Gender Differences in Entry Wages and Early Career Wages

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Abstract:

This paper investigates the gender wage gap in entry wages and in the early career for German skilled workers in the period 1975-1990. We use a new administrative longitudinal data source that allows to observe complete work and skill accumulation histories from the beginning for up to 13 years in the labour market. Descriptives show an entry wage differential of 22 percent between male and female full-time workers. Furthermore, the differential stays almost constant throughout the first 8 eight years in the labour market. Among the factors that explain the entry wage gap, pre-market choices of training schemes are found to be particular important. Gender differences in the timing of work account only for a small fraction of the gap during the early years of the career.

JEL classification: J16, J3, J7

Key words: Male-female wage differentials, entry wages, apprenticeship training, work experience.

1 Introduction

For most industrialised countries wage differentials between men and women are shown to be between 25 to 30 percent. A substantial part of these remain unexplained even after taking into account individual human capital characteristics, such as education, age or work experience and work place characteristics.[2] One may be concerned that this is due to discriminatory forces in the labour market, or that productivity related differences are measured imprecisely and, hence, unobserved heterogeneity may account for a substantial part of the unexplained wage differentials. This study contributes to this literature by using a particular sample of young West-German male and female workers for which the skill accumulation process as well as wages can be measured very precisely from the beginning of the working career.

We investigate entry wage differentials and the development during the early career. To perform such an analysis, one needs retrospective information on work and wages. Existing empirical studies rely mostly on survey data. Apart from common caveats of these data sets, such as measurement error problems in wages and work history variables (Bollinger, 1998), a shortcoming is that individual working careers are often not observed from the beginning, after completion of education, onwards. This is the so-called

[2] See Blau and Kahn (1995) for an international comparative study, and O'Neill and Polachek (1993), Harkness (1996), Blau and Kahn (1997), Groshen (1991).

left censoring problem.[3] This makes it difficult to measure complete work histories and disentangle the factors that determine wage differentials in entry wages and the differential evolving over the career.[4]

As a result, only a few studies demonstrate that a significant entry wage gap exists. For example, in Loprest (1992) for samples of 18 to 25 year old men and women of all education groups taken from the NLS[5] for 1979 to 1983 an entry wage gap of about 11 percent was found. Furthermore, Dolten and Makepeace (1986) found an entry wage gap of 7 percent using a sample of U.K. graduates in 1970. We know little, however, about explanations for this entry gap and whether it persists over careers. Some related evidence has been presented in Light and Ureta (1995) who estimated wage regressions that included controls for previous work history and time periods spent out of work. They found that about 7 percent of the wage gap can be explained by male-female differences in the timing of work experience. Evidence from the 70s and 80s in the U.S. seems to suggest an increasing gap that is partly attributed to lower levels of actual work experience of women compared to men, and relatively higher returns to work experience

[3]Put differently, the problem is the small sample size of individual records that are not left-censored in this way, for example, in the NLSY, PSID or BHPS - see e.g Harkness (1996), Mincer and Polachek (1974) O'Neill and Polachek (1993), Blau (1998), Light and Ureta (1995).

[4]Instead, studies identify entry wages parametrically by the constant in the wage regressions.

[5]The National Longitudinal Survey conducted in the U.S..

for men (Corcoran and Duncan (1979), Polachek and Robst (2001)). As an explanation of the widening of the gap during the first four years of the career, Loprest (1992) showed that for men, wage gains from job changes are larger than for women[6]. Apart from this factor, she argues that occupational segregation and changes from full-time work to part time work of women contribute to the increase of the wage gap.

In our study, we use a sample of young skilled full-time workers drawn from the German employment statistics, the IABS, for the period 1975-1990. The IABS is an administrative data set. Skilled workers are defined as workers who have undertaken vocational training within the dual system apprenticeships programme. Typically, they have completed 9-10 years of schooling and 2-3 years of apprenticeship. The sample contains approximately the middle 70 percent of the German workforce skill distribution. The main advantages of our data are that work histories are observed from age 16 onwards, and that the sample is large, including approximately 35 000 individuals in total. Thus, precise measures of work histories, skill and wages can be generated for a significant part of the German labour force.

The goal of this paper is to disentangle the dynamics underlying the evolution of the gap. Adopting the human capital model (Becker, 1964), we distinguish factors explaining the entry wage gap and early career gap. An important factor that can explain wage differentials are pre-market factors

[6] Her results show that men are as likely as women to change job.

(Neal and Johnson (1996)). We exploit the fact that we observe entry wages and rich information on training before entry into the labour market to scrutinize the sources for wage variation. In our analysis of early career wages we condition on complete work histories. Descriptives show that among workers in their 20s gender differences in accumulated work experience are not revealed yet. Hence, holding other factors constant, differences in wages can only be due to differences in the coefficients of work experience or the timing of work experience accumulation (Mincer and Polachek (1974), Light and Ureta (1995)). To analyse the impact of timing of work experience we estimate wage regressions where we use the entire path of human capital accumulation and allow coefficients to vary across work history segments.

Three main sets of results are presented in this paper: First, we document a substantial wage gap of about 23 percent in entry wages which remains quite constant over early working careers. Second, holding occupational qualification constant (i.e. the observed apprenticeship occupation) reduces the gap to 8.4 percent. Third, decomposition of the wage gap shows that the timing of working career accounts for 1 percent during the first couple of years of work and its effect increases to 3 to 5 percent at 9 years of experience.

The remainder of the paper is structured as follows: In section 2, we describe the data and the institutions of apprenticeship training. In section

3, we show descriptives. The main empirical analysis on entry wages follows in section 4 and on early career wages in section 5. In section 6, we conclude.

