldsymbol{A} = \left[\begin{smallmatrix} 1 & 0 \\ 0 & 1 \end{smallmatrix}\right]$ is non-singular then $\boldsymbol{W_{it}}$ is two-variate, absolutely continuously distributed

[2] Table 1 contains covariations between initial errors and later changes in errors estimated by assuming the residuals of equation (1) following an ARMA(1,2) process as assumed by Baker (1997) and Gladden and Taber (2009). All correlations fall dramatically after year three and compared to the estimated covariance between θ and γ we find very low covariances between initial errors and later error growth. We thus feel confident using the conservative choice of year six as our first yearly wage growth in our regression analysis.

with joint density[3]

$$
\begin{aligned}
f_{\boldsymbol{W_{it}}}\left(\boldsymbol{W_{it}}\right) &= f_{\boldsymbol{\beta_i}}\left(\boldsymbol{A}^{-1}\left(\boldsymbol{W_{it}} - \boldsymbol{\epsilon_{it}}\right)\right) | \det\left(\boldsymbol{A}^{-1}\right) |) \quad \Leftrightarrow \\
f_{\boldsymbol{W_{it}}}\left(w_{i0}, \frac{\Delta_\tau w_{it}}{\Delta_\tau E_{it}}\right) &= f_{\boldsymbol{\beta_i}}\left(w_{i0} - \varepsilon_{i0}, \frac{\Delta_\tau w_{it}}{\Delta_\tau E_{it}} - \frac{\Delta_\tau \varepsilon_{it}}{\Delta_\tau E_{it}}\right) \\
&= f_{\boldsymbol{\beta_i}}(\boldsymbol{\beta_i}). \qquad (6)
\end{aligned}
$$

Note that the expectation and variance-covariance matrix of $\boldsymbol{W_{it}}$ are given by

$$
E\left[\boldsymbol{W_{it}}\right] = E\left[\boldsymbol{\beta_i}\right] \quad \text{and} \qquad (7)
$$

$$
\Omega(\boldsymbol{W_{it}}) = \begin{bmatrix} Var(\theta_i) & Cov(\theta_i;\gamma_i) \\ Cov(\theta_i;\gamma_i) & Var(\gamma_i) \end{bmatrix}, \qquad (8)
$$

making the joint distribution of initial wages and future wage growth proportional with the joint distribution of unobserved permanent abilities and unobserved individual return to experience. Notice that using this formulation we avoid to make any assumptions regarding the relationship between (θ_i, γ_i) and E_{it}. This is important since any reasonable model would imply that actual experience is correlated with (θ_i, γ_i).

Before we turn to our nonparametric approach we start out analyzing a more simple variant of the relationship between individual permanent abilities (θ_i) and the individual return to experience (γ_i), the covariance. Since θ_i and γ_i, by definition, are unobserved we make use of the model specification (5). A simple OLS regression of wage growth normalized by growth in experience on initial wages gives us a slope coefficient that converges to

$$
\frac{Cov\left(w_{i0}, \frac{\Delta w_{it}}{\Delta E_{it}}\right)}{Var(w_{i0})}.
$$

By the structure of (8), the slope coefficient will converge to

$$
\frac{Cov(\theta_i, \gamma_i)}{Var(w_{i0})},
$$

so the covariance between permanent individual ability and the individual return to experience can thus fairly easy be estimated using OLS. We distinguish between two types of experience; potential and actual. Potential experience is initially set equal to zero and then simply grows one unit per year. Actual experience is an exact measure of experience accumulation each year, but is also set to zero at labor market entry. If the worker has worked full time all year, actual experience accumulation is equal to one unit. To eliminate the serial correlation in the error term, we use yearly wage growth only from period 7 to 10 after entering the labor market. We are not able to bring in later observations because of the linearity in the experience measure in (1).

[3]See (Bierens, 2005, Theorem 4.3).

2.1. Nonparametric Estimation Model

Given the structure of our model and the richness of our data we are able to nonparametrically estimate the joint distribution of γ_i and θ_i using initial wages and future wage growth. First, to estimate the expected level of wage growth for different levels of unobserved worker specific abilities (i.e. $E[\gamma_i \mid \theta_i]$) we consider the nonparametric regression model

$$\frac{\Delta_\tau w_{it}}{\Delta_\tau E_{it}} = g(w_{i0}) + u_i, \quad i = 1, \ldots, N, \quad t = 6, 7, 8, 9, \quad \tau = 1, \tag{9}$$

where the functional form of g is unknown. g can, however, be interpreted as the conditional mean of $\frac{\Delta w_{it}}{\Delta E_{it}}$ given $W_{i0} = w_{i0}$.[4] $E\left[\frac{\Delta w_{it}}{\Delta E_{it}} \mid w_{i0}\right] = g(w_{i0})$ is estimated nonparametrically as

$$\hat{g}(w_{i0}) = \sum_{i=1}^{N} \frac{\Delta w_{it}}{\Delta E_{it}} X_i(w_{i0}), \tag{10}$$

with

$$X_i(w_{i0}) = \frac{K\left(\frac{w_{i0} - \tilde{w}_0}{h}\right)}{\sum_{j=1}^{N} K\left(\frac{w_{j0} - \tilde{w}_0}{h}\right)}.$$

h is the bandwidth smoothing parameter for initial wages. $\tilde{w}_0$ is the grid point for which we evaluate the kernel. Optimally h would be chosen to minimize the asymptotic mean integrated squared error of the kernel estimates, which is the integration of the sum of the approximate variance and squared bias. Unfortunately, this includes unknown terms such as the second derivative of the unknown true density function. Instead of the theoretical optimal bandwidth, we use Silverman's Rule-of-Thumb bandwidth determined as

$$h = 2.34 \hat{\sigma}_{w_{i0}} n^{-1/5}. \tag{11}$$

Alternatively, we could implement a cross-validation method to estimate the bandwidth. Instead, we have tested the robustness of the Silverman rule of thumb bandwidth and found the estimates to be very robust to changes in the bandwidth. Indeed, if the true density is normal, then the rule-of-thumb bandwidth will give the optimal bandwidth, and for g close to normal, h will be close to optimal.[5] $K(\cdot)$ is the second order Epanechnikov kernel given by[6]

$$K\left(\frac{w_{i0} - \tilde{w}_0}{h}\right) = \begin{cases} \frac{3}{4}\left(1 - \left(\frac{w_{i0} - \tilde{w}_0}{h}\right)^2\right) & \text{for } \left|\frac{w_{i0} - \tilde{w}_0}{h}\right| \leq 1 \\ 0 & \text{for } \left|\frac{w_{i0} - \tilde{w}_0}{h}\right| > 1 \end{cases}. \tag{12}$$

[4] See Li and Racine (2007, Chapter 2 and especially Theorem 2.1).

[5] See e.g. Hansen (2010, Chapter 16).

[6] See Li and Racine (2007, Chapter 1) and Zhang, King, and Hyndman (2006)

The fact that we have chosen an Epanechnikov kernel instead of e.g. a Gaussian, Uniform or Triangular kernel is of minor importance. Instead, the important factor for the performance of any nonparametric kernel density estimation is not so much the choice of kernel itself, but rather the bandwidth smoothing selection (Zhang, King, and Hyndman (2006)). However, the Epanechnikov kernel has the advantage of being relatively fast to compute and it is the most efficient in minimizing the asymptotic mean squared error (Silverman (1986)).

