Gender wage gap studies: Consistency and decomposition*

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Abstract:

This paper reviews the empirical literature on the gender wage gap, with particular attention given to the identification of the key parameters in human capital wage regression models. This is of great importance in the literature for two main reasons. First, the main explanatory variables in the wage model, i.e., measures of work experience and the time-out-of-work, are endogenous. As a result, applying traditional estimators may lead to inconsistent parameter estimates. Second, empirical evidence on the gender wage gap hinges on estimates of the parameters of interest. Accordingly, their economic meaning may be limited by restrictive assumptions included in wage models. This challenges both researchers and policymakers who require precise measures of the gender wage gap in order to create and enforce efficient equality policies.

JEL Codes: J16, J3, J71

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1 Introduction

Policymakers have a longstanding concern in confronting the gender wage gap and wage discrimination against women. The assessment of such policies hinges on precise measures of the unequal treatment of male and female workers.[1] Labour economists most commonly define wage discrimination by comparing wages for equally productive workers (Becker, 1964). This is normally implemented through the estimation of wage differentials conditional on human capital characteristics that reflect productivity potential. The raw wage gap is then decomposed into a portion explained by differences in human capital endowments, and a residual or unexplained part, which is the remuneration difference in the endowment of human capital prices. It is the unexplained portion of the wage differential that is often interpreted as an estimate of discrimination. Interpretation of this decomposition is, however, complicated by several factors. An important data issue is that productivity differences must be measured precisely, and should not themselves be an outcome of discriminatory behaviour. Another key concern is the identification problem concerning the key parameters in the wage regression model. In this paper, we review the empirical literature on gender wage differentials, with a particular focus on the problem of consistent estimation of the key parameters in the underlying general wage model and progress in this area.

We focus on the consistent estimation of the return-to-work history variables measuring on-the-job human capital accumulation and depreciation. These are important controls for gender differences in the labour market. Women often have more interrupted work histories due to family responsibilities. This is reflected most strongly in data on the level of actual work experience and by time-out-of-work periods associated with child rearing, commonly zero for men. In the light of human capital theory, the coefficients of variables in a wage equation are interpreted as the

[1] See publications by the European Union such as "Employment in Europe 2002", where gender pay gap in the EU is assessed.

appreciation and depreciation rates of human capital. The identification of these parameters is complicated by the endogeneity of work experience and time-out-of-work due to unobserved heterogeneity, the non-random sample selection into work and the pre-determinedness of the variables in wage growth equations. Ordinary least squares estimators often lead to inconsistent estimates, and therefore policy recommendations based on these techniques may be less meaningful.

Most of the studies in this field depend on the restrictive assumption that the unobserved heterogeneity components are uncorrelated with the key variables and (in wage growth models) that the variables are strictly exogenous. In order to discuss the implications for measuring the gender wage gap, we specify a simple wage regression with an individual-specific intercept. This model nests most models that have been estimated in the literature on the gender wage gap. The underlying economic model is of a human capital form (Becker, 1964). The empirical model itself is of a Mincer type[2] in which logarithmic wages are regressed on measures for individual work histories: namely, actual work experience and time-out-of-work periods, education (or pre-labour market schooling) and other background variables. In contrast to the work history variables, pre-labour market schooling, occupation[3] and other background variables are treated as exogenous following the common assumption in the gender wage gap literature.

The review shows that there is no undisputed method of measuring gender wage gap and there is no consensus on how to treat the identification problem. Even though suitable econometric methods do exist, these have not fully been applied.

[2]The original empirical model was developed in Mincer (1974). This model is based on a life-cycle earnings model, and contains only age as a measure of the individual's work history and years of pre-labour market schooling. In Mincer and Polachek (1974), a model is derived to take into account the more interruptive work histories of women.

[3]This may be a particular limitation in models analysed in the literature. It is widely observed that men and women move into different fields, a process that can be explained by self-selection models (Polachek, 1981). In this paper, we focus on how to treat the endogeneity of the work history variables. Conclusions partly extend to occupation variables.

This is partly due to difficulties in fullfilling the necessary assumptions. Thus, it might be difficult to draw strong statements regarding processes leading to the gender wage gap. More recently, researchers have diverted their attention from standard approaches where the focus is on the mean wage differential and representative samples. It is deferred to future research as to whether these promising approaches will help provide a complete explanation of the gender wage gap and to derive efficient policies for fighting unequal pay and wage discrimination.

