DISCUSSION PAPER SERIES

IZA DP No. 2773

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May 2007

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zur Zukunft der Arbeit
Institute for the Study
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ABSTRACT

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We analyze the joint determination of wage levels, wage growth and firm tenure. Our analysis is built on estimating a reduced form for tenure, a structural wage level equation and a structural wage growth equation. We disentangle returns to a latent type variable from estimates of general returns to tenure and wage gains from job changes. This type is related to unobservable match quality that is allowed to vary over time and to be correlated with the returns to tenure. The obtained results for Germany indicate that the type plays a crucial role in the remuneration of employees. Those types who change jobs more often obtain steeper wage profiles but earn less on average.

JEL Classification: J31

Keywords: wage growth, returns to tenure, unobserved heterogeneity, control function approach, nonseparable model

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1. Introduction

Whether average returns to seniority are substantial is of central interest to economists because they are an important part of the costs of mobility between jobs. Importantly, firm tenure and wages are most likely to be jointly determined. For a given level of general experience the size of these returns is related both to the specificity of human capital that is accumulated in a job (Miller, 1984; Gathmann and Schoenberg, 2005) and to the incentives that are set by firms through deferred earnings (Carmichael, 1989; Hutchens, 1989). In this paper, we estimate the population average returns to tenure and characterize the joint determination of wages and tenure.

For empirical work, it is often the case that detailed information on individual, job and firm characteristics is not available.[1] Therefore, the error term in a wage equation is likely to be positively correlated with tenure so that a regression of wages on tenure yields upward biased estimates of the effect of firm tenure on wages. This is supported by the theoretical model by Jovanovic (1979) and search models such as the one by Burdett (1978) which imply that a high-productive job match, once found, is unlikely to end.[2] This result is generally confirmed in empirical studies (Topel and Ward, 1992; Farber, 1994).

One approach that has been taken to deal with the endogeneity of tenure that arises from the presence of a fixed job-match component in the wage equation is to exploit the within-job variation of tenure. Altonji and Shakotko (1987) calculate the deviation of observed tenure from its mean and use it as the principal instrument for tenure which is, by construction, uncorrelated

[1] Large data sets linking employer and employee information have only recently become available (e.g. Abowd, Kramarz, and Margolis, 1999). However, even in these data sets information on the productivity of the job match and the employment contract is not available.

[2] Jovanovic (1979) argues that a worker's productivity in a current job is not known *ex ante* but revealed over time. His model implies that in equilibrium, at each moment in time a worker is paid his expected marginal product conditional upon all available information at that time. Workers stay in jobs in which their idiosyncratic productivity is revealed to be high over time and quit jobs in which their productivity turns out to be low. This implies that average wages grow as tenure increases since unproductive workers are laid off. Burdett (1978) proposes a search model in which individuals perform costly search while being employed if their wage is below some threshold wage. This model implies that the average wage increases with age, as job changes occur. When individuals become older, less perform search and consequently, tenure and age are positively related. This in turn implies that for a given age group, tenure and wages are positively related.

with the fixed job-match component.[3,4] As an alternative to this IV approach Topel (1991) implements a two-stage procedure which is just as well built on the within-job variation of tenure. In the first stage, he estimates within-job wage growth from first differences using the subsample of individuals who do not change firms. Using these first stage estimates, he calculates initial wages and estimates the return to initial experience on the job in the second stage.[5]

A third approach is to exploit information on firm closures (Neal, 1995, e.g.). Assuming that a firm closure is exogenous conditional on observables it could be used in order to identify a subgroup of individuals whose tenure is exogenously set to zero. For those individuals, the returns to tenure can in principle be estimated by OLS once all individuals are equally likely to find a new job. Therefore, arguably, this approach has advantages over the one proposed by Topel (1991), which hinges on the assumption that individual firm changes, rather than firm closures, are exogenous conditional on observables. Still, the assumption has to be made that the returns to tenure for newly formed job matches are unrelated to their survival probability.

All above mentioned approaches hinge crucially on the assumption that there are no time varying wage components that are correlated with tenure. However, this assumption may not hold, as jobs may not only be 'search' goods, but also 'experience' goods. In particular, workers and employers may learn about the quality of a job match over time. If wages reflect the productivity of the match, job mobility and wages are related (Jovanovic, 1979; Farber, 1994). Also, if deferred earnings are used as an incentive or sorting mechanism (Carmichael, 1989; Hutchens, 1989) it is likely that the match specific components of the wage equation vary over

[3] An alternative approach to eliminate the bias would be to introduce fixed effects for each worker-job pair. This amounts to a within-job-worker estimator similar in nature to the estimator proposed by Altonji and Shakotko (1987). However, this fixed effects estimator would not be able to recover the returns to experience from the data.

[4] A similar instrument is used by Abraham and Farber (1987). In Section 2, we comment on this IV approach and compare it to the techniques used in this paper. For applications of the IV approach see, for instance, Mascle-Allemand and Tritah (2005) comparing wage profiles between states with or without employment protection legislation, Bratsberg and Terell (1997) who analyze the difference in wage growth between young black and white men, and Dustmann and Pareira (2005) who investigate the wage growth in Germany and the UK.

[5] Intuitively speaking, he sets tenure to zero by subtracting within-job wage growth from observed wages. In an application of this method Connolly and Gottschalk (2001) uncover different tenure effects for different levels of education.

time as information is revealed. Therefore, in this paper, we aim at characterizing the unobserved dependence between wages and tenure by estimating identifiable features of a correlated random coefficients model which allows for unobserved dependence between tenure and wages in a general way. In contrast to the IV approach we exploit within-job variation in firm tenure to recover the idiosyncratic difference between observed and expected tenure which we then use to characterize the dependence of wages on unobserved match characteristics that vary over time. If this difference is positive we say that we face a good *type*. This notion is based on the idea that good job matches survive (Hall, 1982; Topel and Ward, 1992).

We implement this by estimating a reduced form for tenure which is used to recover the reduced form error term. This variable is then included into the wage equation in order to disentangle population average returns to tenure from match specific returns. In our specification, we explicitly allow for interaction effects between unobservable factors determining tenure and observable covariates in the structural wage equation.[6]

Our main findings are the following. First, population average returns are positive but low. Second, returns are heterogeneous and correlated with tenure. In particular, good types (matches) have lower returns to tenure but earn more on average. This is well in line with findings by Brown, Falk, and Fehr (2004). They conducted an experiment in which they examine the impact of effort levels on the length of relational contracts. Their results demonstrate that productive workers are characterized by longer tenure than their unproductive colleagues and a parting of rents. Third, after controlling for the endogeneity of tenure, and therefore job changes, we find that wage growth is largest for those individuals who stayed exceptionally long in their previous jobs. This is also well in line with previous findings in the literature. For example, Topel and Ward (1992) analyze wage growth and job mobility in the early phase of a career. They document that in this phase, job changes occur frequently and are associated with

[6]Dustmann and Meghir (2005) apply a control function approach in order to control for the additional endogeneity of the time it takes to find a new job after a firm closure. In addition, we carefully characterize the impact of a latent type variable on wages. Both analyses are for German data. However, Dustmann and Meghir (2005) use data from German Social Security records (IAB data), while we use data from the German Socio Economic Panel (GSOEP). Therefore, both sets of results can be seen as complementary.

large wage gains. They find that the average rate of job changing and the average wage gain declines with age and tenure.[7]

The remainder of the paper is organized as follows. In Section 2, we present the econometric model. We describe our data set in Section 3. Section 4 presents specifications and results for wage levels, Section 5 applies the approach to a wage growth equation, and Section 6 concludes. Appendix 1 and 2 contain additional tables and figures.

2. Econometric Approach

2.1. Econometric Model

We model the real log hourly wage, y_{ijt}, of individual i in firm j at time t as a function of tenure, t_{ijt}, exogenous covariates, x_{ijt}, and a structural vector valued error term, ε_{ijt}, which will be allowed to be correlated with tenure. We include the individual's age into the wage equation in order to contrast the returns to tenure to the returns to general experience. We decided to include age rather than actual experience since the latter is likely to be endogenous.[8]

For simplicity, we present the model with only a linear term in tenure and one exogenous covariate, say age, denoted by x_{ijt}.[9] Under this simplifying assumption our wage equation is given by

$$y_{ijt} = \beta_1(\varepsilon_{ijt}) + \beta_2(\varepsilon_{ijt}) \cdot t_{ijt} + \beta_3(\varepsilon_{ijt}) x_{ijt}. \tag{1}$$

This is a correlated random coefficient model with random coefficients $\beta_1(\varepsilon_{ijt})$, $\beta_2(\varepsilon_{ijt})$ and $\beta_3(\varepsilon_{ijt})$ which are functions of the structural error term. We like to think of this vector valued error term as being composed of several components including a fixed individual specific error

[7] See also Johnson (1978) for a theoretical argument and Kletzer (1989) for a study that uses the Displaced Worker Survey.

