Discussion Paper No. 98-47

Growing into Work

Pseudo Panel Data Evidence on Labor Market Entrance in Germany

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Non-technical Summary

While the potential merits of the German apprenticeship training system seem to be fairly well documented, relatively little is known about those youths who, at one point or another, do not follow the usual track from apprenticeship training to regular work. These youths are the subject of the present study which attempts to empirically evaluate the long-run consequences of a failed start into the labor market on future earnings. Using a sample of West German males born between 1930 and 1965, two groups of former apprentices are identified who do not report a smooth transition from apprenticeship training to work. The first group abandons the apprenticeship training without having obtained any vocational degree, the second group fails to find a regular employment opportunity after successfully completing the apprenticeship training and becomes unemployed. A priori, both groups may be expected to suffer from long-run earnings reductions because they either experienced a discontinuance of human capital formation at the beginning of their career or, at least, give such signals to potential future employers. This paper tries to disentangle these potential effects of a failed labor market entrance on long-run earnings from other observed and unobserved effects caused by individual heterogeneity. This is done by transforming the three repeated cross-sections of the German 'Qualification and Career' survey, conducted in 1979, 1985/86 and 1991/92, into a pseudo panel of birth cohorts and estimating earnings functions with pseudo panel methods. The estimation results indicate that both groups reporting a nonsmooth transition from the apprenticeship training to work do suffer from strong future earnings reductions. While the impact of an unsuccessfully completed apprenticeship vanishes with increasing labor market experience, the negative impact of an early unemployment spell lasts over the entire individuals labor market history.

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Abstract

The German apprenticeship training system is generally acknowledged to solve the youth unemployment problem prevalent in many European countries by providing on-the-job training that often leads into subsequent regular employment within the training firms. Little attention has been paid to those youths who either fail their apprenticeship training or do not find a job afterwards. Both events may not only be associated with a depreciation of human capital but also may serve as a screening device for potential employers. In this paper we try to analyze empirically if a failed labor market entrance reduces subsequent earnings and if a potential reduction lasts over the individual's labor market history. We construct a pseudo panel of birth cohorts for a sample of West German males born between 1930 and 1965 from three repeated cross sections observed in 1979, 1985/86, and 1991/92. Analyzing the pseudo panel data we find a strong negative impact on earnings for both a failed apprenticeship training and a failed transition into regular employment. While the latter effect lasts over the individual's labor market history the former effect is compensated with increasing labor market experience.

Keywords: Apprenticeship Training; Labor Market Entrance; Earnings; Cohorts; Pseudo Panel Estimation
JEL Classification: J24, J31, C23

* Financial support by the *Deutsche Forschungsgemeinschaft* (DFG) is gratefully acknowledged. We thank Friedhelm Pfeiffer and participants at the conference on 'Panel Data and Structural Labour Market Models' in Sandbjerg, Denmark, June 13-17, 1998, for helpful comments.

1. Introduction

Although much research effort has been devoted to disentangle the impact of past unemployment on an individual's labor market success, little is known about how conditions at the time a young worker enters the labor market affect his performance at later stages of the career. The problem is particularly evident for Germany where youth unemployment is traditionally low compared to many other industrialized countries. The low unemployment figures for youths aged 15 to 19 can be attributed to the dual system of vocational training within a firm and a public vocational school. Various policy measures generally assure that the first hurdle of growing into work, i.e. the availability of apprenticeship positions, is kept low. However, the higher incidence and duration of unemployment among young workers (age 20 to 24) reveal that the unemployment problem is simply transmitted to older age groups. Thus the second hurdle of growing into work, i.e. finding an appropriate job after graduation from an apprenticeship program, appears to be a decisive element of a successful start into the labor market. In particular, the inflexibility of the German labor market, e.g. due to legally defined occupational job ladders, renders entrance of unskilled workers to new occupations more difficult. Workers with a failed start into the working life may be in danger to face life-long lower income and employment job opportunities.

In this paper we analyze whether a failed entrance into the labor market generates long lasting ('permanent scars') or just transitory effects ('temporary blemishes') for a worker's earnings capacity. Using retrospective information we estimate the effects on current earnings from a failure during the apprenticeship training and a failed transition from the apprenticeship to a regular job. Both events may not only be associated with a depreciation of human capital but may serve also as a screening device for potential employers. Unlike previous studies (e.g. Ellwood, 1982, Ackum, 1991, Ruhm, 1991) the data allow us to focus on long run effects that may last up to 40 years after completion of the apprenticeship.

Our study extends the work by Franz et al. (1997). Using a cross section they estimate a significantly negative impact of a failed training on the earnings capacity of workers while they cannot find evidence for a long lasting effects of a failed transition into work. The estimates presented in this paper are based on a time series of three cross sections (pseudo panel data) collected in 1979, 1985/86, and 1991/92. This allows us to reconsider the results by Franz et al. in the light of a larger data source capturing a time period of around 21 years. By taking into account individual heterogeneity we control for a potential correlation between the unobserved individual effects and the indicators of a failed start. Moreover, using the time series dimension of the data we are able to distinguish between cohort and age effects. Therefore we test for potential catch up effects in the earnings capacity for those who had a failed start into the working life and, additionally, we examine whether these catch up effects are cohort specific.