Second, we take the estimation one step further and nonparametrically estimate the full joint distribution between initial wages and future wage growth. The estimate of the full joint density of initial wages and wage growth is given by

$$\hat{f}\left(w_{i0}, \frac{\Delta w_{it}}{\Delta E_{it}}\right) = \frac{1}{n h_{w_{i0}} h_{\frac{\Delta w_{it}}{\Delta E_{it}}}} \sum_{i=1}^{n} K\left(\frac{w_{i0} - \tilde{w}_0}{h_{w_{i0}}}\right) K\left(\frac{\frac{\Delta w_{it}}{\Delta E_{it}} - \Delta\tilde{w}}{h_{\frac{\Delta w_{it}}{\Delta E_{it}}}}\right), \tag{13}$$

where $h_{w_{i0}}$ and $h_{\frac{\Delta w_{it}}{\Delta E_{it}}}$ are the bandwidth smoothing parameters for initial wages and wage growth respectively while $K(\cdot)$ remains to be the Epanechnikov kernel from equation (12).[7] When turning from a nonparametric regression model to a nonparametric two-variate joint density model, Silverman's rule of thumb smoothing bandwidth parameter changes to

$$h_j = 2.20\hat{\sigma}_j n^{-1/5} \quad \text{for} \quad j \in \left\{w_{i0}, \frac{\Delta w_{it}}{\Delta E_{it}}\right\}. \tag{14}$$

3. Data

This paper uses Danish data to estimate the models specified above. We utilize two different kinds of data; (1) we use yearly data from the Integrated Database for Labor Market Research (IDA) and (2) we use weekly spell data. Both data sets are kept by Statistics Denmark. The data are confidential but our access is not exclusive. IDA is a matched employer-employee longitudinal database containing socio-economic information on the entire Danish population, the population's attachment to the labor market, and at which firms workers are employed. Both persons and firms can be monitored from 1980 onwards. The reference period in IDA is given as follows; the linkage of persons and firms refers to the end of November, ensuring that seasonal changes (such as e.g. shutdown of establishments around Christmas) do not affect the registration. The creation of jobs within individual firms thus refers to the end of November. Background information on individuals mainly refers to the end of the year.

[7] Li and Racine (2007) show that this is a MSE consistent estimate of the true joint density.

Our gross sample contains all male workers having their main employment at a private firm in the period of $1987 - 2006$ and having entered the labor market after 1980.[8]

The weekly spell data set is a longitudinal data set containing information of labor market transitions for each individual in the Danish population. The spell data is constructed by merging several Danish register data sets. All individuals are at first assigned to one of sixteen mutually exclusive labor market states in each week over the years 1985-2003 using the different register data sets. These states are then narrowed down to two states; non-employment and employment. We use the spell data to split the sample into three mutually exclusive subsamples. The first sample are those making a Job-to-Job transition within the year where we measure wage growth. The second sample is those making a Job-to-Nonemployment-to-Job transition likewise in the year where wage growth is measured. The final sample are those who have not changed jobs (henceforth denoted stayers).

The advantage of IDA is the detailed socio-economic information on each individual from year to year while spell data delivers important information on how each individual acts on the labor market between the last week of November one year to the following last week of November next year. This information is very important since all we can see from IDA is whether or not an individual has changed employer or not, not whether he has switched directly from one job to another or if there has been a spell of un- or nonemployment in between, which is potentially very important for wage growth. The time period of our analysis is 1987-2006 except when we analyze transitions where spell data forces us to narrow down the sample to 1987-2003.

3.1. Sample Selection

In this section we present how we have chosen to narrow down the sample. The raw data consist of the entire Danish male labor force. First of all, we look only at full-time employment within the private sector. Second, we are interested only in labor market participation after the completion of education, so we delete all observations referring to periods before completion of the highest education as well as observations during education. Furthermore, to eliminate educational outliers we delete all observations belonging to individuals finishing their highest education after turning 35. As we are interested in examining the wage structure for the first ten years on the labor market, this ensures that all individuals will be relatively young workers. Also, one

[8]See a more detailed documentation on IDA:

http://www.dst.dk/HomeUK/Guide/documentation/Varedeklarationer/emnegruppe/emne.aspx?sysrid=1013 of the identifying assumptions was that rewardable experience at labor market entry was zero. This is unlikely to be a valid assumption if labor market entry happens when the worker is relatively old. We have split the sample into groups of education crossed with experience, and then trimmed the top and bottom percentile of the wage distribution within each of these groups for each year separately.

This results in a total of 239,871 male workers. Of these, 20 percent have at most a primary or high school diploma, 54 percent are educated at a vocational level, 18 percent hold a bachelor and 8 percent carry a master's degree. 16 percent of all workers are present only once in our sample, 12 percent are in the sample twice, 11 percent enter three times and 61 percent of all workers are present four times. This comprises our sample to 760,100 worker observations.

[Insert table 2 here]

Tables 2 and 3 describe the sample used. Table 2 shows the number of individuals by education transition. The reason we have such a low number of Job-to-Nonemployment-to-Job transitions is that the requirement for being in this sample is that we observe two consecutive November cross-section job spells. I.e. in order for the worker to be in the Job-to-Nonemployment-to-Job sample he will need to be employed at one firm in a given November cross-section, become nonemployed during the year, and then finally find a job before the next November cross-section. This leaves out a lot of transitions that do not fulfill these requirements.

[Insert table 3 here]

Table 3 shows descriptive statistics for initial wage and wage growth by education and type of transition. Those making a Job-to-Job transition has a little higher initial experience and much higher wage growth. Workers that experience a Job-to-Nonemployment-to-Job transition on average have a negative wage growth. There is also a clear pattern across educational groups. The higher the educational level the higher is the initial wage and the wage growth.

In order to get a feeling of the marginal distributions that we later use in our regressions, we nonparametrically estimate the distribution of initial log wages and future wage growth for all workers in our sample.

[Insert figure 1 here]

Figure 1 shows the initial wage and wage growth distributions.[9] Both densities are very smooth with the

[9]See table 3 for descriptive counterparts of these densities.

initial wage density almost log normal while the wage growth density is much more narrow.

4. The Results

In this section we present the results. We first estimate the covariance of θ_i and γ_i in equation (1) also estimated in Gladden and Taber (2009). Secondly, we move to the nonparametric estimation. And finally, we present evidence on the degree of wage catch up.

4.1. The Covariance of Initial Wage Level and Return to Experience

In this section we present results similar to those of Gladden and Taber (2009). Table 4 presents the regression results for both potential and actual experience for each of the four educational groups. Column (1) contains unweighted estimates of the slope. Column (2) contains weighted versions such that each individual gets equal weight regardless if they appear one, two, three or four times in the sample. All groups display significant negative slopes except the weighted bachelor regressions. There are no significant differences in the weighted vs. unweighted regressions. A result of the descriptive fact that most of our workers are represented by four observations. Vocational educations see the steepest negative covariances between wage growth and initial wages followed by workers holding a master's degree and workers with at most a primary or high school diploma. Gladden and Taber (2009) calculate similar numbers for low educated (corresponding to our primary/high school group) and find results of an insignificant magnitude of -0.005. We estimate a significant covariance for primary/high school workers of -0.0139. There is a tendency that the coefficients get more negative when using actual experience, although there is no significant difference.

[Insert table 4 here]

The important coefficient is the significant negative slope coefficient on initial wage which reveals that e.g. a worker with a vocational education earning one percent higher initial wage will on average have 0.032 percentage point less wage growth than the normalized worker and 0.034 percentage point lower wage growth per actual experience year.

Gladden and Taber (2009) report that a worker with a one standard deviation higher level of permanent ability have around 0.61 to 0.87 percentage point lower return to experience. If we calculate the similar number given our sample we find that a primary/high school worker with a one standard deviation higher level of permanent ability have a 0.40 to 0.53 lower return to experience. These are very similar results.

