DOCUMENT RESUME

ED 119 078 CG 010 387

AUTHOR	Staines, Graham; And Others
TITLE	Alternative Strategies for Measuring Sex Discrimination in Occupations.
PUB DATE	[72]
NOTE	29p.
EDRS PRICE	MF-$0.83 HC-$2.06 Plus Postage
DESCRIPTORS	*Demography; Income; Job Satisfaction; Job Tenure; Models; Multiple Regression Analysis; *Occupations; Predictor Variables; Research Projects; *Sex Discrimination; *Statistical Analysis; *Working Women

ABSTRACT

Using data originally report by others, this paper focuses on the relative merits of three separate statistical approaches to measuring occupational sex discrimination. The sample was a national probability sample of 539 women and 993 men. Demographic factors such as race, sex and age, education, job tenure and supervisory status served as the predictor variables; annual income objective and perceived discrimination and various measures of job satisfaction were the dependent variables. Three statistical approaches were used to analyze the data; 1) multiple regression; 2) automatic interaction detector (AID) and 3) multiple classification analysis (MCA) determining the power of sex as a predictor of income. Method two accounted for a higher percentage of the variance in income than the first approach, showing a greater occupational discrimination based on sex. The third method accounted for 47% of the variance in income, somewhat lower compared to the other two approaches. The results indicate that sex is the third most important predictor variable of income after occupation and education; moreover women were found to receive lower salaries than men for the same kind of jobs. (SE)

ALTERNATIVE STRATEGIES FOR MEASURING SEX DISCRIMINATION IN OCCUPATIONS

Graham Staines, Sandra Bouxsein, Amos Bradford, and Laura Klem

Survey Research Center

The University of Michigan

Beginning around 1968, a voluminous literature has appeared on the subject of occupational sex discrimination (e.g., Cohen, 1971; La Sorte, 1971; Martin & Poston, 1972; Martin, 1972). Spanning a wide range of approaches and varying levels of methodological sophistication, these research efforts have sought to document sex differences in incomes and frequently to interpret such income differentials, at least partially, in terms of sex discrimination. Discrepancies between the incomes of working men and women are not solely attributable to discrimination, however, and cautious investigators assess the extent to which other, non-discriminatory factors--defended as legitimate on ideological grounds--make a significant contribution to the income differential. We trust that this caution is exercised here.

This paper, then, attempts to compare and evaluate several alternative strategies for detecting and measuring occupational sex discrimination. The paper involves a reanalysis of data originally reported by Levitin, Quinn and Staines (1971). Using their data, the present paper focuses on the relative merits of three separate approaches to measuring occupational sex discrimination.

(1) First is the method used by Levitin et al. In that analysis, six variables were selected as legitimate predictors of a worker's income on the basis of the prevailing achievement ideology which

justifies the allocation of rewards in terms of a person's merit or performance. The six variables chosen were worker's education, amount of supervisory responsibility, tenure with present employer, tenure on present job with employer, number of hours worked per week and occupational prestige as measured by the Duncan scale (Reiss, *et al.*, 1961). Conventional multiple regression was then used to develop, on a random half of the male subsample, an equation for predicting incomes from scores on the six legitimate predictors. The weights for the predictors in the regression equation were assumed to be the best estimates of how occupational rewards are distributed according to the achievement ideology among a population--namely men--who experience no sex discrimination. On the basis of this same regression equation, the incomes of women were predicted in accordance with their scores on the legitimate predictors. The discrepancies between the predicted incomes for women (that is, the incomes they merited in terms of their qualifications) and the actual incomes that these working women were paid indicated the magnitude of the occupational sex discrimination they encountered.

(2) A second method for measuring occupational sex discrimination departs only slightly from the first. Since conventional multiple regression requires the restrictive assumptions of linearity and additivity, it raises the possibility that the multiple R squared represent~~ed~~s an underestimation of the amount of variance in income scores that is accounted for by the legitimate predictors. An effective way to avoid these two assumptions is provided by the combination of two statistical procedures: Automatic Interaction Detector (AID) and Multiple Classification Analysis (MCA). AID detects interactions and then facilitates the construction of pattern variables that represent the interactions.

MCA incorporates these pattern or interaction variables and, in addition, has the capacity to detect curvilinear relationships. Thus the combined AID-MCA strategy handles both non-additive and non-linear relationships and, when substituted for the conventional multiple regression used in the first method, provides a more powerful equation (i.e., higher R squared) for predicting incomes on the basis of scores on the legitimate predictors.