The outline of the paper is as follows. Section 2 provides a brief survey on recent empirical evidence on the impact past youth unemployment on earnings and employment opportunities of workers. Section 3 describes the data and introduces the Deaton-Nijman-Verbeek estimator for pseudo panels with measurement error which to our knowledge has not been used in applied work yet. Section 4 discusses our empirical findings, while Section 5 concludes and provides an outlook on future research.

2. Causes and Consequences of a Failed Start: Theory and Empirical Evidence

Previous empirical studies on the consequences of youth unemployment mainly focus on the effects of reduced human capital investments caused by non-employment. Since human capital theory in its simplest form suggests that investments should be undertaken preferably at the beginning of the lifetime cycle, it can be argued that reduced investments at the beginning of the career compresses the whole lifetime income profile. Ellwood (1982) examines whether youth unemployment generates persistent ('permanent scars') or only transitory effects ('temporary blemishes') on the income profile. Using longitudinal U.S. data Ellwood finds evidence for income reductions due to unemployment measured as weeks of non-employment. Ackum (1991) presents similar evidence using panel data for Sweden. She finds that being without work for one year creates a (permanent) income loss of 2 per cent. Since both studies rely on income information for young employees only they can hardly be used to infer on the time path of long-run income reductions and potential catch up effects. In his study Ruhm (1991) explicitly takes into account the possibility that a job loss may be preceded by an income reduction. Using the PSID panel (containing men and women aged 21 – 65), he provides evidence for the existence of considerable, permanent income reductions due to unemployment even four years after the job loss. However, it remains an open question whether Ruhm's findings hold for unemployment periods at early stages of the life cycle where unemployment is a consequence of the job matching process. Considering the high incidence of youth unemployment and the relatively low duration, the job search process may rise young workers' productivity because of better occupational matches.

Concerning the employment chances the evidence on persistent effects of unemployment is less clear. While Ellwood as well as Ackum estimate only a quantitatively negligible negative effect of early unemployment phases on the re-employment probability, Lynch (1989) finds in her survival analysis for the U.S. a strong negative duration dependence. She attains similar results for British data (Lynch, 1985). However, other survival studies based on alternative estimation methods and data do not find any significant (Heckman and Borjas, 1980, for the U.S.) or only a moderate negative duration dependence (Narendranathan and Elias, 1993, for the U.K.) of individual youth unemployment.

An alternative view on the consequences of layoffs is taken by Gibbons and Katz (1991) who assume in their model the existence of information asymmetries between the former employer and the future potential employers. In the tradition of the adverse selection models by Waldman (1984) and Greenwald (1986) they argue that the actual employer has superior information on the true productivity of his employees compared to a potential future employer. If there is imperfect information on the true causes of dismissal the latter has to infer that a dismissed employee typically has an expected productivity below average. Therefore, a layoff works as a negative signal for potential future employers who respond by lowering their wage offer. Assuming that employers are well informed about plant closings an employee having lost the job because of a plant closing should not suffer from this negative productivity signal. Hence, Gibbons and Katz argue that relative to dismissed workers future wage offers to workers who were laid off due to plant closings should be higher and unemployment spells should be shorter.

The authors provide empirical evidence which is based on a comparison of pre-unemployment and post-unemployment wages of dismissed workers. They are able to show that the pre-unemployment wages for the two groups of workers were equal, i.e. both types of workers were not distinguishable in terms of their productivity, while the ex post wages turn out to be higher for workers affected by a plant closing. Furthermore they provide evidence that the length of the unemployment spell is significantly shorter for those who had to change the employer because of a plant closing. Contrary to standard human capital approaches not the loss of skills generated from unemployment but inference about the true productivity of laid off workers is responsible for effects of unemployment on subsequent earnings. Gibbons and Katz derive their theoretical results from a two-stage signaling game. Their empirical evidence only refers to the remuneration by the first employer after the unemployment period. It remains an open question whether these results hold for a longer time horizon.

Asymmetric information also characterizes the decision to employ apprenticeship graduates after graduation. Acemoglu and Pischke (1998) argue that a training firm generates monopsonistic power from superior knowledge on the skills of the trainee. Because the beginning of the career is particularly characterized by uncertainty about a worker's ability and its use within a firm the information gathering or screening process is of great importance. In particular for the German labor market where layoffs are legally difficult to enforce and expensive to the employer the informational aspect of a firm's recruitment policy appears to be of greater importance than on less restrictive labor markets. Due to the monopsonistic advantage a training firm is at least partially able to finance general human capital without the danger of losing the returns to its investments due to job changes. Thus Acemoglu and Pischke offer a theoretical framework that is able to explain a firm's willingness to invest in general human capital without, as common, assuming the existence of liquidity constrained employees. This willingness is the basis for the German apprenticeship training programs.

