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ABSTRACT

Wages, Experience and Seniority*

This paper develops and estimates a human capital model of wage growth based on learning by doing. Learning by doing rates are assumed to be heterogeneous and firms offer different career structures in terms of the rate of acquisition of firm-specific human capital. The model is estimated using a unique data set drawn from German administrative records and including a complete employment and earnings history for each worker in our sample. We find evidence of increased labour market attachments for individuals with higher returns to experience. This has important implications for the estimates. The estimated returns to experience are 2.7% a year. The returns to tenure are close to zero. Crucial identifying information is provided by plant closures.

JEL Classification: J24, J31, J41
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NON-TECHNICAL SUMMARY

This paper analyses the sources of wage growth. Investigating the sources of wage growth is important for a number of reasons. First, it is informative for the evolution of life-cycle earnings, which in itself is important for investigating savings behaviour, pensions etc. Second, it helps us understand job mobility. Consider for instance the evaluation of active labour market programmes. Recently governments have become interested in such programmes as a solution to long-term unemployment. Some of these programmes, in say the United Kingdom as well as oversees, take the form of a temporary wage subsidy to encourage the employment of otherwise low productivity individuals. In the process they may enhance their skills and become more employable. To the extent that the unemployed are indeed low productivity individuals, the success of these programmes relies to a large extent on how skills improve on the job and what is the nature of such skill enhancement.

We develop a framework where different firms offer different career profiles. Therefore, investment decisions in human capital take the form of employment choices and choice of firm. Workers with higher learning ability and lower turnover probability will be more willing to join a firm that offers a steeper career profile but lower initial wages. We further assume that all firms offer the same opportunities for growth of general human capital, the accumulation of which is heterogeneous across individuals due to inherent individual characteristics. Moreover, we allow for the possibility that workers may have to search to locate the optimal choice of firm. Hence, job mobility takes place induced by search where workers may obtain offers that improve on their current match and lead to their optimal career choice.

In our model wage growth may be due to the improvement of general skills useful outside the present firm (general human capital), to the development of skills useful only in the current firm (firm-specific human capital) and to job-shopping where the individual improves their wage by finding a job to which he is better matched. Finally aggregate productivity growth due to technical change is also a source of wage growth.

Our analysis is based on a new and unique data set. We use a German data set on apprentices, which provides information on the complete employment and earnings history for a large sample of workers. Hence there is little or no measurement error in computing the number of periods worked overall and in particular firms. Moreover we have enough information to know whether and when the plants in which individuals worked closed down.

We discuss the implications of our model for identification. We come up with a strategy that combines information on plant closures together with selection correction methods to control for the dynamic selection bias that arises from the search strategy of individuals so as to estimate the average returns to experience and tenure in the population. Our estimation method takes into account the possibility that individuals learn at different rates and that the career structures offered by firms may differ.

We find a substantial mobility among young workers in Germany, although this mobility is lower than the mobility observed in the United States. It is also evident that job-shopping does lead to wage growth. Simple Ordinary Least Squares (OLS) regressions overestimate the returns to experience and tenure. The returns to experience are heterogeneous across individuals and there is evidence that individuals take this into account when deciding to take up employment or not. Taking into account the self-selection of workers into employment on the basis of their returns to experience changes our estimates of the average returns substantially. In our sample this seems to be the main source of self-selection and bias in the OLS results for experience. The aggregate wage growth over the period was on average 1.8% a year as estimated by our preferred model.

Our best estimate of the population average returns to experience is 2.7% a year. The estimated returns to tenure are quite small. At a minimum these are estimated to be close to zero (0.38% annually). The precision is low, however, and hence our degree of uncertainty on the precise point estimates.

1 Introduction

In this paper we investigate the sources of wage growth, by specifying and estimating a model where human capital accumulation takes the form of learning by doing and investments take the form of searching for the firm with the most desirable learning by doing characteristics (career structure).[1]

Specifically, in our framework different firms offer different career profiles. Thus, investment decisions in human capital take the form of employment choices and choice of firm. Workers with higher learning ability and lower turnover probability will be more willing to join a firm that offers a steeper career profile but lower initial wages. The low initial wages reflects the fact that the worker will have to pay for the acquisition of firm specific human capital whose return he will enjoy. The firm level heterogeneity could be due to different technologies in place and/or different contracts determining the proportion of human capital acquisition paid by the worker and the resulting return enjoyed by the worker.[2] By assumption, all firms offer the same opportunities for growth of general human capital, the accumulation of which is heterogeneous across individuals due to inherent individual characteristics. Moreover we allow for the possibility that workers may have to search to locate the optimal choice of firm. Hence, job mobility takes place induced by search where workers may obtain offers that improve on their current match and lead to their optimal career choice.

Investigating the sources of wage growth is important for a number of

[1]In general the acquisition of human capital on the job may be a result of decisions to invest as well as purely learning by doing. Examples of models with explicit investment in Human Capital are Ben Porath (1967), Rosen (1976) and Blinder and Weiss (1976) and Jovanovic (1979) amongst others. Examples of models where learning is a by product of work are given in Rosen (1972). Killingsworth (1982) presents a model unifying the features of the earlier literature.

[2]See Becker (1993). Equilibrium models that explain why workers get rewarded for specific training have been developed under many different assumptions. Some examples include Datta (1995), Scoones and Bernhardt (1996) and Harris and Felli (1996).

reasons. First, it is informative for the evolution of life-cycle earnings, which in itself is important in a number of fields (savings, pensions, labour supply etc.). Second, it helps us understand job mobility. Another topical example of where such knowledge might be important is in the evaluation of active labor market programs. Recently governments, particularly in Europe have become interested in such programs as a solution to long term unemployment. Some of these programs in say the UK and Sweden as well as France take the form of a temporary wage subsidy to encourage the employment of otherwise low productivity individuals. The hope is that while in work their skills will be sufficiently enhanced so as to keep their jobs without the wage subsidy, and render them more employable. To the extent that the unemployed are indeed low productivity individuals, the success of these programs relies to a large extent on how skills improve on the job and what is the nature of such skill enhancement. Hence estimates of wage growth on the job as well as the extent to which the acquired human capital is transferable between jobs is a key element to evaluating the potential effects of such programs.

The framework we present leads to a random coefficients wage equation which depends on the number of periods the individual has worked (experience) and on tenure. Random coefficient models are not new of course. The Willis and Rosen (1979) model on the returns to education is one of the early empirical examples of such models in economics. Heckman and Sedlacek (1985) apply the Roy model of self selection to the labour market, which is essentially a random coefficients model. Heckman and Robb (1985) discussed the estimation of such models in the context of evaluation of treatment effects. Bjorklund and Moffitt (1987) apply these ideas to the estimation of the returns to training in Sweden. More recently Imbens and Angrist (1994) and Heckman (1995) consider the interpretability of instru-

mental variable estimation in the context of random coefficient models.

We discuss how the population average returns to experience and tenure can be identified given individual and firm behavior. We also discuss the empirical implications of some aspects of the theoretical model. Drawing from Heckman and Robb (1985) we develop an estimator which allows for such heterogeneous returns.[3]

Despite the numerous empirical research on the subject consensus has not been reached on the returns to experience and tenure.[4] Part of the problem has been that the data used up to now suffered from a number of deficiencies: More often than not experience is not known before a particular date, or wage changes between jobs are not accurately recorded. We can shed new light on this issue by using a new and unique data set. This data, drawn from German administrative records, has a number of unique key features which are important for the analysis. Firstly we observe individuals from the start of their labor market career. We know all transitions they have made. Hence there is no initial conditions problem and the full experience profile is observable. Secondly, wage observations relate to a particular job: When an individual changes employment we observe the wage change. Thirdly, there is practically no attrition. Finally, we know when the plant in which any of our workers has been employed closes down. Hence this data offers a unique opportunity to examine wage growth without the distractions of the usual data problems.

Our data covers workers entering the labor market following apprenticeship education from 1975 to 1990. The oldest worker in our sample is 31. The use of such a young sample has the advantage that we can focus on the age group where most of the job mobility takes place.

[3]We follow a similar approach to Heckman and Vytlacil (1998).

[4]See Altonji and Shakotko (1987), Topel (1991), Topel and Ward (1992), Altonji and Williams (1997), Altonji and Williams (1996) and Neal (1996) .

The paper proceeds as follows: In the next section we present a simple theoretical framework, where we describe the models and discuss identification of the parameters of interest under different theoretical assumptions. This is followed by a section where we describe the sample and provide a description of job mobility for young workers in Germany. The data section is followed by the empirical results and a concluding discussion.