2 Data and institutional settings

We use the IAB employment sample (IABS)[7] for West-Germany that is available for the period 1975 to 1990 and is an administrative event history data set. The IABS is a 1 percent random sample drawn from the event history data file of the social security insurance scheme, the employment statistics, collected by the German Federal Bureau of Labour. The fact that the data was collected for administrative purposes is an obvious advantage and makes the data particularly reliable. The IABS contains all workers in West-Germany who have had at least one employment spell eligible for the social security insurance scheme. As a result, included are all dependent employees in the private sector, i.e. about 80 percent of total employment in West-Germany.[8] The event history data includes information on every change in working status distinguished into full-time work, part-time work, unemployment, interruption which captures national service and maternity - or parental - leave, and gaps. This we summarize as time out of work in the following. One may note, also, the particular event history data

[7]IABS abbreviates the *Institut für Arbeitsmarkt und Berufsforschung Sample*.

[8]Not included are: civil servants, self-employed, unpaid family workers and people who are not eligible for benefits from the social security system. For more details see Bender et al. (1996).

structure implying that a unit of the data is a spell, which is not necessarily the same as a yearly spell. A unique feature of our data is that complete schooling, and work accumulation histories are observed. This allows precise characterization of human capital characteristics.

From the IABS we generate a sample of young workers who have undertaken vocational training within the German dual system apprenticeship programme, the main route into the labour market for decades. Workers have mostly, approximately 90 percent, graduated from school after 10 years of schooling and are observed after entry into apprenticeship, i.e. age 16-22 with a mean age 20. In practice apprenticeship takes 2 to 3 years. In the data individuals are followed over early careers, i.e. the oldest individuals are 30 and the mean age is 23. Hence, by construction we do not have "left-censoring" of work histories problems common in labour economics. Wages in the IABS are reported on a daily basis and are highly reliable given that they are checked by both data collectors and employees. However, hours of work are not reported. By focusing on full-time workers, we mitigate this short-coming.[9] We use wage spells after 1980. Extraction of these workers[10] from the IABS leaves us a sample containing 14456 female workers

[9] This rule leads to exclusion of less than 3 percent of spells for males and 18.6 percent for females as can be seen from the table in the appendix. Hence, this is unlikely to induce selection bias to our estimates.

[10] In summary, the selection rules we apply are that the individual is not older than 15 years in 1975, the individual has undertaken training for at least 450 days without interruption, the individual has never been working part-time or home-work (e.g. family

and 19598 male workers who are observed in at least one full-time working spell after completion of vocational training. In total the number of spells in the sample of females are 84378 and in the sample of males 122708.

Over recent decades approximately 60 to 70 percent of each birth cohort have been vocationally trained. This training programme combines school and work-related training. Apprenticeship programmes can be found in all German speaking countries, and in variations in other countries, such as Britain, where there are also strong interests in its revival. During the period of 1975 to 1990, apprenticeships could be undertaken in about 350 occupations, ranging from technical to service occupations and in all sectors, including large or small, private or public firms of the economy. Typically, after ten years of schooling 60 percent of youth enter apprenticeship training, which lasts 2 to 3 years. Apprentices have an apprenticeship contract with the firm they are trained with; wages amount to about 20-30 percent of the wage of a skilled blue or white collar worker. In order to receive a certificate about the particular qualification acquired, apprentices have to pass written and oral examinations, and practical exercises in craftsmanship.[11]

business) and the individual must be observed in the data before 1988 for the first time.

[11]For a detailed description of the German dual system apprenticeship programme see Münch (1992).

3 Descriptive statistics

In our data, individuals are organized by cohorts according to the year of entry into apprenticeship. This is illustrated in Figures 1 and 2 where post-apprenticeship employment rates for male and female workers are shown. The year of entry varies within cohorts due to variation in the age at entry into apprenticeship and duration of apprenticeship.[12] As expected, males' employment rates monotonously increase to a level of 80 to 90 percent. The employment rates of females increase first, and then decrease below a population average, i.e. approximately 55 percent in 1988 for Germany[13], due to child bearing and rearing. For a longer sample, one would expect employment rates to go up again.

[12] For a few individuals we observe wages for working in a job eligible to social security prior to apprenticeship. We drop these unskilled work wages from our analysis sample.

[13] German Statistical Yearbook, various years.

Figure 1:

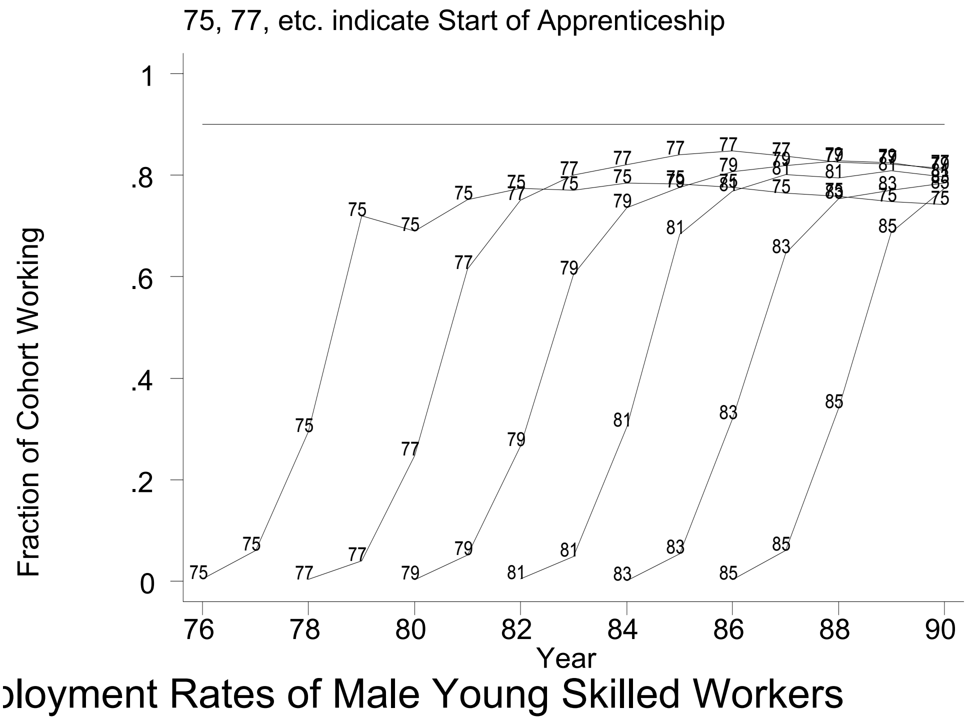
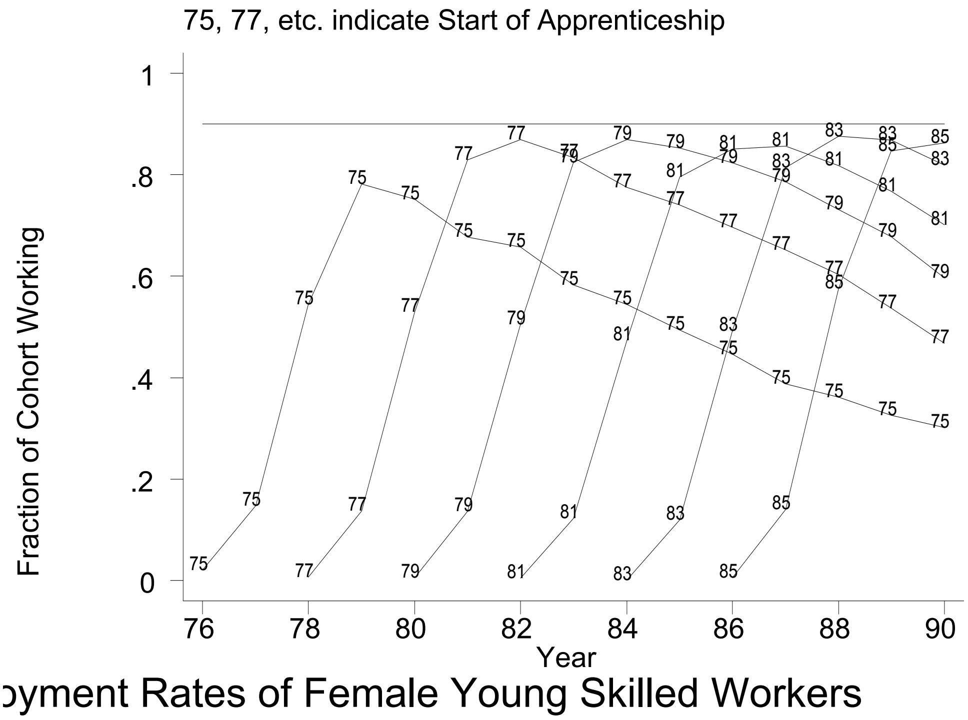

75, 77, etc. indicate Start of Apprenticeship
Fraction of Cohort Working
Year
ployment Rates of Male Young Skilled Workers

Figure 2



The main variables are the wage, the work history variables *work experience* and total *time out of work*, and variables measuring occupation and skill. The wage variable is the logarithm of the daily wage deflated by the consumer price index by the German Statistical Office. Due to the restriction to full-time workers, wages refer to full-time wages meaning that working hours are at least 35 hours per week. We define the variable *time out of work* as the total time not in salaried work, and not in work eligible to social security. It can be directly generated as the sum of days in *unemployment*, *interruptions* and *non-work*. *Unemployment* is reported in the data when individuals receive unemployment insurance. *Interruption*

Table 1: Differentials in log apprenticeship wages and log starting wages

	women mean (std.)	men mean (std.)	gap	t-statistics for H_0: Equality of means
log(apprenticeship wage)	2.8312	2.8764	0.045	-11.4
	(.3628)	(.3483)		
log(starting wage)	3.7531	3.9772	0.2241	-63.79
	(.3093)	(.3178)		
# of individual entry wages	13864	18928		

Note: Sample of young skilled workers from IABS 1980-1990.

periods capture national service for men, that is compulsory for 12 months for men, and maternity leave for women, that can take 2 to 15 months at maximum. $Non\,work$ spells are gaps between spells and capture periods out of work due to other reasons than unemployment or maternity leave.[14]

Table 1 reports raw male-female wage differentials using apprenticeship wages[15] and entry wages[16]. It can be seen that while men and women are still in apprenticeship only a very small, yet significant, differential of 4.8 percent is observed.[17] By the time of first full-time employment, however,

[14] This variable also incorporates, for example, further education, self-employment and employment not eligible to social security, i.e. jobs paid less than a lower social security threshold that was 350 German Mark per month in 1975 and 470 German Mark in 1990.

[15] Apprenticeship wages are measured in the last year (spell) of training.

[16] For technical reasons, starting wages are measured in the second wage spell of an individual's record in full-time employment. While for firm movers (immediately after apprenticeship) the end of apprenticeship is reported precisely in the data, for firm stayers the end of apprenticeship can only be determined with variation of up to one year. Therefore, the first wage spell for stayers may contain apprenticeship wage components and a too low wage in full-time employment may be reported in the IABS. In order to make work histories comparable for firm stayers and movers we drop the first wage reported for each worker.

[17] The differential becomes negligibly small, i.e. 1.3 percent, after the duration in apprenticeship has been taken into account. On average the duration is longer for men,

this differential has increased to 22.4 percent.

