#468-77

INSTITUTE FOR RESEARCH ON POVERTY DISCUSSION PAPERS

WAGE DETERMINATION AND DISCRIMINATION AMONG OLDER WORKERS

Joseph F. Quinn

UNIVERSITY OF WISCONSIN-MADISON

Wage Determination and Discrimination
Among Older Workers

Joseph F. Quinn

Institute for Research on Poverty
University of Wisconsin
and
Department of Economics
Boston College

December 1977

This research was supported by the Social Security Administration under contract #SSA-PMB-73-219, and by funds granted to the Institute for Research on Poverty at the University of Wisconsin-Madison by the Department of Health, Education, and Welfare pursuant to the Economic Opportunity Act of 1964.

ABSTRACT

There are two issues currently before Congress whose outcomes may have significant effects on the labor market experience of individuals around retirement age. These are the abolition (or delay) of the mandatory retirement age and the elimination of the Social Security program's earnings test. Both of these measures, if passed, can be expected to prolong, on average, the labor force participation of older workers.

In this paper, the determinants of the market wage rates of older workers are analyzed, using the 1969 wave of the Social Security Administration's Retirement History Study. The extent and nature of current labor market discrimination by race and sex are then examined by estimating the portion of the race and sex wage differentials which cannot be explained by observable socioeconomic characteristics. Evidence of discrimination appears in both cases, and suggests that occupational segregation or crowding is more of a problem in the male-female than in the white-nonwhite case.

1. INTRODUCTION

There is tremendous dispersion in the income distribution of individuals around retirement age. The most important single factor in explaining these income differences is labor force status--persons who are in the labor force have much higher incomes than those who are not. From a recent national survey of retirement age individuals, Schwab (1974) reports that, for married men with spouses present, the median family income for those who were in the labor force was $8,555, compared to only $4,610 for those who were out.[1] For men without a spouse present, the analogous averages were $5,555 and $1,530, respectively. Earnings are clearly an extremely important income source for people in this age group. The amount of annual earnings for an individual depends on the wage rate and on the number of hours worked per year. There has been considerable research recently on the labor supply decisions of retirement aged individuals (Boskin 1977, Quinn 1977, and Schwab 1974). In this paper, I concentrate on the other component of earnings--the market wage rate. I analyze the determinants of the wage rates for individuals around retirement age, and present estimates of the extent and nature of race and sex wage discrimination. This analysis expands on previous work by including improved measures for one of the most important productivity-related wage determinants--experience--and by attempting to differentiate between occupational and industrial segregation and pure wage discrimination.

This age group is currently of particular interest because of two issues presently before Congress--the abolition (or postponement until at least age 70) of the mandatory retirement age and the elimination of the Social Security program's earnings test. Both of these changes, if they occur, can be expected to affect the labor supply decisions of older workers and, on average, to extend their time in the labor force. If this is true, the effects of race and sex discrimination among this group of workers will be prolonged. In this paper, I present evidence on the extent and nature of this discrimination.

2. MODEL AND EMPIRICAL SPECIFICATION

The basic economic model underlying the research reported in this paper is a human cpaital model of wage determination in which one's market wage rate is primarily a function of one's productivity. Although productivity cannot be measured directly, it is hypothesized to depend upon certain measurable dimensions, such as years of formal education, vocational training, job experience, and health. Differences in these dimensions help explain the differences in individual wage rates.

There are at least two views about the effect of education on productivity. The first is that formal education increases cognitive skills, which decrease training costs or are directly useful on the job. Others have argued, however, that the role of schools is not to improve cognitive skills, but rather to socialize individuals to accept the hierarchical mode of production found in most places of employment. An educational degree signals that its bearer is able to accept authority and discipline, to adjust to a schedule and regimen, and to see projects through to completion. Although the mechanisms are quite different, both theories predict that education will increase worker productivity and therefore wages.

Mincer (1974) has pointed out that post-schooling investment, such as vocational training or on-the-job experience, is also important, and that its exclusion from a wage equation will bias the education coefficients downward.[2] This factor should be included for two reasons. First, training or experience may directly increase a worker's productivity and, therefore, the wage. Secondly, many institutions are characterized by internal labor markets and structured job ladders along which workers advance over time. Even if personal productivity does not increase over time, wages will, as workers progress up the internal job ladder. This institutional mechanism is not necessarily inconsistent with a long run marginal productivity theory and, as suggested by Wachter (1974), may be an efficient response to market forces.

Post-schooling investment, especially informal on-the-job training or experience, is difficult to measure. The most common proxy, first suggested by Mincer, is the number of years since graduation: operationally, A - S - 6, where A is current age, S is years of formal schooling, and 6 is the usual age of school entry. Unfortunately, this has serious drawbacks, and can overstate the training relevant to an individual's current job. Mincer's variable actually measures <u>potential</u> years in the labor force, and it implicitly assumes that <u>all</u> the years since the end of formal education are relevant. It ignores spells of unemployment, and years out of the labor force. And even if there is no interruption in labor force participation, an individual who changes jobs or occupations will not necessarily be rewarded for previous experience. The previous training may not affect productivity on the new job (i.e., if the jobs are quite different), and most job ladders do not recognize seniority with other employers. To account for both the personal (productivity) and institutional (seniority) aspects of labor market experience, I take a different approach to this problem by considering two measures of post-schooling investment. The first is the number of years of specific vocational training (SVP) which is required for satisfactory performance in the individual's occupation. The second is job tenure--the actual length of service with the current employer. The first, SVP, is a characteristic of the job, not the individual.[3] The implicit assumption is that the individual has accumulated the amount of specific human capital required for the occupation, and is being rewarded for these years of experience. It is also assumed, however, that years spent on the job in excess of those required do not further increase productivity, and so no such "credit" is given. The second measure is similar to Mincer's concept of experience, except that it applies only to the current job. Previous experience in other organizations is ignored. (If the previous years were relevant to the current occupation, they should be picked up in SVP.) The tenure variable reflects the institutional effects of seniority. We suggest that these two concepts together measure the accumulation of post-schooling human capital better than does potential years in the labor force.

