Sociological Methods & Research
http://smr.sagepub.com/

The Gender Gap in Earnings : A Two-Way Nested Multiple Regression Analysis with Random Effects

ITA G. G. KREFT and JAN de LEEUW

Sociological Methods & Research 1994 22: 319
DOI: 10.1177/0049124194022003003

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. The authors show that a hierarchical linear model is the best way to evaluate male-female wage differentials. Both interindustry and intraindustry wage disparities between men and women are measured by using a technique that assumes that observations within the same industry have correlated error terms. By simultaneously testing human capital factors and environmental factors, the analysis model serves as a link between theory and empirical analysis. The results show that the wage differences are larger in some industries than in others, so that it can be assumed 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 contradict the hypothesis that gender income differential is largely due to female work preferences and the resulting segregation.

The Gender Gap in Earnings

A Two-Way Nested Multiple Regression Analysis With Random Effects

ITA G. G. KREFT
California State University
JAN de LEEUW
University of California, Los Angeles

1. INTRODUCTION

The purpose of this article is to introduce an econometric methodology that might serve as a link between empirical gender income gap studies and the two theories associated with them; the individual and environmental theory. After some experimentation with traditional linear models, we introduce a variance decomposition model (also known as random coefficient linear model). We will show that the latter yields more efficient estimates of observed industry and individ-

AUTHORS' NOTE: *We would like to thank Dr. David O'Shea for allowing us to base this analysis on his previous work (see O'Shea 1989) and Amy Braverman for editing this article.*

SOCIOLOGICAL METHODS & RESEARCH, Vol. 22, No. 3, February 1994 319-341

ual determinants of gender income gap than do the traditional models. 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 us to evaluate whether 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.

This article is organized as follows: Section 1 describes the background of the hierarchical linear model; section 2 describes the unique features of the data source used in this study; section 3 outlines the assumptions on which the different analysis models are based. Different regression models are used and compared. Section 4 summarizes the main findings. Because the results show that different analysis models give different results, the choice of an analysis model has to be based on the researcher's knowledge of the structure of the data set. The choice of the best model is based on the knowledge of the way the data are collected, in our case in a stratified way. We begin with a brief review of the substantive issues.

Among all employed persons, White women earn 70% of White men's hourly wages, although for younger people (those aged 25 to 34) with a college education, the gap is somewhat smaller. In 1983, the median income of women working year round in this latter group was 73.3% of the income of men (Smith and Ward 1984, pp. 43-45). Given this, the dominant ideology of fair competition in the United States seems to be limited to White males only. What is more, compared to several European countries, the gender income gap in the United States is extremely wide and has hardly narrowed in the last 50 years. In Sweden, for instance, women's earnings have improved from 71% of men's earnings in 1970 to 81% in 1981 (Hewlett 1986), and in Italy, the gap decreased from 74% in 1974 to 86% in 1982, remaining constant from the 1950s to the early 1980s in the United States (Goldin 1990, p. 60).

What are the reasons for the persistence of the gender income gap in the United States 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 United States to explain the income gap because in the younger population, the average female worker is slightly better educated than the average male worker.

There is no shortage of theories to rationalize the existence of different wage rates for equally productive workers. Common explanations are that either women lack work-related skills compared to men (Corcoran and Duncan 1979; Flanagan 1973) and/or that 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 neglects context or industry. We need a multilevel analysis model because we want to incorporate context in our analysis that asks two subsequent questions: Can the gender income gap satisfactorily be explained by individual qualifications and occupational segregation? and if not, is the gender income gap a result of environmental factors? For this purpose a hierarchical linear model is introduced. The existing theories are not well supported by empirical evidence. We consider here two somewhat opposing theories: neoclassical 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 contextual factors (see Marshall 1974; England 1982). The latter makes a distinction between individuals working in different industries when we consider the industry as an environmental factor. We have good reasons to do so because different industries are located in different sectors, either public or private, which have different market mechanisms and different labor union histories (Zucker, Yip, and Kalmijn 1990, 1991). This last difference is of some importance, given Cain's (1986) hypothesis that "wage discrimination is less in competitive industries and greater in monopolistic industries" (p. 731). The result of our analysis will later show that industries do indeed differ in their "tastes for discrimination." This taste is described 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 is caused by differences in qualifications. It is suggested that women might be 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 become more committed to their careers or change their personal relationships within the family to lessen their household burden. Such a theory is individualistic and attempts to explain a complicated phenomenon in an overly simplistic way, by putting the burden for change on individual women and not fully considering 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.