[8] Additionally, an endogenous control for general experience would possibly influence the coefficient of the tenure variable. See also Altonji and Shakotko (1987) for details.

[9] The generalization to the specification we estimate is trivial.

component, ε_i, a fixed job match specific error component, ε_{ij}, an individual specific transitory component, ε_{it}, a transitory match specific component, ν_{ijt}, and an economy wide wage disturbance, ε_t.

The specification in (1) nests a generalized Mincer (1974) type wage equation as the special case in which $\beta_1(\varepsilon_{ijt}) = \beta_1 + \varepsilon_i + \varepsilon_{ij} + \varepsilon_{it} + \varepsilon_t + \nu_{ijt}$ and $\beta_k(\varepsilon_{ijt}) = \beta_k$ for $k = 2, 3$. Altonji and Shakotko (1987) estimate the returns to tenure for such an equation using instrumental variable (IV) techniques. In particular, they use the variation of tenure and its square over a given job match, $\tilde{t}_{ijt}$ and $\tilde{t}^2_{ijt}$, as IVs for a linear and a quadratic tenure term.[10] Formally, denote the average of i's tenure in firm j in the sample by $\overline{t_{ij}}$. Then, $\tilde{t}_{ijt} \equiv t_{ijt} - \overline{t_{ij}}$ is the deviation from this average, and $\tilde{t}^2_{ijt} \equiv t^2_{ijt} - \overline{t^2_{ij}}$ is the deviation of the squared tenure from its average. These instruments are, by construction, uncorrelated with individual match quality, ε_{ij} and individual specific components, ε_i, since $\tilde{t}_{ijt}$ sums to 0 over the sample years in which individual i is in job j and ε_i as well as ε_{ij} are constant for i in job j. Crucially, Altonji and Shakotko (1987) assume that $\tilde{t}_{ijt}$ is uncorrelated with time varying components, ε_{it}, ε_t and ν_{ijt}, of the error term in the wage equation.

Our approach is more general in several ways. First, we do not restrict the slope coefficients $\beta_2(\varepsilon_{ijt})$ and $\beta_3(\varepsilon_{ijt})$ to be degenerate. Second, we will allow the intercept, $\beta_1(\varepsilon_{ijt})$ and the effect of tenure on wages, $\beta_2(\varepsilon_{ijt})$, to be correlated with tenure. This allows for a considerable amount of unobserved heterogeneity.

Let

$$t_{ijt} = \gamma_1 + \gamma_2 \cdot \tilde{t}_{ijt} + \gamma_3 x_{ijt} + \eta_{ijt} \tag{2}$$

be a stylized version of the reduced form for tenure. Here, we include $\tilde{t}_{ijt}$, the instrument of Altonji and Shakotko (1987), on the right hand side so that η_{ijt} is the idiosyncratic—possibly time varying—match specific component of individual tenure that is orthogonal to the within

[10]Once a quadratic function in tenure is estimated, two instruments are of need.

job variation of tenure. Note that $\tilde{t}_{ijt}$ is not used as an instrument here. We assume $\mathbb{E}[\eta_{ijt}] = 0$.[11] If it is positive, then we face a type which is, at the time of the observation, longer than expected in a given firm. The model is flexible because it allows ε_{ijt} and η_{ijt} to be correlated and thereby allows tenure and the unobserved components of the wage equation to depend on each other. Under the conditions stated below this error term can be consistently estimated which allows us to investigate the dependence of wages on the type.

As for *stochastic restrictions*, we assume that the observations are independently distributed across ijt.[12] Moreover, we assume that the vector of unobservables, $(\varepsilon'_{ijt}, \eta_{ijt})'$, is mean independent of the vector of observables, $(\tilde{t}_{ijt}, x_{ijt})$. Importantly, unlike in the IV case, ε_{ijt} and η_{ijt} are allowed to be correlated.

Finally, we assume that

$$\begin{cases} \mathbb{E}\left[\beta_k(\varepsilon_{ijt}) \middle| \eta_{ijt}\right] = \bar{\beta}_k + \phi_k \cdot \eta_{ijt} & \text{for } k = 1, 2 \\ \mathbb{E}\left[\beta_3(\varepsilon_{ijt}) \middle| \eta_{ijt}\right] = \bar{\beta}_3 \end{cases} \tag{3}$$

for some constants ϕ_k.[13] In the empirical analysis, we show evidence for such a dependence of the expected returns to tenure on the type.

2.2. Wage Levels: Parameters of Interest and Identification

In our analysis, we are interested in the expected value of wages given covariates and the reduced form error term, $\mathbb{E}[y_{ijt}|x_{ijt}, \eta_{ijt}]$. Moreover, we are interested in average partial effects, which are given by $\bar{\beta}_1$, $\bar{\beta}_2$ and $\bar{\beta}_3$ in our model, as well as the dependence of the coefficients

[11] This is a normalization given that we include an intercept term.

[12] This assumption is stronger than it is actually needed. For example, our estimator would still be consistent, though not efficient, if η_{ijt} was in fact serially correlated across t for a given i and j. In our analysis, since the panel is unbalanced and very short for a substantial part of the observations, techniques other than random effects panel estimators were not feasible. However, standard errors will be bootstrapped so that the loss we risk is mainly a loss of efficiency.

[13] This assumption could easily be relaxed. For example, the linear functional form could be replaced by higher order polynomials and more coefficients could be allowed to depend on the reduced form error term. However, we experienced for our data that a relatively simple specification worked best.

on the reduced form error term, i.e. the constants ϕ_1 and ϕ_2. Imbens and Newey (2003) show that those features of the structural wage equation are identified from observations once we control for the endogeneity of tenure by including the reduced form error into the wage equation.[14] Essentially, invertibility of the reduced form equation in its scalar disturbance ensures identification. In our case, this condition is satisfied since (2) is strongly increasing in its error term.

In particular, it follows directly from (1), the stochastic restrictions, and (3) that[15]

$$\begin{aligned}
(4) \qquad & \mathbb{E}[y_{ijt}|t_{ijt}, x_{ijt}, \eta_{ijt}] \\
&= \mathbb{E}\Big[\beta_1(\varepsilon_{ijt}) + \beta_2(\varepsilon_{ijt}) \cdot t_{ijt} + \beta_3(\varepsilon_{ijt})x_{ijt}\Big| t_{ijt}, x_{ijt}, \eta_{ijt}\Big] \\
&= \left(\bar{\beta}_1 + \phi_1 \cdot \eta_{ijt}\right) + \left(\bar{\beta}_2 + \phi_2 \cdot \eta_{ijt}\right) \cdot t_{ijt} + \bar{\beta}_3 x_{ijt}
\end{aligned}$$

so that estimates of $\bar{\beta}_1, \bar{\beta}_2, \bar{\beta}_3$, ϕ_1 and ϕ_2 can be obtained from a regression of y_{ijt} on a constant term, tenure, age, the fitted reduced form error term, as well as the interaction thereof with tenure. This proceeding requires that the rank of the matrix of right hand side variables to be 5, a condition which holds in our data.

Finally, an estimate for the expected value of wages given covariates can be obtained by integrating over the sample distribution of the fitted reduced form error term. Trivially, since the mean of the reduced form error term is zero by assumption, we have that by the stochastic restrictions $\bar{\beta}_1$ and $\bar{\beta}_2$ are the population average intercept and the population average return to tenure, respectively.

[14] They show nonparametric identification of several features of the outcome equation and propose a nonparametric two step series estimator. This is in contrast to Newey, Powell, and Vella (1999) who consider additive structures. Blundell and Powell (2003) survey the recent literature for such models and form the terminology "average structural function" for a prominent identifiable feature which is linked to the average treatment effect parameter in program evaluation. Earlier work by Garen (1984) is more similar to our specification but is built on normality as an identifying assumption.

