UCLA Statistics Series #100

April 1992

Gender Gap in Earnings: Preference or Discrimination?

Ita G.G. Kreft
California State Univ., Los Angeles

Jan de Leeuw
Depts. Psychology and Mathematics, UCLA

GENDER GAP IN EARNINGS PREFERENCE OR DISCRIMINATION ?

A Two Way Nested Multiple Regression Analysis with Random Effects

Ita G.G. Kreft
California State University
Los Angeles

Jan de Leeuw
University of California
Los Angeles

ABSTRACT

The gender income gap is a much debated subject both at an analytical and economic level. This article considers both, but emphasizes the different ways the data can be analyzed. We show that a hierarchical linear model is the best way to evaluate male-female wage differentials. Both inter industry and intra industry wage disparities between men and women are measured, by using a technique, which assumes that observations within the same industry have correlated error terms. By simultaneously testing human capital factors and environmental factors, our analysis model serves as a link between theory and empirical analysis. Our results show that the wage differences are larger in some industries than in others so that we can assume that a gender income gap is not only a function of individual differences in qualification but also differences between industries. The between industry differences in gender income gaps contradicts the hypothesis that gender income differential is largely due to female work preferences and the resulting segregation.

We would like to thank Dr. David O'Shea for allowing us to base this analysis on his previous work (see O'Shea, 1988) and Amy Braverman for editing this paper.

Among all employed persons, white women earn 70 percent of white men's hourly wages, while for younger people (those aged 25 to 34) with a college education the gap is somewhat less. In 1983, the median income of women working year round in this latter group was 73.3 percent the income of men (Smith and Ward, 1984, pp. 43-45). Despite the dominant ideology of fair competition in the US, this competition seems to be limited to white males only. What is more, compared to several European countries the gender income gap in the US is extremely wide and has hardly narrowed in the last fifty years. In Sweden for instance, women's earnings have improved from 71 percent of men's earnings in 1970 to 81 percent in 1981 (Hewlett, 1986). A similar narrowing of the income gap is found in other European countries such as Italy, where the gap decreased from 74 percent in 1974 to 86 percent in 1982, while the income gap remained constant from the 1950's to the early 1980's in the US (Goldin, 1990, p.60).

What are the reasons for the persistence of the gender income gap in the US compared to Europe? A difference in education between the continents hardly explains this disparity, given the fact that American women workers are the highest educated in the world (Smith and Ward, 1984). Furthermore one cannot refer to an education gap between males and females within the US to explain the income gap either, since in the younger population the average female worker is slightly better educated than the average male worker (l.c.).

There is no shortage of theories to rationalize the existence of different wage rates for equally productive workers. Scarce however is a theory that is supported by empirical evidence. We consider here two somewhat opposing theories; neo-classical human capital theory, which emphasizes the demand side of the labor market, and environmental theory, which makes a plea for complementary attention to factors such as historical context, group bargaining and other context factors (see Marshall, 1974, England 1982). For that purpose we make a distinction between individuals working in different industries, where we consider the industry as an environmental factor. We have good reasons to do so, since different industries have different labor union histories (Zucker, 1990 and 1991), and are located in different sectors with different market mechanisms, the public and the private sector. This last difference is of some importance, given Cain's hypothesis (1986, p.731) that "wage discrimination is less in competitive industries and greater in monopolistic industries". The result of our analysis will later show that industries do indeed differ in their "tastes for discrimination". This "taste" is defined by Becker (1971), as a monetary offer for a service based on a qualitative attribute that distinguishes one person from another, who are otherwise identical.

According to human capital theory, the difference in earnings between men and women are caused by differences in qualifications. References are made that women are less committed, more family oriented workers than their male counterparts, and as a result less productive. If differences between men and women are derived from perceived differences in their "human capital", the gender income gap is a personal rather than a structural problem. The gap will disappear if women became more committed to their careers or change their personal relationships in the family to lessen the household burden. Such a theory is individualistic, and explains a complicated phenomenon in a too simplistic way, by putting the burden for change on individual women, and not on the structure and discrimination of society. Job segregation is part of this theory, which explains the gender income gap by referring to individual choices resulting in job segregation. Other theories exist however, that describe the problem as more complicated and more structural by reviewing the multiple feedbacks between discrimination, gender-role socialization, and practices within industries.

The purpose of this paper is to introduce an econometric methodology that may serve as a link between empirical gender income gap studies and both theories; the individual and environmental theory. After some experimentation with the traditional linear models we introduce a variance decomposition model (also known as random coefficient linear model). We will show that the last model yields more efficient estimates of the observed industry and individual determinants of the gender income gap than the traditional models do. Variance decomposition means here that the variance in individual income is decomposed into three parts: between individuals, between industries, and between men and women in the same industry. The model allows to evaluate if the gender income gap can be attributed to individual differences, differences between men and women and/or to structural differences between industries.. In this way, the analysis model serves as a link between theory and data. We consider two paradigms derived from human capital theory. First, individual differences in qualifications predict income. And second, occupational segregation cause the gender income gap to persist.

Resulting explanations are that either women lack work-related skills compared to men (Corcoran and Duncan, 1979, Flanagan, 1973), and/or occupational segregation by sex is a crucial barrier to the attainment of economic equality for women (Blau and Hendricks, 1979). As is the case in human capital studies, workers are units of observation and units of analysis. The methodology typically used is single level regression analysis, which describes individuals, but neglecting context or industry. We need a multilevel analysis model, because we want to incorporate the context in our analysis asking two subsequent questions: "Can the gender income gap satisfactory be explained by individual qualifications and occupational segregation?" And if not, "Is the gender income gap a result of environmental factors?" For that purpose a hierarchical linear model, (using also industry as the unit of analysis), is introduced.

This paper is organized as follows; Section one describes the background of the hierarchical linear model; Section two describes the unique features of the data source used in this study; Section three outlines the assumptions on which the different analysis models are based. Different regression models are used and compared. Section four summarizes the main findings. Since the results show that different analysis models give different results, the choice of an analysis model has to be based on the knowledge of the researcher about the structure of the data set. The choice of our best model is based on the knowledge of the way the data are collected; in a stratified way.

1. METHOD

Varying or random coefficient models for analyzing hierarchically structured data have a long history in econometrics, also known as error components models or variance decomposition models. The pre-1970 theoretical work is reviewed in Swamy (1971), and the substantial body of theory developed in the 1970's is reviewed in Chow (1984). A nice application is in Montmarquette and Mahseredjian (1989). Most of these econometric applications are more specific than our model. The difference is in the assumptions on the disturbance terms (see Hsiao, 1986, for more details).