2 A Simple Theoretical framework

In this section we outline a simple theoretical framework that motivates the model we estimate.

We assume that workers acquire general and specific skills while working on the job. Implicitly they pay for all general training through lower wages (and reap all the return). They also pay for a proportion of firm specific training, for which they get the return. This proportion is fixed across workers within a firm but could vary over time as a result of technological factors. To obtain the optimal level of firm specific training, given their individual turnover probability, the workers need to locate the employer offering their optimal career structure. This can be achieved through on-the-job search.

Define by H_{it} that part of human capital for which the worker gets rewarded. This is related to general and firm specific human capital by the function $H_{it} = e^{m_{ift}} G_{it}^{\alpha} S_{it}^{\gamma}$, where G is general transferable human capital, and S firm specific human capital whose return is enjoyed by the worker. [5]The term m_{ift} reflects a match specific effect which may vary over time in a random manner. This formulation implies that all components of human capital are combined in one factor for which the worker is paid by the firm.[6]

[5]See Hashimoto (1981) for a discussion of conditions that imply the existence of a sharing rule for the investment costs and the returns to firm-specific human capital.

[6]The one factor assumption made here is not as restrictive as it seems since our sample

The market price for human capital is r_t. Thus the observed wage of individual i in time period t is $w_{it} = r_t H_{it}$, and we can write a log wage equation as

$$lnw_{it} = \alpha lnG_{it} + \gamma lnS_{it} + m_{ift} + lnr_t. \tag{1}$$

We assume that within a firm $\Delta m_{ift} \equiv m_{ift} - m_{ift-1}$ is serially uncorrelated. However draws of the match specific effect will in general be correlated across firms, due to individual unobserved characteristics. Define p_{it} to be the participation indicator for individual i in period t.[7] We now specify

$$lnG_{it} = lnG_{it-1} + p_{it} g_i \tag{2}$$

$$lnS_{ift} = lnS_{ift-1} + p_{it} s_{ift} \tag{3}$$

where g_i represents an individual specific addition to general human capital. This is heterogeneous across individuals, but the same across firms for the same individual. Equation 2 assumes there is no depreciation of general human capital even when out of work. Given that we will be considering a young sample (between 18 and 30 years of age) this is probably a reasonable assumption. The term s_{ift} represents an addition to firm specific human capital in firm f which may vary over time, t individuals i and firms f. This innovation to firm specific human capital may be drawn from a distribution whose mean varies across firms, a reflection of the heterogeneity in the career opportunities that firms may offer. The process for S starts afresh in a new firm. The initial level of S is the match specific draw. Since this depends on individual characteristics as well as on the firm, it may be correlated across

consists of a relatively narrowly defined education group, i.e. apprentices drawn from a 15 year cohort. Note also that in Germany there has been practically no increase in inequality. Hence allowing just an additive time effect in the log wage equation is consistent with the findings from the German labour market (see Giles, Gosling, Laisney and Geib 1998).

[7]The indicator $p_{it} = 1$ if the person is employed, and zero otherwise.

matches. Moreover, the innovations to S_{ift} embody the notion that firm specific matches may evolve over time with, say, changes in technology. In this case one would expect compensating movements in m_{ift}. The initial levels of G are determined by education and other individual specific productivity characteristics. We assume that human capital does not depreciate.

Define $g_i = \theta_o + \theta_i$, and $s_{ift} = \zeta_0 + \zeta_{ift}$, where $\mathrm{E}\theta_i = 0$ and $\mathrm{E}\zeta_{ift} = 0$; thus θ_o and ζ_0 are the average additions to general and firm specific human capital per period, and θ_i and ζ_{ift} the individual, time or firm specific deviations from the average. Combining these assumptions in the wage equation specification we get that the log wage rate for an individual with X_{it} periods of work experience, who has worked in firm f for T_{it}^f periods is

$$lnw_{it} = lnr_t + \alpha\theta_o X_{it} + \gamma\zeta_o T_{it}^f + u_{it}^f \tag{4}$$

where the unobservable term is defined by

$$u_{it}^f = m_{ift} + \alpha\theta_i X_{it} + \gamma\zeta_{ift} T_{it}^f + \varepsilon_{it}. \tag{5}$$

The error term ε_{it} represents measurement error. Thus our specification leads to a random coefficients model. The aim of the empirical analysis is to identify the parameters $\alpha\theta_o$ and $\gamma\zeta_o$ which we interpret as the average returns to general and firm specific learning by doing respectively.

2.1 The Job Search Strategy of Individuals

Individuals are assumed to receive offers which are distinguishable by the match specific productivity that is associated with them and by the returns to tenure. Both of these characteristics form the quality of the match. One offer is received in every period. We assume that individuals and firms observe instantly the (potential) quality of the current and alternative match (i.e. they know m_{ift}, ζ_{ift} and θ_i). The job change decision has to weigh up

the quality of the match offered to the loss in seniority. Workers may move to another job or to unemployment because the quality of the current match deteriorated relative to these alternative offers, enough to outweigh the loss in seniority. Moves into unemployment can also be induced by changes in the aggregate price of human capital r_t.

In such a model search itself can create value: Workers who have sampled job matches over a longer period of time and moved from job to job will be more likely to have located a better match. Moreover, workers will self-select towards firms that offer their preferred career structure in terms of the amount of growth of firm specific human capital. In part such selection will be motivated by their assessment of the probability that they will be moving again.

Such a search environment is well known to generate returns to experience that have nothing to do with learning by doing. Thus, apart from general experience and aggregate growth, wages in our model *may* grow both because of the acquisition of firm or sector specific skills and because of the improvement in the quality of matches through job search. Both aspects of a match generate real value, in the sense that when a match is destroyed both the search capital and the firm specific skills are lost. Our identification strategy aims to distinguish the returns to experience and tenure due to learning by doing from the returns to search.

The model we have described draws quite closely on the ideas put forward in Rosen (1972). However there are some important differences: The heterogeneity across firms is in the accumulation of firm specific human capital, not in general capital. Individuals can accumulate general human capital at the same rate in any firm they choose to work. Relaxing this assumption makes the model particularly complicated since the number of time periods worked is no longer a sufficient statistic for the stock of accumulated ex-

perience. The other difference with Rosen's framework is that workers do not know the location of the optimal match (given their abilities). Careers improve through on the job search. In the environment we describe workers gradually self-select into the career structure that best suits their abilities and tastes.

The difficulties with estimating the average returns to experience in the environment we have described emanate from the fact that both the level of the wage and its growth are stochastic and from the fact that matches improve with search as well as with on the job learning. Hence all past job mobility decisions matter and there is a dynamic selection problem that needs to be accounted for. We discuss identification and estimation of the average returns to learning by doing of general and specific skills in such an environment.

2.2 Identifying the return to experience

In the following subsection we trace the sources of endogeneity for measuring the average returns to experience. Then we discuss identification in two cases.

2.2.1 The sources of dynamic selection bias

To control for the endogeneity of experience we need to recognize that at each point in time the individual is making the choice between working and not working and between moving jobs. Hence experience is an endogenous variable for the wage equation 4. The distribution of experience will depend on the number of periods over which the individual has been making choices. To identify the returns to experience we model the wages workers obtain upon starting a new job, which we observe. For these individuals the tenure effect is zero. The wages of job entrants can be described by

$$lnw_{it} = lnr_t + \alpha\theta_0 X_{it} + e_{it} \tag{6}$$

where $e_{it} = \alpha \sum_{s=1}^{t} p_{is}\theta_i + m_{ift} + \varepsilon_{it} \equiv \alpha\theta_i X_{it} + m_{ift} + \varepsilon_{it}$ and where p_{is} is the participation indicator for period s. Finally m_{ift} represents the match specific effect and ε_{it} measurement error. The former contains the initial conditions for general human capital.

In modelling wages we condition on accumulated experience at the beginning of the period and on having accepted the current job. Both are potentially endogenous, given our stochastic specification. Thus, we need to characterize the relationship between e_{it} and experience at the beginning of the period and participation in the current period.

We start measuring time at the date of entry into the labor market. Define by τ the number of periods that the individual could have worked at the start of the current pay period (his age in the labor market). The current period for which a wage is observed is $\tau+1$. In each period the individual has a work reservation wage $w^r(\tau, z_\tau)$ where z_τ are exogenous characteristics driving the reservation wage (which takes into account the intertemporal trade-offs). The reservation wage is also a function of unobservables which include the unobserved components of wages i.e. $m_{if\tau}$, θ_i and $\zeta_{if\tau}$. Define the value of working as $V_\tau^w = w_\tau - w^r(\tau, z)$.