[15] For every right hand side variable, say e.g. x_{ijt}, we have that

$$\mathbb{E}[\beta_3(\varepsilon_{ijt}) \cdot x_{ijt}|t_{ijt}, x_{ijt}, \eta_{ijt}] = \bar{\beta}_3 x_{ijt}$$

by the uncorrelatedness between x_{ijt} and ε_{ijt} conditional on η_{ijt}.

2.3. Difference to IV

Only recently, considerable progress has been made in understanding what instrumental variables techniques estimate if the wage equation is given by a random coefficient model such as the one in (1). Yitzhaki (1989), Angrist, Graddy, and Imbens (2000) and Heckman, Urzua, and Vytlacil (2006) show that IV identifies a weighted average of the individual returns to tenure.[16] In general, the weights depend on the instrument that is used. In case of the Altonji and Shakotko (1987) instrument, the within job variation of tenure, weight is put on the returns of individuals with substantial within job variation of tenure which occurs, most likely, in job matches that survive. We find that those individuals exhibit lower returns to tenure. As IV estimation overweights their returns respective estimates are downward biased relative to the population average returns to tenure.

Heckman and Vytlacil (1998) show that under the additional assumption that η_{ijt} is independent of ε_{ijt} the population average return to tenure can be estimated using instrumental variables techniques. However, this assumption is unlikely to hold once there are time varying components of the wage equation which are correlated with tenure conditional on the instrument. We find evidence for such a violation in our data.

In stark contrast to IV, the control function approach that is taken in this paper is built on recovering the idiosyncratic difference between observed and expected tenure which is then used to control for the components of tenure that are correlated with other features of the wage equation. Precisely this correlation prohibits IV estimation.

2.4. Wage Growth

Finally, we show how the framework can be used to characterize wage growth over time, controlling for the endogeneity of job changes by relating it to the type of the employee. We have

[16]See also Card (1999, 2001) for a discussion of the difference between IV and control function techniques.

established in (4) that

$$
\begin{aligned}
&\mathbb{E}[y_{ijt}|t_{ijt}, x_{ijt}, \eta_{ijt}] \\
&\qquad = \mathbb{E}\Big[\beta_1(\varepsilon_{ijt}) + \beta_2(\varepsilon_{ijt}) \cdot t_{ijt} + \beta_3(\varepsilon_{ijt})x_{ijt}\Big| t_{ijt}, x_{ijt}, \eta_{ijt}\Big] \\
&\qquad = \left(\bar{\beta}_1 + \phi_1 \cdot \eta_{ijt}\right) + \left(\bar{\beta}_2 + \phi_2 \cdot \eta_{ijt}\right) \cdot t_{ijt} + \bar{\beta}_3 x_{ijt}.
\end{aligned}
$$

Taking first differences yields

$$
\begin{aligned}
&\mathbb{E}[y_{ijt} - y_{ikt-1}|t_{ijt}, t_{ikt-1}, x_{ijt}, x_{ikt-1}, \eta_{ijt}, \eta_{ikt-1}] \\
&\quad = \left(\bar{\beta}_1 + \phi_1 \cdot \eta_{ijt}\right) + \left(\bar{\beta}_2 + \phi_2 \cdot \eta_{ijt}\right) \cdot t_{ijt} + \bar{\beta}_3 x_{ijt} \\
&\qquad - \left(\bar{\beta}_1 + \phi_1 \cdot \eta_{ikt-1}\right) - \left(\bar{\beta}_2 + \phi_2 \cdot \eta_{ikt-1}\right) \cdot t_{ikt-1} - \bar{\beta}_3 x_{ikt-1} \\
&\quad = \phi_1 \cdot (\eta_{ijt} - \eta_{ikt-1}) + \bar{\beta}_2 \cdot (t_{ijt} - t_{ikt-1}) \\
&\qquad + \phi_2 \cdot (\eta_{ijt} t_{ijt} - \eta_{ikt-1} t_{ikt-1}) + \bar{\beta}_3 (x_{ijt} - x_{ikt-1}).
\end{aligned}
\tag{5}
$$

Note that the notation that is used here allows for the case in which individual i works in firm j in period t and in firm k in $t-1$. If $j = k$, i.e. if i does not change firms from $t-1$ to t, $t_{ijt} - t_{ikt-1} = 1$. Otherwise, $t_{ijt} - t_{ikt-1} = 1 - t_{ikt-1}$, assuming that individuals can only change jobs between periods. Then, (5) is equal to

$$
\phi_1 \cdot (\eta_{ijt} - \eta_{ikt-1}) + \bar{\beta}_2 (1 - \chi_{it} t_{ikt-1}) + \phi_2 \cdot (\eta_{ijt} t_{ijt} - \eta_{ikt-1} t_{ikt-1}) + \bar{\beta}_3 (x_{ijt} - x_{ikt-1}),
$$

where χ_{it} is an indicator variable for the event that i changed his job between $t-1$ and t. Denoting first differences by Δ and dropping the firm subscript, we get for the wage growth equation

$$
\mathbb{E}[\Delta y_{it}|\Delta\eta_{it}, \chi_{it} t_{ikt-1}, \Delta(\eta_{it} t_{it})] = \phi_1 \cdot \Delta\eta_{it} + \bar{\beta}_2 (1 - \chi_{it} t_{ikt-1}) + \phi_2 \cdot \Delta(\eta_{it} t_{it}) + \bar{\beta}_3 \cdot \Delta x_{it}. \tag{6}
$$

In principle, Δx_{it} could be a vector containing a host of explanatory variables. In Section 5, we estimate a flexible functional form that allows for wage premia that are associated with a job change.

Here, we are interested in characterizing wage growth that is associated with a job change, given the type of an individual which is related to $(\eta_{ikt-1}, \eta_{ijt})$. Each component of this tuple can be interpreted as the deviation of i's tenure from its expected value conditional on observables. For example, if we face a good type in the sense of $\eta_{ijt} > 0$, and this good type changes his job between $t-1$ and t, and this job change cannot be predicted, then η_{ikt-1} will be greater than η_{ijt} with $\eta_{ijt} < 0$ so that $\Delta\eta_{it}$ will be negative. Therefore, if such a good type benefits from this job change, ϕ_1 must be negative. Moreover, $\phi_2 > 0$ because $\Delta(\eta_{it} t_{it}) > 0$ since $\eta_{ijt} t_{ijt} > 0$ and $\eta_{ikt-1} t_{ikt-1} < 0$. $\bar{\beta}_2$ can be interpreted as the constant term if individuals do not change jobs so that we expect it to be nonnegative.

It follows from the identification result in Subsection 2.2 that (6) can directly be estimated from observations. Hence, the parameters of interest are identified once the matrix of right hand side variables, $\Delta\eta_{it}$, $(1 - \chi_{it} t_{ikt-1})$, $\Delta(\eta_{it} t_{it})$, Δx_{it}, is of rank 4, a condition that holds in our data.

3. Data and Descriptive Evidence

We use data from the German Socio-Economic Panel (GSOEP), a longitudinal database that started in 1984. We use all samples up to sample F. We only select privately employed men from West Germany as women and individuals working in East Germany decide upon their career based on systematically different circumstances. The outcome of interest is the real log hourly wage, deflated by the consumer price index. Furthermore, we focus only on individuals who are older than 28 and younger than 60 and whose weekly hours in their work contract is at least 35. Moreover, we require them to work for at least 350 hours in a given year.[17] We select observations with at least one year of firm tenure because we fear that wages are measured with

[17] That is, we drop observations whose weekly hours in their work contract exceeds 35 but work only for several weeks in a given year.

Variable	Mean	Std.	Min.	Max.
annual income in Euros of year 2000	34,266.4	18,701.2	613.5	697,524
annual hours worked	2,219.9	436.8	352	5,196
log hourly wage in Euros of year 2000	2.7	0.4	-0.8	6.3
age	42.1	8.9	28	60
tenure	14	9	1	47
year	1993.9	6	1984	2003
number of obs. per individual	5.8	5	1	20
number of firms per individual	1.1	0.4	1	6

6,577 individuals and 38,041 observations across individuals and time.