The remainder of the paper is organized as follows. In Section 2, a wage regression framework is specified and identification of the key parameters is discussed. In Section 3, progress in the empirical literature concerning the gender wage gap is reviewed with respect to identification. Section 4 concludes.

2 The wage model and identification

A simple model of wage determination that nests most past specifications in the gender wage gap literature is:

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

where i indexes individuals and t indexes time periods. The dependent variable is the logarithmic wage, lnW_{it}. The vector of variables, X_{it}, includes work experience, time-out-of-work due to child bearing and rearing and other individual characteristics related to productivity, such as schooling (Mincer, 1974; Mincer and Polachek, 1974). The theoretical background of this specification is human capital theory (Becker, 1964) and the coefficients are then interpreted as the returns to investment or loss from disinvestment in human capital. The error term, ϵ_{it}, is defined as:

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

and contains an individual specific component, ν_i, which is constant over time. This term captures unobserved individual specific skills. Such characteristics incorporate motivation and ability that are sustained throughout life. The idiosyncratic error term, u_{it}, has a zero mean and constant variance σ_u^2, capturing, for example, luck. Identification of β by the simple ordinary least squares (OLS) estimator requires strong assumptions. OLS is only consistent if the components in X_{it} and the unobserved heterogeneity component in the error term are uncorrelated, if the variables are free from measurement error, and if the sample of wage observations is randomly drawn from the population. Violation of any or all of these assumptions may lead to inconsistent estimates. While much of the research in this area recognizes the potential bias from the endogeneity of the regressors, only a few studies adopt estimation methods other than OLS to deal with these problems.[4]

The main source of endogeneity that the literature on gender wage gap has addressed is correlation of the unobserved individual specific effect and the regressors in the model. Kim and Polachek (1994) show that this problem remains, even after using detailed controls for the differences in human capital and background characteristics. One way to deal with this problem is to apply fixed effects estimators, another, instrumental variable estimators. The difference between the two underlying models is that the former is more restrictive than the latter since it relies on an additional restriction that the processes in X_{it} are strictly exogenous.

Several studies (e.g., Mincer and Polachek, 1978) implement the fixed effects procedure by estimating the wage level model in first differences, that is:

$$(3) \qquad \Delta lnW_{it} = \Delta X_{it}\beta + \Delta u_{it} \quad ,$$

where the difference operator Δ transforms levels into differences between periods t and s, $t > s$. The estimator is consistent if:

$$(4) \qquad E[\Delta u_{it}|\Delta X_{it}, d^*_{it} > 0, d^*_{is} > 0] = 0,$$

[4]In several parts of the literature, researchers have carefully discussed the implications of endogeneity, often due to non-random selection into work, but do not then explicitly deal with it; see e.g., Blau and Kahn (1997); Datta Gupta et al. (2006).

where the latent index variable d^*_{ip}, $p = t, s$, is positive if an individual i participates in the labour market and non-positive otherwise. Clearly, this implies that decisions modelled in X_{it} are not affected by unobserved time variance and individually varying shocks in $(t-1)$, u_{it-1}.[5] Given that this relation is, however, important and cannot be ruled out, one can only derive estimates of the joint effect of the direct impact of x_{it}, $x_{it} \epsilon X_{it}$, on wages plus the indirect effects of unobserved shocks through x_{it}. The direction of the bias depends on the sign of the conditional expectation $E[\Delta u_{it}|\Delta x_{it}, d^*_{it} > 0, d^*_{is} > 0]$ where $\Delta x_{it} \epsilon \Delta X_{it}$. A shortcoming of the fixed-effects estimator is that it only permits the identification of the coefficients of individual and time-varying regressors. However, by application of the between-group estimator, and using fixed-effects estimation results, the remaining parameters can be obtained (Kim and Polachek, 1994).

Very few studies have estimated the most general model nested in equation (1) and (2) by instrumental variable estimators. In this model identification of the parameters of interest depends on the validity of the exclusion restrictions, and the instruments are partially correlated with the endogenous variables. A major difficulty is to find valid instruments. The most powerful instruments in the literature have been derived using longitudinal data.