The fact that random coefficient models in econometrics [1] have emphasized slightly different applications was more the result of an absence of efficient computational algorithms, which prevented an application of these methods to problems like ours. Before the development of an estimation procedure for hierarchically nested data (based on early work of Lindley and Smith (1972)) was problematic because of the mathematical complexity of the proposed Bayesian estimation procedure. Dempster, Laird and Rubin (1977) applied a numerical approach to maximum likelihood estimation of covariance components using the EM (Expectation Maximization) algorithm. This produces maximum likelihood estimates for variance components with known large sample properties. Since most models used in multilevel analysis have two levels of observation, estimation methods for these models are developed by Mason, Wong and Entwisle (1984); Aitkin and Longford (1986); De Leeuw and Kreft (1986), Goldstein (1986) and Bryk, Raudenbush, Seltzer and Congdon (1988). The authors differ in the way they calculate parameters and handle the data sets (Maximum Likelihood or Generalized Least Squares, based full or restricted likelihoods), but basically give similar answers (see Kreft, Kim and De Leeuw, 1990).

2. DESCRIPTION OF THE DATA

Data for the study are from a survey conducted by the Higher Education Research Institute (HERI) at University of California, Los Angeles (UCLA). The data are a 1977 follow up to a 1970 survey of a national sample of college freshmen. Given the slow rate with which the gender gap is narrowing over the last decades (e.g.Smith and Ward, 1984, Gunderson, 1989, Roman, 1990), we believe our data to be valid for our purposes.

In 1977 questionnaires were sent to 28,549 people sampled from the 180,000 respondents of the 1970 survey. Accounting for 6,194 undeliverable questionnaires, the response rate was 40.4 percent. For the present study, only white respondents in full time employment are included, which constrains our research to a homogeneous group. To use such a specific group is defensible by referring to literature on gender and race (e.g. Mullings, 1986), which presents evidence that development in the status of women is quite different for minority and white women. Discounting for non response and minority groups, the sample

[1] The new model is also known as "variance component model", "hierarchical linear model", or "error components model". We adopt the name "random coefficient model" throughout this paper, following the convention set by DeLeeuw and Kreft (1986).

is reduced to 2,401 men and 2,840 women.

The people in our study had participated in the work force for only a short period of time when filling out the questionnaire (the mean was little over two years of employment). This information excludes one possible explanation of an gender income gap, namely the interrupted career of women, since a substantial portion of female workers did not yet have a chance to enter the "mommy track". Among women, forty six percent were married but only eight percent had children.

The group is homogeneous in many respects. The people in our sample were all at the start of their careers, and the majority of respondents had built up their work experience in their current job only. The majority has full time employment. Also, the educational level was very similar, since 83 percent of the respondents earned a B.A. degree or higher. We have information over nine background variables (see Appendix A). The industries in which the respondents are employed are known. If human capital theory provides a general explanation for the income gap, based on different qualifications of men versus women, we expect that women lag behind men in income across all industries in the same way. On the other hand, if our data shows that industries differ in seize of gender income gap, human capital theory fails to provide a valid explanations for this difference between industries.

The high non-response rate for the second wave of respondents may cause some generalization problems. However, the bias caused by non-response is limited in for our study, since we compare income of females with income of males. We have no reason to expect that non-response bias is different for male respondents than for female respondents (see Appendix B).

In Table 1 the raw data are summarized over twelve industries, which obviously shows that women are unequally distributed over industries. The three industries that offer lowest salaries for both men and women are: Social Welfare and Health organizations (HW), Postsecondary Education (COL) and Elementary and Secondary schools (ED). In HW three times more females than males are employed, and in ED there are six times more female workers than male workers.

Insert Table 1 here

Thus, women are over represented in industries with relatively low salaries. Clearly this type of discrimination is not direct but indirect, since income across gender is fairly equally distributed in these industries.

Our first research question is: "Is the gender wage gap a general phenomenon, or is it specific to some industries and not others?" To answer that question we must correct for all possible causes that, according to human capital theory, affect the income gap between men and women. For a correction of individual differences in qualifications we used the nine variables mentioned in Appendix A. We are aware of the disagreement in the literature about when it is appropriate to hold a variable constant, for instance the variable that measures "experience". Since the degree of experience may reflect prior discrimination, it is doubtful if such a measure is admissible (see the discussion in Cain, 1986 p. 486 and over).

3. MODELS AND ESTIMATION METHODS

Within the general linear regression framework we have two options for analyzing individuals within industries: a) by using fixed effects linear models, and b) by using random effects linear models. In all models, the outcome variable of interest is individual income compared between males and females working in the same industry, holding constant qualifications, which are assumed to have an effect on income. The difference between models is, that fixed effect models are single level models, with workers as the unit of analysis. The random effect model is a multilevel model, where both workers and industries are units of analysis.

Our research interest focuses on two levels: the individual and the industrial. First, we are interested in gender disparities in income, and second in disparities in income and the gender income gap across industries. The two different levels of measurement are the individual worker with n=5241 and the industry with n=12. Research questions consists of two interrelated parts;

- does a significant difference in payment exist between men and women who are comparable in background characteristics? If so
- are those differences equal over all industries?

We define variables describing individual employees as the micro level observations and industries as the macro level. There are three specifications for the effects.

1) Micro-effects are the effects of individual background variables on income in a multiple regression analysis.
2) Macro-effect is defined as the relation between industry and income, that is equal for all employees within that industry. The effect of industry on mean levels of income can be compared by using values of "intercepts" obtained from separate multiple regression analysis in each industries. (The intercept is defined as the mean income value for an industry after correction for background variables).
3) The macro level may affect micro variables such as gender indirectly. This effect is obtained by comparing differences in the effect across industries of the relation between income and gender.

The multiple regression analysis is repeated within each of the twelve industries, while we also distinguish between the effects for men and women. Our fist analysis will be fixed effects models within each industry. This type of models for the description of the gender income gap are first used and described in the econometric literature by Binder (1973) and Oaxaca (1973) and are advanced by Corcoran and Duncan (1979), Daymont and Andrisani (1984) and Goldin (1990). We will extent this technique by partitioning the residual variance of male and female income in within and between industry parts.

