Gender Wage Discrimination Bias? A Meta-Regression Analysis
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Gender Wage Discrimination Bias? A Meta-Regression Analysis

T.D. Stanley
Stephen B. Jarrell

ABSTRACT
This study provides a quantitative review of the empirical literature on gender wage discrimination. Although there is considerable agreement that gender wage discrimination exists, estimates of its magnitude vary widely. Our meta-regression analysis (MRA) reveals that the estimated gender gap has been steadily declining and the wage rate calculation to be crucial. Large biases are likely when researchers omit experience or fail to correct for selection bias. Finally, there appears to be significant gender bias in gender research. However, it is a virtuous variety where researchers tend to compensate for potential bias implicit in their gender membership. (JEL J7, C8)

I. Introduction

Do female researchers tend to overestimate the gender wage gap? Or are male authors overly dismissive of gender discrimination? Has the magnitude of the gender wage gap been declining as our society attempts to remedy its past sexism and stereotyping? What characteristics of research on discrimination tend to distort its findings? Are there substantial specification errors in the reported gender
wage gaps? It is the purpose of this paper to address these and other questions regarding the large literature on gender wage discrimination. In order to evaluate and summarize this literature, we apply a recently developed, integrative technique—meta-regression analysis.

Historically, there have been large differences in family and economic roles undertaken by men and women. Traditionally, women allocate a greater proportion of their time to raising children and home production, thereby sacrificing long term career development and the concomitant accumulation of human capital. As a result of such social factors, as well as discrimination, researchers have often reported that women receive but 60 percent of the male wage and that ratio has been nearly constant for decades (Blau and Khan 1994; O’Neill and Polachek 1993).

Such a glaring stylized fact attracts researchers like a moth to the flame. Thus, decomposing the overall gender wage gap into a proportion which can be attributed to differences in labor market skills among the sexes and to gender-specific differences in the returns to such skills (gender wage discrimination) has become a cottage industry.

This vast empirical economic literature, containing hundreds of studies, reveals that women are ‘underpaid’ disproportionate to their observed skills. Authors refer to gender wage gaps of thirty to forty percent as if they were well established, stable facts (Evans and Nelson 1989; Steinberg 1984; O’Neill 1985). However, any casual perusal of this literature uncovers great variations in reported wage gap estimates. For example, Fishback and Terza (1989) present estimates that vary from 50 percent to a negative 19 percent of the average male wage, the latter suggesting that never-married women are ‘overpaid’. In our sample of 55 published estimates, the gender gap varies from −2.7 percent to 91 percent of the female wage with a mean of 31.8 percent. Thus, while there may be a wide consensus that gender wage discrimination exists, there is little agreement on its actual magnitude. Our meta-analysis finds that the estimated magnitude is quite sensitive to the precise model specification that a study uses and how wages are measured. We also find a significant downward trend in gender wage discrimination and a tendency for male researchers to report larger gender wage gaps.

II. Estimating Wage Discrimination: Regression, Decomposition, and Bias

As each new study emerges, the question asked is whether the substantial difference in earnings unaccounted for by differences in productivity-related factors represents discrimination or model misspecifications. Recent researchers have pursued a number of hypotheses, sometimes exploiting unique features of specific data sets, in attempts to answer this question.

—Daymont and Andrisani (1984, pp. 408–409)

Culture, tradition, education, and personal choice, as well as discrimination, play important roles in determining the economic well-being of individuals and groups. Gender discrimination in the workplace may be displayed in the hiring, promotion, and pay practices of businesses. Such practices may cause segregation as well as a
gap in earnings. Although discrimination in promotion and hiring can undoubtedly affect the magnitude of discrimination, data limitations force most empirical studies to focus on differences in pay. Such estimates of wage discrimination will almost certainly understate the full effects of gender discrimination.

Following Blinder (1973) and Oaxaca (1973), the standard practice is to decompose the observed average gender gap into two components: a portion attributable to differences in endowments (or skills) and the remainder, which is often characterized as a difference in coefficients (or returns to skills). The latter measures the magnitude of wage discrimination.

The effects of differing skills and returns are estimated by regression models from samples of individual male and female wage earners.

(1) \[ W_f = X_f \beta_f + \varepsilon_f \]

and

\[ W_m = X_m \beta_m + \varepsilon_m \]

Where:

- \( W_f \) is an \( n \times 1 \) vector containing the natural logarithm of wages or hourly earnings of female employees.
- \( W_m \) is an \( n \times 1 \) vector containing the natural logarithm of wages or hourly earnings of male employees.
- \( X_s \) are \( n \times K \) matrices of relevant worker/job characteristics (for example, education, experience, region, union membership, occupation, industry, . . ).
- \( \beta_s \) are regression coefficients often representing the returns to a particular worker/job characteristic.
- \( \varepsilon \) is the usual regression disturbances.
- \( n \) is the number of workers in a given sample.

Occasionally, these two equations are combined into one.

(2) \[ W_i = \beta_0 + \sum_{k=1}^{K} \beta_k X_{ki} + \gamma S_i + \varepsilon_i \]

Where \( S_i \) is the sex of worker \( i \).

From Equations (1) and (2), researchers estimate the magnitude of the gender wage gap found in the \( j \)th study by:

(3) \[ G_j = \bar{X}_f \hat{\beta}_m - \bar{X}_f \hat{\beta}_f = \bar{X}_f (\hat{\beta}_m - \hat{\beta}_f) \]

(Blinder 1973; Oaxaca 1973) or by \( \hat{\gamma} \) of Equation (2). The above wage gap, \( G_j \), measures the difference between the logarithm of female wages from those of male workers due to the fact their job characteristics are valued differently. It is also an estimate of the difference of the logarithm of wages relative to what it would have

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1. Whether some of these variables (for example, occupation) are truly independent or are themselves the product of discrimination is subject to differing interpretations. Although this is a potentially important issue for the estimation of the gender wage gap, it makes little difference for the current study. Our meta-regression analysis does not find any of the more questionable variables (occupation, college major, and union membership) to be statistically significant, thus, they are not included in our MRA estimates.
been in the absence of discrimination. The standard measure of discrimination assumes that the returns to job characteristics would be equal to those of the males, $\beta_m$, in the absence of discrimination.