Table 1: Summary statistics.

error in years firm tenure is equal to zero.[18,19] Some summary statistics are reported in Table 3.[20]

Appendix 1 contains descriptive evidence. Here, we shall only investigate whether job changes are associated with wage growth in our data. Figure 1 contains estimates of the average annual wage growth for those individuals who changed the firm (inter-firm wage growth) and those who did not (intra-firm wage growth). Average wage growth is plotted against previously observed tenure, controlling for differences in age. It shows that the wage gain from changing jobs relative to staying in a given job is the higher the longer an individual has worked in a given firm. Clearly, job changes are endogenous as individuals only change jobs once such a change is advantageous (Johnson, 1978; Topel and Ward, 1992). Therefore, we shall abstain from giving this relationship a causal interpretation.[21]

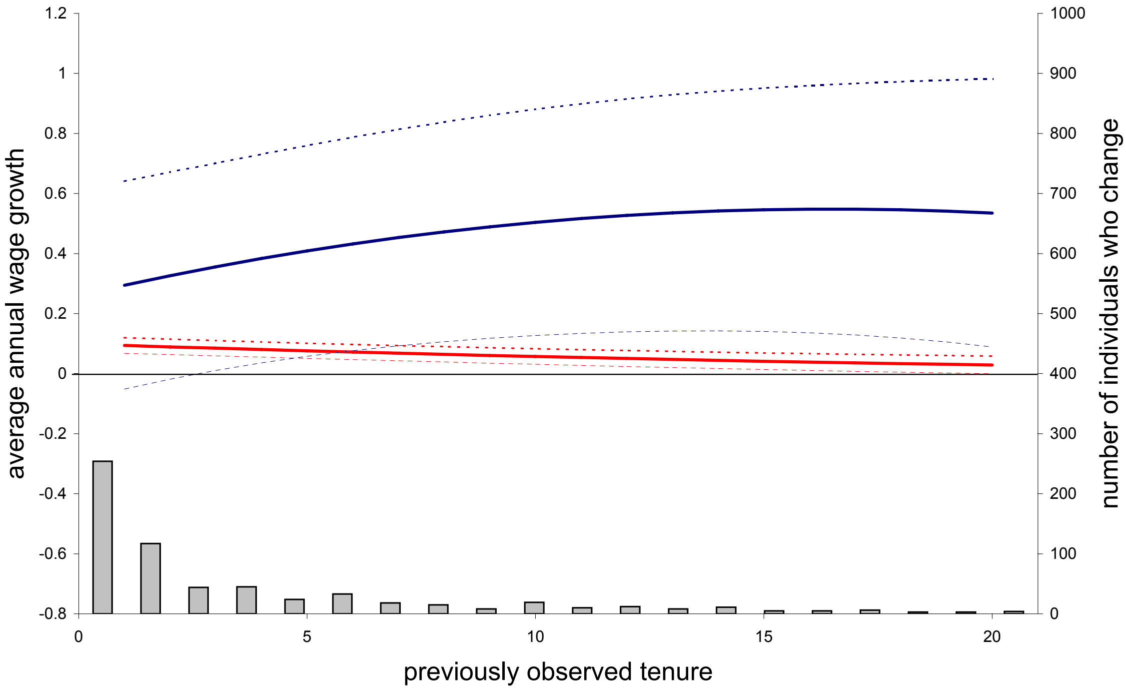
The underlying estimates are contained in column (1) and (4) of Table 5 in Appendix 1.

[18]This is innocuous since identification in our case does not rely on observations with zero firm tenure, as opposed to the approach taken by Topel (1991), e.g. Moreover, it comes in handy as we also use a specification in which we include log tenure on the right hand side of the regression equation.

[19]We found that tenure is measured with error in the GSOEP data and have corrected some values using appropriate algorithms. For example, if tenure was 0, then 1, then 2, then 10, and 4 thereafter, we have replaced 10 by 3. Moreover, we have dropped individuals with large upward jumps in case we were not able to correct the value with an appropriate algorithm.

[20]There is one individual, number 2780201, who is 60 years old in 2001 and has 47 years of tenure.

[21]Kletzer (1989) finds for Displaced Worker Survey data that tenure in the previous job is positively related to between job wage growth that is induced by an exogenous job change. She interprets this as evidence for heterogeneity of the returns to tenure.



Notes: The upper solid line is the estimated average annual wage growth for those who changed the firm (604 observations) plotted against previously observed tenure. The lower solid line is the estimated average wage growth for those who stayed in a firm (30,860 observations) against previously observed tenure. The dotted lines are pointwise 95% confidence intervals. The histogram shows frequencies of previously observed tenure for job changers. Estimates were obtained by regressing average annual wage growth on a second order polynomial for the respective subsample with previously observed tenure, controlling for age. See column (1) and (4) in Table 5 in Appendix 1.

Figure 1: Annual wage growth by previously observed tenure.

Whereas column (2) and (5) are for comparison column (3) and (6) indicate that the difference between inter-firm wage growth and intra-firm wage growth is increasing in age as the coefficient on age is positive for those who change jobs and negative for those who don't. By a similar argument it is increasing in previous tenure. There is a level effect as the previous log hourly wage enters negatively. This level effect is bigger for those who change jobs. In general, observed inter-firm wage growth exceeds intra-firm wage growth.

In turn of next section's empirical analysis, we implicitly control for endogenous firm changes by controlling for the endogeneity of tenure. By the arguments made in turn of the discussion of the econometric model in Section 2, job changers are characterized by a negative value of η_{ijt} if the change occurred just before t and cannot be predicted by the observables in the reduced form equation, (2).

4. Specification and Results for Wage Levels

Our data include a host of information about employers and their employees. For example, there is information on the size of the firm and on the type of position, high or low. Moreover, there are variables containing the number of years the employee was part time employed, full time employed, and unemployed. However, most of these variables are potentially endogenous. Therefore, and since we are interested in juxtaposing the returns to tenure, the returns to type, and the returns to general experience, we do not include the above mentioned variables in our regressions. Additional to the variables in Table 1 our set of variables includes indicator variables for the current state of residence (the "Bundesland").

Throughout, we estimate the first stage regressions by ordinary least squares and obtain fitted values of the residuals which we include in the second stage as a control function for unobservable factors confounding wages and tenure. We then compare these estimates to GLS and two stage IV GLS estimates. Standard errors are obtained from $1,000$ bootstrap replications. For the specification, we draw on the descriptive analysis in Appendix 1 and use a third order polynomial in age and include the log of tenure as a regressor.[22,23]

Reduced form first stage estimates are reported in Table 2. The first column is the reduced form for log tenure which will be used to obtain Altonji and Shakotko (1987) type IV estimates for comparison. Here, instead of $\tilde{t}_{ijt}$ that was used in the original paper, we use $\log(t_{ijt}) - \overline{\log t_{ij}}$ as an instrument because this newly constructed variable is by construction orthogonal to the fixed match specific component in the wage equation once we include log tenure instead of a linear and a quadratic term as a right hand side variable.[24] Column (2) contains the reduced form for tenure which we use in the sequel in order to obtain the fitted residuals $\hat{\eta}_{ijt}$ for the control function estimates. Obviously, $\tilde{t}_{ijt}$ is strongly correlated with tenure. For comparison, since tenure is restricted to be at least equal to one, we report Tobit estimates. Respective coefficient estimates are very similar to the OLS estimates in column (2) so that we decided to base the subsequent control function estimates on the specification in column (2).

Notice that according to the reduced form, equation (2), those individuals with a high value of $\hat{\eta}_{ijt}$, the fitted residual from the specification in column (2) of Table 2, are more likely to be of a type that stays longer in a given firm, as compared to the average. Importantly, and by construction, $\hat{\eta}_{ijt}$ includes individual and match specific factors since $\tilde{t}_{ijt}$ is uncorrelated with them by construction. Therefore, once we include it as a control function in the structural wage equation, we can thereby not only control for the endogeneity of tenure but can, at the same

[22] The solid line in Figure 6 in Appendix 1 is a third order polynomial fit through the estimated coefficients of the indicator variables of the effect of age on wages conditional on tenure. Similarly, the solid line in Figure 7 is an exponential fit. As for formal testing, we can reject the null that the coefficients of the indicator variables on age indicators are jointly zero, with a P-value of 0.0169, once we include a second order polynomial in age into the regression of wages on indicator variables for age, tenure, state of residence indicators, and a linear time trend. However, once we include a third order polynomial in age, with a P-value of 0.9672 we cannot reject the null any more. Therefore, we feel that we should include a third order polynomial in age into the regression. A similar result does not hold for the partial effect of tenure on wages. It turns out that the test statistic for the joint significance of the tenure indicators is 9.21, with a P-value of zero, once we include a second order polynomial in tenure in addition to the above mentioned set of variables. However, once we include log tenure instead of a second order polynomial in such a regression, the test statistic is 5.23, also with a P-value of zero. Based on the fit in Figure 7 we nevertheless decided to go on with a specification in which we include a third order polynomial in age and the log of tenure into our regressions.