(3) The third method, the examination of sex as a predictor of income, represents a sharp departure from the previous two approaches. The whole sample is used to develop a statistical model for predicting annual income. The set of predictors include the six legitimate variables, sex, and a range of major demographic variables such as race and age. The AID-MCA package once again determines how the predictors may be combined to provide the best predictions of annual income. According to the basic idea behind this third method, sex discrimination on the job is present to the extent that sex is a powerful predictor of income, especially when the other predictor variables are held constant.

Method

Sample

The sample was a national probability sample of persons who were living in households, were sixteen years old or older, and were working for pay twenty hours a week or more. Data were obtained through personal interviews with all eligible workers in a household. Since each worker therefore had an equal probability of being selected, the data were self-weighting. The full sample included 539 women and 993 men. A comparison between the demographic and occupational characteristics of the sample and those of larger-scale government surveys is presented in Quinn et al. (1971, 25-28).

The analysis reported below excluded three groups of workers: self-employed workers; part-time workers, defined for the first method as those working 35 hours a week or less and, for the second and third methods, as those working less than 35 hours a week; and workers who were seasonally or otherwise irregularly employed during the year. School teachers were not regarded as seasonally employed. After these exclusions, the remaining sample consisted of 351 women and 695 men for the first method and 384 women and 720 men for both the second and third. For some analyses with the first method, the sample of men was further randomly divided into two half samples.

Measures

(1) Predictors. The predictor variables, listed in Table 1, represent both demographic variables such as race, sex and age, and variables that define a worker's position on the job such as supervisory status and job tenure.

(2) Annual income. Total annual income from the worker's primary job before taxes or other deductions. (Where a worker held more than one job all questions in the interview were asked with reference to the job on which the worker spent the greatest number of hours.)

(3) Objective discrimination. Objective sex discrimination was defined operationally as the difference between the income each woman was receiving and the amount she would be expected to receive on the basis of achievement factors alone.

(4) Perceived discrimination. Each woman was asked, "Do you feel in any way discriminated against on your job because you are a woman?"

(5) Job satisfaction. Several measures of job satisfaction were used to measure the possible effects of objective sex discrimination upon the job-related attitudes of women. These measures were: (a) satisfaction with the comfort aspects of the job (convenient hours, pleasant physical surroundings, and demands that were neither heavy nor conflicting); (b) satisfaction with the challenge provided by the job (opportunity to do interesting, challenging, and self-developing work); (c) satisfaction with financial rewards (pay, fringe benefits, and job security); (d) satisfaction with co-workers; and (e) satisfaction with resources for doing the job (equipment, information, clear assignments, and competent supervision). Also employed in the analyses were two measures of general job satisfaction: for method 1, an index of overall job satisfaction which included all the 23 items from the five indices cited above; and for method 2, an index of general job satisfaction based on these 23 items plus several general or content-free measures of job satisfaction.

Procedure

(1) Method 1. As described in the report of Levitin et al., the first method used conventional multiple regression upon half the male subsample to build an equation for predicting income. The independent variables were education, occupational prestige, working week hours, supervisory status, employer tenure, and job tenure. The incomes for women were then predicted from this equation and residual scores for

women created by subtracting the predicted income from the actual income. The mean and distribution of the residuals were determined. The residual scores were first compared for different values on the main occupational and demographic variables and then correlated with the measure of perceived discrimination and the various indices of job satisfaction. In addition, MCA was used to determine how effectively the occupational variables could predict the residual scores for women.

(2) Method 2. The second method paralleled the first in many respects but departed from the original procedure at several important points. The combined AID-MCA procedure was substituted for multiple regression in the building, on the whole male subsamples, of an equation to predict income and in the generation of residual income scores for the women. The set of predictor variables was identical to the one used in method 1. Instead of a linear regression equation, the result of the AID-MCA program was a more powerful predictive equation.

Used in the combination suggested by Sonquist (1970), AID and MCA offer a powerful methodology. Taken together, the two computer programs enable the identification of useful predictors and measurement of individual and collective relationships of these predictors to a criterion variable.