3.1. RESULTS WITH FIXED EFFECTS MODELS.

3.1.1 Separate models for separate Industries.

The first results are obtained with a model that fits separate models for separate industries. Economists have argued that women do not earn as much as men because they do not have the same education, training and comparable work experience or they have had intermittent careers. The variables used to control for qualification differences between men and women are education, work experience and seniority. Since our sample is a young age cohort we do not need to correct for age nor for intermittent careers.

Each industry has its own best fitting regression model, such as for industry j, corrected for background,

$$\underline{y}_j = \alpha_j + g_j\gamma_j + X_j\beta_j + \underline{\epsilon}_j, \tag{1}$$

Here $\underline{y}_j$ is a random vector with n_j observations on the independent variable income, g_j is the vector coding for gender, and the random vector $\underline{\epsilon}_j$ contains disturbances, where X_j is the $n_j \times 9$ matrix of covariates.

For this model, the estimates of the γ_j are the means for the corrected incomes $\underline{y}_j - X_j\hat{b}_j$, with $\hat{b}_j$ the least squares estimate of the regression coefficients b_j for the covariates. The standardizated gender differences are given in the first column of Table 2, with the standard errors of this difference in the second column. The third column are standard scores, obtained by dividing column 1 by column 2. These scores have the usual interpretation: differences with a score over 2.00 are significant.

Table 2 about here

To make interpretations easier, we used z-scores in Table 2 and in Figures 1 and 2. The figures show z-scores together with their 95% confidence intervals. Figure 1 represents raw z-score differences, while Figure 2 shows the adjusted z-score differences, corrected for differences in the background variables of Appendix B. In both figures the interpretation of confidence intervals that do not include zero is a significant effect for that particular industry.

Figures 1 and 2 about here

In all industries the difference is in favour of men, with the exception of COL in Figure 2, for the adjusted difference. The tendency is in favor of men, even in industries that show no statistically significant difference in income over gender (the confidence interval includes zero).

While raw means (see Table 1) corroborate our common sense belief that women in general earn less money than men, corrected means show that equally qualified men and women are still unequal in income, while this disparity is greater in some industries than others. Although not all differences in male-female income are statistically significant over industries the tendency is in favor of male income, with college (COL) as the exception. The largest gender income differential is found in the retail industry (RET), followed by other business (OBUS) and manufacturing (MFG). A tentative conclusion based on Figure 1 is, that the majority of private sector industries fall outside the shaded area, while public sector industries fall largely within that area.

In the analyses model above we treat each industry in the first analysis step as an independent sample, and subsequently compare the results of the first step in the second analysis step, based on table and figure. Separate models for separate industries has two problems. In the first step we neglect intra cluster (industry) correlation, while we take parameters at face value in the second step without any correction for unreliability of within industry parameters estimates.

3.1.2. Multiple Regression with Dummy Variables for Industries and Gender.

Next, we fit one single model to the data instead of twelve separate ones, to obtain more efficient estimates. The model is again a single level multiple regression analysis with workers as the unit of analysis. The effect of industries is not estimated separately, but together with the individual effects by introducing dummies for the interaction between industry and gender. Since we want to test if the gender income differential is the same over industries, we need a model that allows the predictor gender to have different effects, while assuming that the other nine predictors have the same effects across industries. In Binder (1973) we find support for this last assumption. By creating twelve dummy variables for industries and letting them interact with gender, we tested if industries make a difference.

In the next model nine predictors are held constant over industries. The exception is gender, which interacts with industries. The main effect for gender and the grand mean effect (the intercept) are used for the estimation of the twenty four interactions in the model. The results are in Table 3.

Insert Table 3 about here

Table 3 shows thirty three estimates, including the estimates for interaction between gender and industry. Male coefficient minus female coefficient is the difference in earnings within the same industry (in thousands of dollars, see the last column of Table 3). The coefficients for men are always higher than for women, except for human services organizations (HW) and for college, university, technical institute or professional schools (COL). Large differences are again found in the private sector industries: RET (retail and wholesale), OBUS (other business), and COM (commerce, insurance and finance).

So far both analyses yield similar, or at least compatible results. Both are also based on the fixed effects linear model. Our next analysis fits a random effects model which shares the feature with the previous model that it is parsimonious, It has the advantage that it takes the intra-class correlation into account. Besides, the random model offers more alternatives than the fixed model, using dummies for interactions.

3.2. *RANDOM COEFFICIENT MODELS*

The two fixed effects models presented earlier are based on the assumption of independence of observations. In clustered samples, where observations within the same industry are more similar to each other than observations across industries, Least Squares estimation procedures result in unreliable estimates of standard errors (see Cochran 1977). The random coefficient model, introduced here, does not assume independence of observations within the same context, and can handle data collected at different levels of a hierarchy in an appropriate way.

The techniques stays conceptually very close to the technique proposed by Oaxaca (1973). A multiple regression analysis is preformed within each context or industry separately, but the difference is, that the effect of industries is simultaneously estimated. Both levels are analyzed in relation to each other.

We next present the basic equations for the random coefficient model. Let $\underline{y}_j$ be the responses of individuals in the jth industry on the variable income. In the jth industry, this response can be written as a function of several individual characteristics collected in an $n_j \times 9$ matrix X_j. The model is

$$\underline{y}_j = \underline{a}_j + g_j \underline{c}_j + X_j \beta + \underline{\epsilon}_j. \tag{2}$$

The random variables $\underline{\epsilon}_j$ are the individual error terms, $\underline{c}_j$ is the random coefficient for gender differences, and $\underline{a}_j$ is the random intercept. Coefficients in β are the fixed effects for the nine covariates. We consider the random coefficients as functions of the different industries

$$\underline{a}_j = \alpha + \underline{\delta}_j, \tag{3}$$
$$\underline{c}_j = \gamma + \underline{\eta}_j. \tag{4}$$

Here, index j is for industries Equation (4) shows that the random intercept $\underline{a}_j$ and the random slope for gender $\underline{c}_j$ are composed of a fixed intercept α, a fixed slope γ, and disturbances $\underline{\delta}_j$ and $\underline{\eta}_j$. If we substitute equation (3) and (4) in (2), we obtain the mixed linear model:

$$y_j = (\alpha + \underline{\delta}_j) + g_j(\gamma + \underline{\eta}_j) + X_j \beta + \underline{\epsilon}_j \tag{5}$$

Rearranging random and fixed parts yields equation (6).

$$y = (\alpha + g_j\gamma + X_j\beta) + (\underline{\epsilon}_j + \underline{\delta}_j + g_j\underline{\eta}_j) \tag{6}$$

The model consists of a fixed part and a random part. To judge the aptness of our model, we test whether the variances of the independent variables differ significantly over industries. In this model there are only two random components of interest: one random slope (the slope of gender) and the random intercept. In fact, the fixed part of our model has many more components, which are the previously introduces nine predictors assumed to behave equally across industries. Some fixed effect variables are education, GPA, incentives, parental income, and others (see Appendix A). In other words, all other variables except gender are taken as fixed. A fixed slope reflects the assumption that the slope for that variable is equal for all industries.