Sometimes studies report Oaxaca’s $D$ as a measure of the magnitude of discrimination. It may be interpreted as the amount of wage discrimination as a proportion of the female wage and is related to $G_j$ by:

$$D = e^{G_j} - 1$$

In our meta-regression analysis (MRA), a published study’s estimate of $G_j$ is the dependent variable, and its variation from one study to the next is explained by various model specifications, alternative measurements of wages, passage of time, and the gender of the researchers.

Although regression-based methods are the standard method for estimating the effects of discrimination and are accepted as evidence in legal suits (Jacobsen 1994), they are not unproblematic. Probably the greatest threat to the validity of the regression-based approach is that every study may have omitted important factors that affect wages. Because no one knows the “true” wage equation and every data set omits some potentially important variable, every study’s estimate of the “true” gender wage discrimination, $\Gamma_j$, must be considered to suffer from omitted variable bias. The MRA employed here estimates the size of various omitted variable biases. These omissions of wage-related variables are thought to increase the estimated magnitude of gender discrimination. “Many economists consider that extending regression to include all productivity-related characteristics would lead to a disappearance of the unexplained portion of the gender earnings gap” (Jacobsen 1994, p. 322). Others confirm this tendency by estimating the omitted variable bias to be positive. “Though the empirical estimates of discrimination vary widely, it is clear that traditional OLS estimates are upward biased” (Choudhury 1993, p. 327).

Thus, there is reason to believe that the reported estimates overstate the magnitude of wage discrimination. Because our meta-analysis reviews and integrates these estimates of wage discrimination, it too is likely to suffer from some upward bias. However, a major advantage of meta-analysis is that it permits the estimation of various biases. For example, we estimate the effect of omitting industry, age, or experience, and of not correcting for selection bias. Not correcting for selection bias reduces the estimated gender gap by 18 percent of the female wage. Although meta-analysis cannot remove all biases, it can estimate and compensate for some of the major sources of bias and provide a sensitivity analysis for plausible misspecifications.

### III. A Meta-Analysis of Gender Wage Discrimination

To find the genuine message in the noise, what we need are not just summaries of the literature, such as those found in the introductory chapters of dissertations.

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2. Recall, however, that wage discrimination is only one way that gender discrimination may be exhibited in the workplace. Absent are the indirect effects of hiring and promotion. The omission of these other types of workplace discrimination is likely to bias estimated discrimination downward.
tions and in most literature reviews, but also critical reviews. When empirical
tests reach results that seem irreconcilable, a critical review survey should tell
us which ones to disregard. . . . And even if it is not possible to weed out all
the invalid evidence and to reconcile the rest, it should be possible to reduce
the dissonance to a substantial extent. Meta-analysis reduces the effort required
for such a critical survey and makes its results more specific.

—(Mayer 1993, p. 158)

A. Meta-Analysis

The house of social science research is sadly dilapidated. It is strewn among
the scree of a hundred journals and lies about in the unsightly rubble of a
million dissertations.

—(Glass, McGaw, and Smith 1981, p. 11)

“Meta” refers to a transcendental critical perspective. Meta-analysis is a genuine
“bootstrap,” because the researcher must rise above her own research to critically
assess her field of study. Meta-analysis takes an overview of some field of empirical
research using, more or less, the same techniques found in the original studies. It
provides an empirical framework from which to review and integrate the empirical
findings on a given topic, it can stimulate replication, and it can correct each new
study for the inherent experimental error—not to mention predicting the results of
studies not yet undertaken.

In the 1930s R. A. Fisher, Karl Pearson, and L. H. C. Tippett independently devel-
oped procedures to summarize the overall effect of multiple independent tests (Fisher
1932; Pearson 1933; Tippett 1931). The most widely used and accepted of these
methods is Fisher’s combined test. It takes advantage of the fact that the p-values
are uniformly distributed under the null hypothesis of no effect. Thus,

\[ f = -2 \sum_{i=1}^{L} \ln P_i = \chi^2(2L) \]

for a literature containing \( L \) studies. Fisher’s method assumes independence across
studies and, of course, that each is unbiased. When many tests are combined, the
Fisher test is very generous in ascribing significance. For example, if we combine
25 studies whose effects are all less than their standard errors with p-values of .25
in each case, \( f = 69.3 \) which is significant at the .05 level.

Worse still, there is a powerful tendency when using the Fisher test in economic
applications to find a significant effect whether or not it is actually there. This proce-
dural bias manifests itself in three ways. First, there is the pathological case where
one study has a p-value of .001 showing that some variable of interest has a positive
effect on the target phenomenon and a second study with a p-value of .001 showing
that the same variable exhibits a negative effect. In this case, the combined Fisher
test allows one to conclude with a significance level of .01 that there is an overall
positive effect. Or, if you don’t like that answer, you may alternatively conclude
that it has a negative effect at the same .01 level of significance.

Second, the null hypothesis of the Fisher combined test is that none of the investi-
gations contain a genuine effect. If a literature contains a single non-zero effect, the null hypothesis of the Fisher test is literally false. “It is doubtful if a researcher would regard such a situation as persuasive evidence of the efficacy of a treatment” (Hedges and Olkin 1985, p. 45). A finding of significance therefore does not mean that the average effect is statistically significant (and certainly not that it is somehow practically important), but only that there is some unexpected variation among the research findings. Furthermore, this unexpected variation is measured relative to the ideal empirical literature where all studies are unbiased and independent of one another.

