The Evolution of the Gender Wage Gap

Astrid Kunze (NHH, Bergen and IZA, Bonn)[1]

Discussion paper 3/03

Abstract:

In this paper we investigate when the male-female wage differential arises: Does it evolve over the early career or does it exist right from entry into first employment? For the analysis we use new administrative longitudinal data for Germany. Models with within firm job rationing or equilibrium matching show that from entry into the first job onwards women will be paid less than men. The main reason is that due to higher quit rates of women, firms are less willing to invest in firm specific training for women. In this paper we document empirically that these models can explain a substantial portion of the gender wage differentials among young skilled workers in Germany.

JEL classification: J16, J3, J7

Key words: Male-female wage differentials, human capital, early career, sample selection, occupation, apprenticeship training.

[1]E-Mail address: astrid.kunze@nhh.no. Address for correspondence: NHH (Norwegian School of Economics and Business Administration), Helleveien 30, N - 5035 Bergen. I would like to thank for helpful comments on previous versions of the paper by Christian Dustmann, Wendy Carlin, Michael Lechner, Ken Troske, two anonymous referees and participants in presentations at the CEPR Workshop in Milan on Non-Standard Labour Market Contracts, the University of Bergen, the Aarhus Business School, and ZEW, Mannheim.

1 Introduction

Since the early 90s the gender wage gap has been analysed in an increasing number of longitudinal studies primarily using U.S. data (Loprest (1992), Light and Ureta (1990), Kim and Polachek (1994), Light and Ureta (1995), O'Neill and Polachek (1993), Blau and Kahn (1997)).[2] In contrast to cross-sectional data, the main advantage of panel data is that actual years of work experience can be constructed which provide a more precise measure of human capital. It has been shown that work experience together with information on the timing of interruptions in work can explain up to 30 percent of the total wage gap (O'Neill and Polachek (1993)).

In this study we build on these earlier studies by examining the evolution of the wage gap. More particularly, the issues addressed are whether a wage gap exists from entry into first employment onwards and whether it is a permanent component of the gap across the career, or whether the wage gap evolves over time in the labour market. For this purpose we use new German administrative data on 12 cohorts of workers who have received vocational apprenticeship training that are advantageous over several other data sources to understand the gender wage gap better. In these data we can observe workers' complete training and employment histories. Workers who participate in apprenticeship programmes compose 50-60 percent of the German work force. The sample is large and comprises a group of workers, for which we can measure wages and human capital acquisition very precisely. Since we focus on young workers that are observed from the beginning of their career, we can construct flow variables without using retrospective information that may induce measurement error problems.[3] To anticipate the main

[2]Other studies for Sweden are by Albrecht et al. (1999) and for the U.K. by Bell and Ritchie (1998)

[3]Retrospective information is crucial in the PSID to construct work experience for all work-

descriptives in these data, looking at wages for full time (vocationally) skilled workers[4] conditional on work experience, we find that the male-female differential in entry wages is large, approximately 25 percent. Throughout the early career, it stays virtually constant at this level.

One may expect that if men gain more from an extra year of work than women then the male-female wage gap increases within cohorts over time. This pattern corresponds to what had been found in earlier studies estimating traditional earnings equations using measures of potential work experience. More recent studies for the U.S., using measures of actual work experience, have found that the return to experience for men and women is similar (e.g. Kim and Polachek (1994)). However, others have shown that various aspects of women's work experience contribute to the wage gap. Light and Ureta (1995) find that 7-10 percent of the gap is accounted for by the timing of work experience spells during the early career. Loprest (1992) demonstrates that although men and women are equally mobile (across firms) during the first four years in the labour market, men gain up to 50 percent more than women from each firm change. In this paper we document empirically that the sorting of women into low wage occupational training schemes also explains a substantial fraction of the gender wage differentials. The main reason for this according to models with within firm job rationing and equilibrium matching is that, due to higher quit rates of women, firms are less willing to pay for human capital investment of women.

The fact that women experience more interruptions in their working careers may induce a non-random selection of women into the work force that complicates the empirical analysis of the gender wage gap. This is particularly true when fol-

ers.

[4] We define skilled as those with 10 years of schooling and 2 to 3 years of vocational , that is apprenticeship, training schemes. We provide more details in the empirical section of the paper.

lowing young men and women during their early careers; this is the period when women are most frequently out of the labour force.[5] More particularly, sample selection induces problems for the calculation of simple means, and their decomposition. The exclusion of (female) nonparticipants could understate the gender gap in wage offers, via the biased mean of the female wage offer distribution.[6] In this study, we suggest an extension of the standard decomposition (Blinder (1973), Oaxaca (1973)) in order to account for these effects on the means of the human capital variables in the estimation of the explained fraction of the gap.

The remainder of the paper is organized as follows: First, we review theoretical models on the evolution of the male-female wage differential. Second, we outline the empirical strategy for estimating the gender wage gap. Third, we describe the data and present summary statistics. Fourth, we show the descriptives on wage profiles of young male and female workers. Fifth, we present the estimation results for the decomposition of the gap. Finally, we conclude.

2 Theoretical Models

From economic theory, predictions about the evolution of the gap are ambiguous. General human capital models (Zellner (1975) and Polachek (1981)) predict that women should have higher wages in the first job than men because men tend to invest in more general training than women which is paid for through lower wages. Wage profiles for males are as a consequence relatively steep due to returns to training. Hence, the wage gap increases over time. The prediction of a wage advantage of women at entry into work seems to find empirically little support, which casts doubts on these theories (Light and Ureta (1995), Loprest

[5]This can also be seen from table 5 in Light and Ureta (1995) who do not address this issue.

[6]A similar problem has been addressed in Neal and Johnson (1996) in the context of racial gaps in median wages.

(1992)). More complex models with firm specific human capital and asymmetric information (Lazear and Rosen (1990)) generate an increasing wage gap as well, yet make no predictions regarding entry wages. The following summarises two models that rationalise both a positive wage gap at entry and a positive, possibly increasing wage gap in experience.

The model by Kuhn (1993) generates within firm job rationing based on group demographic attributes. Shared investment into firm specific training is introduced into an equilibrium model of job allocation in which equally-productive demographic groups differ in terms of their labor force attachment. The general model is set in a multiperiod framework where jobs with no training and with firm specific training exist. Training takes place in the first period of the employment relationship. Workers pay a fraction α of the training costs. It is assumed that men stay always in the labour market while females exit with probability p. In the two period case, if $p < 0.5$ gender segregation occurs. Furthermore, it can be shown that male wage profiles are everywhere above the female profile in the post training period as well as in the first period if $\alpha < 0.5$. Hence, non-crossing profiles arise: men are paid up front expected future productivity. With both better job assignments and lower exit rates, men have higher expected future productivity than women. Allowing for re-entry after withdrawal mitigates the adverse consequences for the low labor forces attachment group, yet, does not eliminate them completely. The model predicts lower earnings, slower wage growth and less on the job training for the low attachment group, similar to the models by Zellner (1975) and Polachek (1981), and Lazear and Rosen (1990). In addition, and contrary to the formerly mentioned models, it predicts lower starting wages for the low attachment group.