Equation (6) shows how fixed and random parts of the model are combined. The equation also shows that the model tests effects of the second level (type of industry) on the within industry relation between gender and income.

Our choice of a random instead of a fixed model is based on our knowledge of the way the data are constructed. We assume an intra-class or intra-industry correlation. Intra-industry correlation is a measure of how much the observations within the same industry are replications of each other. A zero correlation means that the observations are independent. In situations where this correlation is non-zero, the random model is more appropriate. In our data, the intra-class correlation for women within the same industry is r=.108, the intra industry correlation for men is r=.110, and between men and women in the same industry, r=.091. Since our data set contains large numbers of observations within industries, these correlations are significant and too large to be ignored (see Cochran, 1977 and Hsiao, 1986).

3.2.1. Results

By again assuming that the nine background variables have the same effect for men and women across industries, we fit a multilevel model that estimates all parameters as fixed with the exception of the parameters for intercept and gender. Intercept and gender are allowed to differ over industries. The random coefficient model can be considered as a combination of the previous two analysis models, and has in common with the first model that it allows parameter estimates to be different over industries, while it has in common with the second fixed model (see Table 3) that industry and individual effects are estimated together, in one single analysis.

To calculate the parameters of our random coefficient model, we use the computer program VARCL (Longford 1986) for variance component analyses. Industry is not introduced as a dummy variable, but is used to define the group to which each individual belongs. Interaction between gender and industry is tested by allowing the parameter for gender to vary over contexts, instead of estimating twenty four different interaction variables as we do in the last analysis.

Results are reported in Tables 4 and 5

Insert Table 4 about here

Table 4 shows the estimates of the fixed and the random effects of the multilevel regression. The fixed effect coefficients are all significant at p=.00 level, since they are larger than two times their respective standard errors. The fixed effects part of our model, the coefficients of the variables 3 through 11 in Table 4, have the same values estimated as in the fixed effect model in Table 3. The random part of the model, the "Variance component estimates" in Table 4, shows that the random components vary significantly over industries. The conclusion from this analysis is, that the effect of industry on income is significantly different in two ways, namely in an overall and a specific way. The overall effect shows in the way industries differ in overall payment, shown in the significant differences in intercepts. The specific effect, the differences in the way gender affects income, shows in the significant differences in the slope of gender on income across industries. Since gender is coded as 1=male and 2=female, a negative sign for gender indicates that females have lower income for that industry.

The difference between the analyses reported in Table 3 and 4 are in the estimates for the interaction between industries and gender, which is not readily available in Table 4. To obtain these estimates for the random coefficient model we need Table 5, which shows posterior means.

Insert Table 5 about here

Posterior means are deviations from the overall estimates of intercept (or Grand Mean, which is -2.821, in Table 4) and gender (which is -1.462 in Table 4) for each industry. To obtain twelve different estimates for the twelve industries, Table 5 and Table 4 are combined in Table 6. Adding the posterior means in Table 5 to the mean effect for the same coefficients in Table 4, we obtain twelve different regression equations. In Table 6, the higher the intercept for an industry, the higher the overall mean income, while the lower the coefficient for gender, the wider the income gap in that industry. For an easy comparison of the estimated gender income gap obtained with the random model and the fixed effects model estimates in Table 3 we constructed the last two columns in Table 6.

Insert Table 6 about here

The estimates for the interaction of gender and industry over the two analysis models are not exactly the same (see also Table 7 for a comparison), but close and in the same direction. Over both models the estimates for the private sector industries RET, OBUS and COM show the highest gender income gaps, since they score in the highest four places in both analyses, while the reverse is true for the public sector industries, ED, HW, and COL, who occupy the lowest four places of the gender income differential scale.

3.2. Ranking of Industries. A Comparison between three analyses.

The outcome of the three different analyses models can be best compared if we rank the industries. The ranking can be done based on two criterions, the amount of overall payment and the amount of discrimination. Only one out of the three analyses allows us to rank industries according to overall payment, which is the random effects model. In Table 6 the industries are ranked in that order. In Table 7 industries are ranked according to a second criterion, from high gender income differential to low gender income differential. The three rankings are based on three types of analyses.

Insert Table 7 about here

The first column in Table 7 shows ranking based on the "separate equations for separate industries" models (see Table 2). The mean residual for men and women is calculated separately and transfered in a z-scores. After substracting the female z-score from the male z-score we obtained a ranking of industries from high difference to low difference in male-female income. The second ranking is based on the difference between the estimates for the dummy variables for men and women in each industry, obtained from the single equation fixed effect model (see Table 3). The last column shows the ranking obtained with the random coefficient model. Rankings do not differ much in the extremes. Industries with the smallest gender income gap remain so over all three analyses, as did the ones with the highest gap. The differences is mainly found in the middle ranks.

The ranking of industries in Table 7 shows that industries in the public sector have a smaller gender income gap than industries in the private sector. For our data we can conclude that low wage industries have the smallest gender income gap, but also proportionally the highest number of women. In the three public sectors with the lowest payments, COL, ED and HW a total of 1471 women are present, while only 398 workers are men. We found the opposite in industries that offer the highest salaries (TRNS, MFG) with more than twice as many male workers as female workers (668 and 258 respectively). These numbers support the theory that job segregation explains part of the gender income gap, and that women are indeed concentrated in industries with low starting salaries, while severely under represented in high salary jobs such as transportation and construction. But job segregation does not provide a complete explanation for the income differential, since industries that have the highest income gaps (RET, COM, and OBUS) have almost equal numbers of male and female employees (865 men versus 870 women, see Table 1).

4. SUMMARY

In this paper we present a methodology in which the gender income gap - viewed either as an individual or as a structural problem - can be analyzed within a common econometric frame work using a multiple regression methodology. The basic ingredient of our approach is a random coefficient model with a complicated error structure that allows for variation among individuals, due to unmeasured individual characteristics, and for second level variation due to unmeasured characteristics at the industry level. This decomposition of the error structure is known as a variance decomposition over two levels of the hierarchy. The income of men and women are analyzed as varying between individuals, between men and women and between industries (holding a number of predictors of income constant).