2. DESCRIPTION OF THE DATA

Data for the study are from a survey conducted by the Higher Education Research Institute (HERI) at the 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 recent decades (e.g., Smith and Ward 1984; Roman 1990), we believe this 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. There were 6,194 undeliverable questionnaires; from the rest the response rate was 40.4%. For the present study, only White respondents are included, which restricts our research to a homogeneous group. To use such a specific group is defensible by referring to literature on gender and race (e.g., Mulling 1986), which presents evidence that development in status is quite different for minority and White women. Discounting nonresponse and minority groups, the sample is reduced to 2,401 men and 2,840 women.

The people in our study had participated in the workforce for only a short period of time when filling out the questionnaire (the mean was a little over 2 years of employment). This information excludes one possible explanation of a gender income gap; namely, the interrupted career of women, because a substantial portion of female workers had not yet had a chance to enter the "mommy track." Among women, 46% were married but only 8% 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 had full-time employment. Also, the educational level was very similar: 83% of the respondents held a B.A. degree or higher.

The dependent variable, income, was self-reported. We have recoded the original 12 categories into 7 categories to get an approximately symmetric distribution. The main independent variable is, of course, gender. In addition, we have information about 9 covariates:

1. parental income, measured on the same scale as respondent's income
2. selectivity of college attended (mean SAT score in nine categories)
3. education (degree none, A.A., B.A., M.A., and up)
4. college grade point average
5. occupation (in seven categories, from unskilled to professional and administrative)
6. economic incentive (how important were the potential earnings in your selection of major: low, medium, or high)
7. hours per week worked in current job (less than 20 hours, 20-40 hours, more than 40 hours)
8. length of employment in current job (in years)
9. human capital (length of employment since college minus length of current employment, in years).

The industries in which the respondents are employed are also known. They are the following:

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 establishment (OBUS)
7. commerce, insurance, finance, or real estate (COM)
8. U.S. military service (MIL)
9. agriculture or mining (AG)
10. U.S. government and civilian employee (USG)
11. manufacturing or construction, and so on (MFG)
12. transportation or public transportation (TRNS).

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 the size of the gender income gap, human capital theory fails to provide a valid explanation for this difference between industries.

The high nonresponse rate for the second wave of respondents may cause some generalization problems. However, the bias caused by nonresponse is limited for our study because we compare income of females with income of males. We have no reason to expect that nonresponse bias is different for male respondents than for female respondents.

In Table 1 the raw data is summarized over 12 industries and obviously shows that women are unequally distributed over industries. The 3 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.

Thus women are overrepresented in industries with relatively low salaries. Clearly this type of discrimination is not direct but indirect, because 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 covariates mentioned above.

TABLE 1: Mean 1977 Income of Male and Female Respondents to HERI[a] 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	(2,401)	$9,753	(2,840)	$2,435

a. HERI = Higher Educational Research Institute at UCLA.

3. MODELS AND ESTIMATION METHODS

Varying or random coefficient models for analyzing hierarchically structured data have a long history in econometrics and are also known as error component models or variance decomposition models. The pre-1970 theoretical work is reviewed in Swamy (1971), and the substantial body of theory developed in the 1970s 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 the early work of Lindley and Smith [1972]), estimation 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. 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 programs differ in the way they calculate parameters and handle the data sets, but basically give similar answers (see Kreft, de Leeuw, and Kim 1990).