In the Barron et al. (1993) model trained workers are more productive, similarly to the Kuhn model, due to more general and firm specific training, and, in addition, due to more efficient use of capital. This model also allows workers to leave the firm either to exit the labour market or to move to another firm because they receive a better wage offer. An assumption of the model is that male and female workers differ with respect to their labour force participation. The authors show that workers with a lower exit probability are more likely to change firms. However, their expected tenure is still higher than for workers with a high exit probability. Those with low exit probability receive higher post training wages in order to lower their probability of moving to another firm. More generally, given women's weaker attachment to the labour market, the model predicts that they will receive lower starting wages and lower wage growth over time. In addition, they will be sorted into jobs offering less training and using less capital. Put differently, workers with low expected exit rate have greater expected tenure and therefore higher expected profits. These are partly paid back to the worker by higher starting wages.

3 Estimation Strategy

The most common approach to measure male-female wage differentials in the literature is the Oaxaca (1973) decomposition. The Oaxaca (1973) decomposition is given by:

$$(\overline{lnw_t^M} - \overline{lnw_t^F}) = \hat{\beta}^M(\bar{X}_t^M - \bar{X}_t^F) + \bar{X}_t^F(\hat{\beta}^M - \hat{\beta}^F) \tag{1}$$

where the price vectors β^M and β^F are recovered after estimating $lnw_{it}^g = X_{it}^g\beta^g + \epsilon_{it}^g$ for males ($g = M$), and females ($g = F$), respectively. We denote the natural logarithm of the wage of individual i in period t as lnw_{it}, X_{it} is a vector of human capital characteristics, β the vector of prices and ϵ_{it} is a random error about which we make standard assumptions. Superbars indicate means. It follows that the difference in mean wages can be decomposed into a component explained by differences in endowments and an unexplained, residual, component due to differences in prices.

In the following, we assume that the individual human capital characteristics included in X^g_{it} are not measured with error, such that they bias gender differences. Furthermore, we assume that the male sample regression coefficients are suitable competitive market prices used as the weight β and estimated consistently. That means that we assume that non-random sample selection leaves estimates unaffected. The intuition for this assumption is that men participate almost constantly once they have entered the labour market.[7] Relaxing this assumption and considering potential upward bias of the parameter estimate of β^M due to unobserved heterogeneity leads to an upper bound estimate of the explained part of the gender wage gap.

We want to apply the approach to decompose the wage gap among workers at entry into first job (i.e. 0 years of work experience), 1 year of experience, two years etc.. In order to draw inference across long employment history data, one must take account of changes in the population, i.e. non-random sample selection, and its impact on mean characteristics, $\bar{X}$. This point is particularly relevant when looking at the early careers of male and female workers, where females are likely to drop out of the sample. The exclusion of (female) nonparticipants could understate the gender gap in wage offers, via the biased mean of the female wage offer distribution.

In contrast to the Oaxaca decomposition, our decomposition approach takes into account this selection problem. While the Oaxaca decomposition only makes use of information on participants, we extend this approach and exploit the information on non-participants as well. This allows for an unbiased comparison of estimates of the differentials in characteristics and the wage gap decomposition

[7] This is a common assumption in the literature used, e.g., in Blau and Kahn (1996).

across time, under the above assumption that the relevant vector of prices, β_t^M, is estimated consistently from the male sample wage regression model.

Suppose the hypothetical overall wage differential between two groups of workers can be written as a weighted average of the observed mean differential within the group of participating workers and the predicted wage differential within non-participating workers.

$$\begin{aligned}\overline{lnw_t^M} - \overline{lnw_t^F} &= (\rho_{pt}^M \, \overline{lnw_{pt}^M} - \rho_{pt}^F \, \overline{lnw_{pt}^F}) \\ &+ ((1-\rho_{pt}^M)\, \overline{lnw_{nt}^M} - (1-\rho_{pt}^F)\, \overline{lnw_{nt}^F}) \qquad (2)\end{aligned}$$

where $\rho_{pt}^M = N_{pt}^M/(N_{pt}^M + N_{nt}^M)$ is the fraction of participating male workers; N_{pt}^M is the total number of male workers paricipating in period t. For females ρ_{pt}^F can be written accordingly. The subscript p indexes participating individual spells, and n non-participating ones.

For illustration, assume two periods: t^*, t, where $t^* < t$. In period t^* everybody is working, and in period t a positive proportion of workers are participating in the labour market, whilst the remainder, *(1-ρ)*, are not. Since everybody is working in period t^*, calculation of the mean differential and the decomposition are straightforward.

For period t, however, we need to predict wages for those who are not participating in the labour market. Predictions are estimated as follows:

$$lnw_{nit}^F = \hat{l}nw_{nit}^F + \hat{u}_{nit}^F \Leftrightarrow lnw_{nit}^F = X_{pit^*}^F \hat{\beta}_t^F + \hat{u}_{nit}^F \qquad (3)$$

where the subscript n denotes non-participation.

If selection is only on observables, and each individual is observed at least once in the wage sample, then one can simply predict wages for each non-participating individual as follows:

$$\hat{l}nw_{nit}^{F} = X_{pit^*}^{F}\hat{\beta}_{t}^{F} \tag{4}$$

where we use $X_{nit}^{F} = X_{pit^*}^{F}$. This is done since we only observe the characteristics as long as the individuals are participants.

If selection is also on unobservables, then one can predict the residuals for non-participants by using an individual's percentile in the residual wage distribution, q, in period t^*.[8] That is: $\hat{u}_{nit}^{F} = F_{pt}^{-1}(F_{pt^*}(u_{pit^*}^{F}))$ where F_{pt} (and F_{pt^*}) is the cumulative distribution of the error term in period t (t^*). An underlying assumption is that for non-participants the position in the residual distribution, or their unobserved characteristics, do not change after the time of withdrawal from the labour market. In order to derive the components of the decomposition following equation (1) and (2), we predict mean wages for females at male prices using equation (3) accordingly.

4 The data and summary statistics

For the empirical analyses, we use the IAB employment sample (IABS)[9] for West-Germany which is an administrative event history data set. The IABS is a 1 percent random sample drawn from all workers in West-Germany with at least one employment spell in which they were eligible for the social security insurance scheme. The population includes all dependent employees in the private sector, i.e. about 80 percent of total employment in West-Germany.[10] The data contains information on whether an individual is in full-time work, part-time work, unemployment and interruption which captures national service and maternity - or

[8] This approach is similar to Juhn et al. (1993).

