IHS Economics Series
Working Paper 143
November 2003

A Meta-Analysis of the International Gender Wage Gap

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Impressum

Author(s):
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Title:
A Meta-Analysis of the International Gender Wage Gap

ISSN: Unspecified

2003 Institut für Höhere Studien - Institute for Advanced Studies (IHS)
Josefstädter Straße 39, A-1080 Wien
E-Mail: office@ihs.ac.at
Web: www.ihs.ac.at

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Reihe Ökonomie

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Founded in 1963 by two prominent Austrians living in exile – the sociologist Paul F. Lazarsfeld and the economist Oskar Morgenstern – with the financial support from the Ford Foundation, the Austrian Federal Ministry of Education and the City of Vienna, the Institute for Advanced Studies (IHS) is the first institution for postgraduate education and research in economics and the social sciences in Austria. The **Economics Series** presents research done at the Department of Economics and Finance and aims to share “work in progress” in a timely way before formal publication. As usual, authors bear full responsibility for the content of their contributions.

Das Institut für Höhere Studien (IHS) wurde im Jahr 1963 von zwei prominenten Exilösterreichern – dem Soziologen Paul F. Lazarsfeld und dem Ökonomen Oskar Morgenstern – mit Hilfe der Ford-Stiftung, des Österreichischen Bundesministeriums für Unterricht und der Stadt Wien gegründet und ist somit die erste nachuniversitäre Lehr- und Forschungsstätte für die Sozial- und Wirtschaftswissenschaften in Österreich. Die **Reihe Ökonomie** bietet Einblick in die Forschungsarbeit der Abteilung für Ökonomie und Finanzwirtschaft und verfolgt das Ziel, abteilungsinterne Diskussionsbeiträge einer breiteren fachinternen Öffentlichkeit zugänglich zu machen. Die inhaltliche Verantwortung für die veröffentlichten Beiträge liegt bei den Autoren und Autorinnen.

Abstract

Since the early seventies, hundreds of authors have calculated gender wage differentials between women and men of equal productivity. This meta-study provides a quantitative review of this vast amount of empirical literature on gender wage discrimination as it concerns differences in methodology, data, countries and time periods. We place particular emphasis on a proper consideration of the quality of the underlying study which is done by a weighting with quality indicators. The results show that data restrictions have the biggest impact on the resulting gender wage gap. Moreover, we are able to show what effect a misspecification of the underlying wage equation – like the frequent use of potential experience – has on the calculated gender wage gap. Over time, raw wage differentials world-wide have fallen substantially; however, most of this decrease is due to an increased labor market productivity of females.

Keywords

Gender wage differential, meta-analysis

JEL Classification

J16, J31, J71

Comments

Rudolf Winter-Ebmer is also associated with CEPR, London and IZA, Bonn. This research was supported by the Austrian Theodor-Körner-Fonds, the Ludwig Boltzmann-Institut for Growth Research and the Austrian Science Funds (P15422). Josef Fersterer, David Haardt, Sandra Leitner, Martin Mauhart and Andrea Kollman provided invaluable assistance with the data collection. Thanks to Erling Barth, Miriam Beblo, Francine Blau, Peter Gottschalk, Stefan Klasen, Wilhelm Kohler, Steve Machin, Ronald Oaxaca, Solomon Polachek, Ken Troske, Andrea Weber, Rainer Winkelmann as well as seminar participants at the AEA meeting (Atlanta), in Bonn, Berlin, Mannheim, St. Gallen, Bilbao, Oslo, Paris, Vienna and in Linz for helpful comments.

Contents

1 Introduction

The literature on the economics of discrimination started with Becker's seminal study in 1957. Since then – due to the proliferation of the use of microdata in the last three decades – the study of gender wage differentials became a routine job for labor economists. Microdata allowed to assess the productivity of individuals and to compare wages of equally productive males and females. In particular the decomposition technique – as pioneered by Blinder (1973) and Oaxaca (1973) – has been frequently applied to data from the most different countries and time periods.

Given the importance and timeliness of the topic, many reviews or surveys of the development of gender wage gaps have been done.[1] Most of them concentrated on single countries, concentrated on econometric issues and were of a narrative type. With regard to the sheer number of available studies, any narrative survey will have difficulties to condense and interpret these papers satisfactorily. In this paper we will complement this survey literature with a meta-analysis which systematically covers the published papers in this field. Meta-analysis makes use of all the published information concerning the research design as well as the results of these studies: In our meta-study for example, we assess the impact of different empirical methodologies some researchers have used or the kind of data they had access to. The meta-analysis then allows to give a quantitative review of the literature and can illustrate the evolution of the gender wage gap over time and across countries. It can summarize the existing literature in a clear and meaningful way and can give suggestions as to how such studies should be accomplished in the future.[2]

Section 2 of the paper discusses the method of meta-analysis in some detail and draws attention to some advantages and caveats with respect to this method. Section 3 shortly reviews the way gender wage differentials are calculated, while Section 4 discusses our data-generation process - a very important step in any meta-analysis. Section 5 introduces our meta-regression-model and discusses problems some of which will be addressed by a weighting mechanism. Section 6 presents results and Section 7 concludes.

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[1] See e.g. Cain (1986) and Altonji and Blank (1999) for authoritative surveys.

[2] Stanley and Jarrell (1998) provided a first meta-analysis on gender wage differentials, but they confined themselves to US studies only.

2 Meta Analysis

Meta-analysis is a helpful tool to cumulate, review and evaluate empirical research. Papers investigating one particular topic are collected and analyzed concerning their data and method. Meta-analysis then allows to evaluate the effect of different data characteristics and methodologies on the result reported, e.g. a regression parameter (Stanley, 2001). Instead of the usual practice of analyzing observations of individual workers, here, results from each previously conducted study represent one data point each. Meta-regression analysis, in turn, uses regression techniques to explain these data points by characteristics of the individual study.

While meta-analysis is a standard procedure in disciplines such as medicine, education, and psychology, it has been discovered in economics only lately.[3] However, within the last ten years a substantial body of research has developed also in economics. Jarrell and Stanley (1990) examined the union-nonunion wage gap, Doucouliagos (1995) the effect of worker participation on productivity and Doucouliagos (1997) the demand for labor in Australia. Phillips and Goss conducted a meta-analysis concerning the effect of tax policy on economic development, Stanley (1998) examined the Ricardian equivalence theorem, and Görg and Strobl (2001) investigated the impact of the presence of multinational companies on domestic productivity. Card and Krueger (1995) as well as Ashenfelter, Harmon and Oosterbeek (1999) focused particularly on the publication bias in their meta-studies on minimum-wages and returns to schooling, respectively. The meta-analysis by Greenberg, Michalopoulos and Robins (2003) evaluates government sponsored training programs. Stanley and Jarrell (1998) conducted a meta-analysis on the gender wage differential also, but they restricted themselves to US data while the goal of our study is to investigate the gender wage gap on an international level.

One of the prime advantages of a meta-study over a narrative or a vote counting review is that it allows a quantitative assessment of the literature in “a way an econometrician would write a survey”. It offers a quick way to assess the merits of different research methods: all methodological features of a particular original study can be used as control variables in the meta-regression analysis; the resulting regression coefficients then give a quantitative measure of the importance of the concerned research methods. As meta-analysis is “constructing” its own meta-data, the principle of completeness and replicability must dictate the choice of original papers. This implies that all papers have to be treated in a standardized way and there is no room for the reviewer for an individual assessment of papers. Typically in a narrative or vote counting review some papers are discarded due to methodological shortcomings, unreliability of the data and the like; on the other hand some papers are highlighted. Obviously, the in- or exclusion of a paper lies in the personal assessment of the author. This can sometimes cause discussions about the legitimacy of the choice of papers.[4] Meta-analysis avoids this problem as it includes all papers. However, differences in the reliability of these original studies should not be disregarded entirely. Therefore, in our meta-analysis we developed some objective and operational indicators for the quality of a paper on the gender wage gap which are used as different weights in our meta-regression.

