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Wages and Gender Composition: Why Do Women's Jobs Pay Less?

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Abstract

Occupational sex segregation and its relationship with wages during the 1973-93 period are examined. Wage level and wage change models are estimated using data from various CPS earnings files matched with information on occupational skills and job disamenities. Standard wage level equations indicate that female and male wages are substantially lower in occupations with high proportions of women. Estimates of gender composition effects are reduced by about a quarter for women and by over one-half for men following control for skill-related occupational characteristics. Longitudinal analysis indicates that two-thirds or more of the standard gender composition effect can be accounted for by occupational characteristics and unmeasured worker quality or taste differences.

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I. Introduction

An important contribution to the understanding of gender differences in the labor market has been the finding that wages of both women and men are lower in predominantly female occupations. Such evidence not only enriches our knowledge about the routes through which gender differentials are realized, but is useful in evaluating the efficacy of comparable worth and other policies intended to alter the wage structure.[1] The finding that individual wages vary systematically with the gender composition of occupations is seemingly well established in cross-sectional empirical studies. For example, Killingsworth (1990, p. 24) provides two stylized facts regarding the "femaleness" of occupations: 1) both women and men earn less as the proportion female in an occupation increases, and 2) the negative relationship between wages and proportion female is stronger among men than women.

Despite a seeming consensus regarding the stylized facts, the magnitude and interpretation of the relationship between wages and gender composition remain in some dispute. Most studies examining gender composition have not controlled for a number of the job characteristics that might be expected to affect equilibrium wages. Nor is there agreement on the wage-composition relationship using longitudinal analysis, wherein individual wage changes are regressed on changes in gender composition.[2] Indeed, Sorensen (1990, pp. 76-77) identifies the estimation of wage change models and inclusion of more job characteristics in micro-level wage equations as two of the most important advances needed in this area. Absent such evidence, one cannot reject the thesis that the proportion female is a proxy for

[1] Among the many studies examining sex segregation or the relationship between wages and gender composition are Bergmann (1974), O'Neill (1983), papers in Reskin (1984), Johnson and Solon (1986), Blau and Beller (1988), Sorensen (1989, 1990), Groshen (1991), Fields and Wolff (1991) and England (1992). Sorensen (1990) provides a comprehensive survey and analysis of the literature on wages and gender composition.

[2] Studies regressing wage changes on changes in proportion female include Gerhart and El Cheikh (1991), and England et al. (1988). Gerhart and El Cheikh examine this issue using the 1983 and 1986 waves of the NLSY (ages 18-25 in 1983 and ages 21-28 in 1986). Following control for fixed effects, they continue to find a negative and significant relationship for young men (N=2,460), but a small negative and insignificant effect for young women (N=2,294). By comparison, England et al. find stronger evidence of a negative gender composition effect in their fixed effects model using the Young Women's and Young Men's cohorts of the original NLS (their sample covers the period 1968-80 for women and 1966-81 for men). Because corresponding estimates from equations without control for fixed effects are not provided, the effect on estimates owing to unmeasured person-specific effects cannot be discerned.

unmeasured skill and taste differences between workers, or of occupational attributes correlated with wages.[3]

This paper utilizes the 132 monthly Current Population Survey Outgoing Rotation Group (CPS ORG) files from January 1983 to December 1993, plus data from several additional sources, to examine how female and male wages vary with gender composition (proportion female) in a worker's occupation. The paper provides recent evidence on changes in the gender wage gap and gender segregation. Principal contributions of the paper include the use of several large data sets, the addition of occupational variables not commonly utilized in wage studies, and the construction of large CPS panels enabling an analysis of individual workers' wage changes and changes in gender composition. The longitudinal analysis enables one to control for unmeasured individual labor quality or taste differences that are correlated with the gender composition of jobs. Thus, we examine whether the wage-composition correlation evident in previous studies is due, at least in part, to occupational characteristics, quality sorting on gender composition, taste differences, or other factors correlated with the proportion female in an occupation.

Section II provides a discussion of the relationship between gender composition and wage rates, with an emphasis on measurement issues and interpretation. Section III describes the construction of the CPS cross-sectional data set and provides descriptive evidence on female and male wages and the gender composition of jobs for the twenty-one year period from 1973 to 1993. Section IV provides cross-sectional evidence for the years 1983-93 on the effect of gender composition on the wages of women and men, decomposes the gender wage gap into its component parts, compares the effects of gender composition among various worker groups, and examines issues of specification. In Section V, longitudinal evidence from three alternative data sets is examined, with considerable attention given to

[3] Filer (1989) estimates aggregate male and female wage equations at the occupational level, first with gender composition and demographic variables included, and then with the addition of a large number of variables measuring occupational characteristics (for a recent effort along these lines, see England, 1992). Filer finds that gender composition has a negative effect on male and female wages in equations excluding occupational characteristics, but no effect when these characteristics are included. Filer's results have been subject to much criticism (Smith, 1989; Sorensen, 1990; Jacobs and Steinberg, 1990, but see the reply by Filer, 1990) and are not widely accepted. In particular, Filer is criticized for not estimating wage equations at the micro level, for the use of an extraordinarily large number of occupational variables in an aggregate wage equation, and for coefficients on several variables at odds with much of the literature. Our study is not subject to these same criticisms.

the issue of measurement error in the change in gender composition variable. A concluding section provides an assessment and interpretation of evidence.

II. Wages and Gender Composition

The relationship between wages and gender composition can be estimated by:

(1) $\ln W_{if} = \Sigma\beta_{kf}X_{ikf} + \theta_f \mathrm{FEM}_{if} + e_{if}$,

(2) $\ln W_{im} = \Sigma\beta_{km}X_{ikm} + \theta_m \mathrm{FEM}_{im} + e_{im}$,

where subscripts f and m designate female and male, respectively, $\ln W_i$ is the natural log of hourly earnings for individual i; X_k consists of an intercept and variables, indexed by k, measuring personal and/or job characteristics and region; β_k includes a constant and coefficients corresponding to variables in X; FEM is the ratio of female to total employment in the worker's occupation and θ is its coefficient; and e is an error term assumed for now to have zero mean and constant variance. A value of $\theta < 0$ implies that wages decrease with respect to proportion female. If $(\theta_f - \theta_m)$ is negative, the logarithmic gender gap widens with respect to FEM; if positive the gap is narrower in predominantly female jobs.

The logarithmic gender wage gap, $\ln W_m$-$\ln W_f$, can be decomposed in the following manner:

(3) $$\overline{\ln W_m} - \overline{\ln W_f} = [\Sigma(p_m\beta_m + p_f\beta_f)(\overline{X}_m - \overline{X}_f)]$$
$$+ [(p_m\theta_m + p_f\theta_f)(\overline{\mathrm{FEM}_m} - \overline{\mathrm{FEM}_f})]$$
$$+ [\Sigma(\beta_m - \beta_f)(p_f\overline{X}_m + p_m\overline{X}_f)$$
$$+ (\theta_m - \theta_f)(p_f\overline{\mathrm{FEM}_m} + p_m\overline{\mathrm{FEM}_f})].$$

where overbars represent means and p_m and p_f are the proportion male and female in the sample. The decomposition utilizes sample proportions to weight the regression coefficients in order to approximate a "nondiscriminatory" or full sample wage structure (see Oaxaca and Ransom, 1994, for an analysis of alternative wage decompositions). The first and second terms in brackets (line 1) represent the "explained" portion of the gap, the first being that accounted for by differences in the X's, and second that owing to differences in gender density between women and men. The first term can be further disaggregated to examine the separate contribution of selected groups of X's; for example, occupational characteristics. The third term in brackets (line 2) represents the "unexplained" portion of the gender differential, that owing to differences in the coefficients on the *X*'s and FEM.

Interpretation of θ_f and θ_m, as well as the decomposition shown in (3), depends on the causes of occupational segregation and the routes through which FEM and wage rates are related (for previous discussion of these issues, see, among others, England, 1992; Blau, 1984; Polachek, 1979). Among the non-mutually exclusive explanations for occupational segregation are human capital differences, employer discrimination (based on preferences or statistical discrimination), and premarket differences in family and school inputs and in the socialization process.[4] The most common characterization of the gender composition effect is that it reflects occupational "crowding" (Bergmann, 1974). Women may be crowded into particular occupations, owing either to preferences or to past or present discriminatory barriers to alternative occupations. For example, many women but relatively few men may crowd into occupations with attractive (but costly) job characteristics. In this case the negative effect of FEM would reflect a compensating differential. Crowding lowers the equilibrium wage in these occupations to a level below that for similarly skilled workers in other occupations; inter-occupational mobility is insufficient to equalize wages.

The crowding model is useful in explaining θ_f<0, but less so in accounting for θ_m<0. If men do not face the same barriers as women, why would men accept the lower wages in predominantly female jobs when higher wages are available in male-dominated jobs? If θ_m<0, then either predominantly female jobs attract lower quality (unmeasured) male workers, or males in predominantly female jobs have tastes for these jobs and choose to accept lower wages. Stated alternatively, if women face barriers to high paying occupations, low-paid occupations will attract a disproportionately large number of women and low proportion of men, hence the negative correlation between FEM and both female and male wages.

The "quality sorting" hypothesis is a related explanation for the wage-gender composition relationship. If women but not men are crowded into low paying occupations because of discriminatory

[4] An additional explanation is the *devaluation* hypothesis, which argues that employers value less highly work done primarily by women than they value the same work done by men (for a discussion, see England, 1992). This explanation has received little attention from economists, since it is either inconsistent with standard theory or reduces to one of the alternative explanations in order to explain wage differentials (e.g., employer discrimination, restrictions on labor mobility, or worker preferences correlated with sex).

barriers, then the gender composition of a job becomes an index of labor quality for men and, to a lesser extent, for women. That is, relatively less productive males accept lower-paying jobs in predominantly female occupations. For women, however, the negative correlation between the wage and FEM represents in part the effects of past or present discriminatory barriers. Differences in gender composition across jobs owing to past occupational discrimination by employers or from societal and familial preferences that no longer prevail are likely to have evolved into quality sorting on FEM. Over time, low-paying occupations crowded by women would attract relatively lower quality males and lose many high quality females; thus, we observe workers in predominantly female jobs with lower average productivities and wages. Today's labor market equilibrium with sorting on gender composition is a result, in part, of the historical path through which labor markets evolved (Heckman, 1991, discusses the difficulty in distinguishing path dependence from worker heterogeneity).

Even in the case of current discrimination, however, FEM serves as a quality index since the probability of a woman being hired into predominantly male jobs is an increasing function of productivity. In short, workers are sorted into occupations based in part on expected productivity, and this productivity may be correlated with gender composition. For example, average and expected tenure may be lower in predominantly female occupations, leading to fewer training investments and a lower equilibrium wage for women and men. If this is a source of the gender composition wage effect, however, it can be measured (i.e., controlled) by inclusion of an appropriate variable measuring average tenure in an occupation.[5]

Taste models of discrimination that posit employer, employee, or consumer prejudices generally lead to the prediction of lower female wages in predominantly female jobs. But if men and women can be rewarded differently within detailed Census occupational categories, such models of discrimination lead to the prediction of a weaker (or positive) relationship between wages and FEM for men as compared to women, and a larger female-male wage gap in predominantly female jobs. For example, discriminatory

[5] If employers are risk averse, wages will be lower within occupations where productivity is less-easily predicted. The issue in this case is not gender differences in productivity but, rather, whether employers can more easily predict productivity for men than for women. Light and Ureta (1992) provide evidence indicating that for recent years (but not previously) tenure can be predicted as accurately for female as for male workers.

employers would pay a premium for men over women, or men preferring not to work with female coworkers would require a wage premium. Employer discrimination can of course be a primary mechanism through which female wages and FEM were initially generated. And the more homogeneous the labor market within occupational cells, the more difficult it is for employers to pay women and men differently. Lower male wages observed currently in such jobs, however, must then reflect the effects of quality sorting on gender composition, worker tastes regarding job characteristics, or immobility or transitional employment among males in predominantly female occupations.[6]

Alternative specifications of cross-sectional models (1) and (2) allow inferences to made about explanations for the relationship between wages and gender composition. If θ is sensitive to inclusion of variables measuring occupation-level tenure, training requirements, and work hours, it suggests that human capital differences across occupations, and worker preferences regarding job attachment, help account for the wage-FEM relationship. Sensitivity of θ to the inclusion of measures of job amenities and disamenities would suggest that the effects of FEM on wages reflect in part compensating differentials and differences in tastes toward these characteristics between workers in predominantly female and male jobs. Equations (1) and (2), however, cannot easily identify unmeasured worker quality and taste differences that may be correlated with FEM (Hwang, Reed, and Hubbard, 1992, show that bias from unobserved heterogeneity can be large). Estimation of longitudinal wage change models that account for unmeasured individual-specific wage determinants provides a means for examining the importance of these factors.