4.2. Nonparametric estimation

One might suspect that the relationship between return to experience and initial wage levels is non-linear. If this is the case, then the covariance will not capture the true relationship. We here present evidence that the relationship may not be linear on the entire support.

We estimate equation (10), the expected wage growth conditional on initial wages using the actual experience measure. As shown above, this relationship contains information on the return to experience we would expect of a worker conditional on his individual permanent ability level.

[Insert figure 2 here]

Figure 2 plots the estimated expected wage growth conditional on initial wage levels with bootstrapped confidence intervals for the four subsamples. The four figures confirm the results from the OLS regressions. Vocational educated workers see a steep negative relationship, primary/high school workers have an overall negative slope, but for lower ability workers the relationship is insignificant. Workers with a bachelor degree exhibit an almost constant initial wage - wage growth relationship and master's degree workers have an overall negative slope. The figure highlights slope differences within especially the groups of primary/high school workers and master's degree holders. The covariance analysis thus only gives an overview over the true relationship while the nonparametric approach is able to give a more thorough picture.

Note how a large fraction of primary/high school workers start out lower than vocational educated, but for workers starting at the same level between the two groups, primary/high school workers can expect a higher wage growth than vocational educated workers. All workers with a bachelor and a master's degree can, on the other hand, expect even higher wage growth for all permanent worker types.

Another very important conclusion from figure 2 is that if we had estimated the model on the entire sample we would get a U-shape of growth by initial wages. This is done in figure 3

[Insert figure 3 here]

However, the U-shape is simply a composition effect from estimating the model on all educational groups at the same time. In general, both initial wages and wage growth is increasing in educational attainment. This leads to the U-shape which was observed in figure 3. Wage growth is thus increasing in observed permanent ability (education), while it is decreasing in unobserved permanent ability (initial wage).

To judge how important initial wages are for future wage growth, table 5 shows expected wage growth conditional on different distributional percentiles of initial wages.

[Insert table 5 here]

This figure is basically a reflection of the results in figure 2. A worker with a vocational education with the median permanent skill level can expect to receive 0.77 percent wage growth per actual experience year. Equally educated workers with very low initial wages at the 5th percentile can expect an extra 1.03 percentage point wage growth compared to the median initial skill worker. The worker at the 25th initial skill percentile can expect 0.53 percentage point extra wage growth than the median worker, while workers at the 75th initial skill level will get 0.65 percentage point less wage growth than the median worker.

4.2.1. Full Joint Distribution

So far we have only estimated the conditional mean wage growth. The full joint distribution between initial wages and future wage growth reveals more of the relationship between permanent abilities and return to experience.

[Insert figure 4 here]

Figure 4 shows the nonparametrically estimated joint density of initial log wages and future wage growth for the vocational educated. To fully capture the 3d image we have depicted the figure in four different rotations around the joint median. It shows that the joint density is not perfectly normal as it is skewed towards low initial log wages while being almost symmetrically in wage growth although the negative tail is somewhat fatter than the positive tail.

If the catching-up effect would have been a fast process we would have expected the joint distribution to be more twisted with lower initial log wages connected to higher wage growth. Instead we see that low initial wages have most mass connected to small positive wage growth while medium initial wage workers have a high mass around zero or small positive wage growth but still with more mass at extreme negative wage growth than at extreme positive. The high initial wage earners seem to have mass equally distributed around a small positive mean.

However, the full joint distribution is not that informative to look at so we proceed with the conditional mean as our main specification.

4.3. Catching Up Or Not?

Given the non-parametric estimations presented above we are able to calculate the expected log wage levels any permanent ability type worker can on average expect at any point in time during his early labor market career. The calculations are based on the results presented in figure 2. From this figure we can find the average wage growth for each group in the initial wage distribution. However, though we can calculate the expected wage increase for each year of extra experience, it is harder to find out how the level should be. We have chosen to use the fifth year wage. E.g. for the fifth percentile (P5) the level is set to the average fifth year wage for all workers within a 0.1 log wage distance of the fifth percentile initial wage and likewise for the other percentiles.

[Insert figure 5 here]

Figure 5 depicts the graphical estimated wage paths for five initial wage distributional groups in each of our educational subgroups. These graphs are interesting in at least two ways; (1) they show how the wage paths are expected to evolve for each subgroup and (2) they give a better picture of the robustness of our estimations. Imagine that the DGP is equation (1) and that all workers have the same permanent ability ($\theta_i = \theta$), and when entering the labor market they each draw an error term, ε_{i0}. Some workers draw a high value of ε_{i0} and therefore a high initial wage while some workers draw a low ε_{i0} and receive a low initial wage. Given that all are the same and the errors are iid, these random draws should be neutralized by time and all workers should see wage paths converging to the same level.[10]

Primary/high school workers below the 75th percentile initial wage in fact do seem to follow a pattern like the example of homogeneous workers. The average fifth year wage is the same for the 5th, 25th and 50th percentile while higher initial wage workers with a primary/high school degree still have a higher wage after five years on the labor market. Because of the steep negative slope in the nonparametric analysis, wee see that the lower wage workers are not only catching up to the higher wage workers, but are overtaking them. Workers with a vocational education see some of the same pattern, only not as clear. As both the covariance and nonparametric analysis indicated, workers with a bachelor degree do not show any kind of catching up for

[10]This is confirmed by our ARMA estimations presented in table 1.

any of the distributional groups, although the median initial wage percentile does have a higher wage growth rate than the 75th percentile. Low initial wage workers holding a master's degree stay at the bottom while the 25th percentile and median workers overtake the top initial wage workers after year seven.

One might be suspicious that these results are an artifact of the estimation procedure, which puts some restrictions on the functional form. Figure 6 shows experience profiles for different groups of the initial wage distribution estimated by log wages on experience and experience squared.

[Insert figure 6 here]

Looking at figure 6 the results regarding catching up seems to be clearly related to the data. Especially for those with either primary/high school or a vocational education it seems that the 5th percentile almost catches up to the 95th percentile. For those with a bachelor or a master's degree there seems to be very little catch up. This is true in particular for the bachelor group.

5. Relation to Theory

In this section we related the above findings to two main theories, namely search and human capital.

5.1. Search Theory

One of the theories that explains the negative correlation between individual return to experience and initial wages is search theory. Imagine a standard search model like Burdett and Mortensen (1998) or Postel-Vinay and Robin (2002). In a wage posting model like Burdett-Mortensen workers will gradually move up the wage ladder. This implies that those who are initially lucky and find a firm with a high wage will later have lower wage growth. This happens because there are simply fewer firms offering higher wages. In Postel-Vinay and Robin (2002) this mechanism is actually enhanced. In the Postel-Vinay and Robin model wages are set in Bertrand competition between firms. High productivity firms will be able to pressure workers to start out with a very low wage in order to later have the potential of very high wage growth as they find outside offers.

However, if any worker becomes unemployed, search models like the above dictate that he will be searching on the grounds of his unemployment benefit and not his former wage, eliminating the relationship with his former wage and later wage growth. We can thus test if search is the main explanation by looking at workers who have been unemployed between entry on the labor market and year six and workers who have not.[11] In order to do this we make use of the weekly spell data previously described. An insignificant relationship between initial wages and future wage growth for those who have been unemployed would thus confirm the search theory explanation, while a significant slope contradicts it.

[Insert figure 7 here]

Figure 7 shows that we can reject the search theory in our Primary/High school and Vocational educational groups while both bachelor educated and workers with a master's degree could confer to the search theory. However, this was also the two groups that had the least negative relationship. In general, there seems to be very little difference between the groups that experienced an unemployment spell and those that did not. So it does not seem that search theory is the main explanation for the negative relationship between initial wages and later wage growth.