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

[10] 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).

parental - leave. A unit of observation in the data is a spell, and not necessarily a yearly spell.

From the IABS we select a sample of young workers who have received apprenticeship training. This group of workers we refer to as skilled in the following, excluding workers who have not participated in an apprenticeship and workers with a university or technical college degree. The data sample from the IABS offers several advantages for our analyses over the data used in the literature so far. First, the data provide administrative reports on earnings, employment and non-employment spells; a clear improvement over the self-reported earnings measures that US data sets typically use.[11] Second, since we observe complete training and employment histories, the data are very precise in human capital investment. We can follow workers from entry into first employment onwards and generate actual years of experience. Furthermore, we have information on education, as well as gender, occupation, and the firm. Third, the sample is very homogeneous with respect to education, most have 10 years of schooling and 2 to 3 years of apprenticeship training. This reduces unobserved heterogeneity problems and strengthens the predictive power of the human capital variables. Fourth, we can construct and follow 12 cohorts from start of apprenticeship training onwards which is much better than most panel data sets.[12] The data cover 15 years, 1975-1990, and post-apprenticeship employment histories can be followed for up to 12 years. Furthermore, it is a large longitudinal data. For comparison the NLSY contains only information on 7 cohorts and the sample size is smaller.

For the final sample, we select only records on young full-time workers[13]. We

[11] See Bollinger (1998) for a discussion on measurement error problems in the CPS data.

[12] Light and Ureta (1995) uses the NLS that includes approximately 9000 individuals aged 14 to 24 when the survey began. Women are followed from 1968 to 1985, and men from 1966 to 1981. Loprest (1992) uses NLSY (The National Longitudinal Survey of Youth) a survey of 12686 young people who were 14-21 years old in 1978 and are followed from 1979-1983.

[13] Full time is defined as 35 working hours or more per week. This rule leads to exclusion of

select individuals who enter training before 1988, who have undertaken training for at least 450 days without interruption[14], who have no further vocational training and who do not obtain a technical college or university degree. To ensure that individual employment and wage histories are observed from the beginning, we select individuals not older than 15 years in 1975. As a result, the data include individuals who are followed over early careers, i.e. the oldest individuals are 30 and the mean age is 23.[15] Our final sample contains 14563 female and 19710 male workers observed in at least one full-time working spell after completion of vocational training. A working spell is defined as a spell with observed wages in full-time work. The wage variable is the logarithm of the daily pre-tax wage deflated by the consumer price index from the German statistics office. In the estimations, we use working spells from 1980 onwards, excluding implausibly short apprenticeships of very young workers. The total number of working spells is 86015 for females and 124540 for males.

A shortcoming of the IABS is that it does not contain a detailed hours of work variable. While focusing on full-time workers does limit the possible difference in hours of work across individuals, there still may be a problem if women on average are working less hours per day than men. To address this problem we use information on weekly hours of work that is available in the Socio-Economic Panel for Germany (SOEP) from 1984 onwards. In Figure 1, average hours of work for male and female full time workers younger than 30 with 11 to 13 years of education are plotted. Females work approximately 40 hours in 1984 and 38-39 hours in 1990. Males work one to three hours more than females.[16] Hence,

3 percent of spells for males and 18.6 percent of spells for females.

[14]This is the recommended selection rule by the IAB.

[15]It turns out that our sample consists of individuals who are strongly attached to the labour market, until the point of time of drop out. See Light and Ureta (1990) who analyse a similar sample for the U.S..

[16]We use actual hours of work, including overtime.

differences in hours of work can account for 7 percent of the wage differential[17], or more in case of non-linearly increasing overtime premiums, leaving more than 18 percent unexplained in our data.

Figure 1 here

The information we have allows us to measure the productivity related characteristics of skilled workers. Apprentices start typically at age 16 and involves 2 to 3 years of training with a firm, and wages amount to about 20-30 percent of the wage of a blue or white collar worker. In order to receive a certificate for the particular occupational qualification acquired, apprentices have to pass written and oral examinations, and practical exercises in craftsmanship. Exams are unified across Germany or the states (*Länder*) and are held externally by the chambers of commerce and trade and chambers of craft.[18] During the period of 1975 to 1990, apprenticeships within the German apprenticeship programme 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.

Human capital characteristics are constructed from the entire records starting at entry into apprenticeship. We measure schooling before apprenticeship, age at entry into training - which proxies further schooling until entry into apprenticeship -, the duration of apprenticeship and the occupational qualification. We define the occupational qualification as the occupation in which apprenticeship training has been undertaken. Furthermore, we can identify the firm and industry that training has been undertaken in. An additional variable that we use is the apprenticeship cohort, that is the year of entry into apprenticeship.

[17]For simplicity, for this calculation we assume that the derivative of daily wages with respect to hours worked is linear.

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

General human capital acquisition during employment is measured by years of actual work experience. This variable is constructed from the individual post-apprenticeship wage spells. These spells also include details on the employer, the industry, occupation of work and a crude measure of job status. Additionally, we consider the transition of human capital from apprenticeship to first employment. In order to take account of firm[19], occupation and industry[20] specific components of training, we generate binary *skill match variables*. Stayers with respect to occupation, for example, are defined as individuals for which in a working spell the *occupation of work* is the same as the *occupational qualification*. Occupation at work as well as occupational qualification are measured on the three digit level.

Employment Rates

Figures 2 and 3 plot employment rates for our male and female workers, respectively, who first entered employment in 1975, 1977, 1979 or 1981. in our sample. In the graph for males the first line shows employment rates for the first cohort. These workers have started apprenticeship in 1975 and the majority enter first employment within 2 to 3 years after training.[21] As expected, males' employment rates for all cohorts monotonically increase to a level of 80 to 90 percent then, and stay relatively constant. By contrast, for females, as is shown in Figure 3, we find that employment rates increase at first, but then decline. This can be seen most clearly for the 1975 cohort where employment rates fall to less than 40 percent by 1990. This decline in participation presumably reflects the effect of child bearing and rearing. For a longer observation window, one would expect employment rates to go up again due to females returning to employment after

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

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

[21]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.

periods of parental leave.

Figure 2 and Figure 3 here

4.1 Male and female workers

We first show means for various characteristics at the entry into first employment spell for males and females in Table (1). Workers are homogeneous with respect to education; virtually all of them have an intermediate secondary schooling degree, i.e. 10 years of schooling. They are also homogeneous with respect to type of tertiary education since all have undertaken an apprenticeship programme. Duration of the programmes varies, however, lasting on average 2.18 years for females and 2.51 years for males. It turns out that females and males are both of similar age in their first employment; women are on average 20.3 years of age whilst men are only 0.2 years older.