For simplicity of exposition, consider first the case where $\theta_i \equiv 0$. Denote by $\tau + 1$ the age in the labour market during the current work period. Thus variables dated τ have been determined before the start of this working period. The joint distribution of $m_{if\tau}$ and $V_1^w, ..., V_\tau^w$ and $V_{\tau+1}^w$ (the value of working in the current period) as $f_\tau\ (m_{if\tau}, V_1^w, ..., V_{\tau+1}^w | z_s, s = 1, ..., \tau+1)$. By a standard change of variable argument we can derive from this distribution the joint distribution of experience, current participation and $m_{if\tau}$; experience is defined by $X_\tau = \sum_{s=1}^{\tau} 1(V_s^w > 0) = \sum_{s=1}^{\tau} p_{is}$ where $1(a)$ is the indica-

tor function which is one whenever a is true and $p_{is} \equiv 1(V_s^w > 0)$. The resulting joint distribution is denoted by $h_\tau\ (m_{if\tau}, X_{i\tau}, p_{i\tau+1}|z_s,\ s = 1, ..., \tau+1)$ and will depend on τ and on the sequence of reservation wages up to $\tau+1$, i.e. $w^r(s,z)$, $s = 1, ..., \tau+1$. Given this we can immediately see how to model this dynamic selection process if we assume linear conditional expectation. Hence we assume that

$$E(\varepsilon_{i\tau}|X_{i\tau}, p_{i\tau+1}, z) = \alpha_{1\tau} v_{X\tau} + \alpha_{2\tau} v_{p\tau+1}\ , \tag{7}$$

where $v_{X\tau}$ is a residual from a reduced form of experience on z estimated on individuals with common age in the labor market, τ. $v_{p\tau}$ is a participation residual for participation during the period in question. The first residual controls for the endogeneity of experience up to that point. The second term controls for participation in the current period.[8]

Extending this procedure to take into account that learning by doing rates may be heterogeneous across the population is relatively straightforward. As a result of heterogeneity the error term contains the extra term $\alpha\theta_i X_{it}$. Assuming linear conditional expectation for both $e_{i\tau}$ and θ_i we obtain that

$$E(e_{i\tau} + X_{i\tau}\theta_i|X_{i\tau}\ , p_{i\tau+1}, z) = \gamma_{1\tau} v_{X\tau} + \gamma_{2\tau} X_{i\tau}\ v_{X\tau} + \gamma_{3\tau} v_{p\tau+1} + \gamma_{4\tau} X_{i\tau}\ v_{p\tau+1}\ . \tag{8}$$

Hence to allow for heterogeneity in the returns we need to allow for an interaction between the residual and experience. The approach we follow is a *control function* approach. It takes explicitly into account that employment decisions depend on the gains from work and that these gains are a function of the unobservable $\alpha\theta_i$. The test that $\gamma_{2\tau}$ is zero is a test that individuals ignore the individual specific returns to experience when making employment

[8]The linear conditional expectation may be too strong. However, this can be relaxed using the results from Lee (1984), by including polynomial terms in these residuals.

decisions. Returns could still be heterogeneous; this can be ascertained by checking whether the variance of earnings increases with experience. However, in practice this may be difficult to do in a statistically clean way, since it would involve making stronger distributional assumptions.

To implement the estimation strategy above we need identifying restrictions, which are discussed in the following sections.

2.2.2 Identification with accumulation of search capital

For expositional purposes, first assume unemployment reservation wages are zero and that individuals remain out of the labor force for a number of spells for completely exogenous reasons. This assumption is relaxed in the next subsection. However, suppose they improve the quality of their match through on the job search. In this case matches improve by age, since older workers would have had a longer period over which to sample from the distribution of match specific effects. The simple OLS regression of wages on experience for new job entrants confounds the impact of learning by doing with that of job shopping. To isolate the effects of learning by doing in this environment we will use job closures. We make the following assumption:

A.1 Workers cannot predict closure before joining the firm. Once closure is announced (possibly in advance) workers have the same search and job acceptance strategy as the unemployed.

The first part of this assumption ensures that workers do not self select into firms that are more or less likely to close down on the basis of their unobserved characteristics and their preferences for career profiles. Using the observed information for our companies we provide a test of this assumption at the end of the results section. To preempt, we find no evidence that this assumption is likely to bias our results. The second part of this assumption ensures that all workers who start a new job after leaving a plant that is

about to close down or has closed down loose all their search capital. Hence, the distribution of unobserved heterogeneity for this population will not depend on their past choices. Given the zero unemployment reservation wage assumption (relaxed below), they will accept any wage offer.

Hence choosing the sample of entrants into work following a job closure provides us with variability in experience, while at the same time solving the initial conditions problem generated by dynamic selection over workers' careers. Using OLS on the sample of entry level wages for job entrants following closure provides consistent estimates of $\alpha\theta_0$ under the assumption is this sub-section. The residual terms in equation 8 are redundant in this case.

2.2.3 Identification with endogenous participation and accumulation of search capital

It is not reasonable to assume that reservation wages are zero. So we discuss relaxing this assumption now. In this case the dependence of experience and current participation on the unobservables is fully described by 8. Hence we need to compute estimates of $v_{X\tau}$ and $v_{p\tau}$ and estimate the wage equation including the residual terms, on the subsample of workers who start a new job following the closure. This approach solves both the initial conditions problem due to job shopping and the endogeneity of experience and current participation. To achieve this, our next assumption is:

A.2 Workers and firms have the same information on the quality of the match. Training and wage policies of firms are common across all workers who choose to work there. In particular they do not depend on age.

We also assume that there are no cohort effects on wages, which is reasonable given the age range is only 15 years. Given our assumptions age is not correlated with the unobservables in the wage equation for the population of workers looking for a job following a plant closure. Moreover, the

complete information assumption excludes the need for Lazear (1979) age related contracts; hence age can be excluded from the wage equation for this subsample. Of course in equilibrium both the level of wages and the observed returns to tenure may depend on age, but this is entirely due to worker self selection.

Age varies independently from the number of periods in the labor market to the extent that there is variation in initial labor market entry. We assume that the latter is exogenous to wages (conditional on education). Finally the reason age induces variability in the employment choices is because other commitments (such as children) as well as the taste for mobility vary with age. The explanatory power of the instrument is testable. Since there are two residuals but only one basic instrument, (age) identification will have to rely on the age effects being sufficiently nonlinear in the experience and participation equation.[9] Such non-linearities are to be expected since mobility does slow down quite significantly with age. Moreover, the processes we are modelling are inherently nonlinear and hence we believe this assumption (which can be verified in the data) is a natural consequence of the model. In fact, in the empirical results we show that the age effects on participation and experience are sufficiently non-linear to provide identification.

To summarize, the estimation method for the returns to experience will be relying on age as the identifying instrument. By choosing the subsample of workers who have been exogenously displaced we ensure (given our assumptions) that age is exogenous for wages.

2.2.4 Implementation of the estimation method

To implement the estimation approach for the return to experience we proceed as follows. We start by estimating a reduced form for experience at

[9]Note that both residuals originate in the same endogenous decision - labour force participation.

the beginning of the current period. This is estimated on all individuals observed completing an apprenticeship (independently of their current or past work status). The reduced form is

$$X_{it} = a_0^X + a_1^X age_{it} + a_2^X \tau_{it} + a_3^X age_{it}\tau_{it} + a_4^{X\prime} ad_{it} + x_{it}'\gamma^X + v_{Xit} \qquad (9)$$

The variables ad are 11 indicators for the ages 20 up to 30, the omitted category being the younger group.[10] The x variables are other regressors included also in the wage equations. These are the duration of the apprenticeship and its square, year indicators and highest level of education. The variable τ_{it} is the number of periods that the individual i has been in the labour market by calendar period t. The inclusion of this variable is a parsimonious way of allowing the reduced form to change with τ. We also estimate a reduced form to control for the current participation. Our data is basically continuous. The exact dates of all transitions are reported. Since within a year individuals can terminate the spell at any time the dependent variable in this "participation" regression is the number of months worked during the current calendar year in the accepted job. In both cases the sample includes all those who have completed an apprenticeship. Non-workers get a zero in the participation reduced form and whatever experience they may have accumulated up to then.

