ALL WOMEN BENEFIT: THE MACRO-LEVEL EFFECT OF OCCUPATIONAL INTEGRATION ON GENDER EARNINGS EQUALITY*

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Macro-level processes transfer many of the income benefits of occupational integration to all women in the labor market, not just to those women who enter predominantly male (and therefore high-paying) occupations. We investigate these macro-level effects in a multi-level model comparing 261 metropolitan area labor markets. We find that occupational integration is strongly associated with gender earnings equality, even after extensive individual- and macro-level controls are introduced. The size of the association implies that the entire gender gap in earnings would be eliminated if occupational integration were complete. This macro-level estimate is far higher than the 9 percent to 38 percent estimates found in individual-level studies. Moreover, an individual-level control for the gender composition of a worker's occupation explains little of the macro-level occupational association between integration and earnings equality. Women in predominantly female occupations benefit almost as much from an integrated labor market as do women in predominantly male occupations.

Gender segregation among occupations is often cited as a major cause of the continuing earnings gap between men and women. The empirical evidence, however, is somewhat mixed. An analysis of 1970 census data concludes that 35 percent of the difference in earnings would be eliminated if women had the same occupational distribution as men but retained their average earnings within each occupation (Treiman and Hartmann 1981). Goldin (1990), however, recalculated that number as 19 percent, and more recent analyses of 1980 and 1990 census data put the number at 14 percent and 15 percent (Cotter et al. 1995b). Regression methods that include the gender composition of an occupation in a standard equation predicting earnings attribute between 9 percent and 38 percent of the gender gap in earnings to gender segregation of occupations (Sorensen 1989; England 1992). Macpherson and Hirsch (1995) calculate 11 separate coefficients from the Current Population Surveys between 1983 and 1993 and find that the gender composition of occupations accounts for 12 percent to 19 percent of the gender gap in earnings. Fixed-effects models conclude that changes in the gender composition of occupations account for only 2 percent to 11 percent of changes in earnings (England 1992; Macpherson and Hirsch 1995).

These estimates imply that occupational segregation is a relatively unimportant determinant of earnings inequality. Goldin (1990),

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for instance, concludes that "the conventional groupings of occupations . . . , even when there are 500 of them, cannot explain a large share of the difference in earnings between male and female workers" (p. 73).

In response to these surprisingly low estimates some have argued that occupations are an insufficiently detailed unit of measurement and that most gender segregation takes place at the job level within occupations (Bielby and Baron 1986; Tomaskovic-Devey 1993; Petersen and Morgan 1995). While this may be a promising direction for analysis, desegregation at the occupational level would still require over one-half of employed women to change their jobs (Cotter et al. 1995a). If occupations still reveal such enormous gender segregation, why does this high level of occupational segregation by gender account for so little of the earnings gap between men and women?

Our research suggests that occupational segregation by gender *does* account for most of the gender gap in earnings, but that the association is primarily a macro-level, contextual association that decreases the relative earnings of all women, not just those women who are employed in female-dominated occupations. Past research, at both the occupation level and job level, has used individual-level data to compare the earnings of women (and men) in male-dominated positions with women (and men) in female-dominated positions. If *all* women are better off working in a gender-integrated labor market (and all men are better off in a gender-segregated labor market), then individual-level comparisons will systematically understate the importance of occupational segregation for earnings. Our research shows that all men benefit from occupational segregation, while all women fare better with occupational integration.

THE MACRO-LEVEL BENEFITS OF OCCUPATIONAL INTEGRATION

There are at least three reasons to expect the benefits of occupational integration to extend to all women in a labor market. First, occupations exist in a market economy, however imperfect, and that market will transfer some of women's gains in the integrating occupations to the women who remain in segregated occupations. For example, school boards can no longer count on a supply of college-educated women as teachers after these women see that previously male-dominated businesses and professions are open to them. To attract the same number of equally skilled teachers, school boards must raise the salaries they offer. According to this "crowding" hypothesis (Bergmann 1974, 1986), occupational segregation lowers *all* women's earnings as a result of women's exclusion from predominantly male occupations and segregation into a limited number of predominantly female occupations. The oversupply of women in predominantly female occupations reduces the cost of all female labor (Sorensen 1990). Conversely, the benefits of occupational integration should extend to women who remain in traditionally female occupations that are no longer so crowded.