Further issues concerning meta-analysis are, firstly, a possible publication bias and, secondly, the question of appropriateness of regression techniques for such a convenience sample. Publication bias occurs when journal editors tend to publish papers with significant results only (see e.g. Ashenfelter, Harmon and Oosterbeek, 1999). It can seriously harm meta-regression analysis when studies with low or insignificant results are systematically missing, because the numerical size of the effect will be overestimated. While, in principle, the possibility of a publication bias can never be totally excluded, it seems to be less relevant in our case of gender wage differentials. Rejecting the existence of sex discrimination, a phenomenon economists have no theoretical explanation for, might be a welcome addition to the empirical labor economics literature. Our conjecture would be that papers rejecting the existence of a gender wage gap would be equally likely to get published as those which confirm differences in wages.[5] Statistical problems of meta-analysis are dealt with in Section 5.

3 Estimates for Wage Differentials

The most common way to analyze discrimination based on gender is to compare male and female earnings holding productivity constant. One method is to simply include a sex dummy in the wage regression model:

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[3] See Glass (1977) for an early characterization of meta-analysis.

[4] See e.g. the discussion between Hanushek (1998) and Krueger (2003).

[5] In our case, the usual method to deal with publication bias – checking the correlation between the measured effect and the reported standard error of this effect – is impossible to use, because in general no standard errors are calculated for the Blinder-Oaxaca decomposition.

$$W_i = \beta \ X_i \ + \gamma \ sex_i + \varepsilon_i , \tag{1.1}$$

where W_i represents the log wage and X_i the control characteristics (e.g. education, job experience, marital status, job characteristics) of an individual i, β and γ are parameters.

However, the standard procedure to investigate differences in wages is the one developed by Blinder (1973) and Oaxaca (1973) which allows that productive characteristics of men and women are rewarded differently. Wages are estimated separately for individuals i of the different groups g, males and females:

$$W_{gi} = \beta_g \ X_{gi} + \varepsilon_{gi} , \tag{1.2}$$

where g = (m, f) represents the two sexes; W_{gi} is the log wage and X_{gi} the control characteristics of an individual i of group g.

The total wage differential between men and women can then be decomposed into an explained part due to differences in characteristics and an unexplained residual.

The difference in mean wages can be written as:

$$\overline{W_m} - \overline{W_f} = (\overline{X_m} - \overline{X_f})\hat{\beta}_m + (\hat{\beta}_m - \hat{\beta}_f)\overline{X_f} \ \equiv \ E + U , \tag{1.3}$$

where $\overline{W_g}$ and $\overline{X_g}$ denote the mean log wages and control characteristics of group g and $\hat{\beta}_g$ represents the estimated parameter from equation (1.2). While the first term stands for the effect of different productive characteristics (the endowment effect E), the second term represents the unexplained residual U which is due to differences in the estimated coefficients for both groups and is often referred to as “discrimination effect”.[6] Since the first use in the early seventies, hundreds of authors have adopted and also extended the Blinder-Oaxaca approach.[7] For our meta-study we accepted all estimates for log wage differentials, dummies as well as the unexplained gender wage residual U and its derivatives. These estimates are taken as the dependent variable in our meta-regression-analysis which we try to explain by the respective papers' data and method characteristics.

4 Meta-Data

In order to make the data construction as transparent as possible, we used an easily accessible but universal research data base. In November 2000 we searched the Economic Literature

[6] Often authors also report a "discrimination index" which is given by D = e^U - 1 and indicates how much higher the average female wage would be if women's endowments would be remunerated such as men's.

[7] For extensions of the B-O decomposition see e.g. Brown et al. (1980), Reimers (1983), Cotton (1988), and Neumark (1988).

Index (EconLit) for any reference to: "(wage* or salar* or earning*)[8] and (discrimination or differen*) and (sex or gender)".[9] EconLit is the most comprehensive data base for economic research papers. There is a bias towards internationally published research, which might be considered a welcome selection with regard to quality; on the other hand, non-English-language studies will be underrepresented, particularly if they represent solely policy reports or unpublished papers from research institutes. However, correcting this bias seems impossible since there is no other suitable research data base available. Our EconLit search led to 1541 references. In the next step, titles and abstracts of the articles were evaluated to find out whether in fact a gender wage gap was estimated. Theoretical papers or those obviously covering a different topic were excluded in a first round. This left us with 457 articles. These papers were examined carefully whether they presented an empirical estimate of the gender wage differential or sufficient information to calculate it. Some papers were only descriptive, reporting just mean wage ratios without any regression analysis, others presented wage decompositions only concerning race, marital status, or work time status (full/part time). Yet another group of authors calculated differences in wage differentials between countries or different points in time, but did not provide explicit information also on the national, static wage differential. Eventually, the desired estimates could be gained from 263 articles.[10]

Table 1 shows the distribution of our sample over time, where we coded a study for the 1980s if its data related to the 1980s. The number of papers increased steadily over time, with a decreasing number in the 1990s, which is easily explained by a "publication backlog" as well as a “research backlog”: data sets for the (late) 1990s are only available after some time. Some authors calculated the gender wage gap for several countries[11] or time periods in one published paper. These estimates can be treated as independent estimates. Therefore, we divided the estimates from one paper into several *“studies”* if the estimates have come from different time periods and/or different populations. This gives us 788 different studies.

Typically authors present a number of estimates for each study, i.e. country and time unit. These estimates are usually based on different specifications of the regression model. Stanley and Jarrell (1998) selected only one estimate per paper for their meta-analysis on the

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[8] Non-English language papers can equally found with this strategy because in the EconLit titles are also given in English.

[9] At the beginning of our study we contacted friends in the discipline to give us access to recent estimates of the gender wage gap in their country. However, we quickly refrained from this strategy as we realized it may lead to a biased sample of papers.

[10] A full list of papers included in the meta-study is available from the following URL: www.econ.jku.at/weichsel/work/meta_papers.pdf.

gender wage differential for the US. In particular they chose “the OLS estimate which the author seemed to promote as the best” (p. 955). This strategy is open to criticism because it lies in the discretion of the researcher which of the available estimates to pick; moreover, the principle of replicability is violated. Therefore, we decided to include all estimates the authors presented for a given study. For each study all estimates as well as all the corresponding meta-independent variables, data characteristics and methodology were collected and coded. (The meta-independent variables included in the analysis are listed in Table 2.) This procedure gives us one observation in our meta-dataset per reported estimate. In total this gives us 1535 estimates of the gender wage gap, on average 2 estimates per study.

However, there are two potential problems associated with allowing multiple estimates from one study: First, obviously, multiple estimates using the same data (same country and time period) are not independent from each other, leading to non-spherical error terms in the meta-regression. Second, there is the problem of biased sampling: if there are multiple estimates of one single study, there is not the same weight given to each study. We deal with these problems using a weighting scheme (see section 4.1.).

While Stanley and Jarrell (1998) use only US studies which are based on one of the broad national data sets (CPS, Census, or PSID)[12], we collected all estimates of the gender wage gap based on data for 67 countries. Table 1 gives a regional breakdown of our data set. Whereas in the beginning of the sampling period, estimates for the US were the majority, their share fell to a mere 23% for the 1990s. Especially, in the later periods, a considerable amount of the estimates of the gender wage gap were for post-communist countries, Asia, Latin-America and Africa.