The longitudinal wage change model follows directly from the wage level model. Let the error term e_i from equations (1) and (2) be divided into a person specific quality or taste component (Φ_i) fixed over time, and a random error term with zero mean and constance variance (e'_i). Adding a time dimension to the earnings equation, the levels formulation in (1) and (2) can be rewritten:

(1') $\ln W_{ify} = \Sigma\beta_{kf}X_{ikfy} + \theta_f \text{FEM}_{ify} + \Phi_{if} + e'_{ify}$,

[6] For related discussion and analysis, as applied to the *racial* composition of jobs, see Hirsch and Schumacher (1992). Hirsch and Macpherson (1994) conclude that the negative relationship between wages and the proportion black in an occupation is due entirely to the correlation of racial composition with skill-related job characteristics and unmeasured worker-specific quality. For this reason, proportion black is not included here as a control variable.

(2') $\ln W_{imy} = \Sigma\beta_{km}X_{ikmy} + \theta_m \text{FEM}_{imy} + \Phi_{im} + e'_{imy}$,

where y subscripts year. If the omitted fixed effect Φ is negatively correlated with FEM, then levels estimates of θ_f and θ_m in (1) and (2) are biased downward away from zero.

Letting the change operator Δ represent changes between adjacent years [y-(y-1)], [(y-1)-(y-2)], etc., the following longitudinal wage equations are obtained:

(4) $\Delta\ln W_{ift} = \Sigma\beta_{kf}\Delta X_{ikft} + \theta_f\Delta\text{FEM}_{ift} + \Delta e'_{ift}$,

(5) $\Delta\ln W_{imt} = \Sigma\beta_{km}\Delta X_{ikmt} + \theta_m\Delta\text{FEM}_{imt} + \Delta e'_{imt}$,

where t represents the time periods over which changes are calculated. Person-specific fixed effects owing to unmeasured quality or taste differences fall out, thus (potentially) allowing unbiased estimation of θ_f and θ_m. For example, workers with a strong preference for a job characteristic associated with lower wages (e.g., flexibility of hours) are more likely to be observed in both years employed in jobs with a wage lower than that predicted by a wage level regression not controlling fully for that job characteristic.

Levels estimation of equations (1) and (2) in previous studies produces negative values of θ_f and θ_m, indicating lower female and male wages in jobs with higher densities of female workers. If this relationship results entirely from a causal effect of gender composition on wages, then longitudinal estimates of θ_f and θ_m from (4) and (5) should be similar to the levels estimates. If the negative wage/gender composition relationship is due entirely to unmeasured person-specific differences correlated with FEM, longitudinal estimates of θ_f and θ_m go to zero. Differences in the levels and longitudinal estimates of θ_f and θ_m, therefore, provide evidence as to the relative importance of unobserved worker skills and preferences versus gender-based occupational discrimination (or unmeasured worker and job characteristics not fixed over time).

III. Data and Descriptive Evidence

The primary database for this study is constructed from the 132 monthly Current Population Survey Outgoing Rotation Group (CPS ORG) files for January 1983 through December 1993. In addition, we provide supplemental evidence on gender composition and wages from 1973 forward by using the 1973 through 1978 May CPS public use files, and the January 1979 through December 1982

CPS ORG files.[7] The CPS ORG files provide unusually large sample sizes. Moreover, because households are included in the CPS in the same month for two consecutive years, construction of large two-year panels of individuals is possible. Appendix 1 provides a detailed description of the construction of our 1983/4 through 1992/3 panel. Variables measuring occupation and industry characteristics are matched to individuals in the CPS. These variables are either calculated by us from the CPS ORG files based on worker occupation and industry codes, calculated from supplementary CPS files containing variables not included in the standard CPS surveys (e.g., company tenure, firm size, and computer use), or are obtained from alternative sources such as the *Dictionary of Occupational Titles*(DOT) and matched to individuals based on their recorded occupation.

In the subsequent analysis, we include all female and male workers ages 16 and over, with complete data provided on usual weekly earnings, usual hours worked per week, occupation, race, and other needed variables. Excluded are workers whose principal activity is school (3.6 percent of the potential sample) or who had either their industry or occupation code allocated by the Census (an additional 1.1 percent). Our principal cross-sectional analysis is for the years 1983-1993, while the longitudinal analysis is based on changes between years for the periods 1983/4 through 1992/3. Wage rates are measured by usual weekly earnings divided by usual hours worked per week, in December 1993 dollars (wages are deflated by the monthly consumer price index, CPI-U). Workers with implied real wage rates less than $1.00 are excluded from the sample (0.1 percent of the potential sample). The Census top-coded weekly earnings at $999 in current dollars for the surveys through 1988; after 1988 they were top-coded at $1,923. For the years 1989 and forward, we assigned mean earnings above the $1,923 cap based on the assumption that the upper tail of the earnings distribution follows a Pareto distribution. The parameters of the Pareto were estimated separately by year and gender. For each month

[7] Beginning in January 1983, new occupation and industry codes from the 1980 Census of Population were adopted by the CPS, and union status was asked of the outgoing rotation groups in each monthly survey rather than only in May. Beginning in 1992, the CPS adopted the 1990 Census of Population occupation and industry codes, but changes between the 1980 and 1990 codes are relatively minor. All constructed variables at the detailed occupation and industry level for 1983-93 have been made time consistent. Major industry and occupation dummies used as regression dummies used in the Table 1 regressions for 1973-93 are time-consistent; occupational categories were defined based on the 1970 to 1980 mappings provided in U.S. Department of Commerce (1983). The CPS ORG or "earnings microdata files" for 1979 forward are made available by the Data Services Group at the Bureau of Labor Statistics (BLS).

in years prior to 1989, mean earnings for those at the $999 cap were assigned based on the mean in 1989 among female or male workers at or above the same real weekly earnings.

The total sample size for the 1983-93 wage level analysis is 1,836,541; 877,070 women and 959,471 men. No individuals in the CPS are excluded because of small occupation sample sizes. Since estimation is across individuals rather than occupation, those in small occupational cells receive correspondingly little weight in the regression analysis. The sample size of the longitudinal data set combining the panels for 1983/4 through 1992/3 is 459,685, or 25 percent the size of the full sample. Appendix 1 describes fully the construction of the CPS ORG matched panel, as well as a similarly sized March CPS retrospective panel used in our wage change analysis.

Gender composition is measured by FEM, the proportion of female workers in the worker's 3-digit Census occupation, calculated from the CPS files. Descriptive evidence on FEM and the wage-FEM relationship is provided for the period 1973-93. FEM is calculated here on an annual basis for the years 1979-93 (we employ three-year moving averages in subsequent regression analysis for the 1983-93 period), and over two years for the 1973-74, 1975-76, and 1977-78 periods. All rotation groups in the CPS were asked earnings questions in the May surveys from 1973 through 1978, whereas the annual ORG files for 1979 forward include only the outgoing rotation groups, the quarter sample of the CPS for whom earnings were measured beginning in 1979. Note that measures of FEM from 1973-82 and 1983-93 are not strictly comparable since the earlier years use the 1970 Census of Population occupation codes and the latter a combination of the 1980 and 1990 Census codes. The modest changes between the 1980 and 1990 codes (the CPS began using the 1990 codes in 1992) permitted us to construct time-consistent categories for 1983-93 (6 small occupational categories were merged into larger categories, reducing the number of potential occupations from 503 in 1983-91 to 497 for 1983-93). Despite substantial changes in occupational definitions and categories between the 1973-82 and 1983-93 periods, we do not observe an obvious break in the FEM series between 1982 and 1983.

Table 1 provides descriptive evidence for the years 1973-93 on sample sizes, mean female and male real wage rates, the female to male wage ratio, gender composition, the Duncan index of segregation, and the relationship between wages and FEM. As widely recognized, the gender gap changed little during the 1970s, and then narrowed substantially throughout the 1980s and early 1990s. The ratio of female to male hourly earnings, W_F/W_M, increased from .648 in 1973-4 to .669 in 1983, and then to .764 by 1993. Following a real wage decline during 1973-81, wages for women increased by 12.6 percent during the 1981-93 period, in contrast to a small decrease observed among men.

Mean values of FEM and the Duncan index of segregation by year indicate declining occupational segregation by sex during the 1970s and 1980s, with slow progress evident during the early 1990s. The occupation percentage female among male workers increased from 17.6 percent in 1973-4 to 28.8 percent in 1993; the percentage female among women declined from 72.1 to 68.2 percent during the same period (for previous evidence on changes in occupational segregation see, among others, Blau and Beller, 1988; Fields and Wolff, 1991; and O'Neill and Polachek, 1993).[8] The Duncan index of segregation, measured by $\frac{1}{2}\,\Sigma|m_j\text{-}f_j|$, where m and f are the proportions of male and female employment, respectively, in occupation j, varies between 0 in the case of an equal occupational distribution and one in the case of complete sex segregation. The Duncan index falls from .685 in 1973-4 to .546 in 1993. Some of the decline appears to result from the change in occupational definitions between 1982 and 1983 (figures for 1973-82 are not directly comparable to those for 1983-93). Indices of occupational segregation are sensitive to the degree of aggregation. For example, at an even more disaggregated level, a large number of jobs are virtually all male or all female (see Groshen, 1991).

Although not a central focus of the paper, our data set allows us to provide a 1973-93 time-series of the relative wage ratio, W_F/W_M, and of the Duncan index of segregation for groups of workers classified by education, age, race, part/full-time status, private and public sector status, production and nonproduction occupational status, and union status. This information is presented in Appendix 2. Although relative wage ratios and the degree of occupational segregation differ significantly among

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[8] Increases in the relative size of the female labor force can produce increases in FEM for both women and men. In Table 1, FEM is averaged over *individuals* (this is equivalent to averaging over occupations, weighted by employment). FEM is calculated alternatively by averaging over the 497 occupations (unweighted), beginning in 1983 with the new occupational codes. Among occupations that were majority female and majority male in 1983, mean FEM decreased from .746 in 1983 to .724 in 1993 among the female occupations, while increasing from .166 to .195 among the male occupations. If instead we calculate changes for occupations that were either two-thirds female or male in 1983, mean FEM decreased from .838 in 1983 to .796 in 1993 among the female occupations, while increasing from .110 to .137 among the male occupations.

groups, there are increases in the wage ratio and decreases in sex segregation among all groups of workers during the past twenty years.

Table 1 also provides estimated slopes of the log wage-FEM relationship, θ and θ_{adj}, unadjusted and adjusted for standard worker characteristics, during the 1973-93 period. The unadjusted coefficients are obtained from female and male log wage regressions, estimated by year, with only FEM on the right-hand-side. The adjusted coefficients are obtained by adding a common set of controls over the entire 20 year period -- years of schooling; years of potential experience and its square; and dummies for marital status (2), race and Hispanic status (3), part-time status, public sector status, large metropolitan area, occupation (5), industry (13), and region (8). Excluded are a measure of union status and separate dummies for federal, state, and local employment, since these variables are not available over all the years. Estimates in Table 1 for 1983 forward differ moderately from results to be shown subsequently (our so called "standard" specification) because of the exclusion of union status and detailed public sector dummies, and because FEM is calculated here on an annual basis rather than as a moving average. Sample restrictions are equivalent to those outlined previously.

Comparison of the unadjusted and adjusted FEM coefficients illustrates the importance of controlling for worker (and job) characteristics. The unadjusted coefficients for women are relatively stable over the 1973-93 period, showing some indication of rising into the mid-1980s and then falling since then. By contrast, the male coefficients begin the period larger than the female coefficients and hit a peak in the late 1970s. They then decline steadily and are effectively zero in the early 1990s. The conventional conclusion that male coefficients exceed those for women is sensitive to time period and choice of control variables. Johnson and Solon (1986) use the May 1978 CPS and find larger coefficients for men (they report unadjusted coefficients of -0.343 for men and -.244 for women). As will be seen subsequently, the low unadjusted coefficient for men in later years reflects a nonlinear relationship in which a large number of predominantly male jobs are low skill and low paying. Accounting for schooling and a few standard controls increases the magnitude of the male coefficient and makes the wage-FEM relationship more nearly linear. For example, with controls, the male coefficient is relatively stable over time. The adjusted FEM coefficient for women displays its lowest value in the 1970s, climbing into the mid-1980s, and stable thereafter.

In subsequent regression analysis for the 1983-93 period, FEM and other occupation and industry measures calculated from the CPS ORG files are measured as three year moving averages. This reduces measurement error that can result from small sample sizes in some occupation and industry cells. Although bias resulting from measurement error within small occupation cells will have little effect on wage level equation estimates, measurement error is a concern in the longitudinal analysis. Because absolute and relative changes in gender composition and job characteristics occur slowly over time, little error is introduced from the use of moving averages. Averages for 1983-85 are matched to both 1983 and 1984, and averages for 1991-93 are matched to both 1992 and 1993.