5.2. Human Capital Theory

Human capital theory is based on the seminal work of Becker (1962), Mincer (1962), and Ben-Porath (1967) and emphasizes the role of human capital acquirement in school and on the job. In the Ben-Porath model workers face a trade-off on the job between earning wages and investing in their human capital, thereby increasing their earnings potential in the future. In order to invest in human capital the worker will have to take a job with a lower wage. Thus, human capital theory will predict a negative relationship between the initial wages and individual wage growth (return to experience). For a survey on this literature see Weiss (1987).

Extending the Ben-Porath model of on the job investment in human capital to also include investment in schooling we can extend the analysis, see e.g. Rubinstein and Weiss (2006). If we allow for individuals to have different abilities to learn (scholastic ability) one of the predictions is that those with high ability will stay longer in school. However, they will then do less investment on the job. This seems to be contradicted by our data, since wage growth is on average higher for more educated.

One version of the human capital model which could explain the dual findings that, 1) wage growth seems to be increasing in schooling, and 2) there is a negative relationship between initial wages and later wage growth, could be the following. Imagine a standard human capital model with on the job training. This would imply

[11] We categorize unemployed to be only those with more than 12 weeks of unemployment to get rid of possible bias from workers with only short-term unemployment in between jobs. The results do not depend on this assumption.

a negative relationship between initial wages and wage growth, since the worker can choose between two types of jobs. In the first type of job the worker devotes a small fraction of his time to training and thus receives a high wage. In the second type he devotes a larger fraction of his time to training and the firm is only willing to pay him a smaller wage initially, but will award him for productivity growth. Thus, in equilibrium the worker is indifferent between the two types of jobs. He faces the trade-off between getting an initial high wage, but no training, and getting initially a low wage and more training and thus a higher wage in the future. If there are multiple worker types, the worker might want to signal his type by taking an education. Thus high ability learning types take a longer education and are thus more productive even at the early stages of their labor market career. Therefore they will earn a higher wage initially and also have higher wage growth, since they select jobs with on the job training compared to low ability workers. However, for a given type of workers there is a negative relationship between initial wages and later wage growth. This happens since some take jobs with a high degree of on the job training and thus low wages. Going further into such a model is beyond the scope of this paper, but would be interesting for future research.

6. Robustness

Imagine that the labor market consists of two groups. The first group has a positive covariance between initial wage and return to experience, while the second has a negative covariance. Estimating the joint covariance using both groups could potentially result in a zero covariance estimate. This highlights the importance of estimating on a homogeneous group of workers. This was one of the reasons to separate by educational groups in the above analysis as we saw that we estimated a U-shape when using the entire sample.

In this section we look for other possible explanations for the negative relationship. We restrict the analysis to those with a vocational education, since this is the largest group and the one with the clearest negative relationship. We look at labor market transitions, differences in industries, differences in occupation, time of labor market entry, and minimum wages. In general we find that none of these explain the negative relationship.

Labor Market Transitions It is a common result that much wage growth can be contributed to job change (see e.g. Altonji and Williams (1992), Topel and Ward (1992), Neal (1995), and Dustmann and Meghir (2005)).

[Insert table 6 here]

[Insert figure 8 here]

Table 6 and figure 8 show the covariance analysis and the non-parametric estimates for the vocational educated divided into stayers, Job-to-Job and Job-to-Nonemployment-to-Job transitions.[12] Generally, those with Job-to-Job transitions have a much stronger negative covariance between return to experience and initial wages than the stayer sample. This result carries through no matter which measure of experience we use. Workers making a Job-to-Nonemployment-to-Job have a more negative covariance if we use real experience, but not if we use potential experience. Comparing to the main results in table 4 the stayer sample has a less negative covariance of about three quarters of what it was before, but it is still very significant. From this it is clear that the negative relationship is not driven by differences in labor market transitions in the year where wage growth is measured.

Industry One could imagine that different industries have different relationships between initial wages and return to experience. Figure 9 shows the results for the four largest industries for vocational educated workers; the financial sector, wholesale, construction and manufacturing.[13]

[Insert figure 9 here]

There are level differences as one would expect. The financial sector enjoys higher wage growth than the others. Wholesale come next, and then the manufacturing industry while construction sees the lowest levels of wage growth for fixed permanent ability types, but all four industries maintain the downward sloping relationship for the vocational educated group as a whole.

Occupations Figure 9 also shows results where we have split the vocational workers into occupations. Once more, there are level differences corresponding to what one would expect, but again the overall pattern of the downward sloping relationship does not seem to be explained by differences between occupations.[14]

Labor Market Entry; 80'ies vs. 90'ies Finally, although wages have been controlled for year effects, one could imagine that entry in different periods of time could play a role in the relationship between permanent

[12] The transitions refer to the year where wage growth is measured.

[13] We measure industry at the time of wage growth. We have also tried to measure it at labor market entry. This makes little difference.

[14] We measure occupation at the time of wage growth. We have also tried to measure it at labor market entry. This makes little difference.

observable ability and the return to experience. The lower right panel of figure 9 divides the vocational educated workers into whether they entered the labor market in the eighties or in the nineties. There seems to be a slight difference in the magnitude of the slopes as the relationship for eighties-enters displays a steeper negative slope, but their overall pattern does not reveal much difference.

Minimum Wages One potential problem with the above specifications is that e.g. minimum wages could enforce a negative relationship. Denmark does not have an official fixed minimum wage level but nevertheless, there are unofficial lower thresholds for wages within occupations negotiated by the trade unions and the employer association.

Think of a very low permanent ability type worker (i.e. a worker with a very low initial wage). He would gain wage increases simply because his wage could only go up. If this sign went through over the entire initial wage support we would see a negative sloping relationship as the ones above. However, we would also see a much lower variance in wage growth for low permanent ability types than for high permanent ability types as there is no such thing as an upper ceiling of wages. In order to address such an issue we have nonparametrically calculated the variance of wage growth conditional on initial wages. Figure 10 shows the estimated conditional variance.

[Insert figure 10 here]

The variance for low permanent ability types is actually higher than for high permanent ability types and the suspicion that minimum wages were driving the result does not seem to hold.

7. Conclusion

The main goal of this paper was to estimate the relationship between wage levels and wage growth. We have estimated a Mincer type wage equation allowing for an individual unobserved permanent effect and an individual unobserved return to experience. We have extended previous analysis of this relationship to cover the entire sample of male workers. We have also extended it to go beyond a covariance analysis.

We find an overall negative relationship between initial wages and return to experience, but a positive relationship between return to experience and educational level (observable individual characteristics). We have done the analysis on several educational subgroups, and find that the negative relationship between unobserved individual permanent ability and individual unobserved return to experience is most clear for lower levels of education (primary/high school and vocational) while higher levels of education (bachelor and master's degrees) see an only borderline significant relationship. In general, and especially for the group of vocational educated individuals, the catching up effect in wages is relatively large.

We have connected the empirical findings with two main theories; search and human capital. Using the structure of search models that unemployment acts as a resetting device, we rejected that search theory was the main explanation. We also found some inconsistencies with the standard human capital framework. We proposed a model that might be able to explain the findings. However, we leave it to future research to go more into this.

Finally, we tested if we could find any observable characteristics that would explain the negative relationship. We found that neither job transitions, industry, occupation, labor market entry time or minimum wages could explain the pattern.

References

Abowd, J. M., F. Kramarz, and D. N. Margolis (1999): "High Wage Workers and High Wage Firms," *Econometrica*, 67(2), 251–333.

Altonji, J. G., and N. Williams (1992): "The Effects of Labor Market Experience, Job Seniority, and Job Mobility on Wage Growth," NBER Working Papers 4133, National Bureau of Economic Research, Inc.