Figure 1 shows the development of the total wage gap (i.e. the raw differential in hourly wages from the original data set) over time. The total wage gap falls significantly over time from around 65% ($e^{0.5}$-1) in the 1960s to only 30% in the 1990s, which is a decline of about 1.2 percentage points per year. That means the total wage differential has more than halved across our time period 1967-1997. However, this decline of the gender gap is almost entirely due to an equalization of productive characteristics: females have become better educated and trained. The reported Blinder-Oaxaca wage residual is practically constant over time.

Figure 2 shows the reported total wage gap and the reported wage residual for the different countries. In those countries plotted above the 45^0 line (e.g. Cote d'Ivoire, Tanzania,

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[11] Likewise, they might use data from different distinct populations, like regional or sectoral entities.
[12] This resulted in 41 studies for the period 1959 to 1986 included in their meta-analysis.

Korea, Kenya, Cyprus, Japan, Indonesia, Nicaragua) women have lower endowments than men. Part of the total wage gap, therefore, can be attributed to differences in human capital. In those countries underneath the 45^0 line (e.g. Singapore, Guinea, Costa Rica, Sudan, Trinidad and Tobago, Philippines, South Africa) the contrary is true. Women have higher endowments than men, nevertheless they are paid less. Considering their human capital, women, in fact, are more discriminated against than suggested by the total wage gap.

5 Meta-Regression-Analysis

Our meta-regression model takes the form:

$$R_j = \sum a_k \, Z_{kj} + b \, t_j + d \, c_j + \varepsilon_j \text{, (j = 1, 2, ... L) (k = 1, 2, ... M)} \qquad (1.4)$$

where R_j represents the unexplained log wage differential of study j, which can either be the Blinder-Oaxaca unexplained residual U_j from (1.3) or the coefficient of the gender dummy γ_j in (1.1), Z_{kj} are the k meta-independent variables, t_j and c_j are a set of time and country dummies, respectively; a_k, b and d are parameters to estimate.

The meta-regressions presented in Table 3 include meta-independent variables describing the data set, the econometric technique and the type of wage information used, the inclusion of certain control variables in the original wage regressions and a dummy for the sex of the researcher. In addition, a full set of country and time dummies is included. The base category concerning the data set is always a random sample of the total population. Concerning the control variables the base category is always the *inclusion* of the respective variable in the wage regressions.

Weighting the studies

While Col. (1) in Table 3 presents unweighted estimates, from Col. (2) on all estimates of one study (same country and time period; i.e. same data set) are weighted with the inverse of the number of estimates. Moreover, a clustering approach is used in all specifications to correct for a possible downward bias due to non-spherical standard errors.

A further problem of meta-regression-analysis concerns the quality of the study. Meta-analysis is "democratic" in that way, that it treats all studies alike. This is not always fortunate, because the researcher might have some priors, how a good study should look like.

Meta-studies typically tackle the question of "study quality" indirectly by including quality characteristics as a part of meta-independent variables – thus showing their effect on the dependent variable. For instance, a meta-study might estimate the effect of a more advanced econometric technique on a regression coefficient. Another approach, however, would be to weight well-done studies more heavily than others. We, therefore, experimented with different weighting schemes in Cols. (3) – (6), always in addition to the weighting that was already applied in Col. (2).[13]

At first, we used only studies published in journals and applied the citation-based journal rankings from Laband and Piette (1990) as weights. This scheme is agnostic about our own priors of study quality, but assumes, that the peer-review process does a good job in letting the very reliable studies be published in the best journals. A drawback of this approach is that studies from exotic countries often find it much harder to get access to top-notch international journals. The next scheme, applied in Col. (4), uses only those papers reporting more than one estimate per study. One could argue that if a researcher used different specifications and got the same results, her study should be judged as more reliable. Therefore we weight with a precision index of the estimates, i.e. with the inverse of the coefficient of variation among the estimates within one study. Of course, this weighting scheme treats the different estimates *within* a study alike, which might not be appropriate when the researcher wants to contrast different methodological approaches and single out the best one. Another quality indicator is the number of observations an estimate is based on. Consequently, we use sample size as a weighting scheme in Col. (5). Since the quality of a gender wage gap estimate should increase with the number of controls for individual productivity, Col. (6) uses the number of regressors in the wage equations as a final weighting scheme. Finally, Col. (7) uses the weighted mean of the R^2s of the original male and female wage regressions as a weight for the precision in the calculation of the gender wage gap.

A general problem in meta-regression analysis is the question whether the usual asymptotic assumptions for the error term in the regression are fulfilled. The first reason for concern is the fact, that the dependent variable is a constructed variable based on original micro-data. The usual solution for constructed regressors (e.g. Murphy and Topel, 1985) is not applicable in our case, because the statistical precision of the calculated gender wage gap is unknown. The second issue concerns correct sampling. What is the appropriate population

[13] A usual approach in meta-analysis is to take the precision of the estimate (in general the standard error) as a quality indicator. This cannot be done in our case, because - as has been noted before - the users of the Blinder-Oaxaca decomposition do not report the precision of this constructed indicator. (See Silber and Weber [1999] for a bootstrap approach to construct standard errors for different decomposition procedures).

to sample our data points from? One possibility is the population of all existing countries during the time period from 1960-2000, the other possibility is the population of studies on gender wage gaps in these countries in the given time period. We are reasonably optimistic to have a random sample of existing studies – with possibly a bias in favor of English-language literature; but we have to be less optimistic to have a random sample of gender wage gaps for each country. Moreover, some of the existing studies of different authors might have used the same or very similar data but different methods, which raises concerns for non-independence of data points. There is no clear solution for this; neither a fully convincing correction for the constructed-regressor-problem nor for the unclear sampling scheme can be offered. We have to take these drawbacks of meta-regression analysis into account and have to interpret our results with appropriate caution.[14] We will, therefore, place particular emphasis on robustness of our results, i.e. consistencies in coefficients across different specifications.

6 Results

6.1 Effects of data and method

Although all of the above-described weighting approaches are somewhat arbitrary and have some particular drawbacks, the general results are very similar.[15] The biggest – and very consistent – impact on the gender wage gap results from the type of data set used. In comparison to a random sample of the population, the gender wage gap is much lower if only a sample of new-entries in the labor market is investigated. Likewise, the wage gap is lower in the public sector and if only a narrow occupation is studied, because in the latter case, holding productivity equal is much easier. Interestingly, the wage gap is higher in the sample with low-prestige occupations (blue-collar jobs) only and lower in high-prestige jobs (e.g. college graduates, academic jobs) as compared to a sample including all occupations. In accordance with Becker's household specialization model (1991), the wage gap is highest for married employees and significantly lower for singles. Among minority workers, the gender wage gap is somewhat smaller.

[14] One way to tackle the non-independence of data points is to use a different weighting scheme. We recalculated our results from Table 3 – using as weights the inverse of the number estimates available per country and year and received qualitatively very similar results. A table is available upon request from the authors.

[15] Differing coefficient estimates in the case of weighted least squares are an indication for mis-specification of the equation. This relative consistency of estimates across specifications is therefore a reassuring sign.

The impact of other variables is less consistent across specifications. In terms of decomposition methods, it does not matter much whether the authors used only a dummy variable approach or one of the variants of the Blinder-Oaxaca decomposition technique; we get some significant coefficients, but no consistent picture across specifications. Instrumental variables approaches – which, in general, instrument for the endogeneity of work experience and/or training – result in slightly lower gaps, although barley significant. The use of panel data and sample selection techniques à la Heckman does not seem to matter in a consistent way.

The income measure in original micro-data is usually given by monthly earnings or hourly wages. One would expect that hourly wages lead to lower wage differentials than other measures, because women often work fewer hours and have more work interruptions, which are not observable in these data. However, in this model we do not find a significant effect whether hourly wages or monthly incomes are observed in the original data. Our next variable captures whether in the original data "work experience" was not explicitly given, but the author instead calculated a "potential experience" (age-6-years of education) and used this in the wage regression. If potential experience was used we observe a higher unexplained gender wage gap, which can be attributed to the specification error in the original wage regression.