Second, changes in norms may reinforce the impact of occupational integration. The visibility of gender integration in occupations may change people's expectations about women's locations in the labor market (Blau and Ferber 1992:197). As more women become television newscasters, school principals, and police officers, other women—sales clerks, factory operatives, and their daughters—may be encouraged to invest more in their own work lives and demand more from their employers. At the same time, employers—responding to perceived social pressure to reward women—may grant women the promotions and earnings that their past contributions have always warranted.

Third, as Jacobs (1992) shows, occupational integration has shifted women into positions of greater authority, from which they have been excluded in the past (Reskin and Ross 1992; Wolf and Fligstein 1979a, 1979b). As more women in these positions make crucial decisions about salaries, promotions, hiring, and firing, gender differences in earnings should decline (although no empirical evidence yet documents that female bosses make more egalitarian decisions).

In the same way that the changes in market pressures, normative expectations, and managerial power induced by occupational integration should lead to higher earnings for women, they should also lead to promotions and better *jobs* within each occupational category. For example, to retain their best woman teachers, school boards in integrated labor markets will have to appoint more women as department heads and "master teachers," positions that have gone disproportionately to men. Otherwise, those women will leave for the new opportunities open to them in business and the professions. Thus, the recent research emphasis on *job* segregation may not be misplaced, but job segregation may itself be a consequence of occupational segregation in the larger labor market.

National trends in occupational segregation and the gender gap in earnings suggest that the macro-level relationship may be stronger than individual-level studies have found. Neither occupational segregation nor the earnings gap changed much until the 1970s, but both have been improving slowly and steadily since then (Bianchi 1995; Cotter et al. 1995b; O'Neill and Polachek 1993). The concurrence of these changes, with occupational segregation perhaps declining somewhat earlier, suggests that occupational segregation may explain the narrowing of the gender gap in earnings.

Of course, occupational segregation and the earnings gap may be correlated over time or across geographical areas because both are products of common micro-level or macro-level causes. One possible common origin is the relative investment in human capital. Women with high levels of education and more work experience are more likely to earn higher incomes and, perhaps, to be employed in predominantly male occupations (although the evidence for human capital as a determinant of occupational segregation is much weaker than it is for earnings; see England 1982:368; Jacobs 1989; Rosenfeld and Spenner 1992). Before drawing a *causal* link between occupational segregation and the earnings gap, the possibilities for their joint determination by other factors must be ruled out. Even after considering these controls, contextual effects bear a special burden of empirical proof (Hannan 1992; Achen and Shively 1995).

RESEARCH DESIGN

At the individual level, two methods have been used to measure the effect of occupational segregation on the earnings gap. One method decomposes the gender gap in earnings into a within-occupation gap and a between-occupation gap to estimate what the earnings gap would be if women had the same occupational distribution as men (Treiman and Hartmann 1981). A second method uses OLS regression models and their extensions (e.g., fixed-effects models) to estimate a coefficient for the gender composition of an occupation on men's and women's earnings. We extend the regression methods to a multilevel design (Bryk and Raudenbush 1992), which has greater flexibility to estimate the macro-level effect of occupational segregation on earnings and the determinants of earnings.[1]

Individual Data

We combine data from the 1 percent and 5 percent 1990 Public Use Microdata Samples (PUMS) (U.S. Bureau of the Census 1993b) to construct a sample of men and women who, in 1989, worked full-time (35 hours or more in the average week) year-round (50 or more weeks per year) in a metropolitan area and had positive earnings. The resulting sample includes 2,747,051 individuals. Even the smallest metropolitan area (Clarksville, TN–Hopkinsville, KY) contributed 749 individuals for these analyses.