[23] Altonji and Shakotko (1987) use a third order polynomial in experience and a second order polynomial in tenure. For comparison, Table 6 in Appendix 2 contains estimates for such a specification. Results are similar.

[24] Column (2) of Table 6 contains IV estimates for the wage equation when we use a quadratic function in tenure and the original instruments.

	(1) IV Reduced Form log tenure	(2) Reduced Form tenure	(3) Tobit tenure
$\log(t_{ijt}) - \overline{\log t_{ij}}$	0.918**		
	(0.012)		
$\tilde{t}_{ijt}$		0.690**	0.718**
		(0.015)	(0.015)
age	-0.102**	-1.087**	-0.779*
	(0.033)	(0.331)	(0.345)
age squared	0.004**	0.036**	0.030**
	(0.001)	(0.008)	(0.008)
age cubed	-0.000**	-0.000**	-0.000**
	(0.000)	(0.000)	(0.000)
R-squared	0.32	0.35	

38,041 observations across individuals and time. The first two columns are OLS estimates. Standard errors in parentheses. + significant at 10%; * significant at 5%; ** significant at 1%. We also included a set of indicator variables for the state of residence as well as a time trend. Bars denote sample averages over t and $\tilde{t}_{ijt} = t_{ijt} - \overline{t_{ij}}$.

Table 2: Reduced form first stage regressions.

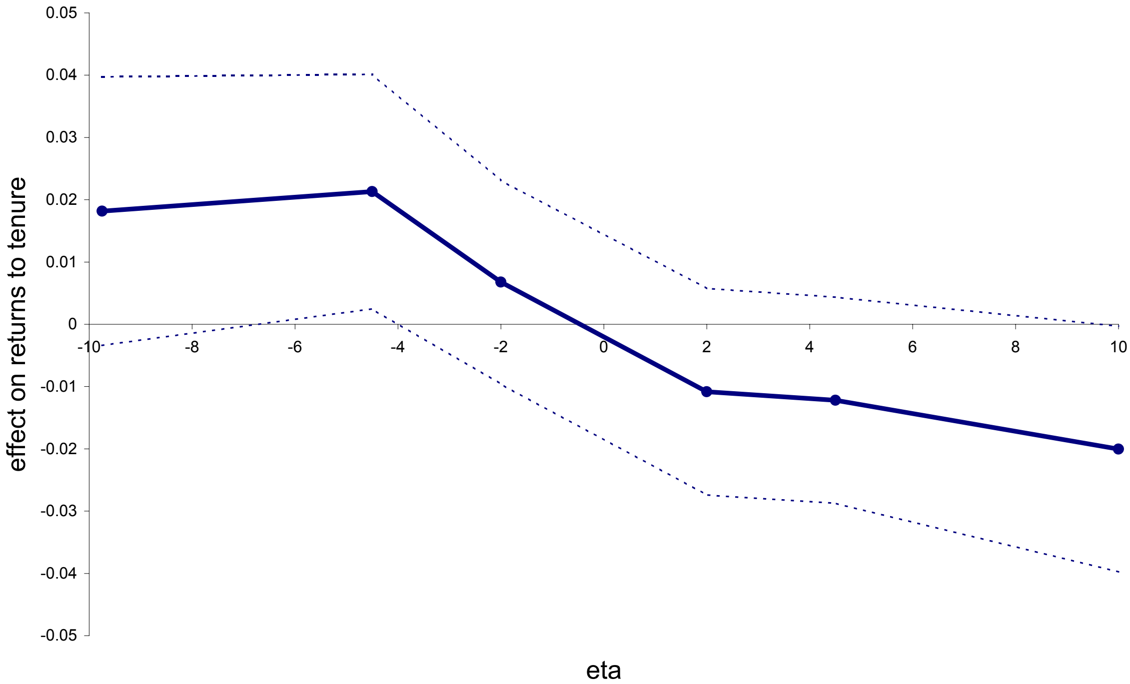
time, assess the impact of high values of this control function on expected wages.

Table 3 contains estimates of the wage equation. The estimates in column (1) were obtained using a standard generalized least squares GLS random-effects panel estimator. They have the interpretation of observed differences and derivatives in the direction of the covariates. The observed wage increase from a duplication of tenure is about 7 per cent. Column (2) contains two stage IV GLS estimates from a random-effects IV panel estimator using fitted values for tenure from the specification in column (1) of Table 2. Compared to simple GLS estimates, IV estimates of the returns to tenure are lower and attribute wage increases to a larger extent to increments in age. A similar observation is made in the analysis of Altonji and Shakotko (1987) and discussed by Topel (1991) who argues that such estimates are misleading. In light of the arguments in Subsection 2.3, an important aspect in such a discussion is the heterogeneity of the effect of tenure on wages. In particular, such an IV procedure estimates the average returns to tenure of those who stay in a given job. In general, it does not uncover the population average

	(1) GLS	(2) IV	(3) Struct. I	(4) Struct. II	(5) Struct. III
log tenure	0.071**	0.050**	0.039**	0.072**	0.036**
	(0.005)	(0.008)	(0.014)	(0.008)	(0.012)
year	0.011**	0.011**	0.012**	0.011**	0.012**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
age	0.064**	0.079**	0.070**	0.064**	0.070**
	(0.019)	(0.019)	(0.020)	(0.019)	(0.019)
age sq.	-0.001*	-0.001**	-0.001**	-0.001*	-0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
age cu.	0.000+	0.000**	0.000+	0.000+	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\hat{\eta}_{ijt}$			0.008*		0.009**
			(0.004)		(0.002)
$\mathbb{I}\{\hat{\eta}_{ijt} \in (-\infty, -6)\}$				-0.008	
				(0.024)	
$\mathbb{I}\{\hat{\eta}_{ijt} \in [-6, -3)\}$				0.012	
				(0.021)	
$\mathbb{I}\{\hat{\eta}_{ijt} \in [-3, -1)\}$				-0.005	
				(0.019)	
$\mathbb{I}\{\hat{\eta}_{ijt} \in [1, 3)\}$				-0.016	
				(0.020)	
$\mathbb{I}\{\hat{\eta}_{ijt} \in [3, 6)\}$				-0.020	
				(0.022)	
$\mathbb{I}\{\hat{\eta}_{ijt} \in [6, \infty)\}$				-0.030	
				(0.031)	
log tenure $\times\, \hat{\eta}_{ijt}$			-0.002+	0.001	
			(0.001)	(0.001)	
log tenure $\times\, \mathbb{I}\{\hat{\eta}_{ijt} \in (-\infty, -6)\}$					0.018+
					(0.011)
log tenure $\times\, \mathbb{I}\{\hat{\eta}_{ijt} \in [-6, -3)\}$					0.021*
					(0.010)
log tenure $\times\, \mathbb{I}\{\hat{\eta}_{ijt} \in [-3, -1)\}$					0.007
					(0.008)
log tenure $\times\, \mathbb{I}\{\hat{\eta}_{ijt} \in [1, 3)\}$					-0.011
					(0.008)
log tenure $\times\, \mathbb{I}\{\hat{\eta}_{ijt} \in [3, 6)\}$					-0.012
					(0.008)
log tenure $\times\, \mathbb{I}\{\hat{\eta}_{ijt} \in [6, \infty)\}$					-0.020*
					(0.010)

$38,041$ observations and $6,577$ individuals. Bootstrapped standard errors from 1,000 replications in parentheses. + significant at 10%; * significant at 5%; ** significant at 1%. The dependent variable is the real hourly wage in prices of 2000. We also included a set of indicator variables for the state of residence.

Table 3: Second stage estimates.