The Acemoglu/Pischke model implies the testable hypothesis that the initial earnings of apprentices who stayed in their training firm after graduation should exceed those of apprentices who either voluntarily or involuntarily left their training firm. The test for the existence of an adverse selection mechanism relies on a methodology similar to that adopted by Gibbons and Katz. Using the three cross sections of the German 'Qualification and Career Survey' the authors find significant differences in initial earnings of males that can be attributed to different entry histories into permanent employment after graduation. In addition, they provide quasi-experimental evidence based on an initial earnings comparison of employees who enter their military or civil service immediately after graduation with changers with different not necessarily productivity related reasons for the separation. Treating military drafting as an exogenous reason for job separation the empirical evidence provided by Acemoglu and Pischke cannot be regarded as fully convincing. Despite the rather large number of observations the estimates are only significant at the 10%-level. Moreover, the pooling approach adopted does not control for unobserved individual factors.

The findings concerning potential adverse selection mechanisms on the labor market lead to the following three implications for our empirical work: (i) The length of the first spell of unemployment after graduation is a less appropriate indicator to pick up information theoretical aspects of the causes of youth unemployment because this variable approximates a potential loss of human capital more closely than an indicator on the pure incidence of not getting a regular job offer by the training firm after graduation. (ii) Dealing with a homogeneous population in terms of vocational background reduces the probability of picking up selectivity effects. In particular, concentrating on individuals' problems finding access to the labor market allows us to take the labor market performance of successful entrants as counterfactual evidence. (iii) The distinction between true signaling effects and unobservable individual factors correlated with individual earnings is essential for regression approaches. Indicators reflecting a failed start into the career are most likely to be correlated with unobservable individual factors. Ignoring unobserved heterogeneity thus may lead to an upward bias (in absolute terms) of the impact of the failed start on earnings.

3. Data and Econometric Approach

Our empirical evidence rests on three repeated cross sections of the German 'Qualification and Career Survey'[1] conducted in 1979, 1985/86, and 1991/92. Each cross section consists of about 30,000 individuals in the age group 15 – 65. We restrict our attention to West German employees which is the only part of the population sampled in each of the three waves. Our sample only includes persons who have entered an apprenticeship training program sometimes in their career. We exclude females as well as part-time-employed and self-employed persons. The exclusion of female workers is justified by the lack of sufficient observations per cohort as well as by the well known difficulties to construct a measure of potential labor market experience (cf. Mincer and Polachek, 1974) which is a key variable in the subsequent

[1] The data were prepared, documented, and provided by the Central Archives for Empirical Social Research (*Zentralarchiv für empirische Sozialforschung*) at the University of Cologne. The Qualification and Career (*Qualifikation und Berufsverlauf*) Survey was conducted by the Federal Office of Vocational Training (*Bundesinstitut für Berufsbildung*) and the Institute for Employment Research (*Institut für Arbeitsmarkt- und Berufsforschung*). None of these institutes is responsible for any content of this paper.

analysis. The exclusions of part-time workers and self-employed reduces the problems of defining an appropriate income measure that is independent of working time.

Earnings are defined in terms of gross monthly wages and reported in 13 (22 and 15) categories in 1979 (1985/86 and 1991/92). We construct a continuous real earnings variable from the log of each category's mean value deflated by the price index of living costs (1985 = 100) published by the German Federal Statistical Office. The varying definition of the highest earnings class is standardized by assigning 7,500 German marks real earnings to the highest category in 1979 and to the upper four and the upper two categories in 1985/86 and 1991/92, respectively.

Our explanatory variables include dummy variables for the sector in which the individual's apprenticeship training was obtained and for the size of the training firm measured in terms of the number of employees. While sector and firm size information for the individual's current employer are fairly standard in earnings function estimation, the training firm equivalents are rather unusual but correspond to our main interest on the transition period from training to employment. In Franz et al. (1997) we have compared the impact of training firm and current firm characteristics on earnings using cross section data. We will extend this comparison here based on pseudo panel data.

The transition process from apprenticeship training to regular employment may be affected by two types of potential failure: Firstly, individuals may not successfully complete their apprenticeship training and secondly, they may not be able to find a job after graduation either inside or outside the training firm. We construct dummy variables for both types of failure. The first information is directly available from the 1979 and 1991/92 surveys but has to be estimated for the 1985/86 cross section. Therefore, we forecast the *Failed Training* information for this cross section using ML probit estimates from pooled data of the first and third wave.[2] The dummy variable *Failed Transition* takes value one if an individual either reports a spell of unemployment directly after the apprenticeship training (1991/92) or indicates an involuntary quit from the training firm without reporting a transition to any other employer, to military service or further vocational training (1979 and 1985/86). The mean earnings over the three cross sections of those individuals who neither report a failed training nor a failed transition is DM 3,398.3 with a standard deviation of DM 1,301.2. Former ap-

[2] The explanatory variables of the probit model include age at the time the apprenticeship training was ceased, dummies for education, and dummies for sector and size of the training firm.

prentices who indicate a failed training (transition) earn DM 2,777.0 (DM 3,076.1) on average with a standard deviation of DM 1,124.4 (DM 1,217.5). Obviously, the mean values for the two groups of individuals reporting some kind of failure are smaller, but the differences to the group of successful apprentices are not significant.