Table 2 presents descriptive statistics for 1993, with the sample segmented into four occupational categories based on gender composition (the breakpoints for FEM are .25, .50, and .75). As evident from Table 2, wages rates for both women and men are substantially lower in predominantly female jobs (FEM $\geq$.75). For men, wages (and schooling) are low in occupations that are almost entirely male, while decreasing with respect to gender composition at higher levels of FEM. Women display a similar wage pattern. Notable in Table 2 are the substantial differences in occupational characteristics between predominantly female and male jobs. This is evident in the occupational means of job tenure, proportion part-time, occupational training requirements (SVP), computer use, strength, hazards, and physical and environmental conditions. Because there are substantial differences in wages, worker characteristics, and job characteristics among workers in predominantly female and male jobs, we turn below to an analysis of how estimates of θ vary with specification.

IV. Wages and Gender Composition: Cross-Sectional Evidence

A. Standard Estimates

In this section we present estimates of θ_f and θ_m, based first on the estimation of annual cross-sectional log wage equations for the years 1983-93. Results are presented for what is referred to as the "standard" model, regressions including variables measuring individual characteristics, location, and broad occupation and industry of employment (i.e., years of schooling, potential experience and its square, and dummies for union coverage, black, other nonwhite, Hispanic, married with spouse present, ever married without spouse present, part-time, federal worker, state worker, local worker, large metropolitan area, region [8], industry [13], and occupation [5]). These results are representative both of standard estimation techniques and of variables available in most data sets. We subsequently provide wage level results from what is referred to as the "expanded" model, which includes a variety of occupation and industry characteristics measures not routinely included in wage equations.

Results from the standard model, presented in Table 3, indicate that the gender composition effect is substantial and similar in magnitude for women and men. Estimates indicate an increase in the absolute value of θ since the early 1980s. A θ of, say, -.18 indicates that wages are about 7 percent lower for both women and men in a typical "female" occupation (FEM $\approx$.68) than in a "typical" male occupation (FEM $\approx$.29). Stated alternatively, a movement toward equality of gender composition across occupations (a change to a FEM of .48, the mean in the combined female and male sample for 1993) would be associated with a 3.6 percent increase in a typical female worker's wage and a 3.4 percent decrease for a typical male. Changes in θ_f and θ_m between 1983 and 1993 (Table 3, standard specification), coupled with changes in FEM during this period (Table 1), imply that changes in the level and impact of gender composition had a negligible effect in narrowing the gender gap. Looking at the difference in the effects of FEM for 1993 and 1983, calculated by

(6) $[(\theta_f FEM_f - \theta_m FEM_m)]_{93} - [(\theta_f FEM_f - \theta_m FEM_m)]_{83} = [-.0640] - [-.0660] = .0020$

indicating the logarithmic gender gap narrowed by only .002 log points owing to changes in gender composition and its wage effects. This is less than 2 percent of the total .124 narrowing of the gap over the 1983-93 period (see the top line of Table 7). Note that the above calculation assumes a causal relationship from gender composition to wages; it is this interpretation that we investigate below.[9]

B. Gender Composition and the Role of Job Characteristics

[9] Utilizing coefficients from our "expanded" model, as presented in Table 3 and discussed below, the effect of the change in gender composition implied by equation (6) is .005. Although changes in gender composition had small effects on the gender wage gap during the 1980s, it did not operate in isolation from other structural changes. Blau and Kahn (1992) show that changes in industry coefficients during the 1980s benefited women relative to men, while O'Neill and Polachek (1993) find that changes in occupational returns favored males. Even and Macpherson (1993) provide estimates of the effects of declining unionization on the gender gap. Blau and Beller (1988) show that changes in occupational segregation also had relatively little effect on female-male wage trends in the 1970s.

One explanation for the wage-composition relationship is that it partly reflects compensating wage differentials resulting from differences in job characteristics between predominantly female and male occupations. Moreover, quality sorting by workers may be not on the basis of gender composition per se but, rather, on the basis of job characteristics correlated with gender composition. The job characteristics hypothesis is tested estimating "expanded" wage regressions that include measures of occupation and industry characteristics. Measured at the occupation level are an index of general education requirements (GED), mean years of necessary occupational training (SVP), proportion of workers who report receiving training on the job (OJT), mean tenure with the current firm, the proportion of part-time workers, the proportion using a computer on the job, the proportion of jobs facing hazards, and indices of physical demands, environmental conditions, and strength. Measured at the industry level are the proportions of workers in firms with at least 1,000 employees and of workers covered by union contracts.[10]

Results from the expanded model are shown in Table 3. The rather clear-cut result is that the magnitude of the relationship between female or male wages and gender composition, following control for job characteristics, is reduced by roughly one-quarter for women and one-half for men. In 1993, for example, the addition of job characteristics variables causes coefficients on FEM to decline in magnitude from -.176 to -.139 among women, and from -.195 to -.090 among men. At least some of the negative relationship between wages and the proportion female in an occupation is the result not of gender composition per se, but of differences in job characteristics correlated with FEM. The magnitude of the wage-FEM relationship appears to be as strong or stronger in 1993 as in 1983. While we would expect FEM coefficients to be sensitive to changes in the economy's valuation of unmeasured skill and job types with which FEM is correlated, we do not probe this issue directly,

[10] A number of previous studies have included DOT occupational measures, and Johnson and Solon (1986) additionally include percentage part-time in their May 1978 wage level equation. None have included measures of occupation-level tenure, computer use, or on-the-job training. Johnson and Solon report larger estimates θ_f and θ_m; differences between our studies include the inclusion here of more control variables, substantially larger sample sizes, a more recent time period, and estimation of longitudinal models. We examine below the sensitivity of estimates to specification and functional form.

In contrast to Johnson and Solon and other studies (and results from our standard specification), the relationship between wages and gender composition is not found to be systematically stronger among men than among women, once we control for detailed job characteristics. The magnitude of the gender coefficient for women in the expanded model exceeds that for men in ten of the eleven years from 1983-93. The sharper reduction in θ_m than in θ_f following control for measurable skill-related job characteristics supports the thesis that occupational crowding and mobility barriers may account for much of the negative wage-FEM relationship among women, whereas measurable differences in job skills account for relatively more of the negative wage-FEM relationship among men. Subsequent longitudinal analysis will provide estimates of the extent to which FEM is a proxy for *unmeasured* worker skills and preferences.

In order to assess the appropriateness of our specification, we examine the signs and magnitudes of the coefficients on the job characteristics variables other than FEM. For ease of presentation, we analyze these (and other) issues using a data set pooled over the 1983-93 period, with year dummies included. Table A2 provides full regression results for the female and male expanded log wage equations, with occupation and industry characteristics; this corresponds to the results shown in Table 4, column 1. Coefficients on earnings function variables measured at the individual level do not warrant comment, apart from the coefficients on years of schooling completed. Their relatively low value (.043 for women and .045 for men) is due to the inclusion of occupation dummies, GED, and SVP. Coefficients on the occupation and industry characteristics variables are generally consistent with theory and expectations. Variables measuring GED, SVP, OJT, computer use, hazards, and proportion in large firms within the worker's industry are positively related to both male and female wages. Results counter to expectations in the female wage equation are a zero coefficient on proportion part-time and small negative coefficients on environmental disamenities and proportion union. Contrary to expectations in the male wage equation are small negative coefficients on mean tenure and the strength index, and a zero coefficient on physical demands. Although our results are largely consistent with expectations, predictions of signs are not unambiguous owing to heterogeneous tastes and sorting and because characteristics such as strength may be correlated with other unmeasured determinants of productivity (in the *change* equation, the only "wrong" sign is on an insignificant DOT-Environment coefficient in the male equation).

C. Further Results

In this section, we examine the issues of functional form, specification, differences in the effects of gender composition among alternative groups of workers, and estimation of θ from a data set containing individual data on tenure and firm size.[11] We first examine the linearity of the log wage-FEM relationship by estimating specifications that replace FEM with the dummy variables FEM25-50, FEM50-75, FEM75+, corresponding to the designated range of FEM (the omitted base category is FEM<.25). In Table 4, we provide estimates for a model with no control variables, for the standard model, and the expanded model including job characteristics. The results with no controls indicate a U-shaped relationship between log wages and FEM, with wages lowest in occupations with low and high proportions of women. The low average wages in predominantly male occupations reflects the low skill requirements in many of these jobs. Once individual characteristics are included, the relationship becomes closer to linear, with coefficients on FEM25-50, FEM50-75, and FEM75+ of approximately -.05, -.10, and -.14 among women, and -.00 -.09, and -.14 among men. When job-level characteristics are added the coefficients on the categorical dummies change to -.03, -.07, and -.08 among women, and .02, -.04, and -.06 among men. In subsequent work, we restrict our analysis to the linear specification.

Table 5 presents the coefficients on FEM obtained from alternative specifications. We include first the equation with no controls, followed by a "base" specification (line 2) including all variables measured at the individual level, with the exception of broad occupation and industry dummy variables. We then add industry and occupation dummies (separately and jointly) to the base model and obtain the "standard" specification (line 5) shown previously. We then add to the standard specification, separately

[11] An additional issue examined is whether an effective wage floor associated with minimum wage laws or binding reservation wages flattens the wage-FEM gradient, in particular for women. If a significant number of workers are in jobs with wages close to the minimum, there can be relatively little negative effect on wages from increases in the proportion female (for a similar analysis with respect to racial composition, see Hirsch and Macpherson, 1994). To address this issue, we created a new sample restricted to workers with wages at least 1.2 times the minimum wage ($3.35 through March 1990, $3.80 from April 1990 through March 1991, and $4.25 after April 1991). This sample restriction resulted in the deletion of 8.8 percent of the men and 16.7 percent of the women. Regression results for workers above the cutoff were highly similar to those shown in the paper.

and jointly, the occupational variables GED, SVP, mean tenure, proportion part-time, proportion OJT, and proportion with computer use (lines 6-12). We also add to the standard model all DOT occupation measures other than SVP and GED (line 13) and the industry measures of firm size and union density (line 14). We then present the expanded model (line 15) and the expanded model minus the DOT index of physical requirements (lines 16). Additional specifications shown are one in which all occupation-level variables (other than FEM and the DOT variables) have been calculated on a gender-specific basis (line 17) and a one including 49 rather than 13 industry dummies in the expanded specification (line 18).

The principal conclusion to be reached from the results in Table 5 is that estimates of the wage-FEM relationship are sensitive to specification. Several results are notable. For women, the inclusion of occupation and/or industry dummies has virtually no effect on the FEM coefficient. By contrast, among males inclusion of industry dummies sharply decreases the magnitude of the FEM coefficient, while inclusion of only 5 occupation dummies sharply increases its magnitude (lines 3 and 4). These results indicate that the negative wage-FEM correlation for males occurs primarily *within* broad occupation groups, that mean FEM and wages are positively correlated across these broad occupational groups (the simple correlation of mean wages and FEM among our 6 occupational categories is .293 for men), and that much of the negative FEM-wage correlation among men can be accounted for by industry differences. As pointed out by Johnson and Solon (1986), industry wage differentials are likely to be little affected by comparable worth policies, making such policies relatively less effective. We find virtually identical results, regardless of specification, when a more detailed set of 49 industry dummies is substituted for the 13 industry dummies (i.e., compare lines 15 and 18).

The separate inclusion of human capital and job attachment variables measured at the occupational level are found to reduce substantially estimates of θ. The addition of SVP, measuring average years training required for occupational proficiency, has a large impact on the magnitude of the FEM coefficients, changing θ_f from -.17 to -.09 and θ_m from -.19 to -.09.[12] The effect of proportion part-time is to reduce the FEM coefficient to -.11 for women and -.09 for men. This variable is likely to

[12] Some authors have included a SVP *index* measuring variable ranges of years, rather than using the DOT conversion of this index to the number of years training. SVP has a smaller impact on wages and the FEM coefficient when included as an index.

provide a measure of job attachment and average work hours, which in turn are positively related to training and earnings.[13] Inclusion of mean tenure reduces θ to -.12 and -.16 for women and men; while inclusion of GED leads to coefficients of -.14 and -.10 for women and men. The addition of OJT has a more moderate effect, while addition of the proportion using computers has little effect on either estimate of θ (women have moderately higher computer use on the job than do men). The joint addition of SVP, OJT, GED, computer, job tenure, and part-time to the standard model (line 12) produces estimates of θ_f=-.12 and θ_m=-.08. These results indicate that a sizable portion of the negative wage-FEM relationship, roughly a quarter among women and half among men, is due to occupational differences in skill requirements and job attachment.

