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The Determination of Wages and the Gender Wage Gap: A Survey

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ABSTRACT

The Determination of Wages and the Gender Wage Gap: A Survey*

In this paper 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.

JEL Classification: J70, J31, C51

Keywords: Male-female wage differentials, human capital wage regression model, model construction and estimation, wage discrimination

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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 .

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 of years of schooling 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

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:

$$lnW_{it} = X_{it}\beta + \epsilon_{it} \tag{1}$$

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:

$$\epsilon_{it} = \nu_i + u_{it} \tag{2}$$

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.

3 Ordinary least squares estimation

The traditional estimator applied to the general model specified in equations (1) and (2) is the ordinary least squares estimator (OLS). Consistent estimation of the parameters of interest requires that the following orthogonality condition holds:

$$E[\nu_i + u_{it}|X_{it}, d^*_{it} > 0] = 0 \tag{3}$$

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 (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 (3), correlation of the unobserved individual-specific error term component, ν_i, with the explanatory variables

[10] A variable x_{it}, $x_{\mathsf{it}} \epsilon X_{\mathsf{it}}$, is strictly exogenous in equation (1) if $x_{\mathsf{t}} \parallel u_{\mathsf{i,t+s}}$ for all s. A variable x_{it}, $x_{\mathsf{it}} \epsilon X_{\mathsf{it}}$, is predetermined in equation (1) if $x_{\mathsf{t}} \parallel u_{\mathsf{i,t+s}}$ 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.

Measurement error in explanatory variables causes consistency problems with the OLS estimates of the corresponding slope coefficients of the model. In general, for any variable x_{it}, $x_{it} \epsilon X_{it}$, that is measured with error, we can write:

$$x_{it}^* = x_{it} + m_{it} \tag{4}$$

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.[12]

Two cases may be captured by the specification in equation (4). One 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

[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] 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 $\sigma_m^2 = 0$.

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 $PotEX_{it} = age_{it} - S_{it} - 6$, 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.[13] 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[14]. Table (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 because working life cycles for both of these groups may be characterised by more frequent interruptions. More specifically, since the proxy variable *age*

[13]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.

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

Table 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, ed, health, part-time, migration, marital status, children, region, oc, ind, class of worker.
Blinder (1973)	PSID, 1969, age: 25+	structural model: age, region, ed, vocational training, oc, union member, veteran status, health, Ten, local labour market condition, geogr. mobility, seasonal employment.
Greenhalgh (1980)	GHS, 1971 and 1975 men and single women	PotEx(sq), ed, 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), Ex (for men), Imputed Ex and Home (for women), ed, race, health, oc, ind.
Gerlach (1987)	Regional survey, Nov. 1981 all employed	PotEx(sq), Ten(sq), ed.
Miller (1987)	GHS, 1980	PotEx(sq) (for men), Imputed Ex(sq) and Home (for women), ed, region, race, health.
Harkness (1996)	GHS 1974 and 1983, BHPS 1992-93, full-time and part-time workers	Human capital specification: age(sq), Ex(sq) for BHPS, ed, extended model: region, ind, oc, children.

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

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.[15]

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[16] or estimate wage regressions for samples of single females, rather than single and married females pooled[17]. Both of these approaches, however, 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 applied 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

[15] 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.

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

[17] See: Greenhalgh (1980).

selection problem.[18] 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.[19] 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.[20]

More formally, to incorporate sample selection into our model framework the process d^*_{it} can be modelled - see equation (3) - and a labour force participation equation of the following form can be added:

$$d^*_{it} = B_{it}\gamma + \eta_{it} \tag{5}$$

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

[18] See Heckman (1979).

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

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

selection.