An example of a common instrument for experience is the variable age.[6] The assumption for being a valid instrument is that once the actual work history is taken into account in a wage regression age should have no effect on wages.[7] This argument derived from a human capital explanation of wages could be violated in case of age related contracts or in case age is correlated with strength or mental

[5] To be precise, we must also rule out non-random sample selection varying across time. For simplicity, in the following discussion we assume that the sample selection process is constant over time. This could apply if the decision to work (by women) depends only on individual specific factors.

[6] See, for instance, Kim and Polachek (1994). Previous studies applying OLS to the wage regression use age directly to control for work experience.

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

agility, which possibly increase wages. The intuition for the use of the variable number of children as an instrument is that women with children are more likely to drop out of the labour force, either temporarily or permanently, than women without children. Primarily from the perspective of economic theories of fertility and marriage (Willis, 1973), it is argued that the variable number of children is endogenous, and that even if the actual work history has been taken into account, according to Becker (1985) it may still have an impact on wages by capturing effort.

In longitudinal studies additional instruments can be obtained from transformations of the endogenous variables in the wage regression model. For example, studies applying the Hausman–Taylor (1981) estimator use de-meaned variables.[8] Validating these instruments requires, nevertheless, strict exogeneity for x, and mean stationarity of the process generating x. Less restrictive is the use of lagged differences in endogenous variables as instruments in the wage level equation[9] to apply estimators following Arellano and Bond (1991). Application of a systems estimator by Arellano and Bover (1995) exploit additional exclusion restrictions by using lagged endogenous variables as instruments in the wage equation in first differences.[10] The most extensive empirical evidence on the application of a range of inconsistent and consistent estimators is presented in Kim and Polachek (1994). The results reveal variation depends on the estimators, as well as the set of instruments. The authors show that the restrictions in the general model are rejected, and hence, the general model is preferred.

Thinking beyond the model framework in equations (1) and (2), additional sources of endogeneity could occur if the error term structure is indeed more complex than that usually assumed in the gender wage gap literature. The error term could contain, in addition to person fixed effects, match value components for the individual–job match, or individual–firm match – and time-varying fixed effects for each person.

[8] For applications see Kim and Polachek (1994) and Light and Ureta (1995).

[9] For an application, see Kim and Polachek (1994).

[10] For an application see Kunze (2001).

Furthermore, there is the suspicion that observed variables, like education, or unobserved variables, such as motivation, have a differential impact on the early or later career. In other words, they could also impact on wage growth.[11]

3 Methods of measuring the gender wage gap

Empirical evidence on the gender wage gap hinges on estimates of the main parameters of interest, and its economic meaningfulness may be limited by restrictive assumptions imputed on the wage model.[12] The most standard approach in the literature to estimate the gap is the Blinder (1973)–Oaxaca (1973) (B–O) decomposition, which can be written as:

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

where the price vectors β^M and β^F are recovered after estimating wage equations $lnw^g_{it} = X^g_{it}\beta^g + \epsilon^g_{it}$ for males ($g = M$), and females ($g = F$), respectively. Variables with upper bars are means calculated as $\sum_t \sum_i x_{it}/T = \bar{x}$. The 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 $(\bar{X}^M)' Var(\hat{\beta}^M - \hat{\beta}^F)(\bar{X}^M)$. The decomposition states that the difference in mean logarithmic wages can be decomposed into a component explained by differences in characteristics, X, weighted by a price vector, β, and an unexplained -or residual - component due to differences in prices weighted by the mean of X.[13]

[11] A more general critic of these models is that they are imbedded in human capital theory and mostly ignore explanations of wage formation related to, for example, job search and internal labour markets. Since theory is not the main focus of this paper, and since gender wage gap studies mainly rely on human capital theory, we do not discuss this in more detail.

[12] Summarizing the empirical evidence on the gender wage gap in the sense of a country or worldwide average has already been attempted in meta-regression analysis studies and will not be discussed in detail. See Stanley and Jarrell (1998) for evidence in the U.S. and Weichselbaumer and Winter-Ebmer (2005) for international work.

[13] In this version, the male price vector serves as the competitive price.