Bagger, J., F. Fontaine, F. Postel-Vinay, and J.-M. Robin (2011): "A Tractable Equilibrium Search Model of Individual Wage Dynamics With Experience Accumulation," Working Paper.

Baker, M. (1997): "Growth-Rate Heterogeneity and the Covariance Structure of Life-Cycle Earnings," *Journal of Labor Economics*, 15(2).

Becker, G. S. (1962): "Investment in Human Capital: A Theoretical Analysis," *Journal of Political Economy*, 70(5), 9–49.

Ben-Porath, Y. (1967): "The Production of Human Capital and the Life Cycle of Earnings," *Journal of Political Economy*, 75(4), 352–365.

Bierens, H. J. (2005): *Introduction to the Mathematical and Statistical Foundations of Econometrics*. Cambridge University Press.

Burdett, K., and D. T. Mortensen (1998): "Wage Differentials, Employer Size, and Unemployment," *International Economic Review*, 39(2), 257–273.

Connolly, H., and P. Gottschalk (2006): "Differences in Wage Growth by Education Level: Do Less Educated Workers Gain Less from Work Experience?," Working Paper, Economics Department, Boston College.

Dustmann, C., and C. Meghir (2005): "Wages, Experience and Seniority," *Review of Economic Studies*, 72(1), 77–108.

French, E., B. Mazumder, and C. Taber (2006): *"The changing pattern of wage growth for low skilled workers" In: Working and Poor: How Economic and Policy Changes are Affecting Low-Wage Workers*pp. 141–172. Russell Sage Foundation: New York, NY; Blank R., S. Danziger, and R. Shoeni (eds).

Gladden, T., and C. Taber (2000): *"Wage Progression Among Less Skilled Workers" In: Finding Jobs: Work and Welfare Reforms*pp. 160–192. Russell Sage Foundation: New York, NY; Blank, R. M. and D. Card (eds).

——— (2009): "The Relationship Between Wage Growth and Wage Levels," *Journal of Applied Econometrics*, 24, 914–932.

Hansen, B. E. (2010): *Econometrics*. University of Wisconsin.

Li, Q., and J. S. Racine (2007): *Nonparametric Econometrics: theory and practice*. Princeton University Press.

Mincer, J. (1958): "Investment in Human Capital and Personal Income Distribution," *The Journal of Political Economy*, 66(4), 281–302.

Mincer, J. (1962): "On-the-Job Training: Costs, Returns, and Some Implications," *Journal of Political Economy*, 70(5), 50–79.

Mincer, J. (1974): *Schooling, Experience, and Earnings*. National Bureau of Economic Research.

NEAL, D. (1995): "Industry-Specific Human Capital: Evidence from Displaced Workers," *Journal of Labor Economics*, 13(4), 653–77.

POSTEL-VINAY, F., AND J.-M. ROBIN (2002): "Equilibrium Wage Dispersion with Worker and Employer Heterogeneity," *Econometrica*, 70(6), 2295–2350.

RUBINSTEIN, Y., AND Y. WEISS (2006): *"Chapter 1 Post Schooling Wage Growth: Investment, Search and Learning," vol. 1 of Handbook of the Economics of Education,* pp. 1–67. Elsevier.

SILVERMAN, B. (1986): *Density Estimation for Statistics and Data Analysis.* London: Chapman and Hall.

SØRENSEN, K. L., AND R. VEJLIN (2011): "From Mincer to AKM: Lessons from Danish Matched Employer-Employee Data," Working Paper.

SØRENSEN, T., AND R. VEJLIN (2009): "The importance of worker, firm and match fixed effects in wage regressions," Working Paper - University of Aarhus.

TOPEL, R. H., AND M. P. WARD (1992): "Job Mobility and the Careers of Young Men," *The Quarterly Journal of Economics*, 107(2), 439–479.

WEISS, Y. (1987): "The determination of life cycle earnings: A survey," in *Handbook of Labor Economics*, ed. by O. Ashenfelter, and R. Layard, vol. 1, chap. 11, pp. 603–640. Elsevier.

WOODCOCK, S. (2011): "Match Effects," Discussion Papers. Department of Economics, Simon Fraser University.

ZHANG, X., M. L. KING, AND R. J. HYNDMAN (2006): "A Bayesian approach to bandwidth selection for multivariate kernel density estimation," *Computational Statistics & Data Analysis*, 50, 3009–3031.

A. Figures

Figure 1: Nonparametrically estimated distribution of initial wages (left panel) and wage growth (right panel).

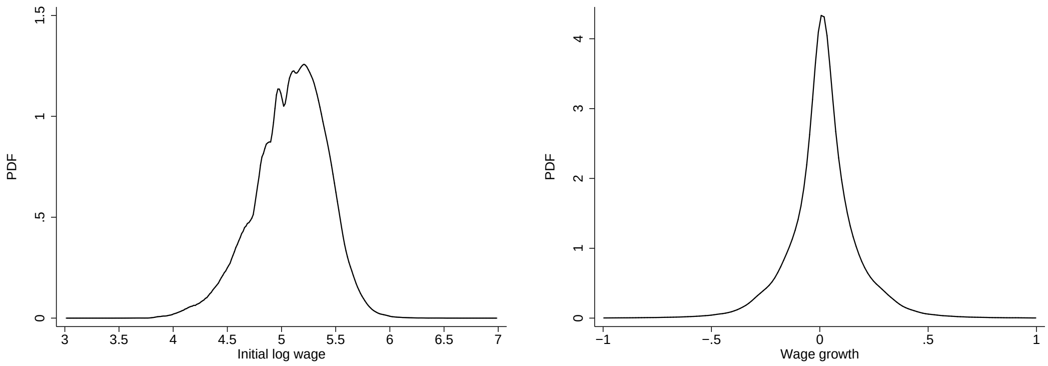


Figure 2: Expected wage growth over initial wages for educational subgroups.

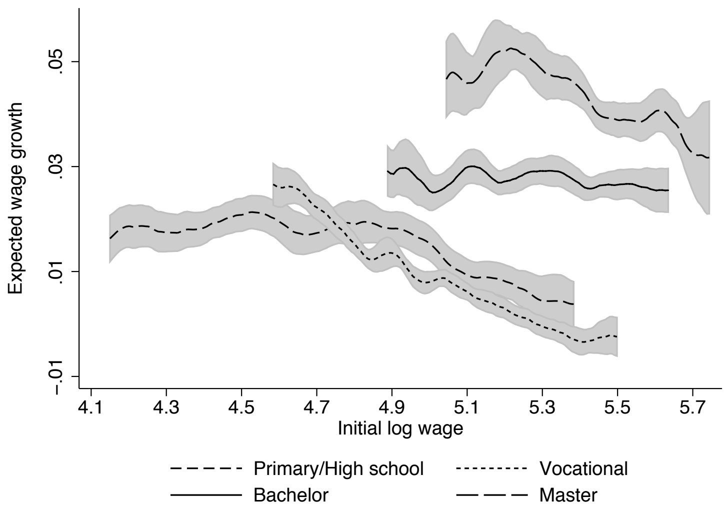


Figure 3: Expected wage growth over initial wages for full sample

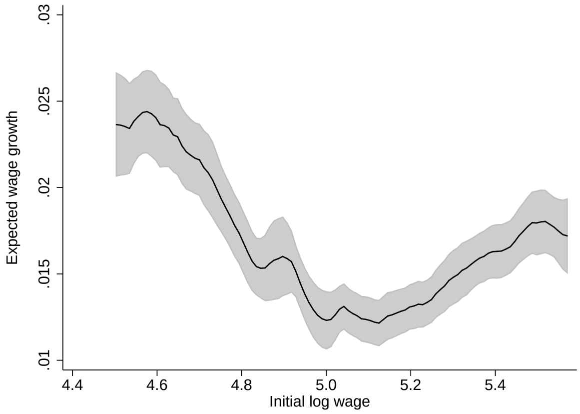


Figure 4: The full joint density of initial log wages and wage growth rotated 60, 150, 240 and 330 degrees, vocational education.

