Male-Female Wage Differentials - A Longitudinal Analysis Of Young Skilled Workers In Germany

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Abstract:

This thesis analyses wage differentials between male and female workers. It is organised in three parts.

In *part one*, the literature on the gender wage gap is surveyed focusing on how the main parameters of interest in a human capital wage model are identified. This discussion illustrates the problems in the existing literature. These include the availability of precise measures of acquired human capital, and the fact that the identification of the key parameters of interest often depends on restrictive assumptions.

In *part two*, we describe a German sample of young male and female workers who have acquired skills within the dual system apprenticeship programme. The dual system is then described. This is followed by an explanation of the data set used in the thesis and the sample drawn from it. The sample has several advantageous features for the analysis of male-female wage differentials. It is a longitudinal and administrative data set and includes the complete work histories of the subjects from the beginning of their careers. This enables us to observe skill and allows us to derive precise measures of both acquired human capital and wages.

In *part three*, an empirical analysis of male-female wage differentials among young skilled workers is undertaken. The examination of the dynamics of the gender wage gap finds that the observed high entry wage gap seems to be attributable to differences in occupational qualifications. Early career wage regressions show that time out of work spells segmented into different types seem to lead to higher wage losses for women than for men. In a second empirical analysis, the links between occupation and male-female wage differentials are looked at. Wage differentials in starting wages seem to be mainly due to differences in the distribution of men and women across occupations. However, over the early career, wage differentials within occupations increase, which can be partly accounted for by differences in promotion between men and women. The third empirical analysis investigates the identification of the main parameters of interest in the wage model by instrumental variable estimators.

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Introduction

Wage differentials between males and females have been the focus of attention in the literature on wage discrimination, alongside studies of wage differentials between other groups of workers due to, for example, race, ethnicity and religion. In this thesis, we use a new administrative longitudinal data set for West-Germany that allows us to generate a sample of young workers who have undertaken vocational training within the dual system apprenticeship programme. The sample has advantageous properties for the analysis of male-female wage differentials. These include, foremost, that the data set is an administrative one as opposed to survey data sets most commonly used in empirical labour economics studies and which often imply measurement error problems that are difficult to control for. Furthermore, because the data set includes complete work histories from the beginning of careers, that is apprenticeships onwards, this enables us to observe skill and to measure wages and actual human capital acquired very accurately. These two features form good preconditions for the empirical analysis of male-female wage differentials.

The thesis is divided into three main parts. As an introduction to the topic of wage discrimination and male-female wage differentials, a literature survey is presented in *part one* of the thesis. Here, the literature is reviewed focusing on the identification of the main parameters of interest in the human capital wage model. The survey is organised in two parts. The first part starts with the specification of a general wage regression model. In this model logarithmic wages are regressed on a vector of measures for acquired human capital. These are, apart from education and work place characteristics, work experience and time out of work; both of which are potentially endogenous. The key parameters we focus on in this survey are the return to work experience and the loss from time out of work. The literature is, then, reviewed according to the assumptions imposed for obtaining consistent estimates of the main parameters of interest. In the second part, implications of such models for the understanding of male-female wage differentials are discussed and a summary of the empirical evidence on male-female wage differentials is given. One major conclusion drawn from this discussion is that identification of the main parameters of interest often depends on restrictive and economically unreliable assumptions added to the general model. This suggests, then, that estimation of wage differentials results in estimates of the explained as well as the unexplained part of the differential that are likely to be biased.

In *part two* of the thesis, we describe a German sample of young skilled male and female workers who have acquired skill within the dual system apprenticeship programme. The sample is taken from the employment statistics of the Institute of Labour Market and Occupation Research, IABS. This is an administrative micro-economic data set for West-Germany, covering the period 1975 to 1990. We categorise workers as skilled if they have undertaken vocational training within the dual system apprenticeship programme. In order to give a broader background to this education and training route, which is the main route of initial education and training in Germany, we describe beforehand, in *chapter two*, the dual system apprenticeship programme. In the description of the education and training system, we discuss, in particular, features with respect to occupational qualification, education histories and gender specific features. Since dual system apprenticeship programmes result in occupational qualifications, occupations are of particular interest and how occupational qualifications are achieved. Furthermore, given that education histories for skilled workers are virtually homogeneous but occupational segregation of men and women is widely observed, this topic is also of particular interest with reference to the gender wage gap discussion. Moreover, the description provides the basis to motivate and formulate selection rules which allow us to design a sample of young skilled workers taken from the employment statistics (IABS). The IABS and the data sample we use are described in the *chapter three.*

In *part three*, we analyse male-female wage differentials empirically using the generated sample. In the introduction, in *chapter four*, a number of features of the data are presented. *Chapter five* examines the dynamics of the gender wage gap. We focus on the analysis of the high entry wage gap found in the raw data, and on the analysis of early career wages controlling for complete work histories. Complete individual work histories are measured by work experience and total time out of work, that can be segmented further into unemployment, interruptions and other non-work spells. It is found that the observed high entry wage gap seems to be attributable to differences in occupational qualifications. Furthermore, simple descriptive analyses of early career wages show that variables accounting for total time out of work and segments of the latter have larger negative impacts on wages for women than for men. *Chapter six* explores the links between occupations and male-female wage differentials. We find that wage differentials in starting wages are not significant within occupations but are due to differences in the distribution across occupations. However, over early careers within occupation wage differentials increase. Separate analysis of within occupation wage differentials seems to suggest that differences in promotion between men and women explain the widening of the gap. *Chapter seven* looks at the identification of the parameters of interest in the wage model by instrumental variable estimators. We apply two estimators that permit variables to be predetermined. Therefore, they do not rely on the strict exogeneity assumption that is often made in the literature in order to justify the consistency of the parameter estimates. Our results seem to suggest that variables corrected for individual means and variables in first differences are not valid instruments for the wage model in levels. Furthermore, we find that returns to work experience are similar for males and females.

This thesis contributes to the empirical analysis of male-female wage differentials, and to the empirical literature on wage discrimination more generally. By using a longitudinal administrative data set which allows us to measure acquired human capital in a more detailed way than by conventional data sets, this study contributes to several central topics in the literature on male-female wage differentials. One area that we address in the survey (*chapter one*) and which is mentioned again in *chapter six* and more extensively in *chapter seven*, is the endogeneity of the work history variables in the human capital wage regression model, and how it affects identification of the main parameters of interest.

In *chapter five and six*, other central topics are discussed such as the dynamics of the gender wage gap and the first instance of a gap between male and female wages. Here, we concentrate on the role of occupations, work experience and time out of work for wage differentials. While findings in the survey and empirical evidence presented may contribute further to the understanding of male-female wage differentials in Germany and similar countries, methodological issues addressed are equally important to the study of wage discrimination against and wage differentials between any groups of workers.

Part One

Literature Survey

Chapter 1

Survey of the determination of wages and the gender wage gap

Abstract:

In this chapter the extensive empirical literature on the gender wage gap is reviewed with particular attention given to the identification of the key parameters in the specified human capital wage regression models. This aspect has been of great importance in the literature chiefly for two reasons. On the one hand, the main explanatory variables in the wage model, i.e. measures of work experience and time out of work, are endogenous and, hence, applying traditional estimators may lead to inconsistent parameter estimates. On the other hand, empirical evidence on the gender wage gap hinges on the estimates of the main parameters of interest and its economic meaningfulness may be limited by restrictive assumptions imputed on the wage model. The survey shows that econometric methods are still more advanced than their applications, and that in applications consistency often is only achieved at the expense of restrictive assumptions that are dubious from an economic perspective. In short, it seems that current measures of male-female wage differentials are likely to be biased because of the failure to appropriately account for endogeneity and selectivity in the wage regression models.

1.1 Introduction

The labour economics literature exhibits a long standing interest in the investigation of wage discrimination. Wage discrimination is generally defined as the unequal treatment of equally productive individuals with respect to remuneration.[1] It follows that the focal point in this strand of the literature is to estimate wage differentials conditional on human capital characteristics that reflect productivity potentials. More formally, this approach is based on human capital theory.[2] Furthermore, an estimate of discrimination is most commonly derived by the decomposition of the total wage differential into the portion explained by differences in human capital endowments, which reflect productivity differences and, hence, justify wage differentials, and the residual. The residual is the measure of the differences in prices with which human capital endowments are remunerated. It is, therefore, the unexplained portion of the wage differential and an estimate of discrimination.[3] Discrimination against whole groups of workers because of particular characteristics, such as race, religion, nationality or sex, has a long history in many regions. The first prominent empirical studies on this issue were published for the U.S. on wage discrimination between blacks and whites and males and females by Oaxaca (1973) and Blinder (1973). Since then, a large number of empirical studies of the estimation of wage discrimination or unjustified wage differentials have been produced for many, mostly Western industrialised, countries.[4] In this survey, the empirical literature

[1] See e.g. Dex and Sloane (1989).

[2] Becker (1964).

[3] Oaxaca (1973).

[4] In these studies not only have samples of the entire labour force been examined, but samples of firms or occupation groups have also been analysed in order to learn about

on male-female wage differentials is reviewed with a particular emphasis on the wage models estimated.

The raw mean male-female wage differential calculated may overstate discrimination against women since men and women in the labour force may not be comparable in terms of acquired human capital. Most obvious in Western industrialised countries, is the fact that on average males and females often have quite distinct work histories. Traditionally, women have more interrupted work histories than men because of family responsibilities. This is reflected most strongly in data on levels of actual work experience, which is on average lower for women than for men and by time out of work periods due to child rearing - often referred to in this literature as home-time - and which are commonly zero for men. Furthermore, men and women in the labour force may differ in other respects which are difficult to measure, such as motivation or ability, which may affect choices of work experience levels and time out of work periods as well. These factors can be summarised as unobserved or unobservable individual-specific effects. Moreover, men and women also used to differ significantly with respect to education. But while this still holds for cohorts of older women, cohorts of younger women have caught up and have quite similar, or even higher, levels of schooling compared to men.

Finally, the distribution of men and women differs across work places. The latter can be described by the occupation, industry and job status, if available. Most typically, while women are more likely to work in service occupations and industries men are more likely to work in manufacturing jobs and industries. Women are less likely to be found in higher job status positions and more likely to work part-time. In conclusion, since comparisons

the amount of discrimination within firms and occupation groups.

of human capital endowments of male and female workers seem to reveal distinctive gender patterns, the estimation of discrimination requires first that the observed raw wage gap is corrected for these differences.

Besides the many empirical issues addressed in the literature, the fundamental methodological issues can be summarised in three points. First and foremost, to make male and female workers comparable for the analysis of wages, precise measures of individuals' human capital characteristics are needed. Second, it is essential to derive consistent estimates of the coefficients of the human capital variables in the wage regression model in order to make male and female outcomes comparable. Third, a general method of decomposition of the raw male-female wage differential needs to be developed in order to estimate the portion explained by differences in human capital characteristics and the residual which is the measure of discrimination. While, obviously, the third point can only be solved if the former two points are solved, and the first point depends on data availability, the second point, the issue of estimation of the model, is the most challenging from an applied econometrician's perspective and depends on the application of appropriate methods of estimation. The underlying motivation for carrying out the present survey and subsequent discussion of developments in this field, arises from the progress that can be observed in the existing literature on consistent estimation of the key parameters in the wage model.

The starting point of this survey is to set up a simple wage regression model and, then, to review the literature according to the assumptions imposed for obtaining consistent estimates of the parameters of main interest. The wage regression model we specify is a regression model with an individual-specific intercept that nests most models that have been estimated in the literature on the gender wage gap. The underlying economic model is a human capital one[5]. The empirical model is of a Mincer type[6] in which logarithmic wages are regressed on measures for individual work histories: actual work experience and home time, or time out of work periods more generally, education (which is pre-labour market schooling) and other background variables, such as occupation. The variable *time-out of work* is the sum of all non-working periods and the variable *home-time* measures periods taken off work for child bearing and rearing (by females). The main parameters of interest we focus on in this survey are the coefficients of the variables work experience and time-out of work, which are likely to be endogenous. The source of endogeneity is the correlation of the work history variables with unobserved heterogeneity components incorporated in the error term of the regression model, and possibly non-random sample selection. In contrast to the work history variables, pre-labour market schooling and background variables are treated as exogenous [7], as most commonly assumed in the gender wage gap

[5] See: Becker (1964).

[6] The original empirical model was developed in Mincer (1974), based on a life-cycle earnings model, and contains only age as a measure of the individual work history and years of pre-labour market schooling. The original model is most appropriate for samples of men taken from the entire population who are practically working all their lives. In order to take into account the more interruptive work histories of women, extensions to the model that included variables for actual work experience as well as home-time were first specified in Mincer and Polachek (1974). Extended wage regressions estimated in most studies have been supplemented by many background variables as well as various measures of the quality of the human capital stock. However, while the original form of the earnings function has a well defined theoretical foundation, this is not the case for the extended version including background variables.

[7] Pre-labour market schooling, however, is as likely to be correlated with unobserved characteristics as the work history variables. In this strand of the literature, though, this aspect has been completely neglected. The nature of the problem dealing with endogeneity of this variable differs from the endogeneity issue of work history variables

literature.[8]

This survey complements existing ones found in the literature. Theories of discrimination, the Mincer type models and the question of what variables to include in the wage model have already been reviewed extensively and will not be repeated here.[9] Furthermore, in examining the consistency of estimates derived in empirical studies, there is no intention of providing a comprehensive coverage. Rather, a selection of studies conducted for the U.K., the U.S. and a number of studies for Germany are referred to.

This paper is organised in two parts. In the first part, a wage regression framework is specified and the literature is reviewed according to the assumptions that are imposed for obtaining consistent estimates of the parameters of main interest. In the second part, measurements of the gender wage gap are discussed and a summary of the main results on male-female wage differentials is presented .

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in longitudinal data somehow since pre-labour market schooling is time constant and the work history variables are varying over time and individuals. Hence, the parameter of interest can only be identified from the wage level regression model and instruments have to be correlated with the schooling variable, and uncorrelated with the individual specific effect and the common random shock component. Apart from this, neglect of the problem will not be an issue if inconsistent OLS estimates of the return to schooling and consistent instrumental variable estimates are equal (and means are equal for men and women) which is among more recent cohorts more likely to be the case.

[8]An important exception is the variable for occupation which we will refer to in the second part of the survey.

[9]See in particular: Cain (1986) and Blau and Ferber (1987). Other surveys are found in: Gundarson (1989) and Blau (1998).

Part I: Estimation of the wage model

1.2 The wage model specification

A simple model of wage determination that nests most specifications that have been estimated in the empirical literature on the gender wage gap is:

$$lnW_{it} = X_{it}\beta + \epsilon_{it} \tag{1.1}$$

where i indexes individuals and t indexes time periods. The dependent variable is the logarithmic wage, lnW_{it}. The vector of explanatory variables X_{it} includes measures for observed individual human capital characteristics which can be time varying or time invariant, so that X_{it} can be partitioned such as $X_{it} = [X_{it}^{(1)}, X_i^{(2)}]$. More specifically, the vector of variables, X_{it}, usually includes measures for investment in human capital, such as years of schooling and work experience, and non-investment, such as time out of work due to child bearing and rearing - summarised by the variable home-time for females. The parameter estimates are then interpreted as the effect of changes in these variables on wages. A constant is included in the vector X_{it}. The error term, ϵ_{it}, defined as:

$$\epsilon_{it} = \nu_i + u_{it} \tag{1.2}$$

contains an individual specific component, ν_i, which is constant over time, and an idiosyncratic error term, u_{it}, with mean zero and constant variance σ_u^2. The unobserved individual specific component, ν_i, captures unobserved individual specific skills. Such characteristics may incorporate motivation and ability which may be sustained all through life. The common error term component, u_{it}, picks up macro-shocks or luck.

1.3 Ordinary least squares estimation

The traditional estimator applied to the general model specified in equations (1.1) and (1.2) is the ordinary least squares estimator (OLS). Consistent estimation of the parameters of interest requires that the following orthogonality condition holds:

$$E[\nu_i + u_{it}|X_{it}, d^*_{it} > 0] = 0 \tag{1.3}$$

where the latent index variable d^*_{it} is positive if an individual i participates in the labour market and non-positive otherwise. Obviously, the validity of the orthogonality condition in equation (1.3) demands the implementation of restrictive assumptions since it may be violated by endogeneity of the explanatory variables of the model, including non-random sample selection.

In the following, we discuss three sources of endogeneity - unobserved heterogeneity, measurement error in variables and non-random sample selection. Endogeneity means that explanatory variables in a regression model are correlated with the error term $E[\epsilon_{it}|X_{it}] \neq 0$, or $E[\nu_i + u_{it}|X_{it}] \neq 0$. In most cases, it is economically reliable to assume that the time varying variables contained in the vector X_{it} are not strictly exogenous, but are predetermined and, thus, $E[u_{is}|X_{it}] = 0$ if $s \geq t$.[10] The intuition behind predeterminedness is that while shocks in the present are likely to have an impact on future decisions, shocks in the present and future do not affect present decisions. Although predeterminedness does not imply violation of the orthogonality assumption, equation (1.3), correlation of the unobserved individual-specific error term component, ν_i, with the explanatory variables

[10]A variable x_{it}, $x_{it} \epsilon X_{it}$, is strictly exogenous in equation (1) if $x_t \parallel u_{i,t+s}$ for all s. A variable x_{it}, $x_{it} \epsilon X_{it}$, is predetermined in equation (1) if $x_t \parallel u_{i,t+s}$ for $s \geq 0$. See: Engle, Hendry and Richard (1983).

and measurement error problems in the variables used for the estimation of the model may do.

Straightforwardly, endogeneity due to an unobserved individual specific effect and its correlation with the explanatory variables of the model implies that $E[\nu_i|x_{it}] \neq 0$, where $x_{it} \epsilon X_{it}$, which causes OLS applied to the coefficient of the variable x_{it} to be inconsistent. The direction of the bias[11] depends on the sign of the correlation of ν_i and x_{it}. Hence, if $E[\nu_i|x_{it}] > 0$, the corresponding component of β is estimated by OLS with an upward bias, and if $E[\nu_i|x_{it}] < 0$ with a downward bias.

While measurement error in the dependent variable causes only the intercept to be estimated with bias[12], errors in explanatory variables cause consistency problems with the OLS estimates of the corresponding slope coefficients of the model. In general, for any variable $x_{it} \epsilon X_{it}$ that is measured with error, we can write:

$$x_{it}^* = x_{it} + m_{it} \tag{1.4}$$

The observed variable x_{it}^* measures x_{it}, the true value of the characteristic, with a random error m_{it} that may vary across individuals and time. As a result, a downward bias of the corresponding estimated coefficient by OLS is induced. It can be shown that the bias of the estimated coefficient of x_{it} is proportional to $\frac{\sigma_m^2}{\sigma_m^2+\sigma_x^2}$ where σ_m^2 is the variance of the measurement error m and σ_x^2 of x correspondingly.[13]

Two cases may be captured by the specification in equation (1.4). One

[11]In the entire text, by bias we mean an asymptotic bias or more precisely $(plim\,\hat{\theta}-\theta)$, where $\hat{\theta}$ is the estimator of θ.

[12]A bias away from zero is induced.

[13]So in either case, whether the parameter is positive or negative, the estimate is biased towards zero in comparison to the true value of the parameter of interest, unless $\sigma_m^2 = 0$.

case is that the observed variable is only an estimate of its counterpart in economic theory. Thus, the reason for the occurrence of measurement error problems can be due to reporting or computing errors and random non-response errors. The second case is that the variable of interest has no observed counterpart at all and, hence, some indicator or proxy is used. Examples for the latter are the use of *age* and *potential work experience* to proxy actual work experience in cases when the data source does not contain information on actual work experience.

The review of empirical studies on gender wage gap, reveals that most of the data sets used are cross sectional and contain no information on the actual work histories of individuals, such as actual work experience, and, hence, proxies are used instead. Accordingly, potential work experience is defined as $EX_{it}^{Pot} = age_{it} - S_{it} - 6$, where age_{it} is corrected for the number of years of formal (and compulsory) schooling S_{it}, which is commonly set equal to 10, and the age at which children start school, which is equal to 6.[14] It is mainly this group of studies that relies on OLS estimation results and is focused on the identification of the return to work experience[15]. Table (1.1) gives a list of selected studies in which OLS is applied.

A caveat of using these proxies is that unless individuals work full-time and continuously, both proxies measure actual work experience with error, and, hence, application of OLS leads to inconsistent estimates of returns. This problem may be particularly relevant in the case of the estimation of wage regressions for samples of females, as well as young workers. This is

[14]Since by construction variation in both proxy variables, i.e. age and potential work experience, is the same, exchange of the two does not affect OLS estimates of the coefficient of the proxied variable, only the intercept of the wage regression changes.

[15]Generally, the loss from time out of work, or home-time, periods cannot be estimated using this approach.

Table 1.1: Application of OLS

Cross-sectional studies with potential work history information		
Study	Data[1] source, Year, Population	Explanatory variables[2]:
Oaxaca (1973)	SEO 1967, workers, age 16+, white and non-white	PotEx, edu, health, part-time, migration, marital status, children, region, oc, ind, class of worker.
Blinder (1973)	PSID 1969, age: 25+	structural model: age, region, edu, vocational training, oc, union member, veteran status, health, job tenure, local labour market condition, geogr. mobility, seasonal employment.
Greenhalgh (1980)	GHS 1971 and 1975 men and single women	PotEx(sq), S, race, age of child, health, same job for 1 year, region, oc, ind.
Zabalza & Arrufat (1985)	GHS 1975, married women and married men	PotEx (for men), Imputed Ex and home (for women), home, ed, race, health, oc, ind.
Gerlach (1987)	Regional survey[3] Nov. 1981 all employed	PotEx(sq), Ten(sq), S.
Miller (1987)	GHS 1980	PotEx(sq) (for men), Imputed Ex(sq) and home (for women), S, region, race, health.
Harkness (1996)	GHS 1974 and 1983, BHPS 1992-93	Human capital specification: age(sq), Ex(sq) for BHPS, S, extended model: region, ind, oc, children.

Note: [1]GHS: General Household Survey for U.K.; WES: Women and Employment Survey for U.K.; SEO: National Survey of Economic Opportunities for U.S.; NLS: National Longitudinal Survey of Labor Market Experience for U.S.; PSID: Panel Study of Income Dynamics for the U.S. [2] Variables: Ex=experience, PotEx= potential experience, Home= home-time; Ten=tenure, region=regional variables, S=schooling; ed=education, oc=occupation, ind=industry, children=the number of children in the family unit, SMSA= size of the largest city in county of residence, x(sq)= variable x in levels and in squares included.[3] Regional Survey for Bremen and Bremerhaven, Germany, includes all employed except for self-employed.

because working life cycles for both of these groups may be characterised by more frequent interruptions. More specifically, since the proxy variable *age* is independent of the unobserved time constant individual-specific factors, $E[\nu_i|Age_{it}] = 0$, but measures actual work experience with error, application of OLS will always result in a downward biased estimate of the return to actual work experience.[16]

To circumvent using *age* or *potential work experience*, alternative approaches have been applied in the literature.. For example, studies use imputed experience instead of potential work experience as a proxy for actual work experience for females[17] or estimate wage regressions for samples of single females, rather than single and married females pooled[18]. However, both of these approaches are problematic. The former, which implies the estimation of imputed work experience, depends on the estimation of a participation equation for women. In this case, again, identification of its parameters depends on exclusion restrictions made; for example, that the variable *number of children* is exogenous, which is debatable. The latter approach, to estimate wage regressions only for single females, may suffer from non-random selection problems since it may be argued that single women older than, say, forty may be extremely dedicated to their careers or extremely averse to marriage and, hence, their characteristics may differ from the average female population.

Finally, a further potential problem that may violate consistency of OLS ap-

[16]If the measurement error enters the error term linearly, application of first difference estimators can cure the problem. More generally, measurement error problems would demand instrumental variable estimation, which is obviously hard to apply in this particular case.

[17]See: Miller (1987) and Zabalza and Arrufat (1985).

[18]See: Greenhalgh (1980).

plied to the wage level equation is that the sample of wage observations may not be randomly drawn from the population. This is the well known sample selection problem.[19] While in Western industrialised countries, traditionally almost all men work continuously, independently of their environment and individual circumstances, labour force participation rates within the group of women vary considerably and, hence, modelling of the decision for women to work is much more complex.[20] Their decisions may depend on various observed factors such as the number of children, provision of child care facilities, costs of child care, income of the husband or partner, institutional framework and unobserved factors, such as views about child-care and motivation.[21]

More formally, to incorporate sample selection into our model framework the process d_{it}^* can be modelled - see equation (1.3) - and a labour force participation equation of the following form can be added:

$$d_{it}^* = B_{it}\gamma + \eta_{it} \tag{1.5}$$

where the latent index variable d_{it}^* is positive if an individual i participates in the labour market and non-positive otherwise. The latent variable is a function of a vector of characteristics B_{it}, and an error term η_{it} with the usual properties. Given such a selection rule, the orthogonality condition stated in equation (1.3) may be violated. It follows that the conditional expectation of wages is: $E[lnW_{it}|lnW_{it}\, is\, observed] = X_{it}\beta + E[\epsilon_{it}|X_{it}, d^* > 0]$, for which in most cases $E[\epsilon_{it}|X, d^* > 0] \neq 0$ due to non-random sample se-

[19]See Heckman (1979).

[20]For further details, see the literature on female labour supply and fertility, e.g. Willis (1973).

[21]Furthermore, one may consider that selection can also be driven by enforced selection or discrimination.

lection. Hence, OLS may result in biased estimates of the parameters of interest. However, the direction of the bias is case dependent on positive or negative selection.

1.4 Fixed effect estimation

Despite the availability of precise measures for the variables *actual work experience* and *home-time*, the application of OLS to the model specified in equations (1.1) and (1.2) may still result in biased estimates of the parameters of interest due to the correlation of the unobserved individual specific effect and the regressors of the model, $E[\nu_i|X_{it}] \neq 0$. Therefore, either instrumental variables estimation procedures, which are discussed in the next section or fixed effect estimators (FE) are more appropriate in order to identify the parameters of interest. However, the consistency of FE can only be achieved under restrictive assumptions.

The FE procedure implies that, in the first step, all individual varying, but time-invariant, observed and unobserved components of the model are removed. This can be achieved either by correction of all variables by individual means, the *within group estimator*, or by taking first differences, the *first difference estimator* (FD). [22] As a result, also, the major source of endogeneity is removed from the model. In the second step, OLS is applied to the tranformed equation. Implied in the use of FE, is that individuals are followed over at least two periods.

More specifically, transformation of the wage level model specified in equa-

[22] Assumptions for consistency for within group estimator and fixed effect estimator differ though, what makes FD advantageous as can be seen from IV-FD and the set of instruments available. See section 1.5.2 and equation (1.16).

tions (1.1) and (1.2), into first differences leads to the more parsimonious equation[23]:

$$\Delta lnW_{it} = \Delta X_{it}\beta + \Delta u_{it} \tag{1.6}$$

where the difference operator Δ transforms levels into differences between periods t and s, $t > s$. In pooled cross sectional applications, $t - s \geq 1$ is often the case. In longitudinal studies, $t - s = 1$ if spells are equally spaced in one year intervals, for example, and $t - s$ may vary in case of event history data sets.

In the following discussion of estimation, non-random sample selection issues can be neglected if the restrictive assumption is used that the sample selection process is at least time constant. Then, it follows, straightforwardly, that the correction term drops out in first differences. An example where this case may apply is female labour market participation if the labour market participation equation is determined by individual specific effects only or variables not varying over time.

Consistency of FD to estimate the parameter vector β requires that:

$$E[\Delta u_{it}|\Delta X_{it}, d^*_{it} > 0, d^*_{is} > 0] = 0 \tag{1.7}$$

Hence, given that the variables in X_{it} are predetermined, consistency of FD is violated. The direction of the bias depends on the conditional expectation $E[\Delta u_{it}|\Delta x_{it}, d^*_{it} > 0, d^*_{is} > 0]$ where $\Delta x_{it} \epsilon \Delta X_{it}$. Positive correlation of u_{it-1} and x_{it} results in FD-estimates of the parameters of interest with downward bias.[24] An example, here, would be the coefficient of the variable *work*

[23]Note that if dummy variables are included in the model, the intercept does not drop out.

[24]This is because $E[(u_{it} - u_{it-1})(x_{it} - x_{it-1})] = E[(-u_{it-1})x_{it}]$.

Table 1.2: Application of FE

Longitudinal studies with actual work history information		
Study	Data source, Year, Population	Model/Explanatory variables:
Mincer & Polachek (1978)	NLS, Cross-sections: 1967 and 1971, age: 30-50	Wage growth model/ for variables see Mincer and Polachek (1974), table (1.3).
Dolton & Make-peace (1986)	Survey of Graduates, Mean age: 29, Crosssections: 1970 and 1977	Wage model including initial wage as explanatory variable in addition to: degree, marital status, # of jobs, part-time, children, oc, ed, unemployment, ex(sq), age.

Note: See table 1.1 for further explanations.

experience since a positive economic shock today may lead to increases in work experience. Conversely, negative correlation results in FD-estimates that are upward biased. An example of this case would be the coefficient of the variable *time out of work*, since a positive economic shock may decrease periods spent in time out of work status.[25]

The FD estimator, as such, permits only the identification of the coefficients of individual and time varying regressors. However, in a second step, coefficients of individual varying but time constant variables can be identified by estimation of the following between-group version of the model:

$$\overline{lnW_i} - \bar{X}_i^{(1)}\hat{\beta}^1 = X_i^{(2)}\hat{\beta}^2 + \nu_i + u_i \tag{1.8}$$

where we have used the partition $X_{it} = [X_{it}^{(1)}|X_i^{(2)}]$. $\hat{\beta}^1$ is the FD-estimate and the dependent variable is constructed from individual means which are calculated as $\sum x_{it}/T = \bar{x}_i$. OLS applied to equation (1.8) will lead to consistent estimates if $E[\nu_i+u_i|X_i^{(2)}, d_i^* > 0] = 0$, given that $\hat{\beta}^1$ is consistent.

Examples in the empirical literature for the FD-estimation, which in practice is the estimation of a wage growth model, can be found in a number of

[25]These conclusions hold only if no measurement error is incorporated in the data.

studies based on two cross-sections following individuals over time. In table (1.2) a couple of studies of this kind are listed.[26]

FD results that have been reported in wage growth studies would be consistent estimates of the parameters of interest under the assumption that the time varying regressors in the wage level model are strictly exogenous and that the sample selection process is time constant.[27] However, although the latter assumption may be economically reliable, it is not reasonable to assume strict exogeneity for the variables *work experience* and *time out of work*. In fact, it is difficult to justify why economic shocks in the present should not have an impact on choices regarding work experience and home-time, or time out of work, in the future.

Further identification problems may be introduced by FD due to the possible multicollinearity of the change in actual work experience variable and the change in home-time, or time out of work, more generally. In particular, this problem may be an issue if observations in the data are equally spaced, for example, in one year intervals and if, in addition, a constant is included in the wage growth model.[28] Since then $\Delta EX_{it} + \Delta H_{it} = 1$ holds[29], the moment matrix of observations has no full rank and identification may be impossible or spurious.[30]

[26]Interesting studies on rebound effects, investigated within the framework of a wage growth model estimated for females, can be found in Corcoran, Duncan and Ponza (1983) and Mincer and Ofek (1982). Growth models estimates were also presented in Kim and Polachek (1994). We refer to their study later in this chapter.

[27]The same holds for the within group estimator.

[28]This is the case if dummy variables are included in the wage level regression model.

[29]Again, this may not hold if variables are measured with error.

[30]This problem was mentioned in Kim and Polachek (1994). Their suggested solution was to measure both of the work history variables using different time scales, which

1.5 Instrumental variable estimation

A common solution to endogeneity problems, in the wage level as well as in the wage growth model, and the estimation of the main parameters of interest is the method of instrumental variables. Given valid instruments, standard instrumental variable estimation (IV) is consistent but not efficient under most general assumptions. Generalised method of moments estimator - hereafter GMM - leads to more efficient estimates. In the following, we refer to all of these estimators as IV.[31] In this section, we first discuss estimation, followed by a section on the instruments used in applications.

1.5.1 Estimation

In order to ensure consistency[32] of IV, the vector of instruments, which we refer to as Z_{it}, must meet the following requirements for the estimation of the wage model in levels:

$$E[\nu_i + u_{it}|Z_{it}, d^*_{it} > 0] = 0 \tag{1.9}$$

ensures that changes do not add up to one. In their particular application, they redefine work experience to encompass hours of work. However, one may argue that their procedure is equivalent to multiplication of a variable with a constant factor which is problematic to correct for this problem, in particular, if only full-time workers are considered in the sample.

[31] They could also be summarised as method of moments estimators.

[32] Under general assumptions, IV does not control for sample selection. This implies that either appropriate complementary estimators have to be applied, such as the Heckman-two-step estimator (Heckman, 1979), or the assumption of no sample selection bias has to be made. (For a survey of the estimation of sample selection models see e.g. Vella (1998).)

and for the wage model in first differences:

$$E[\Delta u_{it}|Z_{it}, d^*_{it} > 0, d^*_{is} > 0] = 0 \tag{1.10}$$

The variables included in the sets of instruments, Z_{it}, depend on whether the model is estimated in levels or in first differences. The higher is the partial correlation of the variables included in Z_{it} with the endogenous variables in the model, the smaller is the variance of the parameter estimates.

Identification

Identification of the parameters of interest by application of IV depends on the following factors. First, identification requires that the instruments included in Z_{it} do not determine wages (the exclusion restriction). In general, if there are k endogenous variables in the regression model, there should be at least k instruments, or k exclusion restrictions. This is the order condition. The instruments, then, have to be correlated with, or determine the endogenous variables. This is the rank condition. Since finding of instruments is often difficult and controversial, it is important to test the exclusion restrictions, the order and the rank conditions.

Tests for endogeneity of the regressors in the wage equation and of the order condition can also be formulated in the expanded regression framework.[33] Here, in the first step the reduced form of x_k, x_k is an element of X, is estimated, where the potentially endogenous explanatory variable is regressed on all exogenous variables and all instruments used:[34]

$$x_k = Z_l \pi_l + \xi_k \tag{1.11}$$

[33]If $k = 1$ a test of the rank condition is straightforward in the framework shown here. If $k > 1$, the rank test becomes more complicated.

[34]For convenience, all indexes, i.e. i,t, are suppressed in the following.

where k indexes the number of endogenous explanatory variable and Z is a matrix including l instruments, where $l \geq k$. To investigate the validity of the instruments in terms of explaining variation in x_k, F-tests can be applied, where H_0: $\pi_l = 0$. Only if k=1 the test for the joint significance of the coefficients π_l is at the same time a test for the rank condition.[35] In the second step the generalised residuals, $\hat{\xi}_{x_k,Z_l}$, estimated from the least squares regression equation in (1.11) are added to the wage equation leading to the expanded wage regression:

$$lnW = X\beta + \hat{\Xi}\alpha + \epsilon \tag{1.12}$$

where $\hat{\Xi}$ is the matrix containing all generalised residuals $\hat{\xi}_{x_k,Z_l}$. Then, the instrumental variable estimator of β is equivalent to the ordinary least squares estimator of β in equation (1.12). A test for endogeneity of x_k is a test of the significance of the corresponding k components in $\hat{\alpha}$, given that the variables included in Z_l are valid instruments.[36]

GLS instrumental variable estimation (GLS-IV)

The main parameters of interest in our wage regression model in levels can be estimated consistently by IV, but GLS-IV is more efficient.[37] If no measurement error is contained in the work experience and the time out of work variables, IV estimation results in smaller values of the estimated coefficients in absolute terms than OLS, usually though with larger standard errors. If endogeneity is due to both, measurement error and unobserved heterogeneity, the difference between the consistent and inconsistent estimates can go in either direction.

[35] If $k > 1$ this cannot be easily done since a simultaneous equation system is given.

[36] Hausman (1978).

[37] In order to apply GLS, distributional assumptions about ν_i need to be made.

First differences instrumental variable estimation (FD-IV)

FD-IV, which estimates the wage growth model formulated in equation (1.6) by IV, is consistent but not efficient. FD-IV leads to inconsistent estimates of the standard errors. Since the application of FD results in downward biased estimates of the return to work experience and upward biased estimates of the loss from time out of work spells, the application of FD-IV should result in greater values of the former parameter and smaller values of the latter, in absolute values. Furthermore, both should be smaller than the corresponding OLS estimates.

Generalised method of moments estimation (GMM)

GMM estimators applied to either the wage level model or the wage growth model result in efficiency gains.

1.5.2 The instruments

Identification of the parameters of interest by the application of IV depends chiefly on availability of valid instruments, Z_{it}. Thus, instruments must be correlated with the endogenous variable, equation (1.11). Also, instruments must meet the orthogonality assumption, equations (1.9) or (1.10). Generally, two groups of potential instruments can be distinguished: exogenous variables, $\tilde{Y}_{it}$, and transformed endogenous variables, $\tilde{X}_{it}$, such that they meet the orthogonality assumption by construction, i.e. $Z_{it} = [\tilde{Y}_{it}|\tilde{X}_{it}]$. Clearly, studies based on cross-sectional data are restricted with respect to the set of instruments, which is then $Z_{it} = \tilde{Y}_{it}$.

In tables (1.3) and (1.4) a selection of studies is listed in which data sets have been used that contain information on the actual work history and in which IV has been applied. Cross-section studies are listed separately from

Table 1.3: Application of IV in cross-sectional studies

Cross-section studies with actual work history information		
Study	Data source, Year, Population	Explanatory variables/Treatment of Ex, Home/Instruments:
Mincer & Polachek (1974)	NLS 1967, SEO, age: 30-44, married and single	Ex, Home, S, age, training certificate, health, children, region/ Ex endogenous, Home exogenous/Instr.: # of children, exposure (= age-schooling-6), health, hours worked per week, weeks worked per month, size of place of residence, years of residence in country, S, ed, current job tenure.
Mincer & Polachek (1978)	NLS, Waves: 1967 and 1971, age: 30-50	See: Mincer and Polachek (1974)/EX and HOME endogenous /Instr.: see Mincer and Polachek (1974).
Wright & Ermisch (1991)	WES 1980, age 16-59, married women and husbands	Ex(sq), Home(sq), S, region / Ex treated as exogenous, Correct for sample selection bias/Instr.: wife's age(sq), wife's ed, region of residence, housing tenure, number and age of children, local unemployment rate, husband's employment status and non-labour income, husband's age(sq), husband's ed, social class, wife's age at marriage.

Note: See table (1.1) for further explanations.

longitudinal studies. The key parameters in these studies are the return to work experience and the loss from home-time; where the latter variable value is zero for men. In the third column of both tables, a full list of the variables used as instruments for *work experience* and *home-time* is given.

Exogeneity assumption

Examples of variables assumed to be exogenous in empirical studies are: *parental education, number of children, variables for region, gender, race, age and occupation.* While correlation with *home-time* and *work experience* for all of them can be expected, the assumption that they are orthogonal to the error term components in equation (1.2) is debatable. In the following we discuss *age*, *the number of children* and *region* in more detail.

An argument in support of usage of the *age* variable as an instrument[38] is that once the actual work history is taken into account in a wage regression *age* should have no effect on wages. This argument derived from a human capital explanation of wages, however, may be violated, for example, in case of age related contracts, or since age may influence strength or mental agility, independent of experience. The latter correlation may only be diminished by controlling for detailed job characteristics. The variable *age* can be expected to be strongly positively correlated with *work experience* for men as well as for women. For the latter, however, positive correlation may exist as well with the variable *home-time*. Thus, in summary, *age* may serve as an instrument under certain assumptions for the work history variables, yet, identification of both parameters, the return to work experience and the loss from time out of work, requires at least one additional instrument.

The variable *number of children* has been used in a few studies, assuming that it is exogeneous once actual work experience and actual time out of work are controlled for in the wage regression model. The motivation behind the choice of such an instrument is straightforward. Women with children are more likely to drop out of the labour force, temporarily or for good, than women without children. The more children women have, the more likely it is that they have in total longer periods of home-time or, more generally, time out of work, than women with few or no children. Hence, the variable *number of children* is expected to be positively correlated with *time-out of work* and negatively with years of *work experience*. However, exogeneity of the variable *number of children* has been subject to debate in a number of papers. Mostly from the perspective of economic theories of

[38]Obviously, the same holds for the variables *potential experience* and *birth dummies*.

Table 1.4: Application of IV in longitudinal data studies

Longitudinal studies with actual work history information		
Study	Data source, Year, Population	Model/Explanatory variables/Instruments:
Kim & Polachek (1994)	PSID, 1976 - 87, white and non-white	Individual specific intercept model/EX (endog.), potential Home (endog.)[1], age, race, hours of work, children, SMSA, ed (endog.), region/ Instr.: mother's + father's education, SMSA size, gender, race, age, occupation, $[EX_{t-1}, EX_{t-2}, ..., Home_{t-1}, Home_{t-2}, ...]$ for IV-FD, $[\Delta EX_t, \Delta Home_t]$ for IV-GLS.
Polachek & Kim (1994)	PSID, 1976 - 87, white and non-white	Individual specific slope and intercept model/ see Kim and Polachek (1994) for variables and instruments.
Light & Ureta (1995)	NLS, period: 1968 - 1984 (women), 1966 - 1981 (men), age: 14-30, born in 1945-52	Timing of work and non-work periods considered/ Ex (endog.), dummy for time out (endog.), Ten (endog.), part-time (endog.), married (endog.), children (endog.), ed (endog.), year of birth, wage index, SMSA, South / Instr.: gender, birth dummies, wage index, region, and these vars. interacted with gender, $[Z_{it} - \bar{Z}]$ (Z is the vector of instruments), within person means of exog. variables.

Note: See table (1.1) for more details.[1] HOME=(age-ed-5-EX).

fertility and marriage [39], it is argued that the variable *number of children* is endogenous, and that, even if the actual work history has been taken into account, it may still have an impact on wages by picking up effort according to Becker's theory.[40]

The variable *region* has also been used as an instrument assuming exogeneity of the latter. The motivation is that the size of the region people live in or

[39]See e.g. Willis (1973).