Having estimated the two reduced forms we compute the respective residuals $\hat{v}_{Xt}$ and $\hat{v}_{pt}$. We then select the first wage record for those who start a new job following a plant closure. Using ordinary least squares we estimate

[10]We include age linearly also to test for non-linearities.

the parameters of

$$\begin{aligned} lnw_{it} = \quad lnr_t + \alpha\theta X_{it} + x'_{it}\gamma^w \quad & + \delta_1^X \hat{\upsilon}_{Xt} + \delta_2^X \tau_{it}\hat{\upsilon}_{Xt} + \delta_1^p \hat{\upsilon}_{pt} + \delta_2^p \tau_{it}\hat{\upsilon}_{pt} \\ & + \delta_3^X X_{it}\hat{\upsilon}_{Xt} + \delta_4^X \tau_{it} X_{it}\hat{\upsilon}_{Xt} \\ & + \delta_3^p X_{it}\hat{\upsilon}_{pt} + \delta_4^p \tau_{it} X_{it}\hat{\upsilon}_{pt} + e_{it} \end{aligned} \tag{10}$$

on this subsample. The coefficients with an X superscript control for the endogeneity of past participation choices. Those with a p superscript control for the endogeneity of the current participation choices. The interaction of these residuals with experience X_{it} control for self selection due to heterogeneous returns to experience. Finally, as explained above, the relationship of these residuals to the unobservables in wages are likely to be changing with age in the labor market τ_{it}. We allow for this by interacting all terms with τ_{it}. Hence we compare the entry level wages for individuals with different levels of experience but no accumulated search capital, having controlled for the endogeneity of past and current choices.

Finally, our two step approach requires that the standard errors are corrected for generated regressor bias, using the delta method.

2.3 Identifying the return to tenure

The general model we present allows the returns to tenure to differ across firms/matches. We now take as known the returns to experience and $\Delta \ln r_t$. We thus define the within firm wage growth exclusively due to tenure and to the changes in match specific and general productivity as

$$\Delta \widetilde{\ln w}_{it} = \Delta \ln w_{it} - \Delta lnr_t - \alpha\theta \ . \tag{11}$$

The adjusted within firm wage growth measure is determined by

$$\Delta \widetilde{\ln w}_{it} = \gamma\zeta_0 + [\alpha\theta_i + \gamma\zeta_{ift} + \Delta m_{ift} + \Delta\varepsilon_{it}] \ . \tag{12}$$

where Δm_{ift} is an unpredictable innovation to the quality of the match. In this case the average growth of within firm wages (adjusted for the returns to experience and changes in the price of human capital) is not a consistent estimator for the returns to tenure. The workers choosing to stay employed in the same firm are those who found staying preferable to moving jobs or to becoming unemployed. That is, in general $E(\alpha\theta_i + \gamma\zeta_{ift} + \Delta m_{ift} + \Delta\varepsilon_{it})|stayer) \neq 0$. For example, if the draw from the distribution of match specific effects is uncorrelated to the current draw, then individuals with good inside innovations will be more likely to stay with the firm, implying an upward bias in the estimated within firm wage growth. To obtain consistent estimates for within firm wage growth we need to correct for the selection bias induced by transitions into unemployment and other jobs.

Defining $\xi_{it} = \alpha\theta_i + \gamma\zeta_{ift} + \Delta m_{ift} + \Delta\varepsilon_{it}$, we need to characterize the joint distribution of ξ_{it} and job mobility at each labor market age τ. Assuming a linear probability model for staying on in the job and making a linear conditional expectations assumption we have that

$$E(\Delta \widetilde{\ln w}_{it}|stay,\ z_{it},\ \tau) = \gamma\zeta_0 + \kappa_\tau\, \upsilon^s_{it} \tag{13}$$

where υ^s_{it} is a residual from the reduced form for staying. As before this will be a function of age in the labor market τ and the instruments z_{it} represents the instruments. As before we impose that $\kappa_\tau = \kappa_1 + \kappa_2\tau$.

Implementation of this approach requires at least one exogenous instrument. Moreover because ξ_{it} contains the term ζ_{ift} which may be match specific, we need to deal with exactly the same initial conditions problem as when estimating the returns to experience. Thus, following on from our earlier discussion on the subject, the basic instrument is age and the estimation sample will include the observations on wage growth in jobs that follow a plant closure. We illustrate in the next section that age has a very strong

influence on the probability of staying on in the job. As before choosing jobs that follow firm closure solves the initial conditions problem due to on the job search.

In a more restrictive version of the model where the returns to tenure are homogeneous (and as a consequence there are no match specific effects in the growth) we can estimate the model on the entire sample. In this case we can add to the set of instruments the incidence of past firm closures.

The incidence of past firm closures can explain mobility for two main reasons. First individuals who have had unemployment spells will have lower seniority on average. If the returns to tenure are positive (and hence firm specific human capital exists) workers with a history of unemployment will be more likely to accept an alternative job offer, since they have accumulated less firm specific human capital and hence their reservation wage will be lower than individuals who have not had such spells in the past.

The second reason provides identification even when the returns to tenure are zero, so long as there is some heterogeneity in matches that is observable to the individual before he takes the job. Suppose workers search on the job. Workers with a longer period of uninterrupted work history, moving from job to job will improve their match and they will become less mobile. A worker who has had his job terminated for exogenous reasons has to start searching at the bottom of the ladder again, since all such search capital has been lost. He will be accepting any job above the unemployment reservation wage. Such a worker will have less accumulated search capital than workers without a spell of unemployment and hence will be more likely to be induced to move. Crucially, this argument does not depend on there being positive returns to tenure.

Given this argument we should observe workers who went through a closure in the past to be more mobile and for this excess mobility to decline

with time from the closure. We find strong evidence in the data of this happening. Moreover, under the assumptions that returns to experience and tenure are not firm specific and that Δm_{ift} is not serially correlated, the incidence of past plant closures is not correlated with the unobservables in the within firm wage growth.

3 The Data and Empirical Results

3.1 The data

The data we use is a 1 percent sample from the German Social Security records, which has been supplemented by information from the official unemployment records. This data is available for the years 1975-1990. We also have information on the size of all establishments employing any worker in our sample. This information is available for the years between 1981 and 1990. We use this information to determine firm closures. We explain the data in more detail in the appendix.

Our data has several advantages compared to data sets used in other studies. The administrative nature of the data ensures that the information on wages and employment spells is very accurate. Thus we largely avoid measurement problems. Furthermore, we can exactly match wages to employment spells with a particular employer – there is no overlapping wage information across firms as in many data sets such as the PSID. We also observe a number of background variables usually not provided in administrative data, like education, occupation, job position, marital status etc. At the same time, the data set is large and covers a long period, which allows us to construct the sample explained below.

The data does not cover the entire German labor force, as the self employed and civil servants are not paying social security contributions, and are therefore excluded. Moreover, as with many administrative data sets,

the data is top coded. However, top coding does not affect the wages of apprentices younger than 30, which constitutes our sampling frame.

3.2 The Sample

Our sample consists of young workers who have participated in an apprenticeship training scheme for at least 700 days by the age of 22.[11]

We include only those individuals whom we observe from the beginning of their labor market entry. To achieve this, we exclude individuals who are older than 15 in 1975 (the beginning of our observation window). This is about the earliest age an individual can enter an apprenticeship scheme, since Germany has a compulsory school system which requires individuals to attend school for at least 9 years (children start school at age 6). Furthermore, we exclude all individuals who finish training after 1988. Accordingly, the longest labor market history in our data set is 14 years, and the shortest 2 years.

We include all individuals who completed apprenticeship in our sample, independently of when they started working following the apprenticeship. This is necessary if we are to control for the endogeneity of past participation decisions.

Before 1984, the reporting procedure did not require employers to report additional payments, like Christmas money, or holiday money, to the authorities. These additional payments can constitute a considerable part of the annual wage bill. They are indicators of the quality of the match, and may affect the selection process we have described above in a non-random manner. After 1983, it was compulsory to employers to include these payments in the reported wage bill. Thus in our analysis we use the entire

[11] This age is chosen to include high school graduates (18), who may enter apprenticeship training (which is reduced to 2 years for high school graduates) after completing their compulsory military service (15-18 month). Our criterion excludes individuals completing "job specific training schools" or volunteerships both of which last at most one year.

Years of Experience	Number of Jobs							
	0	1	2	3	4	5	6	Σ
0	49.77	36.28	8.95	3.11	1.17	0.48	0.24	100.00
1	40.66	31.48	15.02	7.07	3.23	1.69	0.84	100.00
2	34.27	30.02	17.22	9.50	4.92	2.64	1.43	100.00
3	31.18	28.80	17.59	10.74	6.02	3.56	2.10	100.00
4	29.11	28.76	18.30	11.13	6.56	3.71	2.43	100.00
5	28.20	27.66	19.01	11.49	6.88	4.26	2.50	100.00
6	27.98	26.72	18.71	11.77	7.26	4.71	2.85	100.00
7	28.02	27.69	19.00	11.67	6.78	4.09	2.75	100.00
8	27.44	27.55	19.14	12.29	6.64	4.23	2.71	100.00
9	26.10	27.00	20.16	12.63	7.00	4.31	2.80	100.00
Σ	37.06	30.99	15.34	8.27	4.39	2.49	1.46	100.00

Post apprenticeship years of experience and number of jobs,
row percentages
Zero jobs denotes no change of firm post apprenticeship

Table 1: Number of jobs by levels of experience

observation period to compute individuals' labor market histories. However we use wage information only from 1984 onwards.