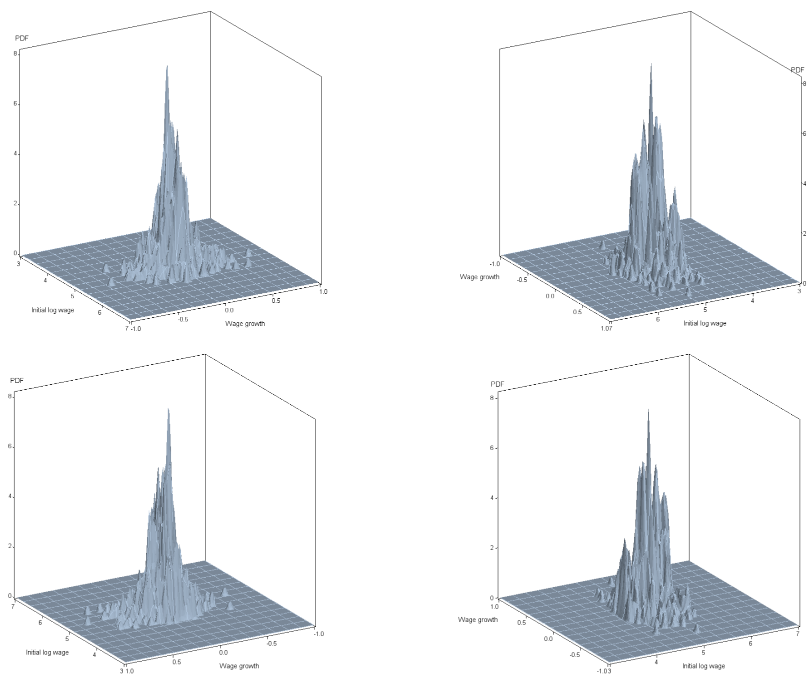


Figure 5: Estimated mean log wages per year after entry. Percentiles P5 to P95 refer to the respective initial wage distributions.

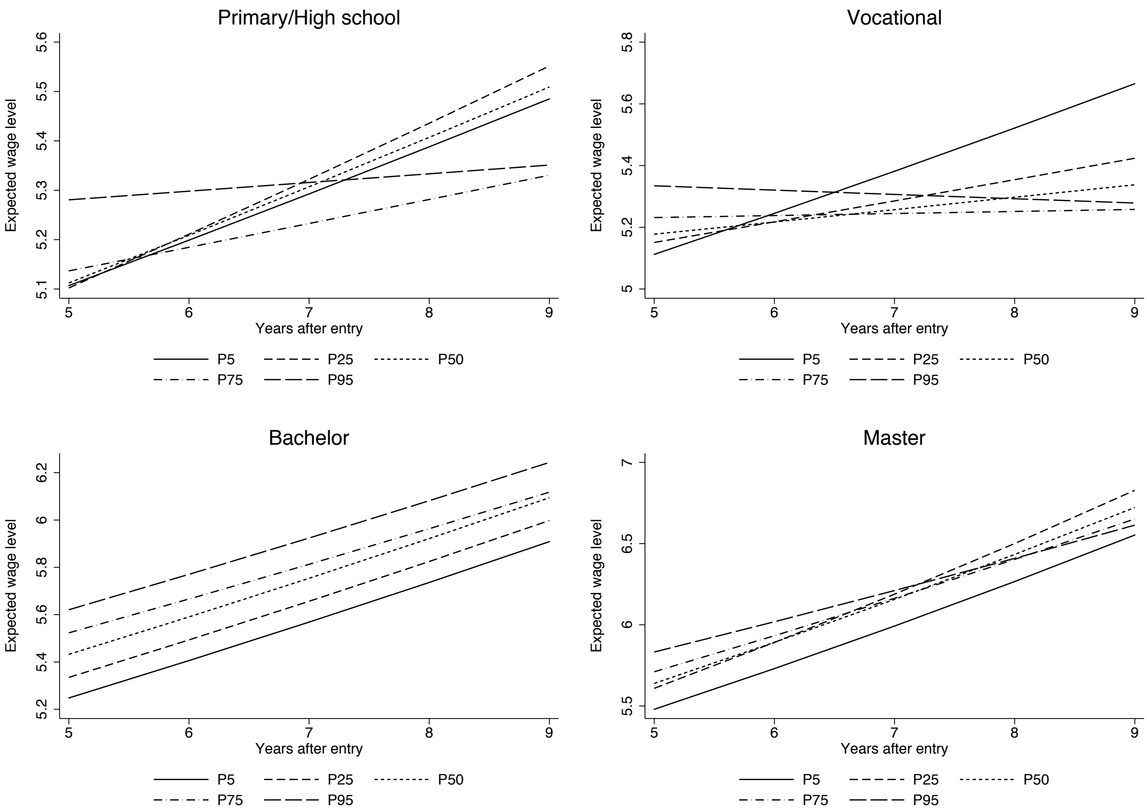


Figure 6: OLS estimates of log wage-experience profiles for different initial wages groups.

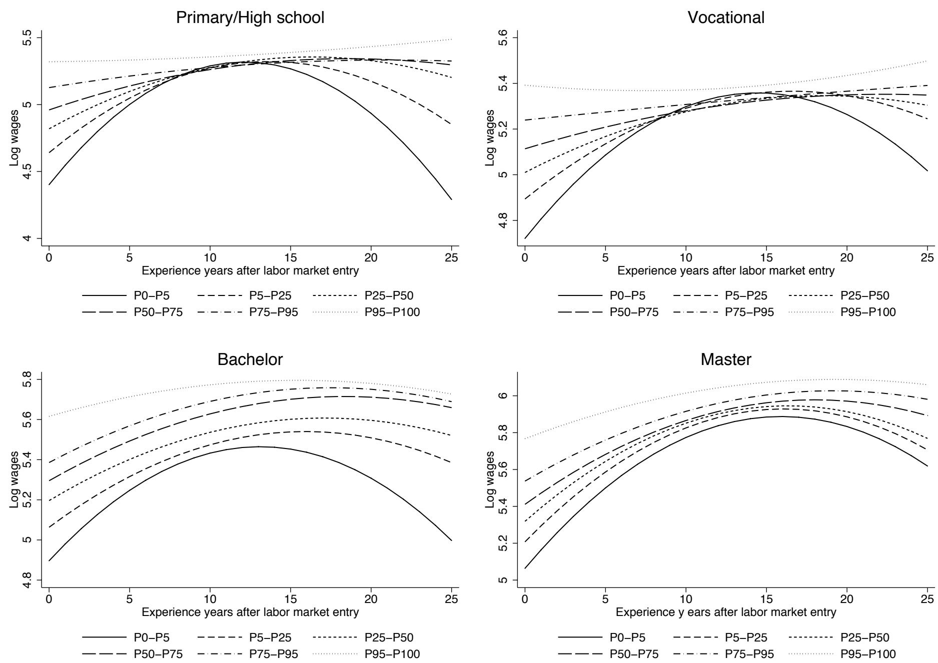


Figure 7: Expected wage growth divided on workers experiencing at least one 12 weeks unemployment spell between entry on the labor market and his 6th year.