Our experience measure reflects potential labor market experience calculated in the usual way as (age-schooling-6) where the continuous schooling measure includes both educational and vocational training similar to the variable suggested by Krueger and Pischke (1995).

Table 1.
Distribution of Individuals over Birth Cohorts

		Number of Individuals					Number of Individuals		
#	Year	1979	1985/6	1991/2	#	Year	1979	1985/6	1991/2
1	1930	159	111	-	19	1948	220	181	129
2	1931	138	87	-	20	1949	237	209	173
3	1932	142	95	-	21	1950	248	225	163
4	1933	143	90	-	22	1951	197	197	146
5	1934	179	117	-	23	1952	251	178	165
6	1935	160	156	117	24	1953	215	222	148
7	1936	204	125	109	25	1954	224	214	158
8	1937	228	163	120	26	1955	236	198	164
9	1938	183	164	148	27	1956	236	199	173
10	1939	244	186	161	28	1957	222	190	148
11	1940	268	178	165	29	1958	183	191	173
12	1941	244	191	167	30	1959	144	229	180
13	1942	215	159	126	31	1960	127	239	173
14	1943	231	187	156	32	1961	-	215	182
15	1944	234	163	127	33	1962	-	191	207
16	1945	154	146	128	34	1963	-	173	192
17	1946	177	184	124	35	1964	-	132	182
18	1947	208	185	125	36	1965	-	117	172
						Σ	6,251	6,187	4,801
						Σ		17,239	

In order to control for unobserved heterogeneity we construct a pseudo panel of birth cohorts from the individual data of the three repeated cross sections. A cohort consists of all individuals in the sample born within the same calendar year. Birth cohorts are most frequently used for pseudo panel estimation although the definition of cohorts could rest on other time-invariant individual characteristics as well. Birth cohorts are particularly useful if the research interest focuses on the evolution of specific variables over the life-cycle of individuals. Therefore, they are perfectly suited to uncover any long-term consequences of a failed transition from vocational training to regular employment on earnings.[3] As will be shown below the number of individuals in each cohort-time cell of the pseudo panel should be large in order to reduce the size of measurement errors. Hence we restrict our sample to individuals born between 1930 – 1965 noting that the last (first) 5 years are excluded from the 1979 (1991/92) cross section because the cell sizes are too small. Table 1 displays the distribution of the remaining 17,239 individuals over the 98 cohort-time cells and Table 2 shows descriptive statistics of the variables used in the subsequent pseudo panel regression analysis.

Table 2.
Description of the Variables and Summary Statistics of the Pseudo-Panel Data

variables	description (individualistic interpretation)	descriptive statistics mean	st. dev.	min	max
Individual characteristics					
Earnings	log monthly gross real wage	8.0678	0.2424	7.455	8.462
Married	married	0.7729	0.2083	0.024	0.989
Experience	$10^{-1} \cdot (\text{age} - \text{schooling} - 6)$	1.7967	0.9829	0.080	3.650
Experience^2	$10^{-2} \cdot (\text{age} - \text{schooling} - 6)^2$	4.2152	3.6897	0.009	13.353
Failed Training	failed apprenticeship training	0.0300	0.0120	0.006	0.066
Failed Transition	failed transition to regular job	0.0390	0.0303	0.000	0.167
Training firm characteristics					
Small Firm	training firm: < 10 employees	0.3249	0.0694	0.200	0.529
Medium Firm	training firm: 10 – 99 employees	0.4483	0.0509	0.299	0.555
Large Firm	training firm: > 99 employees	0.2268	0.0408	0.126	0.316
Manufacturing	training sector: manufacturing	0.2248	0.0397	0.126	0.318
Craft	training sector: craft	0.5068	0.0651	0.360	0.661
Trade	training sector: trade	0.1054	0.0302	0.031	0.178
Services	training sector: services	0.0861	0.0274	0.028	0.138
Public Sector	training sector: public sector	0.0769	0.0294	0.021	0.153
Current firm characteristics					
Small Firm	current firm: < 10 employees	0.1699	0.0605	0.046	0.376
Medium Firm	current firm: 10 – 99 employees	0.4732	0.0389	0.347	0.567
Large Firm	current firm: > 99 employees	0.3569	0.0617	0.181	0.500
Manufacturing	current sector: manufacturing	0.2745	0.0425	0.157	0.394
Craft	current sector: craft	0.3060	0.0800	0.169	0.614
Trade	current sector: trade	0.1094	0.0305	0.031	0.209
Services	current sector: services	0.1243	0.0377	0.046	0.210
Public Sector	current sector: public sector	0.1858	0.0772	0.024	0.378
# of observations		98			

[3] Other applications based on birth cohorts pseudo panels data include life-cycle consumption (cf. Browning et al., 1985, and Blundell et al., 1994) and the evolution of wages (cf. Fitzenberger et al., 1995, and Meghir and Whitehouse, 1996).