The final measure of human capital included is health status--a dummy variable indicating the presence of a health limitation which affects the type or amount of work the individual can do. We hypothesize that workers with a health limitation, on average, will have lower productivities and, therefore, lower wages.

An extension of the basic human capital theory includes the possibility of geographic differences in wage rates, for a number of reasons. First, in an equilibrium nondiscriminatory world, individuals with identical characteristics should earn identical _real_, not money wages. Since the cost of living differs by city and by region, we include a price index (P) as an explanatory variable in our wage equations.[4] Second, local labor market conditions may affect the wage structure, although the direction of the effect is unclear. From a disequilibrium, Phillips-curve perspective, areas with chronic excess supplies of labor (high unemployment) should have lower wage rates, _ceteris paribus_, than areas with chronically tight labor markets. Alternatively, as suggested by Hall (1970), equilibrium may consist of cities with relatively high wage rates and high unemployment and others with low wages and low unemployment. In expected value terms (the wage rate modified by the probability of actually being employed), such cities may be equally attractive to workers, and this might represent a sustainable long run situation. Which of these effects dominates is an empirical question. The research reported here includes the local unemployment rate as a proxy for long run labor market conditions, and the most recent annual rate of change of employment as a measure of the short run situation.

Finally, there may be other labor market differences, such as industrial structure or the extent of unionization, which differ geographically. I attempt to pick up these effects by including four regional dummies. A dummy for SMSA residence was also added, but this was generally insignificant whenever the other geographic variables were included, and so it was dropped from the final regressions.

We have, then, a functional relationship of the following form:

$$W = f(EDUC, SVP, TENURE, HLIM, P, URATE, PCEMP, REGION)$$

Where EDUC is years of formal education,

SVP is the number of years of specific vocational training required for adequate performance on the individual's job,

TENURE is the number of years the individual has worked for the current employer,

HLIM is a dummy variable indicating the presence of a health condition which limits the amount or kind of work the individual can do,

p is an SMSA specific price index,

URATE is the SMSA specific unemployment rate,

PCEMP is the SMSA specific most recent annual percentage change in employment, and

REGION represents a series of four regional dummies.

Since there is no reason to expect the effects of these variables on the wage to be linear, EDUC, SVP, TENURE, URATE and PCEMP are all entered as a series of dummy variables.

The functional specification used is log-linear, with the log of the wage rate hypothesized to be a linear function of the variables described above; i.e.,

$$\ln W = \beta_o + \sum_i \beta_i X_i + \varepsilon,$$

where ε is the disturbance term.[5] In this format, the regression coefficients ($\hat{\beta}$) estimate the percentage effect on W associated with a one-unit change in the variable X_i.

3. DATA SOURCE AND SAMPLE

The data source for this research is the Retirement History Study (RHS), a 10-year study of the retirement process being conducted by the Social Security Administration (Irelan 1973). Over 11,000 men and nonmarried women aged 58-63 were interviewed in the spring of 1969, and are being reinterviewed at 2-year intervals.[6] This research is based only on the original 1969 cross-section.

In an attempt to obtain a more homogeneous group for analysis, the sample was pared to approximately 6,400. The excluded groups were farmers and the self-employed, those who were seriously ill (operationally, the bedridden and the housebound), any respondent for whom missing data made calculation of the hourly wage rate impossible, and a few very small, miscellaneous groups.[7] This subsample was stratified by sex and race, creating four groups for analysis. Because of the small number of nonwhite women, these results are not included.

The SMSA of residence is included for all respondents in an SMSA with a 1969 population over 250,000--approximately 56% of the sample. For those outside these SMSAs, it is known whether the respondent lives in a smaller SMSA, or not in an SMSA at all. In these cases, regional averages for the labor market data were assigned. The unemployment data were drawn from the 1970 Census (U.S. Department of Commerce 1971) and the employment growth data from Employment and Earnings (U.S. Department of Labor, Bureau of Labor Statistics 1971).

The vocational training variable (SVP) is assigned to each individual on the basis of the person's 3-digit Census occupational code. The

Department of Labor has estimated the amount of training (in terms of time) required for adequate performance on each of the nearly 14,000 jobs listed in The Dictionary of Occupational Titles (DOT). Although these estimates are not directly available for the Census jobs, a cross classification matrix which gives, for each Census job, the probability of being in each of the DOT categories, allows us to calculate expected values of SVP for each Census job. These are then assigned to the respondents. (See Quinn 1977, for more details.)

4. WAGE EQUATIONS

The basic regression results are shown in Table 1. (Mean values for the explanatory variables appear in Appendix 1.) For white men and white women, the human capital coefficients are of reasonable magnitude, and are generally significant. They indicate that wages rise monotonically with education (with one exception), and that white male college graduates earn approximately 30% more per hour than high school graduates who, in turn, earn 14% more than those who never proceeded beyond grade school. There is a large college diploma effect but little evidence of an analogous high school effect. For white women, the wage range is larger in percentage terms and there are large diploma effects for both high school and college. The one exception to the wage progression is the slight decrease for white men with postgraduate education. The simplest explanation is that many of these may have chosen occupations in which nonpecuniary benefits offset lower financial rewards.