The main implications of consistent and inconsistent estimation for the measurement of the gender wage gap are summarized in Table (1). For simplicity, we summarize the results regarding work experience (referred to as X in the table) in the wage model, as specified in equations (1) and (2). The conclusions can therefore be viewed as partial, assuming that the prices of the other characteristics are estimated consistently and differences in those characteristics are also measured consistently. In the first three rows, we list various models where prices are estimated inconsistently. Using results from these types of estimators, one can only describe gender differences in experience, if measured without error. Taking account of the direction of the bias, one can get a notion of whether the partial effect is zero rather than positive or negative. It is misleading to interpret the unexplained part as the part due to discrimination because the βs are estimated with bias. If the general model is adequate then only estimators, such as instrumental variable estimators, dealing with unobserved heterogeneity and predetermined variables lead to consistent estimates of prices; this holds under the assumption that the instruments are valid.[14] The parameters of the general model are essential to make inferences regarding the processes leading to the wage gap. Such knowledge is the premise for designing efficient policies aimed at reducing unequal pay.

Taking identification issues into account, decomposition techniques have been mostly used to mechanically decompose the raw gender wage gap and provide very detailed descriptive results on factors that contribute to wage differences among men and women in the labour market (see e.g., Harkness, 1996, and Wright and Ermisch, 1991). Studies based on the B–O decomposition have found that gender distinct labour force participation patterns contribute considerably to the explanation of male–female wage differentials (Mincer and Polachek, 1974). Broadly speaking, the findings appear to suggest that differences in the human capital accumulation process explain about one-quarter to one-half of the gap. These estimates are from the U.S. and the lower bound is based on age (Oaxaca, 1973), which may contain

[14] In addition, one may need to deal with the non-random sample selection into work.

measurement error and hence are downwardly biased. The fractions increase when work experience and time-out-of-work are included (Mincer and Polachek, 1978). Since the weights used in these calculations are likely estimated with bias, we cannot be sure of the robustness of these findings. Based on human capital theory, we would only predict that the contribution is significant. Another problem is that we do not really know the economic meaning of the unexplained part. That is, we cannot identify whether the differences in returns are due to labour market discrimination or some other factor.

Studies that have estimated more elaborate models confirm the importance of heterogeneity in unobserved skills that affect individual choices of work histories. Kim and Polachek (1994) show in the U.S. that the appreciation of earnings power associated with work experience, and the depreciation associated with not working, are comparable for men and women, after unobserved heterogeneity has been taken into account.[15] Similarly, Kunze (2001) finds equal returns to experience during the very early careers of skilled workers in Germany.

Other aspects that have been investigated applying decomposition techniques are the importance of gender specific components and wage structure components for changes in the overall gender wage gap. In this strand of the literature, studies exclusively apply OLS to the wage regression and focus on the more sophisticated decomposition of the gap change. Changes have been studied across time and across countries using the Juhn, Murphy and Pierce (1991) (JMP) decomposition (See e.g., Blau and Kahn, 1995, and Blau and Kahn, 1997). In order to derive the main equation of the JMP decomposition, we let the individual specific effect vary over time, and hence we rewrite equation (2) $\epsilon_{it} = \nu_{it} + u_{it}$. Following the notation in the literature, we rewrite equation (1) as follows:

$$lnW_{it}^M = X_{it}^M \beta_t^M + \sigma_t^M \theta_{it}^M \quad , \tag{5}$$

[15] They also show a remarkable reduction in the unexplained component from zero to 10 per cent.

where θ captures unobserved skills and is defined as the standardized residual, $\theta_{it}^{M} = \epsilon_{it}^{M}/\sigma_{t}^{M}$, where $\sigma_{t}^{M} = \sqrt{Var(\epsilon_{it}^{M})}$. Under the assumption that prices derived from the male sample wage regression (β_{t}^{M})are equivalent to competitive prices and discrimination is neglected,[16] we can write the male–female wage differential in period t as:

$$\Delta\overline{lnW}_t = \Delta\bar{X}_t\hat{\beta}_t^M + \sigma_t^M\Delta\bar{\theta}_t. \tag{6}$$

The impact of gender and wage structure specific components on the change of wage differentials can then be estimated from the following decomposition.