Next we consider the specification of the wage regressions. What effect does the in- or exclusion of a particular variable have on the estimated wage gap? Estimates on the gender wage gap can be biased for two reasons: i) some productive characteristics are observed by the firm, but not by the econometrician. This will in general lead to an upward bias in the resulting gender wage gap or discrimination component. ii) some of the control variables might themselves be caused by unequal treatment of the sexes – e.g. occupational choice and promotion. Inclusion of such variables might give rise to a downward bias, because possible discrimination in promotion or occupational choice is falsely regarded as a difference in productive characteristics. In general, this reasoning could be valid for most of the usual control variables, e.g. job tenure or work experience. To use a consistent specification, we include indicators for the *absence* of each of these variables in the respective papers, while the base category is the inclusion. I.e. the variable "marital status" indicates that the author of a paper neglected the marital status of the individuals studied in his wage regression.

The impact of these variables on the gender wage gap is much lower – and less consistent – than the effect of the sample restrictions: Missing marital status in the wage regression has a negative effect on the wage gap in all specifications, whereas missing tenure has a positive effect. The marital status of an individual can be interpreted as a productivity indicator – household responsibilities make married females less productive at the job, while males benefit from their wife's reproductive work and become more productive. If a researcher neglects this productivity indicator in the wage regression (s)he erroneously calculates a downward biased gender wage gap. As tenure is an important productivity component and females often have less tenure, neglecting tenure in a wage regression can lead to a serious over-estimation of the discrimination component. On the other hand, there is a well-known endogeneity problem with firm tenure and the problem that layoffs could be gender-related. Missing union status has a consistently positive effect on the gender wage gap, because union jobs tend to be better-paid male dominated jobs. The same is true if the information about the share of females in the respective occupation is missing. This means, including information whether the individual works in a female-dominated occupation reduces the measured gender wage gap considerably. There are two possible reasons for this outcome. Either occupational choice is governed by preferences and wages correctly reflect productivity, or pre-market discrimination in schooling as well as discrimination in hiring leads to occupational crowding. If the second is true, including a variable on the female-domination of a job produces a downward bias of the measured discrimination.

Interestingly, the gender of the researcher has no consistent impact on the outcome of the study. One might suspect that women's possibly more frequent personal experience with issues of discrimination makes them more susceptible to accept higher estimates of gender wage gaps - however, considering our results, this does not seem to be the case. Only in the journal-rank-weighted specification, the wage gap is somewhat lower if the researcher was female. One could bravely interpret this finding in such a way that women have to be relatively more prudent if they want to get access to top economics journals.

What are the relative contribution of data selection and the choice of econometric methods in the explanation of the variance in gender wage gaps? To answer this question, we ran separate OLS regressions, in the one case including only the 19 data selection variables, in the other only the 24 method variables (without country, time and gender of researcher dummies). The resulting R^2s are presented in Table 4 and confirm the view that the choice of data set is quantitatively more important than the choice of methodology. Whereas around 20% of the variance in gender wage gaps is explained by the choice of data, the choice of econometric methodology explains only 12%. Within periods, the difference seems to be minor, but the choice of data seems to be better able to explain the evolvement of gender wage gaps over time.

6.2. Fixed-effects estimates

The most time-consuming task of meta-analysis is to carefully read and code all the details of the analyzed papers. The coding of method and data used can only be as precise as the description in the papers provided by the authors. The accuracy of the coding also depends on how well the examined features can be quantified. Some features of a research paper, e.g. specificities of the data set, the exact wording in the underlying questionnaire, how the researcher is treating the raw data and minor econometric decisions coming up in the course of the research, may remain unknown. Therefore, a fixed-effects approach might offer a useful tool to control for these paper-specific effects, which are unobservable to the meta-econometrician. There are two possibilities for the meta-analyst: i) take the paper as the unit of observation and treat all estimates within a paper as deviations from the paper's mean, ii) take the study (i.e. one country and time period within a paper) as the unit of observation. Table 5 reports fixed-effects estimates for both of these variants. It has to be noted, though, that the coefficients in these fixed-effects models are identified only by papers (or studies) having several estimates. Therefore, the precision of some of the coefficients must suffer due to low variation within the group. Regardless of the unit of the fixed-effect the results are rather robust; this applies also in comparison to the OLS results from Table 3.

Again, sample restrictions turn out to be very important; if the sample includes only new entries, single workers or high-prestige occupations, wage differentials are lower, likewise if the sample is ethnically homogeneous. In contrast to the OLS regressions, the effects of econometric methods come out more explicitly. Estimates using panel methods or sample selection techniques find lower wage gaps; estimates using the Neumark decomposition technique as compared to the Blinder-Oaxaca approach find higher wage gaps. While previous regression results did not show any systematic effects for the unit of wage measure available in the data, the fixed-effects model indicates that the use of non-hourly wages (in general monthly or yearly incomes) results in significantly higher gender wage gaps as would be expected.

6.3. Pattern across countries and time

If all authors had used data with identical characteristics and applied identical methods, what would their results look like? In the next step we calculate a "meta wage residual" which is what authors would have received if they would have all used the same rather conservative design: only single individuals from an otherwise representative population would have been considered, all control variables would be included and sample selection procedures would be applied as well as an instrumental variables approach to control for endogeneity of human capital variables. Practically, this approach leads to the lowest gender wage gap empirically obtainable. Of course, our choice of a "conservative design" is only one – and in a way an arbitrary – out of a large number of possibilities. Given the linear OLS regression we use, other choices would simply shift the line in Figure 3 up or down, but would leave the slope unchanged. As we are here only interested in an interpretation of the time (and country) effects, we use a weighting scheme, which weighs by the number of observations in the meta–regression per year and country.

Figure 3 illustrates the trend of the reported wage residual (i.e. the Blinder-Oaxaca wage gap from the examined papers[16]) and the "meta wage gap".[17] While the reported wage residual shows a slight upward trend over time, our constructed meta wage residual falls with a rate of -0.17 log points per year, which is only a small improvement over time.[18] This discrepancy between the development of the reported wage residual and our standardized meta wage residual could be explained by a different choice of data sets over time, which might have led researchers in the early years to a very low discrimination component.[19] Note that Stanley and Jarrell (1998, p. 966) calculate a drop in their meta wage residual of more than 1 log point per year for the US and predict that the differential will totally disappear in the year 2001, which seems a bit overoptimistic given recent US estimates, but also our international trend.

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[16] It also includes the gender dummies for studies not applying a Blinder-Oaxaca decomposition.

[17] Plotting the reported gender wage residual against the meta wage residual for different countries (not shown) illustrates that there are only minor research differences between countries.

[18] Weichselbaumer and Winter-Ebmer (2003a) examine the effect of equal treatment laws and competition on the meta wage residual.

[19] The declining use of restricted data sets is illustrated by Weichselbaumer and Winter-Ebmer (2003b).

7 Conclusions

In this paper we review the existing world-wide literature on the decomposition of gender wage gaps. We investigated more than 260 published papers covering 63 countries during the time period between the 1960s and the 1990s. Meta-regression analysis gives us the tool to review and compare this vast amount of literature in a concise and systematic way. Particular emphasis in our meta-regression analysis is placed on a proper consideration of the quality and reliability of the underlying study which is done by a weighting with quality indicators as well as by a direct inclusion of quality indicators in the meta-regression analysis.