The inclusion of union density and the proportion of workers in large firms, both measured at the industry level, has relatively little effect on estimates of θ_f and θ_m (line 14). Inclusion of the DOT occupational characteristics *other than* SVP and GED -- Environment, Hazards, Physical, and Strength -- *increases* the magnitude of θ for both women and men, to -.19 for women and -.23 for men when added to the standard model (line 13). These results indicate rather clearly that it is *not* differences in occupational working conditions that lead to a negative wage-FEM relationship. In fact, a surprising finding is the sensitivity of θ_f to the inclusion of the index of physical job attributes (stooping, reaching, seeing, and climbing). Deletion of the physical index from the expanded model *reduces* the magnitude of θ_f from -.12 to -.08 (line 16). The reason for this seemingly anomalous result is partly evident in Table 2, where it is shown that predominantly female occupations have a relatively high index value of physical demands, but relatively low pay. The fact that the physical index enters the female wage equation with a positive and highly significant value (Appendix 3) indicates that it in fact belongs in a wage equation estimating the impact of FEM. More detailed analysis with components of the physical index (these results not shown) indicate that it is the reaching and seeing components that are driving this result. Estimation of the model with categorical dummies substituted for FEM indicates that exclusion of the

[13] Rebitzer and Taylor (1991) provide theory and evidence along these lines. In their model, uncertain demand leads firms to choose a mix of primary and contingent workers to perform the same jobs. Firms hire into the primary jobs workers who prefer long hours and with strong job attachment. They predict that jobs with a high percentage of part-time workers will have a large number of contingent workers, and, as in our analysis, that the wages of full-time workers will vary inversely with the proportion part-time.

physical index has little effect on FEM25-50 and FEM50-75, but sharply reduced the magnitude of FEM75+. In contrast to the results for women, exclusion of the physical index in the male equation has no effect on estimates of θ_m (lines 15 versus 16).

Finally, we provide estimates of θ_f and θ_m from a specification where all occupation- and industry-level variables other than FEM and the DOT measures are calculated from the CPS separately by gender (line 17). Inclusion of gender-specific measures may be preferable where an included job characteristic variable is highly correlated with FEM, but a poor proxy for the job attribute expected to provide a compensating differential. Inclusion of gender-specific measures increases the magnitude of the FEM coefficients by about .01 to .02 log points; in the full models with gender specific measures we obtain θ_f= -.13 and θ_m= -.11. We attach relatively less weight to these estimates since the gender-specific job characteristics are measured with greater error (sample sizes by gender are less than with the combined samples) and because it may be more appropriate to treat the occupational category as a unified labor market (as assumed in the case of FEM) than as two distinct markets.

A potentially important issue given little attention in the literature on gender composition is the possibility of differences in gender composition effects across sectors, demographic groups, and types of workers. Knowledge of such differences might allow us to ascertain the generality of our results and has the potential to enhance understanding of why occupations with relatively larger numbers of women have lower female and male wage rates. Table 6 provides coefficient estimates (standard errors are omitted) from both the standard and expanded models, disaggregated on the basis of age, education, race, private-public sector status, union status, part- and full-time status, and production-nonproduction status. These results provide less insight than expected. For both sexes, the effect of FEM on wages is smallest among relatively senior workers (ages 45+). This is consistent with the hypothesis that occupational crowding has been more severe for younger cohorts among whom female labor force participation is highest, or that occupational choice among younger workers is more heavily influenced by unmeasured occupational characteristics correlated with FEM. If gender discrimination and occupational barriers were the primary explanation for the wage-FEM relationship, however, we might have expected a stronger gender composition effect among more senior workers. Difference in FEM coefficients with respect to education level appear erratic among women; the notable finding among men is the *positive* coefficient in the expanded model among workers with post-graduate education.

Among women (but not men), wage penalties associated with gender composition are lower in the public than in the private sector, and in the union as compared to the nonunion sector. Implementation of pay equity policies has been most extensive in these sectors, although it is not clear the extent to which these differences are related to explicit (or implicit) pay policies designed to lessen gender wage differences. Gender composition effects on wages for women are found exclusively among full-time workers, whereas among males, coefficients on FEM are at least as large for part-time as for full-time workers. Part-time female workers receive low wages (for a given set of measured characteristics) independent of the level of FEM (i.e., θ_f is close to zero for part-time women), whereas θ_m is similar among part- and full-time males. Differences in θ between production and nonproduction workers do not display a consistent pattern across specifications or gender.

We next consider problems associated with matching aggregate data on occupations to individual worker data (for a discussion of some of these issues, see Dickens and Ross, 1984, Kloek, 1981, and Moulton, 1990). Matching grouped and individual data presents potential problems of several forms. Information from a single occupation is matched to multiple individual workers in that occupation. This has an effect similar to repeating observations, biasing downward standard errors, but not necessarily biasing coefficient estimates. A second problem is measurement error resulting from the heterogeneity of jobs within an occupational category and the resulting imperfect match between individuals' jobs and occupational values. For example, FEM may be measured accurately for the 3-digit Census occupation for which it is defined, but may overstate or understate the proportion of women in an individual worker's more narrowly defined occupation or job. This type of measurement error may bias coefficients on the grouped variables toward zero. An additional distinction worth making is between occupational variables that proxy unmeasured *individual* characteristics, versus group data measuring relevant *job* characteristics. For example, the variable measuring mean tenure in an occupation is included not only to represent a relevant job characteristic affecting all workers’ wages, but also as a proxy for missing information on individual workers' tenure.

To provide a check on our results, we reestimate the standard and full models using a two-step estimation strategy suggested by Dickens and Ross (1984). In a first step wage equation, only variables measured at the individual level or that vary within detailed occupations are included. We then calculate the mean of the equation's error term for each detailed occupation (this is equivalent to including detailed occupational dummies, but is computationally more efficient). Occupational wage differences calculated in the first step then become the dependent variable in a second-step regression, estimated by WLS, with the square root of occupation sample sizes as weights. Included in the second-step standard equations are FEM and broad occupation dummies, while the second-step expanded model adds all other occupational variables that vary across but not within detailed occupations. We obtain estimates θ_f (and their standard errors) of -.1611 (.0216) and -.1126 (.0246) for the standard and expanded models. Corresponding estimates of θ_m are -.1814 (.0219) and -.1305 (.0249). As expected, WLS point estimates are similar to what were obtained previously using single-step estimation, but standard errors are roughly ten times larger than those shown previously.

Finally, because the CPS does not normally contain measures of tenure on the current job, firm size, or establishment size, we also have estimated identical models using the May 1983 and 1988 CPS Pension Supplements (these results are not shown). Inclusion of individual worker tenure and size variables reduces the unexplained portion of the gender wage gap by a small amount, only .012 in both the standard and expanded specifications. Coefficient estimates for θ_f and θ_m, however, are highly similar to those presented using the CPS ORG files.

D. Wage Gap Estimates and Gender Composition

Examined in this section is the sensitivity of gender wage gap estimates to the inclusion of FEM. The top line of Table 7 provides the total or unadjusted logarithmic gender gap by year, while lines 1a and 1b show the explained and unexplained portions of the gap based on our standard model, absent FEM. The unadjusted log wage gap declined throughout the period, from .359 in 1983 to .235 in 1993. Differences in personal and labor market characteristics included in the standard model account for only a fifth of the gap; in 1993, .192 of the .235 total gap remains unexplained. Although both the explained and unexplained values (lines 1a and 1b) fell over the 1983-93 period, the fraction of the total gap that is unexplained rose (for a similar finding using PSID data, see Sorensen, 1991).

Lines 2a-2c of Table 7 are based on our standard specification, with FEM added to the previous model (specification 1 of Table 3). Inclusion of gender composition reduces the unexplained gap by about .05 log points, while accounting for more than half of the explained portion of the gap during most of the period (and 83 percent by 1993). When job characteristics are added to the model, as shown in the expanded specification on lines 3a-3d, the portion accounted for by FEM is reduced by about a third. The cross-sectional results throughout the 1983-93 period indicate that gender composition differences between men and women account for roughly .05 log points of the total gender wage gap, the latter declining from .36 in 1983 to .24 in 1993.

Although occupational characteristics are jointly not important in explaining the gender wage gap, as opposed to their importance in accounting for the effects of FEM, several are individually important but tend to cancel out each other. In line 3e of Table 7 we list the contribution of several of the more important variables – SVP, proportion part-time, physical conditions, computer use, and GED – on the explained portion of the gender wage gap. Differences between women and men in occupational training requirements, as measured by SVP, account for about 1 percentage points of the gender gap during the early 1980s, but decline to below 1 percentage point by 1993. The proportion part-time can account for roughly 1 percentage point of the gap, while differences in physical requirements accounts for another percentage point. Working in the opposite direction are computer use and GED. Differences in computer use should be associated with about a 1.5 percentage point female wage advantage, and occupational education requirements another .5 point advantage.

V. Longitudinal Analysis of Gender Composition and Wages

A. Results

An important contribution of this study is the estimation of longitudinal wage change models that control for unobserved fixed effects in measuring the relationship between wages and gender composition. If women and men with higher unmeasured skills are more likely to be sorted into predominantly male jobs, and those with lower productivity into predominantly female jobs, then the coefficient on FEM in a longitudinal wage change model should move toward zero (as noted previously, past or present discrimination can produce the sorting pattern described here). That is, workers whose unobserved quality remains constant over a one-year period would exhibit a relatively small wage change due to a change in the gender composition of a job (this assumes that wage losses associated with firm- and occupation-specific skills are uncorrelated with changes in FEM). Although time in the new job is relatively brief in our panel, it is reasonable to expect most wage effects of gender composition to be attached to the occupation and therefore show up quickly in the new wage.

Using similar reasoning, longitudinal models can account for unobserved taste differences correlated with gender composition and unmeasured job characteristics. For example, workers who place a high weight on jobs with flexible schedules and attractive working conditions are likely to be observed in jobs with lower wage rates. If such workers change occupation (and thus FEM), they are likely to have relatively low wages (conditional on measured characteristics) in both jobs. When the wage equation is estimated in levels form, the coefficient on FEM will be negative if gender composition is correlated with worker preferences of this sort, whereas estimation of a longitudinal wage equation will control for the effects of *unmeasured* job characteristics and tastes, to the extent that they remain fixed among occupational switchers.

Table 8 presents results from both levels and longitudinal wage change equations, estimated using the pooled panel data set constructed from the CPS ORG files, and consisting of matched worker pairs for the periods 1983/4 through 1992/3. The levels estimates correspond exactly to the previously estimated standard model (individual characteristics plus broad occupation and industry dummies) and expanded model (the standard model plus job characteristics) except that the sample in Table 8 consists of matched individuals from the CPS panel during their second year in the survey (1984-1993). The panel does not include individuals not employed in adjacent years, those residing in a different households or geographic locations in adjacent years, and those for whom unique matches could not be made (see Appendix 1). Most likely to be excluded from the panel are young workers. Despite these differences, levels results here are highly similar to those obtained previously from the full CPS ORG sample. We obtain estimates of θ_f and θ_m of -.16 to -.18 in the standard model, while in the expanded model θ_f is estimated to be -.11

and θ_m -.08. The similarity in levels estimates between the panel and full samples suggest that the subsequent longitudinal results can be generalized to a representative national sample of female and male workers.

The dependent variable in the longitudinal wage change models is $\Delta \ln W$; longitudinal estimates of θ_f and θ_m are based on the coefficients on ΔFEM. For reasons examined below, we present results here based on occupation changers who also report changing industry over the year (more precisely, ΔFEM times a dummy equal to one if both occupation and industry change). Workers recorded as changing occupation but not industry have separate estimates of the ΔFEM variable (not shown in Table 8), while workers not recording an occupational change are the reference group.[14] In addition to ΔFEM, whose coefficient is shown in Table 8, the standard change model includes control variables measuring changes in experience squared, part-time status, public sector status (federal, state, and local), union coverage status, marital status, broad occupation and industry, and FEM for those changing occupation only (as explained above), plus 9 period dummies. The change in experience is one for all workers and thus reflected in the intercept; variables are not included for changes in schooling (since persons whose principal activity was schooling were excluded), race, large metropolitan area, or region (since households moving drop out of the CPS and cannot be matched). The expanded model includes variables measuring changes in the job characteristics.

The estimates reported in the first two lines of Table 8 indicate clearly that the gender composition effects reflect in part unmeasured worker-specific skills and/or preferences correlated with FEM. For women, the estimate of θ_f in the standard model drops in magnitude from -.16 to -.09, while for men θ_m changes from -.18 to -.09. These results support the hypothesis that more productive women and men sort into or are selected for higher paid "male jobs," while less able workers are more likely to work in occupations that have a higher proportion of women. Alternatively, the reduction in estimates of θ_f and θ_m may reflect worker taste differences regarding unmeasured job amenities and disamenities

[14] Since FEM changes over time within occupations, non-switchers realize very small changes in gender composition. For convenience, we do not include a separate variable equal to a non-switching dummy times ΔFEM; rather, wage change for this group is reflected in the equation intercept. Results with this variable included are virtually identical to those shown.

correlated with FEM. We should emphasize, however, that FEM remains a significant and nontrivial determinant of wage rates, even after controlling for unmeasured person-specific differences.

Once we control for both measured job characteristics and unmeasured worker-specific effects in the expanded longitudinal model, however, the gender composition effect becomes rather small, -.05 for women and -.03 for men. That is, roughly two-thirds of the standard gender composition effect among women is accounted for by job characteristics and unmeasured skills and tastes (i.e., the change from -.163 to -.055), and roughly four-fifths of the effect among men (the change from -.178 to -.034). A coefficient of, say, -.05 suggests that differences in the gender composition of occupations can account directly for only .02 log points (.05 x .40, where .40 is the difference in mean FEM between women and men) of the sizable gender wage gap, which averaged roughly .30 over the 1983-93 period. Our panel results indicate that gender composition has a relatively small direct or causal effect on wages. Rather, FEM is correlated with differences in job characteristics, worker-specific productivity differences between observationally equivalent workers, and taste differences regarding job characteristics. These factors in turn produce labor market sorting such that wages and FEM are negatively correlated.