Third, in a nonexperimental science, such as economics, there are almost certainly published studies on any empirical subject that contain important biases due to model misspecification. Because econometricians can never directly control experimental variation, statistical control is achieved imperfectly through “guess and test.” Even when the guesses are quite enlightened, the econometrician always knows that there are important, contaminating variables for which he cannot account—because the necessary data does not exist. As a result, omitted variable bias and other types of misspecification bias is the rule, not the rare exception. It takes only one study containing a biased finding to overwhelm a literature and make the Fisher test significant. Ironically, studies of the poorest quality are likely to have the largest impact on combined tests using p-values.3

Since the 1930s, many other tests for combined significance have been suggested, but these are not relevant for our current study because almost all researchers agree that there is significant gender discrimination. The interesting questions concern the magnitude of this discrimination and how idiosyncratic researcher choice affects its estimation. We seek a methodology for integrating and explaining an entire empirical literature. Fortunately, such an approach was developed in the 1970s by Glass (1976 & 1977). It was Glass who coined the term “meta-analysis,” and it was Glass who initiated the current interest in meta-analysis that has now reached many fields including: medical research, psychology, educational research, biometrics, and statistics.

Because researchers in education and psychology often use different empirical measures for the same theoretical concept, some type of common denominator is needed if one is to compare and integrate disparate findings. To this end, Glass suggested the effect size:

$$\delta = (\bar{X}_e - \bar{X}_c)/\sigma$$

Where:

- $\bar{X}_e$ is the average outcome for the experimental group.
- $\bar{X}_c$ is the average outcome for the control group.
- $\sigma$ is the standard deviation in the control group.

However, Glass’s estimate of effect size has come under a great deal of criticism.

3. This problem often summons the issue of whether to subjectively weight study outcome by its quality. Although weighting for quality is an appealing idea, it would lead all too quickly to the omission of research which does not employ the currently fashionable theory or methodology. However, there are objective ways to weight studies—for example, the number of specification tests passed and sample size (Stanley 1998b).
and there are several better estimators in the literature. The basic problem is that it is biased and inefficient because it uses the wrong estimate for the standard deviation, or background variation. A pooled estimate, properly corrected for the degrees of freedom of course, needs to replace \( \sigma \) (Hedges and Olkin 1985). Hedges and Olkin have further argued that the conventional methods, notably ANOVA, are inappropriate for analyzing effect size. "... (T)he use of some conventional analyses for effect size data frequently involves serious violations of the assumptions of these techniques" (Hedges and Olkin 1985, p.9). The principal problem is heteroskedasticity across studies. It can mask any design differences that a meta-analyst may wish to investigate with ANOVA.

Many other researchers have by now contributed to the growing field of meta-analysis and have corrected the problems of Glass’s estimator. More importantly, Glass changed the entire perspective. The point now is to estimate the "average" effect found in a literature, to assess its practical significance (as well as its statistical significance), and to explain the variation found among studies as another socioeconomic phenomenon.

B. Methods

Meta-analysis provides a convenient framework to summarize and understand the literature which estimates gender wage discrimination. Moreover, such a framework may be used to organize and encourage replication while, at the same time, estimating the fragility or robustness of the empirical work on a given subject. "Meta-regression analysis" (MRA) is a meta-analytic technique developed specifically for economic research in a series of publications and presentations (Jarrell and Stanley 1987, 1990; Stanley and Jarrell 1989a, 1989b, 1991; Phillips 1994; Doucouliagos 1995; Button 1995; Phillips and Goss 1995; Smith and Huang 1995; Stanley 1998b). More specifically, a regression model may be used to explain differences among empirical estimates of some economic phenomenon.

For example, meta-regression analysis may take the form of a standard regression equation: 
\[
\hat{\beta}_j = \alpha_0 + \sum \alpha_k Z_{kj} + \epsilon_j; \ j=1,2, \ldots, L
\]
Where \( \hat{\beta}_j \) is the estimated regression coefficient for the \( j \)th study and \( Z_{kj} \) are \( k \) meta-independent variables designed to explain the study-to-study variation in an area of research which contains \( L \) studies. Using such models, we found that the unemployment rate has a significant effect on the size of the union wage premium estimated by researchers (Jarrell and Stanley 1990), and that sample size and the number of specification tests passed strengthen the evidence against Ricardian equivalence (Stanley 1998b). In this manner, research itself may be studied, and its results better estimated and understood.

Meta-analysis has been used widely in the biological and psychological sciences. Although it began as a method of combining and summarizing experimental findings, MRA is designed explicitly to estimate and account for the omnipresent biases found in nonexperimental empirical economics. Omitted variable bias, selection bias, along with other types of misspecification biases are well known to plague research on gender wage discrimination. MRA provides a means to estimate the sensitivity of the reported findings to variations in specification and thereby to escape from these biases. While conventional narrative reviews may acknowledge the problems of empirical economic research, they do not resolve them.
Obviously, meta-analysis is no "philosopher's stone"; it too has shortcomings. However, meta-regression analysis with its use of moderator variables largely answers the criticisms of meta-analysis. See Phillips and Goss (1995) and Stanley and Jarrell (1989b) for a discussion of these issues. The most common criticism of meta-analysis concerns the "file drawer" problem which results from the tendency of academic journals to publish only those studies that find a significant effect by rejecting some null hypothesis (Glass, McGaw and Smith 1981). Although meta-regression analysis is subject to this potential bias, so are conventional narrative literature reviews. However, the file drawer problem is less problematic for this particular application of meta-regression analysis. The gender wage gap is not generally estimated by a single coefficient but rather by Blinder/Oaxaca decomposition. Its estimation (and publication) does not depend on any single significance test. Rather, gender wage gap is calculated from a vector of regression coefficients which often have both significant and insignificant elements. Furthermore, because almost everyone in this field accepts the presence of a significant gender bias, a study which finds either no significant bias or reverse discrimination is more, not less, likely to be published (Goldfarb 1995).

Our MRA began with a computer search of the Economic Literature Index on DIALOG for any reference to: "(wages or salary or earnings) and (discrimination or difference) and (sex or gender)." To this list of 180 references, the same keyword search of Dissertation Abstracts yielded another 43 references. Next, abstracts and titles were reviewed to decide whether a study estimated the U.S. gender wage gap. Studies that were exclusively conducted on data from other countries were not included because the history and severity of sex discrimination is known to vary greatly across cultures.