The results show that data restrictions have the biggest impact on the resulting gender wage gap. Generally, studies using restricted data sets – e.g. never-married workers, new entries in the labor market or workers in narrow occupations; workers where the comparability of human capital endowment is better – end up with lower gender wage gaps. In contrast to these strong results, the choice of econometric methods is less important as it concerns the concrete decomposition technique or the use of more advanced methods in the wage regressions. Meta-regression analysis also gives the opportunity to calculate what effect typical misspecifications of the underlying wage equations have on the unexplained residual of the gender wage gap. Frequently, researchers don't have hourly wages or actual experience at their disposal, let alone a complete record of human capital characteristics, like training on-the-job or job tenure with the actual employer. Missing or imprecise data on these human capital factors can result in serious biases in the calculation of the discrimination component which become clear in the meta-regression analysis. For example, using potential instead of actual experience in a study overestimates the unexplained gender wage gap on average by 1.8 log points because this measure does not take into account women's more frequent labor market interruptions.

Over time, raw wage differentials world-wide have fallen substantially at a rate of 1.2 percentage points per year from around 65 % in the 1960s to only 30% in the 1990s. The bulk of this decline must be attributed to better labor market productivity of females which came about by better education, training and work attachment. Looking at the published estimates for the discrimination (or unexplained) component of the wage gap does not yield a very promising perspective: We find no decline over time. Meta-regression analysis allows us to construct a specification for a standardized gender wage gap study: applying such a unique specification – both to data selection and econometric method – gives rise to a slightly more optimistic picture: the part of the gender wage gap which is not due to unequal productivities declines world-wide at a rate of 0.17 log points per year. This indicates that a moderate but continuous equalization between the sexes might be taking place.

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9 Tables

Table 1: Data for Gender Wage Gaps

	1960s	1970s	1980s	1990s	All
# of papers	7	52	161	43	263
# of different “studies”	21	189	429	149	788
# of different estimates	63	352	871	249	1535
% of estimates					
- USA	0.65	0.55	0.37	0.23	0.40
- Europe	0.13	0.12	0.23	0.34	0.21
- Other-OECD	0.13	0.06	0.10	0.05	0.08
- Post-Comm. countries	0	0	0.01	0.11	0.02
- Africa	0	0.05	0.03	0.06	0.03
- Asia	0.06	0.19	0.16	0.14	0.16
- Latin-America	0.03	0.03	0.12	0.08	0.09
Mean total wage gap	0.51	0.43	0.30	0.26	0.33
Mean unexplained wage gap	0.23	0.22	0.20	0.19	0.20

Table 2: Meta-independent variables

A. Paper

		Mean	Std. dev.
Author_female	= percentage of authors who are female	.28	.36

B. Data Sets

New entries	= 1 ... study investigated the wages of new entrants only	.017	.13
Public sector	= 1 ... study investigated the wages of workers in the public sector only	.09	.29
Private sector	= 1 ... study investigated the wages of workers in the private sector only	0.12	0.32
Narrow occup.	= 1 ... study investigated the wages of workers of a narrowly defined occupation only	.14	.34
Low prestige occup.	= 1 ... if a study investigated only low prestige occupations (e.g. blue collar)	.04	.19
Med. prestige occup.	= 1 ... if a study investigated only medium prestige occupations (e.g. white collar)	.07	.25
High prestige occup.	= 1 ... if a study investigated only high prestige occupations (e.g. college graduates, academics)	.18	.38
Single_only	= 1 ... if a study investigated only singles	.04	.20
Married_only	= 1 ... if a study investigated only married people	.03	.17
Minority_only	= 1 ... if a study investigated only minority or immigrant population	.02	.15
Majority_only	= 1 …if a study investigated only majority population	.08	.28
Source	= 0 ... if data come from administrative statistics = 1 ... if data come from survey data	.95	.22
Fullt_only	= 1 ... if a study included only full-time workers	.32	.47

C. Method of estimation

Dummy variable	= 1 ... if a study used a dummy to investigate the gender wage gap and no Blinder/Oaxaca decomposition	.22	.41
IV	= 1 ... if a study used instrumental variables	.01	.10
Panel data	= 1 ... if a study used panel data	.04	.18
Heckman	= 1 ... if a study corrected for selectivity á la Heckman	.24	.42
Blinder-Oaxaca with male	= 1 ... if male coeffients were used for the decomposition instead of female ones	.21	.41

coefficients			
Neumark	= 1 … if Neumark decomposition was used	.09	.29
Cotton	= 1 … if Cotton decomposition was used	.01	.11
Brown	= 1 … if Brown et al decomposition was used	.01	.11
Reimers	= 1 … if Reimers decomposition was used	.01	.09

D. Alternative Measures of Wages

No hourly wages	= 1 ... if a study used daily, monthly or annual earnings	.60	.49
Hourly constructed	= 1 ... if a study used hourly wages computed from daily, weekly, monthly or annual salary	.16	.37
Gross	= 0 … if a study used net wages = 1 … if a study used gross wages	.07	.26

E. Variables for worker's characteristics

Potential exper	= 1 ... if a study used potential experience	.50	.50
Experience	= 1 ... study omitted worker's job experience	.02	.16
Race or immigr	= 1 ... study failed to account for race or immigrant status	.61	.49
Marital status	= 1 ... study omitted worker's marital status	.41	.49
Kids	= 1 ... study omitted whether or not worker has children	.71	.46
Marital/kids inter	= 1 ... study omitted interaction children * marital status	.96	.20
Training	= 1 ... study omitted on the job training	.97	.16
Tenure	= 1 ... study omitted tenure	.73	.44
Occupation	= 1 ... study omitted worker's occupation	.55	.50
Industry	= 1 ... study omitted worker's industry of employment	.65	.48
Government work	= 1 ... study omitted a government/private employment distinction	.57	.50
Union status	= 1 ... study omitted worker's union/nonunion status	.75	.43
Share of females in occ	= 1 ... study omitted the percentage of women in the worker's job	.88	.33
FT-PT	= 1 ... study omitted worker's full time/part time status	.51	.50
Urban	= 1 ... omitted SMSA, city size	.63	.48
Reg	= 1 ... study omitted worker's geographical area of employment	.42	.49
Working time	= 1 … study omitted worker’s working time	.99	.08

Table 3: Meta-regression estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Weighing scheme	**no weights**	**# of estimates in study**	**(2) + journal rank**	**(2) + precision of estimates**	**(2) + # of observations**	**(2) + # of regressors**	**(2) + R^2 of wage regression**
Author female	0.007 (0.014)	0.014 (0.016)	-0.033 (0.019)	-0.013 (0.016)	0.011 (0.023)	0.023 (0.014)	0.033 (0.022)
New entries	-0.096 (0.025)**	-0.077 (0.030)**	-0.179 (0.029)**	-0.074 (0.028)**	-0.098 (0.037)**	-0.092 (0.025)**	-0.076 (0.039)
Fulltime workers	0.015 (0.014)	0.020 (0.016)	0.067 (0.019)**	-0.008 (0.015)	-0.019 (0.021)	0.020 (0.014)	0.006 (0.024)
Private sector	0.000 (0.027)	-0.011 (0.026)	-0.057 (0.026)*	0.023 (0.028)	-0.007 (0.023)	-0.015 (0.023)	0.013 (0.033)
Public sector	-0.049 (0.021)*	-0.068 (0.021)**	-0.089 (0.028)**	-0.058 (0.033)	-0.061 (0.023)**	-0.058 (0.018)**	-0.036 (0.028)
Narrow occupation	-0.060 (0.021)**	-0.062 (0.021)**	-0.043 (0.027)	-0.025 (0.025)	-0.072 (0.028)*	-0.061 (0.021)**	-0.049 (0.027)
Low prestige occ.	0.056 (0.020)**	0.057 (0.020)**	0.146 (0.018)**	-0.026 (0.036)	0.114 (0.022)**	0.088 (0.017)**	-0.016 (0.039)
Medium prestige occ.	-0.033 (0.020)	-0.028 (0.017)	-0.053 (0.017)**	-0.064 (0.038)	-0.032 (0.022)	-0.033 (0.015)*	-0.058 (0.034)
High prestige occ.	-0.112 (0.018)**	-0.105 (0.017)**	-0.127 (0.011)**	-0.098 (0.028)**	-0.146 (0.017)**	-0.110 (0.013)**	-0.065 (0.029)*
Singles	-0.145 (0.024)**	-0.141 (0.021)**	-0.125 (0.024)**	-0.106 (0.044)*	-0.214 (0.045)**	-0.122 (0.019)**	-0.159 (0.030)**
Married	0.085 (0.028)**	0.068 (0.025)**	0.102 (0.023)**	0.073 (0.039)	0.017 (0.047)	0.073 (0.026)**	0.115 (0.048)*
Minority	-0.035 (0.022)	-0.052 (0.025)*	-0.015 (0.033)	0.004 (0.026)	-0.064 (0.006)**	-0.035 (0.026)	-0.068 (0.035)