Table 1 here

Despite similarities of the quantity of education and vocational training, we find striking gender differences in the type of training, i.e. *occupational qualification.* Similarly to other Western industrialized countries, females are more likely to be qualified in services, such as a *professional clerical worker* or *receptionist*, while males are more likely to do apprenticeships in manufacturing, for example, as a *motor vehicle mechanic* or *electrician.*

Occupational segregation in first employment can also be seen from the statistics on the broad measure for *job status*. Results are as expected: 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.[22]

The *skill match variables* reveal quite strikingly 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 percent, respectively. 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. Looking at Figure 4, we see that also across time mobility with respect to occupational qualification is quite low; particularly for female workers. After 6 years of work approximately 60 percent of females and 50 percent of males are still working in the 3-digit occupation they have received their apprenticeship training in.

Figure 4 here

Contrary to evidence from cross sectional data for the entire work force, we find that young females are working more than males in our sample, which is not shown here. At the mean females work 3.69 years and males 3.58, with the difference significant at the 1 percent significance level.[23]

Table 2 here

4.2 Female workers and drop outs

In order to derive evidence on the sample selection bias caused by female workers' withdrawal from work, we show summary statistics for females who drop out and

[22]To do this calculation one needs to keep in mind that about 50-60 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).

[23]One must note that national service is compulsory for men in Germany. It took 15 months (20 months) from 1972 until 1989 depending on whether military service or civil service was served. In Germany, the average age of mothers at first birth was 25.19 in 1980 and 26.93 in 1990 (See *Statistische Bundesamt: Bevölkerung und Erwerbstätigkeit, Fachserie 1, Reihe 1, 1999*). Hence, we have few individual records with an interruption due to having children in the data.

females who work continuously. We define continuously working as those who work in two consecutive periods, *t-1* and t, and drop outs as those who are working in *t-1* but not working in t. To demonstrate the main finding, in Table 2 we show means for the selected group of females who drop out just after completion of two years of working and those who continue working. The results do not change when we look at work experience levels up to 6 years. Most interestingly, we find that drop outs have experienced longer spells of time out of work and they have lower levels of schooling and training. They also are more likely to be employed in blue collar jobs and they are more likely to change occupation to one that is different from their occupational qualification. All of these differences are significant at the 5 percent level. In conclusion, we find that women who drop out of the labour market have less favourable observed characteristics at the mean than those who stay in work. This is consistent with models explaining the gender wage gap, like in Polachek (1981), Kuhn (1993), Lazear and Rosen (1990). These models assume that females have a comparative advantage outside the labour market which is why they are more likely to drop out. We find that females staying on in work are positively selected which will lead to a lower gender wage gap among accepted wages than offered wages.

5 Wage profiles over the early career

In Figure 5 we plot wages as a function of actual work experience. We applied a robust non-linear smoothing technique. At entry into first employment a considerable differential in wages is observed.[24] Thereafter, wage experience profiles for men and women are slightly concavely shaped and seem to develop in almost

[24] What is not shown here is that before entry into first employment - that is while workers are in apprenticeship training and while they earn only approximately 30 percent of skilled workers' wages - the mean wages are very similar for males and females.

parallel fashion. The differential, accordingly, stays almost constant during this period at around 0.25.

Figure 5 here

In the following, we investigate the evolution of the gap further. In order to make workers comparable within periods, we make use of the detailed human capital characteristics. Across periods, we take account of the fact that the sample used in Figure 5 varies in its composition due to drop-outs. This mainly applies to young females withdrawing from work temporarily due to child bearing and rearing. Hence, while in period 0 for all females and males accepted wages are observed by period 8 a selected group of females for which we observe accepted wages is compared with the complete sample of males. In case of positive selection, as the descriptives suggest, this implies the underestimation of the overall gap, as well as the explained gap.[25] In our empirical analysis, we focus on the consistent estimation of the explained part of the gap.

6 Estimation Results

In the regression analysis, we estimate wages as a function of years of work experience and human capital characteristics as detailed before in Table 1. Given the results in Figure 5, we choose to allow for a flexible functional form so we let the coefficient on experience vary across integer years of experience, and allow for (apprenticeship) cohort specific coefficients. This also enables us to break down the total gap into the explained part and the residual at each level of experience.

[25]Since sample selection may not be random, in this graph the slope of female sample wage profile may be biased (Heckman (1979)). In case of positive sample selection bias the slope is likely to be flatter, leading to a relatively larger wage gap. We do not deal with this problem regarding the total gap.

More formally, we estimate the following simple empirical wage equation:

$$lnw_{it} = \beta_0 + ex_{it}\beta_1 + c_{it}\beta_2 + (ex * c)_{it}\beta_3 + T_t\beta_4 + Z_{it}\delta + u_{it} \tag{5}$$

where i indexes individuals and t time. The dependent variable is the logarithmic daily wage, lnw. The variable ex denotes a vector of dummies for each integer year of work experience, c a vector of dummies for each apprenticeship cohort, and T contains dummies for the calendar year. Correspondingly, $(ex * c)$ are the interactions of these variables. Z_{it} is a vector of detailed human capital controls, such as age at entry, duration of apprenticeship training and occupational fixed effects. Note that a subset of these are varying across individuals but are time-invariant. The term u_{it} is idiosyncratic error. We allow for a fully flexible specification in work experience, cohort and time[26]; the coefficients are estimated by ordinary least squares. Assuming that human capital acquisition depends only on work experience and cohort-specific factors, time dummy variables enter the equation in an additive fashion. Hence, it is assumed that the time trend captures the general price of human capital level in the economy and that only shifts of the intercept are relevant (See Dustmann and Meghir (1999)).

The coefficient of the work experience variable can be interpreted as the gain from an extra year of on the job training. Coefficients of the cohort variable capture between cohort differences due to, for example, variation in education institutions during the observation period, or variation in quality of training across cohorts. In addition, cohort effects control for changes in the outside the labour market options or reservation wages, which affects selection into work (Lazear and Rosen (1990) and Kuhn (1993)). Hence, more generally, the flexible functional form takes account of supply and demand factors. Time effects control for general macroeconomic effects. For identification of the experience, (training)

[26]At the same time we lose of efficiency.

cohort and time effect, we use the fact that within a given year we have variation in (training) cohort, and that we have variation in time out of work periods across individuals.

6.1 The gender wage gap decomposition

The estimated parameter vector from the male sample regression[27] is used to generate the decomposition of the male-female wage gap as in equation (1). Taking account of selection due to non-participants the explained part of the wage gap can be separated into three components:

$$\begin{aligned}\beta_t^M(\overline{X_t^M} - \overline{X_t^F}) &= \beta_t^M(\rho_{pt}^M\,\overline{X_{pt}^M} - \rho_{pt}^F\,\overline{X_{pt}^F}) \\ &+ \beta_t^M((1-\rho_{pt}^M)\,\overline{X_{nt}^M} - (1-\rho_{pt}^F)\,\overline{X_{nt}^F}) \\ &+ (\overline{\hat{u}_t^M} - \overline{\hat{u}_t^{*F}}) \qquad (6)\end{aligned}$$

where $\overline{\hat{u}_t^M} = 0$, and $\overline{\hat{u}_t^{*F}}$ is the vector of female wage residuals at male prices of unobservables.[28] In more detail, the first term, neglecting the weights, corresponds basically to the Oaxaca decomposition based on participants.[29] The second term corrects for selection on observables, and the third for selection on unobservables, which are estimated according to equation (3) using male prices. The residual, or unexplained part, can then be derived by subtracting the explained part from the total gap.