Although our fixed effect models yield results comparable to the random effects model, as is shown by the rankings in Table 7, there are some fundamental differences among them. The first analysis that used standard score differences of the residuals provides an estimate for the gender differential, only and not for mean income differences between industries. The same is true for the multiple regression model with dummies for interactions. Only the random coefficient model estimates both effects at the same time. The last model is also more flexible, more parsimonious, and based on more realistic assumptions. Flexibility means that we have the choice which of the coefficients are allowed to be different across industries. This flexibility is not present in the first fixed effect model presented in this paper, where the only option is to allow all coefficients to be different over industries. In the second fixed effect model, using dummy variables for cross level interactions, we have more freedom of choice, although we are limited by the number of parameters that can be reliably estimated in a single model. Introducing more interactions in this last model means that the number of parameters to be estimated will increase considerably. In terms of industry differences, the random coefficient model can easily test if any one (or all) of the nine background variables have the same or different effects across industries, while the number of parameters that has to be estimated stays relatively small. The assumption of the random effects model, that observations within the same industry have correlated error terms, also seems realistic. Both fixed effect models assume, of course, that observations are independently sampled.

As an example of the ease of use and the parsimoniousness of the random coefficient model, we use Goldin's hypothesis (1990, p.84) that males and females are not rewarded identically for the amount of work experience. To test this theory it has been proposed to fit two different regression equations, one for males and one for females. In our case this would have been two regressions for each industry separately. The same can be accomplished in the random model by adding a random slope for the variable "amount of experience" (HUMCAP in Appendix A) to the random coefficient model, whcih means three more parameters. The extra parameters are: a variance for the random coefficient estimated for HUMCAP, plus two covariances of this estimate with coefficients of intercept and gender. Fitting this model with two random slopes showed that for our data the variation for HUMCAP was not significant over industries. We concluded that experience is equally rewarded across industries, and did not report the results in this paper.

Our analysis supports the fact that women more than men choose to work in lower paying industries. Women are under-represented in the highest paying industries and over-represented in the lowest paying industries. Of course we cannot answer the question whether segregation is the cause of gender earnings differentials, or is in some respects a substitute for it. Since job segregation alone does not explain gender income gap entirely, we have to look for other causes.

We are aware that our data do not allow to conclude that the gender income gap is based on a different taste for discrimination across industries. In social research we have no way of being certain that we included all relevant factors that underlie differences in productivity, nor that all are measured without error. Our conclusion that the gender income gap cannot be explained by individual differences in qualifications between males and females is however strengthened by several factors. First many workers' qualifications are included, which are all related to income. Second, the sample is a young and homogeneous age cohort. Thirdly, industries differ substantially in the amount of gender income differences, making arguments addressing the income gap to general weaker female qualities void.

DISCUSSION

Market discrimination is defined under human capital theory as the difference in average wages of men and women who possess the same productive skills. The relatively large gender income gap in some industries, mainly those in the private sector, show that women are more likely to work in lower status and lower paying jobs within these industries, although they are equally qualified, according to background characteristics included in this study. Discriminatory hiring and promotion factors may be one reason for the gender income gap in these industries. Further study is needed here.

Human capital theorists may still try to explain the gender-income gap in some industries in other ways, based on employers' and women's expectations about the future. The explanation of Sandell and Shapiro (1980, p. 351) that "young women's ante labor market plans are significantly related to their post school accumulation of human capital" is not present in our data, since only 8% of the married women in our sample have families with children. The mean years of employment for people in our data set is between two and three years and not many of the respondents changed jobs, nor had interrupted careers. This does not exclude expectations on the part of the employers by labeling women as "bad risk" investments. Such a negative expectation based on gender instead of on individual behavior, is by definition discriminatory.

Discriminatory actions (of employers) or discriminatory tendencies in a society seem to be more logical causes of male-female wage differences in our data than the ones that are traditionally given, such as lack of motivation or low levels of career aspiration on the part of women. This is supported by recent research (Farmer, 1983) that studied women's motivation, work preferences and preparation for the labor market. The finding of this study is, that adolescent women scored higher than adolescent men on a scale of career commitment. Other facts add to this change in attitudes. One, being reported in the "Wellness Letter" (1991), is that the traditional American family unit - a married couple with one or more children- was found in only 26 percent of the American households last year, while this was 40 percent in 1970. Many questions are left to be answered. Firstly, do the higher earnings of men, in a traditional labor market, capture the skills that make a man more valuable than a woman? And secondly, can a society, where female headed households are growing, afford to underpay female employees?

APPENDIX A

VARIABLES , CATEGORIES AND THE NUMBER OF OBSERVATIONS

Income. This is the dependent variable. It is based upon coded values of answers to the 1977 HERI survey. Respondents were asked to indicate which of twelve categories included their current annual income before taxes. To create the income variable, mid-point values of the categories are used. The scale is constructed in a way that makes the distribution of income roughly normal. The mean is 10.96.

cat	3.5	8.5	11.0	13.0	15.5	18.5	22.5
n	468	1331	995	631	552	239	97

Gender, with male coded as one (n=2030) and female coded as two (n=2283).

Parental income. This variable is measured in the same way as respondents' incomes. Parents income has a more extended scale, because they have in general higher salaries than their children. The mean is 16.57.

cat	3.5	8.5	11.0	13.0	15.5	18.5	22.5	27.5	32.5	37.5	42.5
n	195	411	570	832	680	395	708	395	205	116	145

Selectivity of college attended (Select). This is a nine level variable indexing the mean level of SAT scores for entering freshmen at each of the colleges attended by respondents.

Education. The four degree levels are:

level	none=1	A.A.=2	B.A.=3	post-M.A.=4
n	379	358	3171	405

The mean is 2.83.

College grade point average. As self reported by respondents. Mean is 3.96

Occupation has seven categories. The mean is 5.09.