[40]See: Becker (1985). In Korenman and Neumark (1992), by estimating wage regressions for women, it was found that exogeneity of the variable cannot be rejected. They apply a Hausman test including in their sets of instruments background measures and measures of attitudes and expectations. They refer to the result shown in Griliches (1977) that family background variables are exogenous, once ability and schooling have been controlled for in a wage equation.

the region itself may proxy different attitudes of men and women towards role models within the family. In more rural regions, women may be more likely to stay longer at home because of family responsibilities in the family. However, choices of regions may be endogenous and dependent on factors, such as occupation, qualification, industry, number of children and demand and supply factors. Thus, the assumption that *region* is exogenous may not stand up to scrutiny. Finally, if longitudinal data are available, mean deviations of exogenous variables, $(\tilde{Y}_{it} - \bar{\bar{Y}}_i)$, as well as the within person means of exogenous variables, $\bar{\bar{Y}}_i$, are valid instruments.

In conclusion, the discussion suggests that exogeneity of all popular instruments except for the variable *age* used in the literature may depend on assumptions that require further testing to justify their use. Generally, the variables may be used as instruments, if valid, for the work history variables in levels as well as in first differences. However, in order to identify the two parameters of interest, at least two valid instruments are needed that fulfill identification requirements.

Transformed endogenous variables

In table (1.4) longitudinal studies are listed that permit the use of a wider range of instruments. In addition to exogenous variables, instruments can be constructed from endogenous variables included in the wage regression model. Depending on the length of the panel data set the number of instruments may be larger than the number of endogenous regressors and, hence, the model can be estimated by GMM, instead of by standard IV. Reviewing the empirical studies, the following moment restrictions have been used:

For estimation of the wage regression model in levels based on Hausman and Taylor (1981)[41] the instrument $(x_{it} - \bar{x}_i)$, has been used[42] assuming

$$E[\nu_i + u_{it} | x_{it} - \bar{x}_i] = 0 \tag{1.13}$$

However, validating the instrument requires strict exogeneity for x, and mean stationarity of the process generating x. Given that variables, such as *work experience* and *time out of work*, are more likely to be predetermined, these instruments may not be valid and IV estimates of the parameters of interest may not be consistent. Furthermore, lagged differences of endogenous variables have been used[43] assuming that

$$E[\nu_i + u_{it} | x_{it} - x_{it-1}] = 0 \tag{1.14}$$

holds, as well as for further lags of x. This orthogonality condition depends on the assumption that the process generating x is a mean stationary process.[44]

For the estimation of the wage model in first differences, lags of endogenous variables in X_{it} have been used[45] assuming that

$$E[u_{it} - u_{it-1} | x_{it-1}] = 0 \tag{1.15}$$

holds, as well as for further lags of x. Furthermore, lagged endogenous variables in first differences have been used[46] assuming that

$$E[u_{it} - u_{it-1} | x_{it-1} - x_{it-2}] = 0 \tag{1.16}$$

[41] See also Altonji and Shakotko (1995).

[42] See: Kim and Poachek (1994) and Light and Ureta (1995).

[43] Kim and Polachek (1994).

[44] See: Arellano and Bover (1995), Blundell and Bond (1998).

[45] Kim and Polachek (1994).

[46] Kim and Polachek (1994).

holds, as well as for further lags of x. The latter two moment conditions are not violated if variables are only predetermined. However, validity of (1.16) depends on the assumption that the process generating x is a mean stationary process.[47]

In a few studies, instrumental variable estimators based on Hausman and Taylor (1981) have been applied using work history variables corrected for individual means as instruments.[48] While consistency of these estimates depends on the strict exogeneity assumption and mean stationarity, in other studies consistent IV and GMM estimators have been applied that permit variables to be predetermined.[49]

The most extensive empirical evidence on the application of a range of inconsistent and consistent estimators was probably presented in Kim and Polachek (1994). Their results, although plausible in terms of sign and size, reveal great variation depending on the estimators as well as (with respect to IV and GMM) on the set of instruments used. In their discussion, the authors also point out the problem of FD, namely, that transformation of variables, such as of *home-time*, into first differences may substantially reduce variation, and, hence, makes it difficult to use variables in first differences as instruments. They conclude that lagged levels of the variable *home-time* may be better to use in FD. In order to test and justify exclusion restrictions, quite standardly in studies a Hausman type test is applied.[50] However, validity of these tests, again, depends on exclusion restrictions

[47]See: Arellano and Bover (1995).

[48]E.g. in Light and Ureta (1995), Kim and Polachek (1994).

[49]See e.g. Kim and Polachek (1994).

[50]See e.g. Kim and Polachek (1994), Wright and Ermisch (1991), Korenman and Neumark (1991).

which are debatable and not tested.

In summary, consistency of the Hausman and Taylor estimator depends on the critical assumption of strict exogeneity of the variable x, which is restrictive and excludes the case that present economic shocks affect future levels of work experience. On the other hand, the assumption of mean stationary processes used to identify the parameters of interest may be less restrictive.[51] However, in order to validate restrictive assumptions, statistical testing is demanded. This may include - apart from Hausman (1978) tests and Sargan (1980) tests - inference from the direction of bias of inconsistent estimators compared to consistent estimators and inference of first step estimates as shown in equation (1.11).[52] Finally, from the economic perspective a major shortcoming of IV results is that standard errors are usually so large that estimates derived by IV are often not significantly different from (inconsistent) OLS estimates. Hence, new economic insights may be hampered.

1.6 Discussion

In the first part of this chapter, we have set up a framework for a wage model that nests most models estimated within the gender wage gap literature and have discussed the identification of the main parameters of interest, namely, the return to work experience and the loss from home-time, or time out of work, more generally. The survey suggests that identification in many studies depends on restrictive assumptions that are often hard to justify in

[51]To the author's knowledge no empirical evidence has been presented testing this assumption in the literature on gender wage gap.

[52]These results are presented in, for example, Hersch and Stratton (1997).

economic terms, and, thus, may demand further statistical testing.

The best conditions for the consistent estimation of the parameters of interest by application of instrumental variable estimators, or more efficient GMM, are offered by longitudinal data, which contain precise measures of wages and, most importantly, information on actual work experience and actual time-out of work. Here, the evaluation of instrumental variable estimation results could be improved by presentation of more detailed (first step) estimation results, as well as tests of the rank and order conditions. Finally, inference from the evaluation of the bias of parameter estimates could be drawn. This, however, may be blurred by measurement error in variables and, also, usually large standard errors of instrumental variable estimates. In spite of this, awareness of the direction of the bias could be useful too in order to evaluate evidence of whether the size of the gender wage gap, is over or underestimated.

Part II: Estimation of gender wage gap

1.7 Measurement of the gender wage gap

The fundamental technique applied in the gender wage gap literature in order to estimate the gap is the residual approach. The *uncorrected* or *raw* or *gross male-female wage differential* is, straightforwardly, measured by differences in logarithmic wages:

$$\Delta lnW = (\overline{lnW^M} - \overline{lnW^F}) \tag{1.17}$$

where we let the operator Δ represent the mean difference between males and females in period t; the period index is suppressed here and in the following.

In order to correct the raw gender wage gap for justified wage differences due to differences in productivity - related endowments, as a first step, sample wage regressions as specified in equation (1.1) are estimated. The resulting vector of prices, $\hat{\beta}$, for the human capital characteristics included in X_{it}, is then used to calculate a weighted difference in mean human capital characteristics between men and women. This term, which is the *explained part* of the gender wage gap when subtracted from the raw gender wage gap gives the residual, which is *the unexplained* or *corrected* or *adjusted part of the gap*, and is commonly interpreted as a *measure of discrimination.* Based on this approach, three main decompositions have evolved in the literature in order to examine different features of the wage gap.

In the earliest studies on discrimination, the Oaxaca (1973) decomposition has been applied[53] to analyse the decomposition of the wage gap at the

[53] Similarly, it was derived in Blinder (1973).

mean. In the 90's, when wage inequality had become a topical issue in the policy debate as well as in the economics literature more generally, the Juhn, Murphy and Pierce (1993) decomposition was developed. It extended the Oaxaca (1973) decomposition of the wage gap by taking the residual distribution into account. One shortcoming of these two decomposition techniques is that, when occupation is controlled for in the wage regression model, the distribution of men and women across occupations is taken as exogenous. Given that in most Western industrialised economies, strong occupational segregation is observed between genders, one may argue that this is unsatisfactory and defines discrimination away. Brown, Moon and Zoloth (1980) suggested an extended decomposition technique in which occupation is treated as endogenous. In other words, they supplement the wage regression equation by a occupation selection equation; thus, they model selection into occupation groups. In addition, their technique permits the quantification of the share of the total wage gap that is due to within occupation wage differences and the share that is due to between wage differences. In what follows, we discuss the three decomposition approaches, before giving a summary of the main findings in the literature concerning the explanation of uncorrected male-female wage differentials observed in Western industrialised countries.

1.7.1 Oaxaca (1973)

The decomposition technique derived in Oaxaca (1973) applies to the estimation of wage differentials at the mean and was developed for cross-sectional data. In the first step, wage regressions are estimated for a sample of men and a sample of women separately, as discussed in the first part of this chapter. Then, using the derived consistent estimates, the residual approach is applied. The decomposition uses the fact that we know, from the properties of the ordinary least squares estimator, that:

$$\overline{lnW^M} = \bar{X}^M \hat{\beta}^M \tag{1.18}$$

and

$$\overline{lnW^F} = \bar{X}^F \hat{\beta}^F \tag{1.19}$$

where, in equation (1.18), $ln\overline{W}^M = (\sum_i^{N_M} lnW_i)/(N_M)$, and N_M is the number of males in the sample and $\bar{X}^M = (\sum_{i=1}^{N_M} X_i)/(N_M)$. For females, the terms are defined correspondingly. Superscripts indicate sex, g=M (males), F (females). To continue, suppose that $\hat{\beta}^M$ is the competitive price and that females are remunerated at the same price as men.[54] Then, the predicted mean wage for females using competitive prices can be written as:

$$\overline{lnW^{1F}} = \bar{X}^F \hat{\beta}^M \tag{1.20}$$

In a second step, the components of the decomposition of the raw wage differential are calculated. Subtracting (1.20) from (1.18), $(\overline{lnW^M} - \overline{lnW^{1F}})$, results in the difference of the mean wage for men and the mean hypothetical wage for women in the absence of discrimination. Subtracting (1.20) from (1.19), $(\overline{lnW^{1F}} - \overline{lnW^F})$, gives the difference of the hypothetical mean wage for the sample of women and their actual mean wage. Adding those two components up results in:

$$\underbrace{(\overline{lnW^M} - \overline{lnW^F})}_{\textit{raw wage gap}} = \underbrace{\hat{\beta}^M(\bar{X}^M - \bar{X}^F)}_{\textit{explained part}} + \underbrace{\bar{X}^F(\hat{\beta}^M - \hat{\beta}^F)}_{\textit{unexplained part}} \tag{1.21}$$

[54] For the coherence of the chapter, we derive all of the three decomposition approaches based on male sample regression coefficients.

Standard errors of each of the components can be estimated by $(\bar{X}^M - \bar{X}^F)'Var(\hat{\beta}^M)(\bar{X}^M - \bar{X}^F)$ and $(\bar{X}^M)'Var(\hat{\beta}^M - \hat{\beta}^F)(\bar{X}^M)$. This is the standard decomposition derived in Oaxaca (1973) as well as in Blinder (1973).[55]

The first term on the right hand side of equation (1.21) is a measure of the explained part of the raw wage gap and it is non-zero if the two groups are not equally endowed with human capital at the mean. This part can also be interpreted as the wage gain women would experience if they had the same human capital on average as men. The portion due to differences in coefficients is the unexplained part of the raw wage gap. It is the wage gain women would experience, given their mean characteristics, if they were remunerated like men. This portion of the differential is defined in Oaxaca (1973) as a measure of wage discrimination and, since, has become the most common procedure in order to estimate wage discrimination. Initially, the Oaxaca (1973) decomposition was developed for cross section wage models. However, assuming time constant parameters, application to longitudinal wage models follows straightfowardly.

1.7.2 Juhn, Murphy and Pierce (1991)

Juhn, Murphy and Pierce (1991) extended the Oaxaca decomposition by taking the residual distribution into account. In this section we derive the decomposition for one period. As usual, in the first step, wage regressions are estimated separately for samples of men and of women. Then, given consistent estimates of the parameters of interest, predictions of wages for

[55] One must note that in Oaxaca's notation the intercept is included in the unexplained part, whereas in Blinder (1973) those two components are written separately. This notational difference results in Blinder interpreting differences in coefficients separately which may be misleading. See e.g. Jones (1983).

males (M) and females (F) can be written as:

$$\widehat{lnW^M}_{it} = X_{it}^M \hat{\beta}_t^M \tag{1.22}$$

$$\widehat{lnW^F}_{it} = X_{it}^F \hat{\beta}_t^F \tag{1.23}$$

where all indexes are used as before.[56] The authors show that three hypothetical wage distributions can be generated which can be used to decompose the wage differential into the components accounting for differences in endowments, differences in coefficients and differences in the residual distribution.

For illustration, we assume, again, that competitive prices are equal to prices estimated from the wage regression model for a sample of men.[57] It follows that for men, only one (hypothetical) wage distribution is derived, while for women three hypothetical wage distributions can be derived. Hence, for completeness, we can write for males:

$$\widehat{lnW^M}_{it} = \widehat{lnW}_{it}^{1M} = \widehat{lnW}_{it}^{2M} = \widehat{lnW}_{it}^{3M} \tag{1.24}$$

where all of the three "hypothetical" wage distributions, indicated by superscripts, are equivalent to predicted wages from equation (1.22). The distribution of residuals follows from $\hat{\epsilon}_{it}^M = lnW_{it}^M - X_{it}^M \hat{\beta}_t^M$, using non-discriminatory prices.

For women, we are in the position to generate three hypothetical distributions of wages. First, we can predict wages for women using non-discriminatory prices for observables and unobservables:

$$\widehat{lnW}_{it}^{1F} = X_{it}^F \hat{\beta}_t^M + \hat{\epsilon}_{it}^{(F)} \tag{1.25}$$

[56]In Juhn, Murphy and Pierce (1991) it is assumed that $\beta_t^M = \beta_t^F = \beta_t$. Hence, it is simulated what the wage equation in a nondiscriminatory labour market would look like.

[57]The decomposition follows straightforwardly in the case where an average price is used as the competitive price.

where $\hat{\epsilon}_{it}^{(F)}$ are the predicted "percentile ranks" of the residuals that follow from equation (1.23), estimated for the sample of women matched into the distribution of "percentile ranks" of residuals for the sample of males.[58] Second, wages can be predicted for women using prices from the regression estimated for the sample of women and non-discriminatory prices for unobservables:

$$\widehat{lnW}_{it}^{2F} = X_{it}^F \hat{\beta}_t^F + \hat{\epsilon}_{it}^{(F)} \tag{1.26}$$

Finally, we can use prices and predicted residuals from the wage regression estimated for women:

$$\widehat{lnW}_{it}^{3F} = X_{it}^F \hat{\beta}_t^F + \hat{\epsilon}_{it}^F \tag{1.27}$$

which replicates the true wage distribution for females.

It follows that the male-female wage differential, using the first hypothetical wage distribution for women, lnW_{it}^{1F}, is an estimate of the part of the gap due to differences in observed characteristics:

$$\Delta w^1 = \widehat{lnW}_{it}^{1M} - \widehat{lnW}_{it}^{1F} = \hat{\beta}_t^M (X_{it}^M - X_{it}^F) \tag{1.28}$$

Any additional part of the wage differential explained by the difference in wages, using the second hypothetical wage distribution for women, lnW_{it}^{2F}, is an estimate of the part of the gap due to differences in prices of observables, since:

$$\Delta w^2 = \widehat{lnW}_{it}^{2M} - \widehat{lnW}_{it}^{2F} = (\hat{\beta}_t^M X_{it}^M - \hat{\beta}_t^F X_{it}^F) \tag{1.29}$$

[58]In the literature the most common approach is to choose a number of percentiles and generate the outcomes, as in Blau and Kahn (1997), for example. Fortin and Lemieux (1998) proposed a rank-based procedure.

Finally, any additional part of the gap explained by the true distribution of wages over the second hypothetical distribution of wages results in an estimate of the gap due to differences in unobservables (prices and quantities), since:[59]

$$\Delta w^3 = \widehat{lnW}_{it}^{3M} - \widehat{lnW}_{it}^{3F} = (\hat{\beta}_t^M X_{it}^M - \hat{\beta}_t^F X_{it}^F) + (\hat{\epsilon}_{it}^M - \hat{\epsilon}_{it}^F) \quad (1.30)$$

In summary, the total gender wage gap can be written as:

$$\underbrace{\Delta w^3}_{raw\ wage\ gap} = \underbrace{\Delta w^1}_{diff.\,in\,obs.endow.} + \underbrace{(\Delta w^2 - \Delta w^1)}_{diff.\,in\,prices\,of\,observ.} + \underbrace{(\Delta w^3 - \Delta w^2)}_{diff.\,in\,unobserv.} \quad (1.31)$$

or:

$$\underbrace{(lnW_{it}^M - lnW_{it}^F)}_{raw\ wage\ gap} = \underbrace{\hat{\beta}_t^M (X_{it}^M - X_{it}^F)}_{diff.\,in\,obs.endow.} + \underbrace{X_{it}^F (\hat{\beta}_t^M - \hat{\beta}_t^F)}_{diff.\,in\,prices\,of\,obs.} + \underbrace{(\hat{\epsilon}_{it}^M - \hat{\epsilon}_{it}^F)}_{diff.\,in\,unobs.} \quad (1.32)$$

Calculation of standard errors as well as interpretation follows straightforwardly.

1.7.3 Brown, Moon and Zoloth (1980)

The innovative aspect of the Brown, Moon, Zoloth (1980) approach is that the wage gap is decomposed across the entire distribution of occupations and that it allows for endogeneity of the distribution of women across occupations.[60] To derive their approach, the uncorrected gender wage gap can be rewritten as the difference in weighted average log-wages taken across K occupations.

$$\overline{lnW^M} - \overline{lnW^F} = \Sigma_{j=1}^K P_j^M lnW_j^M - \Sigma_{j=1}^K P_j^F lnW_j^F \quad (1.33)$$

[59]In order to identify price and quantity effects separately, changes over time of the wage differential can be used. See e.g. Blau and Kahn (1992) and Juhn, Murphy, Pierce (1993).

[60]In this approach it is assumed that the distribution of men across occupations is exogenous and is the outcome of purely free choice.

where $\overline{lnW^M}$, $\overline{lnW^F}$ are the log mean wages for men and women and P_j^F and P_j^M are the proportions of men and women in occupation j, where $j = 1, ..., K$. lnW_j^F and lnW_j^M are the log mean wages for men and women within occupation j. Extension of equation (1.33) by plus and minus $\Sigma_{j=1}^K P_j^F lnW_j^M$ allows to decompose the total wage gap in the following way[61]:

$$(\overline{lnW^M} - \overline{lnW^F}) = \underbrace{\Sigma_{j=1}^K (P_j^M - P_j^F) lnW_j^M}_{interoc.\ effect} + \underbrace{\Sigma_{j=1}^K P_j^F (lnW_j^M - lnW_j^F)}_{intraoc.\ effect} \tag{1.34}$$

The first term on the right hand side measures the part of the gap that is due to differences in the distribution of men and women across occupations. The second term measures the part of the gap that is due to differences in mean wages within occupations. If the proportion of men and women were the same in each occupation, the first term would be equal to zero. This is the non-segregation case. If within each occupation men and women earned on average the same the second part would be equal to zero. This is the case when on average no wage differentials exist at all.

Both terms can be decomposed further into an explained and an unexplained, or discriminatory, component. Decomposing the component due to inter occupational effects further, Brown, Moon and Zoloth (1980) use the predicted distribution of women across occupations in the absence of discrimination. The distribution is predicted using the estimate of a reduced form multinomial logit model for men. Therefore, it is assumed that outcomes for men are not the outcome of discriminatory processes. It follows

[61] All indices for time, t, are suppressed.

that:

$$P_{ij}^M = \frac{exp(B_i^M \gamma_j^M + \omega_{ij})}{\Sigma_{j=1}^K exp(B_i^M \gamma_j^M + \omega_{ij})} \tag{1.35}$$

The expression specifies that the probability of a male worker i being in occupation j is a function of worker characteristics B_i^M. ω_{ij} is an idiosyncratic shock component.[62] Using predictions for women based on the estimated parameters $\hat{\gamma}_j^M$ of this model the inter occupational component and the intra occupational component from equation (1.34) are decomposed further. It follows that:

$$\begin{aligned}
&(\overline{lnW^M} - \overline{lnW^F}) = \qquad (1.36)\\
&\underbrace{\overbrace{\Sigma_{j=1}^K (P_j^M - \hat{P}_j^F)\bar{X}_j^M \hat{\beta}_j^M}^{interoc.\,effect} + \overbrace{\Sigma_{j=1}^K P_j^F (\bar{X}_j^M - \bar{X}_j^F)\hat{\beta}_j^M}^{intraoc.\,effect}}_{explained\,part}\\
&+ \underbrace{\overbrace{\Sigma_{j=1}^K P_j^F (\hat{\beta}_j^M - \hat{\beta}_j^F)\bar{X}_j^F}^{intraoc.\,effect} + \overbrace{\Sigma_{j=1}^K (\hat{P}_j^F - P_j^F)\bar{X}_j^M \hat{\beta}_j^M}^{interoc.\,effect}}_{unexplained\,part}
\end{aligned}$$

where $\hat{P}^F$ is the vector of predicted proportions of women in occupations j in the male occupation outcomes model. The explained part of the wage gap is, hence, a composite of the inter occupational effect and the intra occupational effect and, correspondingly, the unexplained part is a composite too. Accordingly, standard errors can be estimated in a straightforward way if proportions P are treated as fixed, and in a more complicated way if P is treated as a random variable.

[62] The identification of the parameters of the model requires independence of the residuals in the wage regression and the multinominal logit model, hence that $E[u_{ijt}|\omega_{ijt}] = 0$, when notations in equations (1.1) and (1.35) are adjusted accordingly.

1.7.4 Comments on decomposition approaches

Whether valid and meaningful measures of the explained and unexplained part of the differential can be derived on the basis of any of the aforementioned decomposition approaches depends on the critical assumptions that

- the sum of differences in endowments are consistently estimated,
- the coefficients of the wage model are consistently estimated and
- the competitive market price or, more generally, an appropriate price is used to weight differences in human capital characteristics.

Consistent estimation of the sum of differences in endowments can be violated by omitted variables, variables measured with error and inclusion of variables that are themselves the outcome of discriminatory processes. The inclusion of the latter group can have the undesired consequence of defining discrimination away. Critical examples are occupation and the sample selection correction term.

Inconsistently estimated prices, used to weight differences in endowments, clearly leads to over or underestimation of the explained and the residual component depending on the direction of the bias of estimated prices. Also, efficiency of the estimates of the decomposition is affected by the standard errors of the coefficients estimated.[63] One may consider, thus, that while

[63]A special case is if dummy variables for occupation and industry, (variables reflecting gender segregation,) are added to the wage model. Then, the decomposition can be improved in terms of efficiency by the choice of the sample, the coefficients that are used as weights in the decomposition are estimated with. This is because, in a wage regression for men that includes dummies for occupation standard errors of male-atypical occupations are often high. The same is relevant for the female equation. In order to calculate the

application of IV instead of OLS may result in consistent estimates of the parameters of interest, it also leads to loss of efficiency. Here, only better instruments may help or application of GMM which is more efficient.

Even if prices were estimated consistently from the wage regression models, the estimate of discrimination would be sensitive to the choice of the competitive price.[64] To illustrate this point, the Oaxaca decomposition can be written in a more general form as:

$$(\overline{lnW^M} - \overline{lnW^F}) = \underbrace{\hat{\beta}^*(\bar{X}^M - \bar{X}^F)}_{explained\ part} + \underbrace{\bar{X}^M(\hat{\beta}^M - \hat{\beta}^*) + \bar{X}^F(\hat{\beta}^* - \hat{\beta}^F)}_{unexplained\ part}$$

where

$$\hat{\beta}^* = \Omega\hat{\beta}^M + (I - \Omega)\hat{\beta}^F \tag{1.37}$$

In this notation, the competitive price, $\hat{\beta}^*$, depends on the specification of the matrix Ω. It follows that the unexplained part of the gap is decomposed into two parts that can be interpreted as the sum of the wage advantage of the group of males and the wage disadvantage of the group of females.

In Oaxaca (1973), it was proposed to use either the male or the female sample regression coefficients to measure the non-discriminatory wage structure;

explained share of the decomposition in either case imprecisely estimated coefficients are multiplied with large differences in proportions of men and women. Therefore, for a wage model where occupation or industry variables are included the coefficients of the model estimated for the pooled sample may be more appropriate to use. The problem of the interpretation of the coefficients of dummy variables and the estimation of the correct standard errors has been discussed in the literature on industry wage differentials too. See e.g. Krueger and Summers (1988) and Haisken-DeNew and Schmidt (1995).

[64]This is the well known index-number problem in economics. The index number problem arises whenever heterogeneous collections of goods, which are the variables in the vector X, are summed with two sets of prices. In our case the prices are the coefficients from the male and female sample wage equation.

Table 1.5: Summary of weighting matrices

Study	sample	weighting matrix
Oaxaca (1973)	male	$\Omega = I$
	female	$\Omega = 0$
Reimers (1983)	male/female	$\Omega_r = 0.5I$
Cotton (1988)	male/female	$\Omega_c = (N_m/N)I$
Oaxaca & Ransom (1994)	male/female	$\Omega_o = (X'X)^{-1}(X'_m X_m)$

Note: N_i = Number of observations for group i, i=f,m (female, male). $N = N_f + N_m$. X_m = matrix of observations for group i. $X' = [X'_m|X'_f]$.

which corresponds to $\Omega = I$ or $\Omega = 0$ in equation (1.37). This is still the most commonly adopted approach in the gender wage gap literature. A justification for using male sample regression parameters as the vector of competitive prices is that one may assume that in the economy male workers are the biggest group and face virtually no discrimination. More generally, the idea behind Oaxaca's approach is that these two vectors of prices bracket the actual non-discriminatory wage structure. This, however, is not necessarily the case.[65] Since then, a number of alternative specifications of Ω have been suggested in the literature. In table (1.5) we give a summary of the most important ones.

Apart from Oaxaca's approach, another often used and intuitively appealing set of weights was suggested by Reimers (1983). Here, the competitive wage structure is related to a weighted average of female and male sample regression coefficients. Similarly, Cotton (1988) proposed a weight related to the composition of the sample since many samples are not a composite

[65]See: Oaxaca and Ransom (1994).

of 50 percent of each of the two groups. Finally, Oaxaca and Ransom (1994) proposed a more general specification of the weighting matrix Ω which incorporates sample cross product matrices and nests the weights suggested by Cotton and by Reimers.[66] Hence, their approach may be less arbitrary.

In summary, the derivation of consistent estimates of the total explained part of a wage differential and an estimate of discrimination depend on consistency of the measures of the human capital characteristics included in the wage model, consistency of the estimates of the parameters of interest and the choice of the market price. Consideration of standard errors of the parameter estimates can be used to evaluate efficiency of the estimated components of the decompositions. Furthermore, one may note that while estimation and interpretation of the total explained and unexplained part of the gap is straightforward, estimation of the contribution of single factors is only possible for variables included in the explained part. This interpretation is not possible for the unexplained part. While the wage gap due to the sum of the differences in all coefficients, including the intercept, is well defined, the wage gap due to differences of a subset of coefficients is not.[67] This problem may become even more relevant if dummy variables are included in the vector of regressors X_{it} since the decomposition may then critically depend on the chosen reference point.[68]

[66] It holds that $\Omega_0 = \Omega_c$ if the first and second moments are identical for males and females; hence $\frac{N_m}{N}(XX)^{-1} = (X_m X_m)$. If the sample size of males and females is the same, $N_m = N_f$, then $\Omega_r = \Omega_c$ follows.

[67] Therefore, the measure of the difference in the intercepts, as separated in the Blinder (1973) notation, may not be useful. This has been pointed out by Jones (1983), Cain (1986) and Brown and Corcoran (1997).

[68] This was shown in Jones (1983) by an example. Solutions to this problem have been suggested by Schmidt (1998) and Nielsen (1988).

1.8 Empirical evidence

Throughout the empirical literature, estimates of the explained and unexplained portion of the wage differential are extremely varied. Generally, measures may vary across studies because there is no clear agreement on which observed characteristics have to be included in the wage regressions estimated for men and women,[69] and on how to deal with unobserved characteristics in the wage model framework. Furthermore, inclusion of some characteristics may be problematic in itself since they may be the outcome of discriminatory processes in the labour market. We have referred to examples earlier: the occupation variable and the sample selection correction term. Moreover, measures of male female wage differentials presented may be biased because of failure to account for endogeneity and selectivity appropriately in the estimation of the wage model.[70]

To illustrate implications of the (in)consistent estimation of the parameters of the wage model, we summarise estimators of the explained portion and the unexplained portion of the gap used in the literature in table (1.6), referring to our model specification and notation in equations (1.1) and (1.2). From the previous discussion, we can draw inference about consistency and the direction of the bias of estimates of the corrected gender wage gap presented in empirical studies. In the benchmark case, we take the consistent estimator of the parameters of main interest, listed in the first row of table (1.6). In rows two to four, we list one after the other the three estimation strategies, discussed before: First, if the model is estimated by OLS and a proxy is used for the actual work history, discrimination may be overesti-

[69]This argument has been stressed also by Cain (1986). In reference to unobserved characteristics it has also been mentioned in Blau and Ferber (1987).

[70]This, also, was pointed out in Kim and Polachek (1994).

Table 1.6: Estimators for explained and unexplained differentials

Work history measure, Estimator	Estimate of explained diff.	$\hat{\beta}$	$(\bar{X}^M - \bar{X}^F)$	Estimate of unexplained diff.
actual work history[1]: $X = (EXP, HOME)$, IV-GLS, FD-IV	$\hat{\beta}_1(\bar{X}^M - \bar{X}^F)$	consistent	consistent	consistent
potential experience: $X = (EXP^{POT})$, OLS	$\hat{\beta}_2(\bar{X}^M - \bar{X}^F)$	downward bias due to meas. error	downward bias due to meas. error	upward bias
actual work history[1] : $X = (EXP, HOME)$, OLS	$\hat{\beta}_3(\bar{X}^M - \bar{X}^F)$	upward bias due to $E[\nu_i \| X_{it}] \neq 0$	consistent	downward bias
actual work history[1] : $X = (EXP, HOME)$, FD	$\hat{\beta}_4(\bar{X}^M - \bar{X}^F)$	downward bias due to $E[\Delta u_{it} \| \Delta X_{it}] \neq 0$	consistent	upward bias

Note:[1] Variables are measured without measurement error (meas. error). See text for further explanations.

mated. Second, if the model contains variables for the actual work history measured without error and is estimated by OLS, the estimate of the unexplained gap may underestimate the true degree of discrimination. Third, if the same model is estimated by FD and, given that all parameters are identified and no measurement error is present in the data, FD may lead to an overestimate of discrimination. These cases, explained here for the Oaxaca decomposition, can be extended to the other more elaborate decomposition approaches.

Keeping these results in mind, in the following sections we give a brief summary of the evidence found in the literature on the *uncorrected* or *raw* male-female wage differential and the *corrected* male-female wage differential with particular attention to the factors that have been found to explain wage differentials. In tables (1.7) to (1.11) we present summaries of the empirical results from a number of selected studies mostly conducted for the U.S., the U.K. and Germany. In our prior discussion on the estimation of the general wage regression model we referred to these studies and, consequently, details (data set used, model, etc.) are not repeated here.

1.8.1 The uncorrected wage differential

Across the entire population of Western industrialised countries, one finds an uncorrected gender wage gap of similar size. Furthermore, over the last three decades, a decreasing trend has been observed. For the U.S. and the U.K., for instance, the differential decreased from about 40 percent to 20-30 percent.[71] Typically, from the comparison of married men and married

[71] See e.g. O'Neill and Polachek (1993) for the U.S. and Harkness (1986) for the U.K.. The trend was interrupted by a period when the gap stabilised or even increasesd slightly in the late 70's and early 80's.

women, the gap calculated is higher than from the comparison of men and single women.[72] Also, wage differentials that women face seem to be about 10 to 20 percent smaller if they work full time in comparison to female part-time workers. [73]

For young workers, empirical evidence from raw wages suggests that, right from the start of working careers, women earn on average less than men and that this gap is increasing over the career to a level comparable to population averages. However, little evidence is found in the literature and, also, differs considerably. For example, for the U.S. using data from the NLSY, Loprest (1992) found a raw wage gap in starting wages in workers' first jobs of 11 percent[74], whereas Light and Ureta (1995) estimated a gap of 19 percent for workers with zero years of work experience. While these two studies are based on samples including all education groups, Dolton and Makepeace (1986) analysed a survey on U.K. graduates and found a much lower entry wage gap of only 7 percent. Thus, this seems to suggest that wage differentials differ by education as well and that education and raw wage differentials are negatively correlated.[75] Further support for this hypothesis can be drawn from the comparison of the evolution of the wage gap over the early career. While for graduates, Dolton and Makepeace (1986) found a gap of only 26 percent seven years after graduation, Light and Ureta (1995) found a gap of 31.2 percent already for young workers with four years of work experience and an even higher gap, 46.3 percent,

[72]See e.g. Mincer and Polachek (1974) and Blau and Kahn (1995).

[73]For evidence see e.g. in Harkness (1996).

[74]Loprest (1992) used data from the National Longitudinal Survey of Youth (NLSY) on individuals who were 14-21 year old in 1978, who were observed over the first four years in the labour market and who were full-time workers.

[75]See also Brown and Corcoran (1997).

for young workers with 9 years of actual work experience.[76]

1.8.2 The corrected wage differential

Applications of the Oaxaca decomposition

The most important finding in studies applying the Oaxaca decomposition is that the gender distinct labour force participation patterns contribute considerably to the explanation of male-female wage differentials. This was shown first by Mincer and Polachek (1974). Although general agreement on the explanatory contribution of this factor can be found in the literature, it is not clear yet what share of the uncorrected wage gap can be explained. Results from a selection of studies that refer to samples of the entire population and samples of young workers are summarised separately in tables (1.7) to (1.9).

Oaxaca (1973) had already shown that about one fourth of the uncorrected wage gap can be explained by the work history proxied by the variable *age*. The separate measurement of actual work experience and home-time leads to the result that approximately half of the gap is explained after endogeneity of the work history variables is controlled for as in Mincer and Polachek (1978). Hence the use of a proxy for work experience leads to an overestimate of discrimination, as expected.[77]

Evidence for the hypothesis that heterogeneity in unobserved skills affects individual choices of work histories and, therefore, has to be considered when wage differentials are estimated, was demonstrated in Kim and Polachek (1994). The authors conclude that the appreciation of earnings power

[76]However, Loprest (1992) found a gap of only 15 percent four years after entry into the labour market.

[77]Compare with table (1.6).

Table 1.7: Empirical results from Oaxaca decomposition - studies for the entire labour force (16-65 years old)

Study	Uncor. gap (Sample)	Unexpl. gap in % of uncorr. diff.	Estimator	Comments
Studies for the U.S.				
Panel A: Proxy used for actual experience				
Oaxaca (1973)	43.1	78.4	OLS	occupation, industry excluded
		53	OLS	occupation, industry included
Blinder (1973)	45.8	65.7	OLS	structural model
Panel B: Actual work history variables used				
Mincer & Polachek (1974)	52 (married men and women)	58	TSLS	
	16 (married men/ single women)	60	TSLS	
Mincer & Polachek (1978)		~ 80	OLS	results from authors' short model
		~ 50	TSLS	
Corcoran & Duncan (1979)	43.8	56	OLS	
Kim & Polachek (1994)	54	41	OLS	results refer to the entire sample
		7.22	GLS-IV	
		9	FD-IV	

Note: For details about studies see tables (1.1) to (1.4).

Table 1.8: Empirical results from Oaxaca decomposition - studies for the entire labour force (16-65 years old), continued

Study Year	Uncor. gap (Sample)	Unexpl. diff. in % of uncorr. gap	Estimator	Comments
		Studies for the U.K.		
		Panel A: Proxy used for actual experience		
Harkness (1996)				
1975:	40.8	83	OLS	short model est.
1983:	31.8	75	OLS	for full-
1992-93:	22.1	89	OLS	time women
Zabalza &	62.3	97.3 (PotEx)		69.7 expl. by
Arrufat (1985)				sampl. selec. corr.
		19.2 % (ImputEx)		
Greenhalgh (1980)				
1971:	16.9 (singles)	24	OLS	
1975:	2.9 (singles)	10		
		Panel B: Actual work history variables used		
Wright &				
Ermisch (1991)				full-time women/
1980:	36 (married)	48.4 (married)	OLS-Heck	all men
		Studies for Germany		
		Panel A: Proxy used for actual experience		
Gerlach (1987)				
1981:	11	84.95 (singles)	OLS	
	38.7	92.19 (married)	OLS	

Note: For details see tables (1.1) to (1.4).

Table 1.9: Empirical results from Oaxaca decomposition - studies for young workers (16-30 years old)

Country	Study Year of observation	Uncor. gap (Sample)	Unexpl. gap in % of uncor.gap	Estimator	Comments
U.S	Light & Ureta (1995)				here: unexpl.= 100% - share expl. by timing of work experience and time out of work
	pooled sample	40.3			
	0 years of EX	19			
	1 year of EX	32.5	93	IV-GLS	
	9 years of EX	46.3	88	IV-GLS	
U.K.	Dolton & Makepeace (1986)				
	1970	7			1970: entry wages
	1977	26	18-20	FE/OLS	1977: 7th year after graduation

Note: For details see tables (1.1) to (1.4).

with work experience and the depreciation associated with not working are comparable for men and women after unobserved heterogeneity has been taken into account. They found that the unexplained portion of the gap is in some cases less than 10 percent.[78]

Furthermore, it has been demonstrated that the timing of the work history also contributes to the explanation of the gender wage gap.[79] In Light and Ureta (1995), a model controlling for timing of the work history in most flexible form was estimated for young workers.[80] The intuition behind the

[78]In the authors' model, all coefficients except for the coefficients of the work history variables are constrained to be equal across genders. Furthermore, estimation results in non-significantly different parameter estimates of the work history variables for men and women. Thus, they can estimate discrimination by the difference in intercepts of the male and female sample wage regressions.

[79]See: Mincer and Polachek (1974) and Light and Ureta (1995). See, also, studies estimating rebound effects (for women), e.g. Mincer and Ofek (1982) and Corcoran et al. (1983).

[80]The model is nested within the general model set up by us. Define ΔEX_{it} = share of

detailed segmentation of work experience and home-time is to allow spells in the past to affect wages less or more than spells in the more recent past or in the present. Light and Ureta (1995) found that for the wage differential between men and women with one year of work experience, only 7 percent of the gap can be explained by timing of work experience. This share increases the more years of work experience have been accumulated and reaches 12 percent for men and women with 9 years of experience.

In addition to work history variables, occupation has been found to contribute significantly to the explanation of the wage gap. But since the variable *occupation* may be the outcome of discriminatory processes in the labour market itself, inclusion of this variable may lead to an underestimate of discrimination. Vice versa, estimates of discrimination without controlling for occupation may be interpreted as an upper bound estimate of discrimination.

Applications of the Juhn, Murphy and Pierce decomposition

The Juhn, Murphy, Pierce (1991) - decomposition has been applied in empirical studies in order to examine wage structure effects on the difference in wages over time or countries. Henceworth, the basic Juhn-Murphy-Pierce decomposition outlined, in section 1.7.2, has to be extended to two periods, or two countries.

To adopt the Juhn, Murphy, Pierce (1991) notation, the general wage regression model, as we have specified it in equations (1.1) and (1.2), can remain unchanged except for the individual specific effect that is now al-

year worked in year t. Then the vector X in our model specification includes now ΔEX_{it} for all periods $t = 1, ...T$ and the coefficient vector is redefined as β_t with t components varying across segments of the work experience variable. Correspondingly, the variable home-time is redefined and the vector of coefficients extended accordingly.

Table 1.10: Emp. results from Juhn, Murphy, Pierce decomposition

Study	Country data and sample	Estimate [1] sum gender specific	sum wage structure	change in raw wage gap
Blau & Kahn (1994)[3]	U.S.	-0.215	0.071	-0.1442
	PSID 75,87			
	CPS 71,88			
	full-time			
	nonagricultural			
	age: 18-65 years			
	(no self employed)			
Blau & Kahn (1995)[3]	international comparison[2] :			
	data mostly taken from			
	ISSP for 1985-88			
	Australia	0.02	-0.11	-0.095
	Austria	0.3	-0.4	-0.1
	Germany	0.29	-0.35	-0.06
	Hungary	0.56	-0.53	0.025
	Italy	-0.002	-0.17	-0.17
	Norway	0.25	-0.32	-0.065
	Sweden	-0.003	-0.14	-0.14
	Switzerland	0.1	-0.067	0.04
	U.K.	0.45	-0.36	0.08
Dolton, O'Neill & Sweetman (1996)	U.K.	1967-1977:		
	survey of graduates in	-0.16	0.02	-0.106
	1960, 1970, 1980			
	cross-sections used	1986-1977:		
	for 1967, 1977, 1986	0.023	0.009	0.032
	(7 years after graduation)			
	mean age: 28-29			

Note: [1] All models are estimated by OLS. [2] Between country changes in male-female wage differentials are decomposed, where *raw wage gap* = $(\bar{w}^i - \bar{w}^{USA})$ for country i. See countries listed above. [3] Wage regressions in both studies include controls for education, potential experience in levels and squares, union status, occupation and industry. ISSP: International Social Survey Programme.

lowed to vary over time, hence $\epsilon_{it} = \nu_{it} + u_{it}$. Then, under the assumption that prices derived from the male sample wage regression are equivalent to competitive prices and discrimination is neglected, the wage structure effect on the change of wages over time can be estimated from the following decomposition:

$$\underbrace{(\Delta\overline{lnW}_t - \Delta\overline{lnW}_s)}_{change\ in\ raw\ wage\ gap} \tag{1.38}$$
$$= \underbrace{(\Delta\bar{X}_t - \Delta\bar{X}_s)\hat{\beta}_t^M}_{observed\ X's\ effect} + \underbrace{\Delta\bar{X}_s(\hat{\beta}_t^M - \hat{\beta}_s^M)}_{observed\ prices\ effect} + \underbrace{(\Delta\bar{\theta}_t - \Delta\bar{\theta}_s)\sigma_t^M}_{gap\ effect} + \underbrace{\Delta\theta_s(\sigma_t^M - \sigma_s^M)}_{unobserved\ prices\ effect}$$

Here t, s index time periods, where $t > s$, and all variables are used in the same way as before in this chapter. θ captures unobserved skills and is defined as the standardised residual, $\theta_{it}^M = \nu_{it}^M/\sigma_t^M$, where $\sigma_t^M = \sqrt{Var(\nu_{it}^M)}$. Under the assumption that σ^M does not change over time due to measurement error, pricing error or change in the number of unobserved characteristics included in the vector $(\sigma_u^M\theta_{iu})$, where $u = t, s$, the change in σ^M can be interpreted as the change in the price of unobservable skills.[81]

According to the decomposition shown in equation (1.38) the change in the male-female wage differential over time can be decomposed into four components. The first component measures the impact of the change in differences in observable human capital endowments between men and women. The second term measures the impact of a change in wage inequality measured for men by prices of observed characteristics. The third term, the gap effect, captures changes in the relative positions of men and women - that is, whether women rank higher or lower in the male wage residual distribution - after controlling for observed (human capital) characteristics and holding the degree of inequality in the male wage distribution constant.