B. Measurement Error and Alternative Estimates

An important concern in the longitudinal analysis is possible measurement error in the explanatory change variables. Measurement error biases toward zero regression coefficients, and this downward bias is most severe in models where intertemporal variance owing to measurement error is large relative to true variance of a right-hand-side variable (see, for example, Freeman, 1984). Measurement error bias may be particularly serious where a substantial number of persons have occupation misclassified (Mellow and Sider, 1983) and where the time period is sufficiently short so that there are few true occupational changers.

Although we expect bias from measurement error to be present in our analysis, several points are in order. Our sample has excluded all worker-year pairs where occupation or industry has been allocated by the Census in either the first or second year. Second, there exists serial correlation in response error (for related evidence on earnings, see Bound and Krueger, 1991), so that a respondent who reports the incorrect occupational category in year 1 may report the same category in year 2. In this case, “two wrongs make a right" since the person would be classified correctly as having ΔFEM=0. Third, even among those workers misclassified by occupation, it is likely that they have recorded a closely related occupation whose FEM may not be too different from actual FEM (we present evidence below). This is in contrast to the frequently discussed case of mismeasurement of union status, where workers are assigned values of 0 or 1. Finally, we can gauge the seriousness of measurement error by comparing our results with those from other data sets where occupational change is unlikely to be measured with significant error.

We consider several pieces of evidence. Our most important control for measurement error in the longitudinal analysis is to present only coefficient estimates on ΔFEM for workers who are recorded as changing both occupation and industry, since workers who report changes both in industry and occupation are less likely to have remained in the same job than those workers recorded with changes only in occupation. Thus, estimates of θ should be less affected by measurement error for industry movers than for industry stayers. In order to illustrate the importance of this distinction, we provide in Table 9 results from longitudinal equations with alternative treatment of ΔFEM. In addition to providing the coefficients on ΔFEM for those changing occupation and industry (column 1), we present ΔFEM coefficients for occupation switchers who did not change industry (column 2), and coefficients for all occupation switchers with no distinction based on industry change (column 3). Results are consistent with the expectation that measurement error biases coefficients toward zero. Indeed, in the standard model, our preferred coefficients for occupation and industry switchers are roughly 3 times larger (in absolute value) than corresponding estimates for occupation only changers.

As argued above, those reporting a change in occupation in the CPS are likely to realize a change in gender composition smaller than if their new occupation were randomly misreported. Evidence supports this proposition. The average absolute value of ΔFEM for those who change both occupation and industry is .23; for those reporting only a change in occupation the corresponding value is .20. By contrast, if these same persons are randomly assigned a CPS occupation (an equal probability is assigned to each eligible occupation), the mean absolute value of ΔFEM is .36 for both samples. Recorded occupations for workers falsely categorized as changing occupation are clearly not selected randomly.

And the relatively large absolute value of ΔFEM among designated switchers (.23) suggests that it provides a high ratio of signal to noise.

In order to explore further the degree of measurement error owing to misreported occupational changes, we utilized supplementary information from the January 1987 CPS public-use survey, which explicitly asked individuals in all rotation groups whether they had changed occupations during the previous year and, if so, their previous occupation and industry. Individuals from rotation groups 5-8 in January 1987 are matched with their previous responses in outrotation groups 1-4 in our January 1986 sample (we use the same sample restrictions as in our prior analysis). We first use the January 1986 and January 1987 occupation and industry codes to calculate (as previously done) the number who change reported occupation only, and the number who change both occupation and industry. We then utilize information from the January 1987 CPS to see which workers explicitly say they changed occupation during the previous year. For purposes of exposition, we refer to this latter group as "verified" changers. Of those measured as changing reported occupation but not industry (*N*=4,116), just 7.2 percent are found to be verified changers, as measured by the January 1987 CPS. But among those reporting both occupation and industry change between 1986 and 1987 (*N*=2,673), 28.3 percent are verified changers. These results strongly support our decision to utilize coefficient estimates only for those who change both occupation and industry in order to reduce measurement error in the DFEM variable. But they also suggest that substantial measurement error remains even in this measure.

In order to further assess the generality of the longitudinal results from the constructed CPS ORG panels, we estimate similar wage level and wage change models using two alternative data sets. The first is a data set constructed from the March CPS files for 1983-93. The March CPS records not only information on current occupation, earnings, and other characteristics, but also on an individual's occupation, industry, and class of worker in the longest job held during the previous year; annual earnings, weeks worked, and hours worked per week the previous year; and state of residence the previous March.[15] The major advantage of the March CPS files is that occupational change is far less

[15] Current earnings is reported by only a quarter of the March CPS (the outgoing rotation groups). We retain the full March sample by matching each worker's reported earnings from either the April, May, or June ORG file to the

likely to be measured with error. The constructed CPS ORG panel previously used relies on information from two interviews, one year apart, possibly conducted by different individuals with different household members, and coded by different Census coders. By contrast, the March file relies on information from a single interview with a single household member by a single interviewer and with a single occupation coder (when occupation does not change). Another important advantage of the March files is that they include information on individuals who have changed households or location or who could not be matched from the ORG files from separate years. Disadvantages of the March data set are that the wage change variable is constructed from two different earnings measures (calculated wages from the March retrospective questions are larger than from the ORG earnings supplements) and the previous year's earnings may be determined in part by jobs other than the longest held. Neither of these is likely to seriously bias estimates of θ – differences in the March and ORG wage measures will be largely reflected in the constant of the wage change equation, while mismeasurement of wages owing to multiple occupations should not bias θ if the measurement error is uncorrelated with ΔFEM. There will be a bias toward zero in estimates of θ, however, to the extent that last year's wage reflects the wage on the new occupation (with the new FEM value), lessening the measured wage change associated with ΔFEM. That is, for those changing occupations in the latter half of the previous year rather than in the second year prior to the March survey, there will be bias in the estimate of θ, on the order of about 15 percent.[16]

An additional panel data set is constructed using the January 1984, 1986, 1988, 1990, and 1992 CPS Displaced Workers Surveys (DWS). The DWS provide information on whether workers have lost or left a job during the past five years because of a plant closing, an employer going out of business, a layoff from which a worker was not recalled, or other similar reason. The DWS has the same advantage as the

March record. Similarly, Funkhouser (1993) has matched the April 1983 CPS immigration supplement with the April-July CPS ORG records.

[16] Assume that there is one occupational change and that changes are distributed evenly throughout a year. The mean and median switcher will change occupations during the first week in November, the midpoint between July 1 (the second half of year 1) and March 15 (the approximate date of the March survey). Annual earnings in year 1 will therefore be a weighted average of old and new occupational earnings, with a weight of about 15 percent on the new occupation (53 out of 365 days). Measured wage change and estimates of θ likewise will be understated (i.e., biased toward zero) by roughly 15 percent. Additional disadvantages of the March data are that information is not available for the previous year on the union and marital status variables, and less information about class of worker is available prior to 1989.

March surveys in that it is relatively unlikely that there will be a false identification of nonswitchers as switchers. The DWS has an advantage as compared to the March CPS panel in that the prior wage and occupation refer directly to the last job held. The most important differences between the DWS and either the ORG or March panels is that occupational changes extend beyond a year and job changes among displaced workers are more likely to be exogenous. And the analysis can be further limited to those affected by plant closings, since it can be argued that some layoffs may not be completely exogenous (for similar reasoning and use of the DWS, see Gibbons and Katz, 1992).

Table 8 presents three alternative sets of estimates from the standard and full specifications for wage levels and wage change models, in addition to those from the CPS ORG panels. We provide comparable estimates from the March CPS files for 1983-93, and the five January CPS DWS files for 1984 through 1992 with separate estimates for all displaced workers and for the subset of displaced workers affected by plant closings. Despite differences in samples and specification, the results from the alternative data sets are broadly similar. In all cases, wage change equation estimates of θ_f are about -.10 in the standard specification, and from zero to -.05 following control for job characteristics. Estimates of θ_m from the March CPS files are similar to those presented previously from the CPS ORG panel, being -.08 in the standard and -.02 in the expanded models. Estimates of θ_m from the DWS wage change equations are only about -.04 prior to controls for job characteristics and positive (but not statistically significant) following inclusion of controls. Interestingly, the DWS estimates of θ_m from the standard wage *level* equations are larger in absolute value than those obtained in the other data sets. Although sample sizes are small and significance levels low, the suggestion from the DWS results is that changes in gender composition owing to exogenous occupational change have little effect on wages, following control for person specific effects and job characteristics.

Our primary concern with the CPS ORG panel results was the possibility of bias toward zero in estimates of θ_f and θm owing to measurement error in the ΔFEM variable, or bias due to endogenous occupational change. Based on the results in Table 8 it appears that bias for these reasons is not serious. Longitudinal estimates of θ are in fact larger in magnitude using the matched ORG files than the retrospective March CPS, where occupational change is measured far more accurately and coefficient bias should be relatively minor (roughly 15 percent). Results from the DWS, which should not have such bias and which reflect exogenous occupational change, suggest that the direct effect of gender composition on wages is quite small.[17]

VI. Interpretation and Conclusions

Previous literature exploring the relationship between the gender composition of occupations and wages has emphasized the negative effect of proportion female on the earnings of both women and men. Past estimates based on levels estimation have not accounted for several important dimensions of worker productivity, tastes, and job characteristics. The few longitudinal studies examining this issue have been plagued by relatively small sample sizes. Little attention has been given to issues of specification or linearity of the wage-FEM relationship, bias from measurement error in wage change equations, or demographic and sectoral differences in the effects of gender composition.

This paper takes advantage of large representative national samples from the January 1983 through December 1993 monthly CPS surveys, as well as data on occupation and industry characteristics constructed from the *Dictionary of Occupational Titles* and various CPS supplements. The data base allows us to examine changes over time in the gender composition of jobs for both women and men, and its changing effect on wages and the gender wage gap. Most important, we are able to estimate longitudinal wage change models for large samples of worker-year pairs for 1983/4 through 1992/3. Supplementary analysis is provided using data sets constructed from the 1973-78 May CPS, the 1979-82 CPS ORG files, the March CPS for 1983-1993, the five Displaced Worker Surveys for January 1984-92, the 1983 and 1988 May/June Pension Supplements, and CPS supplements containing information on tenure, firm size, job training, and computer use.

Prior to controlling for detailed job characteristics, the cross-sectional relationship between proportion female in an occupation and wages was found to be highly negative for women and men. Estimates of the effects of proportion female are substantially lower (by roughly half) using longitudinal

[17] In results not reported, we investigated whether there exist symmetric responses to increases and decreases in gender composition. Separate estimates of θ for workers increasing and decreasing FEM produced opposite results using the March CPS from those using the ORG and DWS panels. Since we have no convincing explanation for why there should be an asymmetry in coefficients or differences across data sets, we did not further explore this issue.

analysis and our standard specification, indicating that person-specific labor quality or preferences account for much of the previously observed relationship. When variables measuring occupation and industry characteristics are added to wage change equations, the estimated effects of gender composition again are substantially reduced. The remaining effects of gender composition on female or male wages appear rather small. Two-thirds to all of the gender composition effect is accounted for by measured job skills and characteristics and by unmeasured worker-specific skills and preferences.

We conclude that predominantly female jobs pay lower wages to women and men largely because of their skill-related characteristics and quality sorting on FEM. This is in part the result of past and present occupational discrimination that has led to an equilibrium in which the *unmeasured* skills of women and men increase with the proportion male in an occupation. Measured job characteristics matter, but are less important than unmeasured worker specific skills and tastes. The job characteristics that are most important are related to training and job attachment. Wages decrease with respect to FEM because predominantly female occupations generally require less training to acquire proficiency, are more likely to have large numbers of part-time workers, and have a lower level of worker tenure. Other measurable occupation and industry characteristics, reflecting, for example, job amenities and disamenities, computer use, formal OJT, the job environment, industry unionization, and presence of large firms, have a relatively small effect on FEM coefficient estimates.

What are the implications of this study for pay equity or other public policies that aim to adjust relative wages of occupations, based in part on measured worker and job characteristics? Our results indicate that the direct effect of gender composition on wages is rather small, following what we argue are appropriate controls for job characteristics and unmeasured skills and preferences. Policies that eliminate only the remaining relationship of wages and FEM would have little effect on the sizable gender wage gap, Policies that alter wage rates more substantially run the risk of distorting what appear to be legitimate compensating differentials for skills or job attributes, although such policies are likely to narrow gender wage differentials.