Figure 3: Non-parametric estimates of wages and wage differential using two sets of smoothing parameters

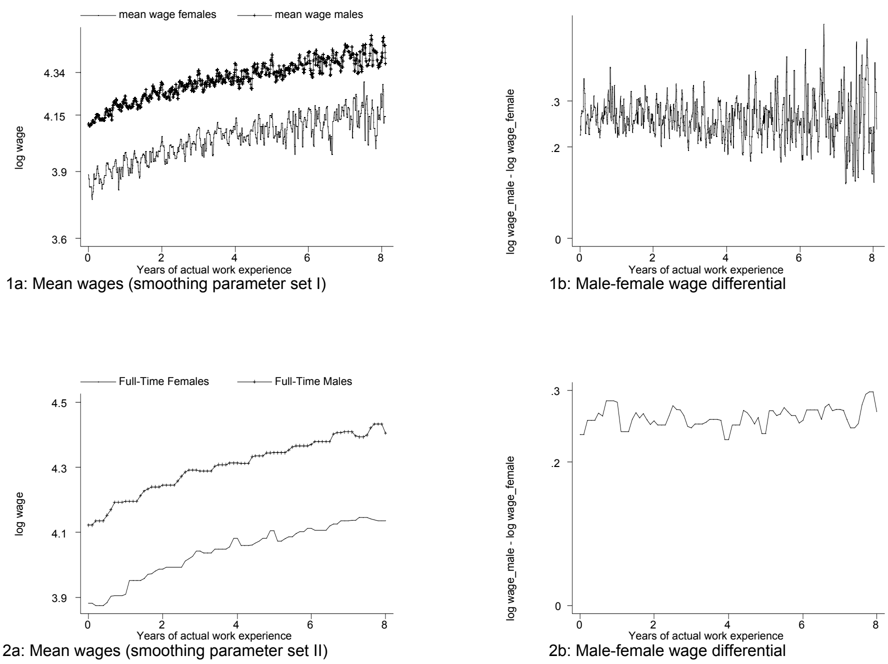


Figure 3 plots logarithmic wages estimated non-parametrically as a function of work experience.[18] We apply a robust smoothing method[19] and display results for two different smoothing parameters, shown in Figure

as can be seen from Table 2.

[18] Wages shown here are predicted logarithmic real wages after growth due to time dummy variables has been netted out. Time dummy coefficients are estimated consistently from entry wage spells separately for males and females. Confidence bands not shown in the graph are rather narrow, given the number of observations, and wages are significantly different across work experience levels as well as gender.

[19] Note that work experience is measured in the original data on a daily basis.

3.1a/b and Figure 3.2a/b.[20] It appears that wage experience profiles for men and women are slightly concavely shaped and develop in almost parallel fashion.The differential, accordingly, stays almost constant during this period and fluctuates around 0.23. Looking at the less smoothed picture it appears that variation increases with experience. This may be partly due to the decreasing number of observations and disappears after smoothing the graph further. Our main findings seem to contrast results for the U.S. which show an increase of gender wage gap from an initially low level. (Loprest (1992), Light and Ureta (1995))

4 Entry wages and pre-market factors

We conduct the analysis of entry wages for the sub-sample of wages in the first job. Taking a human capital theory approach, differentials in entry wages between genders are due to the relatively larger human capital endowment males have acquired by entry into first employment, in comparison to females. First of all, human capital in the beginning of the career can be described by (general) education, age and qualification - vocational or college degree. The corresponding mean characteristics for our sub-samples of female and male workers are presented in Table 2. It turns out that females and males are both of similar age in their first employment. Furthermore,

[20] We use a standard procedure implemented in Stata. We apply running means to the logarithmic wages at the most disaggregated level. Smoothing parameter set I: running means at span three and repetitions until convergence. Smoothing parameter set II: running means at span nine.

Table 2: Sample means for males and females at entry wage spell, training cohorts 1975 to 1988

	female		male		t-test for
	mean	(std.)	mean	(std.)	H_0: Equality of means
age at entry into training	16.9467	(1.2888)	16.5559	(1.1552)	28.8
age in first job	20.3416	(1.5725)	20.5000	(1.5815)	-9.18
			education		
1 if interm. degree	.9547	(.2078)	.9814	(.1350)	-14.37
1 if *Abitur* *	.0453	(.2078)	.0185	(.1350)	14.37
apprentice. duration	2.18	(.7318)	2.51	(.7418)	-40.96
*occupational qualification*** *:*					
Natural products production	.0187	.1356	.0280	(.1649)	-5.53
Extraction of natural resources	.0	(.0)	.0090	(.0946)	-11.5
Investment goods production	.0138	(.1166)	.0846	(.2783)	-28.88
Consumer goods production	.0636	(.2441)	.0887	(.2844)	-8.58
Construction	.0054	(.0739)	.1702	(.3758)	-52.15
Installment of technical machines	.0247	(.1552)	.3548	(.4784)	-80.20
Services	.8542	(.3528)	.2105	(.4076)	152.87
Infrastructure services	.0193	(.1378)	.0539	(.2258)	-16.35
			skill related variables		
job status:					
unskilled	.0896	(.2856)	.1786	(.3831)	-23.62
skilled blue collar	.1481	(.3552)	.6483	(.4775)	-106.47
other (foreman)	.0004	(.0219)	.0009	(.0310)	-1.60
skilled white collar	.7617	(.4260)	.1720	(.3774)	135.31
*skill match variables**** *:*					
1 if Qual.stayer	.7367	(.4404)	.6551	(.4753)	16.20
1 if Firm stayer	.6368	(.4809)	.7015	(.4576)	-12.64
1 if Firm+qual.stayer	.5301	(.4991)	.5295	(.4991)	.11
1 if Industry stayer	.7950	(.4036)	.7983	(.4012)	-.7345
# of individuals	13864		18928		

Note: Sample of young skilled workers from IABS 1980-1990. * In Germany, the *Abitur* school degree takes 13 years and qualifies for university. ** For calculations, the occupation of qualification classifications of the last spell in apprenticeships are used. Groups are constructed according to Dietz (1988). *** Definition of *skill match variables*: Qual. stayer: stayer in occupation of qualification (apprenticeship) measured at 3-digit level. Firm stayer: stayer with training firm. Firm + qual. stayer: stayer in occupation of qualification and training firm. Industry stayer: stayer in industry measured at 2-digit level.

young skilled workers are homogeneous with respect to education; virtually all of them have an intermediate secondary schooling degree, i.e. 10 years of schooling (*Haupt*-or *Realschule*). They are also homogeneous with respect to type of tertiary education since all of them have undertaken an apprenticeship programme lasting on average 2.18 years for females and 2.51 years for males at the mean. This does imply that males should receive a higher wage to compensate for the extra 0.33 years of training.