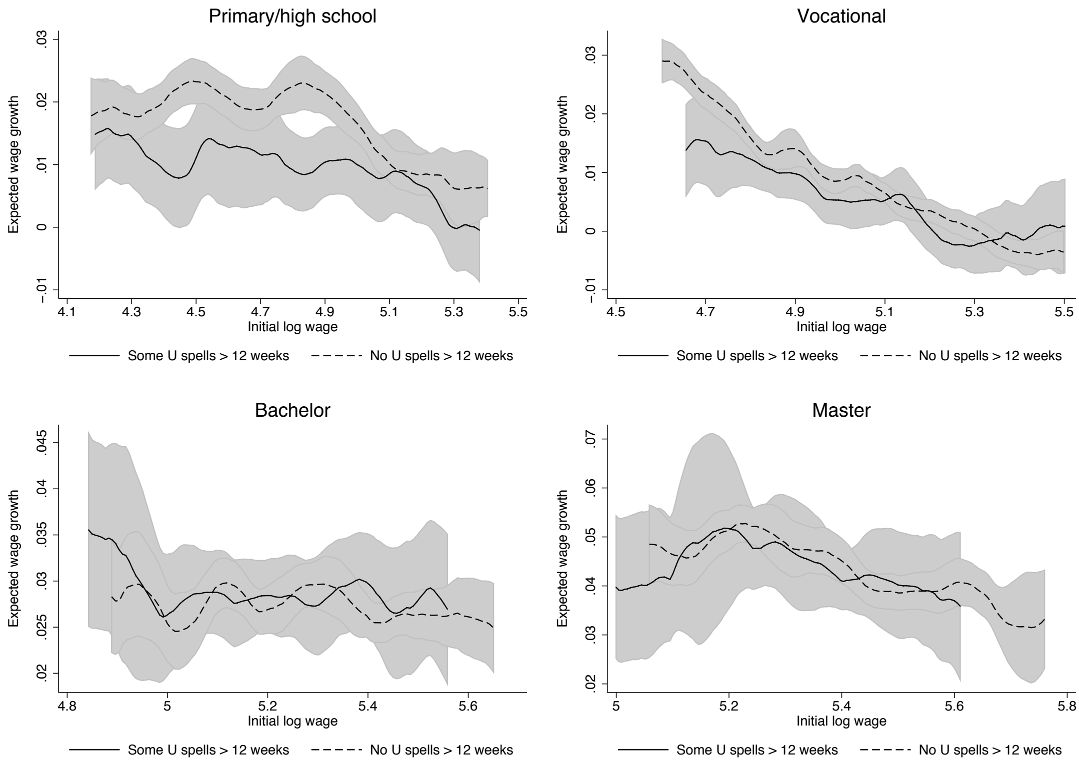


Figure 8: Expected wage growth over initial wages for stayers, job-to-job switchers, and job-to-nonemployment-to-job switchers, vocational education.

Figure 9: Expected wage growth over initial wages. Vocational educated workers divided into industries (upper panel), occupations (lower left panel) and entry (lower right panel).

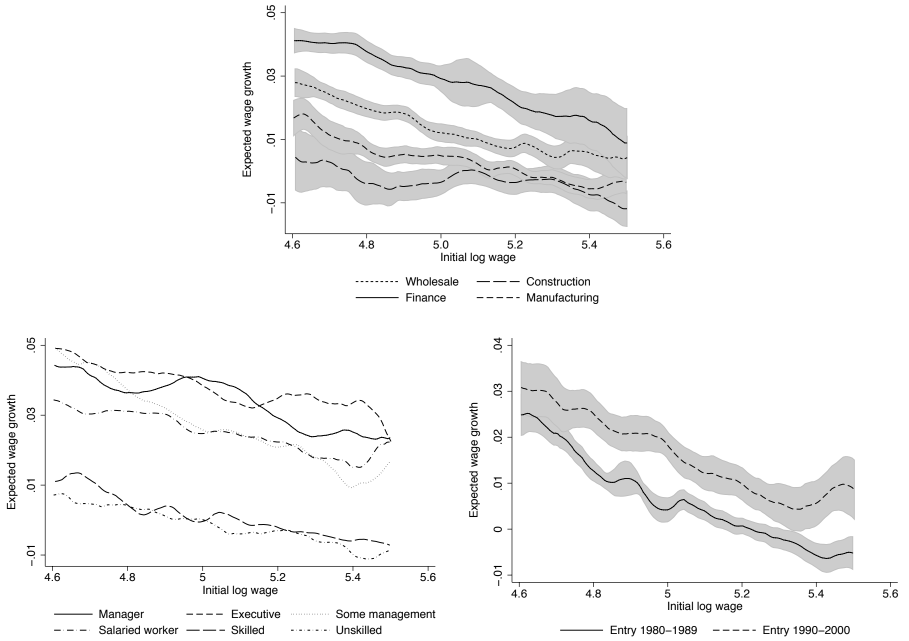
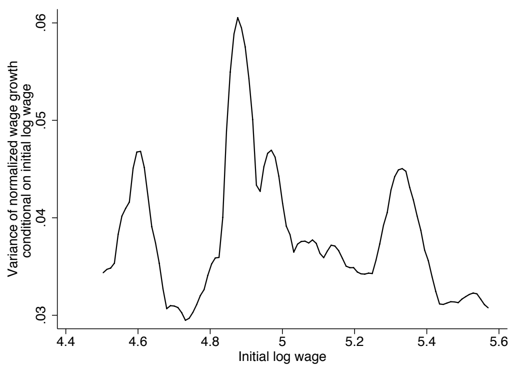


Figure 10: Nonparametrically estimated variance of normalized wage growth conditional on initial log wages, vocational education



B. Tables

Table 1: Covariations between initial errors and future error growth from an ARMA(1,2) model.

Coefficients	Primary / High school	Vocational	Bachelor	Master
μ	0.7308	0.6865	0.6835	-0.4017
ρ_1	-0.6994	-0.7801	-0.7759	0.6354
ρ_2	-0.0393	-0.3128	-0.3202	0.1314
σ_ν^2	0.0127	0.0102	0.0086	0.0120
$\text{Cov}(\varepsilon_0, \Delta\varepsilon_1)$	-0.01229	-0.01120	-0.00944	-0.00923
$\text{Cov}(\varepsilon_0, \Delta\varepsilon_2)$	-0.00061	-0.00290	-0.00251	-0.00236
$\text{Cov}(\varepsilon_0, \Delta\varepsilon_3)$	0.00006	0.00121	0.00105	-0.00063
$\text{Cov}(\varepsilon_0, \Delta\varepsilon_4)$	0.00004	0.00083	0.00072	0.00025
$\text{Cov}(\varepsilon_0, \Delta\varepsilon_5)$	0.00003	0.00057	0.00049	-0.00010
$\text{Cov}(\varepsilon_0, \Delta\varepsilon_6)$	0.00002	0.00039	0.00033	0.00004
$\text{Cov}(\theta, \gamma)^*$	-0.00201	-0.00248	-0.00006	-0.00087

ε is the error term estimated from equation (1).

Model: $\varepsilon_t = \mu\varepsilon_{t-1} + \nu_t + \rho_1\nu_{t-1} + \rho_2\nu_{t-2}$.

*Calculated from the estimates in table 4.

Table 2: Individuals in the sample.

	Primary/ High school	Vocational	Bachelor	Master	Full sample	Vocational educated: Stayers	Vocational educated: JtJ[†]	Vocational educated: JtNtJ[*]
1 obs	38,028	43,419	61,601	9,841	38,028	22,609	34,570	5,836
2 obs	29,794	42,610	17,720	719	29,794	22,432	10,375	399
3 obs	25,712	51,258	3,501	116	25,712	28,353	2,299	51
4 obs	146,337	73,549	407	15	146,337	43,863	287	10
Total	239,871	210,836	83,229	10,691	239,871	117,257	47,531	6,296

[†] Job-to-Job transitions.