For the nonwhite men, the education pattern is less clear. Although there is evidence that those with college degrees or postgraduate

TABLE 1: WAGE EQUATIONS, WITHOUT OCCUPATIONAL OR INDUSTRIAL CATEGORIES

(dependent variable: ln (wage))
(t-statistics in parentheses)

		White Men		Nonwhite Men		White Women	
Human Capital Variables							
Education	0-8 yrs	-.135	(6.46)**	-.004	(0.05)	-.232	(6.03)**
	9-11	-.020	(0.86)	.018	(0.18)	-.131	(3.14)**
	12	---	---	---	---	---	---
	13-15	.117	(3.67)**	.022	(0.16)	.073	(1.44)
	16	.304	(7.85)**	.433	(1.93)	.318	(4.62)**
	17+	.297	(6.84)**	.863	(4.70)**	.594	(7.26)**
Specific Vocational Training (SVP)							
	0-3 mo.	---	---	---	---	---	---
	4-23	.083	(3.68)**	.067	(1.00)	.199	(5.79)**
	24-47	.213	(10.20)**	.140	(1.77)	.321	(6.14)**
	48+	.382	(15.73)**	.360	(3.13)**	.353	(5.53)**
Job Tenure	0-2 yrs	---	---	---	---	---	---
	3-5	.059	(1.94)	.065	(0.79)	.132	(2.91)**
	6-10	.123	(4.19)**	.055	(0.64)	.269	(5.87)**
	11-15	.207	(6.82)**	.113	(1.32)	.320	(6.53)**
	16-20	.269	(8.76)**	.178	(1.91)	.407	(7.59)**
	21+	.353	(15.39)**	.338	(5.14)**	.527	(12.40)**
Health Limitation (0,1)		-.058	(3.28)**	-.166	(3.21)**	-.144	(4.31)**
Geographic Variables							
Region	NE	-.033	(1.58)	.026	(0.35)	.075	(2.00)*
	NC	---	---	---	---	---	---
	W	.028	(0.99)	.191	(1.66)	.090	(1.61)
	S	-.098	(4.06)**	-.223	(2.99)**	-.017	(0.38)
Price Index (ln(P))		1.004	(7.08)**	.422	(0.79)	1.462	(5.64)**
Unemployment Rate							
	0-3.9%	.040	(1.90)	-.105	(1.71)	.052	(1.33)
	4.0-5.9	---	---	---	---	---	---
	6.0+	.089	(2.31)*	.042	(0.33)	-.020	(0.29)
% Δ Employment	Neg-2.4%	.040	(1.90)	.075	(1.11)	-.007	(0.19)
	2.5-3.9	---	---	---	---	---	---
	4.0+	.063	(2.77)*	.003	(0.04)	.005	(0.11)
Constant		5.480		5.383		4.918	
$\bar{R}^2$		.26		.30		.36	
N		4506		433		1445	

---designates reference category

*significant at 0.025 level (one-tailed)
**significant at 0.010 level (")

education earn more than those without, there is no significant pattern in the 0-15 years range.[8]

The training and tenure results are very similar. For white men and women, very strong relationships appear. Increases in vocational training or in years on the job mean higher wages, and this is true for every one of the increments shown. For nonwhite men, the evidence is less clear. Although the point estimates indicate similar patterns for both SVP and tenure, the coefficients are not significant until the highest category is reached--specific vocational training exceeding 4 years, or more than 20 years on the job.

There are a number of possible explanations for the insignificance of the nonwhite results. The simplest is that nonwhite men, at least in this age group, have not been as well rewarded as whites for education, training, or job experience. Another possible explanation is sample size. There is a third, however, which is especially relevant to the tenure variable. There has been, over the past two decades, an improvement in the job options available to nonwhites. Many of the nonwhites who were able to move up into better paying jobs would have done so relatively recently, and can therefore be expected to have relatively few years on the job. Here, then, is a negative relationship between job tenure and the wage--not because of a causal link, but because of recent changes in the occupational environment. The result of this phenomenon, of course, is to mask the positive wage-tenure relationship we expect.

The impact of the health variable is relatively straight-forward. A health limitation results in lower wages for all three groups. The size of the effect, however, is much larger for nonwhite men and white women than it is for white men. This may be because the health limitations of the former are more serious than those of white men, or because the former are more likely to hold jobs in which a health limitation is a serious detriment.

The geographic variables are primarily control variables, included so that their influence will not bias the other coefficients. But they are of some interest in themselves. According to this evidence, wages do compensate for cross-sectional price differences. All three of the price coefficients are well within two standard deviations of 1, and the coefficient on the largest group, the white men, is almost exactly 1. (The evidence is even stronger in the expanded wage equations in Appendix 2.) In addition to compensating for cost of living differences, wages vary by region, and are highest in the West and lowest in the South. (Industrial structure and degree of unionization may explain the latter.) The coefficients on the unemployment terms, for men at least, offer weak support for the Hall hypothesis, that high unemployment rates are generally accompanied by high, not low, wages. There is even weaker evidence that very recent labor market strength significantly increases wage levels.

In general, these questions support the predictions of economic theory--that human capital accumulations are important determinants of individual wage rates.[9] There is also evidence of regional differences, and small effects of local labor market conditions. Overall, the adjusted coefficients of determination ($\bar{R}^2$) are very respectable, especially since the sample has already been stratified by race and sex. This may reflect the importance of two very important variables (SVP and job tenure) not usually available.