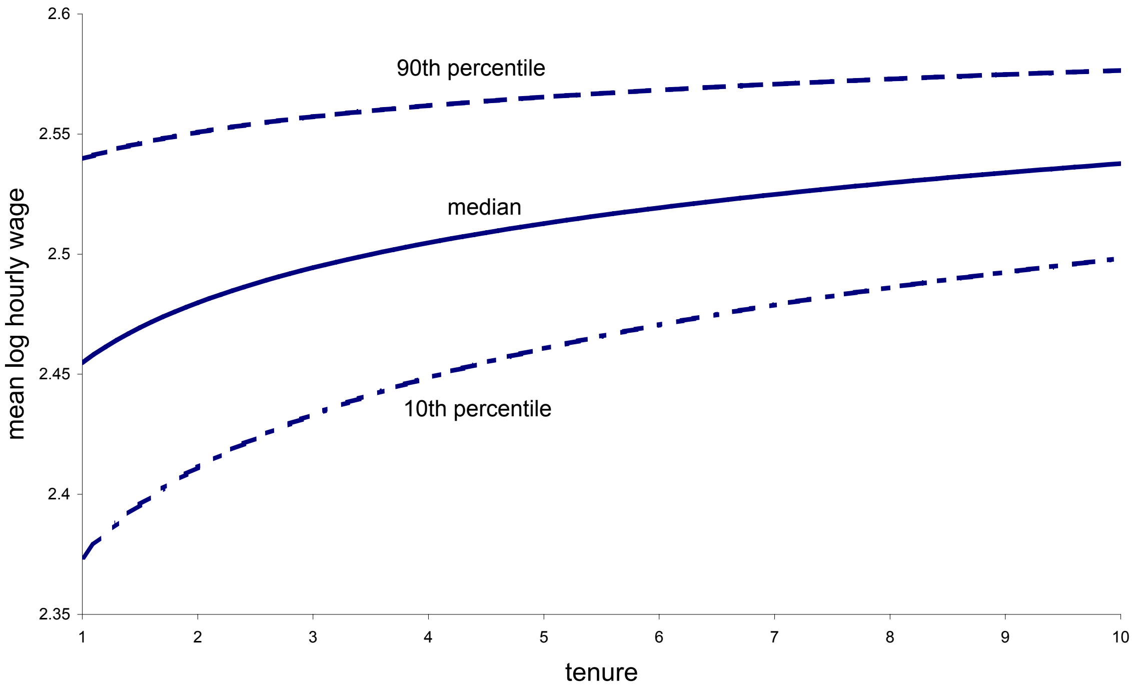
Notes: Estimates were obtained using the results in column (5) of Table 3. The dotted lines are 95% confidence intervals.

Figure 2: The impact of η_{ijt} on the returns to tenure.

effect of tenure on wages which is sought to be estimated in this paper.

Column (3) through (5) contain control function estimates built on the econometric model that was laid out in Section 2. They are based on the residuals obtained from the specification in column (2) of Table 2.[25] Under the assumptions made, as shown in Section 2, our control function estimator uncovers the population average effect of firm tenure on wages. Column (3) contains our baseline specification. Column (4) contains a specification in which we include indicator variables for $\hat{\eta}_{ijt}$ in order to get an idea about the impact of the type on wage levels

[25]For some individuals there is just one observation in our data. Therefore, a fixed effects model could not be implemented. In fact, it follows from our restrictions that the model should be estimated using pooled OLS since the observations are assumed to be independent across ijt. However, the stochastic restrictions stated in Section 2 are actually stronger than needed and stated in that way for the ease of the exposition. They can readily be relaxed.



Notes: Profile was calculated from the coefficient estimates in column (5) of Table 3 and centered at the population average log wage conditional on tenure being equal to 1, 2.46.

Figure 3: Mean wages as a function of firm tenure for different percentiles of η_{ijt}.

without imposing too much structure. It turns out that the set of indicator variables is jointly insignificant with a P-value of 0.7933. Arguably, the spline function in $\hat{\eta}_{ijt}$ does not allow us to control for the endogeneity of tenure. This is confirmed by the fact that the coefficients in column (4) are very close to the ones in column (1), the GLS estimates.[26]

Notably, our preferred specification in column (5) indicates that for high η_{ijt}-types, wages are higher on average but returns to tenure are lower. The latter effect is depicted in Figure 2. As for statistical inference, the interaction terms between $\hat{\eta}_{ijt}$ indicators and log tenure are jointly significant with a P-value of 0.0435. Figure 3 summarizes both effects by showing wage tenure profiles for different percentiles of $\hat{\eta}_{ijt}$.[27] In general, this empirical result supports the idea of wage growth that has been laid out in the introduction.

Taking the robustness check in column (4) aside, we interpret our results as evidence for population average returns to tenure to be lower than observed returns to tenure. We estimate the effect from doubling firm tenure to be a real wage increase of about 3 per cent. Average wages increase by about 1 per cent per year for those types who stay longer than expected in a given firm. At the same time, as shown in Figure 3, they exhibit lower returns to tenure.

Finally, our results suggest that IV estimates are downward biased as they put weight on good job matches.

5. Endogenous Job Changes and Structural Wage Growth

As we have shown in Figure 1 between job wage growth is substantial and clearly, job changes are endogenous. In this section, we complement our results for the within job wage level equation with results for the structural wage growth equation that was developed in Subsection 2.4. We use it to relate both within and between job wage growth to previous tenure and age. This

[26]We experimented with several specifications. It turned out that more flexible specifications did not reveal a specific pattern. For example, we included a third order polynomial in $\hat{\eta}_{ijt}$ interacted with log tenure instead of the set of indicator variables interacted with log tenure in column (4).

[27]Figure 9 in Appendix 2 shows that the effect of $\hat{\eta}_{ijt}$ on average log hourly wages is similar to the effect on the exponential of average log hourly wages.

	(1) Descr. I	(2) Descr. II	(3) Struct. I	(4) Struct. II
χ_{it}	0.688**	0.586**	0.674**	0.641**
	(0.032)	(0.040)	(0.053)	(0.056)
t_{ikt-1}		-0.003**		
		(0.000)		
$\chi_{it} \cdot t_{ikt-1}$		0.019**		
		(0.006)		
$\Delta\hat{\eta}_{it}$			-0.039**	
			(0.010)	
$\hat{\eta}_{ijt}$				-0.047**
				(0.010)
$\hat{\eta}_{ikt-1}$				0.045**
				(0.010)
$1-\chi_{it}t_{ikt-1}$			0.021*	0.021*
			(0.010)	(0.009)
$\Delta\hat{\eta}_{it}t_{it}$			-0.000	0.001
			(0.000)	(0.001)
age	0.071**	0.073**	0.068**	0.065**
	(0.018)	(0.019)	(0.021)	(0.020)
age sq.	-0.002**	-0.002**	-0.002**	-0.001**
	(0.000)	(0.000)	(0.000)	(0.000)
age cu.	0.000**	0.000**	0.000**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)

31,464 observations across individuals and time. Bootstrapped standard errors from 1,000 replications in parentheses. + significant at 10%; * significant at 5%; ** significant at 1%. The dependent variable is average annual wage growth calculated as the difference in log wages over the time difference. $\hat{\eta}_{ijt}$ and $\hat{\eta}_{ikt-1}$ were calculated within each bootstrap replication using the specification of the reduced form for tenure in column (2) of Table 2.

Table 4: Determinants of wage growth.

is different to the approach that is taken by Topel and Ward (1992) who estimate a proportional hazard model.

Column (1) and (2) of Table 4 contain results for specifications in which we do not control for the endogeneity of job changes since we do not control for the type of an individual which, given our assumptions, is a sufficient statistic for the factors confounding tenure and wages, and thereby job changes. Column (3) and (4) contain estimates for different specifications of the structural wage equation, (6), controlling for those confounding factors. Column (3) is our preferred specification and column (4) is a robustness check.[28] Throughout, the additional wage growth that stems from a job change, χ_{it}, is estimated to be positive. Moreover, column (2) shows that average wage growth is slightly decreasing in tenure if individuals stay in a firm and increasing in tenure if individuals change firms.

Column (3) shows that the impact of $\Delta\eta_{it}$ on wage growth is negative. In particular, if η_{ijt} decreases by, say, 10 years between periods since individual i changed jobs so that tenure decreased from 11 to 1 year, we estimate the difference in log wages to be increasing by 0.39. Following our idea of a type, this estimate means that on the one hand, types who are most unlikely to change jobs, e.g. since they have been working for the same employer for a long time, experience the largest between firm wage growth. On the other hand, the coefficient of $1-\chi_{it}t_{ikt-1}$ is estimated to be positive which indicates that previous tenure is negatively related to between job wage growth in general. This latter observation could be interpreted as evidence confirming that human capital acquired on the job is only partly transferrable to other firms.