[81]For the detailed derivation of the decomposition for two time periods of countries see Juhn, Murphy and Pierce (1991) and Juhn, Murphy and Pierce (1993).

In other words, it reflects changes in the levels of unobervables. Finally, the unobserved price effect measures the impact of a change in inequality on the change of the male-female wage differential, assuming that females keep the same position in the residual wage distribution of men. This can be interpreted as changes in the returns to unobservable skills. The Juhn, Murphy, Pierce - decomposition allows wage structure factors to be distinguished from gender specific factors that explain part of the wage gap. The impact of *gender specific factors* is measured by the sum of the "observed X's effect" and the "gap effect". The sum of the remainders, the "observed prices effect" and the "unobserved prices effect", measures *wage structure effects* and their impact on the development of the gender wage gap.[82]

In the literature several critical points regarding the Juhn-Murphy-Pierce decomposition have been risen. As was pointed out in Blau and Kahn (1997), clearly, wage discrimination makes the interpretation of the decomposition more complicated since changes in wage discrimination may be incorporated in each of the components. Thus, estimates of the wage structure effects, for example, may be biased. The same problem applies if non-random sample selection and changes over time in this process are relevant. Apart from the fact that this may violate consistent estimation of the parameters of the wage regression as has been discussed in part one of this survey, changes in labour force participation behaviour of women may as well be incorporated in the *gap effect*.

Further potential drawbacks of the Juhn-Murphy-Pierce decomposition can be listed in four points: The first is the strong interpretation of changes in the distribution of male wage residuals. Ideally, changes could be interpreted

[82]Obviously, the decomposition can be applied as such to samples with two countries, instead of two time periods.

as changes of prices. However, they may as well capture, for example, measurement error, sample composition, equation misspecification, and the distribution of unmeasured male productivity characteristics.[83]

Second, the use of the prices derived from the male sample wage regression implies that the same set of prices applies to females. Hence, it is assumed that inequality affects men and women equally and wage structure is, therefore, measurable for both men and women by the prices derived from the male sample regression.

Third, Suen (1997) argued that interpreting the decomposition as prices and quantities of unmeasured ability is subject to bias. He shows that, under the normality assumption for the error term is the wage regression, estimates are unbiased, only, if percentile ranks are independent of the standard deviation. This, however, is often a problematic assumption. Clearly, the effect arises because more dispersed distributions tend to have thicker tails. Therefore, for any fixed wage near the lower (upper) end of the distribution, its percentile ranking will rise (fall) with an increase in the dispersion of the wage distribution. This has an impact on the movement of percentile ranks. If percentile ranks are dependent on the standard deviation, the decomposition is correct only in an accounting sense, and the resulting decomposition of price and quantity effects of unobservable characteristics may be arbitrary. It may, however, still be useful to apply the decomposition for detecting asymmetries in the upper and the lower ends of the wage distribution, as Suen (1997) pointed out.

Fourth, Fortin and Lemieux (1998) showed that residual improvements in the relative position of women and the estimated wage structure effects

[83] Blau and Kahn (1997), Suen (1997).

critically depend on which distribution is assumed to be the distribution of reference; hence, whether the male, pooled or female sample distribution. Finally, it may be stressed, that as all the other decompositions as well, the Juhn-Murphy-Pierce decomposition depends on consistently estimated parameters of the wage regression model.

The Juhn, Murphy, Pierce decomposition, as shown in equation (1.38), has been adapted by Blau and Kahn[84] to analyse the U.S. and international gender wage differentials and in Dolton, O'Neill and Sweetman (1996) to analyse the U.K. gender wage gap among graduates. The main results are summarised in table (1.10). In these studies, a decrease in the gap was observed for the U.S. during the period of the mid 70's to the mid 80's and for the U.K. for the period of the mid 60's to the mid 70's. It was demonstrated that the decrease is explained by gender specific factors, yet is counteracted by wage structure effects. The latter effect seems to be greater in the U.S. than in the U.K.. On the one hand, this shows that women improved their position in terms of observed human capital characteristics; particularly in terms of occupation as Blau and Kahn (1997) pointed out for the U.S.. On the other hand, it shows that if no change in the wage structure had taken place, the gap would have decreased even more. During the period of 1977 to 1986 in contrast to the U.S., in the U.K. the gap slightly increased by 3 percent. Dolton, et al. (1996) found that the major portion of this increase is explained by gender specific factors as well. Hence, this implies that among U.K. graduates female workers fell further behind men in an environment that was becoming more unfavourable. Authors have suggested that this may also reflect that qualified women hit a "glass ceiling"[85] and,

[84]See: Blau and Kahn (1992), (1994), (1995), (1996), (1997) and Blau (1998).

[85]See e.g. Gregg and Machin (1994).

Table 1.11: Emp. results from Brown, Moon, Zoloth decomposition

Study Year of observation data set	Uncor. gap	Decomposition:			
Dolton & Kidd (1994)		interoc.effect		intraoc.effect	
sample of U.K. graduates		unexpl.	expl.	unexpl.	expl.
of 1980,	0.2083	0.0254	0.032	0.1169	0.0201
cross-section for 1987,		(13.1%)	(16.46%)	(60.1%)	(10.3%)
6 occupation groups					
		total expl. gap		total unexpl. gap	
		26.8%		73.4%	
Miller (1987)		interoc.effect		intraoc.effect	
GHS 1980		unexpl.	expl.	unexpl.	expl.
6 occupation groups	0.495	-0.0718	0.134	0.242	0.1908
		(-14.5%)	(27.1%)	(49%)	(38.5%)
		total expl. gap		total unexpl. gap	
		0.3248		0.1702	
		(65.6%)		(34.4%)	
Kidd & Shannon (1996)					
LMAS 1989		total expl. gap		total unexpl. gap	
9 occupation groups	0.295	0.047		0.248	
		(15.9%)		(84.1%)	
36 occupation groups		0.038		0.256	
		(13.1%)		(86.9%)	

Note: LMAS: Canadian Labour Market Activity Survey. For further details see tables (1.1) to (1.4).

hence, are prevented from improvements.[86] In the international comparison by Blau and Kahn (1995), further evidence demonstrating the importance of rising inequality was shown. It was found that in all but two cases gender specific factors favour U.S. women, but that the U.S. level of inequality greatly raises the U.S. gender wage gap compared with each of the other countries in their sample.

Applications of the Brown, Moon, Zoloth decomposition

Application of the Brown, Moon, Zoloth (1980) decomposition allows for

[86] This could be one form of discrimination against women.

the estimation of the explained and unexplained portion of the wage differential in a similar fashion to that of Oaxaca (1973). The most interesting aspect about this decomposition approach is, thus, that more insights can be gained from the estimation of the portion due to within occupation wage differentials and the portion of the gap due to the gender distinct distribution across occupations. In table (1.11), we list results found in a number of studies.[87]

Surprisingly, it has been found that most of the wage gap results from within occupation wage differentials rather than occupational segregation. Dolton and Kidd (1994) and Miller (1987) reported that more than half of the uncorrected wage gap is due to within occupation wage differentials.[88] To some extent this result may be driven by the number of occupations that can be distinguished in the data. Kidd and Shannon (1996) work with Canadian data in which 36 occupational groups can be used. Given that men and women may work in about 300 occupations[89] grouping of occupations into a more narrow range may result in the effects due to within occupation wage differentials being confounded with effects due to those between occupations.

[87]Since in all of the studies, the models are estimated by OLS, estimates are likely to be inconsistent. This affects the interpretation of the estimated decomposition as explained earlier. One may note that Kidd and Shannon (1996) use potential experience in their model and Dolton and Kidd (1994) use actual work experience.

[88]On the contrary, in other studies such as Lazear and Rosen (1990) it is noted that within occupation wage differences are very small. But this conclusion seems to be justifiable, so far, purely on theoretical grounds.

[89]About this number of occupations are distinguished in German data, see IABS (Institute for employment and occupational research) and SOEP (Socio-economic panel).

1.9 Conclusions

The question of whether discrimination against women can be identified in labour markets or not has been linked in the literature on the gender wage gap to the two questions: Is the explained part of the gap close to the total raw gender wage gap? and Are the returns to work experience and the loss from time out work equal for men and women?

The answers to both questions depend, mainly, on the availability of precise measures of wages and human capital acquired, as well as on consistent estimation of the parameters of interest in the wage model. A lot of attention has been paid to the latter issue within the gender wage gap literature and more broadly in the literature on estimation of wage regression models. In this paper we have reviewed the literature with respect to the progress that has been made in this field. We have found that the econometrics methods are still ahead of the applications. This becomes clear from the often restrictive assumptions made in empirical studies to justify consistency of the estimated parameters, which frequently lack econometric as well economic reasoning. Furthermore, estimates presented often lack robustness, which may be due to invalid exclusion restrictions imposed or poor instruments, for instance. Moreover, empirical studies mostly based on survey data have to deal with the additional problem of measurement error in the human capital variables. To explore endogeneity problems further, there has been a tendency for authors to present consistent and inconsistent estimates for the parameters of interest derived from the application of alternative estimators. More detailed use for comparison of these sets of estimation results and increased attention to the analysis of the bias may produce further progress in unraveling the questions around the gender wage gap.

Another promising avenue in the quest for consistent and robust estimates is opened up by more recent approaches using administrative data from social security data bases. These are not likely to suffer from measurement error problems associated with (longitudinal) survey data. Furthermore, these data sets promise to be very powerful since they usually contain long time series for individuals, which should provide the basis for finding good instruments. Moreover, information can often be linked to other data sets containing more detailed background information, for example, on employers that may provide additional exogenous variables also useful as instruments for the work history variables in the wage regression model.

Part Two
Institutional background and data

Chapter 2

The apprenticeship programme, occupational qualification and working careers

Abstract:

In this chapter, we describe the German dual system apprenticeship programme. For decades, the main portion of the German workforce has received (occupational) qualification by this method. This has let to its perception as a highly stable system. On the other hand, induced by demographic changes, and other factors, it has proven to be a highly dynamic system, which may have helped its maintainance. Both features are discussed in this chapter. Furthermore, we focus on occupational qualification, education and work histories, and gender specific features. By doing so, this chapter provides background information for the following empirical analysis. Moreover, the description motivates the selection rules, we formulate in order to draw a sample of young skilled workers from the employment statistics for Germany (IABS).

2.1 Introduction

In the last decade, education and training has become a major issue in many countries, as they are seen as playing a key role in restoring or maintaining international competitiveness.[1] Furthermore, the empirical and theoretical analysis of skill formation is of great interest from the perspective of many issues, such as the analysis of growth, wage differentials, inequality, poverty, migration, crime, pensions, social policies, public (spending) policies and international comparisons. Characterising features of skill formation systems are the organisation of skill formation and the type of skill formed. The organisation of skill formation may be under the authority of the State or firms, and skills formed may be distinguished into vocational and academic types. Existing skill formation systems are combinations of these types of organisation and types of skills delivered. Examples where the majority of the workforce is trained by school based learning are the U.S., the U.K. and France. In contrast, in the German-speaking countries the majority of workers have acquired qualifications by vocational training or, more particularly, within dual system apprenticeship programmes.[2]

Generally speaking, dual-system apprenticeship programmes - DSAP hereafter - are understood as vocational training programmes that combine school and work based educational programmes.[3] Hence, this system is distinct from vocational training programmes that incorporate full time on the job training, in a firm, and others in which vocational skills are acquired in full-time education, in technical colleges. Although at present apprentice-

[1]See e.g. Finegold and Soskice (1988).

[2]See: Green and Steedman (1997).

[3]Definition of the OECD.

ship systems are only really common in the German-speaking countries, in the English-speaking countries apprenticeships have also had a long history.[4] Yet, in all of these countries they had virtually disappeared by the 1950's, except for Australia.[5] The reestablishment of dual system apprenticeship programmes is, however, a topical issue in both the U.S. and the U.K. and is seen by its proponents as a desireable aim to ensure the provision of skilled workers to the economy.[6] These developments make the German case particularly interesting. In this chapter, we present a discussion of the German apprenticeship programme which has been for decades the major route to obtaining inital qualification for the 16 to 22 years old.

There is presently a vast number of publications on the German (DSAP) and its international comparisons. The most thorough discussion on the German apprenticeship programme is perhaps Münch's (1992) monograph published by the European Centre for the Development of Vocational Training (CEDEFOP).[7] Münch gives not only a description of the German education system in general and the dual system apprenticeship programme in particular, but also documents facts around the system with many statistical details. Another strength of his discussion resides in the description of the legal framework.[8] Further valuable descriptions are contained in papers where it is questioned why firms participate in the training scheme.[9] Others

[4]Going back to the middle ages, forms of apprenticeships were common all over Europe and were administered by guilds that had major political and economic powers.

[5]See: Gospel (1994).

[6]See e.g. Marsden and Ryan (1990), Finegold and Soskice (1988).

[7]His paper is part of a series in which education and training systems in a number of countries are discussed.

[8]For other descriptions of DSAP see, for instance, Deutscher Bundestag (1974), Kempf (1985), Franz and Soskice (1994a,b) or Casey (1986), (1991).

[9]See: Franz and Soskice (1994a,b), Soskice (1994), Acemoglu and Pischke (1996),

discuss the system in international comparisons[10] and whether apprenticeship programmes are actually "better" than alternative systems.[11]

Related to this discussion, is the view that (external) occupational labour markets exist in Germany.[12] In the framework of occupational labour markets, workers' skills are assumed to be largely tradable and, thus, workers receive also skilled workers' wages outside the training firm. In contrast to occupational labour markets, internal labour markets function on the basis of on the job training and promotion schemes within firms. These imply high losses of human capital and, thus, wages, if workers change firm. Therefore, a particular interesting feature of the German DSAP is that it results in occupational qualification which may have strong impact on the organisation of labour markets. Furthermore, occupations also become particularly interesting when analysing male-female outcomes in the labour market since occupation segregation between these groups is traditionally observed and, at the same time, wage differentials can be observed. Thus, one can question whether there is a link between the two. In the following description, we focus on these aspects, occupational qualification and gender specific features. Furthermore, the aim of this section is to characterise education and work histories of young skilled workers in Germany in order to prepare the grounds for defining selection rules to generate a sample taken from the Institute of Occupational and Labour Studies administrative event history data set. Most of the descriptions in the existing literature[13]

Harhoff and Kane (1993).

[10]E.g. in Steedman (1993) and Finegold and Soskice (1988) comparisons to the U.K. and in Buechtemann, et al. (1993) comparisons to the U.S. have been drawn.

[11]See e.g. Marsden and Ryan (1990), Soskice (1994).

[12]See: Marsden (1990).

[13]Except for Münch (1992),

refer to former West-Germany, and in the following it is also the case.

Empirical evidence about DSAP, mainly comes from the wealth of information published in form of aggregate time series data by the *Bundesinstitut für Berufsbildung* (BIBB) published in the reports on education and training, *Berufsbildungsberichte*, since the late 70's. Survey data at the micro-level, the Socio-Economic Panel (GSOEP) available from 1984 to 1994 and the BIBB-IAB survey about qualification and work history from 1979 and 1985-86[14], provide some basis for empirical analyses. However,they suffer from many problems, such as lack of detailed measures of human capital stock acquired, measurement errors in variables and lack of longitudinal information or background information. The sample we generate, as we will describe, offers a wide range of precise information and, more particularly, allows us to measure wages as well as human capital acquired by young skilled workers in a more detailed way than in convential data sets. Since the data is available for the period 1975 to 1990, we concentrate on this period in the following description.

The structure of this chapter is as follows: First, we give a brief history of apprenticeship programmes in Germany. In section two, the German education system is described, supplemented by statistics on demographics and education. In section three, the framework of the apprenticeship scheme is described and, finally, a more empirical section documenting dynamics of the system is presented.

[14]Qualifikation und Berufsverlauf, Zentralarchiv für empirische Sozialforschung an der Universität zu Köln.

2.2 Overview of the history of apprenticeships

Forms of apprenticeship programmes, which may be seen as predecessors of the actual DSAP, can be followed back to the middle ages in craft sector, and to the 19th century in industry. In the beginning, "apprenticeship" was called journeymanship and involved only training and working in the firm. Coinciding with the introduction of school laws prescribing compulsory years of schooling, school attendance was integrated, first on a voluntary basis in Sunday and evening schools and then as a compulsory weekly component during working days. As a result, comparable "apprenticeship programmes" can be traced back to the late 19th century. In the following, we give a brief sketch of the history of the DSAP and its predescessors.[15]

Youth training in the craft sector can be traced back to the middle ages. At that time, guilds had the major economic and political power and they administered training and certificates which were the only way to enter trade. The first certificate giving evidence of an apprenticeship scheme, or journeymanship, regulated by guilds is the *Ordnung der Drechsler zu Köln*, in 1182.[16] Already, at that time guilds prescribed strict regulations for entry into journeymanship and acquisition of the certificate. Journeymanship was only undertaken by men. These regulations contained, for example: age of entry (12-18 years), duration of training, duration of the probation period, journeyman exams and ceremony of absolution and individual conditions for

[15]For more details, see in Kempf (1985), Steedman (1993), Deutscher Bundestag (1974) and Münch (1992).

[16]See: Münch (1992), p.28.

entry, such as birth in wedlock.[17] From the 16th century onwards, under the influence of upcoming economic liberalism and increasing manufacturisation and industrialisation, destruction of the guilds took place and, without the regulatory power of the guilds, youth training degenerated into a system of youth exploitation.[18] The introduction of freedom of trade in 1811 and the trade certificate (*Gewerbeschein*) lead to the complete destruction of organised vocational training. Revival only occured from 1850 to 1900 when several trade regulations, *Gewerbeordnungen*, were enacted, in particular, the *Gewerbeordnungsnovelle* (craftsmen protection law) from 1897 which gave more rights, *Korporationsrechte*, to the guilds, which were now called *Innungen*. Furthermore, from 1908 trainers in craft had to have the *kleinen Befähigungsbeweis* (small proof of qualification).[19]

Apprenticeships started in artisan firms, and, also, in the process of industrialisation until the mid 19th century apprenticeships were common only in craft sector. However, while from 1800 to 1870 the upcoming industry sector absorbed workers from craft and agricultural sectors it became more and more apparent that on the job training would not suffice to qualify workers thoroughly. During the last third of the 19th century, training corners (*Lehrwerkstätten*) were founded where workers were trained off the job.[20] Gradually, a vocational training system similar to the one in the craft sector was adopted by the industry sector.

Almost simultanously, and in recognition of the fact that work practice

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[17]See: Münch (1992), p.28.

[18]This view is expressed in Münch (1992).

[19]See: Münch (1992).

[20]The first training corner was founded in 1820 in a firm near Würzburg. From 1890, Siemens and other large firms as well as the Eisenbahnverwaltung established training corners. Deutscher Bundestag (1974), p.9.

cannot be developed anymore without theory, advanced training schools, first in form of Sunday schools, became more and more important. In 1869 a trade regulation was enacted that allowed cities to introduce compulsory advanced schooling, for the first time.[21] By 1900, most bigger cities had made advanced schooling compulsory.[22] The Weimar Republic made schooling compulsory until the age of 18. However, it was not completely enforced. Since 1949, in Germany a general full time school as well as a part time school compulsion is enforced in all *Länder.* As a result of the law that makes vocational school compulsory for juveniles who are in vocational training or have a working contract and who are younger than 18, vocational schools have become the most important educational and training components in the German education system.[23]

In summary, the predecessors of the DSAP can be traced back to the middle ages. First, independently vocational training schemes in firms and vocational schools developed. Since the end of the 19th century, which may have been reinforced to some extent by compulsory school laws,[24] those two components have become more and more integrated and, as a result, firms sent their apprentices to schools once a week. One distinguishing feature to apprenticeships in industry, however, is the concept of *Lehrwerkstätten.* Until recently, this form of training is rare in trade, craft sector and agricultural

[21]See: Münch (1992).

[22]See: Deutscher Bundestag (1974), p.11.

[23]See: Münch (1992), p.30.

[24]As expressed in Steedman (1993). On the other hand, in the literature school laws ensuring a high broad general school level are seen as a policy suggested by proponents of liberalism, such as the father of liberalism A. Smith, who were against apprenticeship programmes governed by guilds and which form a restriction for entry into trade. See: Kempf (1985).

sector.[25]

Looking back in the history of DSAP, it is quite interesting to note that until 1869 journeymen had to pay the trainer or supervisor for being trained as well as for food and living expenses. Inability to pay fully lead to extension of training. Since 1900, payment of a relatively low apprenticeship wage to the journeyman or apprentice has become common practice. Since then, more and more apprenticeship wages have become an integral part of collective wage agreements.[26]

Since 1925, occupations have been listed by an association of employers for which training regulation titles were given.[27] The number of recognised occupations was about 1000. However, the content of vocational training in firms was chosen by the firm or trainer. No detailed descriptions of apprenticeship occupations seemed to have existed at that time.[28] Shares of women in apprenticeships, like in any form of education and in the labour force, were extremely low at the beginning and middle of the century in comparison to today. This share reached only 24.9 percent by 1950.[29]

Since the foundation of the Federal Republic of Germany in 1949, the DSAP has gained general approval. This may have also resulted from continuous improvements and further developments, such as[30] investment in appropriate and centrally located modern school buildings, improvement of the standards of training of vocational teachers at universities, regulation of

[25]See: Deutscher Bundestag (1974).

[26]See: Deutscher Bundestag (1974).

[27]See: Deutscher Bundestag (1974).

[28]See: Deutscher Bundestag (1974).

[29]See: Berufsbildungsbericht (1980).

[30]See: Münch (1992).

vocational training in firms in the form of the 1969 Berufsbildungsgesetz - BBiG - (law of vocational training) and the reduction of the number of recognised apprenticeship occupations. Later in this paper we describe, in more detail, the BBiG, which forms the institutional basis of the DSAP in its actual form.

2.3 The German education system

Before we discuss the DSAP in detail, we briefly describe the German education system and selected features of the labour market and demographics.

2.3.1 The German schooling and education system

In Germany, two education routes[31] are of importance: Either, secondary school is completed after 10 years of schooling (*Mittlere Reife*), which is approximately at the age of 16, and an apprenticeship programme is undertaken afterwards, or secondary schooling is completed after 13 years of schooling (*Abitur*), which is approximately at the age of 19, and a study at universities or other higher education institutions follows.

In more detail, after (optional) Kindergarten and primary school, which is usually completed after four years at the age 10, there is the choice between three types and levels of schools plus the integrated system school (*Gesamtschule*).[32] *Hauptschule* is the most vocationally orientated of the

[31]School attendance is compulsory from the age of 6 to 18; i.e. for 12 years. Depending on the states pupils must attend full-time school during 9 or 10 years.

[32]We neglect the *Sonderschule* which includes various types of schools for pupils with learning difficulties or disabilities.

three main types of schools, and *Gymnasium* is most academically orientated in the curriculum. *Realschule* is intermediate between the two. *Hauptschule* and *Realschule* can be terminated both after 10 years of schooling. However, generally, the *Hauptschule* leads to a lower degree than *Realschule* and can be left after 9 or 10 years of schooling.[33] A *Realschul degree* or equivalent degree can be acquired by successful completion of the tenth grade on a *Realschule*, in a *Realschul class* at a *Hauptschule* or *evening Realschule.* Equivalent to the *Realschul degree* is the record of the 11th, 12th and 13th grade class at *Gymnasium* if the *Hochschulreife* (matriculation) was not achieved, as well as the final record of a *Berufsaufbauschule* or a two year *Berufsfachschule.* The *Abitur* is received after 13 years of schooling at *Gymnasium* - the *Fachabitur (technical Abitur)* after 12 years of schooling - and depends on the grades in the final school record. Transition from 10th grade, generally, also from Hauptschule and Realschule, to 11th grade in a Gymnasium depends on the grades in the final record leading to the *Realschul degree.* All of these degrees can be achieved as well at the Gesamtschule which is the integrated system of the three types of schools; however, this type of school is relatively uncommon in Germany.

Broadly speaking, only the Abitur permits entry into higher education and all school degrees allow vocational training which includes apart from apprenticeship programmes within the DSAP, for example, vocational training at full-time vocational schools. Accordingly, typical education histories are observed. However, simultaneously with a general increase in numbers of juveniles doing *Abitur*, during the 80's more and more graduates with *Abitur* would go for apprenticeship training programmes as well straight

[33]However, if school is left after 9 years, and since 10 years of full time schooling is compulsory, education must be continued then in another school.

after school. For example, in 1986 12.7 percent of apprentices had obtained the *Abitur.*[34] Afterwards, they start studying or continue working.

2.3.2 Demographics and education

The period ranging from the 70's to the 90's reveals considerable changes in the composition of the German labour force with respect to education, as can be seen from table (2.1). A dramatic impact on the number of school graduates caused by the baby boom generation is observed. Gradually, the number of school graduates has increased from 780,700 in 1970 to a peak in 1983 of about 1,140,000 and has declined afterwards.

A trend towards higher or more academically orientated education can be also observed. As can be seen from table (2.1), during the period of the 70's and 90's, numbers of pupils in *Hauptschule* have decreased while numbers in *Realschule* have risen. Furthermore, an increasing number of pupils have been doing the *Abitur.* Moreover, the number of apprentices has increased by one third, and even more dramatically the number of students has tripled.

Statistics by gender show that womens' shares in *Gymnasium* and *Realschule* are slightly higher than men's, and their shares in *Hauptschule* are lower. Hence, women's school education may be more of an academic type as opposed to a vocational type of men. Futhermore, while in 1950 only 24.9 percent of apprentices were female, and in 1971 35.9 percent, by 1981 the share had risen to 38.2 percent, and further to approximately 42 percent by the 90's.[35] The development of participation of women in higher education in Germany, which comprises mainly universities and technical universities,

[34]See tables (2.8) and (2.9).

[35]See various years Berufbildungsbericht, and see also table (2.12) in this chapter.

Table 2.1: Distribution across education and training

Year	1970	1975	1980	1985	1990
total pop.	61001	61645	61658	61020	63727
male	29072	29382	29481	29190	30851
female	31929	32263	32177	31830	32875
foreigners	-	-	4566	4482	5447
total working pop.	26668	25810	26328	25540	28486
male	17086	16202	16499	15789	16997
female	9582	9608	9829	9751	11489
	(35.9%)	(37.2%)	(37.3%)	(38.1%)	(40.3%)
total school graduates	780.7	954.6	1144.7	1110.2	1205.5
from Hauptschule (9 yrs)	489.1	461.6	500.8	391.6	392.5
	(62.6%)	(48.1%)	(43.7%)	(35.2%)	(32.5%)
with Hauptschul degree	348.8	347.1	391.4	319.9	320.0
without Hauptschul degree	140.3	114.6	109.4	71.7	72.5
from Realschule (10 yrs)	200.0	318	422.2	419.7	415.9
	(25.6%)	(33.2%)	(36.8%)	(37.8%)	(37.4%)
from Gymnasium (13 yrs)	87.9	175	221.7	298.9	298.1
	(11.2%)	(18.2%)	(19.3%)	(26.9%)	(26.8%)
total students	510.5	840.8	1044.2	1338.0	1338.0
total apprentices	1268.7	1328.9	1715.5	1831.3	1831.5

Source: Grund - und Strukturdaten 1997/1998. Shares are in brackets.

Table 2.2: Secondary schooling levels, by gender

	total			female pupils		male pupils	
	1980	1990	1994	1980	1990	1980	1990
Gymnasium	28.6	32.8	34.2	29.3	34.3	27.9	31.4
Realschule	29.4	30.7	31.6	31.9	32.7	26.9	28.8
Hauptschule	42.0	36.4	34.2	38.8	33.0	45.2	39.8

Source: Berufsbildungsbericht (1997), p.117.

Table 2.3: Share of women in higher education

	share of women in first enrollment	all semesters
1960	4.4	2.1
1970	9.1	5.1
1980	15.8	11.9
1990	25.8	17.4
1995	31.8	25.4

Source: Grund - und Strukturdaten (1997/1998).

is shown in table (2.3). As can be seen, until only 30 years ago, the share of women in higher education amounted to only 15.8 percent and, by 1995, still less than one third of students were women.[36]

2.4 The German dual system apprenticeship programme (DSAP)

Because for decades the essential features of the German DSAP have virtually remained unchanged, it may be considered as a highly stable training and education system that has continued into the present. However, continuous modifications of the institutional settings of the system, and demographic changes of apprentices make it a highly dynamic system. In the following, we describe the system in characterising its static and dynamic features. Furthermore, with respect to the empirical part of this thesis we focus on the education and work histories of this group of juveniles who undertake apprenticeships, occupational qualifications achieved and group specific, i.e. gender specific[37], features.

[36]In the appendix, section (2.6) more statistics on gender and labour market are presented.

[37]Apart from gender specific features it would be interesting to extent the discussion to immigrants, in particular for the 90's, and to incorporate the new states, after 1990.

2.4.1 Description

Institutions and organisation

In the *Berufsbildungsgesetz (BBiG)* from 1969 (valid on a Federal level) the most important regulations for the DSAP[38] are collected.[39] Kempf (1985) wrote that this law has considerably changed the development of the character of the DSAP. In particular, in the early steps of the development of the DSAP, and before 1969, the curriculum of the vocational training component was adapted to the needs of each individual firm, while from 1969 curricula in specific apprenticeship occupations have been prescribed to training firms.[40] Since 1969, the content of apprenticeships within specific occupations does not substantially differ across training firms.[41] A novel aspect introduced by this law was that for the first time apprenticeships are regulated in the craft sector, as well as in the industry and manufacturing sector, trade, agricultural sector, etc.. Previously, no legal regulations had existed except for the craft sector.[42]

The BBiG contains regulations about the apprentice relation, the institutional organisation of the DSAP and, also, regulations about the recognition

[38]In the following we translate *ausserschulische Berufsausbildung* as dual system apprenticeship programmes (DSAP).

[39]In addition to the Berufsbildungsgesetz three laws are essential for the German DSAP. These are Jugendschutzgesetz (9.8.1960, amendments: 12.4.1976), Protection rights for juveniles in employment. Arbeitsförderungsgesetz (26.06.1969), containing, for example, regulations about vocational guidance. Betriebsverfassungsgesetz (10.09.1971, 15.1.1972) regulates participation rights of juveniles in firms (announcement of representatives) as well as the participation of work councils in carrying out vocational training.

[40]Loosely comparable procedures to create lists of recognised apprenticeship occupations can be traced back to 1925. For example, in 1939 in trade and business 1,000 "apprenticeship occupations" were recognised. However, in contrast to the craft sector where the procedure was more complicated, here, regulations were not legally enforced. See: Deutscher Bundestag (1974), p.10.

[41]Furthermore, Kempf (1985) conjectures that a high substitutability between closely related apprenticeship occupations may be implied, which may have lead to the high concentration of apprentices in a relatively few numbers of apprenticeship occupations.

[42]See: Deutscher Bundestag (1974).

of apprenticeship occupations, the examination, organisation and supervision of apprenticeships, further vocational training and the composition and tasks of the boards.[43] Following the BBiG, a commission was founded, that advises the government in educational matters, as well as a research institute, the Federal Institute of Education - *Bundesinstitut für Berufsbildung (BIBB)*[44] - that carries out empirical research on the DSAP, and, for example, updates regulations for vocational training in specific occupations. Also, since the early 80's the report on education and training, *Berufsbildungsbericht*, is published annually.

Whilst the organisation of vocational schools, and the schooling system in Germany more generally, is under the authority of the *Kultusminister* of the different states, the *Bund* is responsible for the DSAP. The direct administration of DSAP is under the authority of the responsible institutions - according to the BBiG -, namely the chambers, and are supervised by the Federal Minister of Economics or the Federal Minister of Labour and Social Affairs.[45] Finally, regulations for vocational training in the specific occupations *(Ausbildungsordnungen für die einzelnen Ausbildungsberufe)*, according to the BBiG, are declared by the relevant ministers.[46]

Apprenticeship programmes

Dual-system apprenticeship programmes (DSAP) are vocational training programmes that combine school and work-based educational programmes.[47] Typically, while juveniles are still in tenth grade of lower secondary schools

[43]See: e.g. Münch (1992).

[44]First situated in Berlin, and now in Bonn.

[45]Other institutions in close relation to the dual system are *Gewerbeaufsichtsämter*, *Arbeitsämter*, *Ämter für Ausbildungsförderung*.

[46]For more details about the legal background see Deutscher Bundestag (1974) and Münch (1992).

[47]Definition of the OECD.

they choose occupations[48] they want to undertake training in and, formally, apply with firms, usually in the region or state of residence[49], which train within these occupations.[50] If they are accepted by a firm for apprenticeship they are offered a contract at a fixed apprenticeship wage according to the relevant wage settings. On average, apprenticeship wages amount to about 20-30 percent of the wage of a skilled blue or white collar worker.[51] Most commonly, apprenticeship starts in autumn (two or three months after the schoolyear has finished) and final exams take place in spring or autumn depending on the duration of the apprenticeship. A minor proportion may also start in spring or at another point in time during the year. Apprenticeships last two to three years.[52] When apprenticeship starts, firms register the apprentice with the relevant chamber.[53]

Curriculum

Apprentices attend vocational schools on a part-time basis, usually one day a week, and in the remaining time they are trained within the firm they have an apprenticeship with.[54] The curriculum at vocational school contains to

[48]Here, they obtain or seek occupational guidance, for example through the labour office or through the school they attend directly. Many pupils do work placements whilst still at school, and a survey by the BiBB showed that many pupils make the decision about apprenticeship training on their own referring to this experience. See: Berufsbildungsbericht (1997).

[49]This is more a conjecture based on the fact that apprenticeship wages are too low to live on, and there is only a small chance of getting grants. Statistics are available on demand and supply of apprenticeships on a regional level, but not to our knowledge flow information about where apprentices come from.

[50]To some extent, juveniles may continue full-time education first doing, for example, a vocationally preparatory school year, *Berufsvorbereitungsjahr* before entering DSAP.

[51]See: Franz and Soskice (1994a).

[52]Since 1987, apprenticeships in specific fields may take 3.5 years.

[53]In Germany, chambers and guilds have an umbrella organisation and firms can become voluntarily a member with their local chamber. Firms in industry, for example, become a member with the chamber of commerce and industry, and firms in crafts become a member with the *handwerk* chamber.

[54]A considerable part of the actual debate about costs of training and giving firms incentives to train more in order to meet the demand refers to the amount of time

a considerable extent general components, as well as occupation specific components that are adapted to the needs of specific occupations.[55] The organisation of the training schedule in the firm may vary; however, only in the framework of legally binding regulations in the BBiG. The common procedure in all firms is that one person with a particular qualification, e.g. the *Meister* in artisan sector firms, supervises the apprentice and is responsible for the allocation of tasks he or she learns over the years of training. Also, reports may be written by the supervisor about the apprentice. Furthermore, firm specific knowledge may be taught in additional internal classes or seminars. Depending on the size and organisation of the firm apprentices may also be sent around all departments in the firm instead of staying in one department all through training, in order to understand, for instance, coordination between production and services within the firm.[56]

Examinations and (skilled workers') certificates

Generally, apprenticeships involve two exams: a mid-term exam and a final exam that must be passed in order to receive the apprenticeship certificate. Mid-term exams as well as final exams are unified and organised by the responsible chambers, for example, the chamber of industry and commerce and the *handwerk* chamber. At half term (one to one and half years) apprentices sit a mid-term exam. Final exams take place after two to three years depending on the occupation. Here, grades[57] are given and individuals

apprentices attend school. This has been more and more extended and takes place usually only in the morning which leads to a lot of absence of apprentices from the firm and, thus, may lead to reduced training on the job, as well as reduced benefits the firm may gain from the apprentice. Bardeleben (1994).

[55] This may of course also include industry specific components, for example, in case of metal worker in the chemical industry.

[56] See: Berufsbildungsbericht (1986).

[57] Grades are given on a scale from very good which is one, (*sehr gut*), to fail which is five or six.

can be failed, but can resit exams. In order to receive a certificate apprentices have to pass written and oral examinations, and practical exercises in craftmenship. The contents of the exam are general as well as occupation specific. After having passed the exam, apprentices receive a skilled workers' certificate for the occupational qualification issued by the responsible chambers. About 80 percent of apprentices pass exams at the first go. The remaining resit exams.[58] Occupational qualifications certified by the chambers are only those occupations that are recognised as apprenticeship occupations as we discuss later in more detail. Certificates are widely accepted by firms in Germany and are used to apply for jobs and to give evidence of the occupational qualification. This has led to the view of some authors that in Germany there are external occupational labour markets.[59]

2.4.2 Empirical features

Characteristics of demand and supply

Although over decades a continuously high supply by firms of apprenticeship places and a continuously high demand by juveniles for apprenticeship places could have been observed - as shown in table (2.5) -, supply and demand vary across years, partly due to demographic changes and business cycle effects, industry, which may reflect also business cycle effects, regions, which may reflect additionally structural differences, and occupations, which may reflect scarcity and excess of skills. In table (2.4), total numbers of apprentices are shown for the period 1963 to 1993. In 1963, about 1,268,000 juveniles were in apprenticeship; this is a similar level to seven years afterwards. Until the second oil crisis numbers have increased

[58]See: Münch (1992).
[59]See: Marsden (1990).

then, and they decreased again slightly from 1,715,481 in 1980 to 1,676,877 in 1981. In the following few years numbers have continued to increase again, due to entrance of the baby boom generation, reaching a peak of 1,831,265 in 1985. From then on numbers of apprentices have declined again and have returned to a level of 1,341,745 in 1993 which is comparable to the level of 20 years before. Also, this development virtually holds for men and women separately, and for the two main sectors of the German economy, *industry, commerce and service* and *craft.* as shown in table (2.5).

As can be seen from table (2.6), more than 80 percent of apprentices are trained in *industry, commerce, services* and *craft sector.* Taken together with *professions*, in these sectors of the economy 90 percent of all apprentices are trained in. Since the 70's trends show that while the proportion of apprentices in *industry, commerce and services* and *professions* continuously has increased, in the craft sector the proportion in the 90's, has returned to a comparable proportion observed in 1970. In table (2.7), supply and demand ratios of apprentices are shown broken down by states. Numbers reflect the South-North devide in Germany, and show uniformly that across states the ratio was more to the disadvantage of applicants in 1982 than in 1989. Furthermore, demand and supply varies by occupations which is not shown here.[60] An increase in demand for clerical professions has been observed during the early 80's coinciding with an increasing number of women entering apprenticeships.[61]

Demand

From table (2.8), it can be seen that on the demand side for apprenticeship a shift in the educational level at entry can be observed, particularly

[60] Numbers are available for single occupations from the BIBB. See webpage of the BIBB for selection of occupations.

[61] Berufsbildungsbericht (1997).

Table 2.4: Number of apprentices, total and by gender

Year	Total				Industry, commerce and services*	Craft sector
	total	men	women	%		
1963	1268503	805490	463013	36.5		
1965	1331948	846793	485155	36.4		
1967	1402465	813241	523114	37.2		
1969	1281762	816110	468521	36.5		
1970	1268714	821342	447372	35.2	723415	419530
1975	1328906	858960	469946	35.3	633958	504662
1976	1316562	841631	474931	36.0	611173	510356
1977	1397429	887182	510247	36.5	643817	556088
1978	1517373	950984	566389	37.3	691985	614905
1979	1644619	1023004	621615	37.7	748400	676215
1980	1715481	1060472	655009	38.1	786917	702331
1981	1676877	1029113	647764	38.6	771347	673564
1982	1675861	1021827	654034	39.0	764708	665525
1983	1721686	1045451	676235	39.2	791895	674903
1984	1800001	1081217	718784	39.9	841081	693233
1985	1831265	1087497	743768	40.6	874614	687454
1986	1805247	1059000	746247	41.3	882185	657780
1987	1738687	1006644	732043	42.1	865963	617823
1988	1657960	944147	713813	43.0	827213	577873
1989	1552534	883439	669095	43.0	783274	532546
1990	1476880	847069	629811	42.6	756416	486911
1991	1430211	826613	603598	42.2	734336	460417
1992	1388322	810888	577434	40.3	690605	459588
1993	1341745	790252	551493	41.1	646484	459018

Source: "Anerkannte Ausbildungsberufe" (1995). * includes banking, insurance, Catering, transport.

Table 2.5: Demand and supply of apprenticeship: balance

Year	New Apprenticeship contracts	Supply	Demand	Supply / Demand ratio	Change to previous year
1977	558400	583900	585400	99.7	
1978	601700	624000	625500	99.8	7.8
1979	640300	677200	660000	102.6	6.4
1980	650000	694600	667300	104.1	1.5
1981	605636	642984	627776	102.4	-6.8
1982	630990	650985	665170	97.9	4.2
1983	676734	696375	724142	96.2	7.2
1984	705652	726786	764078	95.1	4.3
1985	697089	719110	755994	95.1	-1.2
1986	684710	715880	730980	97.9	-1.8
1987	645746	690287	679626	101.6	-5.7
1988	604002	665964	628793	105.9	-6.5
1989	583736	668649	602014	111.1	-3.4
1990	545562	659435	559531	117.9	-6.5
1991	539466	668000	550671	121.3	-1.1
1992 (old states)	499985	633363	511741	121.8	-7.3
1993 (old states)	471169	554824	486010	114.2	-5.8
1994 (old states)	450210	502977	467666	107.6	-4.4
1995 (old states)	450128	493359	469524	105.1	0.0
1996 (old states)	449314	483180	473951	101.9	-0.2

Source: Berufsbildungsbericht (1997), Table (1).