5. DISCRIMINATION ANALYSIS

In this section, I attempt to estimate the extent of current labor market wage discrimination, by race and sex, among people of early retirement age, and to analyze its nature. I look first at race discrimination, by comparing white and nonwhite men, and then at sex discrimination, by comparing white men and women.

Whites and nonwhites (or men and women) have different wage distributions for two reasons. First, they come to the labor market with different personal characteristics, some of which are related to productivity. Second, the return to these characteristics may differ by race (or sex). The basic methodology of this section is straightforward.[10] We take as given the distribution of personal and geographic characteristics, and estimate the race (and sex) differences in average wage rates which _would_ occur if there were no current labor market discrimination. If the actual wage differential exceeds this, we will attribute the excess to discrimination. Two points should be emphasized. First, it is undoubtedly true that some of the differences in the distributions of characteristics are themselves results of previous racial discrimination. For instance, quality of schooling and ease of entrance into certain skilled trades have traditionally differed by race. To the extent that this is true, this methodology understates the total effects of racial discrimination by focusing on only one component--_current_ labor market treatment. At the same time, however, it can always be argued that certain important human capital dimensions may be missing from the equations, and therefore that it is not legitimate to attribute the unexplained residual to any particular factor. This is true and, in fact, the residual should always be attributed to discrimination _and_ to unobserved differences. The unprovable implication, however, is that a discrimination component would remain even if these unobserved human capital dimensions were included.

The characterization of nondiscriminating labor market used here is one in which the coefficients in white and nonwhite (or male and female) wage equations are the same. In other words, everyone is paid according to the same formula. In such a world, individual wages differ, but only because personal characteristics differ. The first question is, what would the coefficients in these common formulae be? Although this is impossible to answer, we have two sets of estimates. We can assume either that the current white (male) coefficients would apply to everyone or that the current nonwhite (female) coefficients would. In the case of race, the former is clearly the better assumption. Since approximately 90% of the <u>population</u> is white, it is reasonable to expect that the new coefficients would look more like the current white coefficients than the current nonwhite ones. And secondly, since almost 90% of the RHS <u>sample</u> is white, we have more confidence that our white estimates look like the white population parameters than we do for nonwhites. The estimates based on the assumption that the white coefficients would apply to everyone in a nondiscriminating world are used here. In the analysis of sex discrimination, the male coefficients are assumed to apply in the nondiscriminating world.

<u>Race Discrimination</u>

The average hourly ln (wage) for the white men in the sample is 5.8085 ($3.33). For nonwhite men, the average is 5.4591 ($2.35). The difference is .3494. How much of this differential can be attributed to differences in observable characteristics? To estimate this, we assume that the white coefficients apply to all, and calculate what the differential would be if nonwhites had their own characteristics but had the coefficients enjoyed by the whites. We estimate this hypothetical nonwhite mean by inserting the nonwhite means into the white wage equations.

As shown in Table 2, the nonwhite male ln (wage) is predicted to average 5.6112 ($2.73), rather than 5.4591 ($2.35), _if_ there were no current labor market discrimination--this is, _if_ nonwhite men had the white male coefficients. Of the overall .3494 differential, then, .1973 (5.8085-5.6112) would still occur even if there were no current labor market discrimination and is explained by differences in characteristics. The amount that has disappeared (.1521) is, with the above caveat concerning unobserved differences, attributed to discrimination. In percentage terms, this is 44% of the current differential.[11]

Since a sizeable portion of the actual differential _is_ explained by differences in observed attributes, one might ask which of these attributes are important. In other words, if there were no labor market discrimination, _why_ would wages still differ by as much as they would? Since

$$\overline{\ln(\hat{W}_W)} = \Sigma\hat{\beta}_W \bar{X}_W \quad \text{and}$$

$$\overline{\ln(\hat{W}_{NW})} = \Sigma\hat{\beta}_W \bar{X}_{NW}$$

where $\overline{\ln(\hat{W}_W)}$ is the predicted (and actual) average log of wages for white men,

TABLE 2: MALE WAGE DIFFERENTIALS BY RACE

		As % of total differential
Actual differential	5.8085 - 5.4591 = .3494	100%
Explained component	5.8085 - 5.6112 = .1973	56%
Residual	5.6112 - 5.4591 = .1521	44%

NOTE: The underlined figures are hypothetical nonwhite log means based on nonwhite male characteristics and white male regression coefficients.

$\overline{\ln\ (\hat{W}_{NW})}$ is the predicted average log of wages for nonwhite men, using the nonwhite characteristics but the white coefficients,

$\hat{\beta}_W$ is the (1xN) vector of estimated white male regression coefficients, and

$\overline{X}_W$ and $\overline{X}_{NW}$ are (Nx1) vectors of variable means, for white and nonwhite men, respectively,

then $$\overline{\ln\ (\hat{W}_W)} - \overline{\ln\ (\hat{W}_{NW})} = \Sigma\hat{\beta}_W\ (\overline{X}_W - \overline{X}_{NW}).$$

The total differential between the expected average logs, in other words, can be decomposed into differences contributed by each of the X's. The X's are aggregated into categories (such as education, training, job tenure, etc.) and the total contribution of each category calculated. This decomposition is shown in Table 3.

For men, nonwhite wages would be lower even in the absence of current labor market discrimination because they have a less favorable distribution in every single category--nonwhite men have less education, less training, fewer years on the job, and poorer health and, in general, they live in areas in which wages are lower. More than three-quarters of the predicted difference, however, is explained by the two main human capital variables, education and vocational training, with job experience explaining another 14%.