Given the data for cohort $c = 1,\cdots,C$ observed at time $t = 1,\cdots,T$[4] we specify the mean log earnings $\overline{y}_{ct}$ of each cohort-time cell as a linear function of the mean explanatory variables $\overline{x}_{ct}$ in terms of a fixed effects model as follows

$$\overline{y}_{ct} = \overline{x}'_{ct}\beta + \overline{\alpha}_{ct} + \overline{u}_{ct}. \tag{1}$$

For a finite number of periods (T) and an infinite number of individuals (N), cohorts (C), and individuals per cohort (N_C) the unknown parameter vector β can be estimated consistently by the standard within estimator for panel data (cf. Verbeek, 1996). The latter assumption ($N_C \rightarrow \infty$) ensures that the mean cohort effect can be treated as time-invariant ($\overline{\alpha}_{ct} = \overline{\alpha}_c$). However, small sample evidence presented by Verbeek and Nijman (1992) indicates that the within estimator may be substantially biased even for fairly large numbers of individuals per cohort-time cell (e.g. 100). Therefore we use an errors-in-variables estimator suggested by Deaton (1985) and refined by Verbeek and Nijman (1993) that remains consistent for finite N_C (cf. Verbeek, 1996). The Deaton-Nijman-Verbeek-Estimator (DNVE) is defined as

$$\begin{aligned}\hat{\beta} &= \left(\tfrac{1}{CT}\sum_{c=1}^{C}\sum_{t=1}^{T}(\overline{x}_{ct} - \overline{\overline{x}}_c)(\overline{x}_{ct} - \overline{\overline{x}}_c)' - \tau\hat{\sigma}_{xx}\right)^{-1}\left(\tfrac{1}{CT}\sum_{c=1}^{C}\sum_{t=1}^{T}(\overline{x}_{ct} - \overline{\overline{x}}_c)(\overline{y}_{ct} - \overline{\overline{y}}_c) - \tau\hat{\sigma}_{xy}\right) \\ &= \left(\tfrac{1}{CT}\overline{X}'M\overline{X} - \tau\hat{\sigma}_{xx}\right)^{-1}\left(\tfrac{1}{CT}\overline{X}'M\overline{Y} - \tau\hat{\sigma}_{xx}\right)\end{aligned} \tag{2}$$

where $\tau = (T-1)/T$ and $\overline{X}'M\overline{X}$, $\overline{X}'M\overline{Y}$ are matrix equivalents of the double sums using a sample within transformation matrix $M = I_{CT} - D(D'D)^{-1}D'$ with D, a CTxC matrix indicating each cohort's position by a Tx1 vector of ones (and zeros elsewhere). This is a modified within estimator that corrects the sample moments by the corresponding elements of the estimated variance-covariance matrix $\hat{\Sigma}$ of the multivariate normal i.i.d. measurement error $(\overline{z}_{ct} - \tilde{z}_{ct})$ between the cohorts means $\overline{z}_{ct} = (\overline{y}_{ct}, \overline{x}'_{ct})'$ and its population counterparts $\tilde{z}_{ct} = (\tilde{y}_{ct}, \tilde{x}'_{ct})'$. The estimate $\hat{\Sigma}$ can be obtained from the individual data by

$$\hat{\Sigma} = \tfrac{1}{T}\sum_{t=1}^{T}(\overline{z}_t - \overline{\overline{z}})(\overline{z}_t - \overline{\overline{z}})' \quad \text{with} \quad \overline{z}_t = \left(\tfrac{1}{N(t)}\sum_{i=1}^{N(t)} y_{it},\ \tfrac{1}{N(t)}\sum_{i=1}^{N(t)} x_{it}\right)' \quad \text{and} \quad \overline{\overline{z}} = \tfrac{1}{T}\sum_{t=1}^{T}\overline{z}_t \tag{3}$$

where the elements of variables unaffected by measurement error (e.g. time dummies) are set to zero. It can be seen from (2) that DNVE is asymptotically equivalent to the standard within

[4] For the sake of notational convenience, it is assumed here that each cohort is observed over the same period.

estimator if either N_C or T tend to infinity. In the former case τ approaches zero, in the latter case the measurement error variance tends to zero.

Let $E = M(\overline{Y} - \overline{X}\hat{\beta})$ denote the vector of residuals for the whole sample. Then the variance-covariance of the DNVE can be estimated by (cf. Deaton, 1985, equ. 38)

$$\hat{V}(\hat{\beta}_D) = \frac{1}{CT}\left(\frac{1}{CT}\overline{X}'M\overline{X} - \tau\hat{\sigma}_x\right)^{-1}\left(\frac{1}{(CT)^2}\left(\overline{X}'M\overline{X}E'E + \overline{X}'M'EE'M\overline{X}\right)\right)\left(\frac{1}{CT}\overline{X}'M\overline{X} - \tau\hat{\sigma}_x\right)^{-1}. \qquad (4)$$

From (2) and (4), it becomes clear that the DNVE depends crucially on the nonsingularity of the first expression in parentheses.