4 Fixed effects 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) and (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 effects 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 groups estimator*, or by taking first differences, the *first difference estimator* (FD). [21] 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 equations (1) and (2), into first differences leads to the more parsimonious

[21] Assumptions for consistency for within groups estimator and fixed effects estimator differ though, what makes FD advantageous as can be seen from IV-FD and the set of instruments available. See section 5.2.

equation[22]:

$$\Delta lnW_{it} = \Delta X_{it}\beta + \Delta u_{it} \tag{6}$$

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 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:

$$E[\Delta u_{it}|\Delta X_{it}, d^*_{it} > 0, d^*_{is} > 0] = 0 \tag{7}$$

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.[23] An example, here, would be the coefficient of the variable *work experience* since a positive economic shock today may lead to increases in

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

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

Table 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 (3).
Dolton & Makepeace (1986)	Survey of UK Graduates, Mean age: 29, Cross-sections: 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) for further explanations.

work experience. Conversely, negative correlation results in FD-estimates that are upward biased.[24] 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.

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:

$$\overline{lnW_i} - \bar{X}_i^{(1)}\hat{\beta}^1 = X_i^{(2)}\hat{\beta}^2 + \nu_i + u_i \tag{8}$$

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 (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

[24] 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 (2) a couple of studies of this kind are listed.[25]

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.[26] 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.[27] Since then $\Delta EX_{it} + \Delta H_{it} = 1$ holds[28], the moment matrix of observations has no full rank and identification may be impossible or spurious.[29]

[25] 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 paper.

[26] The same holds for the within groups estimator.

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

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

[29] 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

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.[30] In this section, we first discuss estimation, followed by a section on the instruments used in applications.

5.1 Estimation

In order to ensure consistency[31] 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:

$$E[\nu_i + u_{it}|Z_{it}, d^*_{it} > 0] = 0 \tag{9}$$

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.

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

[31] 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:

$$E[\Delta u_{it}|Z_{it}, d^*_{it} > 0, d^*_{is} > 0] = 0 \tag{10}$$

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.[32] 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:[33]

$$x_k = Z_l \pi_l + \xi_k \tag{11}$$

[32]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.

[33]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.[34] In the second step the generalised residuals, $\hat{\xi}_{x_k,Z_l}$, estimated from the least squares regression equation in (11) are added to the wage equation leading to the expanded wage regression:

$$lnW = X\beta + \hat{\Xi}\alpha + \epsilon \tag{12}$$

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 (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.[35]

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.[36] 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.

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

[35] Hausman (1978).

[36] 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 (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.

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 (11). Also, instruments must meet the orthogonality assumption, equations (9) or (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 (3) and (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

Table 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, ed, age, training certificate, health, children, region/ Ex endogenous, Home exogenous/Instr.: 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), ed, 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) for further explanations.

IV has been applied. Cross-section studies are listed separately from 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 (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[37] 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

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

Table 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	Individual specific intercept model with 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) for more details.[1] Home=(age-ed-5-Ex).

fertility and marriage [38], 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.[39]

The variable *region* has also been used as an instrument assuming exogeneity

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

[39] 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; i.e. 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.

of the latter. The motivation is that the size of the region people live in or 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.

In conclusion, the discussion suggests that exogeneity of all popular instruments used in the literature seem to depend on assumptions that require further testing to justify their use. In addition, if longitudinal data are available, mean deviations of exogenous variables, $(\tilde{Y}_{it} - \bar{\bar{\tilde{Y}}}_i)$, as well as the within person means of exogenous variables, $\bar{\bar{\tilde{Y}}}_i$, are valid instruments. 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 (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)[40] the instrument $(x_{it} - \bar{x}_i)$, has been used[41] assuming

$$E[\nu_i + u_{it}|x_{it} - \bar{x}_i] = 0 \tag{13}$$

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[42] assuming that

$$E[\nu_i + u_{it}|x_{it} - x_{it-1}] = 0 \tag{14}$$

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.[43]

For the estimation of the wage model in first differences, lags of endogenous variables in X_{it} have been used[44] assuming that

$$E[u_{it} - u_{it-1}|x_{it-1}] = 0 \tag{15}$$

holds, as well as for further lags of x. Furthermore, lagged endogenous variables in first differences have been used[45] assuming that

$$E[u_{it} - u_{it-1}|x_{it-1} - x_{it-2}] = 0 \tag{16}$$

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

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

[42]Kim and Polachek (1994).