6. Concluding Remarks

In this paper we have analyzed between and within firm wage growth. Using a flexible control function approach, we have disentangled returns to observable tenure from returns to an

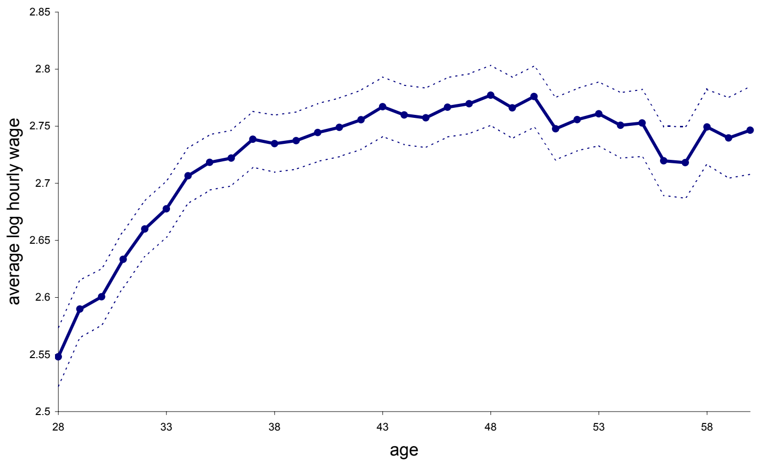
[28] In the latter, we let the two components of the type enter separately. (6) implies that the coefficient of $\hat{\eta}_{ijt}$ should be the same as the negative of the coefficient of $\hat{\eta}_{ikt-1}$, which in turn should be the same as the coefficient of $\Delta\hat{\eta}_{it}$ in column (3). This is not the case here. A formal test yielded a rejection of the hypothesis that the coefficient of $\hat{\eta}_{ijt}$ is the same as the negative of the coefficient of $\hat{\eta}_{ikt-1}$. However, they are still reasonably close.

unobservable type variable and have shown that there exist interaction effects between the two. In particular, we find that those types who stay longer in a given firm (i) earn higher wages on average, (ii) have lower returns to tenure and, (iii) once they change jobs, experience large between job wage growth.

The fact that more productive types have flatter wage profiles in firm tenure could reflect a parting of match specific rents between the firm and the employee from the beginning of the relationship on. This idea is in line with the literature on relational contracts, in particular the literature on efficiency wages. In contrast to models such as the one by Lazear (1979, 1981) in which effort is induced by the employer using a steep profile of wages in tenure, the literature on efficiency wages argues that firms have an incentive to pay high wages from the beginning of the relationship on in order to increase the workers' opportunity cost of being fired (Shapiro and Stiglitz, 1984) or pay a "fair" wage that induces workers to reciprocate by providing effort (Akerlof and Yellen, 1990). Interestingly, Abowd, Kramarz, and Margolis (1999) find that the firm specific intercept and the firm specific return to tenure are negatively correlated in their French data. This is in line with our finding and shows that both differences across firms and individuals are important.

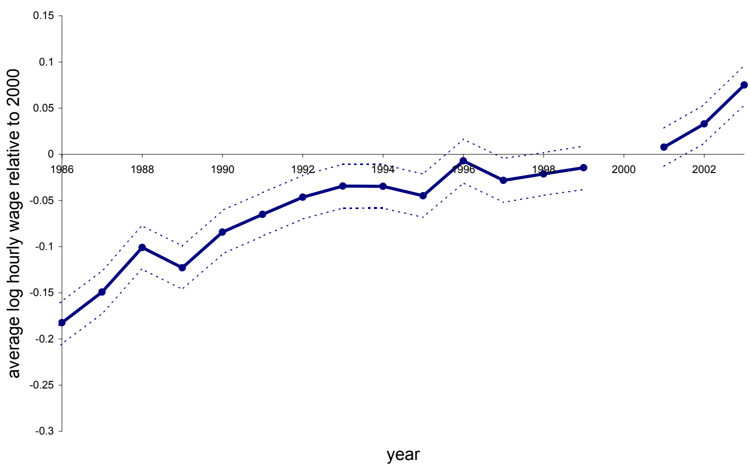
Appendix 1: Descriptive Evidence

This appendix contains descriptive evidence. First, we regressed real log hourly wages on a full set of age and year indicators. Figure 4 shows the wage profile against age. Average wages rise sharply until the age of about 43. This is a stylized fact that is well established in the literature. It has been linked to job-shopping in the early phase of a career (Johnson, 1978; Topel and Ward, 1992). Here, we remain silent about the sources of wage growth as we do not condition on tenure or firm changes, for example. Figure 5 shows that real wages for a given age have been growing considerably over the last 20 years. In Figure 6 we juxtapose the total effect of age on wages, the dash-dotted line, and the partial effect of age on wages once we condition on firm tenure, the solid line. Interestingly, the partial effect of age on wages is negative from the age of 43 on. This is because we now control for the wage growth which is associated with firm tenure. However, note that this graph is descriptive and should therefore not be given a structural interpretation. Figure 7, in turn, shows the partial effect of tenure on wages once we control for age differences. To conclude our descriptive analysis, Figure 8 shows the probability to observe a job change for a given age which is constantly declining over the life span.



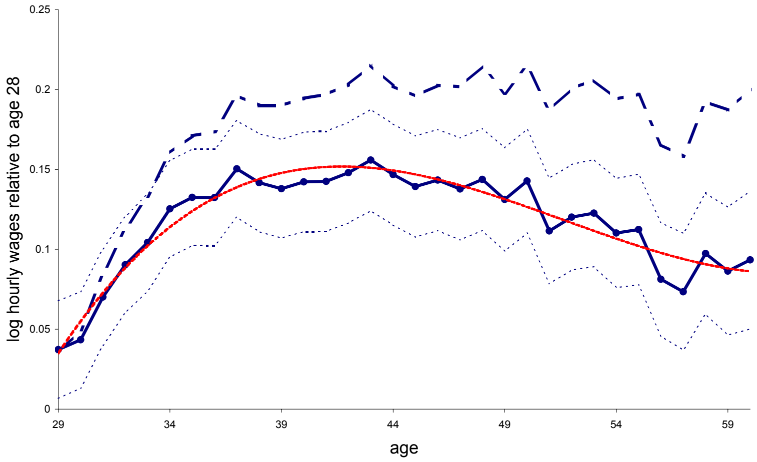
Notes: Estimates were obtained by regressing real log hourly wages on a full set of indicator variables for age and year. The dotted lines are pointwise 95% confidence intervals.

Figure 4: Average real log hourly wage by age.



Notes: Estimates were obtained by regressing real log hourly wages on a full set of indicator variables for age and year. The dotted lines are pointwise 95% confidence intervals.

Figure 5: Average real log hourly wage relative to year 2000.



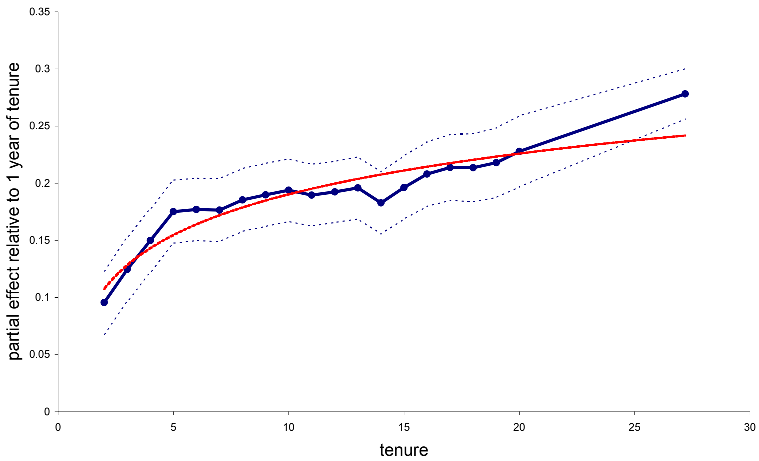
Notes: The dash-dotted line is the difference between the average real log hourly wage at a given age and the real log hourly wage at the age of 28. The connected dots are the partial effect of age on wages once we control for differences in tenure. Estimates were obtained by regressing real log hourly wages on a full set of indicator variables for age (and tenure for the connected dots) as well as region indicators and a linear time trend. The dotted lines are pointwise 95% confidence intervals. The solid line is a third order polynomial fit through the dots.

Figure 6: Partial and total effect of age on wages.