Metropolitan Areas

We compare occupational segregation and earnings inequality across 261 metropolitan areas (MAs) that follow the June 30, 1993 definitions (U.S. Bureau of the Census 1993a).[2] Metropolitan area labor markets are

[1] Previously, we used standardization methods to estimate the between-occupation and within-occupation components of the earnings gap. Those calculations yielded estimates of the macro-level effect of occupational integration on the within-occupation gender gap in earnings that are similar to the multilevel results reported here (Cotter et al. 1996a).

[2] The 1993 definitions incorporate population totals and commuting patterns from the 1990 census. New England County Metropolitan Areas (NECMAs) are used for the six New England states rather than the more common town- and city-based MAs. Using county definitions makes New England MAs more comparable to MAs elsewhere, and some of our data are available

an appropriate unit of analysis. Gender inequalities vary across these areas more than they vary nationally over time (Lorence 1992).[3] Across 261 MAs in 1989, the ratio of women's annual earnings to men's earnings ranged from 51 percent (in Decatur, IL) to 80 percent (in McAllen–Edinburg–Mission, TX). The (unweighted) standard deviation of the earnings ratio is .48. Nationally, this ratio varied from 60 percent to 71 percent between 1979 and 1992 (Bianchi 1995). Occupational segregation in 1990, as measured by a slightly modified index of dissimilarity, varied from 40 (in Columbia, MO) to 61 (in Houma, LA) with a standard deviation of 3.3. The national level of occupational segregation ranged from 67 in 1950 to 51 in 1990 (Cotter et al. 1995a). Macpherson and Hirsch (1995), using Current Population Survey data, find indexes that range from 69 in 1973–1974 to 55 in 1993.

Although some interesting cross-national comparisons of earnings inequality have emerged (Treiman and Roos 1983; Roos 1985; Rosenfeld and Kalleberg 1990; Charles 1992), the MA data are more consistent and detailed than data available cross-nationally. This detail is especially important for analyses of occupational segregation because reliance on single-digit occupation codes masks most of the segregation.

Multilevel Models

Our multilevel models incorporate in a single design a standard micro-level earnings function and macro-level equations that predict the coefficients in the earnings function. In effect, the micro-level earnings equation is estimated separately for each of the 261 MAs and the coefficients for each MA become the dependent variables in the macro-level analysis. We are especially interested in the macro-level determinants of the gender coefficient because this gender coefficient is a measure of the earnings gap in each MA.

The full multilevel model is:

$$\begin{aligned} w_{ia} &= \beta_{0a} + \beta_{1a}(Gender_{ia}) \\ &\quad + \sum \boldsymbol{\beta}_{ja}(\mathbf{X}_{jia} - \overline{\mathbf{X}_{j..}}) \\ &\quad + \sum \boldsymbol{\beta}_{ka}(Gender_{ia})(\mathbf{X}_{jia} - \overline{\mathbf{X}_{j..}}) + r_{ia}, \\ &\quad (j = 2, 3, \ldots, J), \\ &\quad (k = J+1, J+2, \ldots, 2J-1) \end{aligned} \tag{1a}$$

and

$$\begin{aligned} \boldsymbol{\beta}_{ja} &= \gamma_{j0} + \gamma_{j1}(D_a^*) \\ &\quad + \sum \boldsymbol{\gamma}_{jm}(\mathbf{Z}_{ma} - \overline{\mathbf{Z}_{m.}}) + u_{ja}, \\ &\quad (j = 0, 1, \ldots, 2J-1) \end{aligned} \tag{1b}$$