The variables included in the wage equations are not able to explain all of the difference in average white and nonwhite male wages. A residual remains, suggesting discrimination. Two scenarios can be drawn concerning its nature. In the first, disadvantaged groups (such as women or blacks) are segregated--through socialization, custom or conscious discrimination--into certain low-paying industries and occupations. Within any industry or occupation, however, they are treated the same as white men. But since

TABLE 3: DECOMPOSITION OF THE DIFFERENCE IN PREDICTED MALE WAGES BY RACE

Predicted[a] white ln(wage)	5.8085	($3.33)
Predicted nonwhite ln(wage)	-5.6112	(2.73)
Difference	.1973	
CATEGORY		
Education	.0560	(28%)
Vocational Training (SVP)	.0989	(50%)
Job Tenure	.0274	(14%)
Health	.0023	(1%)
Geographic Characteristics	.0127	(6%)
	.1973	

[a]and actual

the occupational distributions differ, the average wage rates differ, even after adjustment for personal and geographic characteristics. In this scenario--occupational crowding or segregation--the discrimination occurs in the allocation of jobs, not in the compensation on the job. We contrast this with pure wage discrimination, which refers to wage differentials for identical people within industries and occupations. To exaggerate the distinction, with crowding, identical blacks and whites (or men and women) working side by side are paid identical wages. The problem is that they are not usually working side by side. In the second scenario, those working side by side are compensated differently.

The methodology here is identical to that above, except that the equations used to predict what nonwhite wages would be in the absence of labor market discrimination are equations which contain industrial and occupational dummies.[12] (See Appendix 2.) We are now treating occupation and industry as exogenous explanators of the wage (like education, training or job tenure), and are implicitly assuming that they are "legitimate" reasons for wage differences. The discrimination differential computed in this case is attributed to pure wage discrimination within industries and occupations and, of course, to unobserved differences. We will find less discrimination (unexplained difference) here, since one source of discrimination--the crowding of nonwhites into lower paying occupations and industries, has been removed. The question is, how much less?

As is shown in Table 4, the race discrimination differential changes very little. As a percentage of the total (log) differential, the proportion attributed to discrimination drops from 44% (Table 2) to 37% (Table 4). Since most of the racial discrimination remains even after

TABLE 4: MALE WAGE DIFFERENTIALS BY RACE, FROM EQUATIONS WITH INDUSTRIAL AND OCCUPATION CATEGORIES

		As % of total differential
Actual differential	5.8085 - 5.4591 = .3494	100%
Explained component	5.8085 - 5.5885 = .2200	63%
Residual	5.5885 - 5.4591 = .1294	37%

NOTE: Same as Table 2.

occupational and industrial distributions have been taken into account, it appears that the problem, among men, is more race discrimination within occupational and industrial categories than segregation into the low-paying categories.

The conclusions concerning racial discrimination can also be seen in Table 5, in which the breakdown of the nondiscriminatory differentials are shown. Although industry and occupation are important, they explain only 25% of the differential. As before, the primary determinants are the white-nonwhite differences in education and vocational training.

Sex Discrimination

The same questions can be asked about wage differences by sex. How large is the differential? Can the differential be explained by differences in the distributions of personal characteristics? If there is evidence of sex discrimination, does it take the form of occupational and industrial crowding or pure wage discrimination?

In the tables which follow, it is assumed that the white male coefficients would apply to white men and women in the hypothetical non-discriminatory world. In Table 6, the actual wage differential by sex is broken down into a component which can be attributed to differences in characteristics, and a component which cannot. There is much stronger evidence of discrimination here, since only 18% of the total differential can be explained by differences in observed characteristics.[13]

Although less than 20% of the differential can be explained, it is interesting to note which dimensions do explain this portion of the differential. As shown in Table 7, white women have a more favorable education distribution than white men, and slightly better health, but

TABLE 5: DECOMPOSITION OF THE DIFFERENCE IN PREDICTED MALE WAGES BY RACE, WITH INDUSTRIAL AND OCCUPATIONAL CATEGORIES

Predicted[a] white ln(wage)	5.8085	($3.33)
Predicted nonwhite ln(wage)	-5.5885	(2.67)
Difference	.2200	
CATEGORY		
Education	.0561	(25%)
Vocational Training (SVP)	.0714	(32%)
Job Tenure	.0235	(11%)
Health	.0020	(1%)
Geographic Characteristics	.0135	(6%)
Occupation	.0456	(21%)
Industry	.0079	(4%)
	.2200	

[a]and actual

TABLE 6: WHITE WAGE DIFFERENTIALS BY SEX

		As % of total differential
Actual differential	5.8085 - 5.2817 = .5268	100%
Explained component	5.8085 - 5.7115 = .0970	18%
Residual	5.7115 - 5.2817 = .4298	82%

NOTE: The underlined figures are hypothetical female log means based on white female characteristics and male regression coefficients.

TABLE 7: DECOMPOSITION OF THE DIFFERENCE IN PREDICTED WHITE WAGES BY SEX

Predicted[a] male ln(wage)	5.8085	($3.33)
Predicted female ln(wage)	-5.7115	(3.02)
Difference	.0970	
CATEGORY		
Education	- .0125	(-13%)
Vocational Training (SVP)	.0692	(71%)
Job Tenure	.0523	(54%)
Health	- .0019	(- 2%)
Geographic Characteristics	- .0101	(-10%)
	.0970	

suffer from less vocational training and fewer years of job experience. These last two human capital factors more than explain the difference which would remain in the absence of current labor market discrimination.