	(1) change	(2) change	(3) change	(4) no change	(5) no change	(6) no change
previous tenure	0.044**	0.013*	0.016**	-0.005**	-0.003**	-0.001*
	(0.015)	(0.006)	(0.006)	(0.001)	(0.000)	(0.000)
previous tenure sq.	-0.001*			0.000*		
	(0.001)			(0.000)		
age	0.012*	0.011*	0.011*	0.001*	0.001*	0.001**
	(0.005)	(0.005)	(0.005)	(0.000)	(0.000)	(0.000)
previous log hourly wage			-0.323**			-0.280**
			(0.071)			(0.006)
constant	0.190	0.298+	1.072**	0.095**	0.081**	0.799**
	(0.186)	(0.180)	(0.246)	(0.014)	(0.012)	(0.019)

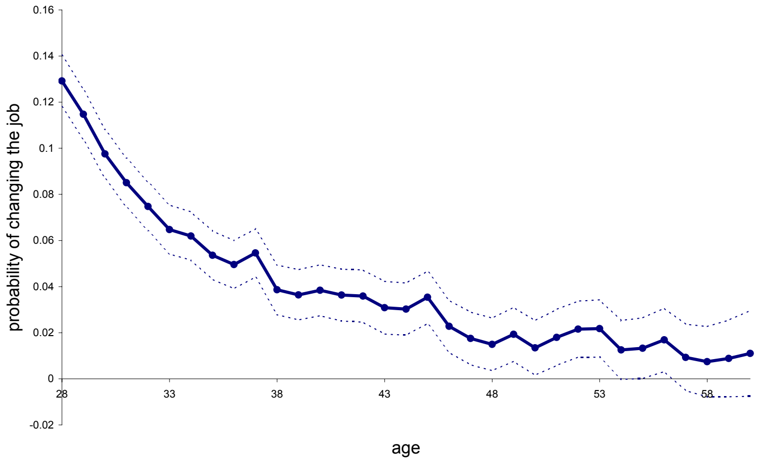
Standard errors in parentheses. + significant at 10%; * significant at 5%; ** significant at 1%. Estimates were obtained by regressing annualized wage growth, for the respective subsample, on previous tenure, its square in column (1) and (4), age, and the previous log hourly wage in columns (2), (3), (5), and (6). The annualized wage growth is defined as the difference between the log wage in t and t' over $t - t'$ for all $t > t'$.

Table 5: Wage growth by previous tenure.



Notes: The connected dots are the partial effect of tenure on wages once we control for differences in age. Estimates were obtained by regressing real log hourly wages on a full set of indicator variables for age and tenure (up to 20 years of firm tenure) as well as region indicators and a linear time trend. The dotted lines are pointwise 95% confidence intervals. The solid line is an exponential fit through the dots.

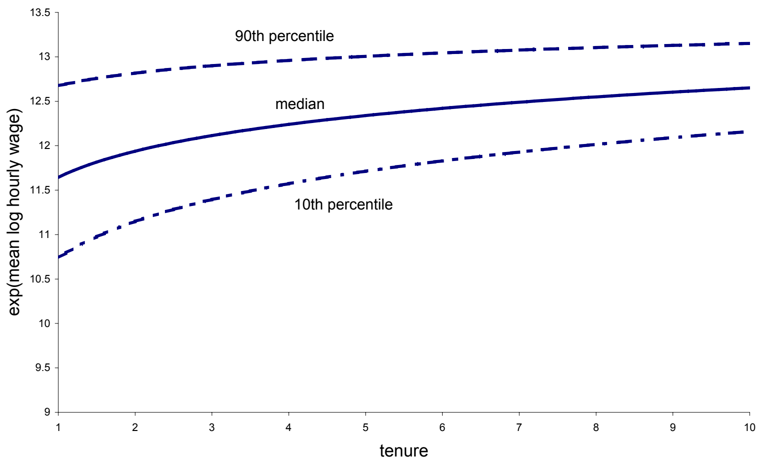
Figure 7: Partial effect of tenure on wages.



Notes: Estimates were obtained by regressing an indicator for a firm change on age indicators. The dotted lines are pointwise 95% confidence intervals.

Figure 8: Probability of a job change by age.

Appendix 2: Additional Figure and Robustness Checks



Notes: Profile was calculated from the coefficient estimates in column (5) of Table 3 and centered using the population average log wage conditional on tenure being equal to 1, 2.46.

Figure 9: Mean wages as a function of firm tenure for different percentiles of η_{ijt}.

	(1) GLS	(2) IV	(3) Structural I	(4) Structural II	(5) Structural III
tenure	0.012**	0.001	-0.003	0.014**	0.008+
	(0.001)	(0.002)	(0.003)	(0.002)	(0.005)
tenure sq.	-0.000**	-0.000**	-0.000	-0.000**	-0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
year	0.011**	0.014**	0.014**	0.012**	0.014**
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
age	0.080**	0.079**	0.067**	0.064**	0.063**
	(0.019)	(0.019)	(0.021)	(0.020)	(0.022)
age sq.	-0.002**	-0.001**	-0.001+	-0.001*	-0.001*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
age cu.	0.000**	0.000*	0.000	0.000+	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\hat{\eta}_{ijt}$			0.022**		0.018**
			(0.003)		(0.003)
tenure $\times$ $\hat{\eta}_{ijt}$			-0.001**	-0.000*	
			(0.000)	(0.000)	
tenure sq. $\times$ $\hat{\eta}_{ijt}$			0.000**	0.000**	
			(0.000)	(0.000)	
$\mathbb{I}\{\hat{\eta}_{ijt} \in (-\infty, -6)\}$				-0.085**	
				(0.025)	
$\mathbb{I}\{\hat{\eta}_{ijt} \in [-6, -3)\}$				-0.026	
				(0.022)	
$\mathbb{I}\{\hat{\eta}_{ijt} \in [-3, -1)\}$				-0.020	
				(0.020)	
$\mathbb{I}\{\hat{\eta}_{ijt} \in [1, 3)\}$				-0.002	
				(0.022)	
$\mathbb{I}\{\hat{\eta}_{ijt} \in [3, 6)\}$				0.008	
				(0.023)	
$\mathbb{I}\{\hat{\eta}_{ijt} \in [6, \infty)\}$				0.003	
				(0.032)	
tenure $\times$ $\mathbb{I}\{\hat{\eta}_{ijt} \in (-\infty, -6)\}$					0.007
					(0.005)
tenure sq. $\times$ $\mathbb{I}\{\hat{\eta}_{ijt} \in (-\infty, -6)\}$					-0.000
					(0.000)
tenure $\times$ $\mathbb{I}\{\hat{\eta}_{ijt} \in [-6, -3)\}$					0.009+
					(0.005)
tenure sq. $\times$ $\mathbb{I}\{\hat{\eta}_{ijt} \in [-6, -3)\}$					-0.000
					(0.000)
tenure $\times$ $\mathbb{I}\{\hat{\eta}_{ijt} \in [-3, -1)\}$					-0.000
					(0.004)
tenure sq. $\times$ $\mathbb{I}\{\hat{\eta}_{ijt} \in [-3, -1)\}$					0.000
					(0.000)
tenure $\times$ $\mathbb{I}\{\hat{\eta}_{ijt} \in [1, 3)\}$					-0.007+
					(0.004)
tenure sq. $\times$ $\mathbb{I}\{\hat{\eta}_{ijt} \in [1, 3)\}$					0.000
					(0.000)
tenure $\times$ $\mathbb{I}\{\hat{\eta}_{ijt} \in [3, 6)\}$					-0.010**
					(0.004)
tenure sq. $\times$ $\mathbb{I}\{\hat{\eta}_{ijt} \in [3, 6)\}$					0.000*
					(0.000)
tenure $\times$ $\mathbb{I}\{\hat{\eta}_{ijt} \in [6, \infty)\}$					-0.016**
					(0.004)
tenure sq. $\times$ $\mathbb{I}\{\hat{\eta}_{ijt} \in [6, \infty)\}$					0.001**
					(0.000)

38,041 observations and 6,577 individuals. Bootstrapped standard errors from 1,000 replications in parentheses. + significant at 10%; * significant at 5%; ** significant at 1%. The dependent variable is the real hourly wage in prices of 2000. We also included a set of indicator variables for the state of residence.

Table 6: Second stage estimates with a quadratic function in tenure.

Acknowledgements

We would like to thank Bernd Fitzenberger, Christina Gathmann, Friedhelm Pfeiffer and Thomas Zwick for helpful comments. Moreover, we are grateful for comments received at the workshop "Wage Growth and Mobility: Micro-, Macro and intergenerational Evidence" held at the ZEW in Mannheim March 24 and 25, 2006 and in a workshop held at the University of Frankfurt. The authors thank the Deutsche Forschungsgemeinschaft for financial support.

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