where w_{ia} is the log earnings for individual i in MA a; β_{0a} is the intercept for MA a, which is the natural log of earnings in MA a for the average male; β_{1a} is the gender difference in (ln) earnings in MA a; $Gender_{ia}$ is the gender of individual i in MA a (coded 1 = female); $\boldsymbol{\beta}_{ja}$ is a vector of individual-level coefficients for variables X_{jia} in MA a; $\mathbf{X}_{jia}$ is a vector of j individual-level variables (e.g., education) describing individual i in MA a; $\overline{\mathbf{X}_{j..}}$ is a vector of j grand means of the individual-level variables; $\boldsymbol{\beta}_{ka}$is a vector of k individual-level coefficients for the interaction of *Gender* with variables $\mathbf{X}_{jia}$ in MA a; r_{ia} is the individual-level error term for individual i in MA a; γ_{j1} is the effect of occupational segregation on the $\boldsymbol{\beta}_{ja}$; D_a^* is the adjusted index of dissimilarity measuring occupational segregation in MA a; $\boldsymbol{\gamma}_{jm}$ is a vector of m macro-level coefficients for the effects of $\mathbf{Z}_{ma}$ on the micro-level coefficients β_{ja}; $\mathbf{Z}_{ma}$ is a vector of m macro-level variables (e.g., MA size) describing MA a; $\overline{\mathbf{Z}_{m.}}$ is a vector of m grand means of the macro-level variables; and u_{ja} is the macro-level error term for coefficient β_{ja} in MA a. Note that we begin with j = 2 in equation 1a, and with j = 0 in equation 1b.

only at the county level. Six small MAs were combined with other MAs in the same state because these small MAs were not identified in the 1-percent PUMS data (U.S. Bureau of the Census 1992b). These MAs are Kokomo, IN (combined with Indianapolis); Dubuque, IA (combined with Iowa City); Lawrence, KS (combined with Kansas City); Lewiston–Auburn, ME (combined with Bangor); Bismarck, ND (combined with Grand Forks); and Sheboygan, WI (combined with Green Bay). The Jacksonville, NC area was dropped from the analysis because of extreme scores on several variables caused by the predominance of a military installation there. This leaves 261 MAs in the analysis.

[3] This design omits nonmetropolitan areas, which contain one-fifth of the U.S. population. Earlier research shows that gender inequalities in nonmetropolitan areas resemble those in metropolitan areas (Cotter et al. 1996b).

The central coefficients in the analyses are β_{1a}—the gender difference in log earnings for each MA.[4] We are especially interested in the size of the γ_{11}— the effect of macro-level occupational segregation on these gender differentials. The analyses proceed in three main phases.

First, we focus on the individual-level analysis and ignore the variation across MAs (i.e., we constrain the $\boldsymbol{\gamma}_{jm}$ to equal 0). This resembles conventional OLS analyses of earnings except that we include controls for overall earnings differentials across the 261 MAs (the u_{0a}). We compute alternative models, stepwise, to examine the impact of different sets of individual-level controls on the coefficient for gender. We divide the micro-level variables ($\mathbf{X}_{jia}$) in equation 1a into two groups: individual characteristics, like education and race, and characteristics of the individuals' occupations, including the gender composition (percent female) of the occupation. We are especially interested in comparing the gender coefficients (β_{1a}) before and after introducing a control for the gender composition of the occupation, as this control provides an estimate of the *individual-level* effect of gender segregation across occupations on the earnings gap. We also report results from a regression decomposition that estimates what proportion of the gender gap in earnings is accounted for by differences in the gender composition of the occupation (Jones and Kelley 1984).

Second, we allow the gender coefficients to vary across MAs and model these coefficients as a function of the occupational segregation in the MA, controlling for other characteristics of that MA ($\mathbf{Z}_{ma}$). We are especially interested in the effect (γ_{11}) of macro-level segregation (D_a^*) on the gender gap in earnings (β_{1a}), and how estimates of this effect vary with different sets of individual-level and macro-level controls. At first, we do not include controls for individuals' occupational characteristics because a main path by which occupational segregation affects earnings is by concentrating women in predominantly female (and therefore low-paying) occupations. These estimates are, therefore, estimates of the *total* effect of the gender segregation of occupations on the earnings gap, both the compositional part mediated through individual occupations and the contextual effect that is common for all women regardless of occupation. Then we add individuals' occupational characteristics and re-estimate the impact of macro-level segregation. This is the best estimate of the contextual effects from our hypothesis that the occupational segregation of an MA will predict the gender coefficients for earnings, even after controlling for individuals' occupational characteristics.