Table 2.6: Distribution of apprentices across sectors

Year	Total	Industry, Commerce and Services	Craft Sector	Agricul-ture	Pro-fessions	Public Service	Others
1970	1268714	57.0	33.0	3.0	4.4	1.6	1.0
1975	1328906	47.7	37.9	2.5	7.7	3.5	0.7
1976	1316562	46.4	38.8	2.8	8.1	3.3	0.6
1977	1397429	46.1	39.8	2.9	7.4	3.2	0.6
1978	1517373	45.6	40.5	3.0	6.9	3.5	0.5
1979	1644619	45.5	41.1	2.8	6.7	3.3	0.6
1980	1715481	45.8	40.9	2.8	6.8	3.1	0.6
1981	1676877	46.0	40.2	2.8	7.4	3.2	0.4
1982	1675861	45.6	39.7	3.0	7.7	3.5	0.5
1983	1721686	46.0	39.2	3.0	7.6	3.7	0.5
1984	1800001	46.7	38.5	3.0	7.4	3.8	0.6
1985	1831265	47.7	37.5	2.9	7.2	4.0	0.7
1986	1805247	48.8	36.4	2.8	7.2	4.0	0.8
1987	1738687	49.8	35.5	2.6	7.2	4.1	0.8
1988	1657960	50.0	34.9	2.3	8.1	4.1	0.6
1989	1552534	50.4	34.3	2.2	8.3	4.0	0.8
1990	1476880	51.2	32.9	2.0	8.8	4.3	0.8
1991	1430211	51.3	32.2	1.9	9.6	4.3	0.7
1992	1388322	49.7	33.1	1.8	10.3	4.7	0.4
1993	1341745	48.2	34.2	1.8	10.7	4.6	0.5

Source: "Anerkannte Ausbildungsberufe" (1995).

Table 2.7: Supply/demand ratio of apprenticeships, by state

State	1982	1989
Schleswig Holstein	95.9	104.1
Hamburg	95.3	98.1
Lower Saxony	95.3	104.0
Bremen	93.7	98.2
North Rhine-Westphalia	96.8	102.6
Hessen	95.1	110.3
Rheinland-Pfalz	95.6	112.6
Baden-Würtenburg	100.9	119.7
Bavaria	101.2	128.0
Saarland	95.4	108.4
Berlin (west)	95.6	107.3
Federal Republic	97.6	111.1
Coef. of variation	0.0248	0.098

Source: Casey (1991).

Table 2.8: Transition of school leavers into vocational training

Transition year	Schooling degree received from:		
	lower or intermediate degree secondary school	lower and intermediate degree secondary school leavers, previous years	upper degree secondary school leavers, the same year and previous year
	percent	percent	percent
1977	61.5	12.7	9.0
1978	62.9	12.1	10.0
1979	59.7	17.0	11.0
1980	57.4	20.1	12.0
1981	52.7	21.6	14.0
1982	53.8	23.8	17.0
1983	54.5	28.1	23.0
1984	54.5	31.8	28.2
1985	55.1	31.6	32.3
1986	57.1	34.5	32.9
1987	56.8	31.6	32.1

Source: Berufsbildungsbericht (1988), Table 33, p.48. See text for further explanations.

in the 80's. While the proportion of school leavers with a lower or intermediate secondary school degree who have done apprenticeship afterwards has decreased continuously, the proportion of school leavers with an upper secondary school degree (*Abitur*) who do apprenticeship has almost tripled from the late 70's to 1987.[62] In 1987, for example, while 56.8 percent of school leavers with a lower or intermediate school degree have done apprenticeship immediately after leaving school, another 31.6 percent of those who take an extra year after school enter apprenticeship. On the other hand, 32.1 percent of upper secondary schooling graduates have done an apprenticeship.

Average education levels of apprentices within sectors are reported in table (2.9), for 1986.[63] Across all sectors, as shown in the last row of the table, it can be seen that 67.7 percent of all apprentices have either a lower secondary school degree (*Hauptschulabschluss*) or an intermediate secondary school degree (*Realschulabschluss*). Only 12.5 percent have an upper secondary degree (Abitur). A negligible small proportion, about 2.1 percent, have no school degree at all. Furthermore, looking at the educational background of apprentices broken down by sector, quite considerable differences become apparent. For example, in the craft sector the share of apprentices with a degree from the more vocationally orientated *Hauptschule* is remarkably high, 52.5 percent, and the shares of apprentices with a *Realschul degree* are quite high within the public sector and professions. Hence, between sectors

[62]However, in terms of total numbers as well as shares of birthcohorts, upper secondary degrees became more popular since the beginning of the 80's. Hence, this development may not imply that those who used to study are doing now apprenticeship instead. Likewise, it could mean that a share of juveniles postpones entry into apprenticeship for three years while they are doing an upper secondary school degree.

[63]Although an upward shift in educational levels of apprenticeship can be observed, presumably, the distribution across sectors may have stayed quite constant over time over the period 1975 to 1990.

Table 2.9: Schooling levels of apprentices in 1986, by sector

Sector	Without lower secondary school degree	With lower secondary school degree	Intermediate secondary school degree or comparable	Higher secondary school degree (Abitur / techn. Abitur	Full-time vocational education foundation year*	Vocational technical school**	Vocational preparation year
Industry and Commerce	1.1	28.3	36.5	17.4	3.8	12.3	0.6
Craft sector	3.9	52.5	20.0	5.2	9.0	7.7	1.7
Agriculture	1.7	27.0	25.4	14.3	25.9	5.4	0.4
Public service	0.1	11.0	54.5	15.6	11.3	7.6	-
Professions	0.1	10.2	60.9	17.1	0.6	10.8	0.2
Home Econ.	6.8	37.2	14.2	1.2	13.5	22.3	4.8
Navigation	6.3	45.7	27.3	17.9	2.7	-	-
All sectors	2.1	35.2	32.5	12.7	6.5	10.1	0.9

Source: Bundesbildungsbericht (1988), p.35, Table 20. * Translation used for *schulisches Berufsgrundbildungsjahr* and ** *Berufsfachschule.*

Table 2.10: Age of vocational school pupils, by gender

Year	Average Age		
	Males	Females	Total
1970	16.8	16.4	16.6
1975	17.1	16.8	16.9
1980	17.6	17.5	17.6
1985	18.2	18.2	18.2
1990	19.0	19.0	19.0
1991	19.0	19.0	19.0

Source: Berufsbildungsbericht (1995), p. 56.

Table 2.11: Share of apprentices in 1984, by age and gender

Age	Males	Females	Total
15 and younger	3.0	2.8	2.9
16	13.1	12.6	12.9
17	24.3	23.9	24.2
18	25.5	24.0	24.9
19	16.8	16.7	16.7
20	8.2	10.1	9.0
21	3.7	5.3	4.3
22 and older	5.4	4.6	5.1

Source: Berufsbildungsbericht (1986), p. 44.

the schooling degrees seem to reflect differences in skill levels acquired before apprenticeship, which are on the one hand vocationally orientated and on the other hand academically orientated.

Coinciding with the change in educational attainment, age of apprentices has increased considerably, from 1970 to 1990 by almost 2.5 years, as shown in table (2.10). Generally, apprentices are 16 to 21 years old, as can be seen from table (2.11). Furthermore, the age structure is almost identical for males and females. However, in the early 70's the average age of female apprentices was slightly lower due to high shares of females in apprenticeships that took only two years. During the period 1984 and 1988 the average age of female apprentices was slightly higher due to less favourable entry conditions into apprentice market.[64] The increase in age is due to longer full-time school attendance, thus, increase of share of pupils completing *Realschul degree* or *Abitur*, and increased attendance of vocational full-time schools prior to apprenticeship, e.g. *Berufsgrundbildungsjahr* and *Berufsvorbereitungsjahr*, which were attended more frequently in the 1980's.[65] Furthermore, the increase in compulsory school attendance of secondary schooling from 9 to 10 years affected the average age as well. Moreover, the age structure differs across occupations and reflects virtually pre-apprentice education.[66] Also, it is found that the average age of males in atypical occupations for males is usually higher than the average and vice versa, so is the average age of females in male occupations. From this, it may be conjectured that in order to realise an apprenticeship in less common occupations takes more maturity, i.e. higher age and higher education.[67]

Finally, another aspect of the demand side is that men and women are distributed differently across sectors and occupations. In table (2.12), we list the proportions of women within sectors. Overall, from 1981 to 1993, although a slight increase is found, the share of women in apprenticeships stayed virtually constant at approximately 40 percent. However, across sectors proportions vary quite a lot. In the most actively training sector, which is *industry, commerce and services*, the share of females was about average, i.e. 42 percent. On the other hand, in the *craft sector* only slightly

[64]See: Berufsbildungsbericht (1995), p.55.
[65]See: Berufsbildungsbericht (1986), p.44 and Berufsbildungsbericht (1995), pp.55.
[66]See: Berufsbildungsbericht (1995), p.55.
[67]See: Berufsbildungsbericht (1995), p.56.

Table 2.12: Share of female apprentices, by sector

Year	Total	Industry, Commerce and Services	Craft sector	Agriculture	Professions	Public Service	Others
1981	38.2	43.4	22.5	27.0	95.4	44.0	88.1
1982	39.0	42.7	23.2	30.5	95.9	46.4	90.1
1983	39.3	42.5	23.8	31.4	95.6	47.5	90.7
1984	39.9	43.0	24.7	31.0	95.7	47.7	90.7
1985	40.6	43.5	25.6	31.4	95.7	47.4	90.5
1986	41.3	43.6	26.7	31.9	95.6	47.7	91.2
1987	42.1						
1988	43.0						
1989	43.1						
1990	42.6	42.9	27.0	32.9	95.9	46.6	-
1991	42.2	42.0	25.5	31.9	95.5	48.4	-
1992	41.6	41.6	23.3	31.5	95.2	50.4	-
1993	41.1	41.4	22.0	30.5	94.9	51.8	-

Source: Bundesbildungsbericht (1986), p.41 and (1997), p.63.

more than one fifth of apprentices were female. Furthermore, the sector where men and women were trained in at most equal shares was the *public sector.* Though, only about 4 percent of apprentices are trained within this sector. In *professions*, an expanding training sector, women are the dominant group.

Supply

At a first glance, table (2.13) illustrates that in 1985 only 34.3 percent of all firms have been training and in 1990 only 28.3 percent according to data from the IAB-establishment panel. This feature stands perhaps in contrast to general belief that the dual system is a very profoundly established component in the German economy. One may note, however, that these percentages are not employment weighted. Thus, the more interesting it is that more than two thirds of firms are very small, one to nine employees, and despite the small size 27.8 percent in 1985 to 21.4 percent in 1990 of these have participated in the apprenticeship training scheme. In total in 1985 498,304 firms participated in the DSAP and 1990 435,425.[68] For comparison, as shown in table (2.17), workers with completed apprenticeships or vocational training are strongly represented across all sectors and all kinds of firms (firm sizes) in the economy.

Considerable variation across firm - sector cells, can be seen from breaking down training and non-training firms by sector and firm size, as summarised in tables (2.13) and (2.14). The likelihood that a small firm participates in the scheme seems to be lower than for a large company. Looking at proportions by sector it is found that firms in *metal and mechanical engineering*, in *electronics* and *leather, textile and food* have remarkably high proportions, higher than 50 percent. A very small proportion is found, for example, in *transport and communication.* From 1985 to 1990, in most sectors, the proportion of training firms has slightly decreased.

Furthermore, the likelihood that an apprentice is employed after completion of apprenticeship by the training firm is positively correlated with the size of the training firm, as shown in table (2.16), and varies across sectors. The latter finding can be seen from table (2.15) where transition rates of apprentices are listed by sectors. Figures show that less than 50 percent of training firms within most sectors employ all skilled workers they have trained and, thus, more than 50 percent of training firms produce a surplus of skilled workers that will move firm after training. However, it can be seen that the share of skilled workers that will change employer is quite low, for example, in *credit and insurance*, but quite high, for example, in *hotel and restaurant.* Furthermore, across all sectors, a high share of 60.4 percent of

[68]See also Pfeiffer (1996).

Table 2.13: Number of firms and training firms, by firm size

firm size		1985	1987	1988	1990
1- 9 employees	firms	1,179,642	1,195,322	1,221,584	1,237,052
	training firms	328,376	319,833	305,704	264,984
	share	27.8	26.8	25.0	21.4
10- 49 employees	firms	217,239	221,627	225,156	236,762
	training firms	125,583	127,412	126,209	122,439
	share	57.8	57.5	56.1	51.7
50-499 employees	firms	52,745	54,588	55,551	59,063
	training firms	40,320	42,114	42,498	43,494
	share	76.4	77.1	76.5	73.6
500+ employees	firms	4,281	4,436	4,474	4,794
	training firms	4,025	4,184	4,241	4,508
	share	94.0	94.3	94.8	94.0
total	firms	1,453,907	1,475,983	1,506,765	1,537,671
	training firms	498,304	493,543	478,652	435,425
	share	34.3	33.4	31.8	28.3

Source: Berufsbildungsstatistik, BIBB - Bundesinstitut für Berufsbildung (http://www.bibb.de/beruf)

apprentices is employed with the training firm afterwards. Finally, it can be seen from table (2.16) that about two thirds of apprentices are trained with firms that employ less than 200 employees. This reflects the historically strong interest of the *craft sector* in highly skilled workers and the participation in the DSAP.

Costs of apprenticeship

Average costs of apprenticeship have increased from 1971 to 1991 from 6,948 German Marks to 29,573 German Marks measured per apprentice and per year. These are gross costs based on a full cost calculation, therefore including, in addition to costs directly accountable to training, also other, *kalkulatorische*, cost components.[69] However, net costs, as well as benefits

[69]See: Bardeleben (1994).

Table 2.14: Number of firms and training firms, by sector

sector		1985	1987	1988	1990
agriculture,	firms	81,111	75,404	72,566	67,166
forestry,	training firms	28,992	25,454	22,157	16,752
fishery	share	35.7	33.8	30.5	24.3
energy, water,	firms	4,219	4,156	4,171	4,137
mining	training firms	1,123	1,178	1,148	1,046
	share	26.6	28.3	27.5	25.3
chemicals,	firms	24,208	24,058	24,266	24,241
plastics, construc-	training firms	6,936	6,870	6,665	6,155
tion materials	share	28.7	28.6	27.5	25.4
metal working,	firms	54,287	55,189	56,431	58,303
mechanical	training firms	27,430	27,503	26,723	24,751
engineering	share	50.5	49.8	47.4	42.4
vehicles, computing,	firms	46,235	48,087	49,262	50,531
electronics	training firms	27,745	28,410	28,196	26,555
	share	60.0	59.1	57.2	52.6
precision mechanics,	firms	22,456	23,230	23,911	24,674
optical equip., clocks,	training firms	9,736	10,287	10,291	9,621
jewellery	share	43.3	44.3	43.0	39.0
wood, paper,	firms	48,870	48,599	49,084	49,411
printing	training firms	23.355	22,679	21,688	20,035
	share	47.8	46.7	44.2	40.5
leather, textile,	firms	79,050	76,602	75,778	70,941
food	training firms	42,667	41,020	38,921	31,981
	share	54.0	53.5	51.4	45.1
construction,	firms	130,372	128,481	130,127	132,234
carpentry,	training firms	63.576	58,620	54,387	48,114
renovation	share	48.8	45.6	41.8	36.4
trade	firms	322,040	325,095	332,663	337,676
	training firms	88,511	88,924	87,105	77,251
	share	27.5	27.4	26.2	22.9
transport,	firms	61,687	64,040	65,941	69,414
communication	training firm	7,349	8,137	8,282	8,021
	share	11.9	12.7	12.6	11.6
credit, insurance	firms	34,202	35,820	37,556	38,870
	training firms	8,977	9,341	9,262	8,629
	share	26.2	26.1	24.7	22.2
services	firms	449,637	472,845	489,822	515,004
	training firms	143,852	147,830	147,578	142,223
	share	32.0	31.3	30.1	27.6
non profit firms	firms	67,699	68,175	68,293	68,418
	training firms	9,217	8,221	7,326	5,941
	share	13.6	12.1	10.7	8.7
local authority/	firms	25,682	26,060	26,309	26,544
social insurance	training firms	8.524	8,974	8,756	8,279
	share	33.2	34.4	33.3	31.2
others	firms	2,143	142	585	103
	training firms	314	93	167	71
	share	14.7	65.5	28.5	68.9
total	firms	1,453,907	1,475,983	1,506,765	1,537,671
	training firms	498,304	493,543	478,652	435,425
	share	34.3	33.4	31.8	28.3

Source: Berufsbildungsstatistik, BIBB - Bundesinstitut für Berufsbildung (http://www.bibb.de/beruf)

Table 2.15: Transition rates of apprentices in 1995, by sector

sector	# of training firms	share taking over all apprentices	# of apprentices who completed certificate	share employed by training firm
Agriculture	8000	30.5	8200	33.3
Industry and mining	47000	51.2	124100	68.0
Construction	26000	75.3	38900	76.4
Trade/transport/ Communication	39000	43.8	74600	55.0
Credit and insurance	9000	41.9	30300	71.3
Hotel and restaurant	10000	31.4	18700	39.2
Education/publishers	4000	16.5	15800	36.7
Health	13000	27.0	38000	52.5
Consultancy (law/economic) and other services	19000	43.8	28300	51.4
Non-profit Organisation /public	12000	44.0	33900	62.5
All sectors	187000	47.0	410800	60.4

Source: IAB-Betriebspanel, 3. wave 1995 - Berufsbildungsbericht, 1997, p.107.

Table 2.16: Transition rates of apprentices in 1995, by firm size

firm size	# of apprentices finished	share employed by training firm
1 to 4	16000	47.3
5 to 9	54000	44.0
10 to 19	52000	48.6
20 to 49	65000	61.3
50 to 99	40000	69.1
100 to 199	41000	62.4
200 to 499	47000	61.5
500 to 999	34000	69.4
1000 to 4999	44000	71.3
5000 and more	18000	81.7
all establishments	411000	60.4

Source: IAB - Betriebespanel, 3. wave 1995, Berufsbildungsbericht (1997), p.108.

Table 2.17: Education in 1987, by sector and firm size

	Number of employees by establishment					
	1	2-10	11-100	101-1000	1001...	total
Manufacturing						
Primary & grounds						
No vocational training	36.8	42.0	43.0	40.3	36.9	39.4
Vocational training	61.1	56.6	54.7	54.9	56.4	55.4
University	2.1	1.3	2.4	4.7	6.7	5.0
Investment goods						
No vocational training	31.4	33.0	32.8	35.7	35.7	34.9
Vocational training	67.3	66.0	65.3	59.9	54.9	59.5
University	1.3	1.1	1.9	4.4	9.5	5.6
Consumer goods						
No vocational training	33.5	38.4	43.1	47.1	44.9	44.0
Vocational training	65.8	61.1	56.0	51.3	52.3	54.8
University	0.8	0.5	0.9	1.6	2.8	1.2
Construction						
No vocational training	32.7	31.4	34.5	34.8	29.6	33.6
Vocational training	66.3	68.1	64.3	60.5	59.9	64.4
University	1.0	0.5	1.3	4.8	10.5	2.0
Trade						
No vocational training	27.5	27.9	28.0	29.9	29.9	28.5
Vocational training	71.0	69.5	70.3	67.9	65.6	69.3
University	1.5	2.6	1.7	2.3	4.4	2.1
Transportation						
No vocational training	38.4	38.2	38.2	37.1	30.9	36.7
Vocational training	60.9	61.0	60.8	61.0	64.8	61.6
University	0.7	0.8	1.0	1.9	4.3	1.7
Credit and real estate						
No vocational training	29.4	22.3	21.8	23.5	24.4	23.2
Vocational training	69.7	74.1	74.6	70.7	67.0	71.4
University	2.9	3.6	3.6	5.8	8.6	5.4
Other personal services						
No vocational training	43.3	37.3	38.2	31.8	25.3	34.3
Vocational training	53.6	58.8	52.6	56.6	55.1	55.8
University	3.0	3.8	9.3	11.7	19.6	9.9
Other productive services						
No vocational training	26.0	28.0	33.1	40.3	33.7	33.0
Vocational training	67.0	63.5	56.6	48.6	46.3	56.7
University	7.0	8.5	10.4	11.1	20.0	10.4
Total economy						
No vocational training	34.2	33.1	34.5	36.0	34.0	39.0
Vocational training	63.2	64.1	62.0	58.6	56.3	57.0
University	2.6	2.8	3.5	5.4	9.7	4.0

Source: Federal Ministry of Labour and Social Affairs. Table taken from OECD (1989), p.124.

Table 2.18: Costs of apprenticeship in 1991

• Personnel costs (apprenticeship wage, contributions to social welfare system)	49 %
• Costs of training personnel	39 %
• Expenses for training facilities	4 %
• Other costs (e.g. learning material, examination fees, external courses, clothing)	8 %
• DEM 29,572 per apprentice per year (full cost calculation)	100 %

Source: See von Bardeleben (1994). Estimates are based on a survey of 1370 training firms in industry and trade, and craft sector conducted by the BiBB in 1992 .

from apprentices' work have increased which leads to a quite constant ratio of gross to net costs of approximately 0.6 all through the period. Furthermore, it is found that gross as well as net costs are positively correlated with firm size and, thus, benefits are higher for small firms. Moreover, total costs are lower in the craft sector.[70]

Generally, calculations of costs of apprenticeship depend on the components included. If all direct and indirect costs are considered, costs that arise to the establishments contain components for personnel costs, costs for training staff, and others. The distribution across those is shown in table (2.18) for 1991. If only direct costs of training were considered, mainly personnel costs for training staff are reduced since most trainers are not employed as such, and rather train the apprentice only part-time while at work. More generally, costs of apprenticeship arise foremost to the firm, but also to the chambers, employer organisations and employee organisations. According to a survey conducted in 1974 by the German Parliament the share of costs establishments have to pay is, though, 97 percent in terms of gross costs, and if estimated benefits produced by apprentices are deducted, the share

[70]All of these results are based on a survey conducted by the BIBB in 1992 questioning 1370 training firms in *industry and trade* and *craft.*

Table 2.19: Average monthly apprenticeship wages in DEM, by sector

Sector	1976	1982		1983		1984	
Industry and trade	438	633	(+44.5)*	653	(+49.1)	669	(+52.7)
Craft	349	501	(+43.6)	512	(+46.7)	525	(+50.4)
Agriculture	365	535	(+46.6)	564	(+54.5)	576	(+57.8)
Public service	424	586	(+38.2)	601	(+41.7)	615	(+45.0)
Professions	347	523	(+50.7)	541	(+55.9)	549	(+58.2)
Total	396	570	(+43.9)	587	(+48.2)	602	(+52.0)

Source: Bundesbildungsbericht (1986), p.112. Nominal apprenticeship wages are reported. * In parentheses increment to 1976 is shown in percentages.

is slightly lower; 95.3 percent[71].

Apprenticeship wages are the major component in the cost calculations scheme, yet vary considerably across occupations, industries, and the year of apprenticeship. From the first year of apprenticeship onwards apprenticeship wages increase according to a scale partly reflecting that apprentices become more productive to the training firm.[72] In table (2.19) (nominal) apprenticeship wages are shown for several years broken down by sector. Among those, *industry and trade* are high paying sectors and *craft* and *professions* are relatively low paying sectors on average across all occupations. In table (2.20) for 1972 costs within selected occupations are shown. Occupations chosen are ones frequently observed. As can be seen, training costs in occupations such as *hairdresser*, are particularly low, while occupations such as *optician*, are high cost apprenticeships. This holds in terms of gross as well as net costs.[73] If apprentice wages paid are lower than marginal products, then apprentices pay part of training costs.

[71]See: Deutsche Bundestag (1974).

[72]See: Franz and Soskice (1994), p.9. Also, school attendance reduces over years of apprenticeship which increase potential benefits to the firm.

[73]Net costs are defined as gross costs minus benefits.

Table 2.20: Gross and net apprenticeship costs in 1972, by occupation

Occupation	Gross costs in DEM	Net costs in DEM
Optician	11969.68	8482.13
Precision mechanic	11376.28	9120.18
Mechanic	10219.14	7642.26
Engine fitter	10042.00	8101.3
Banking professionals	9808.87	6336.17
Clerk Life insurance	9645.01	5157.46
Office Assistant	9058.41	5959.26
Clerk Industry	8210.26	3572.79
Clerk in wholesale and international trade	8012.50	4450.62
Clerk office	7020.00	3170.46
Clear Retail sale	5407.11	2309.69
Sales person	4944.91	2515.46
Hairdresser	3614.93	1879.76

Source: Deutscher Bundestag (1974), pp. 101. Figures are based on a survey of establishments: 16,870 apprentices in 148 apprenticeship occupations were included. Not weighted average costs per year of apprenticeship are shown.

Occupation

The outcome of apprenticeship is the occupational qualification, hence skills also marketable outside the training firm,[74] and the provision of skilled workers to the economy. Thus, it seems that the occupation of a worker becomes a particularly interesting characteristic in the German labour market.

Over the recent decades, the number of recognised apprenticeship occupations has been steadily reduced and adapted to modern work places with respect to organisation (e.g. duration) and contents (e.g. general schooling components). Reduction of apprenticeship occupations, by summary of similar occupations or dropping unoccupied occupations, makes the system more transparent and it is easier to keep regulations up to date. In table (2.21), it is shown that while in 1971 still 600 apprenticeship occupations existed, by 1981 the number had fallen to 446 and by 1990 only 370 remained. Also, one may note that at the same time many new apprenticeship occupations were created in new sectors and technologies, which has also led to the increased participation of women in DSAP. Even though the number of recognised apprenticeship occupations was reduced this may have little impact on actual occupations the vast number of juveniles undertake apprenticeships in.

This is because, empirically, concentration within a relatively small number of occupations has always been high. Thus, as shown in table (2.22), about 50 percent (25 percent) of men are trained in only 15 (5) occupations and 65 -70 percent (35 percent) of women in the 15 (5) most frequently observed occupations. Furthermore, gender segregation between typical female and

[74] See external occupational labour market discussion in, e.g., Marsden (1990).

Table 2.21: Number of apprenticeship occupations

Year	Total #	Year	Total #	Year	Total #
1957	600	1981	446	1990	377
..		1982	438	1991	377
1971	606	1986	420	1992	376
..		1987	383	1993	373
1974	498	1988	382	1994	370
..		1989	378		

Source: Kempf (1985), and Anerkannte Ausbildungsberufe (1995).

typical male occupations is observed. Generally, women are more often in service occupations while men are more frequently in manufacturing occupations. Policies targeting segregation and possibly higher unemployment rates of women in female occupations have aimed at giving incentives both to female juveniles seeking apprenticeship as well as training firms to train women in occupations that are typically occupied by males. This may have led to a slight decrease in concentration between 1980 and 1986. Moreover, concentration of apprentices in a number of occupations regularly leads to unoccupied apprenticeship places within less preferred occupations or applicants who cannot be considered in the specific occupations due to surplus in demand. These problems may, partly, reflect information problems, regional differences - as shown before -, and also lack of attractiveness of apprenticeship place offers or mismatch in preferences.

The level of secondary schooling and training durations, that vary with the nature of the job, may partly capture the level of training required for the corresponding occupational qualification. For example, the highest proportions of *Abitur* holders are in *clerical worker - insurance* and *bank clerk* while highest proportions of *Hauptschul* dropouts are in *homehelp* and

Table 2.22: Concentration of apprentices in occupations

Year	Apprentices in the ... most frequent occupations					
	Male			Female		
	five	ten	fifteen	five	ten	fifteen
1980	26.2	40.4	50.8	40.3	60.7	71.7
1981	26.2	40.0	50.3	38.3	59.4	70.4
1982	25.3	39.2	49.7	37.0	57.8	69.6
1983	24.7	38.5	49.2	36.6	56.8	68.7
1984	24.1	38.0	48.9	36.2	56.6	68.3
1985	23.7	37.2	48.2	36.0	56.1	67.9
1986	23.6	36.9	47.8	35.6	55.6	67.5

Source: Bundesbildungbericht (1986), p.42.

Table 2.23: New apprenticeship contracts in 1995, by training duration

Duration of apprenticeship	total # of new contracts	share of all new contracts
up to 24 months	15988	2.8
30 to 36 months	411301	71.0
42 months	134735	23.3
first step training	16558	2.9
total	578582	100.00

Source: Berufsbildungsbericht (1997), p.64.

Table 2.24: Occupations with apprenticeship up to two years

Occupational qualification	Year qualification was recognised	Number of new contracts
Sales person	1968	9536
Professional in catering	1980	1613
Subassembly management	1940	1305
Specialist packing	1956	1290
Scaffholding builder	1990	496
Photolab worker	1981	404
Professional driver	1973	350
Library assistant	1975	276
Others		713
Total		15983

Source: Berufsbildungsbericht (1997), p.65.

housepainter, for example.[75] As a general rule, one may claim that the shorter the total training period the lower the skill level and vice versa. As a result, the length of time needed to acquire a minimum level of job specific skills will vary from occupation to occupation. However, as can be seen in table (2.23) for 1995 the duration of 71 percent of apprenticeships is 2.5-3 years. Only very few, 2.8 percent, take less than 2 years and 23.3 percent take 3.5 years. Examples for occupations that take less than two years of apprenticeship are listed in table (2.24). Among those are, for example, sales persons. Finally, and as has been shown before in table (2.20), gross costs and benefits vary across occupations.

A further issue is the ranking of apprenticeship occupations or programmes, similarly to a ranking of education or universities in the U.S.. Although this is hard to measure and may vary depending on demand and supply by industry, firm and occupation, some authors seem to be in favour of

[75]See: Berufsbildungbericht (1991).

the existence of such a ranking. Steedman (1993) wrote that in the public mind, a definite and complex ranking of apprenticeship places exists linked to expected lifetime returns. As a general rule, apprenticeships in *industry* are more highly sought after than in *craft* and apprenticeships in large firms in *industry* are most highly sought.

Transition from apprenticeship to work

The most direct transition from apprenticeship to work would be for the trainees to work as a skilled worker in the training firm and in the occupation trained in. According to a survey in 1992 conducted by the BIBB, for 60 percent of apprentices this was the case. The remaining take various routes, among which change in occupation and further schooling are of significance and for men, doing national service. Only a minor proportion is affected by unemployment.[76]

The number of apprentices taken over by firms after completion of training is of importance. On the one hand this figure is the outcome of demand for and supply of skilled work after completion of apprenticeship programmes. On the other hand a lot of attention has been paid to this figure, since to both politicians and economists it is not yet clear why the apprenticeship programme in Germany, and other German speaking countries, has persisted while it virtually ceased to exist in the U.S. after the second world war and in the U.K. even before that.[77]

In table (2.25) tenure with the training firm, counted from completion of apprenticeship training onwards, is listed for various cohorts of apprentices.

[76]See: Berufsbildungsbericht (1997), p.110. These figures show that 12 months after completion of apprenticeship approximately 30 percent of males are doing national service.

[77]Winkelmann (1994).

Table 2.25: Tenure of apprentices with training firm after apprenticeship

Period of completion of apprenticeship	Tenure in years 0	1	1-2	≥ 2	still there
until 1959	21.2	16.9	14.8	32.1	15.1
1960-1969	22.5	18.2	14.7	26.2	20.4
1970-1979	21.4	16.2	8.8	7.9	-
all	21.1	17.0	13.3	24.8	23.8

Source: Bundesbildungsbericht (1987).

Patterns across cohorts seem to be quite similar.[78] About 50 percent of skilled workers stay less than 2 years with the training firm. Motivations behind job changes after training may be manifold. Some have been presented earlier: For example, we have seen in table (2.16) that on average, across all sectors, only 43 percent of firms employ all of their apprentices afterwards; thus, a surplus seems to be trained. On the other hand, in table (2.15) we have seen that 60.4 percent of all apprentices are employed with the training firm straight after apprenticeship. As we have pointed out before, costs of training seem to be lower in the *craft sector* than in *industry sector.* Therefore, one may conjecture that in the craft sector a surplus of skilled workers is trained. Hence, a certain number of skilled workers may change firms (for exogenous reasons) afterwards, for example change to industry. Contrasting evidence, however, is shown in table (2.26). From comparison of industries of apprenticeship and of first employment for movers it can be seen that movers are most likely to stay in the sector they have been trained in. This also holds for the craft sector. On average, across all sectors 20-30 percent change industries.

[78]One must note that for the 1970-1979 cohort not enough time had elapsed to make shares for 2 and more years of tenure comparable to the other figures in the table.

Table 2.26: Comparison of training sector and sector of first employment for movers*

Sector: Apprenticeship	Sector: First employment					
	Agriculture	Manufacturing	Craft Sector	Trade	Others	Total
Agriculture	76.9	3.8	7.5	1.6	10.3	100
Manufacturing	1.0	69.4	9.0	4.4	16.2	100
Craft sector	3.2	13.8	69.8	3.0	10.2	100
Trade	0.9	10.6	3.3	69.1	16.1	100
Others	2.0	9.8	6.6	4.8	76.9	100

Source: Berufsbildungsbericht (1980), p.49. Others includes: Mining and energy, transport, banks and insurances, services, organisations, public services.

* Movers have changed employer immediately after apprenticeship.

Table 2.27: Transition of apprentices with A-levels after apprenticeship

Transition to..or	total	males	females
Work in..			
stay occupation, stay firm	48	37	55
stay occupation, move firm	12	6	15
move occupation, stay firm	1	1	1
move occupation, move firm	2	2	2
study			
technical college	6	7	6
university	15	17	14
Other (e.g. military service)	16	31	7
Sum	100	100	100

Source: Survey in 1990, second survey in 1993.; Berufsbildungsbericht (1995).

While typically apprentices have a lower or intermediate secondary school degree, since the mid 80's a growing number of apprentices have completed an upper secondary school degree. Hence, it may be asked whether transition for this group has different features than for the remaining ones. In table (2.27) transition rates for this group of skilled workers are listed in total and distinguished by gender for 1990. Perhaps, striking is the small proportion of only 20 percent, for both males and females, who study after training. About half of this group stay in the occupation trained in. Hence, it seems that career prospects opened by apprenticeship are sufficiently attractive to upper secondary school level graduates as well. Motives for choosing apprenticeships instead of studying could be the access workers gain to occupational labour markets and (personal) contacts with a firm by an apprenticeship. This may increase employment prospects so much that studying becomes too costly.

2.5 Conclusions

The main route people take to acquire skills in Germany is the dual system apprenticeship programme. Apprenticeships lead to a certificate in one of the recognised occupational qualifications. Since about 60-70 percent of the workforce is taking this route, by international standards a high proportion of the population is skilled and has acquired an occupational qualification at a young age.

The objective of this chapter was to describe the dual system of apprenticeship programme and characterise its static and dynamic features. Generally, the curriculum of apprenticeship, including examinations, has been fairly static since 1969. Empirically, however, we have shown that dynamics are implied on the demand side, with respect to education levels, as well as the supply side, with respect to composition, as well as costs and institutional settings, such as recognised occupations. Also we have shown that while quantitatively men and women participate strongly, not quite equally, in the dual system apprenticeship programme, these groups differ considerably with respect to characteristics, such as the occupations they are trained in and work in.

In the following empirical part of the thesis, the description of the education and training history of apprentices up to the point when they complete training is of particular interest. Here is the direct link to the empirical part of this thesis in which the empirical analysis is based on wage data and work histories from completion of apprenticeship onwards.

From this description, we can summarise that juveniles enter apprenticeship at the age of 16 to 22 and stay on in training for 2 to 3 years, more rarely up to 3.5 years. Apprentices can be distinguished into apprentices with a degree from lower, intermediate and higher secondary schooling. The secondary school degree level as well as duration of apprenticeship may be correlated with the level or kind of apprenticeship, or more specifically with the occupation of qualification. Furthermore, school leavers with lower secondary schooling levels may be more likely in craft sector and more manual orientated apprenticeship occupations. Intermediate and higher secondary school degree holders may be more likely in industry and clerical apprenticeship occupations. Over the period 1975 to 1990, the share of juveniles with matriculation entering apprenticeship has increased considerably. However, the proportion of this group is still not higher than 15 percent. Additionally, this group of graduates usually enters newly created apprenticeships and, hence, one may not expect this group to crowd out graduates with lower degrees from apprenticeships as has been illustrated by the data presented.

Based on these stylised features of apprentices, a sample of young skilled workers is generated from the IABS, as described in the next section and used for the empirical analyses in part three of this thesis.

The empirical analysis of outcomes by education incorporates the selection into education and training programme issue as has been well discussed for the U.S. and the U.K..[79] For Germany, where education and training is highly institutionalised, this may be much less an issue than for other countries. Using the IABS in the empirical part of this thesis, even if one assumes that this is a relevant issue for the German labour market, we have to admit that we are constrained by the information we have.

A selection of young skilled workers who have been trained within the dual system of apprenticeship results in a sample for the major group of workers, which is about 70 percent of the total work force. Ignoring selection, even if it is an issue, may result in empirical results not representative for the entire population. However, as discussed in the survey in chapter 1, in the literature on male-female wage differentials male- female wage differentials may be smaller moving upwards in the distribution of education. Hence, results found for the medium skilled in Germany may not be representative for the highly skilled, nor the unskilled. One of the main reasons for selecting this group of workers is that, the analysis of the gender wage gap hinges on precise measures of human capital characteristics, as well as precise wage data. As we will see, one can derive very accurate measures for these variables using the IABS for this group of workers.

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[79]See e.g. Blundell, et al. (1995).

2.6 Appendix: Demographics by gender

In the following, we present further statistics separately for men and women to document gender specific features of the labour market in Germany. In table (2.28) labour force participation rates for the entire workforce are reported for 1975 to 1994. It can be seen that while the labour force participation of men is constantly high, the labour force participation of women is quite low and has increased only from 48 percent in 1975 to 55 percent in 1994. This increase reflects partly the increasing labour force participation of married women. Until recently, women with children younger than 6 years have carried a high probability to withdraw from work; the labour force participation for this group has been only 32-35 percent until the late 80's and, by 1994, it has increased to 46.3 percent. Labour force participation rates for women, which are low, for example, in comparison to the U.K. and the Scandinavian countries, may capture the relatively low offer of part time work in Germany, and child care policy. For illustration in table (2.29) the distribution of hours worked in 1984 is shown. While virtually all men work full-time, 30 percent of women work less than 35 hours a week.

Looking at demographics for the population, shown in table (2.30), further factors can be found that may have contributed to the increase in average labour force participation rates of women. First, quite a dramatic increase in the age at first marriage is revealed. It follows, most likely, that the age of women when they have their first child has increased as well. For both groups of women labour force participation rates are relatively high. Also, it can be seen that fertility rates have gone down since the 70's, and the share of unmarried mothers has risen.

Another statistic that documents age and gender specific patterns is the

Table 2.28: Labour force participation in West-Germany, 16-65 years old

	Men	Women			
Year	all	all	unmarried	married	with child 0-6 years
1975	86.0	48.2	62.7	43.9	32.9
1976	85.0	48.3	61.9	43.9	32.9
1977	84.6	48.9	61.5	44.7	33.6
1978	84.5	49.0	62.4	44.7	33.4
1979	84.5	49.7	60.7	45.2	33.8
1980	84.4	50.2	60.6	46.1	35.1
1981	83.5	50.6	59.5	46.8	35.6
1982	83.0	51.0	58.5	47.4	35.7
1983	82.0	50.7	61.4	47.3	-
1984	81.4	51.7	58.8	47.5	-
1985	81.9	52.7	-	47.5	34.2
1986	82.0	53.4	-	47.8	34.4
1987	82.3	54.1	-	48.4	34.6
1988	82.5	55.0	-	48.5	-
1989	-	-	-	49.4	-
1994	-	55.1	60.4	52.7	46.3

Source: Statistische Jahrbücher, various years

Table 2.29: Distribution of weekly hours worked

	Hours worked	women	men
1984	≤ 20	7.0 %	1.9 %
	20-34	25.7 %	1.5 %
	35+	67.3 %	98.0 %

Source: Statistisches Bundesamt: EG Arbeitsbeschäftigungsstichprobe.

Table 2.30: Demographics

	Average age at first marriage		Fertility rate	Percentage of unmarried mothers
	Women	Men		
1975	23.7	25.3	1.45	6.1
1980	23.4	26.1	1.44	7.6
1985	24.6	27.2	1.28	9.4

Source: Statistisches Bundesamt, Fachserie 1, Bevölkerung und Erwerbstätigkeit, Reihe 2, Bevölkerungsbewegung, Federal Republic of Germany.

Table 2.31: Unemployment rates, by age groups

	total	15-20*	20-30	30-40	40-50	50-55	55-60	60+
1975	4.7							
1976		7.1	4.7	2.8	2. 6	2.6	3.4	1.8
1978		6.4	4.5	3.0	2.5	2.6	3.3	1.5
1980	3.8	4.9	3.5	2.4	1.9	2.0	3.2	2.0
1982		9.1	7.6	5.0	3.8	3.9	5.2	3.5
1983	9.1							
1985	9.3	12.8	10.5	8.0	6.0	6.1	8.5	3.3
1987	8.9	10.0	9.3	8.0	6.6	6.9	9.9	4.9
1988	8.7							
1989		8.1	7.4	7.3	5.8	6.1	11.7	5.7

Source: German Microzensus and published by the Statistisches Bundesamt.

Table 2.32: Unemployment rates, by gender

Year	Total	Males	Females	Youth
75	4	3.7	4.5	-
79	3.3	2.5	4.5	3.7
83	8.2	7.5	9.3	10.7
86	8	7	9.4	8.4
87	7.9	7.1	9.1	7.4

Source: OECD (1988), p.43. Unemployment is measured in percent of total labour force.

unemployment rate. From tables (2.31) and (2.32) it can be summarised that young workers, generally, carry a slightly higher risk of unemployment than older workers. Furthermore, it seems that unemployment rates for women are higher than for men. These features seem to hold over the entire period looked at here.