As we have seen, however, most of the sex differential cannot be explained by differences in observable characteristics. Does this discrimination appear to be segregation, or pure wage discrimination? According to the estimates in Table 8, there is ample evidence of both. Inclusion of industrial and occupational categories in the equation (see Appendix 2) almost doubles the portion of the male-female differential which can be explained, but still leaves 66% as residual. There is stronger evidence for occupational and industrial crowding by sex than by race. This conclusion is supported further by the decomposition of the explainable component, after the introduction of the job categories. As seen in Table 9, 58% of the explainable component can be attributed to industrial and occupational differences. This is primarily due to the relatively few women who are managers, and the relatively many who are employed in the low-paying service sector. These factors by no means explain the entire difference, however, and there is still evidence of wage discrimination within the industrial and occupational cells.

6. SUMMARY

Wage equations are estimated for three race-sex subsets of a sample of survey respondents of early retirement age (58-63). For white men and women, the human capital dimensions are all very important. Wage rates incrdase monotonically with formal education, vocational training and

TABLE 8: WHITE WAGE DIFFERENTIALS BY SEX, FROM EQUATIONS WITH INDUSTRIAL AND OCCUPATIONAL CATEGORIES

		As % of total differential
Actual differential	5.8085 - 5.2817 = .5268	100%
Explained component	5.8085 - 5.6292 = .1793	34%
Residual	5.6292 - 5.2817 = .3475	66%

NOTE: Same as Table 6.

TABLE 9: DECOMPOSITION OF THE DIFFERENCE IN PREDICTED WHITE WAGES BY SEX, WITH INDUSTRIAL AND OCCUPATIONAL CATEGORIES

Predicted[a] male ln(wage)	5.8085	($3.33)
Predicted female ln(wage)	5.6292	(2.78)
Difference	.1793	
CATEGORY		
Education	- .0120	(- 7%)
Vocational Training (SVP)	.0546	(30%)
Job Tenure	.0442	(25%)
Health	- .0016	(- 1%)
Geographic Characteristics	- .0102	(- 6%)
Occupation	.0111	(6%)
Industry	.0932	(52%)
	.1793	

[a]and actual

job experience, and are higher for those in good health. The coefficients are statistically significant, and of reasonable magnitude. For nonwhite men, except for health, the relationships are less clear, indicating, perhaps, that human capital has not been well rewarded for nonwhites in this age group.

These wage equations are used to decompose the race and sex wage differentials into components due to observed individual characteristics, and components due to discrimination and unobserved differences. When male differences by race are analyzed, the results show that 44% of the wage differential cannot be explained by differences in observed characteristics and, hence, might be attributable to current labor market discrimination. Introduction of industrial and occupational categories into the analysis results in only a small increase in the percentage of the wage differential explained, indicating that the problem is primarily wage discrimination within broad job categories rather than the distribution of white and nonwhite men over these jobs.

With respect to sex differentials, much less (18%) of the divergence can be explained by differences in observed characteristics, leaving the majority to sex discrimination and unobserved differences. When industry and occupation are held constant, the percentage explained nearly doubles, indicating that both occupational and industrial crowding and pure wage discrimination within occupation are important components of current labor market sex discrimination.[14]

The distinction between crowding and pure wage discrimination is an important one. Current legislation is probably sufficient to eliminate the latter over time. Occupational segregation, however, stems not only from intentional discrimination but also from childhood socialization, general cultural expectations and, to a degree, personal choice. These factors are much more difficult to change. This research, as well as earlier work by others, indicates that occupational and industrial segregation is an important component of current labor market discrimination, especially when male-female wage differentials are considered.

Current legislation under consideration concerning compulsory retirement provisions and the Social Security earnings test make these conclusions even more important, since the enactment of these changes would probably prolong the effects of this discrimination by inducing retirement age individuals to remain longer in the labor force. This is not meant as an argument against either of these measures, but rather as an additional reason why discrimination issues should receive continued attention.

APPENDIX 1: MEAN VALUES

		White Men	Nonwhite Men	White Women
Ln(wage)		5.81 ($3.33)	5.46 ($2.35)	5.28 ($1.97)
Education	0-8 yrs	.40	.66	.32
	9-11	.20	.16	.19
	12	.23	.11	.30
	13-15	.08	.04	.11
	16	.05	.01	.05
	17+	.04	.02	.03
Special Vocational Training (SVP)	0-3 mo.	.31	.67	.36
	4-23	.21	.16	.47
	24-47	.27	.12	.11
	48+	.21	.05	.06
Job Tenure	0-2 yrs	.17	.24	.25
	3-5	.11	.13	.16
	6-10	.12	.11	.15
	11-15	.11	.11	.13
	16-20	.10	.09	.10
	21+	.39	.32	.21
Health Limitation		.27	.31	.24
Region	NE	.32	.25	.34
	NC	.34	.21	.32
	W	.16	.14	.16
	S	.18	.40	.18
Ln(Price Index)		-.02	-.02	-.01
Unemployment Rate	0-3.9%	.37	.46	.42
	4.0-5.9	.56	.46	.49
	6.0	.07	.08	.09
% Δ Employment	Neg-2.4%	.19	.16	.19
	2.5-3.9	.63	.60	.63
	4.0+	.18	.24	.18
Occupation				
Professional		.09	.05	.14
Manager		.14	.03	.06
Clerk		.07	.04	.29
Sales		.05	(a)	.08
Craft		.28	.13	.01
Operative		.21	.30	.14
Service		.09	.23	.19
Laborer		.07	.22	(a)
Private Household		(a)	(a)	.09
Industry				
Ag.,For.,Farm		.02	.02	(a)
Construction		.10	.13	(a)
Manufacturing		.36	.31	.19
Trans., Comm.,Public Utility		.11	.10	.03
Trade		.13	.09	.21
Fin., Insur., Real Estate		.05	.04	.08
Service		.15	.25	.44
Public Administration		.08	.06	.05