Blinder-Oaxaca with male coeff.	-0.014 (0.008)	-0.017 (0.009)	-0.017 (0.011)	-0.001 (0.002)	-0.005 (0.009)	-0.005 (0.009)	-0.002 (0.013)
Neumark decomp.	0.022 (0.010)*	0.005 (0.014)	0.050 (0.012)**	0.018 (0.009)*	-0.013 (0.021)	0.004 (0.012)	-0.007 (0.016)
Reimers decom.	-0.006 (0.038)	0.008 (0.025)	0.045 (0.040)	0.023 (0.021)	0.116 (0.026)**	0.032 (0.024)	-0.020 (0.050)
Cotton decomp.	-0.003 (0.023)	-0.013 (0.030)	0.042 (0.020)*	0.015 (0.020)	0.006 (0.037)	0.003 (0.025)	-0.003 (0.029)
Brown decomp.	-0.015 (0.019)	-0.014 (0.021)	0.006 (0.045)	0.026 (0.022)	-0.008 (0.025)	0.006 (0.020)	0.030 (0.043)
Dummy variable	-0.005 (0.015)	-0.014 (0.019)	0.009 (0.018)	0.060 (0.020)**	0.029 (0.021)	-0.005 (0.016)	-0.024 (0.025)
IV	-0.014 (0.026)	-0.015 (0.036)	-0.038 (0.033)	-0.065 (0.027)*	-0.070 (0.038)	-0.031 (0.035)	-0.005 (0.049)
Panel data	-0.006 (0.026)	0.013 (0.028)	0.042 (0.033)	0.097 (0.071)	-0.106 (0.044)*	-0.002 (0.023)	0.142 (0.039)**
Heckman selection	-0.016 (0.012)	-0.021 (0.021)	-0.027 (0.016)	0.020 (0.011)	-0.066 (0.018)**	-0.033 (0.025)	-0.001 (0.026)
No hourly wages	0.014 (0.022)	-0.003 (0.030)	0.005 (0.032)	0.032 (0.023)	0.002 (0.023)	-0.004 (0.026)	-0.046 (0.042)
Hourly wages constructed	-0.004 (0.019)	-0.025 (0.022)	-0.019 (0.023)	0.047 (0.019)*	-0.043 (0.023)	-0.016 (0.018)	-0.043 (0.029)
Gross wages	0.009 (0.038)	0.013 (0.035)	-0.070 (0.048)	0.008 (0.070)	-0.072 (0.051)	0.029 (0.035)	-0.044 (0.075)
Potential experience	0.013 (0.014)	0.038 (0.017)*	0.031 (0.016)*	-0.036 (0.019)	-0.007 (0.019)	0.036 (0.015)*	0.053 (0.019)**
Experience	0.002 (0.027)	-0.020 (0.028)	-0.056 (0.027)*	-0.066 (0.029)*	-0.044 (0.037)	-0.029 (0.024)	-0.009 (0.034)
Race or immigr.	0.012 (0.016)	0.024 (0.020)	0.043 (0.018)*	-0.002 (0.022)	0.058 (0.021)**	0.013 (0.017)	-0.000 (0.027)
Marital status	-0.037 (0.014)**	-0.055 (0.018)**	-0.018 (0.019)	0.043 (0.021)*	-0.049 (0.023)*	-0.071 (0.019)**	-0.056 (0.022)**

Kids	0.012	0.016	-0.018	-0.070	0.034	0.016	0.034
	(0.016)	(0.018)	(0.020)	(0.019)**	(0.020)	(0.016)	(0.022)
Marital/kids inter.	-0.044	0.005	0.003	-0.007	-0.115	-0.029	0.028
	(0.041)	(0.046)	(0.040)	(0.051)	(0.041)**	(0.039)	(0.069)
Training	0.003	-0.007	-0.019	-0.017	-0.031	-0.007	-0.019
	(0.038)	(0.039)	(0.010)*	(0.023)	(0.014)*	(0.021)	(0.049)
Tenure	0.043	0.035	0.032	0.076	0.068	0.016	0.034
	(0.012)**	(0.015)*	(0.018)	(0.017)**	(0.017)**	(0.014)	(0.016)*
Occupation	0.003	0.002	-0.013	0.033	0.029	0.000	0.019
	(0.010)	(0.012)	(0.017)	(0.014)*	(0.012)*	(0.011)	(0.015)
Industry	0.014	0.019	0.019	-0.012	0.012	0.016	-0.010
	(0.014)	(0.014)	(0.018)	(0.019)	(0.013)	(0.013)	(0.020)
Government work	-0.000	-0.017	0.012	-0.040	0.028	-0.011	-0.036
	(0.017)	(0.018)	(0.020)	(0.018)*	(0.020)	(0.016)	(0.022)
Union status	0.030	0.040	0.067	0.040	0.047	0.042	0.048
	(0.018)	(0.024)	(0.026)**	(0.019)*	(0.023)*	(0.024)	(0.033)
Share of females in occupation	0.061	0.057	0.067	0.054	0.068	0.056	0.075
	(0.015)**	(0.018)**	(0.010)**	(0.014)**	(0.010)**	(0.015)**	(0.031)*
Full time / Part time	-0.011	-0.002	0.013	-0.024	-0.031	-0.005	0.001
	(0.013)	(0.016)	(0.016)	(0.013)	(0.018)	(0.014)	(0.021)
Observations	1532	1532	1532	1068	1225	1532	911
Adjusted R^2	0.46	0.45	0.75	0.81	0.79	0.46	0.42

Robust standard errors in parentheses
* significant at 5%; ** significant at 1%

Other variables in the regressions include: indicators whether the sample was official data or survey data, whether gender wage differentials were the main topic of the paper, dummies for a data set with only workers from the majority population in the sample; dummies for regional and urban status missing; dummies if information in the paper about measures of wages, the used data set and the gender of the researcher was unknown. Moreover, all regressions include a full set of country and time dummies.

Table 4: Are data selection or econometric methods more important in explaining the variance in gender wage gaps?