Although our conclusion regarding the desirability of comparable worth policies is similar to that of Johnson and Solon (1986), the reasoning differs. They conclude that comparable worth policies, which are implemented within firms, would be ineffective in eliminating wage differences correlated with gender composition since these are highly correlated with industry wage differentials not subject to direct change via pay equity policies (we provide similar evidence for males). We conclude that occupational wage differences correlated with gender, following use of appropriate controls, are sufficiently small so that they should not be a major focus of public policy. Stated alternatively, after controlling for gender composition, as well as personal and job characteristics, much of the still sizable female-male wage gap remains unexplained. It may be more appropriate for public policy to focus on causes of the gender wage gap per se, rather than on occupational wage differences correlated with gender composition. It is worth recalling that the 1980s and early 1990s have witnessed a substantial narrowing of the gender gap and improvement in relative female earnings, and this narrowing has not been the result of changes in gender composition and its estimated effects.

While gender composition per se may be relatively unimportant as a proximate cause of low wage rates, occupational characteristics and worker skills and preferences correlated with gender composition are important. Narrowing of the gender wage gap will result if there continues to be narrowing of differences in experience, industry structure, and occupation characteristics between predominantly female and male jobs. Far more difficult to evaluate is why a labor market equilibrium has arisen in which predominantly female occupations have become associated with job characteristics and worker endowments leading to lower pay. Among the possible (non-mutually exclusive) explanations are historical patterns of occupational discrimination that led to the current sorting equilibrium; current discriminatory barriers to women in occupations with more job training, longer tenure, and other attributes associated with higher pay; and a sexual division of labor such that relatively many women and few men choose jobs associated with lower-paying characteristics.

Although beyond the scope of this paper, limited evidence suggests that all three factors are important. Historical patterns of sex discrimination have had important effects on the gender composition of occupations. Both formal and informal occupational barriers to women were commonplace, although the incidence and survival of these barriers showed some sensitivity to their economic costs.[18] Moreover, current differences in the occupational choices of, and division of labor between, women and men are influenced heavily by the past. Less certain is the extent to which occupational choices by women currently are constrained by barriers in the labor market. O'Neill (1983) estimates equations with gender composition as the dependent variable and concludes that current occupational segregation results to no small degree from preferences expressed at early ages, prior to entry into the labor market. Because preferences are determined in part by perceptions of the present and expectations of what is possible in the future, interpretation of such evidence is not unambiguous.

More direct tests of occupational barriers are less readily available. Gupta (1993) uses information in the NLSY on job aspirations of young women and men in 1979, and broad occupational level achieved in 1982 ("female" occupations plus three broad groups including non-female occupations). She concludes that gender differences in occupational attainment result both from differences in preferences and employer selection. Given their occupational choice, women were less likely to be chosen from the queue in professional/managerial and service occupations. Research by Padavic (1992) on the attitudes of female clerical workers following their temporary transfer to "male" production jobs during a strike likewise indicates that both differences in preferences and employment constraints affect the occupational distribution.[19]

Finally, our analysis has implications for wage equation specification and interpretation. The inclusion of the proportion female variable in cross-sectional female and male wage equations can be

[18] See, for example, Kossoudji and Dresser (1992), who provide an analysis of the rise and fall of female industrial employment during the 1940s, and Goldin (1990), who examines the economic and noneconomic determinants of female wages and employment during much of this century.

[19] Padavic (1992) provides an analysis of a natural experiment reminiscent of the WW-II experience. During a union strike at a utility company, nonunion female clerical and administrative workers, in addition to nonunion male workers, were moved into predominantly male blue-collar jobs at eight plants. The production jobs paid significantly higher wages, but had less attractive working conditions (less flexibility, less cleanliness, less socializing, and more extensive physical demands). Following conclusion of the strike, workers were returned to their previous jobs. Padavic administered a questionnaire both to the women who had taken the production jobs and those who had not been transferred, asking if they would like to be transferred to the production job. Despite the higher pay, most women did not want to be transferred to the production job. Evidence in the study supports the view that individual choice, job characteristics, and childhood activities were important determinants of occupational choice. A limitation of this study is that women in clerical jobs have selected those jobs based in part on job characteristics; the ideal experiment would shift a representative sample of female (and male) workers to the production jobs and then administer a similar set of questions to both groups. We should note that our interpretation of the Padavic study is not identical to that by the author.

justified on statistical grounds. Absent detailed controls for job characteristics and person-specific skills and tastes, gender composition is an important correlate of wages. It is important, however, that researchers recognize that the direct impact of gender composition on wages is small; rather, FEM serves as a proxy for unmeasured skills, preferences, and job attributes. Progress in understanding gender differences in the labor market is unlikely to be enhanced significantly by further emphasis on pay differences between women's and men's jobs, per se. More promising will be renewed attention given to how and why the labor market sorts women and men into jobs with different characteristics and productivities, and a continuing investigation into the sources of a wage gap that remains sizable, independent of the gender composition of jobs.

Appendix

Construction of Longitudinal Samples from the CPS ORG Files and the March CPS

Households are included in the CPS for 8 months – 4 consecutive months in the survey, followed by 8 months out, followed by 4 months in. Outgoing rotation groups 4 and 8 are asked earnings supplement questions (weekly earnings, hours, union status, etc.). The CPS contains household identification numbers (ID) and record line numbers, but not individual identifiers. Individuals potentially can be identified for the same month in consecutive years; that is, individuals in rotation 4 in year 1 can be matched to individuals in rotation 8 in year 2.

The longitudinal ORG file was created in the following manner. Separate data files were created for males and females, and for pairs of years (rotation 4/1983 and rotation 8/1984, rotation 4/1984 and rotation 8/1985, etc.). Within each file, individuals were sorted as appropriate on the basis of ascending and descending household ID, year, and age. To be considered an acceptable matched pair, a rotation 8 individual had to be matched with a rotation 4 individual with identical household ID, identical survey month, and an age difference between 0 and 2 (since surveys can occur on different days of the month, age change need not equal 1). Several passes were necessary because a single household may contain more than one male or female pair. Checks were provided to insure that only unique matches were selected. For each rotation 8 individual, the search was made through all rotation 4 individuals with the same ID to make sure there was only 1 possible match; the file was resorted in reverse order and each selected rotation 4 individual was checked to insure a unique rotation 8 match. As uniquely matched pairs were identified they were removed from the work file. Incorrect changes in the variables marital status, veteran status, race, and education (e.g., a change in schooling other than 0 or 1, a change from married to never married, etc.) were used to delete "bad" observations in households where there were multiple observations and ages too close to separate matched pairs. Several passes at the data were made. In households where two pairs of individuals could be separated based on a 1 year but not the 0 to 2 year age change, a 1 year criterion was used. If a unique pair could not be identified based on these criteria, they were not included in the data set (e.g., four observations with two identical pairs, or three individuals with two possible matches using the 0 to 2 age change criterion).

The match rate in the longitudinal analysis is just under two-thirds of employed wage and salary workers in any year. The principal reasons that matches cannot be made are if a household moves (thus changing the household ID), if an individual moves out of a household, if a worker becomes self employed, if an individual drops out of the labor market or fails to meet other sample selection criteria, or if the Census is unable to reinterview a household and/or receive information on the individual. Note that the match rate reported here is similar to the match rate of 68.8 percent for the 1987-88 CPS reported by Card (1992) using a broader-based sample and a less stringent probabilistic matching algorithm obtained from the Bureau of Labor Statistics. Peracchi and Welch (forthcoming) analyze attrition rates among matched March CPS files and conclude that age is the most important determinant of a successful match. Other factors that lessen match probabilities are poor health, low schooling, and not a household head, while sex and race are unimportant match predictors following control for other factors.

The sample size of the CPS ORG panel is 25 percent that of the full CPS ORG. The difference can be approximated as follows. Because the unit of observation in the panel is the pair of observations in adjacent years, the potential sample size is initially cut in half. Since we do not match the half of the 1983 sample that entered the CPS in 1982, or the half of the 1993 sample that exits the CPS following their 1994 interview, the potential longitudinal sample is reduced further by 9 percent (i.e., 91 percent of the full 1983-93 sample is in for two years). A 100 percent match rate of workers between adjacent years would produce a sample for each period half as large as the corresponding cross-sections. We achieve a match rate of about 64 percent, owing to individuals who changed households, entered or exited employment between years, or who could not be reliably matched based on available information. Finally, sample sizes are reduced further to roughly half the normal size for the 1984/5 panel and to one-quarter for 1985/6. This is the result of a CPS test sample from July-September 1985 that implemented new population weights. Rotation 4 households interviewed in July 1984 through September 1985 were not reinterviewed a year later in 1985 and 1986. Hence the combined multiplier relating the size of the longitudinal sample to the initial full sample is about .25; that is, .50 x .91 x .64 x .875 = .25, where .875 is the ratio (10-1.25)/10, with the numerator representing the remaining panels following the “loss” of 1.25 panels for 1984/5 and 1985/6.

The March CPS longitudinal file is a retrospective panel. All rotation groups in March are asked information about earnings, weeks worked, and hours worked last year, and occupation and industry on the longest job held last year. A quarter sample in March (the ORGs) are asked current earnings, hours, etc. The entire March sample is matched to their earnings supplement records in their outgoing month, either March, April, May, or June. These records were matched initially on the basis of household ID and line number, followed by checks on changes in sex and age to insure an accurate match. The March retrospective panel is 76.4 percent the size of a March sample based on the presence of earnings last year (and other typical variables). Losses are due to households moving, individuals leaving the household, changing employment status (i.e., leaving the labor force or shifting to self employment), changing line number, a failure to be reinterviewed, and missing hours or weekly earnings in the earnings supplement among employed wage and salary workers who are otherwise matched.

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Table 1
Mean Wages, the Wage Gap, Gender Composition, and the Wage-Composition Relationship by Year, 1973-93

	Female			Male			Female to Male Wage Ratio	Duncan Segregation Index	Female		Male	
Year	*N*	Wage	FEM	*N*	Wage	FEM			θ	θ_{adj}	θ	θ_{adj}
1973/4	30,070	10.26	.721	42,842	15.83	.176	.648	.685	-.184	-.068	-.237	-.148
1975/6	29,981	10.08	.724	40,376	15.45	.186	.652	.675	-.193	-.087	-.234	-.161
1977/8	35,415	10.05	.712	45,276	15.57	.201	.645	.652	-.208	-.101	-.264	-.186
1979	70,930	9.79	.711	89,849	15.03	.215	.651	.636	-.212	-.109	-.214	-.150
1980	84,271	9.41	.708	103,064	14.28	.224	.659	.628	-.222	-.132	-.209	-.163
1981	79,779	9.36	.707	95,702	14.14	.229	.662	.623	-.242	-.138	-.207	-.164
1982	76,254	9.51	.708	88,895	14.27	.237	.666	.618	-.252	-.140	-.186	-.166
1983	76,159	9.68	.699	87,855	14.46	.246	.669	.600	-.248	-.140	-.139	-.135
1984	76,659	9.75	.698	88,234	14.39	.248	.678	.595	-.251	-.151	-.098	-.141
1985	78,753	9.94	.694	89,486	14.59	.256	.681	.585	-.258	-.168	-.072	-.158
1986	79,318	10.24	.694	88,116	14.88	.260	.688	.582	-.259	-.171	-.039	-.171
1987	80,687	10.34	.694	88,233	14.94	.263	.692	.576	-.241	-.163	-.043	-.206
1988	77,356	10.36	.689	84,447	14.83	.266	.699	.569	-.229	-.164	-.010	-.183
1989	79,495	10.36	.687	86,254	14.31	.271	.724	.560	-.222	-.163	-.031	-.183
1990	84,021	10.49	.686	90,378	14.29	.275	.734	.555	-.216	-.165	-.017	-.201
1991	82,152	10.58	.687	87,235	14.13	.279	.749	.556	-.220	-.169	.007	-.191
1992	81,522	10.66	.686	85,330	14.00	.284	.761	.553	-.193	-.160	.009	-.184
1993	80,949	10.71	.682	83,903	14.02	.288	.764	.546	-.181	-.174	.002	-.190

Calculations are from the 1973-78 May CPS and the 1979-93 Annual CPS ORG Files (*N*=2,749,246). Wages are measured by usual weekly earnings divided by usual hours worked, in December 1993 dollars. Adjustments for top-coding are described in the text. FEM measure the proportion of females to total employees in workers' detailed occupation, by year. The female to male wage ratio is the mean of female real wages to male real wages. The Duncan segregation index is calculated by ½ $\Sigma|m_j-f_j|$, where *m* and *f* are the proportions of male and female employment in occupation *j*. θ is the log wage regression coefficient on FEM, without controls. θ_{adj} is the FEM coefficient, with controls for years schooling completed, potential experience (measured by age minus schooling minus 5) and its square, dummies for black, other nonwhite, married spouse present, ever married spouse not present, full-time, public sector, large metropolitan area, region (8), industry (13), and occupation (5). In order to insure a time consistent specification, union status and separate federal, state, and local dummies are not included.