Despite similarities of the quantity of education and vocational training among workers in our sample we find - similar to other Western industrialized countries - more striking differences in the type of training, i.e. occupational qualification. Women are more likely to be qualified in services, for example, as a *professional clerical worker* or *receptionist*, and men are more likely to do apprenticeships in manufacturing, for example, as a *motor vehicle mechanic* or *electrician*. Hence, in analysing entry wage differentials in our sample particular attention is attributed to differences in occupational qualification - which is the main source of heterogeneity in human capital across individuals.

4.1 First jobs and skill

Heterogeneity in qualification can be measured in the data in several ways. First, our data sample includes a broad measure for *job status* that distinguishes between unskilled, skilled blue collar workers, skilled white collar workers and others, e.g. foremen. Percentages of men and women in each of the categories are listed in Table 2. For example, 76.2 percent of women work in white collar jobs, whereas 64.8 percent of men work in blue collar jobs. Perhaps striking in international comparison, however, is that about 70 percent of all workers are categorised as skilled which implies that almost 50 percent of the entire population are categorized as (occupationally) skilled at the young age of 20.[21]

Second, and in contrast to most other data sources, skill can be observed (a) because the records contain individual spells while in apprenticeship and in employment afterwards and (b) because for each of the spells information on the three-digit occupation is given. Hence, skill can be measured by the *occupation of qualification* itself, which is the occupation reported while in apprenticeship, and by matching the *occupation of qualification* and the *occupation of work*. The latter is particularly informative about transferable human capital components. Likewise, skill with respect to firm and industry specific human capital can be measured by comparison of the corresponding firm [22] and industry[23] identifiers in the data.

[21]To do this calculation one needs to keep in mind that about 60-70 percent of the population in Germany undertakes apprenticeships (Münch, 1992). In comparison, in the U.K. for the period 1990-1992 GHS data shows that only 27.9 percent of all male and 19.4 percent of all female aged 25-34 reached a degree or a higher educational level. See: Harkness (1996).

[22]Firm identifiers are given to each establishment in the IABS. Large firms are split into establishments with different firm identification numbers.

[23]Industries are distinguished into approximately 99 groups (2-digits). The category refers to the main sector of value addition.

To describe skill match with respect to occupation, firm and industry, we generate binary *skill match variables* that take the value one if an individual stays and zero otherwise. Stayers with respect to occupation, for example, are defined as individuals for which the *occupation of qualification* on a three digit level is the same as the *occupation of work*. For the *skill match variables*, the means and standard deviations are reported in the lower panel of Table 2.

Quite striking are the extremely high shares of stayers, in particular, in the *occupation of qualification*, i.e. 73 percent for females and 65 percent for males, and with the training firm, 63 and 70 accordingly. High shares of stayers may suggest that one finds positive returns for staying and losses for moving between firms, jobs (occupations) or industries due to non-transferability of human capital. Our wage regression estimates, shown in the next section, support this hypothesis.

4.2 Entry wage regressions

In order to estimate the explained male-female differential in entry wages, we adopt a two step procedure. In the first step, we estimate wage regressions controlling for pre-market characteristics separately for male and female workers. In the second step, we decompose the wage differential, following Oaxaca (1973) and Blinder (1973), into the explained part by the sum of the differences in human capital characteristics weighted by prices,

Table 3: Log wage regressions for entry wages by sex

Variable	males	females	males	females
firm stayer	0.0945	0.1004	0.0600	0.0411
	(12.33)**	(10.32)**	(8.51)**	(5.02)**
qual. stayer	-0.0271	-0.0271	-0.0371	-0.0869
	(3.25)**	(3.29)**	(4.82)**	(12.49)**
firm + qual. stayer	0.0127	-0.0121	0.0035	0.0346
	(1.23)	(1.04)	(0.37)	(3.60)**
training duration	0.0669	0.0511	0.0641	0.0408
	(20.61)**	(14.52)**	(19.66)**	(13.08)**
age at entry	0.0161	0.0620	0.0186	0.0241
	(7.54)**	(29.40)**	(9.23)**	(13.18)**
Abitur	0.0925	0.1367	0.0652	0.0556
	(5.47)**	(11.03)**	(4.09)**	(5.30)**
Constant	3.5294	2.5818	2.9801	2.9903
	(91.28)**	(67.48)**	(75.61)**	(60.85)**
Occupation qualification dummy variables included	no	no	yes	yes
Year dummy variables	yes	yes	yes	yes
Observations	18928	13864	18928	13864
Adjusted R-squared	0.07	0.15	0.26	0.44

Note: The dependent variable is the log of daily real wages in the first job after training. The wage observations are used for 1980 to 1990. The omitted year is 1980. The omitted school degree is 10 years of schooling. Absolute value of t-statistics in parentheses * significant at 5 percent level; ** significant at 1 percent level. For occupation qualification 241 dummy variables are included. Coefficients are not shown here.

and a residual, which is the unexplained fraction. We use the estimated coefficients from the male sample regression for the weights. The main results do not change using the female sample regression results instead.

Estimation results shown in Table 3 are very much in line with human capital theory. Yet, we find significant differences between groups. In column 1 and 2, estimation results are shown for wage regression where the controls for productivity related differences exclude the occupational qualification variables. Coefficients shown in column 3 and 4 are conditional on the complete array including controls for the specific training. Results seem to change very little moving from the shorter to the longer specification. We find that staying with a firm leads to wage gains compared to moving. This becomes smaller after taking out heterogeneity due to type of training. Changing qualification seems to decrease wages. The duration of apprenticeship is positively correlated with wages proxying perhaps quality of training. An upper degree also leads to gains that seem partly correlated with the occupational qualification.