$$\underbrace{(\Delta\overline{lnW}_t - \Delta\overline{lnW}_s)}_{change\ in\ raw\ wage\ gap} \tag{7}$$

$$= \underbrace{(\Delta\bar{X}_t - \Delta\bar{X}_s)\hat{\beta}_t^M}_{observed\ X's\ effect} + \underbrace{\Delta\bar{X}_s(\hat{\beta}_t^M - \hat{\beta}_s^M)}_{observed\ prices\ effect} + \underbrace{(\Delta\bar{\theta}_t - \Delta\bar{\theta}_s)\sigma_t^M}_{gap\ effect} + \underbrace{\Delta\bar{\theta}_s(\sigma_t^M - \sigma_s^M)}_{unobserved\ prices\ effect}$$

Here t, s index time periods.

The first component in equation (8), $(\Delta\bar{X}_t - \Delta\bar{X}_s)\hat{\beta}_t^M$, measures the impact of the change in differences in observed human capital endowments between men and women. The second term, $\Delta\bar{X}_s(\hat{\beta}_t^M - \hat{\beta}_s^M)$, measures the effect of changing prices for the observed labour market characteristics of males. Similarly to the B–O decomposition, interpretation of these components may be affected by bias in the estimates of the components in β. Additionally, the direction of the bias may be complicated if it changes over time. As an example, Blau and Kahn (1997, Table 2) have shown the decline in the gender wage gap between 1979 and 1988 in the US can be partly explained, some 41 per cent of the raw gap, by a relative increase in work experience. If the return to experience is estimated as too high, because it includes indirect effects then the contribution is overestimated. Using male prices may minimize problems due to changes in non-random selection into work since male employment rates are quite stable over time. However, this does not rule out the role played by unobserved heterogeneity.

[16] Thus, it is assumed that $\hat{\beta}_t^M = \hat{\beta}_t^F$.

Furthermore, inconsistent estimates of β also have consequences for the residual components. The direction of the effect is, however, difficult to infer. The third term,$(\Delta\bar{\theta}_t - \Delta\bar{\theta}_s)\sigma_t^M$, the gap effect, captures changes in the relative positions of men and women; that is, whether women rank higher or lower in the male wage residual distribution after controlling for observed (human capital) characteristics and holding the degree of inequality in the male wage distribution constant. In other words, it reflects changes in the levels of the unobservable variables. The final term,$\Delta\bar{\theta}_s(\sigma_t^M - \sigma_s^M)$, is the unobserved price effect that measures the impact of a change in inequality on the change in the male–female wage differential, assuming that females maintain the same position in the residual wage distribution of men. This can be interpreted as changes in the returns to unobservable skills. Note that this holds only under the assumption that σ^M does not change over time due to measurement error, pricing error or a change in the number of unobserved characteristics included in the vector $(\sigma_u^M \theta_{iu})$, where $u = t, s$.[17] Since both the variance of the wage residuals and the distribution of the predicted wage residuals depend on estimates of the parameters of the controls, the contribution of the gap effect and the unobserved price effect to the explanation of the gap may be estimated with bias. Blau and Kahn (1997) also noted that non-random sample selection into work may complicate interpretation of the decomposition. They argue that the use of the male sample regression estimates ameliorates the problem, which nevertheless ignores unobserved heterogeneity problems. Hence, untreated unobserved heterogeneity problems in the wage equation can also have an affect on estimates of the overall impact of wage structure: that is, the "observed prices effect" and the "unobserved prices effect", and gender specific factors as the sum of the "observed X's effect" and the "gap effect".[18]

[17] One should note that a general conceptual problem in the decomposition is that it relies on changes in the distribution of male wage residuals, or some other reference point, and the observed wage structure based on prices derived from the male sample regression. As first shown by Fortin and Lemieux (1998), the results may be sensitive to the distribution of the reference.