Category	frequency
Unskilled	66
Semi-skilled	149
Clerical	731
Skilled	544
Low-professional	787
Semi-professional	958
Professional and administrative	1078

Economic incentive. Respondents were asked to rate the importance of potential earnings in their selection of a college major. The mean is 1.84.

importance	low	medium	high
n	1731	1539	1043

Hours worked per week in current job. This variable has three categories, indicating how much respondents worked. The mean is 6.42.

hrs worked	less than 20 hrs/wk	20-40 hrs/wk	more than 40 hrs/wk
n	82	2208	2023

Q14B: Length of employement in current job. Respondents checked one of six response categories, ranging from six months or less to five years or more. The mean is 3.28

time worked	6 months	6-12 months	1-2 yrs	2-3 yrs	3-4 yrs	4-5 yrs	5+yrs
n	612	701	999	1232	499	146	124

Another variable related to Q14b is **Length of time employed** (full or part time) since college. Measured by the same six response categories used for time employed since leaving college. Both two variables (Q14a and Q14b) are used to construct the next variable.

Human capital. This is length of employment since college minus length of employment in current job. (Q14a - Q14b).

time worked	no change	6 months	6-12 months	1-2 yrs	2-3 yrs	3-4 yrs	4-5 yrs
n	2406	824	550	350	121	35	27

The mean is 0.88. This variable is used to correct for time that respondents have stayed in school and hence lack a long record of employment.

Industries. The twelve industries are:

1) Elementary or secondary school (ED),
2) College, university, technical institute or professional school (COL),
3) Retail or wholesale (RET),
4) Human services organization (HW),
5) Local government (LOCG),
6) Other business or service establishments (OBUS),
7) Commerce, insurance, finance or real estate (COM),
8) US Military service (MIL),
9) Agriculture or mining (AG),
10) US Government and civilian employee (USG),
11) Manufacturing or Construction, etc. (MFG) and
12) Transportation or public transportation (TRNS).

APPENDIX B.

Distribution of the first wave (60%) and the second wave (40%) by gender and educational level.

Gender

Gender	First wave	Second wave
Males	46%	54%
Females	47%	53%

Educational Level

Educational level	First wave	Second wave
None	9.4%	8.8%
A.A	8.0%	8.3%
B.A.	72.9%	73.5%
M.A.	9.6%	9.4%

REFERENCES

Aitkin, M.A. and Longford, N., 1986. Statistical Modelling Issues in SchoolEffectiveness Studies. *Journal of the Royal Statistical Society*, 149A, 1-43.

Becker, Gary S., 1971. *The Economics of Discrimination.* Chicago: The University of Chicago Press.

Binder, Alan S., 1973. Wage Discrimination: Reduced Form and Structural Estimates. *The Journal of Human Resources*, 8, 4, 436-455.

Blau, Francine, D. and Wallace E. Hendricks, 1979. Occupational Segregation by Sex: Trends and Prospects. *The Journal of Human Resources*, 14, 2, 197-21

Bryk,A.S., Raudenbush, S.W., Seltzer,M. and Congdon, R.T.(1988). *An introduction to HLM: Computer program and User's guide.* University of Chicago.

Cain, Glen G., 1986 The Economic Analysis of Labor Market Discrimination: A Survey. Pp 693-785 in *Handbook of Labor Economics,* Volume II, Edited by O.Ashenfelter and R. Layard, Amsterdam, The Netherlands: North Holland Publishing.

Chow, G. C., 1984. Random and changing coefficient models. In: Z. Griliches and M.D. Intriligator (Eds.), *Handbook of Econometrics* (Vol. 2). Amsterdam, The Netherlands: North Holland Publishing. Cochran, W.G., 1977. Sampling Techniques. New York, Wiley and Sons.

Corcoran, Mary and Greg J. Duncan, 1979. Work History, Labor Force Attachment, and Earnings Differences between the Races and Sexes. *The Journal of Human Resources,* 14, 1, 3-19.

Daymont, Thomas N. and Paul J. Andrisani, 1984. Job Preferences, College Major, and the Gender Gap in Earnings. *The Journal of Human Resources,* 19, 3, 408-428.

De Leeuw, J. and Kreft, I., 1986. Random Coefficient Models for Multilevel Analysis. *Journal of Educational Statistics*,11, 57-85.

Dempster, A.P., N.M. Laird, and D.B. Rubin, 1977 Maximum likelihood for Incomplete Data via the EM algorithm. *Journal of the Royal Statistical Society,* B39, 1-38.

England,Paula, 1982. The Failure of Human Capital theory to Explain Occupational Sex Segregation. *The Journal of Human Resources,* 17, 3, 358-370.

Farmer, H.S.,1983. Career and Homemaking Plans for High School Youth. *Journal of Counseling Psychology* 30: 40-45.

Flanagan, Robert J., 1973. Racial Wage Discrimination and Employment Segregation. *The Journal of Human Resources,* 8, 4, 456-70.

Goldin, Claudia, 1990. *Understanding the Gender Gap. An Economic History of American Women.* New York, Oxford University Press.

Goldstein, 1986. *Multilevel models in Educational and Social Reserarch.* London: Griffin.
Hewlett, S. A., 1986. *A Lesser Life.* New York. William Morrow and Company.

Hsiao, Ch., 1986. *Analyis of panel data.* Cambridge University Press, Cambridge.

Kalmijn, M.,Zucker, L.G., 1990. *Gender Differences in Collective Action. A quantitative Analysis of Strikes in the US at the End of the 19th Century.* Department of Sociology, UCLA, Los Angeles.

Kreft, Ita G.G., De Leeuw, J. and Kim, Kyung-Sung 1990. *Comparing Four Different Statistical Packages For Hierarchical Linear Regression, GENMOD, HLM, ML2 and VARCL.* CSE Technical Report 311, UCLA Center for Research on Evaluation, Standards and Student Testing.

Lindley, D.V. and Smith, A.F.M., 1972. Bayes Estimates for the Linear Model.S *Journal of the Royal Statistical Society,* B34, 1-41.

Longford, N.T. 1986. *Statistical modelling of data from hierarchical structures using variance component analysis.* Program developed at the Center for Applied Statistics, Lancaster University.

Marshall, Ray F., 1974. The Economics of Racial Discrimination: A Survey. *Journal of Economic Literature,* 12: 849-871.

Mason, W. M. , Wong, G. Y. and Entwisle, B., 1984. Contextual analysis through the multilevel linear model. *Sociological Methodology,* 72-103.

Montmarquette, Claude and Sophie Mahseredjian, 1989. Does School Matter for Educational Achievement? A two-way Nested Error Components Analysis. *Journal of Applied Econometrics,* 4, 181-193.

Mullings, L. 1986. Uneven Development: Class, Race, and Gender in the United States Before 1900. Pp. 41-58, in: *Women's work: Development and the Division of Labor by Gender.* Leacock, E., Safa, H.I. and Contributors (eds.), South Hadley, Ma.: Bergin and Garvey Publishers.