This process of reviewing and coding yielded 41 estimates of the gender wage gap. The reader may wonder how more than two hundred studies yield only 41 estimates. The rules for including a study in our meta-analysis are:

1. The study must present an empirical estimate of the gender wage gap or sufficient information to calculate it.

2. The estimate must concern gender wage discrimination in the United States.

3. For generalizability, the estimate must be based on a broad national data base.

4. The estimate must also be derived from a regression analysis.

More than half of the studies cannot be included in our meta-analysis because they are not empirical. Many of those which are empirical cannot be used for a variety of reasons. The largest practical problem encountered, however, was that the gender

4. A few estimates of gender wage discrimination are lost by treating the Economic Literature Index (ELI) database as the population of relevant studies. For example, if no mention of "sex" or "gender" is recorded in the database for an article which focuses primarily on some other phenomenon (say, racial discrimination), then it will not be included in our meta-analysis. However, such studies are few and are unlikely to have estimates of gender discrimination which systematically depart from those included in ELI's database.

5. An update of the computer literature search locates an additional 14 estimates or 55 in all—see the Appendix.
wage gap is often not reported and cannot be calculated from those estimates which are presented. For example, an author might have investigated whether the gender gap was declining over time by employing a linear time trend without actually reporting the individual estimates. Or, the magnitude of the gap itself may not have been the central concern of a researcher and thus have gone unreported. We collected multiple estimates from the same study only if they referred to different years. Otherwise, we selected the OLS estimate which the author seemed to promote as the best. If a study assumed that the female wage was the baseline in the absence of discrimination, it was either converted to a male wage basis or excluded. Studies that rely on an individual firm or location were omitted, because their results cannot reasonably be generalized to the entire economy. Furthermore, we did not include a study unless it employed some type of regression analysis. It would be unfair to measure gender discrimination by the ratios of average earnings unadjusted for the many differences in worker skills and characteristics known to affect earnings. Because many papers report ratios of median earnings, this criterion greatly reduces the number of genuine estimates of gender wage discrimination available for meta-analysis.

C. Results

In our sample of 41 estimates, the gender wage gap ($G_j$) ranged from −.0275 to .6471 with a mean of .2904 and standard deviation .1629. See Table 1 for a list of the data, Table 2 for variable definitions, and Tables 3 and 4 for descriptive statistics. By Equation (4), the mean gap may be alternatively expressed as 33.7 percent of the female wage. Obviously, there is statistically significant wage discrimination ($t = 11.4; p < .01$) when viewed across the entire literature. When our sample is expanded to include an additional fourteen estimates of gender wage discrimination ($n = 55$), the mean becomes .2763 or 31.8 percent ($t = 14.03$) with standard deviation .146.

Yet, it is far more revealing to discover which factors are responsible for the large variation among the research findings. Is there a significant downward trend in gender wage discrimination? Are there important selection and omitted variable biases? Does it matter how wages are computed or modelled? To address such questions a more comprehensive analysis, meta-regression analysis, must be undertaken.

1. Meta-Regression Analysis

The twenty-eight explanatory variables considered in this meta-analysis were selected a priori, primarily on the basis of the authors’ previous research on the union wage gap (Jarrell and Stanley 1990). They may be broadly classified as: economic conditions, alternative measures of wages, model specifications, data sets, worker characteristics, and researcher characteristics, namely, the gender of the researchers. See Table 2 for a list of the specific meta-independent variables ($Z_k$) considered. These variables represent potentially important attributes of a given study whose presence or absence may distort the study’s findings; 12 of which explain more than 80 percent of the study to study variation among the reported estimates of gender wage discrimination.
Table 1
Data for Gender Wage Gaps and Selected Meta-Independent Variables

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<td>0</td>
<td>1</td>
<td>1</td>
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</tbody>
</table>
Table 2
Meta-Independent Variables ($Z_k$)

A. Economic Conditions:
$\text{Un}_t = \text{the unemployment rate in the year in which wages are earned.}$
$\text{Year} = \text{the year in which wages are earned (Year } = 0 \text{ in 1970).}$

B. Alternative Measures of Wages:
$\text{Salary} = 1 \text{ if a study used annual salary as its measure of wages.}$
$\text{Week} = 1 \text{ if a study used weekly salary as its measure of wages.}$
$\text{Wageyr} = 1 \text{ if hourly wages were computed from annual salary.}$
$\text{Wagewk} = 1 \text{ if hourly wages were computed from weekly salary.}$

C. Model Specifications:
$\text{Log} = 1 \text{ if a study used the logarithm of wages.}$
$\text{Select} = 1 \text{ if a study did not correct for selection bias.}$
$\text{Dummy} = 1 \text{ if a dummy variable for sex, not Blinder/Oaxaca decomposition, is used.}$

D. Data Sets:
$\text{CPS} = 1 \text{ if a study used the CPS.}$
$\text{Census} = 1 \text{ if a study used the U.S. Census.}$
$\text{PSID} = 1 \text{ if a study used the PSID.}$

E. Worker Characteristics:
$\text{Race} = 1 \text{ if a study failed to account for race.}$
$\text{Age} = 1 \text{ if a study omitted the worker's age.}$
$\text{Exp} = 1 \text{ if a study omitted the worker's job experience.}$
$\text{MS} = 1 \text{ if a study omitted the worker's marital status.}$
$\text{Dep} = 1 \text{ if a study omitted whether or not the worker has children.}$
$\text{Occ} = 1 \text{ if a study omitted the worker's occupation.}$
$\text{Ind} = 1 \text{ if a study omitted the worker's industry of employment.}$
$\text{Govt} = 1 \text{ if a study omitted a government/private employment distinction.}$
$\text{Union} = 1 \text{ if a study omitted the union/nonunion status of the worker.}$
$\text{Fem} = 1 \text{ if a study omitted the percentage of women in the worker's job.}$
$\text{FT/PT} = 1 \text{ if a study omitted the worker's full time/part time status.}$
$\text{WKS} = 1 \text{ if a study omitted the number of weeks worked during the year.}$
$\text{Reg} = 1 \text{ if a study omitted the worker's geographical area of employment.}$
$\text{Maj} = 1 \text{ if a study omitted the worker's college major.}$
$\text{New Ent} = 1 \text{ if a study investigated the wages of new entrants only.}$