Chapter 3

Description of the data source and the sample

In this section, we describe the sample design of our German data and the creation of the analysis sample, a sample of young skilled workers who have received qualification within the dual system apprenticeship programme. We present the definitions of the main variables.

3.1 The IAB employment sample

The German data we use to create a sample of young skilled workers is the IAB - employment sample (IABS). The IABS is a 1 % random sample taken from the event history data file (HF), *Historikdatei*, of the social security insurance scheme which is collected by the German Federal Bureau of Labour (Bundesanstalt für Arbeit) and supplemented by information on the duration of the receipt of social benefits as well as by aggregated firm data information. The data we use is available for the period 1975 - 1990. Only in 1996 was the IABS made available to the public by the Institute of

Labour Market and Occupation Research (Institut für Arbeitsmarkt- und Berufsforschung), in Nürnberg.[1]

The HF, the data sample the IABS is drawn from, is built from the employment statistics, *Beschäftigentenstatistik*, and is a longitudinal event history file that contains approximately 600 million record spells. In the following we give a summary of main features of the sample design.[2] The employment statistic has been built up since 1973 when the integrated social insurance procedure, *integrierte Meldeverfahren zur Kranken-, Renten- und Arbeitslosenversicherung*, was introduced. It compels employers to report within a specific space of time and in data processable form on employees who are subject to a health or unemployment insurance, or who are participating in a pension scheme. All data collected are process produced and the employers forward information as prescribed by the *Datenerfassungs- und Datenüberwachungsverordnung* on education, occupation, wages etc. in a questionnaire. Usually, they take the information from their personnel files. The data set is designed as an event history data set. Hence, each change in the employment relationship between the employee and employer induces a new spell in the data set. As a result, within one year several spells for the same individual may be registered. Spells reported on changes within a year are supplemented by spells at the end of each year, the 31 December or 1 January of each year.[3] The compulsory yearly reporting ensures that

[1] Since autumn 1999 the data set with more information on communal level and for the period 1975 - 1995 has been made available. Our data contains instead more information on firms.

[2] For more details see: Bender and Hilzendegen (1995), Bender, et al. (1996).

[3] See for detailed time intervals of reporting in: Bender, Hilzendegen, 1995, p.2. Note that firm changes must be reported in any case whereas changes within firms during the year need not to be reported.

records are available without gaps for the individual work histories. There are legal sanctions for misreporting.

The data are collected in four steps. Employers report to the health insurance institutions. These supplement the reports and pass them on to the public pensions insurance institutions. From there the data go to the Federal Bureau of Labour. The records on each individual are completed by the classification into industries performed in the Federal Bureau of Labour.

The employment statistics contains continuous individual employment histories about individuals who have been at least once in an employment relation eligible to the social security insurance scheme, thus have earned more than the lower social security threshold, or are eligible due to the duration of the employment contract.[4] Therefore included are all dependent employees in the private sector, i.e. almost 80 percent of total employment in West Germany. Not included in the employment statistic are: civil servants, self-employed[5], unpaid family workers and people who are not eligible for benefits from the social security system. Also enrolled students and men in national service are not included.[6] An important consequence of the method of data collection is that, daily wages contained in the data are censored from above and truncated from below. This is because if the wage is above the upper social security threshold, *Beitragsbemessungsgrenze*, the daily social security threshold is reported instead. For illustration, in 1975 the upper threshold was 2,800 German Mark per month and in 1990 it was 6,300 German Mark per month. Furthermore, if the wage is below the lower

[4]The latter is the reason why apprentices are included in the data.

[5]Self-employed are excluded unless they contribute voluntarily to the social security scheme.

[6]Thus, these spells cause a gap in the individual record.

social security threshold, the employee does not have to pay social security contributions and, therefore, does not appear in the dataset. Thus, a gap in the record is the result. Again, for illustration, in 1975 the lower social security threshold was 350 German Mark per month and in 1990 470 German Mark per month.[7]

Social security related variables contained in the employment statistics are very precise since they are checked by the employer and the relevant institutions. Furthermore, this data is used to calculate contributions to the health and unemployment insurance and the public pension scheme, as well as benefits from the latter two. From the employment statistics the HF is generated which is cleaned from inconsistencies, double spells, etc..

From the HF, separately for Germans and foreigners, a 1 % sample is drawn. A stratified sampling procedure results in a sample representative with respect to individuals, but not representative with respect to firms. The file contains the *individual identification number* and the variables gender, year of birth, nationality, education, occupation of work, job status, firm, sector, region, start and end of employment. Using the individual identification number, the data are merged with the social contribution recipients data file (SCF). By this procedure, quite detailed information on non-working spells is added. The SCF contains information about social benefits individuals have received, such as unemployment insurance, unemployment assistance and assistance (*Unterhaltsgeld*). However, many benefit categories have been aggregated in the data.[8]

[7]Bender and Hilzendegen (1995).

[8]In the IABS used in this study only the duration in each status is available, but not the amount of benefits received. In the newly issued IABS the latter information is included.

The sample is supplemented by firm level data generated from the entire HF. These information are, for example, the share of employees within a firm without any post-school training, with further training and with a degree from university. Before the completed data set is available as a scientific use file anonymisaton procedures are conducted. These transformations do not change the representative character of the data set and statistical results.[9] In the cross-sectional dimension, the IABS contains information on approx. 200.000 individuals per year and in the longitudinal dimension, i.e. 16 years, there is data on approx. 430.000 individuals.

3.2 Sample selection and definition of variables

The creation of the sample of skilled workers involved the selection of desired individuals records and the construction of the variables measuring human capital acquisition. Furthermore, in this section we describe the variables of interest for the subsequent analysis of male-female wage differentials.

3.2.1 Selection rules

Our sample taken from the IABS available for the period of 1975 to 1990 contains workers who meet the following selection rules: The individual

- is not older than 15 years in 1975.
- has undertaken training for at least 450 days without interruption.

[9] See: Bender and Hilzendegen, 1995, p.3. Anonymisation is conducted with respect to individuals, firms, and longitudinal information.

- has never been working part-time.
- must be observed in the data before 1988 for the first time.
- must not be observed in further education and training.

The first rule ensures that the sample drawn contains only young workers, who are observed right from entry into apprenticeship and then followed over their early careers. Hence, we do not have "left-censoring" of work history problems common in labour economics. The second selection rule separates individuals doing vocational training within the dual system of apprenticeship training from other courses of vocational training which take less than one year.[10] Furthermore, we restrict the sample to full-time workers. Moreover, we exclude individuals who we observe later than 1988 for the first time in the data. Basically this means that individuals have not started training later than 1988, and for each individual at least two wage spells are available. Finally, we exclude individuals for whom more than one apprenticeship is observed in the data, or who have obtained higher education after training. As a result, extraction of these workers from the IABS leaves us a sample containing approx. 15000 female workers and approx. 20000 male workers who are observed in at least one full-time working spell after completion of vocational training.[11]

[10] As the transition from vocational training to work cannot be determined precisely, we choose the period of 450 days as the selection rule which is recommended by the Institute of Labour and Occupational Research (IAB).

[11] In more detail, as a result of the application of the selection rules to the female sample, we loose 15.7 percent of individuals because of exclusion of part-time workers and 9.5 percent due to observed higher education. Correspondingly, for the male sample the percentages are 2.7 percent and 12.8 percent. Thus, the female sample includes finally approximately 75 percent of all skilled workers of the original sample, and the

For generation of most of the variables the entire sample is used; therefore, employment and non-employment spells. For the analysis of wages and male-female wage differentials, however, a sample including only wage spells is used. One caveat of the data is that due to variation of reporting in the data, transition from apprenticeship to first full-time employment may not be exactly observable. More particularly, this problem may apply for those who stay with the firm of training. Thus, to avoid downward bias of the average skilled workers wage due to inclusion of apprentice wage components, we exclude the first wage spell in each individual's record.

3.2.2 Wages

In the following empirical analysis, our *wage variable* is the logarithm of the daily wage deflated by the CPI index. The daily wage reported in the data refers to a job match.[12] In the IABS wages are recorded as pre-tax daily wages received while in full-time employment compulsory to social insurance. Generally, as pointed out before wages are censored from above and truncated from below. However, the latter seems to leave wages reported for young medium skilled workers unaffected.[13] The pre-tax daily wage at date calendar xx.yy.19zz is calculated as the total pre-tax income for the period from the previous spell onwards until the date of the spell divided by the number of days of continuous employment since the previous spell. One shortcoming of the wage data is that over time the income components

male sample 84.5 percent correspondingly. Although, differences between the two groups occur, application may still not violate representativeness of both samples for young skilled workers.

[12]Thus, multiple jobs at a given day or period may cause multiple wage spells for a worker.

[13]See: Fitzenberger (1999).

being subject to the social security tax were extended[14]. In particular, starting in 1984 one-time payments to the employee had to be taxed.[15] We deal with this by including time dummies in the wage regressions.

3.2.3 Work experience

The variable *work experience* counts accumulated years in full-time employment spell by spell. In the IABS, full-time work is defined as work for more than half of full time working hours, thus 20, per week. Since the first wage is dropped from our data sample, we start pratically counting work experience from the second wage onwards. Furthermore, assuming that wages are negotiated and fixed in the beginning of the contract, we lag the variable work experience by one spell with respect to wages and set the intial value to zero. Finally, division by 365 leads to accumulated work experience in years.

3.2.4 Unemployment

The variable *unemployment* labels periods when individuals have registered as unemployed and receive unemployment insurance or assistance. The state of being unemployed is, therefore, an administrative definition rather than a behavioural, ILO-type, definition. From our complete data set, including employment and non-employment spells, duration in unemployment is

[14] See Bender et al. (1996), p.15.

[15] See: Bender and Hilzendegen (1995). p.5. Steiner and Wagner (1994) note that this redefinition of wages results in a structural break in the wage data. See Fitzenberger and Kurz (1996), Fitzenberger (1999) who correct for this effect in their study in a heuristic way.

generated as accumulated days reported as such.[16] Finally, division by 365 leads to accumulated years in unemployment.

3.2.5 Interruption

The variable *interruption* labels periods that have been spent out of work while the job has been kept for the employee by the employer. This case also could apply, for example, in the event of long sickness. However, mostly the variable interruptions takes non-zero values if women (for men this is more a theoretical case) take maternity or parental leave[17] and men do national service. However, it may not measure the complete time in national service. From our complete data set, including employment and non-employment spells, duration in interruption is generated as accumulated days reported as such.[18] Finally, division by 365 leads to accumulated years in interruption.

3.2.6 Non-work

As *non work* we label gaps between spells in individual's records. Hence, this variable captures periods of neither of the other statuses and may measure time spent in, for example, studying and advanced training of any kind, but also work in jobs that are not compulsory to social insurance and, partly, national service. We generate the *non-work* variable from gaps between spells within individuals' records, thus including employment and

[16] Identification is possible by the variables TYP and BTYP in the IABS.

[17] Since 1986 leave is not restricted to mothers and the maternity protection law prescribing maternity leave has been replaced by the Federal education law prescribing parental leave.

[18] Identification is possible by the variables TYP and BTYP in the IABS.

non-employment spells, which are identifiable from the calendar dates given for the start and ending of each spell. Finally, division by 365 leads to accumulated years in non-work.

3.2.7 Time out of work

Time out of work is defined as the total time not in salaried work and is calculated as the sum of the values of the variables *unemployment*, *interruption* and *non-work.*

3.2.8 Age

Age if generated from the year of birth contained in the IABS.

3.2.9 Age at entry into apprenticeship

Selection of individuals in our sample who are not older than 15 years in 1975 results in cohorts entering the data set encompassing a growing age range of individuals. Thus, by 1980, for example, 16 to 21 year old individuals enter the data set. For the analysis of wages it may be crucial to control for this difference in age at the beginning of apprentice since those who start later may have undertaken further schooling, for example, the *Berufvorbereitungsjahr*, which is not observed in the data directly. Thus, in order to control for this elapsed time and possible differences in pre-apprenticeship educational levels we generate a variable for age at entry into apprenticeship. Since we know that those individuals have not been working in employment compulsory to the social welfare system under normal circumstances before entry into apprenticeship this should be quite good proxy for further schooling. More specifically, the variable *age*0 is the age at the first spell in apprenticeship and is a time invariant variable.

3.2.10 Occupation

The IABS contains detailed information on the occupation of an individual in each employment spell. In our analyses we use directly the variable *occupation* (BERUF) from the IABS that is defined on a three digit level and distinguishes 328 occupations. Furthermore, occupations can be aggregated into eight groups according to Dietz (1988).[19]

Furthermore, availability of detailed information on occupation in spells of apprenticeship and employment allow us to observe skill. Since in our sample individuals are observed from entry into apprenticeship onwards, we can identify individuals' occupations while in apprenticeship, which may be named the *occupation of qualification.* By comparison of the *occupation of qualification* and the *occupation of work* after training has been completed, a well defined skill variable can be generated. If the values of the two variables are equal individuals keep their skill, with respect to occupation specificity in the most narrow sense. Otherwise, in case of moves, skills may become superfluous, and, hence, a move may imply loss of skill.

[19]A full list of occupations can be found in Rohwer (1995).

3.2.11 Industry and firm

In each employment spell information on the firm of employment[20] as well as the industry[21] are given. Both pieces of information could be used in the same way as occupation in order to identify the training firm and the firm of employment, the industry of training and the industry of employment, and, eventually, separate between stayers and movers after apprenticeship.

3.2.12 Gender

Information on gender is included in the IABS.

[20]Firm identifiers are given to each establishment. However, large firms are split into establishments with different firm identification numbers.

[21]Industry is disaggregated into 99 groups and refers to the main sector of value addition. Since categorisation is conducted by the Federal Bureau of Labour the information is regarded as highly reliable. A full list of industries can be found in Rohwer (1995).

Part Three
The Empirical Analysis

Chapter 4

Introduction to the empirical analysis

In this part of the thesis three pieces of empirical work on the analysis of male-female wage differentials are presented in which the aforementioned sample of young skilled workers is used. Using data on young skilled workers drawn from the IABS has several advantages for this analysis. First, the administrative character of the data ensures that the information on spells of employment, such as wages and duration, and spells of non-employment are very accurate. Second, the selection of young skilled workers who are observed from the beginning of their working careers onwards enables us to measure human capital stocks and flows in a very detailed and precise way. The information in the IABS enables us, also, to distinguish full-time work from part-time work, and time out of work periods into unemployment, interruptions and other non-work periods. Hence, we can extend the array of work history variables commonly used in the gender wage literature.

The IABS includes detailed information on occupation on a three digit level for each spell, hence in apprenticeship spells as well as in employment spells,

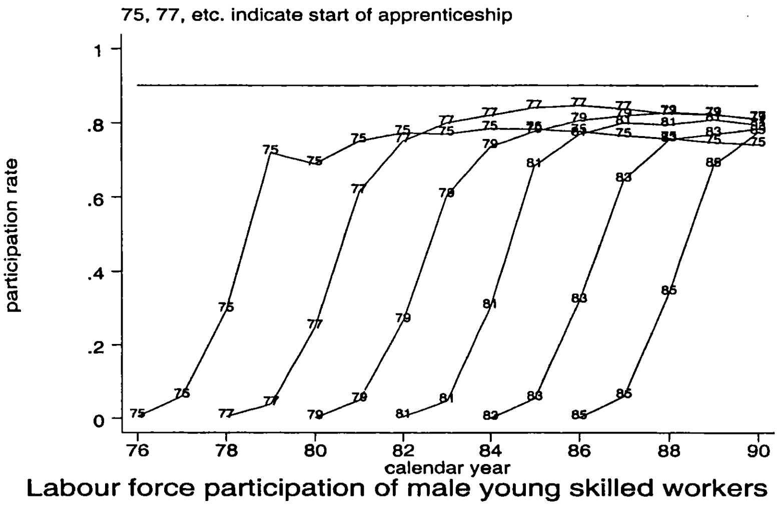


Figure 4.1:

which enables us to observe skill and, hence, measure the main source of heterogeneity of qualification across young skilled individuals. This information together with the large sample size and multiple spells within occupation cells can be used to analyse within occupation wage differentials in more detail. Finally, the longitudinal dimension of the data and the precise wage and work history information provided by the event history data set form good conditions to apply instrumental variable estimators to wage regressions in order to control for unobserved heterogeneity that may have an impact on the investigation of wage differentials between men and women. In the following three chapters we draw on these sets of information.

Before exploring issues on gender wage gap using the data, we present a number of summary statistics. The sample we use enables us to observe young workers, who are aged 16 to 30, during their early careers which includes up to approximately eight years of work experience. The time

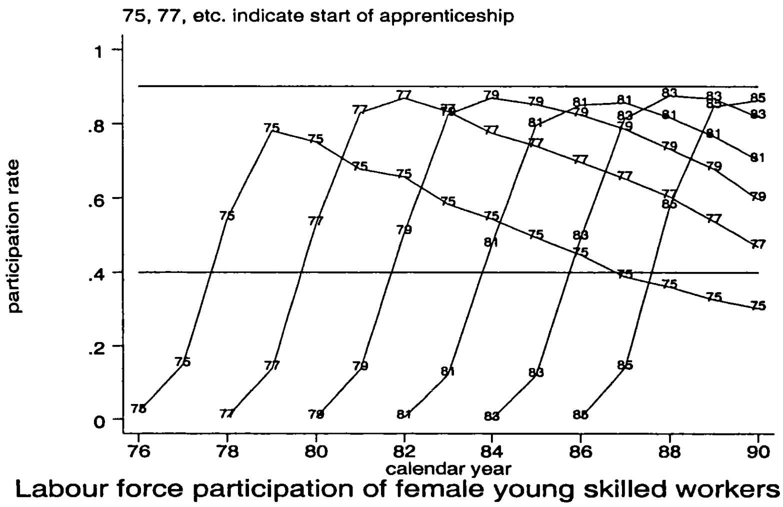


Figure 4.2:

span depends on when they have started apprenticeship. By construction of the data sample, young workers enter the sample in apprenticeship cohorts. The first cohort enters apprenticeship in 1975 and includes only 16 year old workers.[1] The second cohort includes 16 and 17 year olds starting apprenticeship in 1976, etc.. For each cohort, the first wage in full-time work is then observed two to three years after entry into apprenticeship.

If young workers stay in work all through the sample period, wage spells are reported until 1990. As can be seen in figure (4.1), this case applies mostly to male young skilled workers. Labour force participation rates are plotted for selected apprenticeship cohorts. It appears that 80 percent of young men in our sample enter full-time employment within two or three years after completion of apprenticeship. The participation rates then stay constant. The seemingly early entry of some of the individuals into the labour market

[1]For further explanations see chapter 3.

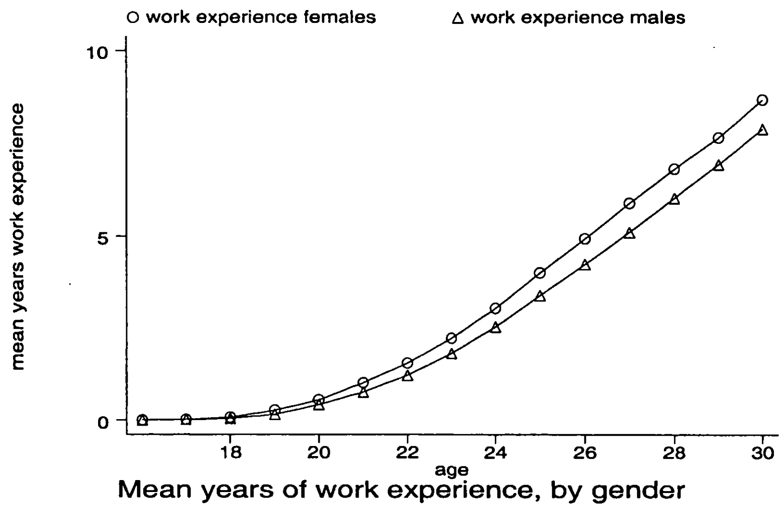


Figure 4.3:

is due to the applied selection rule, that individuals have been reported in the IABS in apprenticeship for at least 450 days. Relatively slow or late entry of men into employment reflects compulsory national service.[2]

For female workers in our sample, the case is more likely that wage records stop before 1990. This is because, typically, women drop out of the labour market, temporarilly, due to child bearing and rearing. Labour force participation rates, plotted in figure (4.2), document clearly the withdrawal from work of young women during their early careers. Due to the too short length of the panel, re-entry into employment is not observed for the majority of women. Therefore, the expected upswing in partication rates cannot be seen yet in the graph.[3]

Comparison of work histories observed in the data for male and female

[2]For further information see appendix (A).

[3]In 1994, for young women with children younger than 4 year old, the average labour force participation rate was 40 percent. See Statistisches Jahrbuch (1996).

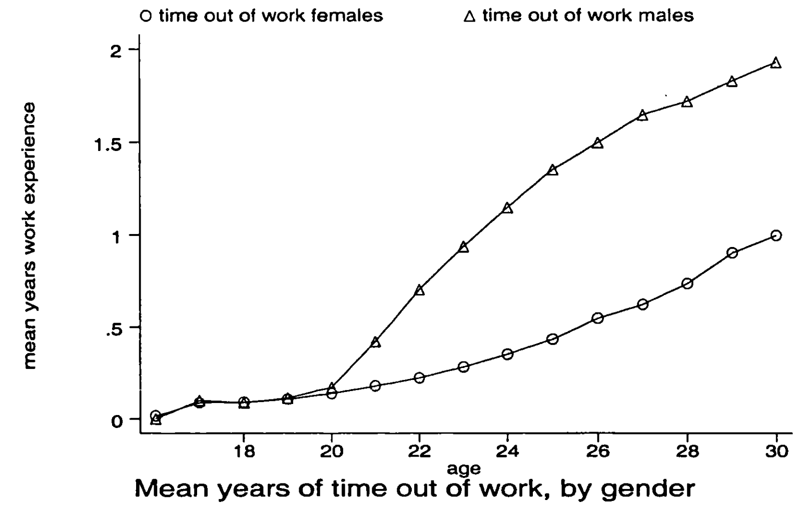


Figure 4.4: .

workers can be summarised by the evolution of average work experience. In figure (4.3), we plot average work experience levels against age. As can be seen, the distinctive "gender pattern" has not evolved yet. On the contrary, women seem to have accumulated more years of work experience than men of comparable age. Comparing averages of total time out of work periods between wage spells, as shown in figure (4.4), it can be seen that men's averages are higher than women's reflecting the importance of national service in the data. Average time out of work periods for women appear here in the graph to be quite low because of the short length of the data set. Also, in Germany women tend to have children rather late; on average from age 25 or even later. Therefore, a longer panel is needed to observe more women taking parental leave and to observe women, after taking parental leave, re-entering employment. This would drive average time out of work periods, holding age constant, up in figure (4.4).

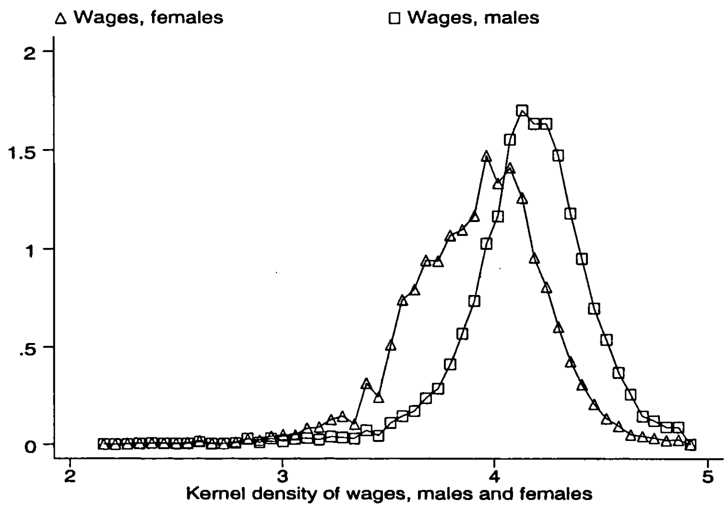


Figure 4.5:

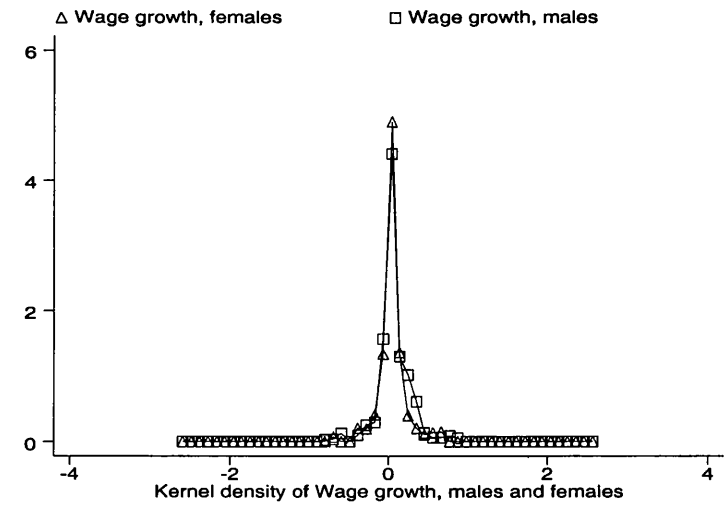


Figure 4.6:

Finally, kernel densities of logarithmic real daily wages and growth in logarithmic real daily wages are shown in figures (4.5) and (4.6). From the distribution of wages in levels it seems that pronounced differentials between males and females exist all over the wage distribution. In contrast, distributions in wage growth for young workers seem very similar. In the following analyses we look at mean differentials in wage levels and in wage growth rates. Distributions seem to show that this type of analysis captures a main feature of the gender wage gap in our data. Furthermore, similarity of wage growth rates across the entire distribution seems to support our approach to pay particular attention to the analysis of entry wage differentials.

The next three chapters are organised as follows: In *chapter five*, the dynamics of male-female wage differentials over early career are explored. In *chapter six*, the links between occupational segregation, occupations and male-female wage differentials are investigated. In *chapter seven*, we discuss the application of instrumental variable estimators in order to derive consistent estimates of the main parameters of interest, which are the return to work experience and losses from time out of work, in the wage regression model.

Chapter 5

Gender differences in entry wages and early career wages

Abstract:

In this chapter we investigate empirically the dynamics of the gender wage gap over the early careers of skilled workers in Germany using longitudinal microeconomic data from an administrative data set. The data reveals that high wage differentials in raw wages exist right from entry into first employment after apprenticeship and all through early careers. Entry wage differentials decrease considerably, but stay significant, when fixed effects for occupational skill are controlled for. Furthermore, simple descriptive analyses of early career wages show that variables for complete work histories, which include in addition to work experience, variables accounting for total time out of work or time out of work segmented into interruptions, unemployment and other non-work periods, seem to contribute further to the understanding of male-female wage differentials.

5.1 Introduction

Much of the research on male-female wage differentials has focused on the analysis of cross-sections and dynamics over time. The latter has been motivated in parts by the interest in the evaluation of anti-discrimination policies.[1] From the 70's, when employment of married women was becoming more and more common in Western industrialised countries, a steady decrease in male-female wage differentials has been found. For example, for the U.S. the gap declined from approximately 40 percent in 1970 to approximately 29 percent in 1990[2], and for the U.K. from 41 percent in 1975 to 22 percent in 1992-93[3].

Through cross sectional analyses it has been found that a considerable share of the gender wage differential can be explained by lower levels of human capital acquired by female workers than by male workers. More specifically, women are found to have on average lower levels of work experience, for earlier cohorts they have lower levels of education and, finally, longer periods out of employment due to family responsibilities.[4] In longitudinal studies it has been demonstrated that the observed decline in the raw wage gap is partly accountable by improvements in human capital characteristics of females, such as increases in education and more continuous and longer participation in the labour market. However, evidence also suggests that this trend has been counteracted by increases in inequality.[5]

[1] For a summary of evidence for the U.S. see Blau and Ferber (1987).

[2] See: O'Neill and Polachek (1993).

[3] See: Harkness (1996).

[4] See e.g. Mincer and Polachek (1973).

[5] Levy and Murnane (1992) find that wage differentials, for example, between the more- and less-educated expanded, and, also, that wage residual dispersion among workers with

In spite of the interest in the literature in the time trend of male-female wage differentials, little attention has been explicitly paid to the dynamics of the latter over working careers.[6] More particularly, it is not quite clear whether the gender wage gap exists right from the beginning of careers and becomes (partly) permanent or whether it arises only in the process of careers. The objective of this chapter is to scrutinise this point in more detail by analysing a sample of skilled workers in Germany who are followed over their early careers from the beginning of their careers onwards.

Overall evidence on the dynamics of the gender wage gap over working careers is scarce. In a few studies, it has been demonstrated that a significant entry wage gap exists.[7] For example, in Loprest (1990) for samples of 18 to 25 year old men and women of all education groups taken from the NLS[8] for 1978 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, what explains this entry gap and whether it becomes permanent over careers.

More generally, the dynamics of the male-female wage gap over the career

the same level of experience and education have increased during the 80's. Blau and Kahn (1997), under the assumption that the wage distribution of reference is the male wage distribution, estimated that the gender wage gap would have declined by 6-7 percentage points more if the wage structure had remained stable. However, Fortin and Lemieux (1998) find that these results are weakened if the overall wage structure is used as the distribution of reference.

[6]This is mostly attributable to the fact that most data sets are constrained by left censoring of individuals' work histories.

[7]Entry wages and starting wages for the first job should not be confused with studies on starting wages after job changes, a topic which has received far greater attention in the literature. See e.g. Topel and Ward (1992).

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

were examined in Light and Ureta (1995) who estimated wage regressions that included, apart from standard characteristics, controls for the timing of working periods and time out of work periods, mostly due to child rearing.[9] They found that about 7 percent of the wage gap can be explained by male-female differences in the timing of work histories. In the study by Albrecht et al. (1999) estimation results for wage regressions including controls for complete work histories rather than just gender specific segments, i.e. work experience and time out of work due to child bearing and rearing - or home time -, were presented for samples of males and females.[10] In their study based on Swedish survey data they segmented total time out of work into parental leave, household time, other time out of work, diverse leave, unemployment and military service. The authors found that estimated coefficients on the types of time out of work variables were partly negative and partly positive. Hence, their results may cast doubts on human capital depreciation as the sole explanation of the negative effect of career interruptions on subsequent wages.[11] The latter study is most closely related to our approach to analyse the impacts of complete work histories on wages of young male and female workers.

In this chapter we investigate the factors that drive the gender wage gap over early careers by the separate analysis of individuals' starting wages in the first job and wages of men and women over their early careers. Three main sets of results are presented: First, we document a substantial wage

[9]Already, Mincer and Polachek (1974) addressed this issue estimating a reduced form model.

[10]To the author's knowledge, this is the only study in which complete work histories are controlled for. Related, also, is the study by Hersch and Stratton (1997) who control for house work in their wage regression model.

[11]As an alternative explanation they sketch a signaling model.

Table 5.1: Differentials in apprenticeship wages and starting wages

	women mean (std.)	men mean (std.)	gap	t-statistics for H_0: Equality of means
log(apprenticeship wage)	2.8224	2.8713	0.0489	-12.68
	(.3598)	(.3465)		
log(starting wage)	3.7428	3.9719	0.2291	-66.22
	(.3115)	(.3201)		
# of individuals	14563	19710		

Note: Starting wages are measured by the second wage spell of an individual's record in full-time employment. For further explanations, see chapter 3. The apprenticeship wage is measured in the last year (spell) of training.

gap of about 23 percent in starting wages which remains quite constant over early working careers. Second, a separate analysis of the starting wage differentials holding occupational qualification, i.e. the observed apprenticeship occupation, constant shows that the gap diminishes to only 6 percent, but remains significant. Third, simple estimation of wage regressions for the entire early career, which include an array of work history variables for the complete work history, show that coefficients on the time out of work segments vary in sign and size across gender and type of time out of work.

5.2 Wage profiles over the early career

To start the analysis, we compare raw male-female wage differentials using apprenticeship wages, starting wages and wages conditional on actual work experience over the early career. From table (5.1) it can be seen that while men and women are still in apprenticeship only a very small, yet signifi-

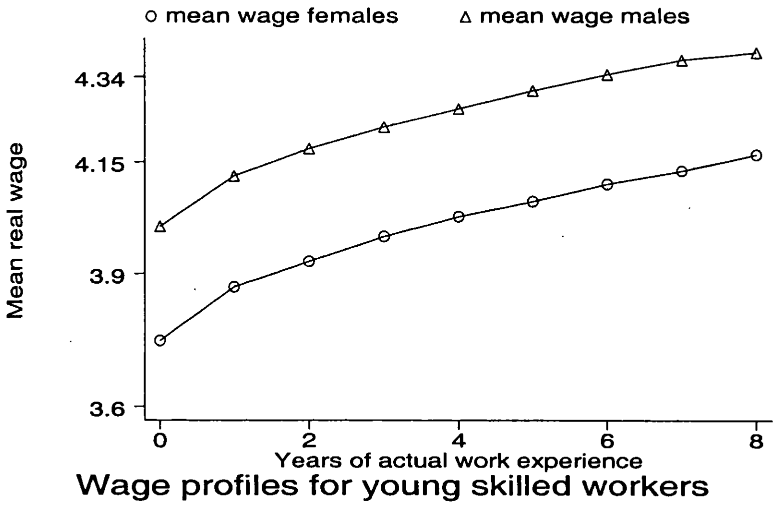


Figure 5.1:

cant, differential of 5 percent is estimated.[12] By the time of first full-time employment, however, this differential has increased to 23 percent. From then onwards, as can be seen from figure (5.1), the differential remains quite constant and wage experience profiles for men and women seem to develop in almost parallel fashion.[13] In the following, we investigate further the differentials in starting wages and wages over the early career.

5.3 Starting wages in the first job

In the framework of a human capital model[14], age, education and qualification acquired by entry into first employment are the variables that are generally expected to explain the major share of differentials in starting

[12]In what follows, we do not explore this differential further. However, the differential seems to remain after occupation of qualification is controlled for.

[13]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.

[14]Ben-Porath (1967).

Table 5.2: Means for males and females at entry wage spell

	women		men		t-test for
	mean	(std.)	mean	(std.)	H_0: Equality of means
			main characteristics		
age	20.3416	(1.5725)	20.5000	(1.5815)	-9.18
apprentice. duration	2.1896	(.7318)	2.5198	(.7418)	-40.96
			skill related variables		
job status:					
unskilled	.0896	(0.2856)	.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		

Note: The entry spell is defined as the second wage spell of each individual's record in full-time employment. Definition of "stayer": stayer in occupation (3-digit) of apprenticeship (qualification), training firm (firm) or industry (3-digit) while in first employment.

wages between genders. In our sample, young skilled workers are homogeneous with respect to education; virtually all of them, thus men and women, have 10 years of schooling. Furthermore, they are also homogeneous with respect to type of tertiary education since all of them have undertaken an apprenticeship programme lasting 2 to 3 years, as can be seen from means presented in table (5.2). Moreover, summary statistics show that women and men 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. It is, thus, possible to conclude that all remaining heterogeneity explaining the gender gap in starting wages may be captured by the occupational qualification received.

One may note, that by construction of our sample, which is drawn from an event history data set, the units of analyses are spells. In table (5.2), thus, summary statistics for entry wage spells are given which still may vary in the length of the spell. In our data set we have defined the first wage as being negotiated in the beginning of the spell, and, thus, consistent with a human capital approach, work experience is set equal to zero for the first wage spell. Nevertheless, we can observe the length of the first spell which varies between 1 day and 365. Accordingly, means, not reported in the table, are 231 days for female workers and 202 days for male workers. 25 percent of spells are shorter than 100 days in the sample of females, and shorter than 82 days in the sample of males. In the following analysis, we check whether the distribution of the length of a spell has an impact on estimation of the wage gap.

5.3.1 First jobs and skill

Heterogeneity in qualification, or skill, can be measured and observed in the data in several ways. First, the data 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 (5.2). Perhaps striking in international comparison is that about 70 percent of all workers are categorised as skilled which implies, given that about 60-70 percent of the population undertakes apprenticeships[15], that almost 50 percent of the entire population are categorised as (occupationally) skilled at the young age of 20.[16] On the other hand, data reveals that only 8 percent of women

[15]See chapter two of this thesis.

[16]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).

trained in apprenticeship programmes are categorised by employers in their first job as unskilled, while 18 percent of men are in the same category. Furthermore, most skilled women work in white collar jobs, whereas men work mainly in blue collar jobs. Second, and most importantly, skill can be observed (a) because the records included in the data contain individual spells while in apprenticeship and in employment afterwards and (b) because for each of the spells information on the actual occupation is included. Hence, skill can be measured, first of all, by the occupation of qualification itself, which is the occupation reported while in apprenticeship, and, secondly, by matching the *occupation of qualification* and the *occupation of work* which is the occupation in full-time employment. Likewise, skill with respect to firm and industry specific human capital could be measured by comparison of the corresponding firm and industry identifier in the data. We define these matching variables (*skill match variables*) as binary variables that take the value one if the 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 illustration, table (5.3) shows the distribution of men and women across the occupations of qualification aggregated into eight groups. Obviously, and as reflected in virtually all Western industrialised countries, strong gender segregation is found. 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.*

For the *skill match variables*, the means and standard deviations are reported in the lower panel of table (5.2). Quite striking is the extremely high share of former apprentices who work afterwards in exactly the occu-

Table 5.3: Distribution of men and women across occupations

Occupation of qualification group	share of women	share of men
Natural products production	2.2	3.5
Extraction of natural resources	0.0	0.8
Investment goods	0.4	5.4
Consumer goods	5.5	8.7
Construction	0.6	17.8
Installment of technical machines	1.4	42.8
Services	89.3	19.3
Infrastructure	0.6	2.2
Total	100.0	100.0

Note: For calculations, the occupation of qualification classifications of the last spell in apprenticeships are used. For group definitions see to Dietz (1988).

pation matching their *occupation of qualification* on a three digit level, and, furthermore, the considerable share of workers that stays with the training firm as well. The binary variables generated for stayers with respect to qualification, firm and industry listed in table (5.2) show that overall in their first job more than 60 percent of men and women are employed in their *occupation of qualification* when occupation is grouped into 328 occupations, or stay with the training firm or the industry, which is grouped into approximately 90 categories. We find that women are more likely to stay in the *occupation of qualification* (73 percent) than are men (65 percent). With respect to industry, no significant differences are found. Furthermore, while women are less likely to stay with the training firm than men are, quite interestingly, both for men and women about 53 percent of all individuals stay with the firm of training and in the occupation of qualification.[17] In

[17]Also, it can be seen that the share of individuals staying with the training firm is higher than the share of those staying in their occupation of qualification and the training firm. This suggests that firms train more within particular qualifications than demanded and, hence, offer to workers to stay, yet in a different occupation or (better) job position. One may note also that occupation changes partly capture promotion or demotion.

Table 5.4: Estimates of entry wage regressions

	(1)		(2)		(3)	
	coef.	(s.e.)	coef.	(s.e.)	coef.	(s.e.)
1 if male	0.2277	(0.0033)	.0642	(.0047)	.0724	(.0042)
1 if qual.stayer					.0673	(.0065)
1 if firm stayer					.0186	(.0057)
1 if firm + qual.stayer					-.0253	(.0065)
1 if industry stayer					.0184	(.0053)
appr.duration					.0310	(.0020)
age at entry					.0188	(.0010)
1 if unskilled					-.0431	(.0054)
dummies for qualification	no		yes		yes	
trend	0.0229	(.0.0005)	.0184	(.0004)	.0137	(.0004)
constant	3.5599	(.0.049)	3.69	(.0048)	3.2098	(.0197)
R^2 adjusted	0.1584		0.3879		0.4543	
# observations	34273		34273		34273	

Note: Stayer: stayer in occupation (3-digit) of apprenticeship (qualification), training firm (firm) or industry (3-digit) while in first employment.

summary, comparing summary statistics for men and women in their first employment, we find, on the one hand, significant differences in skill measured by the *occupation of qualification* as well as skill match variables and, on the other hand, that even though mean age and mean duration of apprenticeship seem to be quite similar, estimated differences are significant.

5.3.2 Male-female differential in starting wages

In order to describe the male-female differential in starting wages we regress wages on a dummy for being male, a set of variables describing skill, a time trend and other regressors that may capture remaining heterogeneity. Our finding is that the main factor contributing to the differential seems to be the occupation of qualification or occupation more generally. Estimation results are shown in table (5.4). In the first column, we show the raw wage gap, including only controls for the calendar year. It amounts to 22.77

percent. In the second column, the estimate of the gap is shown when we control for fixed effects for the occupational qualification observed. We see a substantial decrease of the unexplained gap to 6.4 percent. Finally, we add the explanatory variables apprenticeship duration, age at entry into apprenticeship[18], a dummy for being unskilled, and the set of skill match variables described above. As shown in the third column, it seems that inclusion of these does not change the results much. The unexplained gap increases only slightly to 7.2 percent; but it is not significantly different from 6.4 percent. Consequently, we find that only 25-30 percent of the raw differential in starting wages found initially is left unexplained once we control for occupational skill.[19]

5.4 Early career wages

Figure (5.1) shows that the wage differential conditional on actual experience seems to stay quite constant. Thus, the gap does not increase nor does it decrease. In the following section, we explore this feature of the early career.

5.4.1 Work history during early career

From the summary statistics for the variables describing age and work histories, listed in table (5.5), we find that the early careers of young skilled

[18]For further details see chapter 3.

[19]From the perspective of a human capital approach the length of the spell should not have an impact on wages. According to it wages are positively correlated with accumulation of human capital, regardless of the length of the contract or spell. To check the impact on the estimate of the entry wage gap, though, we include as a further regressor the variable *duration of the entry wage spell.* While we find that the duration has a strong positive coefficient, approximately 16 percent, and which is not significantly different for both males and females, inclusion of the variable has virtually no impact on the estimate of the unexplained male-female wage gap.