We present the results in Tables 3 broken down by work experience as formulated in equation (6). In the table results in panel A are derived from a wage equation including in addition to year, cohort and work experience fixed effects

[27]In order to conserve space only the results for the decomposition estimation results are presented. For more details see Kunze (2002).

[28]See Juhn et al. (1993). For estimation we split the wage residual distribution into 100 percentiles that allows a very detailed matching.

[29]This can be seen from substituting $\rho^M = \rho^F = 1$ and $\bar{\hat{u}}_t^{*F} = \bar{\hat{u}}_t^F$.

the detailed human capital variables as we have listed them in Table 1, yet *excluding controls for occupational qualification.* Results in panel B are based on the estimates from our most extensive model *including approximately 300 dummies for each occupational qualification.*

Table 3 here

The first column reports the total observed wage gap. The second column lists the part that can be explained in absolute terms and as a percentage of the total wage gap. From panel A, we see that only 9.44 percent of the entry gap, i.e. zero years of work experience, can be explained by differences in human capital characteristics, excluding occupational fixed effects. The contribution of each component is relatively small and not reported here.[30] Moving to panel B and the estimate of the explained part of the entry wage differential, we see that additional 52 percent are explained by the occupational fixed effects. This factor also remains very important when we estimate the explained part of the gap correcting for selection on observables (column 3) and selection on unobservables (column 4). Looking at the evolution of the gap across rows one can see that while the total gap does not change very much, the explanatory power of the occupation specific effects seems to become stronger in relation to the other characteristics. This result changes only when controlling for selection on unobservables. Then, the fact that females are relatively better endowed with respect to unobservables than males means that the explanatory power decreases with the increase in work experience. In summary, across work experience we find that differences in occupational qualifications result in a permanent wage disadvantage for women, explaining more than 50 percent of the gap at all points in the early career[31].

[30]From Table 1, however, one can see the unweighted differences in means for the entry wage spell.

[31]In addition, we find a strong decline across cohorts of the total gap as well as of the explained fraction of the gap, as shown in the Appendix Table A. This may indicate substantial

Our estimation results, to some extent, depend on consistent estimation of β for the male sample wage regression. Consistency is achieved by imposing the restriction that unobserved individual specific effects, captured by the error term, are orthogonal to the explanatory variables in our model. Relaxing this assumption implies that our parameters of interest are estimated with (upward) bias as well as the explained part of the wage differential. If the bias is time constant across work experience, however, this caveat does not apply to the change of the explained part of the gap. In general, one could get around problems due to unobserved heterogeneity by applying fixed effects estimators. However, while in ordinary least squares estimates identification of the occupation specific fixed effects comes from cross-sectional variation, in fixed effects estimation variation across time drives the parameters. As a result, occupational mobility, which is another potentially endogenous process, further complicates identification. Therefore, in this study we ignore somehow these more complicated matters and maintain rather simple estimators. We argue, however, that although the quantitative result arguably may be sensitive to the applied estimation technique, the qualitative results remain unchanged.

6.2 Discussion

Consistent with theory we find a large gender gap in employment rates and that gender differences in human capital investment are important. Furthermore, consistent with the models by Kuhn (1993) and Barron, et al. (1993) our descriptives

changes that have helped to improve the relative position of young skilled females in the labour market. Like in other countries, occupational segregation is high and has not changed over time. On the other hand the 1970s and 1980s have seen structural changes that have increased the importance of the service sector. In turn efforts have been made to improve the quality of apprenticeship training schemes. Since males are often trained in the 'old' craft sector that traditionally has high quality training schemes, it is more likely that females profited more from these improvements. They are more likely to be in training schemes in new service and telecommunications jobs. See Münch (1992).

show an entry wage gap after completion of training and a significant gap in work experience.

Wage differences in the above models accrue to differences in firm specific training, and, possibly, differences in general training. It follows, that the wage differential conditional on detailed human capital investment variables is expected to go to zero. As we have shown this is not supported by our findings. More than 40 percent of the gap in daily wages, for example 0.4*252=10.08 at entry, are left unexplained. Taking account of the fact, however, that men may indeed work longer hours than women, as we have pointed out, and assuming for simplicity that wages increase linear in hours, a gap of only 3 percent is left unexplained.

In addition, we document the great importance of occupational qualification. This seems in contrast to the theory that stresses the importance of firm specific human capital. Still, it documents the fact that women are selected into low wage occupations, that may be less productive due to relatively less human capital investment of a general, occupation specific, or firm specific type. This is in line with the prediction of gender segregation from the Kuhn model, for example.

Also, similarly to Neal and Johnson (1996) we find that pre-market factors, in distinction to post-market factors, are quite important determinants of wage differentials. Neal and Johnson document that the main fraction of the racial wage gap can be explained by differences in scores of a test, measuring skills and ability, administered to teenagers in the U.S. prepared to leave high school. The authors argue that this pre-market variable is free of discriminatory bias. In our case, occupational qualification, the pre-market factor, is interpreted as a measure of productivity within occupations and the question is whether it is biased due to non-random selection into apprenticeship occupations, and discriminatory forces, in particular. For example, entry barriers that prevent young women from choosing freely the occupational training scheme may be such factors. Similarly, societal rules or images pupils are taught at school and by their parents may work through the pre-market factor variable. In general, these forces may result in females from being discouraged from going into high productivity - male - jobs. Such forces may have strong effects on the choice behaviour of the very young ones, like in our analysis.

7 Conclusions

We have examined the male-female wage differential during the early career. For the analysis we have used German administrative data on young skilled workers that can be followed over the period 1975 to 1990. The data allow us to compare a relatively homogeneous group of workers and control for a large number of detailed human capital characteristics.

Simple descriptive statistics show an entry wage gap of approximately 25 percent that persists throughout the early career. The decomposition of the gap into the explained part and the residual shows that already at entry a substantial part of the raw entry wage gap, approximately 50 percent, is due to differences in occupational qualification, with a further 10 percent due to other differences in initial human capital. This result holds under the assumption that choices of education, i.e. until age 16, and occupational qualification or apprenticeship, i.e. made approximately at age 16, are exogenous.