F. Researcher Characteristics:
$\text{Female} = 1 \text{ if a study was authored solely by women.}$
$\text{Male} = 1 \text{ if a study was authored solely by men.}$

---
a. Education could not be included in the meta-analysis because all studies accounted for the effects of education.
### Table 3

**Correlation Matrix**

<table>
<thead>
<tr>
<th></th>
<th>Gj</th>
<th>Year</th>
<th>Salary</th>
<th>Week</th>
<th>Wageyear</th>
<th>Select</th>
<th>New Ent</th>
<th>Dummy</th>
<th>Govt</th>
<th>Age</th>
<th>Exper</th>
<th>Ind</th>
<th>Male</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Gj</strong></td>
<td>1.000</td>
<td>-.652</td>
<td>.792</td>
<td>.644</td>
<td>.705</td>
<td>-.680</td>
<td>-.600</td>
<td>.516</td>
<td>.550</td>
<td>.439</td>
<td>.447</td>
<td>-.475</td>
<td>.673</td>
</tr>
<tr>
<td><strong>Year</strong></td>
<td>-.652</td>
<td>1.000</td>
<td>.410</td>
<td>.544</td>
<td>.606</td>
<td>-.604</td>
<td>-.501</td>
<td>.390</td>
<td>.394</td>
<td>.377</td>
<td>.460</td>
<td>-.409</td>
<td>.481</td>
</tr>
<tr>
<td><strong>Salary</strong></td>
<td>.792</td>
<td>.410</td>
<td>1.000</td>
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<td>-.622</td>
<td>.436</td>
<td>.563</td>
<td>-.327</td>
<td>-.406</td>
<td>-.204</td>
<td>-.163</td>
<td>.523</td>
<td>-.609</td>
</tr>
<tr>
<td><strong>Week</strong></td>
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<td>.544</td>
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<td>1.000</td>
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<td>.584</td>
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<td>-.586</td>
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<td>-.582</td>
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<td>-.512</td>
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<td>-.438</td>
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<td>1.000</td>
<td>-.426</td>
<td>.616</td>
<td>.456</td>
<td>.511</td>
<td>.608</td>
<td>-.586</td>
<td>.774</td>
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<tr>
<td><strong>New Ent</strong></td>
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<td>.468</td>
<td>.597</td>
<td>-.426</td>
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<td><strong>Dummy</strong></td>
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<td>-.188</td>
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<td>.394</td>
<td>-.406</td>
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<td>-.265</td>
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<td>-.188</td>
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<td>-.531</td>
<td>.352</td>
<td>.406</td>
</tr>
<tr>
<td><strong>Exper</strong></td>
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<td>-.163</td>
<td>-.392</td>
<td>-.438</td>
<td>.608</td>
<td>.290</td>
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<td>-.531</td>
<td>1.000</td>
<td>.403</td>
<td>.507</td>
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<tr>
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<td>-.409</td>
<td>.523</td>
<td>.453</td>
<td>.496</td>
<td>-.586</td>
<td>-.508</td>
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<td>-.586</td>
<td>-.551</td>
<td>.774</td>
<td>.530</td>
<td>-.528</td>
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Table 4
Descriptive Statistics

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<td>.44857</td>
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<td>.75610</td>
<td>.43477</td>
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<td>Exper</td>
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<tr>
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<td>.51220</td>
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</table>

Our meta-regression model may be expressed as:

\[
G_j = \alpha_0 + \sum_{k=1}^{K} \alpha_k Z_{kj} + \gamma Year_j + \nu_j \quad j = 1, 2, \ldots, L
\]

\[
G = Z\alpha + \gamma Year + \nu
\]

Where \( Z_{kj} \) are the study characteristics defined in Table 2, \( Year_j \) is the year in which wages were earned, \( L \) is the number of estimates in the literature, and \( \alpha_k \) are meta-regression coefficients which estimate the biasing effect of particular characteristics of the original study (often the omission of a potentially important variable).

Implicit in the above meta-regression model, is the assumption that the ‘true’ gender wage gap, \( \Gamma_j \), has a linearly decreasing trend, \( \Gamma_j = \gamma Year_j \), and that the remaining meta-independent variables, \( Z_{kj} \), each represent an independent bias in the estimation of \( \Gamma_j \). The error terms, \( \nu_j \), are estimation errors which are likely to satisfy all the conventional assumptions of the classical regression model with the possible exception of heteroskedasticity (Stanley and Jarrell 1989a, b; Jarrell and Stanley 1990). Therefore, standard OLS or GLS estimates of this MRA model, Equation (7), should possess all the desirable statistical properties.

Usually, researchers only employ a more complex estimation procedure when there is reason to suspect an unusual error structure, which is not the case in the

---

6. Vanhonacker (1996) assumes a more complex specification of the underlying structure of the meta-regression model where the “true” effects or coefficients are themselves stochastic (p. 295). As a result, he questions the suitability of OLS estimation of MRA. Proper statistical specification is essential in any viable econometric methodology (Stanley 1998a). To insure that our chosen model is not misspecified, we enlist three different types of specification tests and a holdout sample.
Table 5
Meta-Regression Results

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<th>Count</th>
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<th>Adjusted $R$-squared</th>
<th>Standard Error</th>
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</table>

Analysis of Variance Table

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<th>Mean Square</th>
<th>F-test</th>
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</table>

Estimated Coefficients

<table>
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<th>Significance Level</th>
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<td>.0001</td>
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<td>.0001</td>
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<td>.0001</td>
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<td>.0005</td>
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<td>3.185355926</td>
<td>.0035</td>
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<tr>
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<td>3.488012695</td>
<td>.0016</td>
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<td>4.809174906</td>
<td>.0001</td>
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</tbody>
</table>

present application. For instance, there is greater reason to expect Gaussian errors in a meta-regression model than in the typical econometric application. Because each dependent variable is a linear function of estimates of conditional means, the central limit theorem will apply for each observation (note the sample sizes of these studies in Table 1). We expect heteroskedasticity because of these different sample sizes in the original studies, and we suspect some autocorrelation because applied research often exhibits trends in methodology. However, conventional tests reported below find no evidence of either problem in our estimated MRA model. In addition, a conventional correction for heteroskedasticity (GLS) has little effect on our estimates and does not change our principal conclusions. Finally, the trend term, $\gamma Year_j$, probably dispatches any autocorrelation. Hence, our MRA estimates should be BLUE.