(a) AID. The AID program examines the associations between predictors and a criterion variable in an attempt to determine the dichotomous split, on any predictor, which will yield the greatest reduction of variance in the criterion scores. Once AID has made this initial dichotomy, it examines each of the two new groups to determine the group, the predictor, and the split point which account for the largest variation in the criterion scores. AID makes the best split and then examines each of the existing groups to find the best dichotomization at still a third level, and a fourth, and a fifth, and so on. With this breakdown of the sample through such successive AID dichotomizations, the analysis comes to resemble a tree with one trunk, two major limbs, and increasing numbers of branches as one nears the tips of the tree. The tree configuration makes it possible to detect interaction effects by noting different relationships between predictors and criterion appearing in groups on different forks of the same branch (i.e., groups of workers already dichotomized in earlier steps of the AID analysis). If interactions are identified through AID, new predictor variables are constructed which incorporate both the main effects and the interactions of the original variables. The AID algorithm, moreover, can handle non-linear as well as non-additive relationships in the data.

(b) MCA. The MCA program is able to take advantage of the findings from AID. MCA resembles a multiple regression using dummy variables, with a criterion score which consists of the sum of a series of main effects. These main effects are coefficients associated with membership in a particular response category of each predictor. The program thus handles curvilinear relationships since the distribution of coefficients may be curvilinear for any particular predictor. MCA is limited, however, by the assumption that the effects of the predictor variables on the criterion are strictly additive. That is, it assumes that there are no interactions among the predictors. Yet the AID findings concerning interaction may be applied to the MCA procedure. The interaction terms (or pattern variables) developed with AID may be included in the roster of additive components that are used in the final MCA analysis, in which case the original predictors on which the interaction terms were based must be excluded from the MCA analysis. If, on the other hand, no substantial interactions are identified, no interaction terms are constructed for the MCA analysis and the MCA may proceed under the assumption that the relationships in the data between the predictors and the criterion are strictly additive.

(c) AID-MCA combination. Clearly, the joint use of AID and MCA obtains the advantages of both while compensating for weaknesses in the other. The resulting model permits curvilinear relations on the basis of the MCA and non-additive or interactive relations on the basis of the AID, with the result that the model is more powerful than analogous methodologies such as conventional multiple regression which requires restrictive assumptions regarding linearity and additivity.

Although methods 1 and 2 employ different procedures for generating residual incomes scores for women, the subsequent search for correlates of the residuals followed almost identical paths for the two methods. Certain slight variations in procedure were permitted and these are noted in a later section.

(3) Method 3. The third approach to studying occupational sex discrimination bears little resemblance to the previous two. The main idea is simply to determine the power of sex as a predictor of income in comparison to legitimate predictors and other non-legitimate predictors. The sample used contains both men and women. The predictors, listed in Table 1, include major demographic and occupational variables. The AID-MCA strategy was again employed to build the statistical model for predicting income.

Results

(1) Method 1. The details of the multiple regression procedure are presented in Table 2. For the first random half-sample of men, multiple R = 0.55 (unadjusted) and 0.53 (adjusted). The highest beta weights belong to education (beta equals 0.28) and occupation (beta equals 0.20).

The mean of the observed minus expected discrepancy in total annual income for women was -$3,459 (SD = $2,200; n = 323). The distribution of these residuals appears graphically in Figure 1. The figure indicates that 50.3% of the women in this sample had total annual income discrepancies ranging from -$3,000 through -$5,999; and the mean annual income of 94.9% of the women was less than the amount they should have received on the basis of the achievement criteria.

The income discrepancies were not expected to be distributed equally throughout the population of working women. To determine the demographic and occupational distributions of reward inequalities, the sample of women was divided into (a) those with total annual income discrepancies that were positive (i.e., indicative of favoritism), zero, or had negative values ranging between -$1 through -$3,499 and (b) those with discrepancies of -$3,500 or more. The percentages of women in the latter higher income discrepancy category are presented in Table 3A for selected demographic and occupational classifications.

Table 3A reveals, for the demographic variables, a nonsignificant tendency for white women to have higher discrepancy scores than black women. The association between age and discrepancy scores was curvilinear, with both the youngest (16-29 years old) and oldest

(55 years old or older) women being more likely than women of other ages to have high discrepancy scores.

Among occupations, discrimination as reflected in the income differentials was greatest among white collar workers; those employed in professional, technical, managerial, clerical, and sales work; those in trade, service, finance, insurance, and real estate; those who did not belong to a union; and those in comparatively small establishments (i.e., where less than 500 employees worked). In view of the obvious correlations among the five occupational variables, MCA was used to determine which of the variables were more closely related to the income discrepancies when the effects of the other variables were removed. The multiple R between the five occupational predictors and the income discrepancies was .52 (adjusted). The beta weights of the five predictors were .53 for major occupational group, .24 for major industry group, .19 for size of place of employment, .15 for union membership, and .12 for collar color. The form of the relationship between each predictor and the adjusted mean discrepancies did not differ from the first-order relationships as suggested in Table 3A.