In figure 1 we present information on wage growth in our data. Within job average annual wage growth is on average lower than between job wage growth. This is true both over time and over different experience groups (figure 2). The difference is striking, particularly for those with less than a year's experience. The most plausible explanation for this observed difference in wage growth is of course selection due to endogenous job mobility choices: Since the worker's reservation wage when working is the current wage (in the absence of other forms of compensation or of moving costs) the average accepted wage will be such that it is higher than the wage obtained by the stayers. The difference in the growth rates in figure 2 declines rapidly in the first three years of experience. This may reflect the higher variance of job offers early in ones career when workers have not sorted into their preferred match yet.

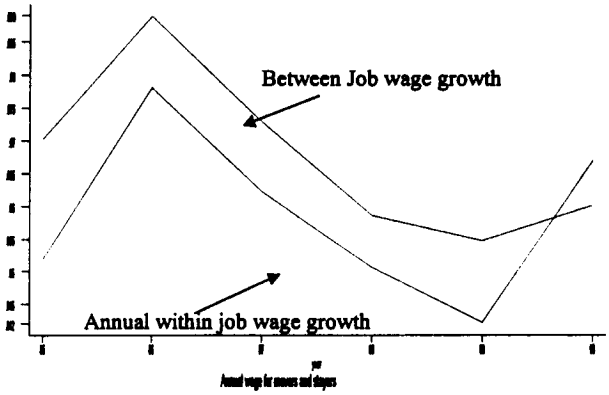


Figure 1:

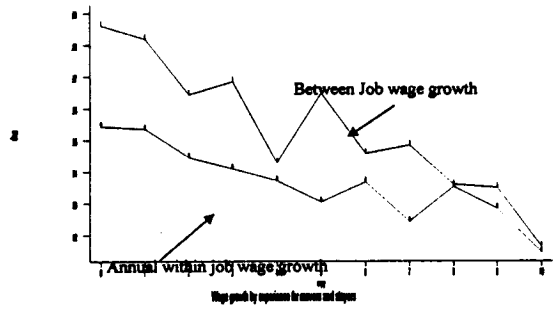


Figure 2:

In Tables 1 and 2 we present information on job mobility. In Table 1 we tabulate the distribution of jobs by the years of completed experience (zero experience corresponds to the first year post apprenticeship and zero jobs corresponds to staying on with the job in which apprenticeship took place). There is a large proportion of individuals who remain within the job in which they carried out the apprenticeship. Even at nine years of experience the proportion is still 26%. However, over half the workers who complete apprenticeships move immediately following completion. Moreover mobility does not stop at that point. In fact as seen in Table 2 those who do move are significantly more mobile than those who stay. Another interesting fact is that those who complete apprenticeships later are generally more mobile. This may reflect the fact that they have more education overall. In summary, although mobility is substantially lower than what has been recorded in the

US, it still is sizeable.[12] Moreover, job shopping constitutes an important source of wage growth in Germany: Within firm wage growth is lower than between firm growth and there is considerable mobility among the young.

We now provide some information on the firms to which our workers are matched. In figure 4 we plot the survivor function for the plants that came into existence during 1983-1991. The annual exit rates are quite high initially, and they steadily decline. Of the plants that flow in only 60% survive beyond eight years. Thus there is quite a lot of mobility on the plant side as well. In fact in our estimation sample 2586 individuals started a new job after leaving a plant that closed down within a year of their departure, while 2976 individuals left a plant that closed down within two years of them leaving. In Figure 3 we show the average log wage of individuals in plants that will close down (in period 0) . Note that the last observation (period 0) is on average six months away from the one in period -1 since closures are distributed more or less uniformly over the year. The other observations are spaced at annual intervals. On average real wages fall by about 6% just before closure. Moreover, there was no wage growth a year before this. Post closure the workers who left the closing plant seem to have a similar growth rate of wages to the rest of the workers. These results are consistent with firms that are about to close down having suffered a bad productivity shock, which in our model would be interpreted as a fall in the match specific effect. Since the match is now worse than average the post closure job looks much better. It is also consistent with selective departures by observed or unobserved skill. This is why we use two definitions for constructing the sample of workers who left due to plant closures as is explained below.

In Figure 5, we show the evolution of average employment for plants

[12]See Topel and Ward (1992) for a comprehensive analysis of the sources of wage growth in the US.

Age	16-17		18-19		20-22	
Months	Change	Same	Change	Same	Change	Same
	First Job					
6	0.7447	0.9876	0.7191	0.9435	0.7116	0.8779
12	0.6063	0.7583	0.5810	0.6875	0.5527	0.6144
24	0.4451	0.5648	0.3922	0.4808	0.3606	0.4104
36	0.3403	0.4223	0.2827	0.3495	0.2415	0.2803
48	0.2743	0.3200	0.2031	0.2532	0.1613	0.1908
60	0.2151	0.2436	0.1441	0.1816	0.1054	0.1277
Sample	795	12699	13407	38211	11837	14019
	Second Job					
6	0.6524	0.7533	0.6716	0.7360	0.6412	0.6863
12	0.5308	0.6122	0.5086	0.5888	0.4668	0.5205
24	0.3814	0.4271	0.3350	0.4020	0.2864	0.3303
36	0.2606	0.3098	0.2300	0.2758	0.1773	0.2086
48	0.1714	0.2237	0.1583	0.1895	0.1075	0.1330
60	0.1188	0.1585	0.1094	0.1245	0.0652	0.0791
Sample	430	6004	6819	16918	5199	5574
	Third Job					
6	0.6595	0.7652	0.6627	0.7405	0.6455	0.7019
12	0.4950	0.6205	0.5099	0.5949	0.4701	0.5373
24	0.3245	0.4466	0.3268	0.4016	0.2742	0.3509
36	0.2308	0.3266	0.2133	0.2759	0.1645	0.2233
48	0.1494	0.2276	0.1454	0.1855	0.1010	0.1370
60	0.1004	0.1605	0.0964	0.1261	0.0603	0.0751
Sample	230	3395	4062	8734	2892	2518

Age: Age at end of apprenticeship. Post apprenticeship durations
Change: First job not in plant where apprenticeship took place
Same: First job with plant in which apprenticeship took place

Table 2: Job Survival rates

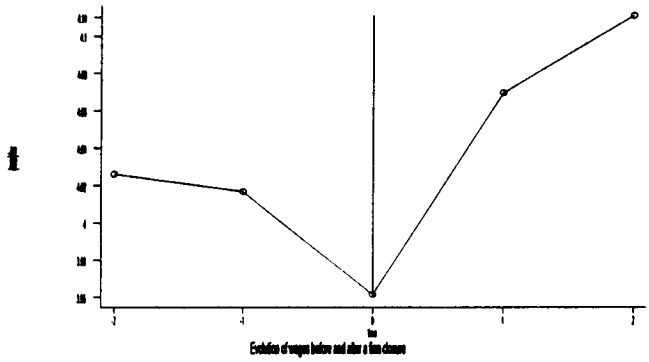


Figure 3:

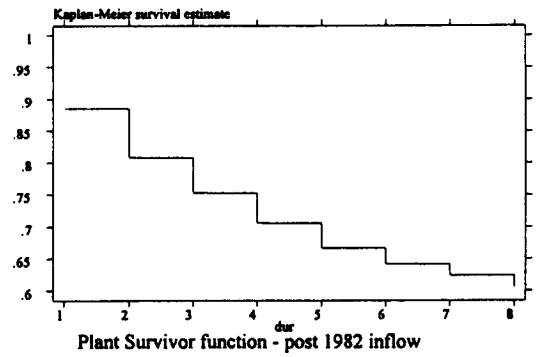


Figure 4:

known to close down. Each line follows the same plants. They are distinguished by the number of periods we observe them before closure.[13] The first obvious drop in employment in the plants that will eventually close down is two years before closure. Selective firing or quits may of course impact on the average quality of the workforce in the plant. We discuss the effects of anticipation of closure by workers in our empirical section.