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

[44]Kim and Polachek (1994).

[45]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 (16) depends on the assumption that the process generating x is a mean stationary process.[46]

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.[47] 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.[48]

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, i.e. equation (15). In order to test and justify exclusion restrictions, quite standardly in studies a Hausman type test is applied.[49] However, validity of these tests, again, depends on

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

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

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

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

exclusion restrictions 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.[50] 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 (11).[51] 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.

6 Discussion

In the first part of this paper, 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

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

[51]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

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 *raw* or *uncorrected* or *gross male-female wage differential* is, straightforwardly, measured by differences in logarithmic wages:

$$\Delta lnW = (\overline{lnW^M} - \overline{lnW^F}) \tag{17}$$

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) 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.* It is commonly interpreted as a *measure of discrimination.* Based on this approach, mainly three 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[52] to analyse the decomposition of the wage gap at the

[52] 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.

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 paper. 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:

$$\overline{lnW^M} = \bar{X}^M \hat{\beta^M} \tag{18}$$

and

$$\overline{lnW^F} = \bar{X}^F \hat{\beta^F} \tag{19}$$

where, in equation (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, M for males, F for females. To continue, suppose that $\hat{\beta}^M$ is the competitive price and that females are remunerated at the same price as men.[53] Then, the predicted mean wage for females using competitive prices can be written as:

$$\overline{lnW^{1F}} = \bar{X^F} \hat{\beta^M} \tag{20}$$

In a second step, the components of the decomposition of the raw wage differential are calculated. Subtracting (20) from (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 (19) from (20), $(\overline{lnW^{1F}} - \overline{lnW^F})$, 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:

$$\underbrace{(\overline{lnW^M} - \overline{lnW^F})}_{raw\ wage\ gap} = \underbrace{\hat{\beta}^M(\bar{X^M} - \bar{X^F})}_{explained\ part} + \underbrace{\bar{X^F}(\hat{\beta^M} - \hat{\beta^F})}_{unexplained\ part} \tag{21}$$

[53] For the coherence of the paper, 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).[54]

The first term on the right hand side of equation (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, that is the second term on the right hand side of equation (21), 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.

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

[54] 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 for discussion Jones (1983).

consistent estimates of the parameters of interest, predictions of wages for males (M) and females (F) can be written as:

$$\widehat{lnW^M}_{it} = X_{it}^M \hat{\beta}_t^M \tag{22}$$

$$\widehat{lnW^F}_{it} = X_{it}^F \hat{\beta}_t^F \tag{23}$$

where all indexes are used as before.[55] 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.[56] 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:

$$\widehat{lnW^M}_{it} = \widehat{lnW}_{it}^{1M} = \widehat{lnW}_{it}^{2M} = \widehat{lnW}_{it}^{3M} \tag{24}$$

where all of the three "hypothetical" wage distributions, indicated by superscripts, are equivalent to predicted wages from equation (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-discrimi-

[55] 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.

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

natory fixed prices for observables and unobservables:

$$\widehat{lnW}_{it}^{1F} = X_{it}^{F}\hat{\beta}_t^{M} + \hat{\epsilon}_{it}^{(F)} \tag{25}$$

where $\hat{\epsilon}_{it}^{(F)}$ are the assigned residuals, for each female worker based on the actual percentile in the females' residual distribution, derived from equation (23), and the male cumulative distribution, equation (22). Second, wages can be predicted for women using prices from the regression estimated for the sample of women and non-discriminatory prices for unobservables:

$$\widehat{lnW}_{it}^{2F} = X_{it}^{F}\hat{\beta}_t^{F} + \hat{\epsilon}_{it}^{(F)} \tag{26}$$