These results suggest that large permanent wage disadvantages during the early career are formed by the occupational qualification while other detailed background characteristics and differences in individual work histories are only of minor importance. This is consistent with models incorporating firm specific human capital that show that firms may be less willing to pay for human capital investment into women due to women's higher probability to quit.

References

[1] Albrecht, James W., Per-Anders Edin, Marianne Sundström, and Susan B. Vroman (1999): Career interruptions and subsequent earnings: A reexamination using Swedish data, *Journal of Human Resources*, 34(2), pp.294-311.

[2] Barron, John M.; Dan A. Black and Mark A. Loewenstein (1993): Gender differences in training, capital, and wages, *Journal of Human Resources*, 28(2), pp.343-64.

[3] Bell, David, and Felix Ritchie (1998): Female earnings and gender differentials in Great Britain 1977-1994, *Labour Economics*, 5, pp.331-357.

[4] Bender, Stefan, Jürgen Hilzendegen, Götz Rohwer and Helmust Rudolph (1996): Die IAB-Beschäftigtenstichprobe - 1975-1990, BeitrAB 197, Institut für Arbeitsmarkt- und Berufsforschung der Bundesanstalt für Arbeit, IAB, Nürnberg.

[5] Blau, Francine, and Lawrence M. Kahn (1996): Wage structure and gender earnings differentials: an international comparison, *Economica*, 63, pp.S29-S62.

[6] Blau, Francine, and Kahn, Lawrence M. (1997): Swimming upstream: Trends in the gender wage differential in the 1980s, *Journal of Labor Economics*, 15(1), pp.1-42.

[7] Blinder, Alan S. (1973): Wage discrimination: reduced forms and structural estimates, *Journal of Human Resources*, 8(4), pp.436-55.

[8] Bollinger, Christopher R. (1998): Measurement error in the current population survey: A nonparametric look, *Journal of Labor Economics*, 16(3), pp.576-594.

[9] Dustmann, Christian, and Costas Meghir (1999): Wages, experience and seniority, Institute for Fiscal Studies, Working Paper, 99/1.

[10] Harkness, Susan (1996): The gender earnings gap: Evidence from the U.K., *Fiscal Studies*, 17(2), pp.1-36.

[11] Heckman, James (1979): Sample selection bias as a specification error, *Econometrica*, 47(1), pp.153-61.

[12] Kim, Moon-Kak, and Solomon W. Polachek (1994): Panel estimates of male-female earnings functions, *Journal of Human Resources*, 29 (2), pp.406-428.

[13] Kuhn, Peter (1993): Demographic groups and personnel policy, *Labour Economics*, 1, pp. 49-70.

[14] Kunze, Astrid (2002): The Evolution of the Early Career Gender Wage Gap, IZA Discussion Paper No.436, February.

[15] Juhn, Chinhui, Kevin M. Murphy and Brooks Pierce (1993): Wage inequality and the rise in returns to skill, *Journal of Political Economy*, 101(3), pp. 410-442.

[16] Lazear, Edward P. and Sherwin Rosen (1990): Male-female wage differentials in job ladders, *Journal of Labor Economics*, 8(1), pp.S106-S123.

[17] Light, Audrey, and Ureta, Manuelita (1990): Gender differences in wages and job turnover among continuously employed workers, *American Economic Review*, 80 (2), pp.293-297.

[18] Light, Audrey, and Ureta, Manuelita (1995): Early-career work experience and gender wage differentials, *Journal of Labor Economics*, 13(1), pp.121-154.

[19] Loprest, Pamela J. (1992): Gender differences in wage growth and job mobility, *American Economic Review*, 82(2), pp.526-532.

[20] Münch, Joachim (1992): Das Berufsbildungssystem in der Bundesrepublik Deutschland, European Centre for the Development of Vocational Training (CEDEFOP), Berlin.

[21] Neal, Derek A. and William R. Johnson (1996): The role of premarket factors in black-white wage differences, *Journal of Political Economy*, 104(5), pp.869-895.

[22] Oaxaca, Ronald (1973): Male-female wage differentials in urban labor markets, *International Economic Review*, 14(3), pp.693-709.

[23] O'Neill, June, and Polachek, Solomon (1993): Why the gender gap in wages narrowed in the 1980s, *Journal of Labor Economics*, 11(1), pp.205-228.

[24] Polachek, Solomon W. (1981): Occupational self-selection: A human capital approach to sex differences in occupational structure, *Review of Economics and Statistics*, 63(1), pp.60-69.

[25] Zellner, Harriet (1975): The determinants of occupational segregation, in: C.B. Lloyd, ed., Sex, discrimination, and the division of labor (Columbia University Press, New York), pp.125-145.

Figure 1: Actual Hours of Work for Full-Time Workers with 11-13 Years of Education, Age 18-30 (Source: Socio Economic Panel (SOEP) for Germany)