4. Estimation Results

Our empirical findings are based on a pseudo panel consisting of 36 annual birth cohorts starting with birth year 1930 and ending with 1965. We only present the estimation results based on the Deaton-Nijman-Verbeek errors-in-variables estimator which is consistent for a fixed (small) number of periods and observations per cohort-time cell. In previous work (Inkmann, Klotz, and Pohlmeier, 1998) we compare this estimator to the standard fixed effects estimator using pseudo panels based on different definitions of cohorts. It turns out that neither the estimator nor the cohort definition being used change the qualitative results for the main variables of interest seriously. Since our analysis concentrates on male individuals who took part in an apprenticeship training program our sample can be regarded as fairly homogeneous in terms of educational background. Hence we refrain from modeling the schooling effect explicitly. This allows us to separate the impact of experience from calendar time even by controlling the year of birth through our cohort definition without violating the identification conditions for longitudinal data (cf. Heckman and Robb, 1985).

Table 3 contains the results of a more traditional specification of the earnings function using characteristics of the current firm as explanatory variable. Estimates of the earnings function with size and sector of the training firm as predictor for the current income are presented in Table 4. The latter specification is more informative in terms of the employee's background at the start of the career. In particular, it is well known that large German manufacturing firms are more likely to make their apprentices a job offer after graduation (cf. Harhoff and Kane, 1993, or Winkelmann, 1996). Hence ignoring the size of the training firm might exaggerate, i.e. bias downwards, the effect of youth unemployment on earnings at later stages of the career.

Table 3.
Pseudo-Panel Earnings Function Estimates – Characteristics of Current Firm

	(1) estimate	(1) t-value	(2) estimate	(2) t-value	(3) estimate	(3) t-value
Married	-0.06	-0.80	-0.05	-0.64	-0.13	-1.58
Medium Firm	0.16	0.67	0.09	0.38	-0.01	-0.03
Large Firm	0.73	2.73	0.70	2.70	0.54	2.18
Manufacturing	-1.16	-3.93	-1.20	-4.04	-0.79	-2.88
Craft	-1.53	-4.47	-1.48	-4.29	-1.26	-3.72
Trade	-0.93	-2.88	-0.85	-2.65	-0.62	-2.16
Public Sector	-2.22	-7.33	-2.21	-7.48	-2.01	-7.40
Experience	1.16	15.60	1.12	14.60	1.04	12.28
Experience^2	-0.06	-4.52	-0.05	-3.64	-0.05	-3.89
Failed Training	-1.39	-2.15	-3.45	-2.37	-6.59	-4.00
Failed Training · Experience	–	–	0.98	1.57	–	–
... for cohorts 1930 – 1938	–	–	–	–	1.78	2.97
... for cohorts 1939 – 1947	–	–	–	–	1.95	2.44
... for cohorts 1948 – 1956	–	–	–	–	1.28	1.15
... for cohorts 1957 – 1965	–	–	–	–	5.85	3.68
Failed Transition	-2.99	-8.63	-3.07	-7.30	-1.79	-3.38
Failed Transition · Experience	–	–	0.19	0.77	–	–
... for cohorts 1930 – 1938	–	–	–	–	-0.09	-0.36
... for cohorts 1939 – 1947	–	–	–	–	-0.57	-1.21
... for cohorts 1948 – 1956	–	–	–	–	0.99	1.24
... for cohorts 1957 – 1965	–	–	–	–	-1.04	-1.18
Wave 1979	0.25	12.97	0.26	13.45	0.23	8.98
Wave 1991/92	-0.24	-12.95	-0.24	-13.30	-0.21	-11.12
R^2 adjusted	0.9543		0.9547		0.9617	

Joint significance of 'Failed Training' interactions in (3): $\chi^2(4) = 20.52$ p-value = 0.0004
Joint significance of 'Failed Transition' interactions in (3): $\chi^2(4) = 7.76$ p-value = 0.1010

Interpreting the size of the estimated coefficients one has to keep in mind that the coefficients represent effects on cohort means. Thus a coefficient of a dummy variable at the individual level represents the impact of a population ratio on the dependent variable. For instance, the dummy regressor of a failed transition from occupational training to work is a specifically defined unemployment ratio. Therefore Moffit (1993) interprets estimation results based on pseudo panels as a link between results obtained on the micro and the macro level. Diverging results between estimates at the aggregate and the individual level may result from differences between micro and macro effects (e.g. through equilibrium effects) or from differences between cross section and panel data estimates. In terms of size but not in quality our estimates are rather different from typical results for earnings functions at the individual level based on cross sections or panel data. Due to different choices for the set of explanatory variables the empirical evidence based on pseudo panels is hardly comparable.