Within the general linear regression framework, we have two options for analyzing individuals within industries: (a) using fixed effect linear models, and (b) using random effects linear models. The difference between models is that fixed effect models are single-level models, with workers as the unit of analysis. The random effects 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 industry. First, we are interested in gender disparities in income; and second, in disparities in income and the gender income gap across industries. Research questions consist 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 microlevel observations and industries as macrolevel observations. There are three specifications for the effects:

1. Microeffects are the effects of individual background variables on income in a multiple regression analysis.
2. Macroeffect 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 analyses in each industry. (The intercept is defined as the mean income value for an industry after correction for background variables.)

3. The macrolevel may affect microvariables 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 12 industries, whereas we also distinguish between the effects for men and women. Our first analysis applies a fixed effect model within each industry. This type of model for the description of the gender income gap was first used and described in the econometric literature by Binder (1973) and Oaxaca (1973) and is advanced by Corcoran and Duncan (1979), Daymont and Andrisani (1984), and Goldin (1990). We will extend this technique by partitioning the residual variance of male and female income in within-industry and between-industry parts.

3.1. RESULTS WITH FIXED EFFECTS MODELS

The first results are obtained with a technique 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. Because 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,

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

Here $\underline{y}_j$ is a random vector with n_j observations on the dependent variable income, g_j is the dummy coding for gender, and the random vector $\underline{\varepsilon}_j$ contains disturbances, where X_j is the $n_j \times 9$ matrix of covariates. The α_j are the intercepts and the β_j are the slopes for the different industries. We follow de Leeuw and Kreft (1986) in underlining all random variables in the model, to distinguish them from fixed coefficients or fixed predictors.

For this model, the estimates of the γ_j are the gender-means for the corrected incomes $y_j - \hat{a}_j - X_j\hat{b}_j$, with $\hat{a}_j$ and $\hat{b}_j$ the least squares estimates of the slopes and intercepts. Another way of saying this is that $\hat{\gamma}_j$ estimates the effect of gender in industry j on the differences in income. The standardized 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 contains 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.

Although raw means (see Table 1) corroborate our observation that women in general earn less money than men, corrected means show that equally qualified men and women are still unequal in income, with this disparity greater in some industries than in others. Although not all differences in male-female income adjusted means are statistically significant over industries, the tendency is in favor of male income, with COL as the exception. The largest gender-income differential is found in RET, followed by OBUS and MFG. A tentative conclusion, based on Table 2, is that the majority of private sector industries shows significant differences, whereas public sector industries have less pronounced gender discrepancies.

In the 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 2. Separate models for separate industries suffers from two problems. In the first step, we neglect intracluster (industry) correlation, whereas we take parameters at face value in the second step without any correction for unreliability of within-industry-parameters estimates.

Next, we fit a single model to the data instead of 12 separate ones, to obtain more efficient estimates. The model is 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. Because we want to test if the gender income differential is the same over industries, we need a model that allows gender to have differential effects, while assuming that the other 9 predictors

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

NOTE: ED = elementary or secondary school; COL = college, university, technical institute, or professional school; RET = retail or wholesale; HW = human services organization; LOCG = local government; OBUS = other business or service establishment; COM = commerce, insurance, finance, or real estate; MIL = U.S. military service; AG = agriculture or mining; USG = U.S. government and civilian employee; MFG = manufacturing or construction, and so on; TRNS = transportation or public transportation.

have the same effects across industries. In Binder (1973), we find support for this last assumption. By creating 12 dummy variables for industries and letting them interact with gender, we tested if industries make a difference. The results are in Table 3.

Table 3 shows estimates for the effects of independent variables and estimates for interaction between gender and industry. A male coefficient minus a 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 HW, and for COL. Large differences are again found in the private sector industries: RET, OBUS, and COM.

So far, both analyses yield compatible results. Both are based on the fixed effect linear model. Our next analysis fits a random effects model, which shares a feature with the previous model in that it is parsimonious. It does not assume independence of errors for different individuals in the same industry. The correlation between those errors is called the intraclass correlation. The random effects model also offers more modeling possibilities than the fixed model, which uses dummies to code interactions.

TABLE 3: Coefficients for a Fixed Model With 24 Dummies for the Interaction Between Gender and Industries

Variables	*Estimates*	*Standard Errors*
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 24 dummy variables over industries and gender are

Industries[a]	*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

a. See Table 2 for definitions.