Table 5.5: Summary statistics for early career

	women		men		t-test for
	mean	(std.)	mean	(std.)	H_0: Equality of means
age	24.5168	(2.6953)	24.9871	(2.9744)	-15.05
work experience	3.6999	(2.6706)	3.5834	(2.7843)	3.89
interruption	.0756	(.2763)	.2785	(.5357)	-41.78
unemployed	.1697	(.4498)	.2818	(.6234)	-18.44
non-work	.2145	(.7542)	.5991	(1.1753)	-34.58
time out of work	.4598	(.9917)	1.1595	(1.4181)	-51.03
# of indiv.	14563		19710		

Note: Variables are measured at the last wage (working) spell.

males and females do not reveal yet the gender distinctive labour force participation patterns. In fact, females in our sample, who work 3.7 years on average, seem to work even slightly more than men do.[20] Furthermore, mean years in interruptions for females, which may measure maternity leave spells, are lower than mean years in interruptions for men, which are partly acounted for by national service. The same relation is found for durations in unemployment and non-work periods. Moreover, comparison of total time out of work years for females and males shows that men have accumulated almost three times as many years in time-out of work than women have; that is 1.2 years compared to 0.45. Of course, the latter comparison may hide the fact 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 time-out of work.[21]

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

[21]However, even then a difference would remain, as we have found in additional calculations not shown here.

Table 5.6: Early career wage regression results

	women				men			
	coef.	(s.e.)	coef.	(s.e.)	coef.	(s.e.)	coef.	(s.e.)
work experience	.0412	(.0004)	.0426	(.0005)	.0422	(.0003)	.0400	(.0003)
interruption			-.1458	(.0050)			.0422	(.0015)
unemployment			-.0989	(.0027)			-.0354	(.0015)
non-work			-.0212	(.0018)			-.0004	(.0008)
time out of work	-.0545	(.0013)			-.0038	(.0006)		
trend	.0269	(.0003)	.0270	(.0003)	.0209	(.0003)	.0220	(.0003)
constant	3.5655	(.0034)	3.5662	(.0034)	3.8461	(.0028)	3.8346	(.0028)
R^2 adjusted	0.1987		0.2060		0.1930		0.2023	
# observations	87254		87254		125782		125782	

5.4.2 Wage regression results

In order to describe male-female wage profiles over the early career, we present by gender simple regression estimates for wages conditional on measures for individuals' complete work histories and a time trend.[22] In the first step, we estimate wage regressions including controls for accumulated work experience, total time-out of work and a time trend only.[23] This specification closely matches the one commonly applied in the gender wage gap literature, in which time out of work is defined as home time, which is, then, non-negative for women and zero for men. Our estimation results are provided in the first and the third column of table (5.6). As expected, we find positive coefficients for the work experience variable and negative ones for the coefficient of the time out of work variable. However, while coefficients of the work experience variable, in both the male and female sample

[22]In this section, we do not address the impact of occupation or other work place characteristics on wages and male-female wage differentials. In gender wage gap studies, however, it is usually found, that coefficients of the work history variables are invariant to the inclusion or exclusion of the latter variables. Hence, in relation to our previous analysis it would affect only the intercept and it should leave the descriptive exercise undertaken here unaffected.

[23]None of our results would change if we included dummies for each calendar year instead of a time trend.

regression, are about 4 percent, coefficients of the time out of work variables are considerably greater (- 5 percent) in the female sample regression than in the corresponding male one (- 0.4 percent).[24]

As a further step, the variable *time-out of work* is segmented into three types: interruptions, unemployment and other non-work periods. Estimation results reveal that coefficients differ significantly across types of time out of work as well as gender. For females, the coefficient of the variable *interruptions* turns out to be particularly high. Hence, the variable years in maternity leave has a strongly negative coefficient of approximately -14 percent. Each year of unemployment seems to decrease wages of women by 9 percent, yet, non-work seems to reduce wages by only 2 percent. On the other hand, for males the variable *interruption* has a positive coefficient. Furthermore, for the male sample spells in unemployment seem to lead only to a decrease in wages by 3 percent and non-work spells seem to have virtually no effect.

In the final step of this descriptive analysis, we relax the linearity assumption implied previously and allow coefficients to vary across the length of the spell according to the different types of time out of work. The main motivation for this exercise lies in the fact that maternity or parental leave are, broadly speaking, granted and taken at fixed intervals regulated by relevant laws, rather than for an indefinite period. Also, unemployment can be thought of as reported at fixed intervals. This is because unemployment status reported in the data is equivalent to receipt of unemployment insur-

[24]One may note that for regression results reported in tables (5.6), and in the following table (5.7), the unit is a spell. Therefore, individual records with many short spells, as well as with a long record, are more heavily weighted than others. To check the impact we have restricted the sample, for example. to individuals with three to six years of work experience. Furthermore, we have defined a minimum cut off length for wage spells, such as 30 or 100 days. Re-estimations have shown that our results remain valid.

Table 5.7: Early career wage regression results, splines

	women		men	
	coef.	(s.e.)	coef.	(s.e.)
work experience	.0439	(.0004)	.0409	(.0003)
1 if unemployed for:				
0< years $\leq$ 0.2	-.0280	(.0031)	-.0132	(.0024)
0.2 < years $\leq$ 0.5	-.0795	(.0038)	-.0269	(.0026)
0.5 < years $\leq$ 1	-.0966	(.0046)	-.0289	(.0029)
years > 1	-.0958	(.0057)	-.0465	(.0033)
1 if non-work for:				
0< years $\leq$ 0.2	-.0678	(.0025)	-.0153	(.0020)
0.2 < years $\leq$ 0.5	-.0688	(.0054)	-.0990	(.0041)
0.5 < years $\leq$ 1	-.0619	(.0061)	-.1077	(.0044)
years > 1	-.0641	(.0051)	-.0107	(.0023)
1 if interruption for:				
0< years $\leq$ 0.2	-.0470	(.0099)	.0142	(.0055)
0.2 < years $\leq$ 0.5	-.0914	(.0090)	.0030	(.0052)
0.5 < years $\leq$ 1	-.1567	(.0069)	.0298	(.0054)
1 < years $\leq$ 2	-.1235	(.0074)	.0486	(.0021)
years > 2	-.2312	(.0364)	.0924	(.0102)
trend	.0260	(.0003)	.0218	(.0003
constant	3.6028	(.0035)	3.8518	(.0029
# observations	87254		125782	
R^2	0.20		0.19	

Note: The coefficients of splines represent differential effects.

ance which is only granted up to a maximum length of time depending on previous employment and on age. Compulsory national service has lasted 15 months throughout the observed period.[25]

In table (5.7) estimation results are shown. Splines are defined so that they are broadly compatible with legislation on social insurance benefits (unemployment and parental benefits). We define splines for periods between zero and 8 weeks, 8 weeks and half a year, half a year and one year, and one year and two years. [26]

The regression results show that the large negative coefficients that were found before in the female sample regressions seem to be related to maternity leave taken for longer periods than 6 months; the coefficients increase even more in absolute terms when interruptions last longer than 2 years.[27] One conjecture would be that women, when returning to work after longer periods of parental leave, are more likely to take less favourable, full-time, jobs.[28] Furthermore, it is seen from the results that the coefficients of the *unemployment* variable for both men and women increase in absolute terms with respect to unemployment duration. Short spells seem to lead to small, yet significant, losses, and long spells to larger ones. Finally, a positive correlation between negative coefficients and duration is also found for the

[25] See for more details on institutional background in the appendix at the end of the thesis, section (3).

[26] Hence, we distinguish *maternity protection* which amounts to 8 weeks, minimum length of protected leave observed throughout the entire period, 1975-1990, which corresponds to 6 months, and the maximum length of receipt of unemployment benefits which equals to one year. For simplification purpose the length of national service has been approximated to one year. It should be noticed also, that in order to gain employment status men have to serve a minimum of two years in the Army. For more details, see appendix (A).

[27] Although not shown here, we found this finding does not change either when we add controls for firm changes and whether women for whom interruptions are reported in the data have a spell of unemployment afterwards or before as well.

[28] Another reason may be related to our sample which includes only very young women returning to work since the panel is otherwise too short.

non-work variable in the male sample regression. However, in the female sample regression, coefficients are constantly approximately -6 percent, independently of duration.

5.5 Conclusions

We have examined male-female wage differentials during the early careers of young skilled workers in Germany over the period 1975 to 1990. The main focus has been to analyse descriptively when the wage differential first occurs, and to what extent the complete actual work history of men and women provides further insights into the evolution of wage differentials over early careers.

In summary, evidence seems to show that an unexplained wage differential of about 6 percent exists right from the entry into the labour market and that women do not improve their position during early career because interrupted careers, generally, seem to be more heavily penalised in their case than for men. The observed wage differential in starting wages amounts to 23 percent which is surprisingly high by international standards[29]; however, after conditioning on fixed effects for occupational qualification, the unexplained differential drops to 6.4 percent which is more in line with international evidence. Furthermore, estimating wage regressions for the entire early career conditional on complete work histories seems to show that coefficients of the *work experience* variable are similar or even higher in the female sample regression than in the male counterpart. Furthermore, we find strongly negative effects for the variable total time out of work as well as for segments of the latter. For females, however, coefficients are larger

[29] See e.g. Loprest (1990), Dolton and Makepeace (1986).

in absolute terms than for males. Thus, these counteracting forces seem to prevent a closing of the gap over early career.

The finding of a positive coefficient in the male sample regressions for the interruption variable is rather puzzling. Although, this result seems to be out of line with the other estimated *time out of work* variable coefficients, it was also found in Albrecht et al. (1999) using Swedish data. One possible explanation is that since the variable mainly captures the effect of national service in the male sample, this may be remunerated by employers on the same scale as work experience or at the very least not penalised. An alternative explanation would be that the interruption variable is positively correlated with unobserved heterogeneity not controlled for in our reduced form analysis, which causes an upward biased estimate of the structural parameter whereas the true one may still be negative as expected from human capital theory.

This descriptive evidence raises further research questions. It would be of interest to understand why women work in occupations that are already remunerated five percent lower, on average, during apprenticeship and consequently lead to an even higher male-female differential in starting wages. Likewise, it can be asked why differentials in starting wages seem to be higher in Germany than, for example, in the U.S. or the U.K.. Furthermore, one may ask whether differences in the reduced form parameters across gender and type of time out of work are spurious and vanish once endogeneity is accounted for appropriately, and thus, the structural parameters of a more elaborated model are derived.[30] Answers to these questions, though, would demand more structural approaches.

[30]In Albrecht et al. (1999) structural parameters are derived under the restrictive assumption of strict exogeneity of the variables measuring complete individual work histories.

A conjecture, referring to the first two questions, is that one feature of the labour market in Germany is that individuals have, on average, higher qualification at a young age than, for example, in the U.K. and the U.S., due to the well established apprenticeship programme. However, on the other hand, occupational labour markets may play a dominating role in Germany opposed to internal labour markets which implies that changes in occupations may be difficult after completion of apprenticeship. Additionally, in Germany wage settings are tightly linked to occupational qualification and seniority or age. Hence, entry wage levels may have an important function and wage differentials may be established that become permanent over the career due to little prospect for later changes.

Chapter 6

Male - Female Wage Differentials and Occupational Segregation

Abstract:

This chapter investigates when male-female wage differentials arise over the early career and how occupational segregation contributes to the understanding of these differentials. Decomposing the gender wage gap among young workers into intra and inter occupational wage differentials, we find that, initially, the total gap is due to inter occupational wage differentials; however, increases in work experience coincide with a considerable increase in the intra occupational wage differential component. Estimation results from the application of a first difference estimator to a human capital wage regression model, seem to provide support for a human capital theory view that women work in occupations with relatively flat wage-experience profiles. On the other hand, evidence also shows that entry wages seem to be higher in male occupations than in female occupations, which may be in conflict with a human capital approach. The analysis of wages and male-female wage differentials, holding actual work experience and time out of work constant within particular occupations, allows us to get a handle on unobserved heterogeneity in our sample. Here, we find that differences in promotion of men and women seem to drive the widening of the intra occupational gap over the early career.

6.1 Introduction

In most Western industrialised countries, a raw gender wage gap of 20-30 percent is observed.[1] Most importantly, for samples of the entire population, it has been found that a major part of the gender wage gap is explained by differences in work experience, time out of work due to child bearing and rearing responsibilities,[2] and also workplace characteristics, such as occupation and industry.[3] The latter group of variables becomes even more important if one considers samples of young workers where gender distinct work histories have not yet evolved.[4] Amongst variables that characterise work place, occupation has received most prominent attention in the literature. Once occupations are considered in the analysis of male-female wage differentials, the aim is, on the one hand, to control for occupational wage differentials. On the other hand, the aim is to explain differences in the distribution of men and women across occupations - the so-called occupational segregation found in the data for most Western industrialised countries - and take these factors into account in the gender wage gap analysis.

In a few empirical studies it has been shown that gender segregation with respect to an array of work place characteristics contributes to the explanation of male-female wage differentials.[5] In Groshen (1991), it was found that gender segregation with respect to occupation explains the largest share of the variation of male-female wage differentials. However, considering segregation by firm, industry and occupations within firms reduces the unexplained portion of the gender wage gap further. More specifically, in a number of

[1]See e.g. Blau and Kahn (1992).
[2]See e.g. Mincer and Polachek (1974).
[3]See e.g. Groshen (1991).
[4]See: Dolton and Makepeace (1986).
[5]See e.g. Groshen (1991) and Carrington and Troske (1995).

studies the gender wage gap with particular focus on occupational segregation has been investigated. All of these studies are based on cross-sectional data and decompose the total gender wage gap into an intra occupation wage differential component and a component due to the gender distinct distribution across occupations according to the Brown, Moon and Zoloth (1980) decomposition. The occupation variable that has been used in those studies distinguishes between 11 and at maximum 56 occupational groups.[6] It has been found that the major share of the gap is attributable to intra occupation wage differentials. For the U.K., for instance, it has been found that more than 60 percent of the wage gap could be attributed to the difference of wages within the same occupation.[7] This result seems to contrast with economic theory, which would predict that within well defined job cells wage differentials should be negligible.[8] In this chapter, we reexamine this issue and explore the decomposition of wage differentials into within and between occupation wage differentials.

In the most simple case, where men and women were randomly distributed across occupations, the sole issue in the analysis of wage differentials controlling for occupation is to explain occupation wage differentials. Several economic theories explain occupation wage differentials. First of all, differentials may be due to differences in human capital endowments[9], which may reflect differences in general human capital or occupation specific human capital. The latter variable refers to the extent of transferability of human capital in the case of changes of occupation. Second, occupation differen-

[6]See: Miller (1987) and Kidd and Shannon (1996).

[7]See: Miller (1987), Dolton and Kidd (1994).

[8]See e.g. Lazear and Rosen (1990). This implies that workers within well defined job cells are (should be) equally productive.

[9]See: Becker (1964), Ben-Porath (1967), Polachek (1981).

tials can be explained by compensation wage theories.[10] Accordingly, wages contain components to compensate for undesirable non-monetary characteristics of specific occupations, such as increased health risks or lack of union status. Third, supply and demand factors can also explain occupational wage differentials.[11] Empirically, in the gender wage gap literature, the most common approach is to estimate wages conditional on work experience, home-time - which refers to time out of work due to child bearing and rearing - and dummy variables for occupation.[12] Hence, it is assumed that wages differ only by a constant between occupations. However, this approach implies that the distribution of men and women across occupations is exogenous. This assumption is relaxed in studies that model occupational choices.

The main contributions to the development of a theoretical framework to explain occupational segregation and the resulting male-female wage differentials can be found in (a) Becker (1971) and Bergmann (1974), whose approach is based on discriminatory tastes, (b) Mincer and Polachek (1974) and Polachek (1981), whose approach is based on the human capital model and the maximization of life cycle earnings, and (c) Lazear and Rosen (1990), whose model is a three period model with firm specific human capital and training. In the following, we give a brief summary of these models, predictions and relevant empirical evidence. Alternative approaches, not discussed here, refer, for example, to male-female differences in preferences[13], subjects chosen at college or test scores and grades achieved at college.[14]

[10]See e.g. Rosen (1986), Sattinger (1977).

[11]Given occupational segregation, it is argued that crowding of females into relatively few occupations leads to a surplus in labour supply, and therefore to downward bidding of wages. This leads to the observed gender wage gap. Bergmann (1974).

[12]Other background variables may be added as well.

[13]See e.g. Sorenson (1989).

[14]See e.g. Brown and Corcoran (1997) and Paglin and Rufolo (1990).

More generally, models suggested in the literature explain occupational segregation either by discriminatory or non-discriminatory processes.

Becker (1971) and Bergmann (1974) viewed discriminatory tastes of firms as the major cause of segregation outcomes. However, it is not evident straightforwardly how discrimination under the assumption of competitive markets can persist over time. Moreover, empirical studies have not found support for their models.[15]

The role of human capital was emphasized in Mincer and Polachek (1974) and Polachek (1981). In Mincer and Polachek (1974), it was assumed that child care and other responsibilities lead women to invest less heavily in market human capital. In consequence, this could lead to lower earnings of women and to segregation of women into occupations and firms that require less human capital. These conclusions were shown more formally in a model derived in Polachek (1981). In his model the choice of optimal human capital investment and occupation are the outcome of the life-time earnings maximization problem. The main results are that costs of interruptions[16] or home-time vary across occupations; hence, women are more likely to choose occupations for which losses from home-time are small. Another prediction is that women choose occupations that are characterised by relatively flat wage-work experience profiles with relatively high entry wages.[17]

Even though this is the model that is mostly favoured within the gender wage gap literature, so far Polachek's prediction about wage profiles have been rejected.[18] The first evidence was presented in England (1982) where

[15]See e.g. Carrington and Troske (1995) who find evidence against Becker's (1971) using a data set of small firms in the U.S. for 1982.

[16]Polachek (1981) labels this as the atrophy rate.

[17]This interpretation goes beyond Polachek's own interpretation given in the 1981 paper, and incorporates Zellner's (1975) results. However, it is compatible with his results as pointed out in England (1982).

[18]See: England (1982) and Cocoran, Duncan and Ponza (1983), England et al. (1988),

Polachek's predictions were tested with a cross-section taken from the NLS 1967 for 30 to 44 year old females. On the basis of OLS estimates of the parameters of interest, i.e. the constant and the coefficient of work experience, she rejected all hypotheses. However, unobserved heterogeneity and measurement error in variables may undermine the consistency of her estimates. In two studies, these endogeneity problems are dealt with by the application of fixed effect estimators. In Corcoran et al. (1983) a longitudinal sample of women taken from the PSID 1967-1979 was used and parameters were estimated by first difference estimation. However, their estimates may still suffer from endogeneity bias given that the work history variables are only predetermined. Hence, rejection of Polachek's hypotheses may be based on inconsistent estimates. The same criticism applies to England et al. (1988) where data from the NLS 1966-1980 for men and women are used.

Lazear and Rosen (1990) suggested a model in which promotion generates segregation outcomes. In their three period model, jobs with high and low training content exist. In the first period, all individuals work in the same type of jobs. In the second period, workers are promoted into jobs that contain training while others stay in the same job without further training. Hence, training takes place in period two before productivity gains are recovered by workers and firms in period three. However, in their framework workers may drop out of the labour market in period three. Here, the authors make the assumption that women have better outside options than men. It follows that female workers carry a higher risk of drop out due to comparative advantages outside the labour market. Therefore, firms are less likely to promote women into jobs that demand training. As a consequence, females are more likely to be in jobs with relatively flat wage-

in particular and, also, Brown and Corcoran (1997) and Blau and Beller (1988).

profiles, and males in jobs with relatively steeper profiles. Furthermore, it is shown that women have to be better than otherwise comparable men in order to get promoted. [19]

This chapter has two purposes. The first aim is to analyse the decomposition of the gender wage gap into intra and inter occupation wage differentials. The second is to derive consistent estimates of wage-work experience profiles within occupation groups and particular occupations in order to collect new evidence about the validity of predictions concerning wage-work experience profiles implied by the Polachek (1981) and Lazear and Rosen (1990) models. In summary, predictions from Polachek's model are that (a) costs of interruptions vary across occupations and women are more likely to choose occupations for which losses are small, (b) women choose occupations that are characterised by relatively flat wage-work experience profiles with relatively high entry wages in order to maximize their life cycle earnings. Furthermore, Lazear and Rosen's (1990) model implies further testable predictions about wage-work experience-profiles, namely that men may have steeper wage profiles due to promotion at a faster rate than women who are more likely to be exposed to labour force intermittence.[20] In order to investigate wage differentials controlling for occupation we refer mostly to neoclassical theories stressing differences in observed human capital characteristics, in particular work experience and time out of work, or interruptions more specifically, and promotion.

[19] See for a test of the prediction about the probability of promotion in Winter-Ebmer and Zweimüller (1997).

[20] Related to Lazear and Rosen's (1990) model is that of Hashimoto (1979, 1981) which makes predictions about wage tenure profiles that differ by sex and age. Here, the main focus is general and firm specific human capital. Assumption is made that young women face larger variation in outside options than men and older women. Basically, this is the same assumption made by Lazear and Rosen (1990). See also the application in Becker and Lindsay (1994) who found evidence in favour of Hashimoto's predictions using PSID data.

The article is organised as follows. First, we set up the framework of the analysis by specifying a simple wage model allowing for heterogeneity in human capital. In section two, the decomposition of the gender wage gap into intra occupation wage differentials and inter occupation wage differentials is studied. In section three, occupations grouped into female, integrated and male occupations and wage outcomes are analysed. In section four, male-female wage differentials within particular occupations are estimated. The final section contains a summary and a brief discussion of the robustness of the results.

6.2 Model

In the following empirical analysis, we estimate a simple wage regression model using longitudinal data that contains explanatory variables for timing and heterogeneity of human capital acquisition. Timing is captured by the individual work history and heterogeneity by the occupation individuals work in. Thus, the wage equation we consider looks as follows:

$$lnW_{ijt} = \beta_{0j} + EX_{it}\beta_{1j} + OCEX_{ijt}\beta_{2j} + To_{ijt}\gamma_j + \epsilon_{ijt} \qquad (6.1)$$

where t indexes time, i individuals and j occupations. lnW_{ijt} is the logarithm of real daily wages. In addition to an occupation varying constant, regressors included are actual work experience, EX_{it}, occupation specific actual work experience, $OCEX_{ijt}$, and (total) time out of work, To_{ijt}[21]. A further important regressor, education, is neglected since in the empirical part of the chapter our sample of young skilled workers is used containing individuals

[21]The occupation index j refers here to the occupation prior to the time out of work spell. Hence, only if the individual returns to the same occupation after the out of work spell can losses be given a straightforward occupation specific interpretation as Polachek (1981) suggested.

homogeneous in respect to years of education. Finally, the error term ϵ_{it} which we write as:

$$\epsilon_{ijt} = \nu_i + r_t + u_{ijt} \tag{6.2}$$

is added to the model, where ν_i stands for an individual specific component that picks up individual varying but time invariant characteristics, such as ability or motivation, r_t is a time effect and, finally, u_{ijt} is a common macro-shock component.

In addition to the intercept, which gives an estimate of entry wages, the main parameter of interest is the coefficient of the work experience variable that may vary across occupations and, more importantly for the analysis of male-female wage differentials, may differ across gender groups as well.[22] Finally, and, with respect to the female sample regression, we are also interested in estimation of the loss from time out of work spells.

6.3 Intra and inter occupation differentials

In order to measure the importance of inter and intra occupation wage differentials for the gender wage gap over the early career, the total gender wage gap can be decomposed into a component due to male-female differences in the distribution across occupations, which is the *inter occupational part of the differential*, and a component due to within occupation wage differentials, which is the *intra occupational part of the differential*[23].

[22]Note that for stayers the return to work experience is the sum of β_{1j} and β_{2j}; a feature we use in our approach to derive consistent estimates of the returns.

[23]This decomposition approach is based on Brown, Moon and Zoloth (1980).

6.3.1 Decomposition

In a first step, the male-female wage differential is written as the difference in weighted average log-wages taken across n occupations.

$$\overline{lnW^M} - \overline{lnW^F} = \Sigma_{j=1}^{n} P_j^M lnW_j^M - \Sigma_{j=1}^{n} P_j^F lnW_j^F \tag{6.3}$$

where $\overline{lnW^M}$, $\overline{lnW^F}$ are the means of logarithmic wages for males and females taken across all occupations and P_j^F and P_j^M are the proportions of males and females in occupation j[24]. lnW_j^F and lnW_j^M are the means of logarithmic wages for males and females within occupation j. Extension of equation (6.3) by plus and minus $\Sigma_{j=1}^{n} P_j^F lnW_j^M$ allows us to decompose the wage gap in the following way:

$$\overline{lnW^M} - \overline{lnW^F} = \underbrace{\Sigma_{j=1}^{n}(P_j^M - P_j^F) lnW_j^M}_{interoc.\ part} + \underbrace{\Sigma_{j=1}^{n} P_j^F (lnW_j^M - lnW_j^F)}_{intraoc.\ part} \tag{6.4}$$

The first term on the right hand side measures the inter occupational part of the gap and depends on the distribution of men and women across occupations. The second term measures the intra occupational part of the gap and depends on the size of wage differentials within occupations. If the share of men and women was the same in each occupation the first term would become zero. This is the non-segregation case. If, within each occupation, men and women earned on average the same wage the second term would be zero. This is the case when on average no within occupation wage differences exist at all.[25]

Table 6.1: Decomposition of gender wage differences using equation (6.4)

		8 occupation groups				occupation at 3-digit level			
Years of work exper.	total dif. (s.e.)	inter oc. (s.e.)	share in %	intra oc. (s.e.)	share in %	inter oc. (s.e.)	share in %	intra oc. (s.e.)	share in %
0	.2340	.0754	32.4	.1585	67.6	.2265	96.8	.0074	3.1
	(.0040)	(.0042)		(.0085)		(.0163)		(.0638)	
1	.2428	.0519	21.4	.1908	78.6	.2429	100.0	-.0000	0.0
	(.0040)	(.0042)		(.0083)		(.0160)		(.0225)	
2	.2456	.0216	8.8	.2240	91.2	.1380	56.1	.1076	43.8
	(.0043)	(.0046)		(.0089)		(.0173)		(.0252)	
3	.2413	-.0027	-1.1	.2441	101.1	.1166	48.3	.1247	51.6
	(.0049)	(.0052)		(.0099)		(.0192)		(.0251)	
4	.2308	-.0144	-6.3	.2453	106.3	.1129	48.9	.1179	51.0
	(.0058)	(.0061)		(.0117)		(.0231)		(.0291)	
5	.2330	-.0256	-10.9	.2586	110.9	.1041	44.7	.1288	55.2
	(.0067)	(.0066)		(.0134)		(.0251)		(.0325)	

Note: We assume that P^F and P^M are non-random variables. For calculations, see appendix A.

6.3.2 Results

The degree of occupational segregation in our sample, according to the Duncan index [26], S_D, is 0.72.[27] Outcomes of the decomposition of the gender wage differentials grouping occupations into 8 groups and on the three digit level, which leads to approximately 300 occupations being distinguished, are shown in table (6.1).[28] Purely male and purely female occupations, or

[24] Note, $\sum_j P_j^F = 1$ and $\sum_j P_j^M = 1$ holds, but $P_j^F + P_j^M \neq 1$.

[25] Following Brown, Moon and Zoloth (1980) both terms are decomposed further into an explained component and an unexplained, discriminatory, component. To illustrate our point we can neglect any further decomposition.

[26] See: Duncan and Duncan (1955). The index is calculated as: $S_D = \frac{1}{2}\Sigma_j |P_j^M - P_j^F|$, where j = occupation on the 3-digit level. The index would equal to 1 when complete gender segregation is observed, and zero when none is observed.

[27] In comparison, Blau and Kahn (1996) calculated on the basis of the ISSP (International Social Survey Programme) data set, which contains a variable for occupation disaggregated into 10 groups, a Duncan index of D=0.42 for the period 1985-1988.

[28] The eight groups are: natural products production, extraction of natural resources, investment goods, consumer goods, construction, installment of technical machines, services, infrastructure. Grouping according to Dietz (1988).

occupation groups, are included in the inter occupational wage differential component of the decomposition in equation (6.4). The initial total wage gap in our sample amounts to 23.4 percent. Holding work experience constant, we find that the total wage gap stays almost constant over the first five years of actual work experience.

Comparison of the estimation results of the decomposition using eight and at the three digit level disaggregated occupation groups shows contrasting results. Using eight groups we seem to find that the major share of the total male-female wage differential is due to intra occupation wage differentials. This results is in line with estimates of the decomposition presented in other studies.[29] On the other hand, when we use approximately 300 occupations to estimate the decomposition, we find that at the beginning of working careers virtually no intra occupation wage differential seems to exist and only over time wage differentials within occupations evolve. Hence, the major part of total differentials in starting wages results from differences in the distribution of men and women across occupations. Furthermore, if work experience is held constant to four years or more, we find that the within occupational wage differential explains the major part of the gap.

Explaining those contrasting results may hinge on the precision of the occupation variable used. In our data, occupation at the three digit level has a well defined occupational qualification interpretation and, moreover, in previous work the occupation variable is usually used at a more aggregated level than the one available in our data base, the IABS. Finally, our finding is much more in line with theory that predicts that gender wage differentials within occupations should be minimal. Hence, our findings support the view

[29]See: Dolton and Kidd (1994) and Miller (1987). This result has been found for samples containing all age groups as well as for a sample of graduate students.

that a major concern is to explain differences in the distributions of men and women across occupations (occupational segregation) and occupation wage differences, as well as the evolution of occupational distributions over working careers. In addition, a question that also follows from our results is to what extent the remaining intra occupation wage differential evolving over the early career is actually due to discrimination. In the following, we examine wage outcomes with respect to these issues.

6.4 Female, integrated and male occupations

To start with, we group occupations into three groups: *female*, *integrated* and *male occupations.* This approach allows us to consider all occupations in the analysis; including those for which only a small number of observations are available. Furthermore, the estimation of wage regression models for these three groups form the basis for a test of the predictions in respect to wage-work experience profiles made in Polachek (1981).

6.4.1 A definition of male/female/integrated occupations.

First, since grouping is somewhat arbitrary, we describe the definition of the three groups we use. We assume that if the distribution of men and women across occupations was completely unaffected by discriminatory processes and men and women had equal preferences and resources, men and women would be expected to be equally distributed across all occupations. However, in our sample of young skilled workers 58.8 percent are male and 41.2 percent female. Thus, we assume that the expected proportion of jobs within occupation j held by men is equal to their proportion in our sample. Apart from allowing for a 10 percent random deviation from the

Table 6.2: Occupation types: female, male, integrated

Sex label	1.spell	2 years of work exper.	3 years of work exper.	5 years of work exper.	7 years of work exper.
Female	77 (28 %)	75	75	70	67 (27.0 %)
Integrated	36 (13 %)	36	36	35	33 (13.4 %)
Male	159 (59 %)	155	155	152	146 (59.3 %)
Total	272 (100 %)	266	266	257	246 (100 %)

expected proportion, we define male, female and integrated occupations in the following way: *Male occupations*, which are non-traditional occupations for women, are occupations in which men's share of employment is greater than 68.8 percent. *Female occupations* are occupations in which men's share of employment is less than 48.8 percent. *Integrated occupations* are the remaining ones in which men's share of employment is in between 48.8 and 68.8 percent.

The outcome of grouping is shown in table (6.2) for different points during the early career. Individuals in the sample start work in 272 different occupations. 77 of those are female occupations, 36 are integrated and the balance (159) are male occupations. Even though during the course of the early career the number of observations used in our analysis diminishes, as shown in table (6.3), this leaves the distribution of occupations in the sample across these three groups unaffected. For instance, individuals with 7 years of actual work experience are observed working in 246 occupations. These are grouped into 67 female occupations, 33 integrated occupations and 146 male occupations.

In table (6.4) the six most frequently observed occupations for males and females are listed. Clearly, men are most often observed in blue collar occupations and women in services. One exception, though, is the profession

Table 6.3: Number of individuals observed within occupation types

Sex label	1.spell female	1.spell male	2 years of work exper. female	2 years of work exper. male	3 years of work exper. female	3 years of work exper. male	5 years of work exper. female	5 years of work exper. male	7 years of work exper. female	7 years of work exper. male
Female	13498	3498	9344	2536	7384	1648	4201	963	1978	467
Integrated	1388	2054	826	1381	654	858	374	564	167	254
Male	1112	16070	705	12540	545	8172	297	4854	122	2287
Total	15998	21622	10875	16457	8583	10678	4872	6381	2267	3008

Table 6.4: Most frequent occupations

Panel A: Most frequent occupations for men				
Occupation in first job	# of men	%	# of women	%
motor vehicle mechanic	1427	6.8	8	~ 0
electrician	1347	6.4	18	~ 0
professional clerical workers	1107	5.3	3508	23.3
machinist/locksmith	896	4.3	7	~ 0
joiner	871	4.2	20	~ 0
pipe fitter	844	4.1	2	~ 0
total	6492	31.2	3563	23.6
....				
total # of individuals	20794	100.00	15055	100.00

Panel B: Most frequent occupations for women				
Occupation in first job	# of women	%	# of men	%
professional clerical worker	3508	23.3	1107	5.3
sales person	2349	15.6	507	2.4
receptionist	1285	8.5	3	~ 0
hygienist	889	5.9	50	~ 0
banking professional	787	5.2	546	2.6
nurse	634	4.2	55	0.26
total	9452	62.7	2268	10.9
....				
total # of individuals	15055	100.00	20794	100.00

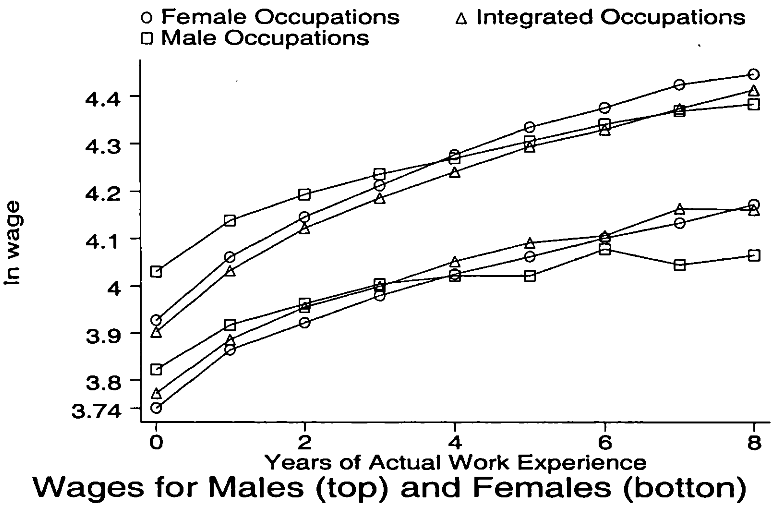


Figure 6.1:

professional clerical worker which is ranked amongst the six occupations for men as well as for women. Furthermore, while five out of the six most frequently observed male occupations are completely segregated, on average in the occupations listed for females the degree of segregation seems to be lower. Finally, for both sexes a substantial part of the sample is observed within these six occupations.[30]

6.4.2 Wage profiles in male/female/integrated occupations

In order to get a first estimate of the gender wage gap within *female*, *male* and *integrated occupations*, we plot means of logarithmic wages within groups k, k=female, integrated, male, holding actual work experience constant. These are shown in figure (6.1). At this stage we do not present

[30]Quite often in the literature the point is raised that women are observed in a more narrow range of occupations than men. See e.g. over-crowding theory, Bergmann (1974), which is partly based on this feature. However, this may simply be due to stronger differentiation of manual skills than services in the data.

standard errors; but we do so in the following sections.[31] The upper group of three graphs shows profiles of men within *female*, *integrated* and *male occupations.* The lower group of graphs shows the corresponding ones for women.

Most strikingly, we find that between occupation groups both for men and women, profiles seem to differ with respect to entry wages as well as slopes of the curves. However, differences seem to be most pronounced at the beginning of the career. Since profiles within occupation groups both for men and women are quite parallel, it seems that the wage gap is substantial from the beginning of the career and remains almost constant afterwards. In more detail, it appears that entry wages are, both for men and women, highest within male occupations. On the other hand, slopes of the profiles seem to be steeper in female and integrated occupations than in male occupations. Hence, assuming that profiles shown in figure (6.1) for the early career extend straightforwardly over the entire working careers of men and women, we gain two findings from the graph contrasting with predictions from Polachek's (1981) model. First, for women entry wages seem to be lower in female occupations than in male occupations and wage-work experience profiles seem to be steeper in female occupations than in male occupations. In order to investigate these findings in more detail, we apply regression analysis.

[31]More formally, we plot predictions from the following regression:

$$lnW_{ikt} = EX_{ikt}\beta_k + \epsilon_{ikt} \tag{6.5}$$

where logarithmic wages are regressed on dummies for integer numbers of years of work experience, and ϵ_{ikt} is an error term. The constant as well as the coefficients vary across the k groups of occupation.

6.4.3 Wage regression analysis

Unless the findings in the previous graph are spurious because the differences are insignificant, one may conjecture that male-female wage differentials within occupational groups occur for two reasons. First, individuals differ with respect to human capital acquired during the early career; excluding work experience and education which have been held constant. Second, returns to work experience differ between occupational groups, and, furthermore, losses from time out of work, for example, may differ too.

Descriptive statistics of work histories

In table (6.5) we list mean values of the main work history variables for men and women separately. We have calculated mean human capital endowments accumulated until 1990, the last period observed in the data. In order to analyse the effect of time out of work periods in more detail we present mean values for the entire sample and the sub sample with exposure to time out of work. To make the description of the work history complete, we also present mean durations of apprenticeship although we may have to interpret these numbers more cautiously.[32]

Generally, we find that during the early career higher proportions of men are exposed to a 'time out of work' spell and that mean durations of such spells are higher for men than for women. The latter is found when individuals without time out of work spells, which appear as zeros in the data, are included or excluded. The high share of men, 80 percent, who do have a spell

[32]The problem is that the exact point in time of completion of training cannot be determined for all individuals in the IABS. Only for firm movers, who must be reported within six weeks, do we possess that information with certainty; otherwise, the report of transition from apprentice status to employment status must be made at least by the end of the calendar year.

Table 6.5: Summary statistics, by occupation types and gender

Variable	Occupation type female (1)	integ (2)	male (3)	t-statistic (1)=(2)	(1)=(3)	(2)=(3)
		female workers				
		all individuals				
time out of work until 1990	.894	1.130	1.314	-4.237	-7.262	-2.213
work experience until 1990	3.75	3.548	3.452	2.490	3.562	.8844
apprenticeship duration	2.19	2.15	2.2	1.85	-0.53	-1.85
# observations	12781	1204	1124			
		individuals without time out of work spells excluded				
time out of work until 1990	1.66	1.67	1.64	-.0480	.262	.235
work experience until 1990	3.90	3.55	3.54	3.58	3.927	.126
apprenticeship duration	2.16	2.11	2.15	1.86	0.3	-1.3
# observations	6859	815	898			
	(53%)	(67.7%)	(80%)			
		male workers				
		all individuals				
time out of work until 1990	1.46	1.57	1.39	-1.98	1.96	3.88
work experience until 1990	3.47	3.501	3.62	-0.36	-2.77	-1.68
apprenticeship duration	2.31	2.39	2.58	3.55	-18.15	-9.68
# observations	3196	1717	15248			
		individuals without time out of work spells excluded				
time out of work until 1990	2.04	1.97	1.78	1.0	6.13	3.59
work experience until 1990	3.61	3.59	3.83	0.2	-3.5	-3.0
apprenticeship duration	2.34	2.40	2.57	-2.38	-13.47	-7.92
# observations	2285	1365	11893			
	(71.5%)	(79.5%)	(78%)			

in time out of work may reflect compulsory national service. Furthermore, while for men means of work history variables seem to be similar across occupation groups for women we find a more diverse picture. It is found that the proportion of women with a time out of work spell is higher in male occupations than in female occupations. A feature that contrasts with the prediction of Polachek's model. Also, for women mean durations in time out of work are largest in male occupations when zeros are included; however, they are equal when zeros are excluded. This finding may reflect on the one hand the feature that female occupations provide often better, more flexible conditions to combine work and having children, the main reason for women to drop out of the labour market. On the other hand maternity leave is regulated by laws which may lead to quite similar levels of time out of work at the mean. Moreover, we find that mean apprenticeship duration is longer for men than for women. Also, while for women mean durations are virtually the same across occupations, means reveal that for men apprenticeships take longer in male occupations than in female ones.

OLS estimator

Here we briefly describe the estimation procedure we apply throughout the chapter. We estimate the following wage regression model:

$$lnW_{ikt} = \beta_{0k} + EX_{ikt}\beta_k + To_{ikt}\gamma_k + \epsilon_{ijt} \tag{6.6}$$

by ordinary least squares. k indexes the three groups of occupations. For convenience, we assume a function linear in variables.[33] EX_{ikt} measures years of work experience in occupational group k, and To_{ikt} measures years

[33]This specification is advantageous for the first-difference estimator we apply, and, furthermore, makes the presentation of results clearer. However, change of the functional form would not alter the main findings.

of time out of work. Extending the regression, we also consider segments of time out of work, according to the information given in the data, into time out of work due to interruption - which is maternity leave or national service for men - unemployment and periods due to other non-work periods. The dependent variable is logarithmic wages adjusted for a gender specific time trend.[34]

The gender specific time trend is estimated from a wage regression using entry wages only in the following way:

$$lnW^{g}_{ikt0} = \beta^{g}_{0k} + \delta^{g} trend_t + \nu^{g}_{i} + u_{ikt} \tag{6.7}$$

where lnW^{g}_{it0} denotes entry wages for each individual in calendar year t. The regression is run separately for men and women; index g=F,M for females and males. Hence, the time trend coefficient varies across sex, but is constant across occupation groups. The time trend adjusted wage is then predicted as:

$$lnW^{+g}_{ikt} = lnW^{g}_{ikt} - \hat{\delta}^{g} trend_t \tag{6.8}$$

Estimation results

In table (6.6) OLS estimation results are presented. Entry wages are lowest for females in female occupations (3.59); in integrated occupations they are 2.4 percent higher and in male occupations 7.8 percent higher. For males the ranking is different. The entry wage is lowest in integrated occupations (3.756), intermediate in female occupations (+3.1 percent) and, as for females, highest in male occupations (+5.6 percent). Furthermore,

[34] At this stage, this estimation approach may seem awkward, but in the next section where we apply a first difference estimator, it becomes clearer why such a approach was adopted. At this stage, however, it serves to make OLS estimation results comparable to first difference estimation results presented later on.