Few other variables were correlated significantly with the residual scores. While most women experienced objective discrimination as indicated by their residual scores, only 7.9% reported differential treatment when asked, "Do you feel in any way discriminated against on your job because you are a woman?" Furthermore, perceived sex discrimination was not significantly associated with the discrepancy scores. Thus objective discrimination was measured by method 1 is unrelated to perceived discrimination. Table 4 shows the correlations between objective discrimination and attraction to the job as reflected in several job satisfaction measures. Women who were most economically discriminated against were significantly more likely than others to be dissatisfied with the financial aspects of their jobs. Otherwise, there was no significant association between objective discrimination and job satisfaction.

(2) Method 2. Since the results for methods 1 and 2 were quite similar, only the slight differences in their findings need be emphasized. Table 2 presents the results of the AID-MCA procedure when it was applied to the whole male subsample with income as the dependent variable. Multiple R (adjusted) for the MCA was 0.57 compared to 0.53 (adjusted) for the regression multiple R. Both multiple regression and AID-MCA computed beta weights for each of the six legitimate predictors. Though the overall pattern was similar, the AID-MCA betas were generally larger and one predictor--job tenure--which proved useless in the regression equation (beta was 0.01) was the fifth most important predictor (beta was 0.11).

Methods 1 and 2 generated similar findings when the residuals were designated as the dependent variable. With method 2, the mean discrepancy was -$3,416 (SD = $2,230; n = 352) compared to -$3,459 for method 1--a difference of $43. The distribution of residuals for method 2 appears in Figure 1 and closely resembles the original distribution for method 1.

As presented in Table 3B, the demographic and occupational distributions of the residuals for method 2 again followed the pattern of method 1. Two additional illegitimate variables thought to affect women's earnings--marital status and number of children--were added to the list of demographic variables for method 2. Although the differences were not statistically significant, single women appeared to suffer more economic discrimination than women in other marital categories; and women who were the major source of support for one or more children tended to experience more discrimination than women who did not have to support children.

With method 2, the correlations between objective discrimination on the one hand and measures of perceived discrimination and job satisfaction on the other were again non-significant except for a low correlation ($r = 0.20$, $p < 0.01$) between residual scores and dissatisfaction with financial aspects of the job.

(3) Method 3. The statistical model based on AID-MCA and designed to predict the incomes of men and women accounted for almost half the variance of income. Multiple R^2 was 0.47 ($p < 0.01$) when adjusted to correct for capitalization on chance in fitting the model. Full details on the MCA including multiple R appear in Table 5. The model involved only additive relations since AID detected no interactions; yet the MCA did take curvilinear relationships into account.

Sex proved to be an important predictor of income. Table 6 shows that being male adds a coefficient of $976 to the sample mean; being female subtracts $1,847 from that mean. According to both measures of the importance of predictors--eta squared and beta squared--sex is the third most important variable in a list of fifteen variables. In both cases only occupation and education surpass sex in predictive power. Full details of the eta-coefficients which show how single independent variables relate to income, and the beta-coefficients, with their built-in adjustment for multi-collinearity, are presented in Table 7.

Discussion

(1) and (2). Methods 1 and 2. Whereas method 3 represents a wholly different approach, the findings of methods 1 and 2 bear direct comparison. There were several minor ways in which the procedures for methods 1 and 2 were not strictly comparable. Although these variations were not thought to have any substantive impact, they should be noted at the outset:

(a) Method 1 excluded as part time employees those workers who worked 35 hours per week. Method 2 (and method 3) included these workers in the sample for analysis. Methods 1 and 2 were therefore applied to slightly different samples: method 1 (695 men, 351 women), methods 2 and 3 (720 men, 384 women).

(b) For method 1, the general measure of job satisfaction was an index based on 23 items about specific components of the job. With method 2, the general measure was a combination of this 23 item index plus several content-free questions designed to measure overall job satisfaction.

(c) With method 1, the regression equation was developed on a random half-sample of the men. The remaining half-sample was thereby made available for cross-validation. For method 2, this additional step was not taken and the equation generated by AID-MCA was based on the full male subsample.