Predictably, not all 29 characteristics are helpful in explaining the variation found in the gender discrimination literature. Table 5 reports the statistical estimates for
a meta-regression model containing twelve independent variables, all of which are statistically significant. Table 3 gives the correlation matrix, and Table 4 presents descriptive statistics. To minimize the potential biases of specification searches, we did not employ stepwise, or any other model search algorithm. Like all econometric applications, we must confront a dilemma (Stanley 1998a). The threat of omitted variable bias in our meta-regression model compels the inclusion of all relevant variables. Yet, specification searches carry their own risks. They can bias the reported coefficients and cause the level of significance to be overstated—(Copas 1983) (Leamer 1978). We attempt to minimize model experimentation while at the same time permitting significant factors to be identified. However, with 29 potentially relevant variables and only 41 observations, some specification searching is unavoidable. The independent variables reported are all statistically significant and no other variable is significant when added to the reported model. Furthermore, fourteen additional estimates of wage discrimination identified from a more recent literature search are used to validate the chosen model through out-of-sample forecasting—see the Appendix. Overall, the meta-regression model explains over 80 percent of the study-to-study variation in the reported gender wage gap ($R^2 = .867$, adj. $R^2 = .81$, $F_{12,28} = 15.19; p < .01$).

Further statistical testing and out-of-sample forecasting supports this MRA specification. After ordering the data by time, a Lagrange multiplier test shows no signs of autocorrelation: $LM = [2.17; 2.60]$ with d.f. = {1; 2}. The Breusch-Pagan test does not suggest heteroskedasticity when the sample size (or any other variable) is used: $BP = .70$. Also, $RESET$ finds no misspecification of any type: $F_{2,26} = 1.94$. Nor does there appear to be any problem of multicollinearity; $R^2$ for an auxiliary regression among the independent variables is .25. The Appendix also discusses a GLS estimate of the model that is not substantially different from what is reported here. However, with no evidence of heteroskedasticity, the OLS estimates should be adequate.

Using this estimated meta-regression model to forecast an additional fourteen estimates of the gender wage gap yields a mean absolute deviation of .087 or root mean square error of .093. For further out-of-sample results, see the Appendix. As expected, the out-of-sample forecast errors are somewhat larger, though not significantly so ($F_{14,28} = 1.72$).

2. Trend and Biases

There is a significant time trend ($t = -4.55; p < .01$), which implies that the estimated gender wage gap is falling by 1 percent per year. This is nearly three times the rate of the decrease exhibited by the unadjusted gaps. For example, the CPS data for 1963–86, shows an unadjusted gender wage gap, $G^t$, declining by one-third of a percent per year.

\begin{equation}
G^t = .556 - .00339 T \quad R^2 = .43
\end{equation}

\[(-4.07)\]

(Murphy and Welch 1991). Several other studies have identified a similar decline in the gender wage gap during the 1980s (O’Neill and Polachek 1993; Blau and
For example, O’Neill and Polachek (1993) find the gap narrowing at approximately the same rate as the meta-regression model—0.011 for the Current Population Survey and 0.012 for the Panel Study of Income Dynamics.\(^7\)

In contrast, how researchers calculate the wage rate seems to be the most important consideration in explaining variation in the gender wage discrimination literature. When annual salary is used, the gap estimate is increased on average by 0.262 or 30 percent of the female wage \((t = 6.85; p < .01)\). Employing weekly salary raises the gap by nearly as much, 0.216 \((t = 4.46; p < .01)\), and calculating an hourly wage from annual salary also significantly increases the gap relative to estimates based directly on hourly wages, 0.175 \((t = 5.26; p < .01)\). Together, these wage-related variables explain more than a third of the variation found in this literature, increasing \(R^2\) by 0.34 \((F_{1,28} = 7.94; p < .01)\). The coefficients of these wage-related variables are of the expected sign and relative magnitude. “The use of average weekly wage fails to control for the length of the work week which is getting shorter, especially for women” (Oi 1991, p.73). Annual salary would then exaggerate the gender gap even more because it also fails to control for the fact that men, on average, work more weeks per year (Blau and Beller 1988). Lastly, the effects of the variable \(Wageyr\) would be expected to be less, because it imperfectly adjusts for differences in both weeks worked per year and hours per week.

How researchers choose to specify their wage models also influences their estimates of discrimination. It matters whether the coefficient of a dummy variable for sex is used as the estimate of the gender wage gap or whether a Blinder/Oaxaca decomposition is employed, \((t = 3.19; p < .01)\). Not allowing for different returns to other wage determinants has an effect similar to omitting relevant human capital variables. Both tend to overestimate the gender wage gap.

Since Heckman (1979), it has become standard practice to correct for selection bias. The decision to participate in the labor force is itself a function of the wage rate which, in turn, depends on the amount of gender discrimination. Therefore, the estimation of wage equations from samples of employed workers alone induces a sample selection bias. Not correcting for this selection bias can substantially reduce the estimated gap, by 0.197 or nearly 18 percent \((t = -4.9; p < .01)\).