[18] This problem may partly explain contradictory results on the gender twist story by Blau and

Moreover, interpretation of the results from international studies is likely to be complicated since bias may also vary across countries. As an example, Blau and Kahn (1995) compared the U.S. to other countries and found that with few exceptions 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 the other countries in their sample. These results assume consistency of the estimates of prices (for all countries).[19]

Studies in the personnel economics literature (firm-level studies) and on occupational groups present one approach to reduce the unobserved heterogeneity problem by focusing on selected samples of more homogenous groups of workers. These studies use data on workers that are basically identical with respect to education and (unobserved) motivation or ability. Hence, one could hope that ν_i in equation (2) becomes redundant. While the results of these studies are not representative, they provide suggestive evidence of the role of gender in all labour markets.[20] Other attractive features of this group of studies also include the fact that they can investigate occupation specific returns to experience and that they can more credibly investigate whether wage gaps still exist when job characteristics and rank are controlled for. Within firms as well as within a number of occupational groups ranks and promotion ladders are well defined and hence measure more precisely work place than in more heterogeneous samples. One should note that conclusions are conditional on selection into occupations or firms. Oaxaca and Ransom (2005) find in their study of the food sector no significant wage gap within work places.[21] They show that an important source of the gender wage gap is lower level entry jobs for women and the lower probability of promotion.

Kahn (1997) and Datta Gupta et al. (2006).

[19]Similar problems can apply to meta-analysis studies estimating pooled regressions for various countries, as in Weichselbaumer and Winter-Ebmer (2005).

[20]Representative studies, on the other hand, may have little detailed information on the processes leading to the gender wage gap. An example of a detailed study is Bayard et al. (2003).

[21]Similar conclusions are drawn by Jones and Makepeace (1996).

Several studies on occupational groups, by contrast, do find within workplace or within rank significant wage gaps after controlling for qualification. Wood et al. (1993) showed substantial wage differentials for lawyers 14 years after graduation, which remained after conditioning on experience and other differences. One suspicion is that lawyers are quite a heterogenous group and that the data are not detailed enough to exclude unobserved heterogeneity. Bertrand and Hallock (2001) find a very large gender wage gap of about 45 per cent among CEOs and top corporate jobs, which they explain by the over-representation of women in small firms. This suggests that even within relatively homogenous groups, it is important to control for firm heterogeneity. A recent study by Blackaby et al. (2005) for the academic market in Britain employs detailed information on both workers and firms. They explain about two-thirds of the raw gap with individual productivity, including work place characteristics and rank. They find no negative effect of career breaks on earnings using OLS. They show that this estimate is upward biased because of indirect effects through the probability of receiving an outside offer and lower publication. The intuition is the loyal servant hypothesis in that women are less mobile, perhaps because of family responsibilities. Hence, women are less likely to use outside options in order to obtain pay raises with the current employer. They find that this is due to two channels. First, women are less likely to apply for and receive outside offers, and, second, unlike men they do not receive a gain in wages from outside offers.

A growing strand in the literature that has offered new insights on the distribution of the gap is the quantile regression approach.[22] The quantile regression (QR) (Koenker and Basset, 1978) approach allows the coefficient estimates, β, to vary across the wage distribution. In application to our wage model, the QR technique

[22] Some studies using the JMP decomposition have also taken account of distributional aspects by decomposing the gap at various percentiles. However, coefficient estimates are derived from ordinary mean regression estimation. See e.g., Blau and Kahn (1997) and Datta Gupta et al. (2006).

estimates the θth quantile of log wages conditional on the covariates. The estimator of the coefficient vector $\beta(\theta)$ is the solution to:

$$(8) \qquad min\{\sum_{i, lnW_i \geq X_i\beta(\theta)} \theta|lnW_i - X_i\beta(\theta)| + \sum_{i, lnW_i < X_i\beta(\theta)} (1-\theta)|lnW_i - X_i\beta(\theta)|\},$$

suppressing the index t. This assumes that the conditional quantile of log wages, q_θ, is linear in X, that is $q_\theta = X\beta(\theta)$. The coefficient estimates can be interpreted as the estimated return to individual characteristics at the θth quantile of the log wage distribution assuming exogeneity of the regressors. New methods modelling the endogeneity of explanatory variables (Abadie et al., 2002) have not, to the author's knowledge, been applied in the gender wage gap literature. An exception is García et al. (2001) who deals with the endogeneity of educational choices and non-random sample selection.[23]

Using the quantile regression estimates of the wage equations separately for men and women, the gap can be decomposed at different percentile points in the wage distribution into the components due to differences in characteristics and differences in prices applying the Machado and Mata (2004) (MM) technique. Corresponding to the B–O decomposition, the idea of the MM technique is to generate two counterfactual densities. The first is the female log wage density that would arise if women were given men's labour market characteristics, but were paid prices derived from the female sample regression, $X^M\hat{\beta}^F(\theta)$. The second is the density that would arise if women retained their characteristics, but were given prices derived from the male sample regression, $X^F\hat{\beta}^M(\theta)$.[24] Identification in this framework depends on the exogeneity of the controls in the underlying wage regressions. The decomposition of the raw gap can then be written as follows.