The major difference between methods 1 and 2 lay in the power of the analytical techniques used. Method 1 used conventional multiple regression on (half) the male subsample to build an equation for predicting income. Method 2 used the AID-MCA strategy. To the extent that the legitimate predictors were related to the income scores for men by curvilinear and interactive (or non-additive) relationships, AID-MCA was able to create a more powerful predictive equation. In this instance, however, AID failed to detect any interactions and hence the assumption of additivity that is required for conventional multiple regression proved to be unobjectionable. MCA, nevertheless, did detect curvilinear relationships and thus R^2 for MCA (0.57, adjusted) exceeded the R^2 for conventional multiple regression (0.53, adjusted), a technique that is predicted upon the assumption of linearity. Since MCA detected a more powerful relationship between the legitimate predictors and income, it could attribute more of the variance of income to legitimate factors. Specifically, when MCA is compared to multiple regression it attributes more of the gap between male and female incomes to legitimate factors. It thus produces a lower estimate of objective discrimination. But perhaps what is most striking about the comparison between multiple regression and AID-MCA is how little the more sophisticated strategy modifies the original findings. The assumption of additivity entails no loss in predictive power; and the assumption of curvilinearity alters the estimate of (average) annual discrimination against working women by only $43.

Method 2 clearly provides a more accurate estimate of objective job discrimination than method 1--but how accurate, in absolute terms, is method 2? In all likelihood, method 2 exaggerates, at least to a small degree, the amount of objective discrimination experienced by working women. It may be argued, that is, that the method fails to detect all the variance of income that the six selected (legitimate) variables can explain. Ideally the prevailing achievement ideology would be best represented by direct measures of employee performance, both the quality and quantity of work completed. Yet it has not yet been feasible to devise for use in surveys either direct measures of performance or direct measures of an individual's abilities and skills. In the absence of complete and direct measures of the achievement ideology, less direct measures such as education and experience were substituted. In consequence, the association between legitimate predictors and income was probably underestimated; and thus the estimate of objective sex discrimination based on the residuals was undoubtedly too high but not, it would seem, by very much.

(3) Method 3. Several general properties of the statistical model developed are critical to understanding its implications for sex discrimination.

(a) The model accounts for roughly half the variance of income--49.8% (unadjusted) and 46.9% (adjusted). The remaining variance must be attributed to factors outside the model including, possibly, performance on the job (very difficult to compare across occupations), geographical region of the country and dwelling area (urban versus suburban versus rural).

(b) The statistical power of the model was enhanced by its capacity to incorporate both non-additive and non-linear relationships between the predictors of income. The AID program detected no interactions, however, and the non-additive feature of the model was not required. But the MCA program did detect non-linear relationships between income, the criterion variable, and various predictors--whether ordinal variables such as age or nominal variables such as occupation and industry.

(c) Importance of predictors is not a simple notion and, for method 3, two separate measures of importance were employed. First was the eta coefficient, a correlation ratio computed instead of the product moment correlation when curvilinearity is anticipated in the data. When squared, eta indicated the proportion of income variance accounted for by the predictors considered singly, with no adjustments made for the concurrent effects of other predictors. Eta therefore represented only the first order correlation between the criterion and each of the predictors considered separately. Second was the beta coefficient which, when squared, indicated the relative importance of each predictor with the effects of other predictors held constant. Computation of betas incorporated an adjustment for the extent to which any one predictor was correlated with another. The eta and beta coefficients, the former always larger than the latter if interdependence among predictors exists, thus provided different but complementary information. Table 7 presents the eta and beta coefficients for each predictor and indicates the rank of each predictor in terms of its eta or beta, low numbered rank (e.g., 1) representing a large eta or beta.

The finding that sex is an important predictor of income suggests the widespread presence of occupational sex discrimination. In both the eta squared and beta squared rank orderings, sex is the third most important predictor of income, surpassed only by occupation and education. Of the 49.8% (unadjusted) of the variance accounted for, sex explains 16% when examined on its own; when other predictors are held constant, the best estimate of the variance sex accounts for is beta squared or 7%. While it demonstrates that sex, an illegitimate predictor, determines in large degree the income a person earns, method 3 offers no precise estimate of the amount of sex discrimination experienced by any one woman or even any group of women. Although the conclusions of method 3 lack the neatness and convenience of the findings from methods 1 and 2, the results of all three methods suggest that American working women experience widespread and sizeable sex discrimination.