3.2. RANDOM COEFFICIENT MODELS

The two fixed effect 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 technique stays conceptually very close to the technique proposed by Oaxaca (1973). A multiple regression analysis is performed within each context or industry separately, but the effect of industries is estimated simultaneously. 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

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

The random variables $\underline{\varepsilon}_j$ are the individual error terms, $\underline{c}_j$ is the random coefficient for gender differences in industry j, and $\underline{a}_j$ is the random intercept of that industry. 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 δ_j and η_j. If we substitute equations (3) and (4) in (2) we obtain the mixed linear model

$$\underline{y}_j = (\alpha + \underline{\delta}_j) + g_j(\gamma + \eta_j) + X_j\beta + \underline{\varepsilon}_j. \tag{5}$$

Rearranging random and fixed parts yields equation (6),

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

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 regression coefficients differ significantly from zero 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, the previously introduced nine predictors assumed to behave the same across industries. Some fixed effect variables are education, GPA, incentives, parental income, and others. 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 rather than a fixed model is based on our knowledge of the way the data are constructed. We assume an intraclass or intraindustry correlation. Intraindustry correlation is a measure of how much the observations within the same industry are replications of each other. A zero correlation means, because we assume normally distributed errors, that the observations are independent. In situations where this correlation is nonzero, the random model is more appropriate. In our data, the intraclass correlation for women within the same industry is $r = .108$, the intraindustry correlation for men is $r = .110$, and between men and women in the same industry, $r = .091$. Because our data set contains large numbers of observations within industries, these correlations are significant and too large to be ignored (see Cochran 1977; Hsiao 1986).

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, whereas 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 24 different interaction variables as we do in the last analysis. Results are reported in Tables 4 and 5.

TABLE 4: Random and Fixed Coefficients for the Multilevel Model

	Fixed Effects Estimates	
Variables	*Estimates*	*Standard Errors*
Intercept	–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	
Variables	*Sigma*	*Standard Errors*
Intercept	1.202	0.235
Gender	1.015	0.220

Table 4 shows the estimates of the fixed and the random effects of the multilevel regression. The fixed-effect coefficients are all significant at the $p = .05$ level because they are larger than two times their respective standard errors. The fixed effect part of our model, the coefficients of the variables parental income through human capital 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 an overall and a specific way. The overall effect indicates that industries differ in overall payment, as is shown in the significant variance for the intercepts. The specific effect, the differences in the way gender affects income, shows in the significant variance for the slope of gender on income across industries. Because gender is coded as 1 for males and 2 for females, a negative sign for gender indicates that females have lower income for that industry.

The difference between the analyses reported in Table 3 and Table 4 are in the estimates for the interaction between industries and gender.

TABLE 5: Separate Equations for 12 Industries Based on a Random Effects Model

Industry[a]	*Equation per Industry*	*Total Effects*	
		Males	*Females*
ED	Y = –5.04 – 0.71 g	–5.74	–6.45
COL	Y = –4.60 + 0.30 g	–4.31	–4.01
HW	Y = –3.47 – 0.14 g	–3.61	–3.75
MIL	Y = –3.31 – 1.37 g	–4.68	–6.05
RET	Y = –2.93 – 3.42 g	–6.35	–9.77
LOCG	Y = –2.86 – 1.31 g	–4.17	–5.48
OBUS	Y = –2.52 – 2.01 g	–4.53	–6.54
COM	Y = –2.71 – 2.02 g	–4.73	–6.75
AG	Y = –2.71 – 1.70 g	–4.41	–6.11
USG	Y = –1.53 – 1.33 g	–2.86	–4.19
MFG	Y = –1.45 – 1.84 g	–3.29	–5.13
TRNS	Y = –0.72 – 1.99 g	–2.71	–4.70

a. See Table 2 for definitions.