[23] They use proximity to college as an exclusion restriction for education and marital status, the number of income earners in the household and regional variables as exclusion restrictions in a decision to work probit model.

[24] For further details, see Machado and Mata (2004) and Albrecht et al. (2003), p. 168.

$$(\bar{X^M} - \bar{X^F})\hat{\beta}^M(\theta) + \bar{X^F}(\hat{\beta}^M(\theta) - \hat{\beta}^F(\theta))$$

Studies of European countries have found significant differences in the gender gap at different quantiles of the log wage distribution.[25] In the underlying wage regressions a control variable for experience is included, or if not available, age as a proxy. Evidence in this field is descriptive in the sense that nearly all studies assume orthogonality of the error term and the controls. Hence, the conditional statements need to be evaluated carefully. There is some evidence of heterogeneity of β. Albrecht et al. (2003) and García et al. (2001) report the coefficients of age, used as a proxy for experience, vary significantly across the distribution. A study in Sweden (Albrecht et al., 2003) has shown strong glass ceiling effects during the 1990s that seem to persist after controlling for age, education, and industry.[26] It demands further investigation whether these results are robust when a more general model would be taken into account rather than the simple model with exogenous regressors.

4 Conclusions

In this paper, we have reviewed the gender wage gap literature with respect to the problem of consistently estimating the parameters in typical human capital wage regression models. There is no undisputed method of measuring the gender wage gap. We find that the literature has progressed towards the use of more general wage models taking into account unobserved heterogeneity, non-random sample selection

[25] See Albrecht et al. (2003) for Sweden, Bonjour and Gerfin (2001) for Switzerland, Garcia et al. (2001) for Spain, Fitzenberger and Wunderlich (2002) and Fitzenberger and Kunze (2005) for Germany and Newell et al. (2001) in former communist countries.

[26] The glass ceiling infers that women do well in the labour market up to a certain point in the hierarchy structure, but then fall behind men. This implies that one expects a relatively larger unexplained wage gap at the top of the wage distribution.

and predetermined variables (in wage growth models). These have, however, not reached the level of a general approach. Research has further evolved into various directions using rich data that provide more descriptive empirical evidence on new aspects of the gender wage gap. It is left to future research whether the suggestive evidence regarding the explanation of the processes leading to the gender wage gap is confirmed.

Policy recommendations regarding unequal pay and anti-discrimination policies are complicated. Our review illustrates the problems of and constraints on stretching the results. The economic theoretical background as well as the restrictions imposed on the empirical wage models have to be taken into account and assessed in order to derive statements regarding the processes leading to the gender wage gap. Two important questions remain of interest. First, whether within job differentials exist after differences in work histories and other qualification characteristics are taken into account. This is the fundamental question underlying policies fighting unequal pay and wage discrimination. Research suggests that most suited to disentangling these processes are detailed longitudinal employer–employee matched data sets that contain detailed characteristics, such as complete work histories and skills and job characteristics. Second, in light of increasing levels of education and the greater access of women to top-level jobs an important question is whether a glass ceiling exists and what processes lead to this effect. Quantile regression techniques are one avenue of research that may help resolve this question.

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Table 1: Gender wage gap: Consistency and decomposition

Estimator applied to the wage model*	Explained part $\hat{\beta}^M$	$(\bar{X}^M - \bar{X}^F)$	Unexplained part $\bar{X}^F(\beta^M - \beta^F)$	Problem of the econometric model	Results
OLS	biased	biased	biased	measurement error, unobserved heterogeneity	no final results
OLS	biased	consistent	biased	unobserved heterogeneity	Human capital differences
First differences	biased	consistent	biased	predetermined variables	Human capital differences
IV	consistent	consistent	consistent	validity of instruments	weighted human capital differences, unequal pay

Note: * The wage model is specified in equations (1) and (2) see text. A simple human capital model of wage formation is assumed.