Conclusion

Whatever the analytical method used, occupational sex discrimination is pervasive in the USA. According to method 1 which assumed that the relationships between achievement factors and annual income were linear and additive, the average American working woman receives $3,459 less than a comparably qualified man. Method 2 permitted these relationships to be non-linear and non-additive but the estimate of discrimination dropped only $43 to $3,416. Method 3 established that, after occupation and education, sex is the most powerful predictor of annual income.

References

Andrews, F. M., Morgan, J. N., & Sonquist, J. A. The multiple classification analysis program. Ann Arbor, Mich.: Institute for Social Research, 1967.

Barnowe, T. J., Mangione, T. W., & Quinn, R. P. An empirically derived model of job satisfaction. Ann Arbor, Mich.: Survey Research Center, 1972 (unpublished manuscript).

Cohen, M. S. Sex differences in compensation. Journal of Human Resources, 1971, 6, 434-447.

La Sorte, M. A. Sex differences in salary among academic sociology teachers. American Sociologist, 1971, 6, 304-307.

Levitin, T., Quinn, R. P., & Staines, G. L. Sex discrimination against the American Working Woman. American Behavioral Scientist, 1971, 15, 237-254.

Martin, C. R. Support for women's lib: Management performance. Southern Journal of Business, 1972, 7, 17-28.

Martin, W. T. & Poston, D. L. The occupational composition of white females: Sexism, racism and occupational differentiation. ~~So~~ Social Forces, 1972, 50, 349-355.

Quinn, R. P., Seashore, S., Mangione, T., Campbell, D., Staines, G. L., & McCullough, M. Survey of Working Conditions. Washington, D.C.: Government Printing Office, 1971.

Reiss, A. J., Jr., Duncan, O. D., Hatt, P. K., and North, C. C. Occupations and Social Status. New York: Free Press, 1961.

Sonquist, J. A. Multivariate model building: The validation of a search strategy. Ann Arbor, Mich.: Institute for Social Research, 1970.

Sonquist, J. A., Baker, E. L., & Morgan, J. M. Searching for structure. Ann Arbor, Mich.: Institute for Social Research, 1971.

TABLE 1

LIST OF PREDICTORS

1. Education--(What is the worker's education level?)

2. Occupational Status--(What is the occupational status of the worker's job as measured by the Duncan Decile Scale?)

3. Working Week Hours--(Total number of hours worked per week on primary job)

4. Supervisory Status--(Does worker supervise anyone?)

5. Employee Tenure--(How long worker has been with present employer?)

6. Job Tenure--(How long has worker been on present job?)

7. Race--(Is worker white or black?)

8. Age

9. White Collar-Blue Collar--(Is the worker a white-collar employee or blue-collar employee?)

10. Census Occupation Classification Code--(Taken from the 1960 Census of Population Alphabetical Index of Occupations and Industries --A gross division of workers by occupational group)

11. SIC Industry Divisions--(A gross division of workers by industry)

12. Union Membership--(Does worker belong to a union?)

13. Marital Status

14. Number of children major support--(For what number of children is the worker the major source of support?)

15. Sex

TABLE 2

BETA-WEIGHTS OF SIX PREDICTORS

	Education	Occupational Prestige	Working Week	Supervisory	Employer Tenure	Job Tenure	N	Multiple R[a]
Method 1	.28	.20	.18	.11	.09	.01	326	.53 (adj.)
Method 2	.38	.14	.20	.09	.22	.11	666	.57 (adj.)

[a]The multiple R in the Levitin et al. article was unadjusted; it has been adjusted for comparison with the AID-MCA multiple R.

TABLE 3A

PERCENTAGE OF WOMEN IN SELECTED DEMOGRAPHIC AND OCCUPATIONAL CATEGORIES WITH TOTAL ANNUAL INCOME DISCREPANCIES OF -$3,500 OR MORE (METHOD 1)