These coefficients are not readily available from Table 4. To compare estimates, we have to compute posterior means of the random intercepts and gender slopes. This means we estimate the $\underline{a}_j$ and $\underline{c}_j$ from equations (3) and (4), which take both the fixed components α and γ and the random disturbances δ_j and η_j into account. These posterior means are used in Table 5 to construct regression equations of income on gender for all industries. The higher the intercept for an industry, the higher the overall mean income, whereas 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 effect model estimates in Table 3, we constructed the last two columns in Table 5. They are computed by substituting $g = 1$ for males and $g = 2$ for females.

The estimates for the interaction of gender and industry over the two analysis models are not exactly the same (see also Table 6 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 because they score in the highest four places in both analyses, whereas the reverse is true for the public sector industries, ED, HW, and COL, which occupy the lowest four places of the gender income differential scale.

TABLE 6: The Ranking of Industries According to the Male-Female Income Differential[a]

Fixed Model Table 2 z-Score Differences		*Fixed Model Table 3 Regression Coefficients*		*Random Model Tables 4 and 5 Posterior Means*	
RET	2.87	RET	3.73	RET	3.42
COM	1.51	OBUS	2.05	COM	2.02
AG	1.48	COM	2.04	OBUS	2.01
OBUS	1.45	AG	1.92	TRNS	1.99
MFG	1.27	MFG	1.80	MFG	1.84
LOCG	1.06	TRNS	1.72	AG	1.70
MIL	0.74	MIL	1.70	MIL	1.37
TRNS	0.72	LOCG	1.24	USG	1.33
ED	0.62	USG	1.10	LOCG	1.31
USG	0.30	ED	0.66	ED	0.71
HW	0.11	HW	–0.04	HW	0.14
COL	–1.09	COL	–0.55	COL	–0.30

a. See Table 2 for definitions.

3.3. RANKING OF INDUSTRIES

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 criteria, 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 5, the industries are ranked in that order. In Table 6, 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.

The first column in Table 6 shows a ranking based on the separate equations for separate industries models (see Table 2). The mean residual for men and women is calculated separately and transferred in a z-score. After subtracting 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 are mainly found in the middle ranks.

The ranking of industries in Table 6 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 1,471 women are present, whereas 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, whereas they are severely underrepresented in high-salary jobs such as transportation and construction. But, job segregation does not provide a complete explanation for the income differential because industries that have the highest income gap, RET, COM, and OBUS, have almost equal numbers of male and female employees, 865 men versus 870 women (see Table 1).

4. SUMMARY AND DISCUSSION

In this article, 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 framework 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 incomes 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 6, 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 of which coefficients are allowed to be different across industries. This flexibility is not present in the first fixed-effect model presented in this article, 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, whereas 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 parsimony of the random-coefficient model, we use Goldin's (1990, p. 84) hypothesis 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), to the random-coefficient model, which 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. Therefore we did not report the results in this article.

Our analysis supports the fact that women, more than men, choose to work in lower paying industries. Women are underrepresented in the highest paying industries and overrepresented 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. Because 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 us 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 or 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. Third, industries differ substantially in the amount of gender income discrepancies, making void arguments addressing the income gap to supposed weaker female qualities.

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 might be one reason for the gender income gap in these industries. Further study is needed here.

Human capital theorists might 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) that "young women's ante-labor market plans are significantly related to their post-school accumulation of human capital" (p. 351) is not present in our data because 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 2 and 3 years and not many of the respondents changed jobs or had interrupted careers.

This does not exclude employers' expectations of 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 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* ("Fascinating Facts" 1991), is that the traditional American family unit—a married couple with one or more children—was found in only 26% of the American households last year, whereas this was 40% in 1970. Many questions are yet to be answered. First, do the higher earnings of men, in a traditional labor market, capture the skills that make a man more valuable than a woman? And second, can a society where there is a growing number of female-headed households afford to underpay female employees?

NOTE

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 article, following the convention set by de Leeuw and Kreft (1986).

REFERENCES

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

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

Binder, A. S. 1973. "Wage Discrimination: Reduced Form and Structural Estimates." *Journal of Human Resources* 8(4):436-55.

Blau, F. D. and W. E. Hendricks. 1979. "Occupational Segregation by Sex: Trends and Prospects." *Journal of Human Resources* 14(2):197-21.