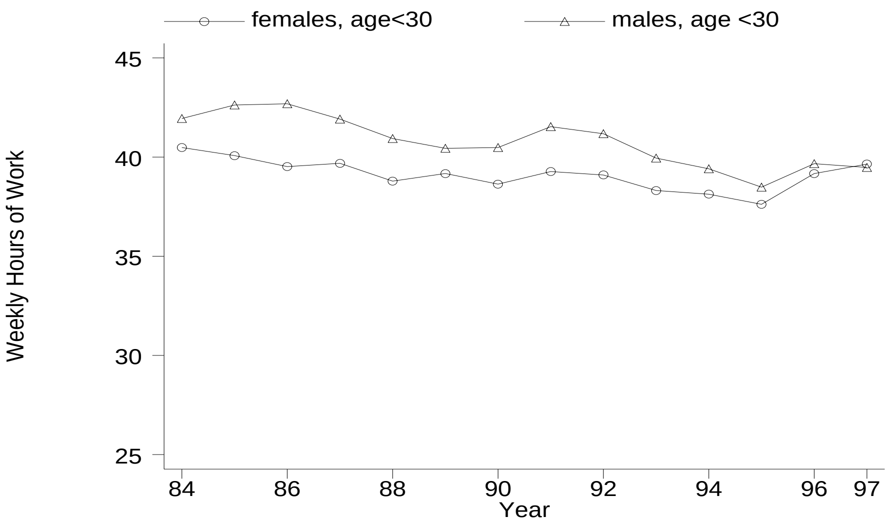

Figure 2: Employment Rates of Male Skilled Workers, age 18-30

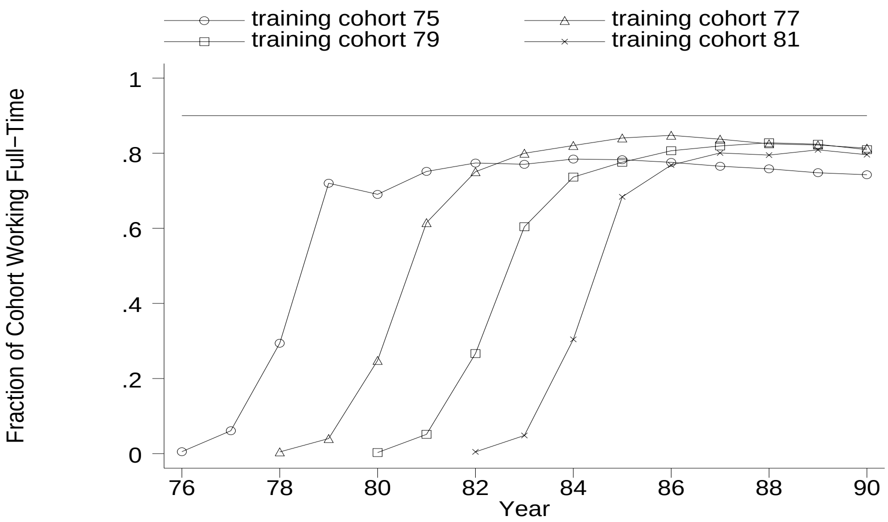

Figure 3: Employment Rates of Female Skilled Workers, age 18-30

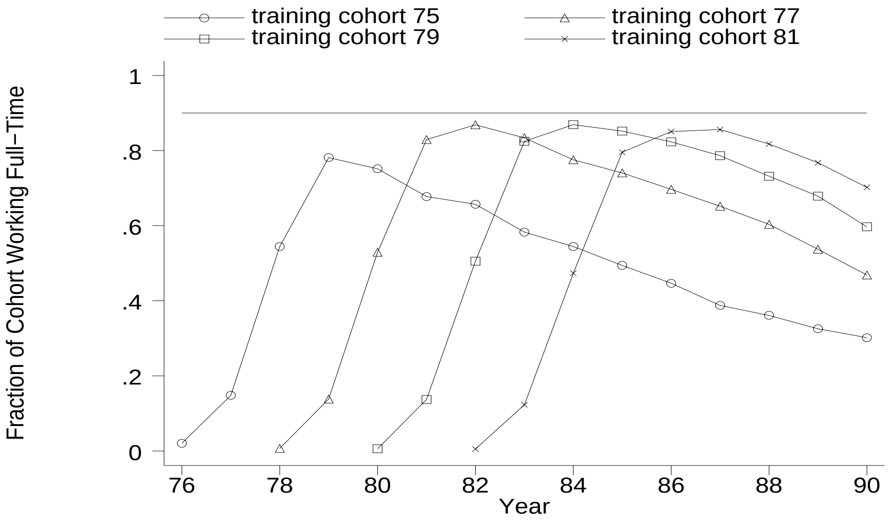

Figure 4: Training to Work Transition: Occupational Mobility

Figure 5: Wages for Full-time Skilled Workers, age 18-30

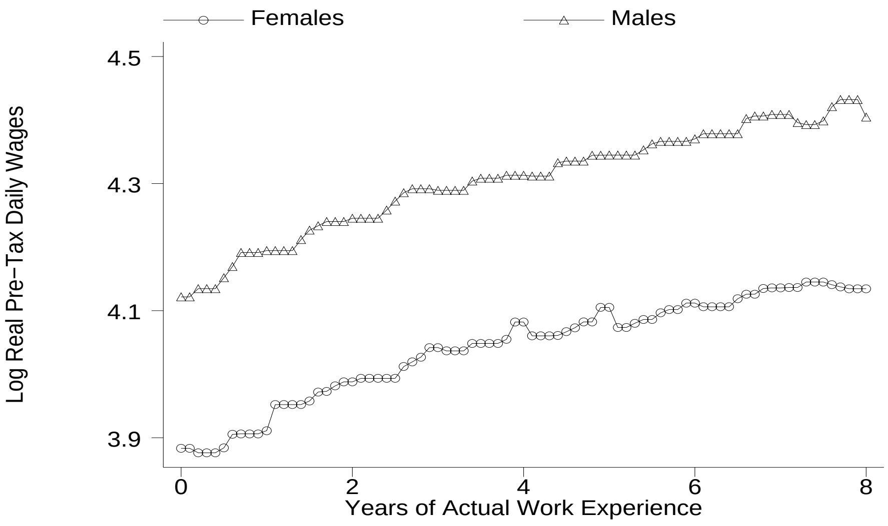

Table 1: Sample Means of (Vocationally) Skilled Workers at Entry Wage Spell, by Gender

	female		male		t-test for
	mean	(std.)	mean	(std.)	H_0: Equality of means
			education		
1 if interm. degree	.9547	(.2078)	.9814	(.1350)	-14.37
1 if upper degree	.0453	(.2078)	.0185	(.1350)	14.37
apprentice. duration	2.18	(.7318)	2.51	(.7418)	-40.96
age in first job	20.3416	(1.5725)	20.5000	(1.5815)	-9.18
			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	14563		19710		

Notes: * 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.

Table 2: Sample Means for Drop Outs and Continuously Working (Vocationally) Skilled Females who have reached Two Years of Work Experience

X	Drop-Outs mean	(std.)	Continuously Working mean	(std.)	t-test for H_0: Equality of means
age	22.7578	(1.6905)	22.8037	(1.4498)	-1.51
time out of work (until last wage)	.5710	(1.1064)	.2300	(.5585)	22.83
1 if non-zero years of time out	.5613	(.4962)	.4429	(.4967)	11.91
			education		
age at entry into apprenticeship	16.4714	(1.2086)	16.8310	(1.2547)	14.46
1 if interm. degree	.9809	(.1366)	.9574	(.2019)	6.30
1 if upper degree	.0190	(.1366)	.0425	(.2019)	-6.30
apprentice. duration	2.077	(.6761)	2.1066	(.7083)	-2.07
			skill related variables		
job status:					
unskilled	.1376	(.3445)	.0992	(.2990)	6.15
skilled blue collar	.1543	(.3613)	.1130	(.3166)	6.27
other (foreman)	.0020	(.0452)	.0009	(.0310)	1.52
skilled white collar	.7060	(.4556)	.7867	(.4096)	-9.55
*skill match variables**:*					
1 if Qual.stayer	.6067	(.4885)	.6355	(.4812)	-2.98
1 if Firm stayer	.6026	(.4894)	.6723	(.4693)	-7.33
1 if Firm+qual.stayer	.4202	(.4936)	.4706	(.4991)	-5.06
1 if Industry stayer	.7888	(.4081)	.8029	(.3978)	-1.75
# of individuals	3415		9300		

Notes: Variables are defined as in table 1. Drop-Outs are defined as individuals working, or with observed wages, in period $t-1$ and not working in period t. Continuously working are individuals with wages observed in period $t-1$ and t. Cells show the conditional mean defined for the drop-outs as: $E[X_{it} \mid Experience_t = 2, lnw_{t-1} > 0, lnw_t \text{ is unobserved}]$, and the continuously working as $E[X_{it} \mid Experience_t = 2, lnw_t > 0, lnw_{t-1} > 0]$.