Demographic or Occupational Category	Percentage	Base n	df	X^2	Significance
Race					
White	52.6	279			
Black	39.4	38	1	1.838	N.S.
Age					
16-29 years old	58.4	120			
30-44 years old	42.1	95			
45-54 years old	49.2	63			
55 years old or older	55.8	43	3	7.848	$p < .05$
Collar color[a]					
White collar	66.7	213			
Blue collar	20.9	110	1	58.962	$p < .001$
Occupational group[b]					
Professional, technical and managerial	70.3	74			
Clerical and sales	64.7	139			
Operatives and kindred workers	15.2	59			
Service workers, excluding private household workers	30.4	46	3	65.465	$p < .001$
Industry group[c]					
Manufacturing	27.3	73			
Wholesale and retail trade	65.8	73			
Finance, insurance, and real estate	63.3	30			
Services	57.4	115	3	26.107	$p < .001$
Union membership					
Worker belongs to a union	36.9	84			
Worker does not belong to a union	56.1	239	1	8.383	$p < .01$
Number of workers at worker's place of employment					
49 or less	58.4	137			
50 o499	55.9	102			
500 or more	34.8	69	2	11.051	N.S.

[a]Farm workers were excluded.

[b]Managerial workers (n=19) were combined with professional and technical workers (n=55). Sales workers (n=17) were combined with clerical workers (n=122). Otherwise, occupational groups with less than 30 women were omitted from table and computations.

[c]Industry groups with less than 30 women were omitted from table and computations.

TABLE 3B

PERCENTAGE OF WOMEN IN SELECTED DEMOGRAPHIC AND OCCUPATIONAL CATEGORIES WITH TOTAL ANNUAL INCOME DISCREPANCIES OF -$3,500 OR MORE (METHOD 2)

Demographic or Occupational Category	Percentage	Base n	df	X^2	Significance
Race					
White	49.0	150			
Black	34.1	14	1	2.640	N.S.
Age					
16-29 years old	51.5	67			
30-44 years old	35.9	37			
45-54 years old	44.9	31			
55 years old or older	64.6	31	3	12.188	$p < .01$
Collar color[a]					
White collar	57.7	135			
Blue collar	26.3	31	1	29.831	$p < .001$
Occupational group					
Professional, technical and managerial	72.4	55			
Clerical and sales	50.6	80			
Operatives and kindred workers	19.4	12			
Service workers, excluding private household workers	32.0	16	3	43.997	$p < .001$
Industry group					
Manufacturing	22.5	18			
Wholesale and retail trade	55.0	44			
Finance, insurance, and real estate	51.5	17			
Services	58.4	73	3	27.996	$p < .001$
Union membership					
Worker belongs to a union	37.1	133			
Worker does not belong to a union	50.6	130	1	4.331	$p < .05$
Marital status					
Single	53.0	35			
Married	48.3	101			
Widowed	45.5	10			
Separated	26.7	4			
Divorced	40.0	16	4	44.403	N.S.
Number of children major support for					
Zero	46.2	135			
One	53.8	14			
Two	47.1	8			
Three	60.0	3			
Four and above	44.4	4	4	0.921	N.S.

[a]Farm workers were excluded.

TABLE 4

PRODUCT-MOMENT CORRELATIONS BETWEEN INCOME DISCREPANCY VALUES AND JOB SATISFACTION MEASURES

Female Subsample Total Annual Income	Comfort	Challenge	Financial Rewards	Relations with Co-workers	Resources	General Job Satisfaction
Method 1	.07	-.06	.20	.06	.03	.06
Method 2	.07	-.04	.20	.02	.03	.03[a]

[a]As noted in the text, the general job satisfaction measure used in the Method 2 analysis differed slightly from that in Method 1.

TABLE 5

UNADJUSTED AND ADJUSTED R AND R^2 FOR BOTH STATISTICAL PROCEDURES

	Unadjusted		Adjusted	
	R	R^2	R	R^2
AID	0.688	0.474	--	--
MCA	0.706	0.498	0.685	0.469
Number of cases = 972				

TABLE 6

COEFFICIENTS FOR MALES AND FEMALES USED TO PREDICT INCOME

	Coefficient	Self Weighting N
Male	947	636
Female	-1,847	336

TABLE 7

EFFECT OF PREDICTOR VARIABLES IN EXPLAINING A WORKER'S INCOME
(FROM THE MULTIPLE CLASSIFICATION ANALYSIS)

	Importance Taken Singularly Eta Squared	Rank	Importance Taken Together Beta Squared	Rank
Census Occupation Class Code	.189	1	.081	2
Education	.184	2	.133	1
Sex	.161	3	.072	3
Working Week Hours	.121	4	.036	5
Supervise Anyone	.101	5	.003	12
Number of Children Supported	.092	6	.011	9
Duncan Decile--Collar Status	.081	7	.021	7
Age	.045	7	.003	7
Employer Tenure	.047	9	.026	6
Marital Status	.040	10	.003	12
White Collar-Blue Collar	.038	11	.055	4
Job Tenure	.024	12	.011	9
SIC Industrial Divisions	.011	13	.010	11
Race	.007	14	.000	14
Union Membership	.000	15	.000	14