Oaxaca, Ronald L. 1973. Male-Female Wage differentials in Urban Labor Markets. *International Economic Review,* 14, 693-709.

O'Shea, D.W., 1989. *Gender Earnings Gap among College Educated Persons in Early Career.* Paper presented at the annual meeting of the American Educational Research

Association, San Francisco, March 27-31, 1989.

Smith, J. P. and Ward, M.P., 1984. *Women's Wages and Work in the Twentieth Century.* Santa Monica, CA, Rand Corporation.

Swamy, P. A. V .B., 1971. *Statistical inference in random coefficients regression models.* New York: Springer Verlag.

Treiman, Donald J. and Hartmann, Heidi J., 1981. *Women, Work and Wages. Equal Pay for Jobs of Equal Value.* Washington D.C. National Academy Press.

Fascinating Facts. *Wellness Letter,* 1991. September, Berkeley: University of California.

Zucker, L. G., Yip, K and Kalmijn, M., 1990. *Explaining Process and Outcome of Collective Action: Multilevel effects of Industrial Context and Strike Characteristics in the 1880's.* UCLA, Institute of Industrial Relations. Series... no..

Zucker, L. G., Yip, K and Kalmijn, M., 1991. *Institution Building by Workers in the 1880Us : Multilevel Effects of Industrial Regional Context and Strike Characteristics on the founding of Knights of Labor Local.* UCLA, Institute of Industrial Relations. Series... no..

TABLE 1. MEAN 1977 INCOME OF MALE AND FEMALE RESPONDENTS TO HERI SURVEY BY TYPE OF EMPLOYMENT ORGANIZATION

Type of Employment	Male Income (N)	Female income (N)	Difference
Elementary or Secondary School (ED)	$ 9,956 (152)	$ 9,172 (812)	$ 784
College, University, Technical Institute, or Professional School (COL)	$ 9,874 (113)	$ 9,389 (169)	$ 485
Retail or wholesale (RET)	$ 11,986 (238)	$ 8,344 (218)	$ 3,642
Human services organization (HW)	$ 10,516 (134)	$ 10,246 (489)	$ 270
Local government (LOCG)	$ 11,493 (133)	$ 9,882 (119)	$ 1,135
Other business or service establishments (OBUS)	$ 12,105 (398)	$ 9,674 (376)	$ 2,431
Commerce, insurance, finance or real estate (COM)	$ 12,510 (229)	$ 9,630 (276)	$ 2,880
U.S.military service (MIL)	$ 11,385 (109)	$ 10,250 (11)	$ 270
Agriculture or mining (AG)	$ 12,130 (112)	$ 9,547 (16)	$ 2,585
U.S. government, civilian employee (USG)	$ 13,266 (111)	$ 11,787 (95)	$ 1,479
Manufacturing or construction (MFG)	$ 13,460 (567)	$ 11,142 (204)	$ 2,318
Transportation (TRNS)	$ 13,964 (101)	$ 12,875 (54)	$ 1,089
Mean 1977 Income	$ 12,188 (2401)	$ 9,753 (2,840)	$ 2,435

TABLE 2. ADJUSTED DIFFERENCE SCORES OF MALE- FEMALE INCOME

Industry	Difference	SD	Z-score
ED	0.6227	0.2148	2.8995
COL	-1.0853	0.4429	-2.4504
RET	2.8715	0.3693	7.7758
HW	0.1143	0.3229	0.3540
LOCG	1.0643	0.3700	2.8766
OBUS	1.4463	0.2656	5.4460
COM	1.5073	0.3220	4.6808
MIL	0.7434	1.1475	0.6479
AG	1.4840	1.3257	1.1194
USG	0.3044	0.4051	0.7515
MFG	1.2702	0.2731	4.6518
TRNS	0.7207	0.5437	1.3255

TABLE 3. COEFFICIENTS FOR A FIXED MODEL WITH 24 DUMMIES FOR THE INTERACTION BETWEEN GENDER AND INDUSTRIES

Fixed effects estimates. Variable numbers and names	Estimates	Standard errors [2]
Grand Mean	no estimate	
Gender	no estimate	
Parental Income	0.020	0.007
Select	0.231	0.035
Education	1.053	0.096
GPA	0.265	0.046
Occupation	0.616	0.036
Incentive	0.893	0.069
Hours worked	0.405	0.081
Q14B (job experience)	0.793	0.050
Human capital (experience)	0.277	0.058

The estimates for the twenty four dummy variables over industries and gender are

Industries	Coefficient Women	Coefficient Men	Difference
ED	-7.17	-6.51	-0.66
COL	-6.23	-6.78	+0.55
RET	-6.61	-2.88	-3.73
HW	-5.22	-5.26	+0.04
LOCG	-5.21	-3.97	-1.24
OBUS	-5.33	-3.28	-2.05
COM	-5.50	-3.46	-2.04
MIL	-6.08	-4.30	-1.70
AG	-5.44	-3.52	-1.92
USG	-3.78	-2.68	-1.10
MFG	-4.12	-2.32	-1.80
TRNS	-3.18	-1.46	-1.72

TABLE 4. RANDOM AND FIXED COEFFICIENTS FOR THE MULTILEVEL MODEL.

Fixed effects estimates. Variable numbers and names	Estimates	Standard Errors [3]
Grand mean	-2.821	
Gender	-1.462	0.326
Parental Income	0.021	0.007
Select	0.326	0.035
Education	1.034	0.096
GPA	0.268	0.046
Occupation	0.612	0.036
Incentive	0.896	0.069
Hours worked	0.411	0.081
Q14B (job experience)	0.790	0.050
Human Capital (experience)	0.277	0.058

Variance component estimates for industries

Variable Name	Variance	Sigma	Standard Error of Sigma
Grand mean	1.445	1.202	0.235
Gender	1.030	1.015	0.220

TABLE 5. POSTERIOR MEANS FOR INTERCEPT AND GENDER OVER TWELVE INDUSTRIES.

industry	intercept	slope
ED	-2.224	0.746
COL	-1.786	1.762
RET	-0.107	-1.957
HW	-0.651	1.330
LOCG	-0.040	0.153
OBUS	0.299	-0.551
COM	0.115	-0.560
MIL	-0.485	0.088
AG	0.109	-0.239
USG	1.290	0.134
MFG	1.374	-0.380
TRNS	2.102	-0.520