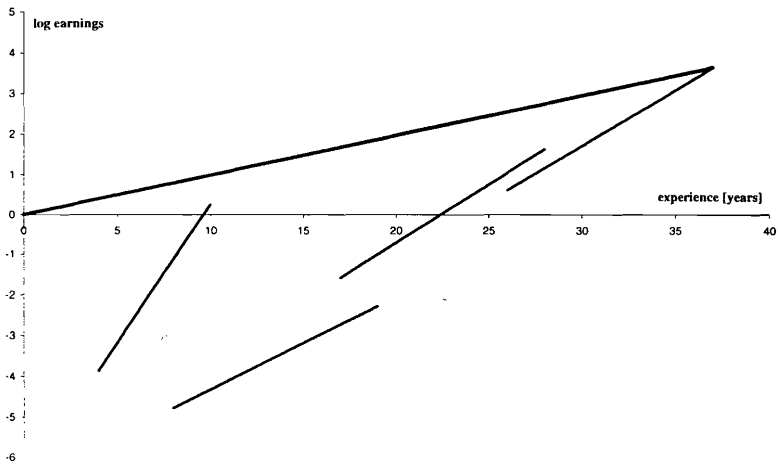
Notice that the aggregation of individual covariates to cohort means leads to a reduced variation in the data. The conventional comparative statics for dummy variables appears to be no longer meaningful from both the theoretical and econometric point of view. For instance, at the cohort level this would imply measuring the effect of a change in the instantaneous youth unemployment rate (share of youths not finding a job after graduation from occupational school) from zero to hundred percent and an inference based on extreme out of sample forecasts. Hence the evaluation of traditional elasticities or the evaluation of the impact of a percentage point change of an explanatory variable on the dependent variable is more appropriate.

Market entrance problems of youths are captured by two different sets of explanatory variables. *Failed Training* indicates whether an individual did not complete a vocational training program successfully, while *Failed Transition* indicates a period of unemployment after graduation from an vocational training program. Table 3 summarizes the estimation results for three specifications which differ by the underlying assumptions on the effects of a failed labor market entry across the life cycle. The first two columns report the estimates for the most parsimonious specification assuming a permanent effect of early market entrance problems on earnings, while the second specification (col. 4 and 5) allows for catch up effects with increasing work experience. The results for the parametrically richest specification are given in col. 6 and 7. This specification allows for catch up effects that vary across four different cohort groups. The estimates obtained for the remaining coefficients are quite robust with respect to the three alternative specifications. Regardless of the specification chosen we find a significantly negative impact of youth unemployment on earnings. This effect does not vanish over the life cycle and is independent of the cohort group. The estimates based on the parsimonious specification suggest that an increase of the unemployment rate of labor market entrants by one percentage point reduces earnings by 2.99 percent. This finding contradicts previous cross sectional estimates by Franz et al. (1997) who do not find an impact of youth unemployment on earnings at a later stage of the career.

Interpreting the effects of *Failed Training* on earnings at later stages of the career one has to keep in mind that an individual who dropped out of the apprenticeship training program generally receives some other vocational training. Thus this regressor does not serve as a simple proxy for unskilled labor. Dropping out of the apprenticeship training program turns out to be an indicator for reduced income opportunities in later stages of the life-cycle. Unlike youth unemployment this effect is larger at the beginning of the career but decreases with experience. The catch up effect differs by cohort group. In particular, for the youngest group (birth year 1957 to 1965) this effect vanishes after ten years of work experience. In contrast, members of older groups who dropped out a training program catch up with those of a successful labor market entrance as late as in their last years of their work career. The more transitory character of *Failed Training* may reflect the fact that this indicator picks up unobserved heterogeneity in productivity (e.g. individual differences in motivation). Since workers with a vocational degree face an income ceiling according to the worker's age and industry specific wage agreements, workers with lower productivity catch up with their more productive colleagues at later stages of the life cycle.

Figure 1 demonstrates how the four cohort groups manage to catch up after experiencing a failed training. The slightly concave curve going through the origin depicts the age-earnings-profile in the case of non-failing. The nearly straight lines present the age-earnings-profiles for the case of a failed training. These lines are calculated for the experience of the mean cohort of the aggregated nine years cohort group, e.g. 1961 for the youngest cohort. As pointed out earlier, this cohort group catches up with their non-failing counterparts faster than the older groups. Figure 1 suggests an alternative interpretation as well. Assume the catch up process might be described by a concave curve rather than by a straight line. Then, the different slopes of the four lines can be explained by the fact that, due to the different experience intervals of the four cohort groups, they try to fit different parts of the same concave curve using a common intercept. So the question whether the cohort group interactions capture cohort or experience specific effects remains to be investigated.

Figure 1.
Catching up after a Failed Training



Contrary to *Failed Training*, *Failed Transition* seems to generate a permanent scar in terms of income opportunities. While dropping out of the training program can be seen as an element of a matching process that only generates transitory frictions, youth unemployment seems to put young workers on inferior job ladders. Since a large fraction of workers who do not find a job after completion of the vocational training program, work in jobs they have not been trained for, our findings parallel the results of income studies which find a substantial negative impact of occupational mismatch on earnings for Germany.