Table 2
Means of Selected Variables by Gender Composition, 1993

	Value of FEM				
Variable	0-.25	.25-.50	.50-.75	.75-1.0	All
Means for females:					
Wage (December 1993 $)	10.823	11.867	11.127	10.040	10.709
Schooling	12.628	13.047	13.501	13.006	13.096
Experience	18.551	19.984	19.179	19.708	19.595
Part-time	.177	.197	.231	.290	.251
Federal	.036	.058	.023	.022	.031
State	.054	.046	.066	.052	.054
Local	.063	.080	.132	.146	.124
Black	.123	.108	.101	.109	.108
Union	.194	.128	.161	.166	.158
DOT-GED	2.827	3.452	3.526	3.187	3.295
DOT-SVP	1.815	2.966	2.545	1.240	1.920
Occupation-tenure	7.156	7.112	6.460	5.559	6.175
Occupation-part-time	.131	.154	.214	.295	.238
Occupation-OJT	.366	.412	.451	.403	.413
Occupation-computer	.373	.506	.537	.577	.542
DOT-environment	.416	.231	.130	.086	.145
DOT-hazards	.182	.067	.054	.035	.054
DOT-physical	1.665	1.218	1.165	1.623	1.442
DOT-strength	2.469	1.960	1.850	1.772	1.868
Industry-union	.186	.168	.172	.170	.171
Industry-big firm	.452	.467	.456	.412	.435
N	4,514	17,757	16,721	41,957	80,949
Means for males:					
Wage (December 1993 $)	12.842	16.060	14.751	11.380	14.018
Schooling	12.342	13.501	14.097	13.449	12.995
Experience	19.914	19.528	18.644	16.519	19.422
Part-time	.074	.090	.108	.209	.092
Federal	.027	.055	.034	.036	.037
State	.033	.045	.076	.073	.045
Local	.071	.051	.157	.131	.078
Black	.082	.080	.085	.119	.084
Union	.248	.153	.205	.210	.209
DOT-GED	2.801	3.466	3.584	3.037	3.124
DOT-SVP	1.970	2.980	2.779	1.040	2.334
Occupation-tenure	7.337	7.231	6.771	5.525	7.120
Occupation-part-time	.092	.139	.186	.304	.132
Occupation-OJT	.358	.416	.465	.391	.392
Occupation-computer	.282	.515	.572	.531	.408
DOT-environment	.524	.229	.114	.093	.353

Table 2 (continued)
Means of Selected Variables by Gender Composition, 1993

	Value of FEM				
Variable	0-.25	.25-.50	.50-.75	.75-1.0	All
DOT-hazards	.287	.073	.042	.034	.173
DOT-physical	2.167	1.242	1.138	1.484	1.702
DOT-strength	2.703	1.967	1.801	1.806	2.301
Industry-union	.206	.175	.200	.183	.194
Industry-big firm	.377	.458	.455	.463	.418
N	41,440	27,290	9,791	5,382	83,903

All means are calculated across individuals in the 1993 CPS ORG. Occupation-tenure is calculated from the May 1983 and 1988 CPS Pension Supplements and the January 1983, 1987, and 1991 CPS; Occupation-OJT from the January 1983 and 1991 CPS; Occupation-computer from the October 1984 and 1989 CPS; Industry-big firm from the May 1983 CPS Pension Supplement and the March 1989-1992 CPS; and Occupation-part-time and Industry-Union from the CPS ORG files. DOT measures are constructed from data in the *National Occupational Information Coordinating Committee Crosswalk*. This provides data for approximately 12,000 occupations from the 1986 revision of the fourth edition of the *Dictionary of Occupational Titles*, plus a "crosswalk" code identifying the 1980 Census of Population occupation code. We construct DOT values for each Census occupation code by aggregating and taking the unweighted average (employment weights are not available) among all detailed occupations within each census occupation.

Table 3
FEM Coefficients by Specification, Gender, and Year from Wage Levels Equations, 1983-93

Specification	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993
Females:											
Standard	-.1473	-.1583	-.1703	-.1764	-.1693	-.1683	-.1661	-.1669	-.1718	-.1646	-.1762
	(.0064)	(.0064)	(.0065)	(.0065)	(.0066)	(.0069)	(.0066)	(.0064)	(.0066)	(.0067)	(.0068)
Expanded	-.1001	-.1095	-.1131	-.1327	-.1214	-.1194	-.1242	-.1155	-.1267	-.1133	-.1389
	(.0085)	(.0086)	(.0086)	(.0086)	(.0087)	(.0090)	(.0085)	(.0083)	(.0085)	(.0086)	(.0087)
N	76,159	76,659	78,753	79,318	80,687	77,356	79,495	84,021	82,152	81,522	80,949
Males:											
Standard	-.1502	-.1551	-.1714	-.1818	-.2194	-.1943	-.1956	-.2134	-.1989	-.1985	-.1951
	(.0081)	(.0081)	(.0081)	(.0081)	(.0083)	(.0086)	(.0082)	(.0080)	(.0081)	(.0082)	(.0084)
Expanded	-.0887	-.1009	-.1029	-.1038	-.1364	-.0989	-.0920	-.1100	-.0877	-.1063	-.0899
	(.0101)	(.0100)	(.0100)	(.0100)	(.0101)	(.0106)	(.0101)	(.0098)	(.0099)	(.0100)	(.0102)
N	87,855	88,234	89,486	88,116	88,233	84,447	86,254	90,378	87,235	85,330	83,903

The "standard" specification includes variables measured at the individual level: years of schooling completed and potential experience and its square; dummies for union coverage, part-time, race (2), marital status (2), public sector (3), large metropolitan area, region (8), industry (13), and occupation (5). The "expanded" specification adds variables measuring means at the occupation and industry levels. Occupation variables included are years of tenure, proportion part-time, proportion receiving on-the-job training, proportion using computers at their job, a 1-6 index of general educational development (GED), years required for occupational proficiency or specific vocational reparation (SVP), number of work environment disamenities from 0-5, the proportion in hazardous jobs, number of physical demands from 0-4, strength required measured by a 1-5 index from low to high. Industry variables included are proportion union and proportion in firms with $\geq$1,000 employees. Standard errors are in parentheses.

Table 4
Gender Composition Coefficients from Linear and Dummy Variable Models, Pooled Data Set, 1983-93

Specification	Model 1 FEM	Model 2 FEM 25-49	 FEM 50-74	 FEM 75+
Females:				
No controls	-.2305	.0754	.0013	-.0971
	(.0021)	(.0026)	(.0026)	(.0024)
Standard	-.1651	-.0538	-.1035	-.1387
	(.0020)	(.0022)	(.0022)	(.0021)
Expanded	-.1173	-.0253	-.0653	-.0813
	(.0026)	(.0022)	(.0022)	(.0024)
N	877,070		877,070	
Males:				
No controls	-.0375	.1476	.0224	-.1951
	(.0025)	(.0013)	(.0020)	(.0026)
Standard	-.1858	-.0030	-.0888	-.1412
	(.0025)	(.0013)	(.0017)	(.0022)
Expanded	-.0986	.0198	-.0426	-.0608
	(.0030)	(.0013)	(.0018)	(.0025)
N	959,471		959,471	

Model 1 includes FEM, while Model 2 includes the dummies FEM25-49, FEM50-74, and FEM75+. The reference group is FEM<.25. Standard and expanded specifications are described in the note to Table 3. All pooled models include year dummies. Standard errors in parentheses.

Table 5
FEM Coefficient Sensitivity to Specification, Pooled Data Set, 1983-93

	Specifications	Females	Males
1.	No controls	-.2305	-.0375
2.	Base (individual characteristics only)	-.1719	-.1387
3.	Base + 13 industry dummies	-.1775	-.0512
4.	Base + 5 occupation dummies	-.1543	-.2584
5.	Standard model (base model + 5 occupation, 13 industry dummies)	-.1651	-.1858
6.	Standard + GED	-.1356	-.1031
7.	Standard + SVP	-.0886	-.0935
8.	Standard + job tenure	-.1242	-.1579
9.	Standard + part-time	-.1059	-.0930
10.	Standard + OJT	-.1476	-.1489
11.	Standard + computer	-.1620	-.1924
12.	Standard + SVP, GED, tenure, part-time, OJT, computer	-.1192	-.0824
13.	Standard + DOT environment, hazards, physical, strength	-.1910	-.2326
14.	Standard + industry firm size, union	-.1561	-.1997
15.	Expanded (standard + all job characteristics)	-.1173	-.0986
16.	Expanded minus physical	-.0814	-.0986
17.	Expanded, with job characteristics measured gender specific	-.1279	-.1135
18.	Expanded, with 49 rather than 13 industry dummies	-.1170	-.1064
N		877,070	959,471

Shown are the regression coefficients θ_f and θ_m. The standard and expanded specifications are described in the text and the note to Table 3. Specifications 5 and 15 correspond to standard and expanded models shown in Table 4. All models include year dummies. Standard errors are approximately .0020 to .0025.

Table 6
Gender Composition Coefficients among Alternative Worker Groups, Wage-Level Equations, Pooled for 1983-93

	Females			Males		
Group	*N*	Standard	Expanded	*N*	Standard	Expanded
All Workers	877,071	-.1651	-.1173	959,471	-.1858	-.0986
Age:						
16-29	271,800	-.1596	-.1174	293,665	-.1989	-.1524
30-44	353,996	-.1842	-.1398	387,446	-.2117	-.1074
45-99	251,275	-.1117	-.0550	278,360	-.1417	-.0161
Education (in years):						
0-11	100,758	-.1591	-.0308	148,138	-.1305	-.0856
12	364,501	-.1459	-.0977	359,693	-.1314	-.0736
13-15	219,245	-.1182	-.0752	215,393	-.1757	-.0785
16	122,836	-.2172	-.1376	138,650	-.2910	-.1381
>16	69,731	-.2272	-.0587	97,597	-.1010	.0702
Race:						
White	749,327	-.1610	-.1178	844,855	-.1828	-.0942
Black	95,104	-.1658	-.0781	79,429	-.1242	-.0782
Other race	32,640	-.2098	-.1329	35,187	-.3071	-.1979
Class:						
Private	698,093	-.1678	-.1284	804,611	-.1527	-.0792
Public	178,978	-.1252	-.0462	154,860	-.2305	-.0793
Union Status:						
Nonunion	735,434	-.1633	-.1193	732,407	-.1660	-.0879
Union	141,637	-.1244	-.0594	227,064	-.1884	-.0966
Hours Status:						
Part-time	222,074	.0039	-.0605	79,135	-.1791	-.1415
Full-time	654,997	-.2091	-.1340	880,336	-.1808	-.0884
Production Status:						
Nonproduction	777,075	-.1462	-.1198	545,499	-.1921	-.0620
Production	99,996	-.2122	-.0924	413,972	-.0994	-.1032

The standard and expanded specifications are described in the note to Table 3. All models include year dummies. Standard errors range from about .0020 to .0100.

Table 7
Decomposition of Gender Wage Gap, by Specification and Year

Specification	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993
Total log gap	.359	.352	.346	.338	.331	.324	.295	.280	.261	.245	.235
Standard specification: without FEM:											
1a. Unexplained	.251	.252	.251	.250	.245	.243	.223	.215	.205	.195	.192
1b. Total explained	.108	.099	.095	.088	.086	.081	.072	.065	.056	.050	.043
Standard specification:											
2a. Unexplained	.208	.207	.202	.201	.191	.194	.175	.166	.158	.149	.147
2b. Total explained	.152	.145	.144	.138	.140	.130	.119	.114	.104	.096	.089
2c. Explained due to FEM	.067	.070	.074	.078	.083	.077	.075	.078	.075	.073	.074
Expanded Specifications											
3a. Unexplained	.207	.207	.204	.202	.192	.193	.173	.166	.156	.146	.145
3b. Total explained	.152	.145	.142	.137	.139	.131	.122	.114	.105	.098	.090
3c. Explained due to FEM	.042	.047	.047	.052	.055	.046	.045	.046	.043	.044	.045
3d. Explained due to all job characteristics	.015	.006	.006	.000	.001	.002	.005	.002	.001	-.006	-.010
3e. Explained due to selected occupational characteristics:											
SVP	.015	.015	.015	.012	.011	.010	.012	.012	.011	.008	.008
Part-time	.008	.006	.006	.008	.009	.011	.015	.012	.010	.006	.010
Physical	.004	.005	.004	.003	.004	.004	.005	.006	.005	.005	.007
Computer	-.011	-.014	-.016	-.017	-.018	-.018	-.015	-.015	-.016	-.016	-.015
GED	-.001	-.002	-.003	-.003	-.004	-.005	-.005	-.006	-.006	-.007	-.008

The standard and expanded specifications are described in the note to Table 3. The sums of “unexplained” and “total explained” may not sum to the total gap owing to rounding error. The calculations are outlined in the text. Decompositions are based on the use of a weighted average of female coefficient and male coefficient “multipliers” in the explained portion of the calculation, with weights being the sample proportions of women and men.