Third, we investigate the impact of the MA's occupational segregation on other individual-level coefficients, especially the interaction coefficients involving gender. This evaluates whether macro-level segregation is more important for some women than for others. For example, does occupational segregation hurt the earnings of women in predominantly female occupations more than it does women in predominantly male occupations?

The 261 MAs that are the macro-level units of analysis for this research constitute the entire universe of U.S. metropolitan area labor markets. Although we report conventional tests of statistical significance, there is no larger universe to which we are trying to generalize. For this reason, the *size of the coefficients* indicates substantive significance, not the *t*-tests of statistical significance. At the individual level, the sample is so large that all individual-level coefficients (β_j) are statistically significant.

Occupational Segregation

Gender differences in occupational distributions are usually measured by the dissimilarity index, D (Duncan and Duncan 1955). The dissimilarity index enables comparability with other studies and is readily interpreted as the percentage of workers of either gender who would have to change occupations for the two occupational distributions to match.

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[4] Because the micro-level model, equation 1a, includes a vector of gender interaction terms, these β_{1a} estimate the gender differences in log earnings only when all other variables ($\mathbf{X}_{jia}$) equal 0. As is common in multi-level designs, to make the coefficient for gender meaningful all the micro-level variables (except *Gender*) are centered at their grand means. The β_{1a} then estimate the earnings gap that would result if men and women in each MA had the grand mean on all the micro-level control variables.

The index can be computed for each MA from county-level occupational distributions supplied by the census (U.S. Bureau of the Census 1992a).

The dissimilarity index has an important disadvantage when comparing MAs, however. When a sample is small, random fluctuations alone can produce a high index (Cortese, Falk, and Cohen 1976). For instance, the Enid, OK area could have as few as 4,355 census respondents who were classified into 364 (out of a possible 501) occupations.[5] Of these occupations, 54 had no more than one person and so were, by definition, totally segregated. Another 50 occupations had only two people, and by chance alone, one-half of these occupations would be totally segregated. This problem has not been serious when calculating *residential* segregation indexes because the number of tracts (or block groups, etc.) varies across MAs such that average tract size is large and approximately constant for all MAs (Massey 1978). For *occupational* segregation, however, the number of occupations is fixed, so small MAs have only a few people in each occupation and random fluctuations in gender composition become more consequential (Baron, Mittman, and Newman 1991).

The expected value of the dissimilarity index can be computed assuming that the gender distributions across occupations follows a purely random hypergeometric distribution (Cortese et al. 1976). These expected dissimilarity indexes closely follow MA size: The census samples would produce, by chance alone, an expected dissimilarity index of 1 in New York, but 19 in Enid. Given that dissimilarity indexes calculated from the census have a range of only 22 points, these random differences in expectations create an important complication. In fact, the calculated dissimilarity index is correlated .59 with the random expectations (and .55 with the natural log of MA size).

We therefore calculate an adjusted dissimilarity index, D^*, to measure occupational segregation; calculations are described in Appendix A. The adjusted measure can be interpreted as the percentage of workers of either sex who would have to change occupations in order for the two distributions not to differ by any more than would be expected by chance. For the 261 MAs in this analysis, D^* is highly correlated with the unadjusted index (.84) but has a much lower correlation with the expected value of the indexes (.07).

Individual-Level Variables

We include controls for education, potential work experience and its square, race/ethnicity as defined by four dummy variables (Hispanics, non-Hispanic African Americans, non-Hispanic Asian Americans, and non-Hispanic Native Americans), marital status, number of children, and typical hours worked per week. Percent female in each occupation is taken from the 1990 census (U.S. Bureau of the Census 1992a). Nine other characteristics of occupations are included from the scales defined by Kilbourne et al. (1994); most of these are based on codes from the *Dictionary of Occupational Titles* (DOT) (England and Kilbourne 1988).