Surprisingly, no significant differences among the various data sets (for example, CPS, PSID, U.S. Census) were found. However, four worker characteristics are of consequence. Omitting the industry \((t = -2.86; p < .01)\) or the governmental status \((t = 3.49; p < .01)\) of a worker’s employment or omitting the age \((t = 2.58; p < .05)\) or the experience \((t = 2.64; p < .05)\) of that worker has substantial practical effect on the estimate of gender discrimination. Of particular interest is the omission of experience, which has a large impact on the estimated gap, raising it by 0.243 or nearly 28 percent of the female wage. Again, these meta-regression coefficients may be interpreted as estimates of omitted variable bias when various individual worker characteristics are ignored.

---

\(^7\) One should note, however, that their estimated trend concerns the unadjusted gap while the meta-regression model refers solely to gender wage gaps previously adjusted for differences in skills and endowments. Nonetheless, these trends are quite reconcilable. Blau and Khan (1994) find a trend in the adjusted gap (for human capital variables) of 0.015.
Generally, researchers believe that the more numerous the wage-related factors included as independent variables, the lower the estimated discrimination will be. However, the use of industry variables seems to be the lone exception, for omitting these variables lowers the gap by .089. This effect actually reinforces gender discrimination. It implies that the gender wage gap widens when one properly controls for differences across industries so that low male wages in one industry do not attenuate high female wages in another industry.

Contrary to conventional wisdom, the omission of a worker’s occupation has no significant effect on estimated wage discrimination beyond what is uncovered by the other twelve variables in Table 5 (Cain 1986). Because wages vary greatly among different occupations, the omission of such a potentially powerful explanation of observed wage differences is thought to bias the estimated gender gap upward. The conventional view presumes that apparent wage discrimination is an artifact of omitting relevant productivity variables; thus, if all workers productivity differences are properly accounted for, measured gender wage discrimination would evaporate. ‘‘Many economists consider that extending regression to include all productivity-related characteristics would lead to a disappearance of the unexplained portion of the gender earnings gap’’ (Jacobsen 1994 p.322).

Although there may be merit to the conventional view, the inclusion of occupational variables is likely to induce considerable complications which could easily obscure the expected effect. First, the complex interrelation of discrimination, segregation, and occupational choice evolved greatly over the study period. Traditional gender-stereotypes were challenged and increasingly crossed. Gender discrimination in pay and occupation also changed. Likewise, the effects of including occupational variables would be expected to shift. Furthermore, returns to various traditionally male and female occupations have been greatly transformed as our economy moved from manufacturing to service and information. For instance, blue collar (disproportional male) wages fell sharply, while the skill level of women’s occupations increased (O’Neill and Polacheck 1993, p.224).

Second, occupational choice itself depends on wages, discrimination, and many of the same independent variables normally employed in the wage equation. Thus, if occupational choice is also included in the wage equation and estimated by OLS, we must expect simultaneous equations bias among the estimated regression coefficients, thereby distorting the estimated gender gap. Because the extent of such bias potentially depends on all of the parameters of the entire structural system of equations, typically involving dozens of variables, the direction of such bias cannot be anticipated and would likely vary from study to study.

Third and related, multicollinearity among occupational variables, gender, and the many other variables that comprise the wage equation is likely. As suggested above, there are good economic reasons to suspect that occupational choice depends on education, experience, industry. . . . Worse, it is well known that there are strong patterns to the gender composition of different occupations—whether arising from discrimination, tradition, or socialization. Suppose that occupational variables are added to the models which researchers use to estimate the gender gap, Equation (2), and are highly correlated with the sex of the worker. Such multicollinearity will cause the estimated gender gap, \( \hat{\gamma} \), to be unreliable, possessing a large standard error.
As a result, the meta-independent variable, \( \text{Occ} \), would be expected to be insignificant in a meta-regression. Of course, multicollinearity among the independent variables of the MRA model may also obscure the effect of occupation. However, we find little evidence of such multicollinearity in our MRA—\( R^2 \) from the auxiliary regression of \( \text{Occ} \) with the twelve independent variables in Table 5 is .405.

Finally, the conventional wisdom might be wrong. Perhaps, there is, in fact, considerable gender wage discrimination which becomes only more pronounced when occupational variables are properly considered. Many researchers would argue that there has been so much segregation and gender stereotyping that the measured effect of occupation on wages is itself gender discrimination rather than a reflection of unobserved skill differences. In any case, it is controversial whether it is appropriate to use these occupational variables.

What is remarkable is that our meta-regression analysis uncovers so many statistically significant and practically large effects—not that a few factors, conventionally thought to be important, fail to be significant. With 41 observations (55 in the expanded sample), we cannot expect to identify all the complex and subtle effects in this rich field of research. A meta-regression analysis is successful if it identifies a few of the more influential effects. This MRA should not be seen as refuting the conventional view of the effects of adding occupational variables to measured gender discrimination. Rather, it merely suggests that such effects may be more complicated than sometimes argued.

The gender wage gap appears to be much smaller for new entrants into the labor force, reducing the estimate by 22.4 percent (\( t = 3.97; p < .01 \)). This may reflect the apparent fact that younger women experience less discrimination. \( \text{New Ent} \) is the only variable added after analyzing the data. The first model chosen was the same as that reported in Table 5 with the exception that \( \text{New Ent} \) was not included. That model produced an outlier for Green(1983) which contained samples of only new entrants. Thus, a new variable, \( \text{New Ent} \), was coded and added to the meta-analysis. The inclusion of this new variable has little impact on the overall assessment of the meta-regression model or the coefficients of the individual variables; however, it improves the statistical accuracy of all of these estimates.

Finally, does the gender of researchers affect their results? It is widely recognized that social science research is exposed to the “Pygmalion effect” or researcher expectations (Rosenthal 1976). That is, a researcher’s expectations can consciously or unconsciously affect subjects’ behavior and thereby their findings. In empirical economics, there are always vast numbers of combinations of model specifications, data sets, and estimation techniques from which a researcher must choose. Expediency may dictate the choice, but often the applied economist has little basis for this choice other than his or her expectations. Although such expectations may be generally formed through knowledge of the literature, might not the researchers’ own experiences of gender discrimination or evaluations of its importance influence, consciously or unconsciously, what they expect to find? In a similar meta-analysis of gender differences (analyzing conformity rather than wages), Eagly and Carli (1981) found that research findings were significantly related to the researcher’s gender. No doubt, applied econometrics provides great potential for experimenter bias. In this study, researcher gender is used as a proxy for the Pygmalion effect or researcher
expectations. The results of our meta-regression analysis indicate that male researchers report a considerably larger gender wage gap than would otherwise be expected, .152 or 16.4 percent ($t = 4.81; p < .01$).