Results for the decomposition of the entry wage gap into explained and unexplained fractions due to differences in endowments are summarised in Table 4. As shown before, the total entry wage gap is 22.4. Using the male wage regression estimates of the parameters and human capital characteristics excluding occupational qualification, as shown in column 1 and 2 in Table 3, we find that only 8.6 percent can be explained by differences in the controls. This fraction increases to 89.9 percent when we add the occupational qualification, using results in column 3 and 4. Hence, pre-market differences play a crucial role for wage differentials.

This result may be highly sensitive to the exogeneity assumption of occupational qualification. The exogeneity assumption can be violated mainly for two reasons: non-random self-selection into occupational qualification bias, and market discrimination. If the exogeneity assumption does not

Table 4: Decomposition of male-female entry wage gap

Variables	Explained	Unexplained
Pre-market characteristics excluding occupational qualification	8.6 %	91.4 %
Pre-market characteristics including occupational qualification	89.9 %	10.1 %

Note: Calculation of the decomposition follows Blinder (1974), Oaxaca (1974). We use the male sample regression results from table 3.

hold our results can be interpreted as reduced form in these variables. Self-selection into occupational qualification schemes takes place among the group of juveniles when they transfer from school to apprenticeship at the early age of 16.[24] The general procedure is that during 9th or 10th grade at school juveniles send out applications to firms who offer apprenticeships in particular occupations. Either in interviews or by other means, such as the CV or application letter, firms decide whether to offer or not an apprenticeship. The applicant then decides among the offered apprenticeship training schemes. One may note, that the choice of the occupational type of training is very important for the later career. This is underlined by few drop outs and low mobility with respect to occupation throughout the early career. Women and men are highly concentrated in relatively few, yet very different, occupations. Women are most likely to go into the occupational careers, such as professional clerical workers, sales person, receptionist, hygienist, banking professional. By comparison, men go more

[24] This is conditional on the education decision to choose an apprenticeship; opposed to remaining unskilled or staying on at school in order to go university.

likely into technical professions such as motor vehicle mechanic, electrician, machinist, joiner. As our results on entry wages show, women are working in less well paid occupations. The question is whether this is due to low productivity of the occupation itself or due to sorting of relatively less able workers into these occupations. One may note that human capital theory predicts the contrary to our finding. Females, who may anticipate more interruptive working careers, maximize their lifetime earnings by choosing occupations with relatively low training content, and relatively flat wage profiles, and hence relatively high entry wages. (Polachek (1981))

Discriminatory factors together with productivity related differences may be removed when controlling for occupational qualification. Underlying is the idea that occupational segregation is partly determined by discriminatory forces, such as entry barriers and social norms. This would bias outcomes and implies that our estimate of the unexplained differential would be estimated with downward bias. Entry barriers set by firms, societal rules or images that pupils are taught at school and by their parents can have such indirect discriminatory effects. They may result in females from being discouraged of going into male jobs, such as manual jobs or jobs in science. While this argument though may be very appealing, it is very hard to find good exclusion restrictions for identification. In our case we do not deal with these problems.

5 Early career wages

For the analysis of the wage determination process we adopt the human capital model by Mincer and Polachek (1974) that segments the work history into work experience spells and non-working spells. Their model allows to estimate the particular effect of each work history segment, and hence considers timing. Furthermore, it allows to give a structural interpretation to the key parameters, i.e. the coefficients of the work experience variables and non-work variables. The parameters measure the net effect of the return to and depreciation of human capital.(Mincer (1974) The empirical implementation is adopted from Light and Ureta (1995).

We estimate a work history model, as specified in equation (1),

$$lnw_{it} = \beta_0 + \sum_{s=t}^{s=t-6} ex_{is}\beta_{1s} + \sum_{s=t}^{s=t-6} out_{is}\beta_{2s} + Z_i\beta_3 + \nu_i + u_{it} \qquad (1)$$

where i indexes individuals and t time. The dependent variable is the logarithmic wage. The controls for the complete work history are defined for individual i as an array of experience variables, ex_{is}, that measure the fraction of time worked in the most recent year, $s = t$, 1 year ago,$s = t-1$, 2 years ago, and so forth, back to the beginning of the career. These fractions can take the value zero either if the worker worked zero days during the year or the career was not in progress. For time out of work, *out*, we define dummy variables taking the value 1 if the worker did not work during the entire year. In addition, we control for pre-market characteristics that are time invariant, denoted by Z. ν_i is an unobserved individual specific effect and u_{it} idiosyncratic noise. We allow effects to vary for up to six years into the past.[25]

The model is estimated by fixed effects estimation for the sample of males and females separately. Fixed effects takes account of unobserved heterogeneity that is likely to bias coefficients of the work history variables. This results in consistent estimates of the effects on accepted wages. If selection into work for females follows a time dependent process estimates are not consistent estimates of the effects on offered wages. Comparison of estimates for our sample of females (including drop outs) and a sample of more continuously working females shows that coefficient estimates are highly sensitive to the use of the sample. In the fixed effects estimation results, that we present, we do not control for time varying non-random selection into work. However, this does not limit the results on the explained fraction of the gender wage gap due to timing of work experience since we do not rely on female sample parameter estimates.

5.1 Summary statistics

From the summary statistics reported in Table 5, we can see that the early careers of young skilled males and females do not reveal yet the gender distinctive labour force participation patterns. At the mean individuals in

[25] Hence, we assume that the coefficients are equal for 6, 7 etc. years ago. Tests do confirm that effects further in the past do not vary significantly.