Bryk, A. S., S. W. Raudenbush, M. Seltzer, and R. T. Congdon 1988. *An Introduction to HLM: Computer Program and User's Guide.* Chicago: University of Chicago.

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

Chow, G. C. 1984. Random and Changing Coefficient Models. In *Handbook of Econometrics*. Vol. 2, edited by Z. Griliches and M. D. Intriligator. Amsterdam, The Netherlands: North Holland.

Cochran, W. G. 1977. *Sampling Techniques*. New York: Wiley.

Corcoran, M. and G. J. Duncan. 1979. "Work History, Labor Force Attachment, and Earnings Differences Between the Races and Sexes." *Journal of Human Resources* 14(1):3-19.

Daymont, T. N. and P. J. Andrisani. 1984. "Job Preferences, College Major, and the Gender Gap in Earnings." *Journal of Human Resources* 19(3):408-28.

de Leeuw, J. and I.G.G. Kreft. 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, P. 1982. "The Failure of Human Capital Theory to Explain Occupational Sex Segregation." *Journal of Human Resources* 17(3):358-70.

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

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

Flanagan, R. J. 1973. "Racial Wage Discrimination and Employment Segregation." *Journal of Human Resources* 8(4):456-70.

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

Goldstein, H. 1986. *Multi-Level Models in Educational and Social Research*. London: Griffin.

Hewlett, S. A. 1986. *A Lesser Life*. New York: William Morrow.

Hsiao, C. 1986. *Analysis of Panel Data*. Cambridge: Cambridge University Press.

Kreft, I.G.G., J. de Leeuw, and K. S. Kim. 1990. *Comparing Four Different Statistical Packages for Hierarchical Linear Regression, GENMOD, HLM, ML2 and VARCL*. (CSE Technical Report 311). Los Angeles: University of California, Center for Research on Evaluation, Standards and Student Testing.

Lindley, D. V. and A.F.M. Smith. 1972. "Bayes Estimates for the Linear Model." *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, United Kingdom.

Marshall, R. F. 1974. "The Economics of Racial Discrimination: A Survey." *Journal of Economic Literature* 12:849-71.

Mason, W. M., G. Y. Wong, and B. Entwisle. 1984. "Contextual Analysis Through the Multilevel Linear Model." *Sociological Methodology* 72-103.

Montmarquette, C. and S. Mahseredjian. 1989. "Does School Matter for Educational Achievement? A Two-Way Nested Error Components Analysis." *Journal of Applied Econometrics* 4:181-93.

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*, edited by E. Leacock, H. I. Safa, and Contributors. South Hadley, UK: Bergin and Garvey.

Oaxaca, R. 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.

Roman, M. 1990. "Women, Beware: An MBA Doesn't Mean Equal Pay." *Business Week*, 10-29.

Sandell, S. H. and D. Shapiro. 1980. "Work Expectations, Human Capital Accumulation, and the Wages of Young Women." *Journal of Human Resources* 15:335-53.

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

Swamy, P.A.V.B. 1971. *Statistical Inference in Random Coefficients Regression Models*. New York: Springer-Verlag.

Zucker, L. G., K. Yip, and M. Kalmijn. 1990. *Explaining Process and Outcome of Collective Action: Multilevel Effects of Industrial Context and Strike Characteristics in the 1880's*. Los Angeles: University of California, Institute of Industrial Relations.

———. 1991. *Institution Building by Workers in the 1880's: Multilevel Effects of Industrial Regional Context and Strike Characteristics on the Founding of Knights of Labor Local*. Los Angeles: University of California, Institute of Industrial Relations.

Ita G. G. Kreft is an associate professor at the School of Education, California State University, Los Angeles. Her research interests are the teaching of statistics and multilevel analysis. She has published in Sociology of Education, Sociological Methods & Research, *and the* Journal of Educational Statistics.

Jan de Leeuw is a professor of mathematics and psychology at the University of California, Los Angeles and the director of the Interdivisional Program in Statistics. His research interests are multivariate analysis, multidimensional scaling, and multilevel analysis. He is the editor of the Journal of Educational Statistics.