TABLE 6. ARATE EQUATIONS FOR TWELVE INDUSTRIES BASED ON A RANDOM EF'TS MODEL

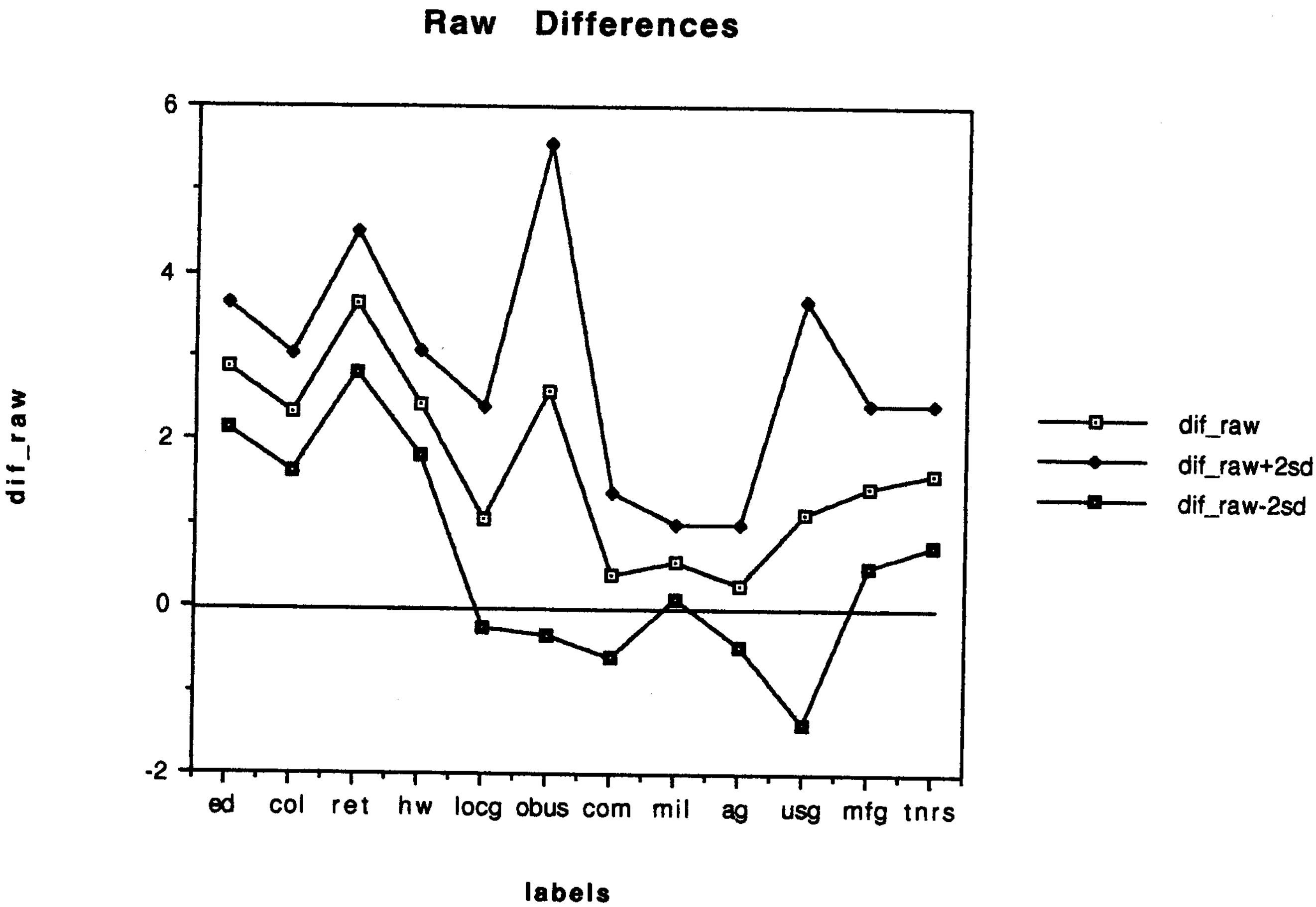
ustry	equation per industry	total effects	
		for males	for females
ED	$Y = - 5.04 - 0.71\ g$	-5.74	-6.45
OL	$Y = - 4.6 + 0.30\ g$	-4.31	-4.01
[W	$Y = - 3.47 - 0.14\ g$	-3.61	-3.75
[IL	$Y = - 3.31 - 1.37\ g$	-4.68	-6.05
ET	$Y = - 2.93 - 3.42\ g$	-6.35	-9.77
)CG	$Y = - 2.86 - 1.31\ g$	-4.17	-5.48
3US	$Y = - 2.52 - 2.01\ g$	-4.53	-6.54
OM	$Y = - 2.71 - 2.02\ g$	-4.73	-6.75
\G	$Y = - 2.71 - 1.70\ g$	-4.41	-6.11
SG	$Y = - 1.53 - 1.33\ g$	-2.86	-4.19
'FG	$Y = - 1.45 - 1.84\ g$	-3.29	-5.13
RNS	$Y = - 0.72 - 1.99\ g$	-2.71	-4.70

TABLE 7. THE RANKING OF INDUSTRIES ACCORDING TO THELE-FEMALE INCOME DIFFERENTIAL

Fixed Model Table 2 z-score differences		Fixed Model Table 3 regression coefficients		Random M Tables 4 ar posterior m	
RET	-2.87 *	RET	-3.73	RET	[illegible]
COM	-1.51 *	OBUS	-2.05	COM	[illegible]
AG	-1.48	COM	-2.04	OBUS	-
OBUS	-1.45 *	AG	-1.92	TRNS	[illegible]
MFG	-1.27 *	MFG	-1.80	MFG	[illegible]
LOCG	-1.06 *	TRNS	-1.72	AG	-
MIL	-0.74	MIL	-1.70	MIL	-
TRNS	-0.72	LOCG	-1.24	USG	-
ED	-0.62 *	USG	-1.10	LOCG	-
USG	-0.30	ED	-0.66	ED	-
HW	-0.11	HW	+0.04	HW	-
COL	+1.09 *	COL	+0.55	COL	+

The standardized difference scores in the first column are multiplied wi1.00, in order to make them comparable to the other coefficients in the table.

* The industry estimates marked with a * in the first column are significbased on the z-test in Table 2.



Raw Differences
6
4
2
0
-2
dif_raw
ed
col
ret
hw
locg
obus
com
mil
ag
usg
mfg
tnrs
labels
dif_raw
dif_raw+2sd
dif_raw-2sd

Corrected differences