(a) Less than .01

APPENDIX 2: WAGE EQUATIONS WITH OCCUPATIONAL AND INDUSTRIAL CATEGORIES

(dependent variable: ln(wage))
(t-statistics in parentheses)

		White Men		Nonwhite Men		White Women	
Human Capital Variables							
Education	0-8 yrs	-.131	(6.20)**	-.010	(0.13)	-.203	(5.54)**
	9-11	-.019	(0.80)	.015	(0.16)	.093	(2.44)**
	12	---	---	---	---	---	---
	13-15	.116	(3.70)**	.042	(0.33)	-.002	(0.04)
	16	.306	(7.85)**	.340	(1.45)	.139	(1.96)*
	17+	.363	(7.69)**	.909	(4.60)**	.425	(5.19)**
Special Vocational Training (SVP)							
	0-3 mo.	---	---	---	---	---	---
	4-23	.047	(2.85)**	-.006	(0.08)	-.007	(0.17)
	24-47	.179	(4.38)**	.108	(0.94)	.020	(0.34)
	48+	.255	(5.66)**	.380	(2.70)**	-.041	(0.45)
Job Tenure	0-2 yrs	---	---	---	---	---	---
	3-5	.061	(2.07)*	.061	(0.77)	.098	(2.39)**
	6-10	.120	(4.14)**	.108	(1.30)	.169	(4.05)**
	11-15	.186	(6.20)**	.043	(0.53)	.213	(4.78)**
	16-20	.226	(7.43)**	.086	(0.94)	.253	(5.15)**
	21+	.305	(12.82)**	.240	(3.53)**	.351	(8.74)**
Health Limitation	(0,1)	-.050	(2.90)**	-.143	(2.87)**	-.092	(3.03)**
Geographic Variables							
Region	NE	.037	(1.80)	.025	(0.34)	.038	(1.12)
	NC	---	---	---	---	---	---
	W	.029	(1.03)	.168	(1.51)	.106	(2.11)*
	S	-.103	(4.32)**	-.156	(2.18)*	-.024	(0.60)
Price Index (ln(P))		1.031	(7.42)**	1.057	(2.04)*	1.394	(5.97)**
Unemployment Rate	0-3.9%	.039	(1.87)	-.100	(1.70)	.018	(0.50)
	4.0-5.9	---	---	---	---	---	---
	6.0+	.096	(2.54)**	.110	(0.88)	-.074	(1.23)
% Δ Unemployment	Neg-2.4%	.044	(2.11)*	.067	(1.04)	-.005	(0.15)
	2.5-3.9	---	---	---	---	---	---
	4.0+	.066	(2.98)**	-.002	(0.04)	.031	(0.80)

- continued -

APPENDIX 2: WAGE EQUATIONS WITH OCCUPATIONAL AND INDUSTRIAL CATEGORIES

(continued)

	White Men		Nonwhite Men		White Women	
Job Categories						
Occupation						
Professional	.058	(1.21)	-.020	(0.13)	.353	(4.88)**
Manager	.158	(3.29)**	-.145	(0.82)	.213	(2.12)*
Clerk	-.022	(0.58)	.066	(0.48)	.066	(1.22)
Sales	.147	(3.15)**	---	---	-.090	(1.23)
Craft	-.022	(0.57)	.040	(0.35)	-.107	(0.81)
Operative	---	---	---	---	---	---
Service	-.066	(1.98)*	-.109	(1.54)	-.134	(2.49)**
Laborer	-.085	(2.41)**	-.040	(0.57)	(a)	
Private Household	(a)		(a)		-.796	(11.67)**
Industry						
Ag., For., Farm	---	---	---	---	---	---
Construction	.102	(3.52)**	.018	(0.21)	---	---
Manufacturing	---	---	---	---	---	---
Trans.,Comm.,Pub. Util.	-.016	(0.62)	.040	(0.49)	(b)	
Trade	-.246	(9.32)**	-.344	(3.94)**	-.202	(4.00)**
Fin.,Insur.,Real Est.	-.090	(2.26)*	-.479	(3.92)**	-.096	(1.63)
Service	-.215	(8.09)**	-.197	(2.76)**	-.129	(2.88)**
Public Administration	.023	(0.72)	.237	(2.26)*	.075	(1.12)
Constant	5.587		5.531		5.307	
R^2	.29		.43		.48	
N	4506		433		1445	

--- designates reference category
(a) included in service occupation
(b) included in Fin.,Ins.,Real Est

*significant at 0.025 level (one-tailed)

**significant at 0.010 level (one-tailed)

NOTES

[1]These differences are not explained by differences in spouses' earnings. The percentage of married men whose spouses reported earnings was almost identical for those men in and out of the labor force (43 and 41% respectively) and the earnings distributions of these two groups of wives were very similar. (See Schwab 1974, pp. 51-52.)

[2]The reason for the downward bias is that individuals who remained longer in school will, in general, have fewer years of job experience than those in the same age cohort who dropped out early. This will tend to lower the education differential from what it would be if experience were held constant.