Since *Failed Transition* only reflects the fact of not having received a job offer after graduation and the duration of youth unemployment is small compared to other age groups it is unlikely that a loss in human capital is the major driving force for the reduced income expectations at later stages in the life cycle. Although not presenting a formal test of the existence of asymmetric information our findings appear to be more in accordance with asymmetric information being a major determinant of youth unemployment.

Table 4 summarizes the results for the estimates based on the characteristics of the training firm. Since size of the training firm and the probability of receiving a job offer after graduation are positively correlated the impact of *Failed Transition* on earnings increases in absolute terms. Again we do not find significant evidence that this effect is a temporary blemish, i.e. decreases with work experience. A similar argument holds for a potential bias of the estimated coefficients on *Failed Transition*. If youths are more likely to drop out of the training programs in large firms the effect of a failed transition on earnings is biased downwards if the regression does not properly control for the size of the training firm. For the alternative specifications using characteristics of the training firm we find larger effects in absolute terms for *Failed Training* but can generally replicate the aforementioned caching up pattern.

Table 4.
Pseudo-Panel Earnings Function Estimates – Characteristics of Training Firm

	(1)		(2)		(3)	
	estimate	t-value	estimate	t-value	estimate	t-value
Married	-0.04	-0.28	-0.05	-0.36	-0.23	-1.72
Medium Firm	-0.50	-1.55	-0.47	-1.52	-0.38	-1.52
Large Firm	0.37	0.76	0.41	0.86	0.19	0.49
Manufacturing	0.09	0.17	0.03	0.05	0.65	1.18
Craft	0.35	0.68	0.36	0.63	0.64	1.32
Trade	-0.31	-0.48	-0.16	-0.25	0.39	0.68
Public Sector	-2.88	-3.37	-2.69	-3.22	-1.85	-2.36
Experience	1.22	10.21	1.14	8.97	0.94	7.06
Experience^2	-0.10	-4.61	-0.09	-3.78	-0.08	-4.08
Failed Training	-2.38	-2.09	-5.89	-2.34	-10.32	-3.83
Failed Training · Experience	–	–	1.73	1.62	–	–
...for cohorts 1930 – 1938	–	–	–	–	2.79	2.91
...for cohorts 1939 – 1947	–	–	–	–	3.49	2.69
...for cohorts 1948 – 1956	–	–	–	–	2.91	1.64
...for cohorts 1957 – 1965	–	–	–	–	9.20	3.39
Failed Transition	-4.96	-6.27	-4.69	-5.60	-2.67	-3.16
Failed Transition · Experience	–	–	0.02	0.05	–	–
...for cohorts 1930 – 1938	–	–	–	–	-0.31	-0.77
...for cohorts 1939 – 1947	–	–	–	–	-1.41	-2.14
...for cohorts 1948 – 1956	–	–	–	–	0.84	0.73
...for cohorts 1957 – 1965	–	–	–	–	-0.17	-0.13
Wave 1979	0.14	3.19	0.15	3.55	0.10	2.18
Wave 1991/92	-0.29	-6.67	-0.28	-6.89	-0.21	-6.60
R^2 adjusted	0.8643		0.8680		0.9068	

Joint significance of 'Failed Training' interactions in (3): $\chi^2(4) = 15.07$ p-value = 0.0046
Joint significance of 'Failed Transition' interactions in (3): $\chi^2(4) = 8.35$ p-value = 0.0795

5. Conclusions

In this study we analyze the impact of a failed start into regular work on earnings for male workers in Germany. Using retrospective information we are able to identify the effects on current earnings from a failure during the apprenticeship training and a failed transition from the apprenticeship to a regular job. Unlike previous studies the data allow us to focus on long-run effects that may last up to 40 years after completion of the apprenticeship.

Contrary to the findings by Franz et al. (1997) we find a significant persistent effect of a failed transition on earnings. Experiencing an unemployment spell after graduation from the apprenticeship training program seems to put workers on inferior job ladders with flatter age-earnings profiles. Therefore a policy of reducing youth unemployment by expanding the supply of apprenticeship positions and not accounting for the second hurdle to labor market entrance is in danger to postpone the youth unemployment problem to older age groups. Without offering a formal test of adverse selection mechanisms our results appear to be congruent with models that explain unemployment by information asymmetries. The pure incidence of initial unemployment is a significant predictor of current earnings.

Failing a training program leads to negative earnings prospects as well. In general, the income gap can be narrowed with increasing experience. However, only for the youngest age group we find a complete catching up.

The profitability of pseudo panel data techniques compared to simple pooling techniques ignoring individual heterogeneity depends on the particular problem under investigation. Aggregation of individual information leads to a loss of information and sample variation. The identification of time invariant effects like our indicators for a failed entrance into the labor market rests only on the variation of measurement errors of the true cohort population moments. The use of pseudo panel data techniques raises interesting questions for future research. Monte Carlo studies on the small sample performance of pseudo panel data methods usually ignore aggregation effects. The causes for the obvious discrepancy between the estimated coefficients on the individual and the cohort level should be analyzed in future research. Finally, our findings concerning the differences in the catch up effect among cohort groups suggest that future research should raise the question whether the impact of the determinants of earnings vary with cohort size.

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