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

$$\widehat{lnW}_{it}^{3F} = X_{it}^{F}\hat{\beta}_t^{F} + \hat{\epsilon}_{it}^{F} \tag{27}$$

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:

$$\Delta w^1 = \widehat{lnW}_{it}^{1M} - \widehat{lnW}_{it}^{1F} = \hat{\beta}_t^{M}(X_{it}^{M} - X_{it}^{F}) \tag{28}$$

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:

$$\Delta w^2 = \widehat{lnW}_{it}^{2M} - \widehat{lnW}_{it}^{2F} = (\hat{\beta}_t^{M}X_{it}^{M} - \hat{\beta}_t^{F}X_{it}^{F}) \tag{29}$$

Finally, any additional part of the gap explained by the true distribution of wages over the second hypothetical distribution of wages results is an estimate of the gap due to differences in unobservables (prices and quantities), since:[57]

$$\Delta w^3 = \widehat{lnW}_{it}^{3M} - \widehat{lnW}_{it}^{3F} = (\hat{\beta}_t^M X_{it}^M - \hat{\beta}_t^F X_{it}^F) + (\hat{\epsilon}_{it}^M - \hat{\epsilon}_{it}^F) \tag{30}$$

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

$$\underbrace{\Delta w^3}_{raw\ wage\ gap} = \underbrace{\Delta w^1}_{diff.\,in\,obs.endow.} + \underbrace{(\Delta w^2 - \Delta w^1)}_{diff.\,in\,prices\,of\,observ.} + \underbrace{(\Delta w^3 - \Delta w^2)}_{diff.\,in\,unobserv.} \tag{31}$$

or:

$$\underbrace{(lnW_{it}^M - lnW_{it}^F)}_{raw\ wage\ gap} = \underbrace{\hat{\beta}_t^M (X_{it}^M - X_{it}^F)}_{diff.\,in\,obs.endow.} + \underbrace{X_{it}^F (\hat{\beta}_t^M - \hat{\beta}_t^F)}_{diff.\,in\,prices\,of\,obs.} + \underbrace{(\hat{\epsilon}_{it}^M - \hat{\epsilon}_{it}^F)}_{diff.\,in\,unobs.} \tag{32}$$

Calculation of standard errors as well as interpretation follows straightforwardly.

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.[58] To derive their approach, the uncorrected gender wage gap can be rewritten as the difference in weighted average log-wages taken across K occupations.

$$\overline{lnW^M} - \overline{lnW^F} = \Sigma_{j=1}^K P_j^M lnW_j^M - \Sigma_{j=1}^K P_j^F lnW_j^F \tag{33}$$

[57]In order to identify price and quantity effects separately, changes over time of the wage differential can be used, as will be shown on pp.52 in this paper. See e.g. Blau and Kahn (1992) and Juhn, Murphy, Pierce (1991). We come back to this in more detail in section 8.2. in the context of the empirical evidence.

[58]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 (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[59]:

$$(\overline{lnW^M} - \overline{lnW^F}) = \underbrace{\Sigma_{j=1}^K (P_j^M - P_j^F) lnW_j^M}_{interoc.\ effect} + \underbrace{\Sigma_{j=1}^K P_j^F (lnW_j^M - lnW_j^F)}_{intraoc.\ effect} \tag{34}$$

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

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

that:

$$P_{ij}^{M} = \frac{exp(B_i^M \gamma_j^M + \omega_{ij})}{\Sigma_{j=1}^{K} exp(B_i^M \gamma_j^M + \omega_{ij})} \tag{35}$$