[*] Job-to-Nonemployment-to-Job transitions.

Table 3: Descriptive statistics on initial wages and future wage growth.

	Primary/High school			Vocational			Bachelor			Master		
	w_0	Δw	$\frac{\Delta w}{\Delta E}$	w_0	Δw	$\frac{\Delta w}{\Delta E}$	w_0	Δw	$\frac{\Delta w}{\Delta E}$	w_0	Δw	$\frac{\Delta w}{\Delta E}$
Obs.	134,514	134,514	134,514	418,820	418,820	418,820	143,882	143,882	143,882	62,884	62,884	62,884
Mean	4.8170	0.0131	0.0145	5.0592	0.0075	0.0079	5.2769	0.0262	0.0276	5.4007	0.0413	0.0433
Std. dev.	0.3799	0.1587	0.2058	0.2711	0.1529	0.1985	0.2357	0.1430	0.1814	0.2127	0.1516	0.1959
P5	4.1751	-0.2406	-0.2572	4.6028	-0.2488	-0.2607	4.8809	-0.2064	-0.2101	5.0396	-0.1890	-0.1919
P25	4.5282	-0.0625	-0.0657	4.8669	-0.0633	-0.0652	5.1326	-0.0318	-0.0321	5.2676	-0.0203	-0.0204
Median	4.8587	0.0113	0.0118	5.0642	0.0077	0.0079	5.2900	0.0233	0.0234	5.4015	0.0356	0.0357
P75	5.1012	0.0858	0.0907	5.2487	0.0789	0.0816	5.4335	0.0863	0.0871	5.5316	0.1045	0.1051
P95	5.3992	0.2776	0.2990	5.5034	0.2649	0.2792	5.6383	0.2655	0.2730	5.7496	0.2889	0.2963

	Full sample			Vocational educated: Stayers			Vocational educated: Job-to-Job			Vocational educated: Job-to-Nonemployment-to-Job		
	w_0	Δw	$\frac{\Delta w}{\Delta E}$	w_0	Δw	$\frac{\Delta w}{\Delta E}$	w_0	Δw	$\frac{\Delta w}{\Delta E}$	w_0	Δw	$\frac{\Delta w}{\Delta E}$
Obs.	760,100	760,100	760,100	327,984	327,984	327,984	63,365	63,365	63,365	6,827	6,827	6,827
Mean	5.0858	0.0148	0.0157	5.0570	0.0059	0.0067	5.0631	0.0182	0.0174	5.0934	-0.0001	-0.0040
Std. dev.	0.3296	0.1524	0.1968	0.2709	0.1287	0.1398	0.2742	0.2260	0.2578	0.2673	0.2199	0.3544
P5	4.4936	-0.2370	-0.2478	4.6004	-0.2148	-0.2189	4.5993	-0.3629	-0.3992	4.6407	-0.3595	-0.5301
P25	4.8824	-0.0536	-0.0551	4.8663	-0.0545	-0.0559	4.8681	-0.1166	-0.1240	4.9095	-0.1270	-0.1689
Median	5.1140	0.0142	0.0145	5.0636	0.0065	0.0067	5.0661	0.0226	0.0236	5.0943	-0.0008	-0.0009
P75	5.3175	0.0841	0.0866	5.2454	0.0668	0.0685	5.2529	0.1577	0.1656	5.2772	0.1243	0.1628
P95	5.5702	0.2691	0.2828	5.4998	0.2254	0.2343	5.5106	0.3815	0.4115	5.5296	0.3635	0.5102

Table 4: Regression of log wage growth years 6 to 7, 7 to 8, 8 to 9 and 9 to 10 on initial log wages, subsamples.

	Primary/High school		Vocational		Bachelor		Master	
Model	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
$\Delta w_{it} = \alpha + \beta w_{i0} + \varepsilon_{it}$	-0.0105***	-0.0110***	-0.0318***	-0.0322***	-0.0047***	-0.0025	-0.0169***	-0.0156***
	(0.0012)	(0.0015)	(0.0009)	(0.0011)	(0.0017)	(0.0021)	(0.0030)	(0.0039)
$\frac{\Delta w_{it}}{\Delta AE_{it}} = \alpha + \beta w_{i0} + \varepsilon_{it}$	-0.0123***	-0.0139***	-0.0337***	-0.0353***	-0.0043**	-0.0010	-0.0191***	-0.0193***
	(0.0015)	(0.0021)	(0.0011)	(0.0019)	(0.0020)	(0.0030)	(0.0035)	(0.0049)
Observations	134,514	134,514	418,820	418,820	143,882	143,882	62,884	62,884
Individuals	46,477	46,477	129,655	129,655	43,828	43,828	19,911	19,911

The standard errors in parentheses are robust.

(1) Unweighted regressions.

(2) The regressions are weighted such that each individual have equal weights.

***, **, * indicates significance at levels 1, 5 and 10 percent respectively.

Table 5: Nonparametrically estimated expected wage growth and residual wage growth for different distributional initial wage levels.

Expected wage growth	Primary/ High school	Vocational	Bachelor	Master
$E(\gamma_i \mid \theta_i = P5)$	0.0180	0.0260	0.0301	0.0457
$E(\gamma_i \mid \theta_i = P25)$	0.0213	0.0130	0.0297	0.0504
$E(\gamma_i \mid \theta_i = P50)$	0.0191	0.0077	0.0292	0.0449
$E(\gamma_i \mid \theta_i = P75)$	0.0093	0.0013	0.0259	0.0389
$E(\gamma_i \mid \theta_i = P95)$	0.0036	-0.0026	0.0255	0.0220
$E(\gamma_{i\mid\theta_i=P95} - \gamma_{i\mid\theta_i=P50})$	-0.0155	-0.0103	-0.0037	-0.0229
$E(\gamma_{i\mid\theta_i=P75} - \gamma_{i\mid\theta_i=P50})$	-0.0098	-0.0064	-0.0033	-0.0060
$E(\gamma_{i\mid\theta_i=P25} - \gamma_{i\mid\theta_i=P50})$	0.0022	0.0053	0.0006	0.0055
$E(\gamma_{i\mid\theta_i=P5} - \gamma_{i\mid\theta_i=P50})$	-0.0011	0.0184	0.0009	0.0008

Table 6: Regression of log wage growth years 6 to 7, 7 to 8, 8 to 9 and 9 to 10 on initial log wages for vocational educated, labor market transitions.

	Stayers		J-t-J		J-t-N-t-J	
Model	(1)	(2)	(1)	(2)	(1)	(2)
$\Delta w_{it} = w_{i0} + \varepsilon_{it}$	-0.0261***	-0.0259***	-0.0551***	-0.0543***	-0.0255**	-0.0265**
	(0.0008)	(0.0010)	(0.0033)	(0.0040)	(0.0100)	(0.0124)
$\frac{\Delta w_{it}}{\Delta AE_{it}} = w_{i0} + \varepsilon_{it}$	-0.0259***	-0.0261***	-0.0586***	-0.0578***	-0.0352**	-0.0384**
	(0.0009)	(0.0012)	(0.0038)	(0.0049)	(0.0155)	(0.0186)
Observations	327,984	327,984	63,365	63,365	6,827	6,827
Individuals	117,257	117,257	47,531	47,531	6,296	6,296

The standard errors in parentheses are robust.

(1) Unweighted regressions.

(2) The regressions are weighted such that each individual have equal weights.

***, **, * indicates significance at levels 1, 5 and 10 percent respectively.

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