	1960s	**1970s**	**1980s**	**1990s**	**all**
Contribution of data selection					
R^2	0.62	0.30	0.22	0.26	0.20
R^2 adjusted	0.55	0.27	0.20	0.21	0.19
Contribution of econometric methods					
R^2	0.68	0.26	0.13	0.25	0.12
R^2 adjusted	0.56	0.20	0.11	0.18	0.11

Table 5: Fixed Effects Estimation

Group indicator	paper	paper	"Study" within Paper
New entries	-0.093 (0.042)*	-0.093 (0.040)*	-0.091 (0.043)*
Fulltime workers	-0.044 (0.043)	-0.046 (0.042)	-0.047 (0.056)
Private sector	0.024 (0.028)	0.033 (0.028)	0.011 (0.048)
Public sector	-0.030 (0.029)	-0.016 (0.029)	0.000 (0.000)
Narrow occupation	0.017 (0.027)	0.016 (0.026)	0.000 (0.000)
Low prestige occ.	0.075 (0.020)**	0.074 (0.019)**	-0.167 (0.108)
Medium prestige occ.	-0.019 (0.019)	-0.024 (0.019)	
High prestige occ.	-0.077 (0.019)**	-0.079 (0.019)**	
Singles	-0.183 (0.026)**	-0.180 (0.025)**	-0.303 (0.069)**
Married	0.097 (0.028)**	0.098 (0.028)**	
Minority workers	-0.164 (0.044)**	-0.164 (0.043)**	-0.086 (0.102)
majority_only	-0.112 (0.046)*	-0.112 (0.045)*	
Blinder-Oaxaca with male coeff.	-0.010 (0.008)	-0.010 (0.008)	-0.010 (0.006)
Neumark decomp.	0.024 (0.012)*	0.025 (0.012)*	0.027 (0.010)**
Reimers decom.	-0.027 (0.037)	-0.027 (0.036)	-0.026 (0.028)
Cotton decomp.	-0.001 (0.030)	-0.001 (0.029)	-0.001 (0.023)
Brown decomp.	-0.005 (0.032)	-0.007 (0.031)	0.007 (0.047)
Dummy variable	0.039 (0.037)	0.041 (0.036)	-0.005 (0.034)
IV	0.023 (0.038)	0.023 (0.037)	0.007 (0.032)
Panel data	-0.104 (0.049)*	-0.055 (0.049)	-0.220 (0.061)**
Heckman selection	-0.013 (0.010)	-0.012 (0.009)	-0.019 (0.008)*
No hourly wages	0.102	0.100	0.102

Group indicator	**paper**	**paper**	**"Study" within Paper**
	(0.042)*	(0.041)*	(0.034)**
Hourly wages constructed	-0.012 (0.065)	0.008 (0.066)	0.065 (0.103)
Gross wages	0.065 (0.030)*	0.003 (0.092)	
Potential experience	0.044 (0.027)	0.029 (0.027)	0.035 (0.024)
Experience	0.055 (0.036)	0.068 (0.035)	0.086 (0.039)*
Race or immigr.	0.274 (0.032)**	0.004 (0.069)	0.065 (0.069)
Marital status	0.039 (0.022)	0.057 (0.022)**	0.069 (0.023)**
Kids	-0.005 (0.035)	-0.014 (0.034)	-0.051 (0.036)
Training	-0.012 (0.032)	-0.014 (0.032)	-0.003 (0.026)
Tenure	0.022 (0.022)	0.027 (0.022)	0.032 (0.024)
Occupation	0.019 (0.015)	0.019 (0.015)	0.030 (0.015)*
Industry	0.030 (0.018)	0.025 (0.017)	0.030 (0.017)
Government work	-0.004 (0.025)	0.003 (0.025)	0.023 (0.028)
Union status	0.007 (0.028)	0.030 (0.032)	0.032 (0.029)
Share of females in occupation	0.056 (0.019)**	0.056 (0.019)**	0.054 (0.015)**
Full time / Part time	0.031 (0.032)	0.032 (0.032)	0.029 (0.029)
Urban	-0.029 (0.059)	0.047 (0.075)	-0.052 (0.119)
Region	-0.061 (0.036)	-0.068 (0.035)	-0.070 (0.037)
Year dummies	No	Yes	No
Country dummies	No	Yes	No
Observations	1532	1532	1532
Number of no groups	262	262	778
R^2 within	0.25	0.32	0.16

Standard errors in parentheses
* significant at 5%
** significant at 1%

10 Figures

Figure 1:

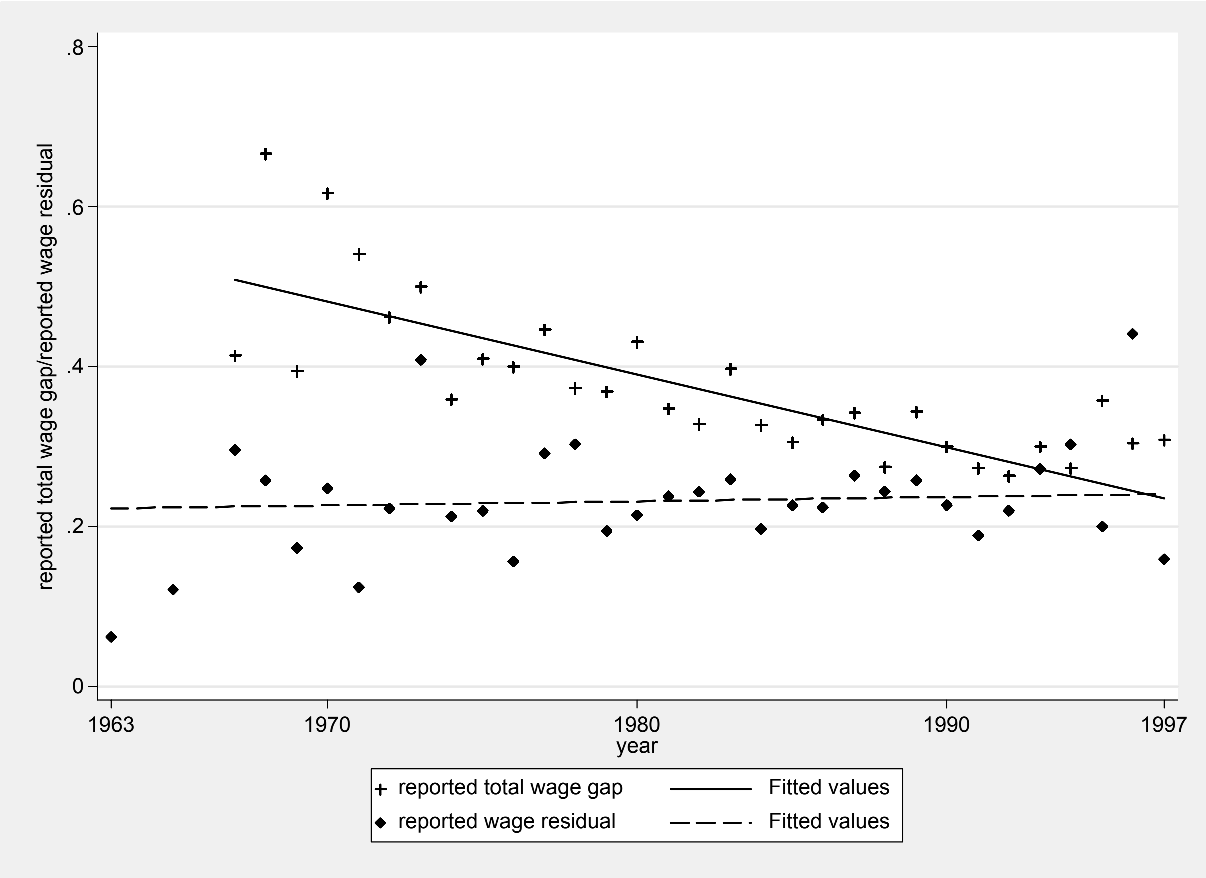
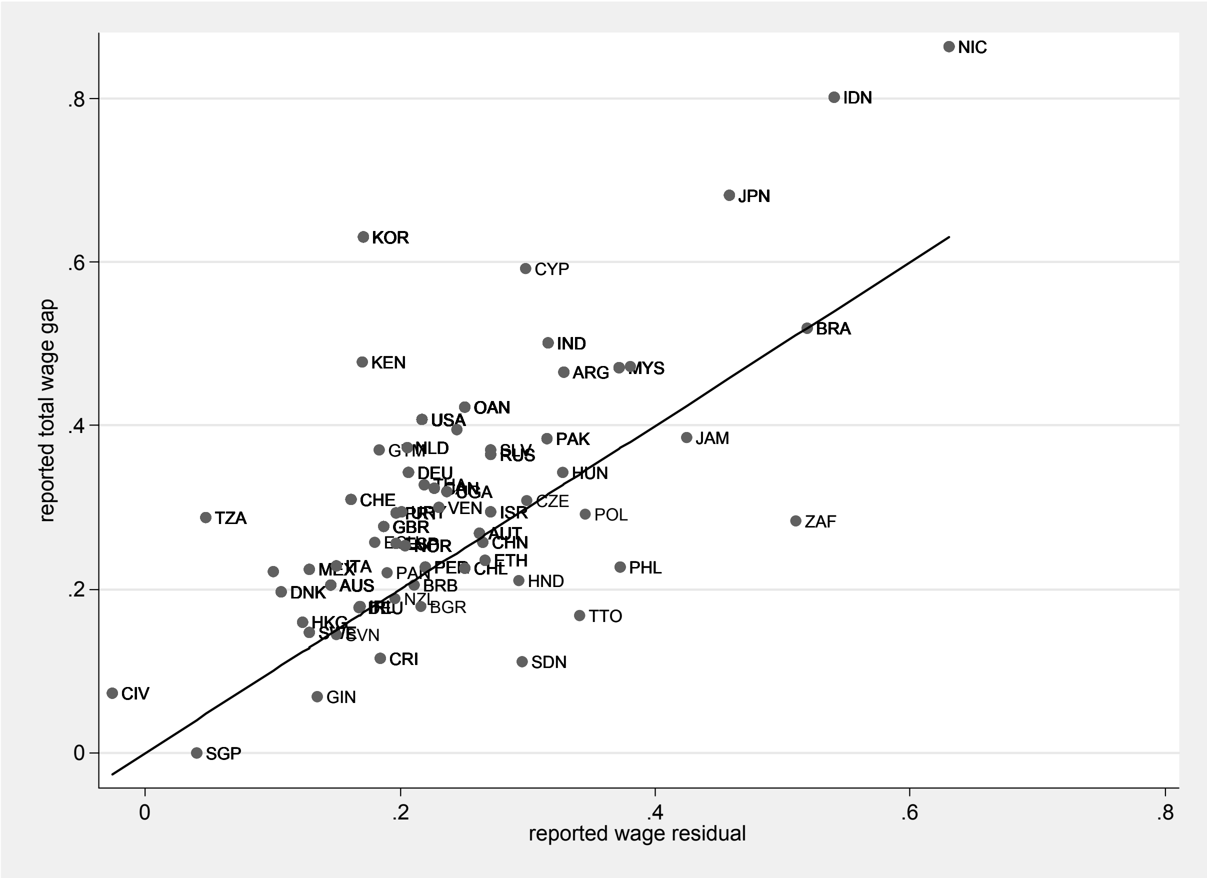
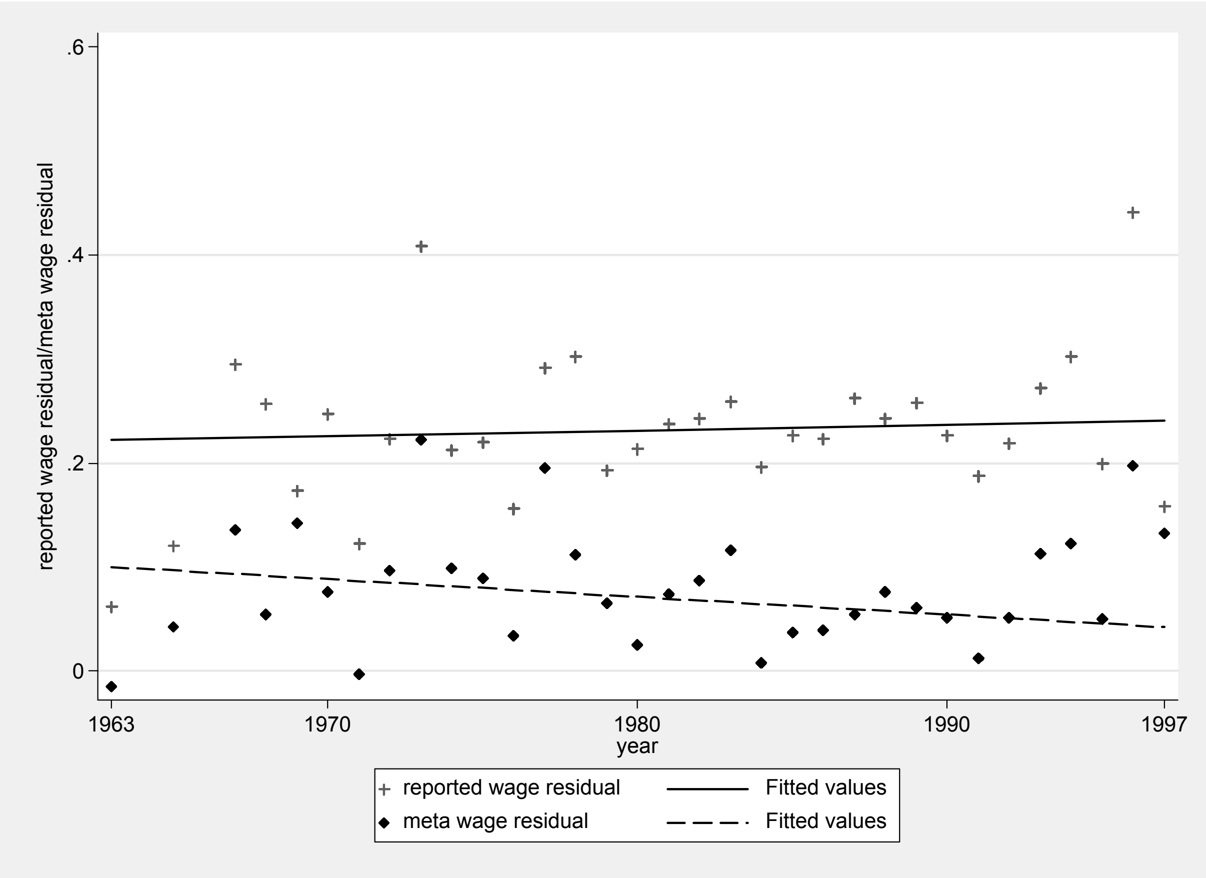


Figure 2:



reported total wage gap
reported wage residual
NIC
IDN
JPN
KOR
CYP
BRA
IND
KEN
ARG
MYS
OAN
USA
PAK
JAM
HUN
CZE
TZA
ZAF
POL
PHL
HND
TTO
SDN
CRI
CIV
GIN
SGP

Figure 3:



.6
.4
.2
0
reported wage residual/meta wage residual
1963
1970
1980
1990
1997
year
reported wage residual
meta wage residual
Fitted values
Fitted values

Authors: Doris Weichselbaumer, Rudolf Winter-Ebmer

Title: A Meta-Analysis of the International Gender Wage Gap

Reihe Ökonomie / Economics Series 143

Editor: Robert M. Kunst (Econometrics)
Associate Editors: Walter Fisher (Macroeconomics), Klaus Ritzberger (Microeconomics)

ISSN: 1605-7996
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Stumpergasse 56, A-1060 Vienna • ☎ +43 1 59991-0 • Fax +43 1 59991-555 • http://www.ihs.ac.at

ISSN: 1605-7996