Table 5: Sample means for early career, training cohorts 1975 to 1988

	women		men	
	mean	(std.)	mean	(std.)
			all spells	
age	22.9462	2.5532	23.4441	2.7069
work experience	2.5300	2.3224	2.4747	2.3078
time out of work	.3174	.7473	.9620	1.1869
potential experience	5.9360	2.5205	6.1309	2.4688
# of indiv.	84378		122708	
	all individuals in last wage (work) spell			
age	24.5537	2.6697	25.0175	2.9550
work experience	3.7222	2.6672	3.6020	2.7811
time out of work	.4614	.9945	1.1653	1.4199
potential experience	4.8429	2.8220	4.8082	2.8231
# of indiv.	14456		19598	
	all individuals in last wage (work) spell excluding individuals with zero years of time out of work			
age	24.8222	2.6947	25.4973	2.8313
work experience	3.9004	2.6118	3.8596	2.7372
time out of work	.8874	1.2345	1.5425	1.4446
# of indiv.	5.4690	2.6465	5.2788	2.6802
potential experience	7517 (51%)		14806 (75%)	

Note: Potential experience is calculated as 1990 minus the year of entry into first employment after apprenticeship training.

our sample have approximately six years of potential experience. In fact, females in our sample, who work 3.7 years on average measured in their last spell, seem to work even slightly more than men do.[26] Comparison of total time out of work years for females and males in their last wage spell shows that men have accumulated almost three times as many years than women have; that is 1.16 years compared to 0.46. One must note, however, that the latter comparison hides the fact, as illustrated in Figure 2, that women drop out of the sample and have not returned to work before 1991 which, once adjusted for, would lead to an increase of years in average time-out of work. Additionally, national service has been compulsory for the period of 12 months for men in Germany between 1975 and 1990. This explains the relatively high share of males, 75 percent, who have ever been observed in a time out of work spell.

5.2 Estimation results

Estimation results of the wage regression are shown in Table 6. In column one and two, we show the results using all cohorts in our sample. In column three and four, results for a highly selected group is shown, these are for the cohorts followed longest in our observation window are shown. Parameter estimates for the *work experience* variable reveal a time effect of the accumulation path. For males we find that most recently acquired work experience

[26]However, calculating means of work experience only for early (apprenticeship) cohorts in the sample, would make apparent that men work more years than women.

Table 6: Work history model for male and female workers: Fixed effects parameter estimation results of log wage regression model by sex

	Cohorts 1975-1988		Cohorts 1975-1977	
	Females	Males	Females	Males
% of year spent working previous year	0.1133	0.0432	0.1238	0.0644
	(17.82)**	(12.30)**	(7.21)**	(9.51)**
1 year ago	0.0921	0.0412	0.0935	0.0440
	(17.65)**	(12.89)**	(6.64)**	(7.32)**
2 years ago	0.0499	0.0485	0.0302	0.0409
	(10.48)**	(17.38)**	(2.59)**	(8.03)**
3 years ago	0.0608	0.0309	0.0331	0.0241
	(11.59)**	(10.35)**	(2.76)**	(4.67)**
4 years ago	0.0449	0.0249	0.0624	0.0226
	(7.64)**	(7.72)**	(4.95)**	(4.27)**
5 years ago	0.0611	0.0332	0.0310	0.0325
	(8.91)**	(8.75)**	(2.46)*	(5.71)**
6+ years ago	0.0485	0.0236	0.0477	0.0276
	(31.68)**	(20.81)**	(15.85)**	(16.18)**
1 if in not working previous year	-0.0047	0.0110	-0.0147	0.0133
	(1.26)	(4.71)**	(1.38)	(3.03)**
1 year ago	-0.0129	-0.0048	-0.0383	-0.0120
	(3.49)**	(2.06)*	(3.89)**	(2.86)**
2 years ago	-0.0204	0.0068	-0.0532	-0.0067
	(6.76)**	(3.74)**	(7.00)**	(1.99)*
3 years ago	-0.0046	-0.0020	-0.0345	-0.0129
	(1.41)	(1.06)	(4.50)**	(3.79)**
4 years ago	-0.0073	-0.0012	-0.0164	-0.0071
	(2.02)*	(0.57)	(2.04)*	(2.03)*
5 years ago	0.0022	0.0021	-0.0359	-0.0048
	(0.53)	(0.93)	(4.26)**	(1.30)
6+ years ago	0.0033	-0.0021	-0.0136	-0.0065
	(0.71)	(0.70)	(1.80)	(1.48)
Time dummies included	yes	yes	yes	yes
constant	3.7582	3.9789	3.6789	3.9881
	(377.33)**	(594.70)**	(166.04)**	(420.42)**
R^2 *	0.3264	0.3074	0.20	0.29
# observations	71223	104668	12560	28422
# individuals	13462	17815	1557	2871

Note: The dependent variable is the log of daily real wages. The wage observations are used for 1981 to 1990. Absolute value of t-statistics in parentheses * significant at 5 percent level; ** significant at 1 percent level. *: adjusted R-squared is reported, or within R-squared for fixed effects estimators.

is remunerated relatively more than work experience acquired earlier. For females the decline is stronger. In general, the return from experience seems to be higher for females than for males. Time out of work seems to have small effects on wages, that are partly negative. In the following we focus on the effect of timing of work experience on the wage gap. Therefore, we do not use the coefficients of the time out of work variables for calculation of the decomposition.