Unadjusted R^2 = .498
Adjusted R^2 = .469
Number of Cases = 972

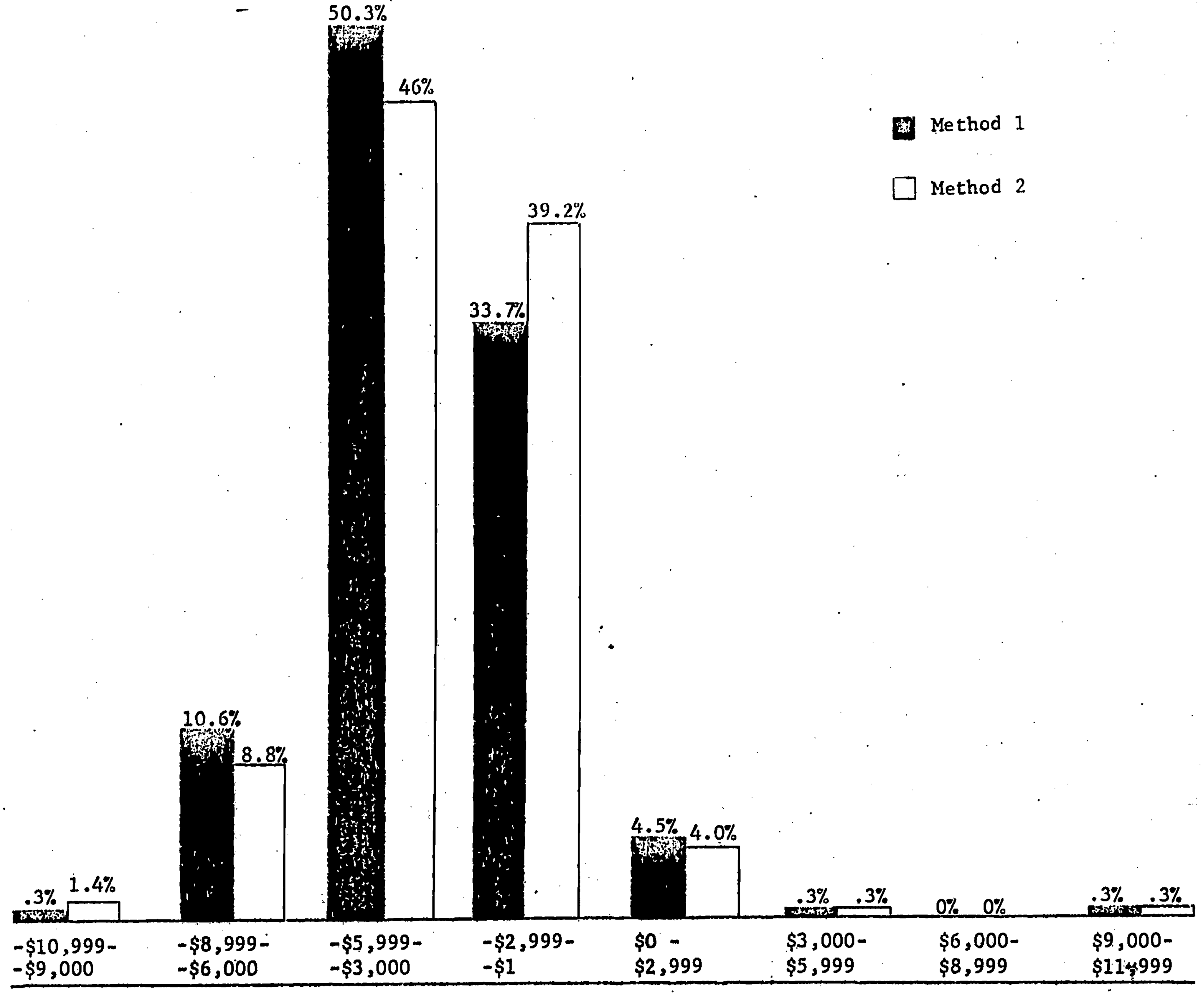

Figure 1.--Percentage distribution of total annual income discrepancies for women by Methods 1 and 2.