This finding might renew one’s faith in the scientific objectivity of the social sciences. Researchers apparently compensate for any inherent bias of their group membership by making decisions regarding design, data and variables that handicap these potential gender biases. This is precisely the scientific disposition that we were taught. Assume the opposite of what you hope to find and give any latitude in interpretation and design to this opposing view. Because of the dichotomous nature of the meta-variable, Male, used for researcher gender, this effect may be attributed either to male authors who ‘bend over backwards’ to find gender wage discrimination or equally to research collaborations containing at least one woman which attempt to minimize the extent of gender discrimination. Of course, researchers of both genders may be giving the benefit of the doubt to the opposite sex in an attempt to be as objective as possible.

3. Estimating and Forecasting Gender Wage Discrimination

Given the above meta-analysis, what is the best estimate of the gender wage gap? The simple average of these 41 estimates implies a gap of .2904 or 33.7 percent, a value which is consistent with the typical unadjusted ratio of median earnings reported in this literature. However, the estimated meta-regression model should improve on this simple average because it explains most of the study to study variation. When all the dichotomous meta-independent variables are zero, the model estimated in Table 5 reduces to: $\hat{G}_j = .2419 - .01017 T$. This estimating equation assumes that some of the researchers are women; the intercept would increase to .3939 (in 1970) when all researchers are male. For purposes of estimating the gender wage discrimination with minimum gender bias, it would seem reasonable to split the difference, making the estimating equation:

(9) $\hat{G}_j = .3179 - .01017 T$

This equation implies that the best estimate of gender wage discrimination is .3179, or 37.4 percent of the female wage, for 1970 (recall $T = 0$ in 1970), .1145 (or 12.1 percent) for 1990, and .0331 (or 3.4 percent) for the current year (1998). At this rate, researchers will report no gender wage discrimination by the turn of the millennium, 2001.

8. When meta-regression analysis is used to provide summary estimates, one must first decide which study characteristics may be reasonably regarded as “standard,” or consistent with the “best practice.” This choice will always be a matter of professional judgment (Stanley and Jarrell 1989b; Jarrell and Stanley 1990). It is our judgment that researchers should not omit relevant worker characteristics; they should correct for selection bias, employ the Blinder/Oaxaca decomposition rather than a dummy gender variable, and use the hourly wage rate to measure earnings. Those who disagree can still use these meta-regression results to form their own estimates of the best practice for the field of gender wage discrimination.

9. The usual caveats about extrapolating beyond the sample apply. These predictions do not imply that gender wage discrimination will end, in fact. Rather, the trend suggests only that economists’ estimates of gender discrimination will approach zero if the trend continues. When the rate of closure is allowed to decrease over time and there is a floor to the wage gap (namely, a semilog trend), the gap is forecast to close a little later, 2007.
IV. Conclusion

This meta-regression analysis of gender wage discrimination reveals:

1. The estimated wage gap has steadily decayed. However, significant gender wage discrimination may be found throughout the 1980s even after corrections for omitted variable bias, selection bias, etc. are made. If the observed rate of decrease is maintained, the estimated gap may be closed by 2001.

2. The manner in which the wage rate is calculated can have a large impact on the estimated gender wage gap. The more ineffectual the control for difference in weeks worked per year and/or hours per week, the larger the reported wage gap will be.

3. Correcting for selection bias and using Blinder/Oaxaca decomposition may also create important differences in the estimated gender gap. The former raises the estimated gender discrimination, the latter lowers it.

4. Several worker characteristics are found to be significant. It makes a material difference whether a researcher’s wage equations include: age, experience, industry, and the government status of a worker’s employment. Excluding any of these factors, especially experience, may induce notable omitted variable bias.

5. There seems to be gender bias in gender research, but it is a virtuous variety. Researchers appear to adopt a scientific attitude and over-compensate for the potential bias implicit in their gender membership.

Appendix

To validate the chosen meta-regression model, a holdout sample was obtained by updating the computer literature search. Using the same set of descriptors uncovered twice as many references as were found when the study began two years before. From these new references, 14 usable estimates of the gender wage gap were obtained; they covered years 1972 to 1987 and ranged from .1370 to .4105.10

Table A1 compares the meta-regression forecasts to the actual estimates found in the holdout sample—$MAD = .087$ and $RMSE = .093$. Because the holdout sample tends to cover later years, some of which are beyond those found in the estimation sample, some erosion of accuracy must be expected. Nonetheless, the out-of-sample forecasting errors are not statistically larger than the in-sample residuals ($F_{14,28} = 1.72$).

10. Only one reported estimate of the gender wage gap is not included in this analysis. In their study of differences in wage distributions, Schmitz, Williams and Gabriel (1994) report a Blinder-Oaxaca decomposition of the mean wage differential which attributes a negative proportion of the gender gap to differences in endowments. In addition, these results were tangential to their study and admittedly outside the range reported by other researchers.
When all estimates of the gender wage gap are combined, the estimated meta-regression model changes little, see Table A2.

Finally, the meta-regression model was also estimated by GLS using the square root of the sample size as a proxy for the differential estimation error of each study. Again, there is little substantive effect on the results. The coefficients are slightly altered along with the significance levels of some worker characteristics (notably, age is no longer statistically significant), but the interpretation of the overall meta-regression model and principal hypotheses are not affected. This result is to be expected because the meta-regression model exhibits no indication of heteroskedasticity.

### Table A1

*Out-of-Sample Forecasting Errors*

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$\text{MAD} = .087$

$\text{RMSE} = .093$
Table A2  
Further Meta-Regression Results

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Analysis of Variance Table

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Estimated Coefficients

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Meta-Regression References


References