In Table 7 we summarise the decomposition of the wage gap at particular work experience levels using estimation results for the coefficients of the work experience variables. In panel A, we show the results for all 13 cohorts pooled. In the first column we list the raw gap. Initially, the gap increases slightly and declines then for workers with more than 4 years of experience. The gap due to timing of, and returns to experience, can be calculated by multiplying each individual's observed values for the vector of experience variables by the estimated coefficients for his or her gender and then by subtracting the women's average from the men's average. The gap due to timing is computed by multiplying each individual's values for the experience variables by the men's estimated coefficients, and we then subtract the women's average from the men's average. In this case both endowments and coefficients are held constant, and therefore timing of work experience is the sole source of wage gap. While the latter factor is unaffected by the coefficients from the female sample wage regression estimation, the former

Table 7: Decomposition of the male-female Wage Gap, based on estimates from table 6

Years of Work Experience	Raw (Log) Wage Gap	Gap due to Timing of, and Returns to Experience	Column 2 as a Percentage of Column 1	Gap due Timing of Experience	Column 4 as a Percentage of Column 1	No. of Obs. Men	No. of Obs. Women
	Panel A: Cohort 1975 to 1988						
0	.2231	.	.	.	.	18040	13155
1	.2361	.1486	.6292	-.0061	-.0259	15974	11467
2	.2458	.1078	.4386	-.0004	-.0017	14016	10438
3	.2471	.0929	.3758	.0031	.0128	12109	9288
4	.2468	.0730	.2959	.0042	.0173	9842	7429
5	.2366	.0503	.2127	.0058	.0245	8109	6177
6	.2360	.0280	.1189	.0059	.0251	6128	4594
7	.2328	.0058	.0252	.0060	.0258	4330	3246
8	.2343	-.0161	-.0687	.0071	.0304	2862	2119
9	.2299	-.0405	-.1763	.0070	.0306	1639	1235
10	.2096	-.0672	-.3207	.0050	.0242	746	646
11	.2044	-.0950	-.4645	.0033	.0164	262	279
12	.2283	-.1189	-.521	.0025	.0112	66	87
13	.2571	-.1494	-.5813	-.0042	-.0165	6	13
	Panel B: Cohort 1975 to 1977						
0	.2554	.	.	.	.	1420	442*
1	.2921	.2353	.8056	-.0144	-.0493	2173	761*
2	.2782	.2125	.7637	-.0018	-.0065	2625	1210
3	.2798	.2040	.7293	.0013	.0046	2655	1330
4	.2935	.1942	.6618	.0031	.0107	2538	1184
5	.2818	.1810	.6423	.0067	.0240	2551	1238
6	.2792	.1649	.5909	.0081	.0290	2408	1124
7	.2679	.1542	.5758	.0089	.0335	2214	1012
8	.2630	.1359	.5167	.0093	.0356	1907	897
9	.2521	.1149	.4560	.0082	.0325	1345	726
10	.2170	.0929	.4281	.0053	.0246	698	520
11	.2074	.0714	.3442	.0041	.0197	261	274
12	.2283	.0505	.2215	.0028	.0124	66	87
13	.2571	.0249	.0970	-.0046	-.0182	6	13

Note: * Since we drop spells before 1981 for the wage regression estimations, we loose wage observations at low levels of experience for the cohorts 1975 to 1977.

is affected. Hence, bias due to non-random selection of females into work is likely to affect these estimates. Results in Panel A seem to suggest that in the beginning of the career a quite high fraction is "explained" and its power declines and reverses sign.[27] Furthermore, we find that timing of work experience accounts for an increasing fraction of the gap. Among workers with 8 to 9 years of experience timing accounts for 3 percent.

For comparison, we present results for highly selected cohorts of workers with very similar education histories where selection bias should be most severe as could be seen from Figure 2. As reported in panel B of Table 7, for the cohorts 1975 to 1977 the raw gap seems a bit higher than at the mean for the full sample. The evolution of the gap is slightly (more) concavely shaped. The timing effect is very similar to the average and varies between 0 or 1 percent in the beginning and increases to 3-4 percent at eight years of experience. Again, the effect of timing becomes important between 5 to 9 years after completion of training. Hence, conditional on other factors, very early and later than 9 years after training the timing of work appears less important for wage gap.

6 Conclusions

We have examined male-female wage differentials during the early career using new administrative data for West-Germany. In the raw data we have

[27]Estimation of several models and estimators have shown that these estimates are highly sensitive to the sample and specification.

found an entry wage gap of 22 percent and an almost constantly high differential at a similar level all through the early career. The main findings are that pre-market factors play an important role in determining the starting position of the career. In addition, for men and women at comparable levels of experience, we find that the timing of the work experience matters but explains only 1 to 4 percent.

Our result is in line with other international studies that have demonstrated that occupational segregation between men and women is a strong feature of labour markets and that women are working in relatively low paid jobs (e.g. Blau and Kahn, 1996). Distinctive features of our study on German skilled workers are that we find a strong tendency towards gender segregation already when we look at the distribution of occupational qualification of young people at age 16 to 20, and that its effect on wages is extremely large. In other more college education driven systems, such as the U.S., no such segregation can be observed in the choice of a college degree in the 1990s (Brown and Corcoran, 1997). For the early career, we find that differences in on the job training and time out of work do not have strong explanatory power for the gender wage gap. Hence, one may conclude that the pre-market factor occupational qualification may have permanent effects in an environment of low mobility.

If policy makers are concerned with gender wage gap, one may conclude that it would be perhaps better to postpone choices on specific careers towards a later age. At present, the German education system seems to force people to make occupational choice very early during their life. Postponing specialisation may counteract choices being dependent on attitudes towards professions and it may promote dependency on market factors. A way towards that could be the provision of more general training schemes. In practice this could mean to decrease the number of apprenticeship training occupations by grouping them into few more homogenous groups and allowing for specialisation and mobility within these groups later on.

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Appendix: Summary of selection of data sample		
Selection rule	sample of males	sample of females
original sample:		
# of observations	265.098	209.900
(# of individuals)	(25.020)	(25.020)
part time:		
# of observations	- 8.422	- 39.138
(# of individuals)	(- 688)	(- 3.218)
higher education:		
# of observations	- 39.604	- 21.942
(# of individuals)	(- 3.208)	(- 1.944)
analysis sample:		
total # of observations	217.072 = 81.97 %	148.820 = 70.91 %
(total # of individuals)	(21.124 = 84.5 %)	(15.267 = 74.8 %)