[13]Note that this brakedown is made so as to avoid the composition effects that are induced by the fact that young firms are both smaller and more likely to close down. The differences in firm size across the lines reflect a different age composition of each group.

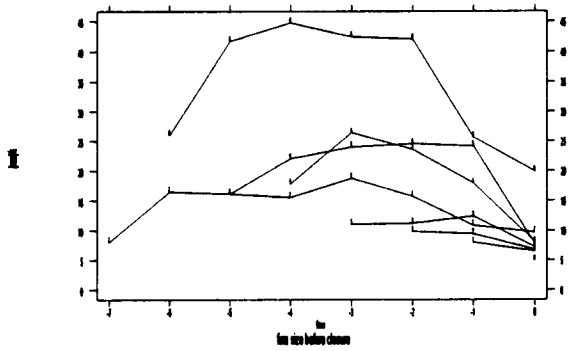


Figure 5:

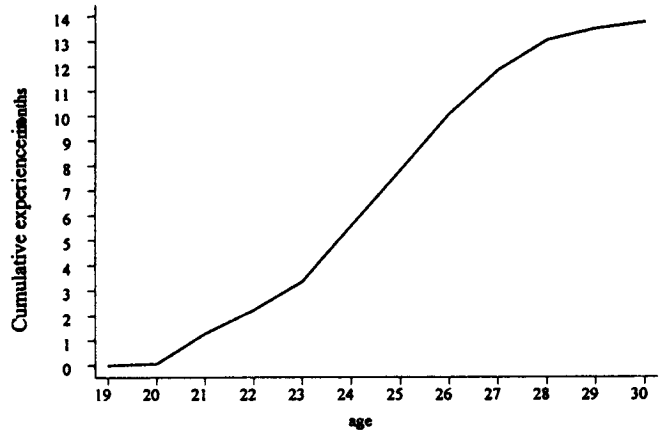
4 Results

4.1 The reduced forms for Experience, participation and job mobility

There are three reduced forms in our model. One for the accumulation of past participation decisions (experience), one for current participation and one for staying in the current job rather than moving to a new job or becoming unemployed. Experience in the wage equation is the number of months worked following apprenticeship up until the beginning of the current period. The first two reduced forms include age indicators, age in the labour market and interactions (see equation 9) the duration of apprenticeship and its squared, initial education and time effects and are used to control for the endogeneity of experience and participation when estimating the effects of experience on wages in equation 10. The third reduced form includes only the age effects and age in the labour market and interactions. It is used to control for selection in the within firm wage growth equation 13. We estimate two sets of reduced form equations, one also including an indicator of whether the individual was displaced in the past due to a plant closure, and one excluding this indicator. We discuss the effects of closure below.

In the appendix we present details on one set of reduced forms. To ensure identification we require the age effects in the two first reduced forms to be sufficiently nonlinear. This ensures that $\hat{v}_{X\tau}$ and $\hat{v}_{p\tau}$ in equation 10 are not colinear. As naturally expected, in all reduced forms the age indicators are important and highly significant with p-values of zero over and above a linear age affect. To illustrate the effects we present the age profile of experience, the effect of age on the number of months worked during the year (in the same job)[14], and the probability of changing jobs in figures 6,

[14]If we ignored the fact that individuals worked different proportions of a year this would be like a linear probability model of participation. The actual estimated equation



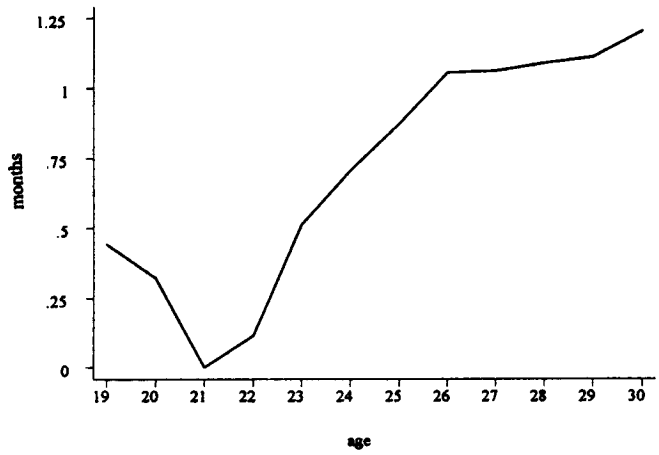
Cumulative growth in experience with age given time in the labour market

Figure 6:

7 and 8. The first graph illustrates the differences in the accumulation of work experience by age, given the time spent in the labor market. It shows that older individuals have a significantly stronger labor market attachment (for a given overall time spent in the labor market). The other two graphs presents the effect of age on months worked during the year (figure 7), and the cumulative increase in the staying on probability with respect to age (figure 8). The graphs clearly indicate that older people are more likely to be employed at any point in time; furthermore, older people are much less likely to move to a new job.

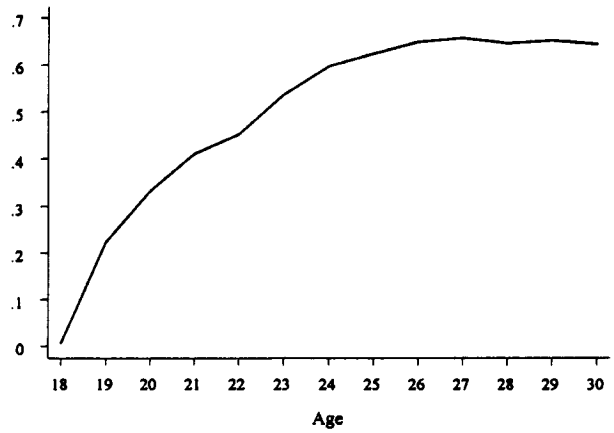
We have argued that exogenous separations are likely to increase sub-

is a linear count model with dependent variable the number of days worked with the current employer during the current year.



Effect of age on months worked during a year

Figure 7:



Cumulative increase in the staying on probability with age

Figure 8:

Years post closure	Excess Mobility	Stand. Error
1	0.024	0.013
2	0.100	0.014
3	0.090	0.016
4	0.070	0.019

Table 3: Post-Displacement Excess Mobility

sequent mobility for some time at least. Of course the variability induced by past plant closures on staying on can only help us in the identification of tenure effects under the assumption that the returns to tenure are homogeneous across firms. Moreover they cannot help us in the identification of the returns to experience since we use the post displacement sample only in that case. However we report these effects as evidence that job shopping may be an important factor.

In Table 3 we present the unconditional mobility rates post displacement. The figures show the mobility of workers post displacement relative to those not displaced. The excess mobility rates are substantial. Individuals who have started a job after a displacement are much more likely to move. In the experience reduced form, past displacements lead to a reduction of experience by 2.58 months (se 0.119). In the staying on reduced form past displacements have a coefficient of 0.153 (se 0.0028), implying a substantial increase in mobility. We have interpreted this as the effect of loosing ones search capital on the mobility reservation wage: The average quality of a match post closure is likely to be lower; hence it becomes more likely that a new acceptable job offer will be made and mobility observed.

In conclusion, employment and mobility seem to change substantially with age and workers who go through a displacement are subsequently more mobile.

4.2 The Returns to Experience and Tenure

We now turn to the investigation of the growth of wages with experience and tenure. The main set of results are presented in Table 4. In interpreting the results note that the oldest worker in our data is 30. The median experience is 4.5 years and the median tenure is one year (with the mean being 2.4 years).

All wage equations include indicators for education, a quadratic function of the duration of apprenticeship and annual time effects. The duration of apprenticeship is included to control for differences in initial human capital between apprentices. Our experience variable is measured starting after the end of apprenticeship. Our estimation approach allows for effects of accumulated specific and general human capital during the apprenticeship period. Since the returns to experience and tenure are estimated separately in two steps (except in the OLS case) the Table is split into two parts. The top part refers to the returns to experience, estimated using levels equations on appropriate subsamples and the second refers to the returns to tenure, estimated using the suitable wage growth measure. In the Table we also report, whenever relevant, the coefficients on the residual terms.

In the first column of the Table we present the simple OLS results. This is a simple linear regression of log real wages on actual labour market experience and tenure in the current firm as well as time effects, the duration of apprenticeship and its squared and initial education indicators. These results imply a 3.6% annual growth of wages due to experience and a 2% annual growth rate due to tenure. In the second column we present the results obtained by Topel's (1991) approach. This involves estimating the returns to experience using OLS on entry level wages for all new jobs (including time effects education and the duration of apprenticeship as in all levels regressions). As Topel also points out this approach is likely to lead to an

overestimate of the returns to experience. In fact the returns to experience are now estimated to be 3.9% a year, higher than OLS. In the second half of the table we report the implied average within firm wage growth, after removing the estimated time effects and experience effects as implied by the previous regression. This is a simple OLS regression of the adjusted wage growth measure defined in 11 on a constant. The returns to tenure become negative. This is consistent with a low or zero true tenure effect, together with an overestimation of the returns to experience.