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.[60] 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 (34) are decomposed further. It follows that:

$$(\overline{lnW^M} - \overline{lnW^F}) = \tag{36}$$

$$\underbrace{\overbrace{\Sigma_{j=1}^{K}(P_j^M - \hat{P}_j^F)\bar{X}_j^M\hat{\beta}_j^M}^{interoc.effect} + \overbrace{\Sigma_{j=1}^{K}P_j^F(\bar{X}_j^M - \bar{X}_j^F)\hat{\beta}_j^M}^{intraoc.effect}}_{explained\,part}$$

$$+ \underbrace{\overbrace{\Sigma_{j=1}^{K}P_j^F(\hat{\beta}_j^M - \hat{\beta}_j^F)\bar{X}_j^F}^{intraoc.effect} + \overbrace{\Sigma_{j=1}^{K}(\hat{P}_j^F - P_j^F)\bar{X}_j^M\hat{\beta}_j^M}^{interoc.effect}}_{unexplained\,part}$$

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.

[60] 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) and (35) are adjusted accordingly.

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.[61] One may consider, thus, that while

[61] 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 is often sensitive to the choice of the competitive price.[62] 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

$$\hat{\beta}^* = \Omega\hat{\beta}^M + (I - \Omega)\hat{\beta}^F \tag{37}$$

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 (1997).

[62] 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 5: Summary of weighting matrices

Study	Sample	Weighting matrix
Oaxaca (1973)	male	$\Omega = I$
	female	$\Omega = 0$
Reimers (1983)	male/female	$\Omega_{\mathsf{r}} = 0.5I$
Cotton (1988)	male/female	$\Omega_{\mathsf{c}} = (N_{\mathsf{m}}/N)I$
Oaxaca & Ransom (1994)	male/female	$\Omega_{\mathsf{o}} = (X'X)^{-1}(X'_{\mathsf{m}}X_{\mathsf{m}})$

Note: N_{i} = Number of observations for group i, i=f,m (female, male). $N = N_{\mathsf{f}} + N_{\mathsf{m}}$. X_{m} = matrix of observations for group i. $X' = [X'_{\mathsf{m}}|X'_{\mathsf{f}}]$.

which corresponds to $\Omega = I$ or $\Omega = 0$ in equation (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.[63] Since then, a number of alternative specifications of Ω have been suggested in the literature. In table (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

[63]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.[64] 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.[65] 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.[66]

[64]It holds that $\Omega_0 = \Omega_\mathsf{c}$ if the first and second moments are identical for males and females; hence $\frac{\mathsf{N_m}}{\mathsf{N}}(XX)^{-1} = (X_\mathsf{m} X_\mathsf{m})$. If the sample size of males and females is the same, $N_\mathsf{m} = N_\mathsf{f}$, then $\Omega_\mathsf{r} = \Omega_\mathsf{c}$ follows.

[65]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).

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

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,[67] 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.[68]

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 (6), referring to our model specification and notation in equations (1) and (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 main parameters of interest, listed in the first row of table (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-

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

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

Table 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]: $X = (Ex, Home)$, IV-GLS, FD-IV	$\hat{\beta}_1(\bar{X}^{M} - \bar{X}^{F})$	consistent	consistent	consistent
potential experience: $X = (PotEx)$, 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] : $X = (Ex, Home)$, OLS	$\hat{\beta}_3(\bar{X}^{M} - \bar{X}^{F})$	upward bias due to $E[\nu_i \mid X_{it}] \neq 0$	consistent	downward bias
actual work history[1] : $X = (Ex, Home)$, FD	$\hat{\beta}_4(\bar{X}^{M} - \bar{X}^{F})$	downward bias due to $E[\Delta u_{it} \mid \Delta X_{it}] \neq 0$	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 (7) to (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.

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 two and a half 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.[69] Typically, from the comparison of married men and

[69]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.

married women, the gap calculated is higher than from the comparison of men and single women.[70] 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.[71]

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[72], 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.[73] 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,

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

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

[72] 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.

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

for young workers with 9 years of actual work experience.[74]

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 (7) to (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.[75]

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

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

[75] Compare with table (6).

Table 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.	Esti-mator	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	
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) to (4).