[3]Special vocational training is defined as "the amount of time required to learn the techniques, acquire information, and develop the ability needed for average performance." (U.S. Department of labor, Bureau of Employment Security 1965). The derivation of this variable is described below.

[4]The Bureau of Labor Statistics (BLS) estimates living costs for 39 U.S. SMSAs. (U.S. Department of Labor, Bureau of Labor Statistics 1972.) Indices were assigned for the other SMSAs in the following manner. If a BLS index was known for an adjacent (or closely neighboring) SMSA, that index was assigned. If not, the appropriate regional metropolitan average was assigned. For those not in an SMSA, the regional non-metropolitan average was used.

[5]The price variable is also entered in logarithmic form, so that the coefficient is interpretable as an elasticity.

[6]Preliminary sampling indicated that for most married women in this age group, retirement had very little meaning, or was defined in terms of the husband's labor force status. Therefore, married women were excluded from the survey population. From the point of view of this study, this exclusion may be fortunate, since nonmarried women (especially those never married) exhibit a labor force attachment more similar to men than do married women.

[7]Whenever possible, the hourly wage rate was derived from survey data on the respondent's current job. When this was not possible (e.g., the respondent was not currently employed, or did not answer one of the relevant questions), data on the individual's previous job were examined. If the respondent left this previous job within 5 years of the date of the interview (that is, since 1964), and if the data were complete, a wage was derived from these data and inflated to 1969 wage levels. Otherwise, the respondent was dropped from the sample. Of those in the sample, approximately 15% of the men and 20% of the women had wage rates assigned on the basis of the previous job.

[8]This is not a new result. In a sample of black males of approximately the same size, drawn from Michigan Survey Research Center's "Panel of Income Dynamics," Blinder (1973) found the education coefficients generally insignificant. For white males, in contrast, the coefficients were significant, and monotonically increasing, except for a small decrease at the advanced degree level.

[9]This general conclusion is also reached by Kalachek and Raines (1976), in a study of wage determination among mature men, using the 1966 and 1969 National Longitudinal Surveys.

[10]The methodology is basically the same as that used by Oaxaca (1973), and expanded by Blinder (1973).

[11]These discrimination estimates are very close to those presented by Blinder (1973), who used a different sample and a different data source. Blinder attributes 40% of the white-black wage differential to discrimination.

[12]It is interesting to note that the one anomaly among the education coefficients is corrected when the industry and occupational dummies are included--the postgraduate coefficient for white men now exceeds the coefficient for completion of college. This is consistent with the hypothesis that individuals with advanced degrees often choose occupations with lower monetary rewards, but that the degrees still augment the wage <u>within</u> the occupation.

[13]These estimates, which attribute 82% of the white male-female differential to discrimination, are slightly higher than the results of previous work. Blinder (1973) attributes 66% of the male-female differential to discrimination and Oaxaca's (1973) estimate is 78%.

[14]The industrial and occupational categories used in this research are the Census 2-digit categories. Some of these categories contain a tremendous variety of jobs. Occupational segregation in addition to that estimated above may occur at the 3- or 4-digit level. Since I have not disaggregated beyond the 2-digit level, this would appear as wage discrimination in this analysis. For this reason, the estimates of occupational crowding noted above should be viewed as lower bounds of the extent of the problem.

REFERENCES

Alan S. Blinder. "Wage Discrimination: Reduced Form and Structural Estimates." Journal of Human Resources 8 (Fall 1973):436-55.

Michael J. Boskin. "Social Security and Retirement Decisions." Economic Inquiry 15 (January 1977):1-25.

Robert E. Hall. "Why is Unemployment So High at Full Employment? Brookings Papers on Economic Activity (3:1970):369-402.

Lola Irelan. "Retirement History Study: Introduction." Social Security Bulletin 35 (November 1973):3-8.

Edward Kalachek and Fredric Raines. "The Structure of Wage Differences Among Mature Male Workers." Journal of Human Resources 11 (Fall 1976): 484-506.

Jacob Mincer. Schooling, Experience, and Earnings. National Bureau of Economic Research. New York: Columbia University Press, 1974.

Ronald Oaxaca. "Sex Discrimination in Wages." Discrimination in the Labor Market (eds. Orley Ashenfelter and Albert Rees). Princeton: Princeton University Press, 1973.

Joseph F. Quinn. "The Microeconomic Determinants of Early Retirement: A Cross-Sectional View of White Married Men." Journal of Human Resources 12 (Summer 1977):329-346.

Karen Schwab. "Early Labor Force Withdrawal of Men: Participants and Non-Participants Aged 58-63." Social Seuurity Bulletin 37 (August 1974): 24-38.

U.S. Department of Commerce, Bureau of the Census. 1970 Census of the Population. General Social and Economic Characteristics: U.S. Summary, Final Report PC(1)-C1. Washington: U.S. Government Printing Office, 1971.

U.S. Department of Labor, Bureau of Employment Security. Worker Trait Requirement for 4000 Jobs. Washington: U.S. Government Printing Office, 1965.

U.S. Department of Labor, Bureau of Labor Statistics. Employment and Earnings 17 (May 1971).

U.S. Department of Labor, Bureau of Labor Statistics. 3 Budgets for an Urban Family of Four Persons, 1969-70. Supplement to Bulletin 1570-S. Washington: U.S. Government Printing Office, 1972.

Michael L. Wachter. "Primary and Secondary Labor Markets: A Critique of the Dual Approach." Brookings Papers on Economic Activity (3:1974): 637-680.