We next implement our estimation method. In all the following models the returns to experience are estimated on samples of entry level wages for workers who start a new job following displacement due to plant closure. Before we present these results we need to discuss the choice of this sub-sample. In our data we know the 12 month period during which the plant closed down. This could take place between two consecutive June months. Moreover we know whether a closure took place independently of whether the worker is still with the firm. Workers are likely to know that the plant is in trouble before the actual event of closure. Moreover, workers may be laid off in stages. To check whether selective departure from the firm that is closing down has a large impact on the results we use two definitions of displacement: First we take all those workers who left a firm that closed down within two years of their departure. We then narrow it down to the workers who left a firm that closed down within one year of their departure. With the first definition we guard against selective departures. However it is possible that the second part of assumption **A.1**, i.e. that workers expecting the plant to close down behave like the unemployed in their job acceptance strategy, is violated; they may become more picky in the jobs they accept. The second narrower definition is less sensitive to the latter problem, but the set of workers are less of a random sample. The first set of results we

present are obtained by estimating the model on post-displacement jobs as defined by the first broader definition. We then discuss what happens when using the second narrower definition.

The results in column 3 are estimated under the assumption that self selection into work only takes place on the basis of unobservables in the level of wages and not on the basis of the returns to experience. The sample includes only post-displacement workers. The effect of the selection correction is significant. However the estimates of the returns to experience fall only moderately to about 3.6%. The residual for experience has its strongest impact early on and decreases with time spent in the labor market (τ). The effect of selection into work is highly significant and increases slightly with τ.

To obtain an estimate of the return to tenure we estimate equation 13 on the entire sample of job stayers. This assumes either that the returns are homogeneous across firms, or that individuals do not act on the returns to tenure (say because they do not know them). The results are consistent with heterogeneity of the returns to tenure across individuals. The returns to tenure estimated by this model are significantly lower than those obtained using OLS but now they are positive. The t-test for equality with the OLS coefficients is 2.1, marginally rejecting the OLS results. The residuals controlling for the endogenous selection of stayers is highly significant with a p-value of 0. Thus, just on the basis of this model it is clear that the selection process significantly biases the returns to tenure upwards.

We can now extend the model by allowing for the possibility that the returns to experience are heterogeneous across individuals and that individuals take this into account when making participation decisions. This is achieved by introducing an interaction of the residuals with the level of experience when modelling entry level wages post-displacement. In this case

the estimated equation is 10 again on the entry level wages for jobs post displacement. The results are now quite different and consistent with the idea that individuals with stronger labor market attachment are those with the higher returns to experience. Once self selection by the returns to experience has been accounted for, the estimate for the average returns to experience falls to 2.7% annually. This is not a surprising result: For individuals with higher rates of learning by doing the costs of spells out of work are higher.

Furthermore, not only is the current loss higher, but the future loss is higher compared to those with lower returns (lower θ_i in equation 5); not working now reduces future wages by more for high return individuals. The t-statistic for the equality of the returns to experience as implied by the last two columns is 4.1. In addition, the interactions of the residual terms with experience are jointly significant ($\chi^2(4)$ test is 10.24, p-value 3.7%). Thus although we find self-selection by the returns to experience to be very important it is evident from these results that controlling for self-selection just on the basis of unobservables in the level of wages may hide the true impact of self-selection.

We now turn to the returns to tenure in this model. The estimated equation here is 13. We estimate two models, both consistent with the heterogeneous returns to experience model. In model A the returns to tenure may be heterogeneous across individuals, but not across firms. This equation is estimated on all job stayers and the identifying instruments are two: The incidence of previous job closures and age (conditional on τ) both of which explain mobility. It turns out that the returns to tenure we obtain are 1.6% which is higher than those in column 3, probably reflecting the lower estimated returns to experience. However, they are lower than what they would have been if in this model we imposed the assumption that mobility decisions are not affected by wage growth.

In model B we allow the returns to tenure to be match specific. In this model individuals are allowed to self-select into jobs with higher or lower returns to tenure, depending on their tastes, abilities and individual specific turnover probabilities. To eliminate the effects of such dynamic selection on the estimated returns to tenure we estimate the model only on the first job accepted post closure. The point estimate for the returns to tenure falls to 0.38% a year as would be predicted by the presence of search capital. However, the difference is not very significant, partly due to the lack of precision of the estimate for model B. The t-statistic for the equality of the tenure coefficients in models A and B is 0.62.

The basic conclusion from these results is that there is evidence of selection into work on the basis of the returns to general human capital and that the returns to tenure are at best very low. We now investigate some remaining issues.

4.3 The effects of the definition of the closure sample

In our data we know whether a plant closed down independently of when the worker left, since the plant size variable is constructed from the entire database of workers (see appendix). Up to now we have defined the population of displaced workers due to plant closure as the set of workers who left the plant which closed down within two years of their departure. We did this to take account of workers who may leave the plant in the knowledge of an imminent closure. At the same time, we assume that these workers behave like the unemployed in their search strategy. There is clearly a tension between controlling for early departures and the latter assumption.

We reestimate the model with heterogeneous returns to experience using the narrower definition: All workers who leave a plant that closed down within a year of their departure. The returns to experience are now esti-

	Levels OLS	Topel	Stochastic Growth		
			Homog return	Heterog Return	
Experience	**3.557**	**3.944**	**3.645**	**2.731**	
	(0.080)	**(0.117)**	**(0.562)**	**(0.604)**	
u exp			3.076	2.463	
			(1.301)	(1.665)	
u exp×age in l			-0.360	-0.491	
			(0.156)	(0.204)	
u part			12.69	10.081	
			(2.82)	(3.215)	
u part×age in l			0.283	1.942	
			(0.678)	(0.922)	
u Exp × Experience				1.379	
				(0.7016)	
u exp × Exper × age in l				-0.0773	
				(0.0977)	
u part× Experience				0.6652	
				(2.3021)	
u part × Exper × age in l				-0.6121	
				(0.3676)	
Sample for returns to Experience	75359	25945	2976	2976	
	All	Job starts	Job starts post closure		
				Model A	**Model B**
Tenure	**1.936**	**-1.578**	**0.793**	**1.577**	**0.379**
	(0.083)	**(0.055)**	**(0.543)**	**(0.545)**	**(2.008)**
u stay			2.314	2.586	2.835
			(1.033)	(1.035)	(3.698)
u stay × age in l			-1.480	-1.468	-0.879
			(0.152)	(0.153)	(0.671)
Sample for returns to tenure	75359	31600	31600	31600	1611 wage growth in job post closure
	All	All wage growth observations			

Experience and tenure measured in years. All coefficients × 100. Time efects included. Wage equations include, pre-apprenticeship education and the duration of apprenticeship. Standard errors robust to heteroskedasticity in parentheses. **age in l**: Number of years in the labour market. **u exp** residual from experience reduced form. **u part** residual from participation rf. **u stay** residual from staying rf. **Model A**: No match specific effects on tenure. **Model B**: With match specific effects on tenure

Table 4: Experience and Tenure Profiles

mated at 2.659 (se 0.938) compared to 2.731 in column 4 of table 4. The returns to tenure rise a little bit. These become 2.18 (se 0.545) for model A and 0.73 (se 2.34) for model B. Thus the results change but only marginally. There is no formal way of choosing between them. However, this exercise shows that the biases due to selective departure once closure is known or strongly suspected are unlikely to be very large.

4.4 Does self-selection by company closure probability bias the estimates?

Finally we have assumed throughout that workers have no way of knowing which firms are more likely to close. This assumption is important: Workers with higher returns to tenure would avoid firms more likely to close down, since they suffer a larger loss form closure. This would lead to a downward bias in the estimated returns to tenure. If the heterogeneity in the returns to tenure is positively correlated with the returns to experience the returns to experience would also be downwards biased. However, if the returns to tenure are zero and there are no other mobility costs, no bias is induced for the returns to experience, since general human capital is not affected by firm closure.

Our data provides enough information to test that no such self selection takes place, biasing the returns to tenure. As we have seen, young plants are more likely to close down (see figure 4). If workers with high returns to tenure were trying to avoid plants with high closure probability they should avoid employment in younger firms. In our data we observe the inflow of companies from 1982 onwards. Hence we can test the hypothesis of no selection by the age of the firm by re-estimating our model based only on the closure of older companies.