Table 8
Panel Data Estimates of FEM and ΔFEM Coefficients for Wage-Level and Wage Change Models, Using the CPS ORG, March CPS, and CPS Displaced Worker Surveys

	Females		Males	
	Levels	Change	Levels	Change
CPS ORG Panel:				
Standard	-.1632	-.0917	-.1783	-.0852
	(.0039)	(.0066)	(.0049)	(.0078)
Expanded	-.1143	-.0549	-.0798	-.0336
	(.0050)	(.0077)	(.0061)	(.0088)
N	219,323		240,362	
March CPS Panel:				
Standard	-.1709	-.1050	-.1617	-.0833
	(.0037)	(.0112)	(.0047)	(.0129)
Expanded	-.1223	-.0361	-.0700	-.0223
	(.0049)	(.0143)	(.0058)	(.0155)
N	238,299		262,918	
DWS - plant closings and layoff sample:				
Standard	-.2021	-.0913	-.2336	-.0496
	(.0309)	(.0270)	(.0311)	(.0279)
Expanded	-.0610	.0024	-.0911	.0326
	(.0428)	(.0381)	(.0381)	(.0340)
N	3,883		7,037	
DWS - plant closings only sample:				
Standard	-.2289	-.1061	-.1904	-.0312
	(.0415)	(.0354)	(.0443)	(.0406)
Expanded	-.0801	-.0483	-.0598	.0491
	(.0582)	(.0515)	(.0543)	(.0488)
N	2,200		3,595	

The standard and expanded specifications are described in the note to Table 3. All models include year dummies. Standard errors are in parentheses. Change equations have $\Delta\log(W)$ as the dependent variable and coefficients on ΔFEM are presented. Change equations from the March CPS files differ in specification from the CPS ORG by the inclusion of changes in region and public sector status, but exclusion of changes in marital status, union status, and in federal, state, and local worker status. The DWS results are based on the January 1984, 1986, 1988, 1990, and 1992 CPS Displaced Worker Surveys. The sample consists of workers who were age 20 and older and who were displaced from a full-time, private-sector job because of a plant closing, slack work, or a position of shift that was eliminated. The sample was further restricted to workers who were reemployed at the survey date in a full-time wage and salary job, and excluded those displaced from the construction industry. The dependent variable in the change equation is the difference between the log of current weekly earnings and the log of pre-displacement weekly earnings. In addition to the usual change variables, panel estimates include dummies for year of displacement and survey year.

Table 9
ΔFEM Coefficients Based on Alternative Definitions of Occupational Switching

Specification	Matched CPS ORG, 1983-93 Occupation and Industry Changers	Occupation-Only Changers	All Workers
Females:			
Standard	-.0917	-.0271	-.0549
	(.0066)	(.0059)	(.0046)
Expanded	-.0549	.0142	-.0161
	(.0077)	(.0071)	(.0061)
Males:			
Standard	-.0852	-.0282	-.0538
	(.0078)	(.0072)	(.0056)
Expanded	-.0336	.0234	-.0018
	(.0088)	(.0082)	(.0069)

The standard and expanded specifications are described in the note to Table 3. Standard errors are in parentheses.

Table A1
Female/Male Wage Ratios and Duncan Segregation Index, by Worker Group and Year, 1973-92

Group	1973-74	1975-76	1977-78	1979	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993
Female to male wage ratio:																		
Age:																		
16-29	.766	.783	.766	.769	.781	.785	.796	.819	.812	.825	.832	.839	.845	.855	.881	.893	.904	.919
30-44	.618	.607	.614	.626	.633	.647	.654	.662	.674	.673	.681	.700	.702	.731	.736	.754	.775	.779
45+	.597	.610	.591	.595	.601	.593	.596	.583	.590	.595	.601	.593	.608	.630	.639	.657	.665	.665
Education (in years):																		
<12	.617	.645	.635	.646	.652	.666	.659	.667	.665	.664	.689	.680	.700	.702	.727	.754	.763	.756
12	.643	.648	.643	.650	.657	.662	.673	.675	.682	.689	.699	.701	.706	.718	.728	.746	.755	.757
13-15	.675	.657	.659	.671	.682	.684	.695	.700	.701	.710	.710	.715	.731	.747	.751	.762	.784	.787
16	.667	.642	.634	.640	.648	.639	.640	.648	.658	.654	.661	.672	.675	.714	.735	.743	.751	.746
>16	.731	.759	.737	.719	.718	.720	.709	.704	.721	.718	.714	.723	.714	.750	.739	.742	.767	.771
Race:																		
White	.642	.645	.635	.641	.649	.653	.657	.661	.668	.672	.678	.683	.690	.714	.724	.738	.753	.754
Black	.747	.766	.795	.771	.787	.775	.790	.788	.800	.810	.823	.826	.819	.858	.871	.888	.900	.897
Other race	.716	.705	.698	.725	.715	.732	.715	.706	.718	.732	.726	.709	.738	.779	.793	.795	.782	.808
Class:																		
Private	.613	.619	.613	.652	.660	.663	.666	.671	.679	.683	.689	.693	.700	.725	.734	.750	.763	.765
Public	.745	.738	.729	.681	.681	.686	.702	.681	.696	.689	.708	.723	.710	.721	.756	.758	.777	.777
Union Status:																		
Nonunion	.648	.645	.635	--	--	--	--	.658	.667	.670	.674	.678	.687	.711	.719	.735	.749	.750
Union	.712	.746	.738	--	--	--	--	.755	.762	.772	.789	.796	.794	.823	.838	.844	.853	.860
Hours Status:																		
Part-time	.528	.569	.606	.804	.834	.835	.845	.841	.877	.844	.906	.870	.901	.931	.912	.982	.979	.893
Full-time	.657	.667	.661	.662	.669	.676	.681	.685	.697	.701	.704	.709	.713	.739	.749	.762	.775	.785
Production Status:																		
Nonproduction	.612	.612	.615	.616	.627	.627	.629	.630	.632	.633	.635	.635	.640	.669	.677	.688	.702	.702
Production	.618	.625	.619	.636	.635	.647	.654	.654	.654	.658	.666	.670	.673	.681	.675	.700	.698	.700

Table A1 (continued)
Female/Male Wage Ratios and Duncan Segregation Index, by Worker Group and Year, 1973-92

Group	1973-74	1975-76	1977-78	1979	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993
Duncan segregation index:																		
Age:																		
16-29	.682	.670	.643	.627	.622	.620	.610	.608	.604	.594	.589	.582	.575	.565	.563	.566	.560	.550
30-44	.699	.683	.667	.640	.635	.619	.615	.594	.586	.583	.577	.572	.563	.559	.558	.556	.556	.548
45+	.700	.704	.685	.675	.663	.661	.664	.643	.644	.625	.628	.623	.616	.605	.596	.599	.594	.591
Education (in years):																		
<12	.692	.685	.668	.652	.647	.653	.656	.635	.630	.626	.620	.612	.604	.605	.588	.596	.595	.583
12	.728	.718	.705	.691	.687	.684	.677	.660	.659	.651	.652	.645	.638	.637	.629	.630	.625	.620
13-15	.706	.692	.673	.646	.652	.638	.635	.624	.617	.608	.604	.608	.603	.588	.592	.594	.590	.583
16	.671	.661	.606	.592	.571	.560	.546	.536	.527	.520	.519	.509	.495	.477	.476	.478	.473	.464
>16	.533	.558	.520	.490	.473	.474	.486	.472	.463	.448	.450	.444	.444	.431	.437	.431	.442	.451
Race:																		
White	.688	.680	.657	.641	.634	.629	.621	.606	.601	.591	.588	.585	.574	.564	.560	.561	.558	.553
Black	.699	.666	.657	.636	.615	.618	.621	.597	.591	.588	.582	.566	.566	.569	.559	.571	.568	.537
Other race	.751	.697	.604	.613	.599	.586	.597	.572	.554	.550	.563	.536	.544	.554	.541	.519	.509	.519
Class:																		
Private	.697	.685	.665	.639	.632	.627	.621	.604	.599	.590	.586	.581	.574	.566	.561	.562	.558	.551
Public	.636	.637	.608	.564	.553	.537	.551	.505	.502	.504	.492	.472	.470	.443	.453	.456	.431	.429
Union Status:																		
Nonunion	.688	.677	.662	--	--	--	--	.599	.594	.583	.580	.572	.564	.554	.549	.550	.546	.538
Union	.673	.672	.640	--	--	--	--	.625	.622	.613	.615	.608	.613	.605	.606	.610	.609	.604
Hours Status:																		
Part-time	.665	.650	.628	.598	.612	.595	.592	.584	.589	.586	.580	.574	.571	.549	.542	.536	.529	.530
Full-time	.677	.667	.640	.626	.617	.611	.605	.587	.581	.569	.569	.564	.555	.545	.541	.546	.543	.537
Production Status:																		
Nonproduction	.668	.652	.628	.607	.593	.588	.583	.564	.561	.546	.544	.536	.529	.518	.511	.510	.505	.500
Production	.670	.663	.652	.633	.625	.617	.610	.603	.595	.588	.587	.587	.582	.586	.578	.575	.570	.567

Calculated from the 1973-78 May CPS and the 1979-93 CPS ORG files (N=2,749,246). Sample includes wage and salary workers ages 16 and over, with the exclusion of earners whose principal activity is school. Further description of the sample is in the text. The female to male wage ratio is the mean of female real wages to male real wages. Wage rates are defined as usual weekly earnings (1993 $) divided by usual hours worked per week. The Duncan segregation index is calculated by $\frac{1}{2}\,\Sigma|m_j - f_j|$, where m and f are the proportions of male and female employment in occupation j.

Table A2
Regression Coefficients, Expanded Wage Model,
1983-93 CPS ORG

Variables	Females		Males	
FEM	-.1173	(.0026)	-.0986	(.0030)
Individual Characteristics:				
Schooling	.0432	(.0002)	.0455	(.0002)
Experience	.0151	(.0001)	.0257	(.0001)
Experience^2/100	-.0249	(.0002)	-.0398	(.0002)
Union	.1485	(.0013)	.1570	(.0012)
Part-time	-.0967	(.0011)	-.1600	(.0017)
Married with spouse	.0344	(.0012)	.1223	(.0013)
Other ever married	.0321	(.0014)	.0682	(.0018)
Black	-.0441	(.0014)	-.1113	(.0016)
Other race	-.0302	(.0022)	-.0791	(.0023)
Hispanic	-.0543	(.0019)	-.1106	(.0019)
Federal	.0329	(.0028)	.0119	(.0027)
State	-.0433	(.0023)	-.0681	(.0025)
Local	-.0668	(.0018)	-.0841	(.0021)
Large metropolitan area	.1271	(.0010)	.1280	(.0011)
Job Characteristics:				
DOT-GED	.0531	(.0013)	.0225	(.0013)
DOT-SVP	.0135	(.0007)	.0297	(.0006)
Occupation-tenure	.0058	(.0003)	-.0035	(.0003)
Occupation-part-time	.0099	(.0047)	-.1610	(.0055)
Occupation-OJT	.3006	(.0049)	.1325	(.0048)
Occupation-computer	.1485	(.0031)	.1809	(.0034)
DOT-environment	-.0509	(.0027)	.0213	(.0015)
DOT-hazards	.0686	(.0046)	.0188	(.0030)
DOT-physical	.0408	(.0009)	.0000	(.0009)
DOT-strength	.0181	(.0015)	-.0251	(.0015)
Industry-union	-.0456	(.0043)	.0475	(.0042)
Industry-big firm	.1772	(.0024)	.1858	(.0027)
Region (8)	yes		yes	
Industry (13)	yes		yes	
Occupation (5)	yes		yes	
Year (10)	yes		yes	
R^2	.4495		.4894	
N	877,070		959,471	

Mean of the log wage is 2.1884 for women and 2.4941 for men. Standard errors are in parentheses. The omitted reference group is full-time, nonunion, white, non-Hispanic, never married, private sector worker in the northeast and not in a large metro, professional or managerial occupation, agricultural sector, in 1983. Variables preceded by “Occupation” and “Industry” are means of variables in workers’ designated occupation and industry. Occupation-tenure is calculated from the 1983 and 1988 May CPS Pension Supplements and the January 1983, 1987, and 1991 CPS surveys; Occupation-OJT from the January 1983 and 1991 CPS; and Occupation-computer from the October 1984 and 1989 PS. Industry-big firm (proportion in firms with 1,000+ workers) is calculated from the 1983 May CPS Pension Supplement and the March 1989-92 CPS surveys. All other “Occupation” and “Industry” variables are calculated from the 1983-93 CPS ORG files. DOT measures are taken from the *Dictionary of Occupational Titles*, matched at the Census occupation level. DOT-SVP is years required for occupational proficiency or specific vocational preparation, DOT-GED is a 1-6 index of general educational development, DOT-Environment is the number of work environment disamenities from 0-5, DOT-Hazards is the proportion in hazardous jobs, DOT-Strength is measured by a 1-5 index from low to high strength required, and DOT-Physical is the number of physical demands from 0-4.