Table 3: Decomposition Estimation Results for the Wage Gap among (Vocationally) Skilled Workers, by Years of Work Experience

Work Experience	(1) Total wage gap	(2) Explained part, uncorrected for selection	(3) Explained part, corrected for selection on observables	(4) Explained part, corrected for selection on observables and unobservales
	$(lnw_{pt}^M - lnw_{pt}^F)$	$\hat{\beta}_t^M(\bar{X}_{pt}^M - \bar{X}_{pt}^F)$	$\hat{\beta}_t^M(\bar{X}_t^M - \bar{\hat{X}}_t^F)$	
	Panel A: X includes human capital variables, excluding occupation fixed effects			
0	.2520	.0238 (9.44 %)	.0220 (8.73%)	0.0233 (9.25%)
1	.2485	.0151 (6.07 %)	.0132 (5.31%)	0.0222 (8.94%)
2	.2530	.0168 (6.64 %)	.0139 (5.49%)	0.0212 (8.39%)
3	.2460	.0162 (6.58 %)	.0144 (5.85%)	0.0127 (5.18%)
4	.2418	.0158 (6.53 %)	.0144 (5.95%)	0.0081 (3.35%)
5	.2464	.0145 (5.88 %)	.0137 (5.56%)	0.0052 (2.13%)
6	.2448	.0115 (4.69 %)	.0115 (4.69%)	-0.0081 (-3.33%)
7	.2470	.0126 (5.10 %)	.0126 (5.10%)	0.0006 (0.26%)
8	.2287	.0130 (5.68 %)	.0136 (5.94%)	-0.0008 (-0.38%)
	Panel B: X includes human capital variables, including occupation fixed effects			
0	0.2520	0.1573 (62.41%)	0.1583 (62.80%)	0.1559 (61.89%)
1	0.2485	0.1453 (58.49%)	0.1488 (59.89%)	0.1516 (61.01%)
2	0.2530	0.1445 (57.12%)	0.1471 (58.15%)	0.1471 (58.14%)
3	0.2460	0.1453 (59.07%)	0.1465 (59.56%)	0.1374 (55.89%)
4	0.2418	0.1413 (58.45%)	0.1429 (59.10%)	0.1323 (54.74%)
5	0.2464	0.1412 (57.31%)	0.1438 (58.36%)	0.1262 (51.23%)
6	0.2448	0.1400 (57.20%)	0.1403 (57.31%)	0.1122 (45.86%)
7	0.2470	0.1410 (57.09%)	0.1453 (58.82%)	0.1209 (52.89%)
8	0.2287	0.1379 (60.28%)	0.1392 (60.87%)	0.1148 (50.23%)

Notes: Panel A: The vector X^M for males, and X^F for females, includes in addition to the intercept the variables years of work experience specific effects, cohort specific effects, cohort correlated with work experience fixed effects, time fixed effects, age at entry, school degree (intermediate or upper), apprenticeship duration, a dummy for each job status, and skill match variables. *Panel B*: In addition, occupation fixed effects are included.

Appendix A:

Decomposition Estimation Results for the Wage Gap among (Vocationally) Skilled Workers, by Cohort

Cohort	(1) Total wage gap	(2) Explained part, uncorrected for selection	(3) Explained part, corrected for selection on observables	(4) Explained part, corrected for selection on observables and unobservales
	$(lnw_{pt}^M - lnw_{pt}^F)$	$\hat{\beta}_t^M(\bar{X}_{pt}^M - \bar{X}_{pt}^F)$	$\hat{\beta}_t^M(\bar{X}_t^M - \hat{X}_t^F)$	
	Panel A: X includes human capital variables, excluding occupation fixed effects			
75	.3208	.0798 (24.87%)	.0510 (15.89 %)	0.1027 (32.02 %)
76	.2825	.0438 (15.50%)	.0278 (9.84 %)	0.0552 (19.55 %)
77	.2439	.0283 (11.60%)	.0172 (7.05 %)	0.0164 (6.76 %)
78	.2585	.0218 (8.43 %)	.0119 (4.60 %)	0.0216 (8.38 %)
79	.2474	.0037 (1.49 %)	-.0031 (-1.25 %)	0.0062 (2.51 %)
80	.2247	-.0036 (-1.60 %)	-.0096 (-4.27 %)	-0.0154 (-6.87 %)
81	.2206	-.0095 (-4.30%)	-.0122 (-5.53 %)	-0.0225 (-10.21 %)
82	.2247	-.0117 (-5.20%)	-.0134 (-5.96 %)	-0.0127 (-5.67 %)
83	.2078	-.0149 (-7.17 %)	-.0162 (-7.79 %)	-0.0278 (-13.38 %)
84	.1992	-.0151 (-7.58 %)	-.0161 (-8.08 %)	-0.0336 (-16.90 %)
85	.2148	-.0096 (-4.46 %)	-.0105 (-4.88 %)	-0.0282 (-13.16 %)
86	.1974	-.0129 (-6.53 %)	-.0128 (-6.48 %)	-0.0347 (-17.59 %)
87	.1502	.0003 (0.19 %)	-.0000 (0 %)	-0.1193 (-79.43 %)
	Panel B: X includes human capital variables, including occupation fixed effects			
75	0.3208	0.2486 (77.47%)	0.2268 (70.68%)	0.2458 (76.63%)
76	0.2825	0.2094 (74.13%)	0.2003 (70.91%)	0.1888 (66.84%)
77	0.2439	0.1672 (68.55%)	0.1634 (66.99%)	0.1478 (60.63%)
78	0.2585	0.1516 (58.63%)	0.1439 (55.66%)	0.1488 (57.59%)
79	0.2474	0.1327 (53.63%)	0.1282 (51.83%)	0.1333 (53.90%)
80	0.2247	0.1178 (52.43%)	0.1135 (50.53%)	0.1096 (48.78%)
81	0.2206	0.1199 (54.36%)	0.1181 (53.52%)	0.1024 (46.45%)
82	0.2247	0.1019 (45.34%)	0.1040 (46.30%)	0.1138 (50.66%)
83	0.2078	0.1114 (53.60%)	0.1110 (53.40%)	0.0941 (45.32%)
84	0.1992	0.1112 (55.82%)	0.1098 (55.11%)	0.0887 (44.56%)
85	0.2148	0.1192 (55.48%)	0.1181 (54.99%)	0.0920 (42.85%)
86	0.1974	0.0956 (48.41%)	0.0963 (48.78%)	0.0858 (43.49%)
87	0.1502	0.0769 (51.20%)	0.0768 (51.13%)	-0.0044 (-2.94%)

Notes: See table (3) for further details.