To implement this test we reestimate our model based on the firms that

were in existence in 1982 and subsequently closed down in the period 1984-1990. The results are comparable to those of the last column in Table 4. This subsample of plants should on average be older and hence less likely to close down. The results are very similar to the ones obtained earlier. The returns to experience are indeed slightly higher at 3.1% (se 1.15). The returns to tenure for model A are 1.16% (se 0.544) while for model B they are -0.02% annually (se 2.13). The differences with the earlier results are not significant and clearly the conclusions are very similar. From these results there is no indication that self-selection by probability of closure has led to an underestimate of the returns to tenure or experience.

5 Concluding Remarks

In this paper we estimate a human capital model of wages using a unique data set, drawn from German administrative data. The data has the advantage that the entire work history and earnings history of the individual is known. Hence there is little or no measurement error in computing the number of periods worked overall and in particular firms. Moreover we have enough information to know whether and when the plants in which individuals worked closed down.

In our model wages can grow because of the acquisition of general or specific human capital, as well as due to job shopping. Moreover we allow for the possibility that the learning rates differ across individuals and that different firms offer different packages as far as the acquisition of firm specific human capital is concerned. We discuss the implications of this model for identification. We come up with a strategy that combines information on plant closures together with selection correction methods to control for the dynamic selection bias that arises from the search strategy of individuals so as to estimate the average returns to experience and tenure in the population.

The main findings of the paper are as follows:

1. There is substantial mobility among young workers in Germany, although this mobility is lower than the mobility observed in the US.

2. From the data description it is evident that job shopping does lead to wage growth: Those observed moving obtain wage increases on average.

3. Simple Ordinary Least Squares regressions overestimate the returns to experience and tenure.

4. Our best estimate of the population average returns to experience is 2.7% a year.

5. The returns to experience are heterogeneous across individuals and there is evidence that individuals take this into account when deciding to take up employment or not. Taking into account the self selection of workers into employment on the basis of their returns to experience changes our estimates of the average returns substantially. In our sample this seems to be the main source of self-selection and bias in the OLS results for experience

6. The estimated returns to tenure are quite small. At a minimum these are estimated to be close to zero (0.38% annually). However some of our results imply returns at 1.6% annually. The lower point estimate is obtained when we allow for heterogeneity in the returns to tenure across firms. However in this case the precision is much lower and hence our degree of uncertainty on the precise point estimates. The OLS regression overestimates the returns to tenure. In any case the returns to tenure are very small in Germany.

7. Finally it is worth mentioning that the aggregate wage growth (Δlnr_t) over the period was on average 1.8% a year as estimated by our preferred model.

These results imply that there is wage growth due to learning by doing and that workers with long labor market attachment are likely to be earning

substantially more than those with long interrupted spells, given training and education. Perhaps even more interesting is that most of the wage growth seems transferrable. There is little evidence of high returns to tenure to the worker. However the returns to experience we estimate are lower than those in the US.

Some might find this surprising. In the US the estimates of within firm wage growth for young workers are higher than Germany. Topel's (1991) estimate is 12.5%, with the returns to experience being estimated at about 7% and the returns to tenure at 5.5%. Altonji and Williams (1997) present a range of estimates for the returns to experience of between 4.7% and 6.3%. Their instrumental variables results are 4.9%. They key reason for these differences may lie in the different way by which on-the-job training is organized in the two countries. In Germany regular jobs for this group follow an apprenticeship period of up to three years. Wage growth is substantial during the apprenticeship period (about 30%), where a lot of human capital is accumulated fast. Following apprenticeship the nature of on-the-job learning is probably quite different and does not involve learning a trade more or less from scratch. In the US with no formal apprenticeship training, the education that takes place during the apprenticeship in Germany may be spread over a longer period of time. It is likely that the two sets of returns are not directly comparable, due to the differences in timing of the acquisition of general human capital or simply because the early period of accumulation is labelled in Germany explicitly as a training period. It is interesting to study the relative merits of the two systems and the reasons why each has prevailed in the respective country.

6 Appendix: The Data

The data base used for this research consist of three components.

The core data stems from a 1 percent sample from the employees' files, known as the Historical File (HF) of the Federal Employment Office in Nuremberg/Germany. The HF is constructed as an insurance account, and contains a continuous employment history for each employee covered by the social security system over a period of 16 years (January 1975 to December 1990).[15] The 1 percent sample comprises 426,363 individuals in the longitudinal dimension and, on average, 200,000 individuals in the yearly cross-sectional dimension.

The HF excludes individuals who are below the earnings threshold which makes social security contributions compulsory (which is the case for marginal jobs). Accordingly, the sample is left truncated.[16] Furthermore, the sample is right censored at the highest level of earnings which are subject to contributions. Both coding problems are not relevant for the subsample we are using since all individuals are in regular employment and hence very unlikely to be out of the Social Security net. Furthermore, all individuals are at the beginning of their career, which makes top coding negligible.

It excludes the self-employed, civil servants, and individuals who are in compulsory military service, or alternative compulsory activities. For 1980, Herberger and Becker (1983) estimate that the HF comprises 79 percent of the total labor force.

The IAB data contains further information from a second important

[15]The basis for the HF is an integrated procedure for health- retirement- and unemployment insurance, introduced in 1973, which requires employers to report any commencement and termination of an employment relation which is covered by social security. Additionally employers have to provide information on each of these ongoing employment relations on December 31 of every year. The information reported by the employer at every mention includes individual characteristics, such as gender, nationality, and educational attainments, as well as gross earnings over the past employment spell. Furthermore, spells of interrupted employment relations, like maternity leave, or obligatory military and civil service, are also reported.

[16]If an individual has previously been employed in a job where social security contributions were obligatory, he will be in the sample, but wages are left censored. Individual who have never contributed to Social Security he will not be in the files.

data source, the records of registered unemployed of the Employment Office. This data file contains spells of individuals who receive benefit payments from the Federal Employment Office. The combination of these two data sources allows to follow individuals also during periods of registered non-employment.

Finally, information on the plant which employs the individual is added, which is generated from the original historic file HF. Using this entire data base, information about individuals is aggregated to plant level, using plant identifiers attached to each individual observation. This aggregation is done for the first of June in every calendar year. As a result, information on plant size and educational structure of the plant is obtained and can be matched to every individual record. This information is available from 1981 onwards.

6.1 Appendix B: The reduced form results

In Table 5 we present the estimates of the age effects in the three reduced forms we use. The first two are used to control for the endogeneity of experience and participation respectively when estimating wages at job entry. The third reduced form is used to control for the selection by stayers when estimating the returns to tenure in the adjusted wage growth equation. These reduced forms do not include the incidence of past closures. However, as far as the age effects are concerned the results are very similar.

	Experience at beginning of period		Number of months in year worked/12		Linear probability model Stay=1	
age in labor market (τ)/100	-0.5559	*0.0356*	-0.1120	*0.72600*	-7.6917	*1.1738*
age×age in labor market/100	0.0411	*0.00151*	0.0330	*0.02930*	0.3111	*0.0467*
age/100	-0.5529	*0.0281*	0.6470	*0.79600*	20.554	*1.5259*
age=20	0.0041	*0.0003*	-0.01789	*0.01132*	-0.1079	*0.0222*
age=21	0.0092	*0.0006*	-0.05239	*0.01873*	-0.2459	*0.0363*
age=22	0.0141	*0.0009*	-0.05061	*0.02648*	-0.4210	*0.0511*
age=23	0.0191	*0.0012*	-0.02515	*0.03345*	-0.5522	*0.0662*
age=24	0.0250	*0.0014*	0.0168	*0.04228*	-0.7079	*0.0814*
age=25	0.0310	*0.0017*	-0.01078	*0.05027*	-0.8985	*0.0967*
age=26	0.0369	*0.0020*	-0.00319	*0.05835*	-1.0902	*0.1121*
age=27	0.0425	*0.0023*	-0.01062	*0.06652*	-1.2983	*0.1277*
age=28	0.0476	*0.0027*	-0.01601	*0.07486*	-1.5261	*0.1436*
age=29	0.0520	*0.0030*	-0.02196	*0.08337*	-1.7364	*0.1596*
age=30	0.0563	*0.0034*	-0.02203	*0.09221*	-1.9601	*0.1761*
$\chi^2(11)$ for the age indicators	699.5 p-val 0%		303.82 p-val 0%		402.27 p-val 0%	

The first two specifications also include time dummies, educational dummies, and the time spent, in apprenticeship and its square. Experience is measured in years. Standard errors in italics.

Table 5: Reduced Form Equations

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