Table 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				
Greenhalgh (1980)				
1971:	16.9 (singles)	24	OLS	
1975:	2.9 (singles)	10		
Zabalza & Arrufat (1985)	62.3	97.3 (PotEx) 19.2 (ImputEx)		69.7 expl. by sampl. selec. corr.
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
Panel B: Actual work history variables used				
Wright & Ermisch (1991)	36 (married)	48.4 (married)	OLS-Heck	full-time women/ all men
Studies for Germany				
Panel A: Proxy used for actual experience				
Gerlach (1987)	11	84.95 (singles)	OLS	
	38.7	92.19 (married)	OLS	

Note: For details see tables (1) to (4).

Table 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.
	pooled sample	40.3			by timing of
	0 years of EX	19			work experience
	1 year of EX	32.5	93	IV-GLS	and time out
	9 years of EX	46.3	88	IV-GLS	of work
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) to (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.[76]

Furthermore, it has been demonstrated that the timing of the work history also contributes to the explanation of the gender wage gap.[77] In Light and Ureta (1995), a model controlling for timing of the work history in most flexible form was estimated for young workers.[78] The intuition behind the

[76]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.

[77]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).

[78]The model is nested within the general model set up by us. Define ΔEX_{it} = dif-

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, 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 between two groups of workers over time or countries. Henceworth, the basic Juhn-Murphy-Pierce decomposition outlined, in section 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) and (2), can remain unchanged except for the individual specific effect that is now allowed to

ferential period 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.

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,[79] the wage structure effect on the change of wage differentials over time can be estimated from the following decomposition:

$$\underbrace{(\Delta\overline{lnW}_t - \Delta\overline{lnW}_s)}_{change\ in\ raw\ wage\ gap} \tag{38}$$
$$= \underbrace{(\Delta\bar{X}_t - \Delta\bar{X}_s)\hat{\beta}_t^M}_{observed\ X's\ effect} + \underbrace{\Delta\bar{X}_s(\hat{\beta}_t^M - \hat{\beta}_s^M)}_{observed\ prices\ effect} + \underbrace{(\Delta\bar{\theta}_t - \Delta\bar{\theta}_s)\sigma_t^M}_{gap\ effect} + \underbrace{\Delta\theta_s(\sigma_t^M - \sigma_s^M)}_{unobserved\ prices\ effect}$$

Here t, s index time periods, where $t > s$, and all variables are used in the same way as before in this paper. 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.[80]

According to the decomposition in equation (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 observed 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 de-

[79] Thus, it is assumed that $\hat{\beta}_t^M = \hat{\beta}_t^F$ in equation (32).

[80] 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).

gree of inequality in the male wage distribution constant. 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.[81]

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

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

the distribution of male wage residuals. Ideally, changes could be interpreted 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.[82]

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 in the wage regression, estimates are unbiased, only, if percentile ranks are independent of the standard deviation. This, however, is often problematic to assume. 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

[82]See: Blau and Kahn (1997), Suen (1997).

Table 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* $= (\bar{w}^{\mathsf{i}} - \bar{w}^{\mathsf{USA}})$ 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.

the relative position of women and the estimated wage structure effects 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 likewise all the other decompositions, the Juhn-Murphy-Pierce decomposition depends on consistently estimated parameters of the wage regression model.

The Juhn, Murphy, Pierce decomposition, as shown in equation (38), has been adapted by Blau and Kahn[83] 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 (10). Overall, 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 have 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 sug-

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

Table 11: Emp. results from Brown, Moon, Zoloth decomposition

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

Note: LMAS: Canadian Labour Market Activity Survey. For further details see tables (1) to (4).

gested that this may also reflect that qualified women hit a "glass ceiling"[84] and, hence, have been prevented from improvements.[85] 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

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

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

Application of the Brown, Moon, Zoloth (1980) decomposition allows for 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 (11), we list results found in a number of studies.[86]

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.[87] 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 work in more than 300 occupations 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.

[86] 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.

[87] 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.

9 Conclusions

The question of whether wage 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.

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