Table 6.6: OLS regression results: dep. var. $(ln(W_{ikt}) - \hat{\delta}^g t)$

	female workers		male workers	
variable	Coef.(s.e.)	Coef. (s.e.)	Coef.(s.e.)	Coef. (s.e.)
omitted type: female occupations				
cons	3.59 (.0019)	3.59 (.0019)	3.786 (.0039)	3.776 (.0039)
type 2	.0238 (.0068)	.0250 (.0069)	-.0311 (.0064)	-.0222 (.0063)
type 3	.0775 (.0074)	.069 (.0075)	.1117 (.0042)	.1186 (.0042)
work experience	.040 (.0005)	.0411 (.0005)	.0552 (.0009)	.0539 (.0009)
type2 X (work experience)	-.0034 (.0017)	-.0022 (.0017)	-.0011 (.0015)	.0001 (.0015)
type3 X (work experience)	-.0181 (.0019)	-.017 (.0020)	-.0224 (.0010)	-.0225 (.0010)
time out of work	-.0643 (.001)		-.0062 (.0016)	
type2 X (time out of work)	.0238 (.00)		.0059 (.0027)	
type3 X (time out of work)	.0146 (.0044)		-.0030 (.0018)	
interruption		-.1440 (.0053)		.0521 (.0035)
type2 X interruption		-.0104 (.0177)		-.0341 (.0066)
type3 X interruption		.0219 (.0203)		-.0191 (.003)
unemployment		-.1203 (.0032)		-.072 (.0041)
type2 X unemployment		.0227 (.009)		.0294 (.0063)
type3 X unemployment		.0938 (.0083)		.0394 (.0044)
other non-work		-.0241 (.0021)		.0061 (.0021)
type2 X (other non-work)		.0234 (.0060)		.0083 (.0035)
type3 X (other non-work)		-.0315 (.0061)		-.0131 (.0023)
# observations	75695	75695	108536	108536
R^2	0.1039	0.1143	0.1105	0.1233

Note: type 1: female occupation, 2: integ occupation, 3: male occupation.

coefficients of the variable work experience estimated for female workers as well as for male workers differ across occupation groups, and coefficients within occupation groups differ as well across genders. Moreover, we see that OLS estimates of the coefficients of the time out of work variable are different across occupation groups and gender too. Coefficients are lowest, at about -6 percent, in female occupations for females. For males, estimates are negligibly small.

Aiming to identify the structural parameters of the model specified in equations (6.1) and (6.2) and, most importantly, the return to work experience, OLS estimates may only be interpreted as reduced form parameter estimates. This is because OLS estimates of the coefficients of the work experience as well as the time out of work variables, and the segments of time out of work variables may be upward biased estimates of the structural parameters due to correlation of the variables with unobserved heterogeneity components contained in the error term. More specifically, positive correlation of work experience may be assumed with unobserved individual specific components, such as motivation or ability. Thus, more motivated individuals may work more in terms of years. The opposite can be hypothesized for the variable time out of work.

FD estimator

In this section, we propose a two step first difference estimator. In the first step, wages are adjusted for a time trend according to equation (6.8). In the second step, the model is transformed into first differences. A caveat of estimation of a standard first differences wage model is that, given that explanatory variables in equation (6.1) are only predetermined, it will result in inconsistent estimates of the parameters of interest. To circumvent this problem we apply an instrumental variable first differences approach.

For occupational stayers, whose (occupation of) qualification matches with the occupation (of work), in first differences, the wage regression model reduces to:

$$\Delta lnW^{+}_{ikt} = \beta_k + \Delta To_{ikt}\gamma_k + \Delta u_{ikt} \tag{6.9}$$

where $\beta_k = (\beta_{1k} + \beta_{2k})$ if j is replaced by k in equation (6.1). If the variable *work experience* is measured in integer years then one may use as an instrument the approximisation $\Delta EX_{it} = 1$.[35] It follows, that the regressor drops out as shown in the above equation.[36] The error term reduces to the

[35] In the data for approximately 20 percent of observations the difference in work experience is one.

[36] The time trend is already considered on the left hand side.

Table 6.7: FD regression results: dep. var. $(\Delta ln(W_{ikt}) - \hat{\delta}^g)$

variable	female workers Coef.(s.e.)	Coef. (s.e.)	male workers Coef.(s.e.)	Coef. (s.e.)
omitted type: female occupations				
cons	.0286 (.0006)	.0286 (.0006)	.04 (.0016)	.04 (.0016)
type 2	.0063 (.0024)	.0058 (.0024)	-.0071 (.0027)	-.0067 (.0027)
type 3	.0165 (.0026)	.0159 (.0026)	-.0176 (.0018)	-.0173 (.0018)
time out of work	-.0355 (.0021)		.0102 (.0030)	
type2 X (time out of work)	.0407 (.0062)		.0283 (.0051)	
type3 X (time out of work)	.0280 (.0060)		.0273 (.0034)	
interruption		-.1322 (.0058)		.0362 (.0066)
type2 X interruption		.0439 (.0196)		.0125 (.013)
type3 X interruption		-.0000 (.0211)		.0048 (.0073)
unemployment		-.0255 (.0051)		-.0477 (.0094)
type2 X unemployment		.0739 (.0143)		.0541 (.0145)
type3 X unemployment		.0768 (.0135)		.0674 (.010)
other non-work		-.016 (.0030)		.0160 (.0040)
type2 X (other non-work)		.020 (.0081)		.0299 (.0066)
type3 X (other non-work)		.0015 (.0082)		.0263 (.0045)
# observations	75695	75695	108536	108536

Note: type 1: female occupation, 2: integ occupation, 3: male occupation.

noise component, Δu_{ikt}, since ν_i also drops out. OLS applied to this model identifies the returns to work experience within type k.[37]

Estimation results

In table (6.7) FD estimation results are listed. We are primarily interested in the coefficients of the work experience variable which are the constants varying across occupation types in the first differences specification.

A major result is that for the sample of females within female occupations the return to experience is lower in comparison to the other occupation types; hence, we find a relatively flat wage profile within female occupations

[37]The idea is related to Topel and Ward (1992) where in the wage regression the return to tenure is the parameter of interest. Like in their approach, for identification we require that no further non-random sample selection is induced. Additionally, in our application we require that To is strictly exogenous, hence $E[\Delta u_{ikt}|\Delta To_{ikt}] = 0$. Otherwise, positive correlation of u_{ikt-1} and To_{ikt} induces that the constant to be estimated with an upward bias.

as derived in Polachek's model. On the other hand, estimates show that for males the return to work experience is highest in female occupations, which suggests that other factors, for example, job status, may have further impact on estimates. Another aspect of the FD estimation results of the return to work experience is that within all occupation gender cells estimates from FD are smaller than OLS estimates; one exception though is the group females in male occupations. Thus, these results increase confidence in the view that unobserved individual specific omitted variables are positively correlated with the work experience variable and induce OLS estimates of the return to be upward biased. More generally, if symmetry of returns to work experience and losses from time out of work within an occupation were to be assumed, this result would support part of Polachek's predictions.[38]

6.5 Within occupation wage differentials

In the following, we estimate wage-work experience profiles within specific occupations. This analysis has several appealing advantages. As previously illustrated, due to the grouping of occupations, coefficient estimates may still incorporate components of unobserved heterogeneity not controlled for by FD. As an alternative, in order to rule out heterogeneity in most detailed way, we can select occupations at the most disaggregated level. By selection then on occupation stayers, i.e. workers who have been trained in the same occupations measured on a three digit level, we eliminate virtually all heterogeneity, also caused, for example, by differences in job status. Furthermore, it is very instructive to look at wage profiles within particular occupations rather than at averages across groups of occupations. Clearly, disadvantages of this type of analysis are that definitions of single occupa-

[38] Although the entry wages are not in line with his model's predictions.

Table 6.8: Selection of frequently observed occupations

Occupation	Men		Women	
	# of indiv. (%)	# wage spells	# of indiv. (%)	# wage spells
Professional clerical workers (fem)	1107 (5.3)	6487	3508 (23.3)	23622
Sales person (fem)	507 (2.4)	3432	2349 (15.6)	13449
Banking professional (fem)	546 (2.6)	3009	787 (5.2)	5296
Wholesale-and retail sale staff (integ)	419 (2.0)	2470	417 (2.8)	2378
Life-and property insurance staff (fem)	113 (0.5)	895	114 (0.8)	768
Draughtsperson (fem)	161 (0.8)	838	259 (1.7)	1565
....				
Total # of individuals	2853 (13.7)	17131	7434 (49.4)	47078

Note: The sex label is indicated in brackets as we defined before.

tions are restricted by data and number of observations within occupation cells imposes constraints on the analysis.

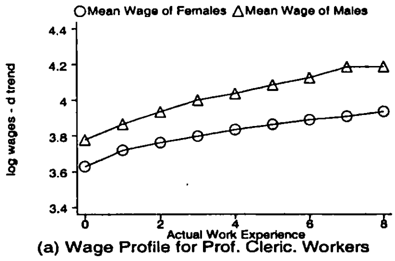
For our analysis of within occupation wage differentials, we focus on six occupations, listed in table (6.8). Most of the selected occupations are "female" occupations, according to the definition of groups given previously. The *wholesale-and retail sales staff* occupation constitutes an exception.

6.5.1 Regression analysis

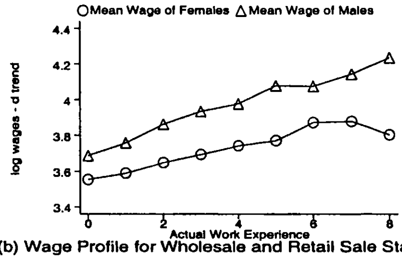
Given our sample of young skilled workers, we expect male-female wage differentials conditional on occupation and work history variables to be insignificant. The empirical evidence based on the occupational groups given in the IABS is contrary to this prediction.

In figure (6.2) and (6.3) the evolution of wages within the chosen occupations are plotted. In each graph, wage profiles on the higher level refer to male workers, and on the lower to female workers. Wage profiles shown here are conditional on workers staying working in the occupation of qualification.[39]

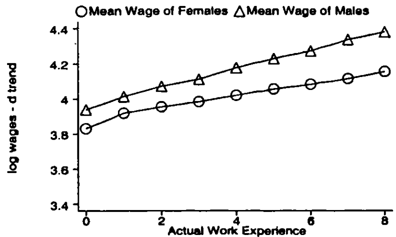
[39]To be precise, until they may change occupation. However, inclusion of all individuals



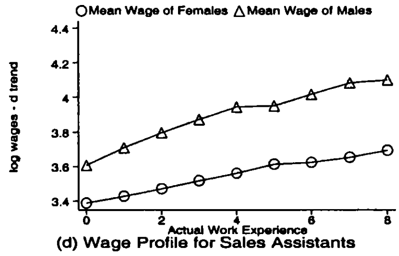
(a) Wage Profile for Prof. Cleric. Workers



(b) Wage Profile for Wholesale and Retail Sale Staff

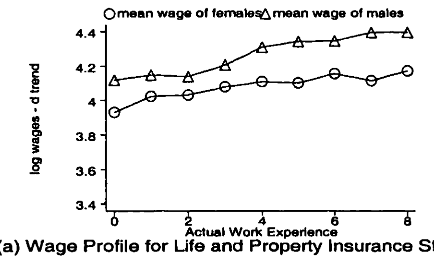


(c) Wage Profile for Banking Clerks

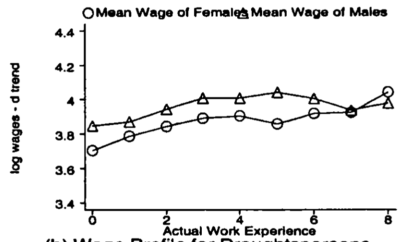


(d) Wage Profile for Sales Assistants

Figure 6.2:



(a) Wage Profile for Life and Property Insurance Staff



(b) Wage Profile for Draughtspersons

Figure 6.3:

Table 6.9: Entry wages and differentials within selected occupations

Occupations	Females		Males		Differential	
	#obs	meanlogw (s.e.)	#obs	meanlogw(s.e.)		t-statistics
Profess. cleric. workers	3432	3.82 (0.004)	976	3.86 (0.009)	0.04	4.28
Sales person	2149	3.55 (0.004)	481	3.71 (0.012)	0.16	14.7
Banking professional	778	4.05 (0.006)	486	4.07 (0.011)	0.027	2.23
Wholesale and retail sale	367	3.73 (0.012)	372	3.76 (0.014)	0.035	1.88
Life-and property ins.	121	4.16 (0.02)	110	4.20 (0.025)	0.04	1.28
Draughtsperson	246	3.90 (0.014)	130	3.95 (0.024)	0.049	1.90

Table 6.10: Entry wage differentials, all occupations

	non sig.*	sig.*	purely male	purely female
mean differential	0.056	0.255		
mean wages			4.09	3.73
(min wage, max wage)			(3.75, 4.71)	(3.53, 4.01)
# of occupations	98	64	52	8

Note: * Significance level is $\alpha = 0.05$.

The wage profiles for occupations all possess the typical shape, i.e. that wages increase over the early career. In the first two years, wage growth seems to be higher than afterwards. Entry wages differ between occupations. *Banking professionals*, *life and property insurance staff* and *draughts* persons are amongst the six most highly paid occupations whilst *sales person* are paid the least. These features of profiles hold for men as well as women. The graphs show considerable male-female wage differentials over the early career within each occupations.

does not change the profiles. We find only that the profile shifts slightly upward, showing slightly larger gains for movers.

6.5.2 Entry wage differentials

In table (6.9), we list precisely estimated entry wages and entry wage differentials within occupations, using only the first wage spell of individuals' records.[40] These are supplemented by t-test statistics for the null-hypothesis of non-significance of gender differentials. In fact, differentials at this stage turn out to be quite small in five out of the six occupations; below 6-7 percent. However, in three out of six cases they are significant at a 5 percent significance level. Within the occupations *life and property insurance* and *wholesale and retail sale* staff differentials are non-significant. In *banking*, the differential is close to zero. Amongst *professional clerical workers*, a significant gap of 4 percent is estimated and female *sales persons* are paid 16 percent less than males on average. Hence, from this selection of occupations we get a less clear result than from the estimation of the decomposition of the total wage differential into intra and inter occupation wage differentials shown in section 6.3.2 of this chapter. Therefore, to get a more general view, we count occupations for which we estimate significant differentials and non- significant wage differentials. The results are listed in table (6.10). In 162 occupations men as well as women are observed. For 98 of them, we estimate non-significant wage differentials, for 64 significant ones. In the remaining completely segregated occupations, we estimate that mean wages are considerably higher in occupations in which only men work than in occupations in which only women work. In conclusion, we find that within occupation differentials, holding education constant, even at the beginning of the career seem, generally, not to be equal to zero as economic theory

[40]This leads to lower differentials than they appear in the graphs shown before. There, mean entry wages are calculated according to the following conditional expectation $E[lnW|EX = 0]$, and, hence, more than the first wage spell of an individuals' record may be included in the calculations.

would suggest. The size of differentials seems to depend on occupation.[41]

6.5.3 Unobserved heterogeneity

One explanation of the wage gap over the early career is that individuals within occupations are observationally equal but differ with respect to unobserved characteristics. More particularly, it is perhaps the case that we compare more able males with less able females, or males in better positions with females in worse ones.[42] To investigate this possibility we estimate wage growth equations in which the parameter of main interest is the return to work experience. We use the same estimation procedure as described in the previous sections.

In tables (6.11) and (6.12), regression results derived by OLS and FD for the six selected occupations are presented. Evaluation of the comparison of OLS and consistent FD estimates shows that all OLS estimates of the return to work experience are upward biased. This is a neat result that supports the conjecture stated earlier that unobserved heterogeneity components and work history variables are positively correlated. On the other hand, we find that across all occupation-sex cells returns estimated by FD are smaller than OLS estimates for both men and women. Hence, only in a few cases does the application of the consistent estimator lead to a reduction in differences in coefficients between genders. Thus, unobserved heterogeneity does cause biased OLS parameter estimates and controlling for it may lead to a reduction in differences in returns to experience across

[41] Another issue here would be coverage by unions which may increase wages. If men were more likely to work in covered occupations than women this may explain differentials. However, union coverage in Germany is extremely high, about 80-90 %, which may make this point irrelevant here. See e.g. OECD (1997). Furthermore, it would be interesting to explore differences in industry or firm size.

[42] Thus, selection on occupations does not lead to complete elimination of heterogeneity.

Table 6.11: Within occupation wage regressions

	Prof. cleric. workers Coef. (s.e.)	Banking prof. Coef. (s.e.)	Sales person Coef. (s.e.)	Wholesale- & retail sale Coef. (s.e.)
For female workers - OLS estimation				
constant	3.64 (0.004)	3.85 (0.005)	3.38 (.004)	3.53 (0.019)
work experience	0.05 (0.0017)	0.04 (0.001)	.044 (.002)	0.053 (0.008)
time out of work	yes	yes	yes	yes
# observations	11004	2569	6502	809
For female workers - FD estimation				
constant	0.037 (0.0013)	0.036 (0.022)	0.025 (0.002)	0.037 (0.005)
d(time out of work)	yes	yes	yes	yes
# observations	11004	2569	6504	809
For male workers - OLS estimation				
constant	3.76 (0.009)	3.89 (0.008)	3.57 (.014)	3.61 (0.018)
work experience	0.067 (0.003)	0.06 (0.003)	.086 (.005)	0.085 (0.007)
time out of work	yes	yes	yes	yes
# observations	2794	1611	1286	843
For male workers - FD estimation				
constant	0.05 (0.003)	0.043 (0.004)	0.055 (0.011)	0.05 (0.005)
d(time out of work)	yes	yes	yes	yes
# observations	2794	1611	1286	843

Table 6.12: Within occupation wage regressions - continued

	Life and property ins. Coef. (s.e.)	Draughtsperson Coef. (s.e.)
For female workers - OLS estimation		
constant	3.97 (0.017)	3.73 (0.013)
work experience	0.0335 (0.007)	0.051 (0.005)
time out of work	yes	yes
# observations	367	835
For female workers - FD estimation		
constant	0.033 (0.006)	0.038 (0.004)
d(time out of work)	yes	yes
# observations	367	835
For male workers - OLS estimation		
constant	4.06 (0.02)	3.81 (0.027)
work experience	0.042 (0.007)	0.047 (0.01)
time out of work	yes	yes
# observations	342	321
For male workers - FD estimation		
constant	0.038 (0.008)	0.045 (0.0116)
d(time out of work)	yes	yes
# observations	342	321

genders. However, the main part of the gap remains unexplained. Thus, other factors must have an impact on the gender wage gap as well.

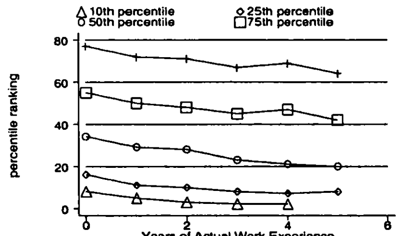
6.5.4 Promotion

Another conjecture explaining wage differentials across early career is promotion. If men are promoted at a faster rate than women, promotion may explain within occupation differences. In the notion of Lazear and Rosen (1990) this would imply that men take jobs with more firm-specific training content than women do. This would lead to steeper wage profiles for males compared to females. However, we cannot directly observe job status or promotion in our data. On the other hand changes in the occupation for which individuals are registered may capture to some extent promotion.[43] Another suitable device in order to identify promotion can be derived from the entire distribution of wages within particular occupations and the longitudinal structure of the data set allowing us to follow individuals over the early career from the beginning onwards. These are the major items upon which we base the following analysis.

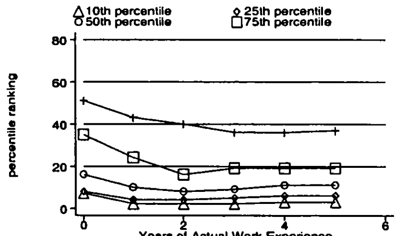
We take the distribution of wages of the sample of men as the benchmark case and look how women starting at a particular percentile in the wage distribution of men perform over their early career.[44] If females move up (down) the distribution it means that they are promoted faster (slower) than comparable men. If women stay in the same part of the wage distribution of men it means that men and women are promoted at an equal rate. The underlying assumption of these interpretations is that the standard deviation

[43] We find evidence in favour of this hypothesis in the data. We have found for both males and females that conditional wage profiles for occupation stayers are slightly lower than the corresponding ones for all individuals including movers.

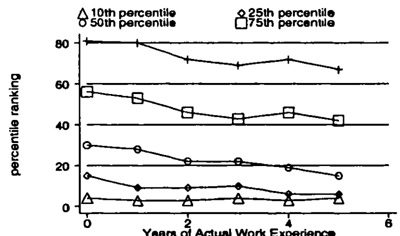
[44] Of course, the analysis can also be based on the wage distribution of females and how wages of men are positioned within that distribution.



(a) Prof. Cler. Work.: Changes Fem. in Male Distr.



(b) Sales Assist.: Changes Fem. in Male Distr.



(c) Banking Clerks: Changes Fem. in Male Distr.

Figure 6.4:

of the wage distribution of men over time stays constant. For our sample of wages for males we estimate a constant standard deviation of 0.26. Hence, we assume that conclusions drawn from this exercise are indeed valid.

We then analyse the change in the percentile ranking of the 10th, 25th, 50th, 75th and 90th percentile females over the early career. This analysis can be conducted for each occupation, given that a sufficiently high number of observations is available. In figure (6.4) we show the outcomes for *professional workers*, *banking professionals* and *sales persons.*[45] On the x-axis of each graph, integer numbers of years of actual work experience are plotted and on the y-axis the percentile ranking of men is shown. The five lines indicate from bottom to top the movement of the 10th, 25th, 50th, 75th and 90th percentile females in the male wage distribution over the early career. Among the occupations selected, *professional clerical workers* and *banking*

[45]Since we split the male wage distribution into 100 percentile points, 100 observations are needed at least within integer numbers of actual work experience.

professionals reveal quite similar patterns, while the outcomes for *sales persons* show a more compressed graph of the five lines. All three graphs have in common the fact that females are ranked lower than comparable men, right from entry into the labour market.

The difference is more remarkable though among *sales persons.* Already, over the first four years in the labour market a quite clear downward movement of females in the wage distribution of men can be observed. Thus, females seem to be promoted at a slower rate than men within occupations looked at here. The decline of females in the wage distribution of men seems to be more dramatic among *sales persons* than among the other two occupations.

These results are perfectly compatible with the wage profiles shown in figure (6.3) where it has been seen that the gap is larger for *sales persons* than in other occupations and grows also at a faster rate during the early career. However, the finding that men are promoted at a faster rate can mean two things: it may suggest that men are promoted more often than women or that they receive larger wage gains from each promotion. From the available data we cannot distinguish between those two hypotheses and, hence, both are compatible with our empirical findings.[46] Evidence in another study using the British Household panel, for example, suggests that women are as likely as men to be promoted but that they gain less from promotion in terms of average wages.[47]

[46]The only evidence we can bring forward, which may support the argument that women are as often promoted than men but gain less from promotion, are counts of the number of positive wage changes reported in the data. For the selected occupations we do not see much of a difference here between the sample of men and women.

[47]See: Booth, Francesconi and Frank (1999).

6.6 Conclusions

In this chapter, we investigate male-female wage differentials and occupational segregation. We use a German sample for the period 1975 to 1990, taken from an administrative event history data set, the IABS, that contains young workers who have undertaken vocational training within the dual system apprenticeship programme.

In the analysis we present three sets of results: First, we find that intra occupation wage differentials are of neglible importance in explaining entry wage differentials but become increasingly important during the early career. For example, at five years of actual work experience, 50 percent of the wage differentials is due to intra occupation wage differentials. While this result seems to be intuitively clear with respect to theoretical predictions, it contrasts with empirical results presented so far in the literature.[48] One reason for this difference may be measurement error in the occupation variable used in other studies. These problems have been avoided in our study by defining occupations in a detailed way and with respect to occupational qualification. This is enabled by the data, since it includes an occupation variable disaggregated into approximately 300 occupations and matches quite well with apprenticeship occupations. Furthermore, we observe occupational skill by construction of the sample.

Second, from our estimates of the parameters of interest in the underlying wage regression model, we seem to gain more evidence in favour of Polachek's hypotheses than has been found in earlier work on this matter.[49] More specifically, distinguishing between *male*, *female* and *integrated* occupations, we find for females that entry wages seem to be higher in *male*

[48]See e.g. Miller (1987) and Kidd and Shannon (1996).

[49]See: England (1982), Corcoran, Duncan and Ponza (1983) and England et al. (1988).

than in *female* occupations, and that returns to work experience are lower in *female* than in *male* occupations. Differences between our results and findings presented in other papers based on U.S. survey data may by due to the use of different estimation procedures. Accordingly, in our analysis for male workers we find that entry wages are also higher in *male* than in *female* occupations, and that returns to work experience are higher in *female* occupations than in *male* occupations. The latter result may seem odd and may reflect omitted variables, such as job status. One may assume that males in *female* dominated occupations may still occupy higher positions in the hierarchy which gives them seemingly a wage advantage.

Third, and finally, the results presented on within occupation wage differentials are aimed at analysing what, if at all, explains the gap if heterogeneity in skill is held constant in a most detailed way. Studying the three exemplifying occupations, constituted by *professional clerical workers*, *sales persons* and *banking professionals*, we find significant differentials in raw wages from the beginning of the careers onwards which seem to become even more pronounced over time. Our results from regression analyses suggest that while these differences are only to a minor extent accountable by unobserved individual specific effects, differences in promotion between men and women seem to explain these differences. These results support a Lazear and Rosen (1990) approach that gender segregation with respect to promotion, which is optimal under the assumption that females have comparative advantages outside the labour market, contributes to the gender wage gap.

In concentrating our analysis on workers' characteristics, the robustness of our results may be undermined by neglect of industry effects as well as employer characteristcs. Calculation of some crude correlation coefficients results in values of 0.5 and smaller. For male workers, the correlation seems to be stronger than for female workers.[50] Hence, one may argue that omitted variable bias may not cause too much of a problem. Also, variables measuring employer and industry characteristics may indirectly reflect otherwise unmeasured dimensions of ability or labour force commitments.[51] Thus, we control for these factors partly in our first differences estimations since industry changes are in practice not found very often. On the other hand, firm changes may well be an important factor; in particular, within the dual system apprenticeship programme where individuals are only trained within 30 percent of all firms.[52] However, more research is needed to distinguish between motives for change of firm after apprenticeship in order to address effects on the gender wage gap if there are any at all.[53] We leave the investigation of firm specific human capital components, which is certainly an interesting point as other research on wages has also shown[54], to future work.

6.7 Appendix to chapter 6

6.7.1 Calculation of standard errors

Assuming that P_j^F and P_j^M, the proportions of males and females in occupation j, are non-random variables the standard error of the intra occupational

[50]Results are reported in section 6.7.3, in the appendix to this chapter.

[51]Rosen (1982) and Kremer (1993) hypothesize that workers sort into firms based on their relative ability and skills because of interdependencies in production. This result refers to team production models. Hence, average wage and skill levels by occupation will be correlated across employers. Empirical evidence in Dickens and Katz (1987) shows that conditional industry wage differentials are highly correlated across occupations. Abowd et al. (1999) find correlation of worker-specific and firm-specific components in French data.

[52]See table (2.13) and (2.14) in chapter two.

[53]Using our data, results seem not to alter greatly by conditioning on workers staying with the training firm.

[54]See e.g. Groshen (1991), Abowd et al. (1999), Carrington and Troske (1995).

component in equation (6.4) is calculated as follows:

$$se(\Sigma_{j=1}^{n} P_j^F(lnW_j^M - lnW_j^F)) = \Sigma_{j=1}^{n}\sqrt{(P_j^F)^2(se_j^M)^2/n_j^M + (P_j^F)^2(se_j^F)^2/n_j^F}$$

Intra occupational wage differential components are calculated for occupation groups or occupations in which both men and women are observed. Obviously, the more aggregated occupation is the more groups enter the calculation of this component. On the other hand, the more disaggregated occupation is the more groups are included which are single sex. We include those groups' contribution to the total raw wage gap into the inter occupational wage differential component. Hence, the inter occupational component, $INTEROC$, can be thought of as a composite of three factors:

$$INTEROC = \underbrace{\Sigma_{j=1}^{n} P_j^M lnW_j^M}_{purely\,male\,oc.} - \underbrace{\Sigma_{j=1}^{n} P_j^F lnW_j^F}_{purely\,female\,oc.} + \underbrace{\Sigma_{j=1}^{n}(P_j^M - P_j^F)lnW_j^M}_{integrated\,oc.}$$

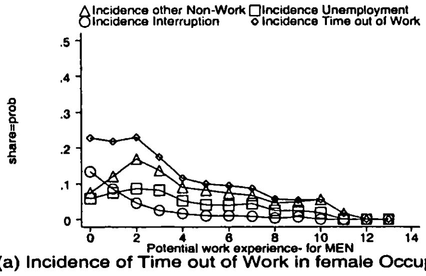
and the standard errors are calculated, accordingly, as:

$$se(INTEROC) = \Sigma_{j=1}^{n}\sqrt{(P_j^M)^2(se_j^M)^2/n_j^M} +$$
$$\Sigma_{j=1}^{n}\sqrt{(P_j^F)^2(se_j^F)^2/n_j^F} + \Sigma_{j=1}^{n}\sqrt{(P_j^M - P_j^F)^2(se_j^M)^2/n_j^M}$$

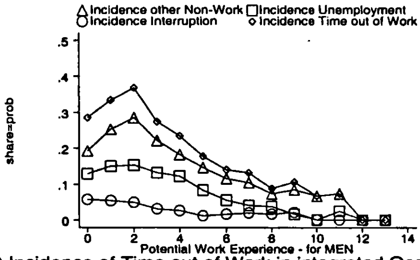
When it is assumed that the proportions of males and females in occupations j are random processes, obviously calculations are more complex. We do not present these results which become more and more sensitive to sample sizes within occupation cells.

6.7.2 Incidence of time out of work, by types

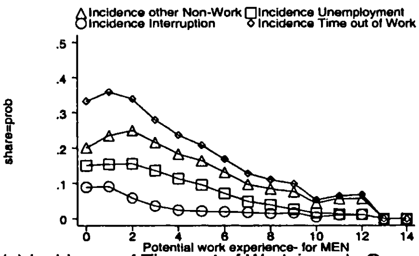
Another way to analyse the variable *time out of work* is to calculate the incidence of time out of work (which we abbreviate by *probout* in the following figures) holding actual work experience constant. Accordingly, the incidence of single components of *total time out of work*, i.e. maternity



(a) Incidence of Time out of Work in female Occup.

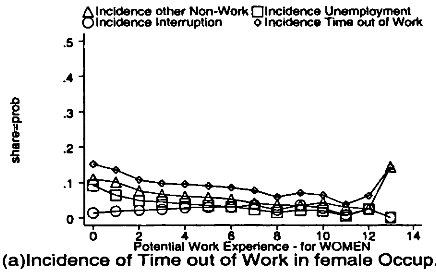


(b) Incidence of Time out of Work in integrated Occup.

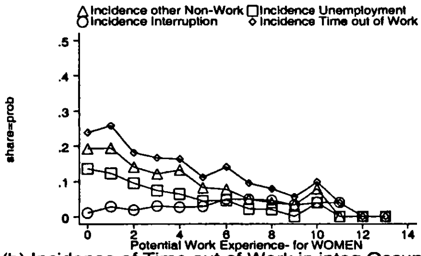


(c) Incidence of Time out of Work in male Occup.

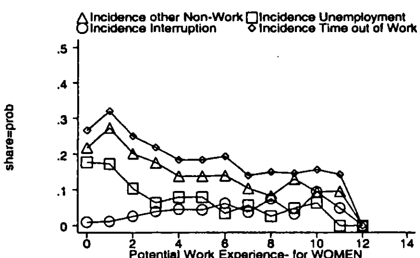
Figure 6.5:



(a)Incidence of Time out of Work in female Occup.



(b) Incidence of Time out of Work in integ Occup.



(c) Incidence of Time out of Work in male Occup.

Figure 6.6:

leave or national service *probm*, unemployment *probu* and other non-work spells *probw*, are calculated as well. The outcomes are shown in figures (6.5) for men and in (6.6) for women, again distinguishing female, integrated and male occupations. The graphs, in line with other descriptive statistics, show that females in female occupations have a lower likelihood to have a time out of work spell than females in male occupations. For example, within one or two years of work experience, the likelihood to have a spell in time out of work is about twice as high in male occupations than in female occupations. Integrated occupations are in the middle of those two extremes. Hence, this is in contrast with Polachek's hypothesis. Accordingly, it would have been expected that females in male occupation face highest costs of interruptions and, hence, have a low propensity to drop out. Thus, the opposite would be expected within female occupations. Another feature of the data going against human capital theory predictions is that differences in incidence of time out of work seem to be due to differences in the incidence of unemployment and other non work periods. The incidence of maternity leave, or interruptions more generally, looks quite similar across occupation groups. This holds both for males and females.

6.7.3 Correlation between occupation and industry

In table (6.13) simple correlation coefficients are shown for the variables *occupation* and *industry*. Both variables can be thought of as 'sorted' from manual work or manufacturing to services. For the calculations occupations and industries are disaggregated in three different ways: (i) into the broad categories agriculture, manufacturing, services, (ii) into eight groups and (iii) at the three (occupations) and two (industries) digit level. As can be seen, correlations are 0.515 and smaller. For male workers, the correlation

Table 6.13: Correlation between occupation and industry

Male workers			
Occupation	Industry		
Aggregation level	3 groups	8 groups	2-digit level
3 groups	0.4636		
9 groups		0.515	
3-digit level			0.4795
Female workers			
Occupation	Industry		
Aggregation level	3 groups	8 groups	2-digit level
3 groups	0.3713		
9 groups		0.3816	
3-digit level			0.3949

seems to be stronger than for female workers.

Chapter 7

Looking again at instrumental variable estimation of wage models in the gender wage gap literature

Abstract:

The evaluation of the gender wage gap, centers on the consistent estimation of the parameters of interest in a human capital wage regression model for males and females. In previous studies, the consistency of the parameter estimates often depends on the restrictive assumption of strict exogeneity and mean stationarity of corresponding explanatory variables in the model. In this chapter, we specify a wage model that allows these variables to be predetermined and we discuss consistent estimation. More specifically, we apply generalised method of moments estimators (GMM) based on Arellano and Bond (1991) and Arellano and Bover (1995) - a GMM first difference and a GMM-system estimator - which allow us to test for overidentifying assumptions made in order to derive consistent estimates. For estimation, we use the sample of young skilled workers.

7.1 Introduction

In the literature, the empirical analysis of male-female wage differentials most commonly is based on the estimation of wage regression models in which controls for human capital acquisition are included.[1] In Western industrialised countries, differences in human capital investment behaviour between men and women are mainly characterised by more interruptive work histories of women, by differences in education and by gender segregation across work places. Therefore, in order to describe work histories, measures of work experience and time out of work, often substituted by home time taken for rearing children, are included in the wage regression model in addition to controls for education and work place characteristics. While endogeneity induced by non-random sample selection depends on the assumptions about the nature of the selection process, endogeneity of the work history variables is due to correlation with unobserved individual-specific components contained in the error term of the wage regression model. As has been shown in the survey of the literature[2], in this case instrumental variable estimators are most suitable in order to derive consistent estimates of the parameters of interest which are the return to work experience and the loss from time out of work.

Nevertheless, in most studies on male-female wage differentials, traditional estimators have been applied which require the restrictive assumptions of strict exogeneity and mean stationarity for identification of the parameters of interest. In more recent studies, based on longitudinal survey data, instrumental variable estimators and generalised method of moments have been applied which allow for the relaxation of the strict exogeneity assumption.

[1]Becker (1964), Mincer (1974), Ben-Porath (1967).
[2]See part I, chapter 1 of this thesis.

Ordinary least squares estimation, usually, does not identify the parameters of interest because it does not control for the possible correlation of the unobserved individual specific effects and the work history variables or for measurement error problems in variables.[3] More general models, where strict exogeneity is still assumed, but in which the correlation of unobserved individual specific effects with the work histories is not constrained, have been estimated by the application of a fixed effects estimator and a generalised least squares instrumental variable estimator (Hausman and Taylor (1981) estimator).[4] The consistency of the fixed effects estimator depends on the validity of the strict exogeneity assumption. Furthermore, the consistency of the parameter estimates of the individual and time varying variables derived by application of the Hausman and Taylor (1981) estimator depends on strict exogeneity as well as mean stationarity of the processes of the work history variables.[5]

By contrast, standard instrumental variable methods, which depend on exact identification, and generalised method of moments estimators, which make use of overidentifying restrictions, can be applied that permit variables to be predetermined and lead to consistent estimates of the parameters of interest. A general disadvantage of instrumental variable estimators, which may hamper more economic insights is that derived estimates of the

[3]For example, in Oaxaca (1973) and Harkness (1986) where in the wage models the proxy *age* for the work history is used, measurement error of the work history variable may cause OLS parameter estimates to be biased.

[4]See e.g. Albrecht et al. (1999) for an application of a within group estimator, and Kim and Polachek (1994) and Light and Ureta (1995) for Hausman and Taylor (1981).

[5]Similarly, studies that base their analyses on a job search model use deviations of work history variables from within job means, applying instrumental variable estimators based on Abraham and Farber (1987) and Altonji and Shakotko (1987). Their parameters of interest are the returns to tenure, and work experience. An application in the gender wage gap literature can be found in Finnie (1993), a study based on NLSY data. Identification of the parameters of interest, however, seem to depend again on strict exogeneity.

parameters of interest usually have larger standard errors than those derived from OLS. Consequently, coefficient estimates derived by ordinary least squares and instrumental variable estimation may differ in values, but may not be significantly different.[6] A further problem of estimates presented in the literature is that they seem not to be very robust to changes in the set of instruments and alternative instrumental variable estimation methods.[7] There is wide range of reasons for this non-robustness. For example, exclusion restrictions are not valid or in cases in which more than one endogenous variable is instrumented for, not each instrument explains independent variation in potentially endogenous variables. Thus, detailed testing of the assumptions made is required.[8] In this chapter, we discuss and apply estimation methods that do not rely on strict exogeneity in order to identify the parameters of interest and that allow for testing the validity of the (over)identifying restrictions. Then, by comparing the consistent coefficient estimates for males and females, we infer whether unexplained wage differences due to work experience and time out of work exist.

Two instrumental variable estimators are discussed and applied. First, Anderson and Hsiao (1981) and Arellano and Bond (1991), amongst others, dealt with the estimation of models with predetermined or endogenous variables by instrumental variable estimation methods using lagged values of the predetermined variables as instruments for the equations in first differences - hereafter GMM-FD.[9] Second, under the assumption that variables

[6]This is a common problem that becomes also apparent, for example, in the literature on returns to training, see e.g. in Card (1994).

[7]This can be seen, in the gender wage gap literature, from comparison of consistent and inconsistent estimates presented in Kim and Polachek (1994).

[8]By standard procedure, only Hausman (1981) - tests or Wu (1973) - tests are applied for exogeneity; which, depend often on untested exogeneity assumptions referring to the used instruments.

[9]The Anderson-Hsiao estimator is less efficient than the one proposed by Arellano and Bond.

in the vector of explanatory variables are mean stationary processes, first differences of the time varying variables included in the model can be used as instruments when estimating the model in levels.[10] These two models can be combined to a system estimator - hereafter GMM-SYS - as has been discussed in Arellano and Bover (1995), which enables us to test over-identifying restrictions by the application of a Sargan test.

The chapter is organised as follows: In section two, to outline the measurement of male-female wage differentials and problems, we describe the Oaxaca decomposition, the most commonly applied procedure to measure male-female wage differentials. In section three, we specify the empirical wage model. In section four, we describe and discuss the consistent estimation of the parameters of interest. We begin the discussion with the Hausman-Taylor (1981) estimator, then, we discuss generalised method of moments first difference estimation (GMM-FD) and generalised method of moment system estimation (GMM-SYS) based on Arellano and Bover (1995). This is followed, in section five, by the application.

7.2 Measurement of male-female wage differentials

To motivate the relevance of consistent estimation, consider the Oaxaca (1973) decomposition. This is the most common approach applied in the literature in order to derive an estimate of the unexplained part of the raw male-female wage differential, which may also be taken as an estimate of wage discrimination.

The decomposition technique is conducted in three steps. In the first step,

[10]Arellano and Bover (1995), Blundell and Bond (1998).

a human capital wage model is estimated for men and women separately.

$$lnW_{it} = X_{it}^{g}\beta^{g} + \epsilon_{it}^{g} \tag{7.1}$$

where lnW_{it} is the logarithmic wage, X_{it} is a vector of human capital characteristics, β the vector of prices and ϵ_{it} is a random error with standard assumptions. g=F,M indicate female and male. In the second step, the decomposition uses the fact that we know, from the properties of the ordinary least squares estimator, that:

$$\overline{lnW_{it}^{g}} = \bar{X}_{it}^{g}\hat{\beta}^{g} \tag{7.2}$$

where upper bars indicate mean values. Assuming a vector of competitive prices, for example $\hat{\beta}^{M}$, the predicted mean wage of females using competitive prices can be written as:

$$\overline{lnW_{it}^{1F}} = \bar{X}_{it}^{F}\hat{\beta}^{M} \tag{7.3}$$

Subtracting equation (7.3) from (7.2) for males, results in the difference of the mean wage for men and the mean hypothetical wage for women in the absence of discrimination. Subtracting (7.3) from (7.2) for females, gives the difference of the hypothetical mean wage for the sample of women and their actual mean wage. Finally, summation of those two components results in the Oaxaca (1973) decomposition:

$$(\overline{lnW^{M}} - \overline{lnW^{F}}) = \hat{\beta}^{M}(\bar{X}^{M} - \bar{X}^{F}) + \bar{X}^{F}(\hat{\beta}^{M} - \hat{\beta}^{F}) \tag{7.4}$$

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.

Interpretation of the estimated decomposition may be problematic for three reasons. First, by construction of the decomposition the well known index number problem in economics may be involved. This may lead, for example, to non-robustness of results due to the choice of the competitive price. Second, the variables, included in X_{it}^{g}, used for measuring the mean values of the acquired individual human capital characteristics may be measured with error. This problem may apply, for example, in case of measures for actual work experience and time out of work derived from survey data. Measurement error in variables implies that male-female differences in human capital characteristics are also measured with error, which leads to biased estimates of both of the components of the decomposition. Finally, consistent estimates of the parameters of interest in the wage regression model, shown in equation (7.1), are required in order to weight the mean differences in endowments. Again, if inconsistent estimates of the prices are used for the estimation of the decomposition, the explained and unexplained parts of the gap are likely to be estimated with bias.

7.3 Wage model

We assume that wages are determined according to the following equation:

$$lnW_{it} = X_{it}\beta + \epsilon_{it} \tag{7.5}$$

where the dependent variable is the logarithmic wage, lnW_{it}, varying over individuals i, $i = 1, ...N$, and time periods t, $t = 1, ..., T$; N is large and T is fixed. Time dummies are added to the model. Generally, regressors included in the vector X_{it} measure human capital acquisition. We concentrate on periods of investment in human capital, measured by work experience (ex_{it}), and periods of non-investment, measured by time out of work (to_{it}). Thus $X_{it} = (1, ex_{it}, to_{it})$ where a constant is added. Parameters β_1 and

β_2, summarised in $\beta' = (\beta_0, \beta_1, \beta_2)$, represent average returns from an additional year of work experience and average losses from time out of work, respectively, and are the parameters of interest for the remainder of the chapter. The error term ϵ_{it} is specified according to equation:

$$\epsilon_{it} = \nu_i + u_{it}, \tag{7.6}$$

where $\nu_i \sim IID(0, \sigma_\nu^2)$ and $u_{it} \sim IID(0, \sigma_u^2)$, and the error term components are independent of each other and among themselves. Since our main interest in what follows is the covariance that results from unobserved heterogeneity across individuals, we assume that the error term contains an individual specific component, ν_i, which is constant over time and a common idiosyncratic error term, u_{it}. Unobserved individual specific characteristics capture, for example, perseverance, motivation and ability which may be sustained all through life. The common error term component, u_{it}, accounts for macro-shocks or luck.

7.4 Estimation

Consistency of OLS requires that the following orthogonality assumption holds:

$$E[\nu_i + u_{it} | X_{it}, d_{it}^* > 0] = 0 \tag{7.7}$$

where the latent index variable d_{it}^* is positive if an individual i participates in the labour market and, hence, the wage is observed, and non-positive otherwise. It follows, given predetermined variables in X_{it}, that the parameters of interest may not be estimated consistently due to unobserved heterogeneity and non-random sample selection.

7.4.1 Hausman and Taylor (1981)

In the gender wage gap literature, the wage model has been estimated by application of the Hausman and Taylor (1981) estimator.[11] Let us consider the model as specified in equations (7.5) and (7.6), supplemented by the assumption of strict exogeneity, $E[u_{it}|X_{i1},...X_{iT},\nu_i] = 0$. Then, applying appropriate instrumental variable estimation, this assumption identifies coefficients of time varying and individual varying variables included in β.[12]

In this case, instruments can be obtained if one utilises variables corrected for individual means. Thus, the following moment condition can be used:

$$E[u_{it} + \nu_i|(x_{it} - \bar{x}_i)] = 0 \tag{7.8}$$

where x_{it} is an element in X_{it} - for example ex_{it} - and $\bar{x}_i = \sum_{t=1}^{T} x_{it}/T$. However, if the variables included in X_{it} are only predetermined, the mean corrected variables are correlated with the error term component, u_{it}, and, therefore, the moment condition in equation (7.8) does not hold. By economic intuition, generally, this may be the more relevant case, and, thus, the Hausman and Taylor (1981) approach may not lead to the identification of the parameters of interest.

7.4.2 GMM-FD and a GMM-system estimator

For the model specified in equation (7.5) and (7.6), given predetermined variables in X_{it} (i.e. $E[u_{it}|x_{is}] = 0$ if $s \leq t$ where $x_{it} \epsilon X_{it}$, and $E[u_{it}|x_{is}] \neq 0$ otherwise) endogeneity may be caused by correlation of the explanatory

[11] See for applications Light and Ureta (1995), Kim and Polachek (1994).

[12] Furthermore, identification of the coefficients of time invariant variables depends on the assumption that part of the time invariant variables included in the model or time invariant variables excluded from the model are uncorrelated with the individual specific component, ν_i, in the error term.

variables and the individual specific error term component, and by non-random sample selection. In order to deal with the bias of traditional estimates of the parameters of interest due to endogeneity, the model can be estimated by generalised method of moments estimators (GMM) applied to the model in first differences or in levels.

The equation in first differences becomes:

$$\Delta lnW_{it} = \Delta X_{it}\beta + \Delta u_{it} \tag{7.9}$$

if time constant sample selection is assumed. However, due to $E[\Delta u_{it}|\Delta X_{it}] \neq 0$ endogeneity is induced. To apply GMM, instruments may be obtained from using lagged variables in levels included in X_{it} for the corresponding potentially endogenous variables. Hence, the following moment conditions can be used:

$$E[\Delta u_{it}|x_{is}] = 0 \tag{7.10}$$

where $x_{it} \epsilon X_{it}$ and $s \leq (t-1)$. However, x_{it} may itself be a more complex process involving correlation over time. This may be an intuitively appealing process to assume for variables such as work experience. It implies that those who work a lot now are likely to work a lot tomorrow as well. Therefore, suppose, for example, an AR(1) process:

$$x_{it} = x_{it-1}\rho + \nu_i + \omega_{it} \tag{7.11}$$

Even in this case, however, the orthogonality assumption, in equation (7.10), is not violated.

Consequently, all the orthogonality conditions can be used and a GMM estimator can be applied. The matrix of instruments can be set up in the following way:

Let us define:

$$Z_i^D = \begin{bmatrix} [x_{i1}] & & & & 0 \\ & [x_{i1}, x_{i2}] & & & \\ & & [x_{i1}, x_{i2}, x_{i3}] & & \\ & & & \cdots & \\ 0 & & & & [x_{i1}, ..., x_{iT-1}] \end{bmatrix} \tag{7.12}$$

then the matrix of instruments is: $Z = [Z^{D'}_1, ..., Z^{D'}_N]$, and the moment equations are $E(Z_i{}^{D'} \Delta u_{it}) = 0$. In order to test for the overidentifying restrictions a Sargan test can be applied[13]. For the Sargan test, the null hypothesis that the overidentifying restrictions are valid is tested against the hypothesis that the overidentifying are not valid.[14] Furthermore, robust consistent estimators of the standard errors have to be applied. One advantage of GMM over standard (exactly identified) instrumental variable estimation (IV) in this respect is that GMM is more efficient than IV. In the following, we label this estimator GMM-FD.

Alternatively, the level wage model, equations (7.5) and (7.6), can be estimated by application of a method of moments estimator, and differences in the explanatory variables, Δx_{it}, can be used as instruments. In this case, the following moment conditions are used:

$$E[u_{it} + \nu_i | \Delta x_{is}] = 0 \tag{7.13}$$

where x_{it} is an element of X_{it} and $s \leq t$. The derived instruments are valid, given predeterminedness and that x_{it} is a mean stationary process. Obviously, the problem is that if the process(es) in X_{it} is (are) not mean

[13]The Sargan test is included in the standard output of DPD for Gauss. For a description of DPD98 for Gauss, see Arellano and Bond (1998).

[14]Hence, one would not like to reject the null, and derive a p-value greater than 0.05, for example.

stationary, correlation with the individual specific effect may still bias estimates of the corresponding component in β. To test for the validity of these overidentifying assumptions, a generalised method of moments system estimator (GMM-SYS) can be applied.[15]

In order to do so the following stacked system of equations is estimated:

$$\begin{aligned} lnW_{it} = &\quad X_{it}\beta + \epsilon_{it} \\ \Delta lnW_{it} = &\quad \Delta X_{it}\beta + \Delta\epsilon_{it} \end{aligned} \tag{7.14}$$

The matrix of all instruments is set up in the following way:

$$Z_i = \begin{bmatrix} [Z_i^D] & & & & 0 \\ & [\Delta x_{i2}] & & & \\ & & [\Delta x_{i3}] & & \\ & & & \cdots & \\ 0 & & & & [\Delta x_{iT}] \end{bmatrix} \tag{7.15}$$

and consequently the matrix of instruments is: $Z = [Z_1', ..., Z_N']$, and the moment equations are $E(Z_i'[\Delta\epsilon_{it}, \epsilon_{it}]) = 0$.

Using this matrix, overidentifying restrictions for the level equations can be tested by applying the Sargan test, given that the overidentifying restrictions used by GMM-FD are valid. Rejection of the null hypothesis means that first differences are not valid instruments, and, hence, that components included in X_{it} may be non-stationary processes.

[15]See: Arellano and Bover (1995) and Arellano and Bond (1998).

7.5 Application

7.5.1 Empirical wage model

In this section we apply the described instrumental variable estimators - GMM-FD and GMM-SYS - to the following specification:

$$lnW_{it} = \beta_0 + ex_{it}\beta_1 + to_{it}\beta_2 + \lambda_t + \nu_i + u_{it} \tag{7.16}$$

On the left hand side, we use logarithmic daily gross wages. On the right hand side, time varying regressors included are the variables *work experience*, ex_{it}, and *time out of work*, to_{it}, both measured in years.[16] Furthermore, in the estimated regressions we include polynomials of second or third order in the two regressors as well. Time dummies or a linear time trend are also included in the wage regression.

We estimate the specified empirical regression model separately for men and women. The main parameters of interest are the return to work experience, β_1, and the loss from time out of work periods, β_2. From equation (7.4) it follows that if wage - work experience profiles, holding other characteristics constant for men and women, are not significantly different, then, we find no unexplained wage differentials, and, hence, no wage discrimination with respect to *work experience.* Accordingly, we can test the same for the coefficient of the variable *time out of work.* However, then is one caveat of the test with respect to the variable *time out of work* that this variable may incorporate different types of time out of work with differing weights for men and women.[17]

[16] In alternative regressions, we included as an additional, time invariant, regressor, f_i, *age at entry into apprenticeship*, *age*0, which serves as a proxy for years of schooling after the 10 years of compulsory schooling completed by the age of 16 and time elapsed until entry into apprenticeship. Since, in our set of results presented, this variable is excluded it is neglected here.

[17] For all individuals, time out of work includes unemployment spells and other non-

Table 7.1: Summary of selection of data sample

Selection rule	sample of males	sample of females
original sample:		
# of observations	125,782	87,254
(# of individuals)	(19,710)	(14,563)
month unequal January	- 33,210	- 19,024
multiple spells in Jan.	- 4.709	- 2,507
spells before 1980	- 31	- 40
not yearly spaced spells	- 24,041	- 15,851
wage outliers	- 307	- 201
total # of observations	60,866	47,772
(total # of individuals)	(12,661)	(10,422)

7.5.2 Data

For calculation of the described GMM estimators we use a sub-sample of the aformentioned sample of young skilled workers. We apply the following rules: First, in the original sample that was drawn, within individuals' records multiple spells per year may be included. For time homogeneity, - thus, to have only one spell per year in each individual's record - we selected spells reported at the end of the year, that is in the data on the 1 January, or the last spell that is observed in January. Second, we also dropped spells reported before 1980, which are only a few and may mean implausibly short apprenticeships reported in the data. Third, we keep only those sequences of individual records that contain yearly employment spells without gap. Finally, we drop spells with implausibly high growth in the logarithmic wage, which we define as greater than 1.1 or lower than -1.1. Application of the selection rules is summarised in table (7.1).

As can be seen, approximately one fourth of observations are lost because spells were not reported in January, and approximately one sixth to one fifth

work spells. For men, in addition to these, spells in compulsory national service are included, and for women spells in maternity leave are included instead of the latter.

Table 7.2: Summary statistics for main variables

	sample of males	sample of females
log(daily wage)	4.24	3.98
	(0.25)	(0.28)
age at entry into first employment	16.25	16.63
	(1.08)	(1.21)
work experience	3.51	3.22
	(2.25)	(2.20)
time out of work	0.92	0.24
	(1.06)	(0.59)

Note: Standard deviations are reported in parenthesis.

of observations are dropped because of wage outliers. The other selection rules leave the sample size almost unaffected.

Summary statistics for the main variables are reported in table (7.2). In the raw data, taking averages across all wage spells by gender, a male-female wage gap of 26 percent is estimated. The mean in work experience is 0.3 years higher for males than the corresponding one for females. However, this difference is obviously too small to explain a considerable part of the wage differential, which is intuitively clear from the decomposition of the gap shown in equation (7.4). Furthermore, the mean of time out of work for men is higher than for women. Thus, this would lead to a further increase in the adjusted estimated wage gap. In order to investigate differences in prices across gender, in the following, we present one set of estimates, applying the GMM estimators described before, which is the result of a series of results generated.

7.5.3 Estimation results

In tables (7.3) and (7.4), GMM-estimation results for the sample of males and females are presented. In each of the tables, the first column shows the

Table 7.3: Male sample wage regressions - GMM estimation results

	OLS	GMM-DIF*	GMM-SYS*
(work experience)/10	0.547	0.594	0.600
	(0.033)	(0.062)	(0.039)
(work experience)^2/100	-0.403	-0.300	-0.491
	(0.079)	(0.063)	(0.070)
(work experience)^3/1000	0.133	-0.076	0.161
	(0.054)	(0.036)	(0.040)
(time out of work)/10	-0.103	0.902	-0.941
	(0.031)	(0.576)	(0.178)
(time out of work)^2/100	0.230	-1.020	3.600
	(0.164)	(3.845)	(0.873)
(time out of work)^3/1000	0.030	2.028	-4.108
	(0.204)	(5.867)	(1.093)
constant	3.9294	0.0569	3.9694
	(0.02)	(0.0221)	(0.0182)
test for 1st order serial corr.	186.66	-17.168	-17.27
(p-value)	(0)	(0)	(0)
test for 2nd order serial corr.	146.7	-3.829	-3.668
(p-value)	(0)	(0)	(0)
Sargan		140.83	365.479
(df)		(138)	(198)
p-value		0.417	0.0
# observations	60866	48205	48205
# individuals	12661	12661	12661
period	1980-91	1981-91	1981-91
Instruments		see text	see text

Note: 1. Year dummies are included in all specifications. 2. Asymptotic standard errors asymptotically robust to heteroscedasticity are reported in parenthesis. 3. Test for serial correlation, distributed N(0,1) under the null of no serial correlation. 4. Sargan is a test for overidentifying restrictions, asymptotically distributed as χ^2 under the null of validity of the instruments, degrees of freedom are reported in parenthesis. *: we present two step estimates.

Table 7.4: Female sample wage regressions - GMM estimation results

	OLS	GMM-DIF*	GMM-SYS*
(work experience)/10	0.706	0.659	0.652
	(0.038)	(0.134)	(0.042)
(work experience)^2/100	-0.655	-0.578	-0.555
	(0.0939)	(0.0558)	(0.080)
(work experience)^3/1000	0.264	0.190	0.182
	(0.064)	(0.039)	(0.049)
(time out of work)/10	-1.821	2.189	-2.172
	(0.060)	(0.764)	(0.2489)
(time out of work)^2/100	6.704	-16.946	7.562
	(0.339)	(3.628)	(1.268)
(time out of work)^3/1000	-6.158	26.471	-7.835
	(0.405)	(4.191)	(1.432)
constant	3.6551	0.0471	3.6804
	(0.0204)	(0.0164)	(0.01057)
test for 1st order serial corr.	174.30	-7.502	-8.029
	(0)	(0)	(0)
test for 2nd order serial corr.	137.687	-2.106	-1.774
	(0)	(0.035)	(0.076)
Sargan		159.61	343.3
(df)		(138)	(198)
p-value		0.101	0.0
# observations	47772	37350	37350
# individuals	10422	10422	10422
period	1980-91	1981-91	1981-91
Instruments		see text	see text

Note: See notes in table (7.3). *: we present two step estimates.

estimation results from OLS. In the second column GMM-DIF estimation results are reported. In the set of instruments for both male and female sample regressions, in addition to the time dummy variables, the lagged values of the variable *time out of work* are included; these are included as a linear, squared and a third order term. The lag length of the latest instrument to be used in each cross section is set to three, and the lag length of the earliest instrument to be used is set to five. Thus, t-3, t-4 and t-5 are used as instruments in each of the cross-section equations, see the matrix defined in (7.12). The third column shows the GMM-SYS estimation results. Applying GMM-SYS we extend the set of instruments, used before, by lagged differences in the variables *work experience* and *time out of work*. Here, the lag length one is chosen.[18] Accordingly, the matrix of instruments follows from equation (7.15).

For estimation, we use the sample of males that includes in total 12,661 individuals and 60,866 observations. In first differences the number of observations is reduced to 48,205. Comparing the estimation results shown in table (7.3), is seems that GMM-FD estimation results are not very different from OLS. According to the p-value of the Sargan test statistic, we cannot reject the validity of the overidentifying restrictions used. One caveat is that second order correlation cannot be rejected in the model estimated in first differences.[19] In order to test whether we can estimate the wage model in levels, using lagged first differences of the explanatory variables as instruments, we estimated the stacked system of levels and first difference equations, as formulated in equation (7.14), by GMM-SYS. The Sargan test

[18]This choice may cause a problem since it is inconsistent with the order of autocorrelation found in the empirical results. It is commented on this in the following discussion of results.

[19]This is why we use as instruments variables in first differences, lagged for at least three periods, in our set of instruments.

for the GMM-SYS estimation results shows, however, that the overidentifying restrictions are not valid.[20] Therefore, lagged first differences in the work history variables do not seem to be valid instruments for the corresponding variables in the wage model in levels. This may indicate that the processes are non-stationary.

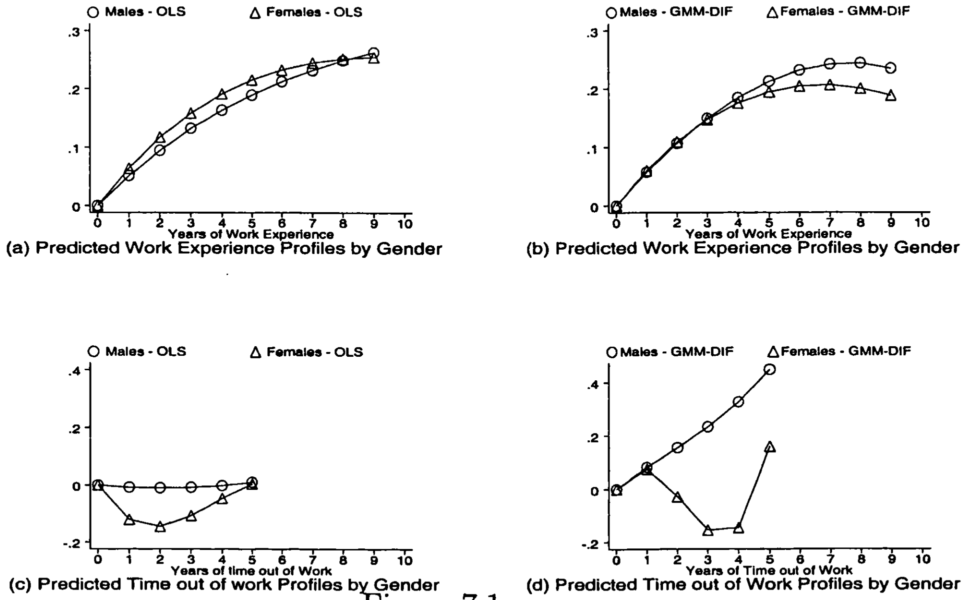
The corresponding set of results are reported for the sample of females in table (7.4). The sample of females used includes 10,422 individuals and 47,772 observations that reduces to 37,350 when first differences are taken. With respect to the test statistics, results seem to be quite similar to the ones for the male sample. Reassuring evidence of estimation results is, however, that according to the test statistics for autocorrelation second order correlation in the residuals can be ruled out.[21] Again, the Sargan test indicates that the set of instruments chosen for GMM-DIF is valid, while for GMM-SYS the overidentifying restrictions are not. In conclusion, tests seem to indicate that GMM-DIF consistently estimates the parameters of interest, while GMM-SYS does not do so, given our set of instruments and because of invalid overidentifying restrictions.

These estimation results, taken from a range of regressions estimated, have so far proven to be robust. Other experiments show that these results seem to be unaffected by modifications with respect to the sub sample used, regressors included in the wage regression in equation (7.16) and the set of instruments.[22] On this basis, we may conclude that identification of

[20]The Sargan statistic does not improve if the lag length of the lagged differences in the instrumental variables is increased to three, which would be more consistent with the findings with respect to the degree of autocorrelation of the error term.

[21]Hence, here variables in first differences, lagged for one period, can be used as instruments as well. Re-estimation of the wage regression has shown that coefficient estimates are unaffected. The p-value for the Sargan statistic decreases to only one percent. Therefore, this may be reassuring evidence in favour of our choice of instruments, to drop more recent lags of instruments.

[22]First, samples differ whether complete records of individuals are used or only the first



(a) Predicted Work Experience Profiles by Gender

(b) Predicted Work Experience Profiles by Gender

(c) Predicted Time out of work Profiles by Gender

(d) Predicted Time out of Work Profiles by Gender

Figure 7.1:

the parameters of interest, under the assumption of mean stationarity and strict exogeneity, is problematic. The more detailed evaluation of OLS and GMM-DIF estimation results shows that, due to an increase in the standard errors of GMM-DIF, as compared with OLS, differences in parameters for *work experience* are not significant. However, for the coefficients of the *time out of work* variables the results seem to change significantly.

In order to evaluate the estimation results based on OLS and GMM-DIF, we plot predictions in figure (7.1a-d) by gender. Analysing male-female wage differentials we may want to ask whether the coefficients are different which, referring to the Oaxaca decomposition, would indicate whether unjustified wage differences exist.

10, 16 spells observed. However, this does not change the estimates, nor the properties of the estimates, with respect to tests for autocorrelation, Sargan statistics and t-tests. Second, we vary the regressors included in the model insofar that we include or exclude *age0* in addition to *work experience*, *time out of work*, and add or drop higher order polynomials of the regressors. The latter is tried to reduce heterogeneity which may affect estimation results and their properties. Third, we vary the set of instruments. Here we vary the shortest lag length used.

As is shown in figure (7.1a), wage - work experience profiles estimated by OLS, holding all other variables equal to zero, seem to indicate that women gain more from every extra year of work experience than men. This result changes when parameters are estimated by GMM-DIF, figure (7.1b). Then, it seems that during the first four years men and women gain equally, but, afterwards, men gain relatively more. Thus, according to equation (7.4), we find weaker evidence in favour of discrimination between men and women with respect to years of work experience.

Predicted time out of work profiles, holding all other variables equal to zero, show a more diverse picture, as can be seen from the lower part of figure (7.1c,d). While for females, very early time out of work spells and a time out of work spell postponed to after four years of work experience, lead to lower losses in terms of wages. For males, estimates by GMM-FD show that time out of work has a positive input and these increase almost linearly.

We can also compare inconsistent OLS predicted profiles and consistent GMM-FD profiles, separately for males and females in our sample; thus, we can compare profiles plotted on the left hand side with profiles plotted on the right hand side of figure (7.1). Estimated standard errors reported before, have already revealed that differences in OLS estimated returns to work experience and the corresponding GMM-FD ones are not significant, for both males and females. Comparison of predictions shows that if, then we find an upward bias, as predicted, for females; however, for males the opposite is found. For the loss from time out of work estimate evidence is much more inconclusive.

7.6 Conclusions

In this chapter, we have discussed instrumental variable estimators applied to a human capital wage regression model in order to identify the parameters of interest, namely the return to work experience and the loss from time out of work. The review of the gender wage gap literature reveals that evidence on the measurement of male-female wage differentials hinges on the consistency of the estimates of the main parameters of interest. Inconsistent estimates may cause severe bias of the estimates of the explained and unexplained portion of the raw gender wage gap, as it is implied by an Oaxaca (1973) decomposition.

Critical assumptions imputed on the wage model, in previous studies, on which consistency of the parameter estimates depends, are strict exogeneity and mean stationarity of the process of the work history variables. While the former, by economic intuition, seems to be a critical assumption, the latter may depend on the sample. For example, for young workers, processes may be thought of as not mean stationary due to increased wage growth during the first years in the labour market.[23]

We have applied GMM estimators in first differences as well as a GMM system estimator which allow us to test in more detail for the overidentifying restrictions, as well as other features of the model. Thus, results may be more transparent with respect to the identifying assumptions made. Application of these estimators and calculation of estimation results using DPD for GAUSS, though, have proved to be quite complex and, here, we have presented a few results that provide the basis for future research.

The estimation results show that only the estimation of the model in first

[23] However, for our sample results do not change either if early spells in each individual record are excluded, which would prevent this problem.

differences, using as instruments the lagged values of the variables in levels included in the model, results in consistent estimates and validation of the overidentifying restrictions. In conclusion, our results, so far, seem to support the view that the mean stationary assumption lacks statistical grounding and cannot be used, generally, for identification.

We refrain from applying the decomposition of the raw wage differential in the traditional way. However, during early careers work histories do not yet reveal distinctive gender patterns; thus, from the perspective of an Oaxaca (1973) decomposition, the result is predictable and not very interesting. Alternatively, one may want to compare returns to work experience and losses from time out of work for males and females in order to detect unjustified treatment, or discrimination, with respect to these variables. As our results suggest, here we find little evidence of gender differences in our sample of young skilled workers.

Concluding remarks

In this thesis, male-female wage differentials among young skilled workers in Germany have been analysed. For the empirical analysis a sample drawn from the newly available administrative and longitudinal IABS data set has been used.

In the survey of the literature, we have discussed empirical findings on the gender wage gap, focusing on the identification of the key parameters of interest, which are the return to work experience and the loss from time out of work, in the human capital wage regression model (Mincer type). This has lead to the identification of problems in this field of research. On the one hand there is a lack of precise information on wages and work histories, i.e. work experience and time out of work, and on the other hand, the consistency of the parameter estimates often depends on assumptions that are difficult to justify in economic terms.

The data sample we use offers advantageous features in this respect for the analysis of male-female wage differentials. First, an obvious advantage is the administrative character of the data and the event history structure. This reduces measurement error problems. Furthermore, because we observe complete work histories for young skilled workers from the beginning of apprenticeship onwards, we can observe (occupational) skill and we can generate very accurate measures of acquired human capital and wages. Therefore, our data is not restricted by the common problem of data sets often used in the labour economics literature in which work histories are "left censored", and skill is not observed. Moreover, in contrast to other studies, we can generate well defined occupation variables that measure, on the one hand, occupational qualification and, on the other hand, occupation of work. Hence, taking a human capital approach to explain wage differentials, all the essential information needed to study male-female wage differentials is included in the data. In addition, the longitudinal structure of the data provides good conditions for the application of consistent instrumental variable estimators to the wage regression model.

In the empirical part, we have conducted descriptive analyses taking advantage of the huge amount of information about wages, actual work histories and occupations that is provided by the data. Here, we summarise the main results.

We find that while young skilled workers' education and work histories are quite similar, occupations capture gender specific patterns. Furthermore, by international standards, we find a surprisingly high entry wage differential between male and female workers and an almost constant differential over the early career, holding actual work experience constant. Three quarters of the entry wage differential seems to be accounted by differences in occupational qualification. The early career wage analysis has demonstrated that inclusion of variables in the wage regression for time out of work periods, both for men and women, shows that coefficients differ according to the type of time out of work as well as to gender. On the other hand coefficients of the variable *work experience* seem to be similar for both genders. Hence, this exercise may give rise to the conjecture that although men and women are treated equally while in the labour market, they are not treated equally with respect to time out of work spells. It would be necessary to go beyond a descriptive analysis in order to test this.

Another result is that at entry, the wage differential is not explained by within occupation wage differentials, but by the distribution across occupations by gender. Over early careers, within occupation wage differentials seem to increase, which may be due to differences in promotion. Whether differences in promotion can be justified or not, goes beyond our analysis and the set of available information. In this analysis, we treat the process of selection into occupations as exogenous, contrary to many other studies in this field. This may imply a restriction to our analysis. On the other hand, one may argue that choices of occupations of work are exogenous and are more or less equivalent to the occupation of apprenticeship in occupationally structured labour markets. Therefore, the process of selection into apprenticeship occupations is the relevant one to model. Here, apart from gender detailed information on secondary schooling levels as well as final grades from schools, best subjects or work placements undertaken would be in the desired set of controls. In the IABS this information is so far not available. Dealing with this problem and scrutinising how it affects the findings reported here are issues for future extensions of this work.

Finally, we looked at the application of instrumental variable estimators in studies on the gender wage gap and presented applications of generalised method of moments estimators. The parameters we seek to identify are the return to work experience and the loss from time out of work in the specified wage model. Our results seem to suggest that with respect to the variable *work experience*, differences in treatment due to gender are negligible. Furthermore, we find that while for the wage model estimated in first differences, instruments obtained from using the corresponding lagged explanatory variables in levels are valid, for the wage model in levels, overidentifying assumptions derived from lagged variables in first differences are not valid. If the latter result holds more generally, this would imply that for the wage model in levels, instruments derived from first difference variables or variables corrected for individual means are not valid, possibly due to non mean stationarity of the processes.

In summary, we have underlined a number of empirical findings concerning male-female wage differentials for the majority of young workers in West-Germany; i.e. those with apprenticeship training. These empirical results may provide a contribution to making politicians, as well as the public, aware of sources that drive wage differentials over early careers and which possibly extend all through working lives of men and women. However, despite the advantageous features of the data, our analyses have also shown the limitations of the data. One of these is the too short length of the panel. As a consequence, in our sample early careers of young women are observed only for a relatively short period and numbers of wage spells after re-entry into work are low. More generally, medium or long term effects cannot be explored by this data set. However, since the study of early careers incorporates certainly many more interesting issues that have not been resolved yet, the use of this data set will be interesting to pursue further issues on early careers and training in future work.

Studying empirically the group of workers who have received qualifications in the dual system apprenticeship programme is also a contribution to the discussion of the dual system apprenticeship programme more generally, which has attracted a lot of interest. Here, the most interesting finding is, perhaps, that working and education histories as well as earning profiles seem to be quite similar for men and women. However, we find that women receive on average higher secondary schooling which supports theoretical approaches that predict that women will choose higher investment in training because opportunity costs are lower. This may suggest that women expect to earn less than men afterwards, given the same level of education. Furthermore, occupational segregation for men and women is found in apprenticeship occupations, and, as a consequence, then again in occupations of work. Despite the similarity of this feature to other countries, it is interesting that this characteristic explains such a great portion of the entry wage gap, which in the raw data is also high. This result may partly reflect the structure of German labour markets which builds upon occupations; a feature not so much recognised in the literature. Therefore, this finding shows that apprenticeship occupations account for variation in skill levels to a great extent and, consequently, play a greater role in explaining wage differentials than in other labour markets which are dominated by internal labour markets.

The methodological problems we have addressed in this thesis may also be applicable to the analysis of wage discrimination between any groups of workers. Here, virtually all of the discussion remains valid for the estimation of the wage model and measurement of wage differentials as outlined in the literature survey.[24] Segregation issues and the problems in controlling for the endogeneity of regressors in the wage determination model may apply as well. However, depending on the groups under study, the variables and parameters of interest, as well as results and interpretations, of course, may vary. For example, in U.S. studies on black-white earnings differentials, differences in education play an important role in the analysis and the return to education is one of the key parameters of interest. Furthermore, the study of wage differentials and discrimination could also be of immense interest in view of European immigration policies. The European Union aims at integration not only of financial and goods markets, but also of labour markets. However, failure to mutually recognise qualifications, which may lead to unjustified differences in wages (or treatment), may reduce mobility

[24]For lists of studies on black-white earnings gap see Cain (1986), Juhn, Murphy and Pierce (1991) and Card and Lemieux (1996).

of workers and, therefore, inefficiencies in the allocation of labour may be caused. Hence, a detailed analysis of wage differentials may form a basis for detecting such problems.

Cross-country comparisons, involve the issue of how to make skill levels across countries comparable. Here, from our analysis it has become clear that for the comparison of work histories in the German labour market with those in other countries, it would be warranted to compare individuals with a well specified occupational qualification and their wage profiles. Furthermore, the comparable group of skilled workers, that accounts for 70 percent in the German workforce, must be identified in the country of comparison. Both points are not easy to solve, given that data sets differ in definitions of occupation groups and education levels, adjusted to the national education and training system. These problems have been well recognised and a number of researchers are working on these issues.[25]

From the perspective of international comparisons, in future work the issue could be addressed as to whether young workers in Germany really do better than young workers abroad. In previous studies, it has been argued that young workers in Germany face lower unemployment rates and are more highly skilled.[26] Both points have been related to the functioning of the dual system apprenticeship programme. However, these findings do not address the issue of medium and long term effects, which can only be analysed by following and comparing workers over their careers. But here, so far evidence is missing.

[25] See e.g. Steedman and Green (1997) and the project by the OECD to develop an international occupation categorisation, which is at the moment ISCO88.

[26] See e.g. Steedman (1993) and Finegold and Soskice (1988).

Appendix A

Appendix: Institutional information

In this section, we provide background information on institutions in Germany for the period 1975 to 1990. As regards the analyses of work histories of young workers in the empirical part, *part three*, of this thesis, we pay particular attention to the description of eligibility criteria and the duration of benefits or compensations received while not in work or not employed. Of main interest are, therefore, the description of the unemployment insurance system and the maternity and parental leave system. Furthermore, we summarise the main features of national service that is compulsory for men in Germany. We complete this section by giving a brief sketch of the German wage setting mechanism which is the outcome of negotiations by unions on the employee side and employer organisations in the main sectors of the economy.

One point of interest for the empirical analysis of wage profiles, is the duration of protected leave granted. Another is the amount of compensation is paid.

Table A.1: Duration of eligibility for unemployment insurance for workers younger than 42

Months worked in base period	Jan.1983 - Dec.1984	Jan. 1985 - Dec. 1985	Jan. 1986 - June 1987	July 1987- Dec 1988	Sep. 1994
12	4	4	4	6	6
16	4	4	4	8	8
20	6	6	6	10	10
24	8	8	8	12	10
30	10	10	10	10	10
36	12	12	12	12	10
60	12	12	12	12	12

Note: See Arbeitsförderungsgesetz from 25.06.1969 and amendments. The base period is 7 years for durations of over 12 weeks. The base period for 12 months or less is four years from January 1983 through June 1987 and three years from July 1987 though December 1994.

Unemployment insurance

Unemployment compensation consists of two parts: unemployment insurance (Arbeitslosengeld) and unemployment assistance (Arbeitslosenhilfe). Unemployment insurance is funded by contributions from workers and employers, while unemployment assistance is funded from general government revenues.[1]

The claim to unemployment insurance is conditional on the claimant be-

[1]For illustration, more than 60 % of the unemployed have been eligible for unemployment insurance over the period 1979 to 1996 in West Germany. For example, in 1979 out of 582,500 who were beneficiaries from the unemployment insurance system, 77 % received unemployment insurance and 23 % received unemployment assistance. A shift towards unemployment assistance can be observed though. In West-Germany, in 1990, for example, 65 % and in 1996 only 62.5 % received unemployment insurance. This trend may reflect increases in shares of the long term unemployed. Thus, these may be unskilled or older workers and we would argue that young skilled workers are much more likely to be in the group of unemployment insurance recipients. Figures are taken from: *http://www.ias-berlin.de/ersep/d_uk/00800028.htm.*

ing unemployed and registered as such at the Employment Office, and has completed the qualifying period. Duration of claims for unemployment insurance are stated in the Arbeitsförderungsgesetz in 1969 and subsequent amendments and depend on the duration of work in a job for which social insurance is compulsory. A summary of durations relevant for workers younger than 42 years are listed in table (A.1).

Independent of the year of the amendment of the law, workers younger than 42 years can claim unemployment insurance only up to a maximum of 12 months. After that period an unemployed person may be eligible for unemployment assistance. As is shown in the first row of table (A.1), until 1987 workers have qualified for unemployment insurance of the minimum duration of 4 months if workers have been working for at least 12 months during the base period. From 1987 the duration of unemployment insurance was extended to 6 months. Until 1984, the base period referred to the previous four years before the person had become unemployed. Since 1985, the base period has been shortened to three years. Various amendments of the law containing changes relevant to workers younger than 42 years have taken action.[2] As is shown in the table these have resulted in increases in duration of claims relative to the period worked in the base period.

Until 1983, the replacement ratio of unemployment insurance was 68 % of the previous net monthly wage.[3] In January 1984, the replacement ratio was cut to 63 % for those without dependent children. Since 1994 the ratio has been 60 %.

Unemployment assistance can be claimed by individuals who are not eligible for unemployment insurance or for whom unemployment insurance has

[2]However, to a greater extent workers older than 42 years were affected by these law changes.

[3]Income must be below a specific contribution assessment ceiling.

expired (after 12 months). It is granted for a maximum of 312 working days, for those unemployed persons who did not demonstrate the qualifying conditions to receive unemployment insurance. For those unemployed who were entitled to unemployment insurance, the duration of unemployment assistance is unlimited, although eligibility has to be proven annually and is means tested. The replacement ratio amounted to 58 % until January 1984. Since then replacement ratios have been slightly reduced to 56%.

Maternity and parental leave

Germany has one of the most generous parental leave and benefit policies.[4] For the period 1975 to 1990, two laws are relevant for the description of the maternity and parental leave system. These are on the one hand the *maternity protection* law (Mutterschutzgesetz) and on the other hand the federal child-rearing benefit law (Bundererziehungssgeldgesetz). Actually, only since 1979 have employed mothers been eligible for maternity leave and benefits.[5] Before this time, *maternity protection* in the form of forbidding work has had a long history, though, going back to trade regulations that took effect in 1878. From 1979 to 1985, legal regulations were restricted to mothers taking leave, while since 1986 fathers have been able to take legally protected leave as well.

The term *protected leave* implies that the parent has the option to return to the job held before pregnancy of the mother; hence, the employer must hold the job available until the protected leave expires. Compensation may be paid in form of benefits by the health insurance, by the state or in form

[4]As is not discussed here, but elsewhere (see e.g. Blau and Kahn, 1995), regulations differ considerably across European and Western industrialised countries.

[5]For comparison, in the U.S. the first law affecting parental leave was the Family and Medical Leave Act of 1993.

of wages paid by the firm.

Until 1985, regulations were based on the *maternity protection* law ("Mutterschutzgesetz"). It contains four main regulations: First, women cannot be dismissed during pregnancy and until 4 months after delivery. Second, mothers must not work 6 weeks before and 8 weeks after delivery (the *maternity protection*). Third, mothers are entitled to 4 months protected maternity leave after the *maternity protection* period. Fourth, mothers are entitled to 6 months of maternity benefits after childbirth. In 1986 the federal child-rearing benefit law ("Bundeserziehungsgeldgesetz") took action which replaced the concept of maternity leave by the concept of parental leave. Durations of maternity or parental leave until 1990, are summarised in table (A.2).

In the federal child-rearing benefit law, as well as in subsequent amendments of the law, the period of protected leave was sequentially extended and, accordingly, the period of entitlement to benefits too. They are listed in table (A.2). For instance, from 1986 to 1988 the protection period was extended to 8 months, and thus, entitlement to benefits to 10 months, which includes two months of *maternity protection*. However, eligibility for full duration of benefits based on the child-rearing benefit law is means tested.

Until 1986, in order to be eligible for maternity benefits mothers had to be employed (and not self employed). Since 1986, all mothers and fathers can claim benefits; also not-salaried parents. Before 1986, benefits ranged from 3.50 to 25.00 German Mark per day[6]. The amount depended on the income during the previous three months before delivery of the child. If the average income was higher than benefits paid, the mother was entitled to an

[6]These correspond to the 600 German Mark per month paid by the health insurance.

Table A.2: Summary of maternity leave durations until 1990

	maternity protection in months	protected leave in months	entitlement to benefits in months
until 1986	2	4	6
since 1986	2	8	10
since 1988	2	10	12
since 1989	2	13	15
since 1990	2	16	18

Note: Periods are counted from delivery of the child onwards. Mothers and fathers are entitled to claim protected leave and benefits since 1986. In addition, one may note that the *maternity protection* period starts already 6 weeks before delivery. A regulation valid althrough the period.

employer supplement during the *maternity protection* period equal to the difference. From the third month onwards the maximum was 17.00 German Mark per day. Since 1986, benefits can be claimed for longer, but depend then on the annual net family income two years before birth of the child. Benefits are reduced on a sliding scale basis.[7]

National service

National service in Germany is compulsory in the form of military service (Grundwehrdienst). However, in particular cases civil service may be served instead, or men are released from service completely, mostly due to medical conditions.

For all men military service (Grundwehrdienst) is compulsory if they live in Germany and are older than 18.[8] Usually, men are drawn to military

[7]No benefits are paid if the family income is greater than 29,400 German Marks per year, or, in case of single parents, if the yearly income is greater than 23,700 German Marks. Each additional child increases the benchmark by 4,200 German Mark.

[8]See: Wehrdienst - Kriegsdienstverweigerung - Zivildienst. in: Presse- und Infor-

service at the age of 19. However, men cannot serve before the age of 17[9] and after the age of 25 (in exceptional cases 28) men cannot be drawn into military service.

The duration of compulsory service varied over recent decades. In 1972 military service was compulsory for 15 months and civil service took one third longer, 20 months. From Oct. 1989 military service was shortened to 12 months and accordingly civil service to 16 months.[10]

Wage setting mechanism

The German wage bargaining process and the German wage structure are quite complex. We give here only a brief description.[11]

Negotiations about wage agreements take place at the level of industries and tariff regions. Within regional industries, wage agreements are distinguished further by job status. In addition to the general wage agreements, supplementary wage increases are negotiated within firms. This implies that within firms, wages can be paid which are above the general tariff. As a result, wages within industries vary by skill group and wages within skill groups may vary across industries and firms.

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mationsamt der Bundesregierung Referat Aussen-, Sicherheits- und Europapolitik, Feb. 1996.

[9]Before the age of 17 military service can be served only with the consent of the parents.

[10]While in military service men receive a very low compensation, which is below the wage of an unskilled worker. Compensation or wages in civil service depend on the employer or institution.

[11]A detailed description on wage agreements can be found in Horn, Scheremet and Zwiener (1999).

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