Macro-Level Variables

While past research offers considerable guidance about the individual-level determinants of earnings, it is more difficult to select a set of macro-level factors that might jointly determine occupational segregation and earnings inequality. We have incorporated a large number of macro-level controls in order to offer a conservative test of the causal effect of occupational segregation on gender differentials in earnings (although this strategy creates other difficulties, in particular, multicollinearity). The MA-level control variables are aggregated from county-level data from a variety of sources; definitions are given in Appendix B. One set of control variables includes size of labor force, region, net migration during the previous five years, men's earnings inequality, the unemployment rate,

[5] The census does not report the number of people in the sample. The occupation tabulations are based on responses to the long-form questionnaire and are then inflated to represent the total population. Sampling rates varied depending on the geographic area but averaged one-in-six. We estimated the actual number of men and women in each occupation by dividing the reported number by 6 and rounding to the nearest integer. Dissimilarity indexes calculated from these estimated counts correlated .99 with indexes calculated from the reported counts.

percentage with some college education, racial/ethnic composition, age structure, religious composition, and percent employed in durable goods manufacturing.

A second set of control variables includes the demand for female labor as indexed by an occupational structure skewed toward female occupations (Oppenheimer 1970), women's political mobilization as indexed by the percentage of local offices held by women (U.S. Bureau of the Census 1990), family structure, fertility, and sex ratios. Because all of these variables measure some aspect of gender stratification in the MAs, including them as controls raises several problems. Some can be thought of as intervening variables between occupational segregation and earnings inequality. To the extent that these control variables measure aspects of gender segregation they may be spuriously correlated with the dependent variable, biasing coefficients upward (Fossett 1988). Finally, *endogeneity* is a major problem with all these control variables. For instance, are balanced sex ratios a *determinant* of more equal earnings, or are they a *consequence* of more equal earnings because women have migrated to metropolitan areas (and men have emigrated from areas) where women's earnings are more favorable? Any such endogeneity will also bias coefficients for the control variables upward.

Thus, we have less confidence in the second set of MA-level control variables. To the extent that estimates of the effects are upwardly biased or variables would be better conceptualized as intervening variables, rather than prior variables, a downward bias is exerted on the estimated effect of occupational segregation on earnings inequality. We enter these variables separately in a final macro-level step so we can assess these possible biases.

RESULTS

The means and standard deviations of all variables are reported in Table 1. Statistics for all individual-level and MA-level variables are weighted by the population weights from the PUMS. Thus, large MAs are given more weight than small MAs.

Table 1. Means and Standard Deviations of Variables Used in the Analysis, by Gender: U.S. Metropolitan Areas, 1990

	Women		Men	
Variable	Mean	Standard Deviation	Mean	Standard Deviation
Individual-Level Variables				
Annual earnings (ln)	9.92	.57	10.32	.66
Years of school completed	13.68	2.51	13.83	2.88
Experience (potential)	17.94	8.79	18.12	8.53
[Experience (potential)]^2	81.58	82.29	76.32	80.46
Hours worked (ln)	3.73	.14	3.80	.17
Formerly married	.24	.43	.13	.36
Never married	.19	.39	.17	.37
Number of children	.79	1.04	1.02	1.18
African American	.13	.34	.08	.28
Hispanic	.07	.26	.08	.27
Asian American	.04	.18	.03	.17
Native American	.01	.07	.00	.06
Occupational Characteristics				
Percent female	.63	.26	.28	.22
Cognitive skills required	–.23	.86	–.20	.96
General educational development	3.95	.78	3.90	.85
Specific vocational preparation	5.50	1.37	5.74	1.47
Authority	.17	.38	.24	.43

(Table 1 continued on next page)

(Table 1 continued from previous page)

Variable	Women Mean	Women Standard Deviation	Men Mean	Men Standard Deviation
Occupational Characteristics (Continued)				
Nurturance	.20	.80	–.16	.70
Physical skills required	.03	.59	–.03	.63
Hazardous	–.33	.50	.11	.87
Exposure to cold	–.10	.55	.03	1.10
Exposure to heat and humidity	–.17	.64	.01	.90
MA-Level Variables				
Occupational segregation (D^*)	.50	.02	.50	.02
Labor force size (ln)	.08	1.47	.07	1.48
(Labor force size (ln))^2	2.17	2.25	2.19	2.27
North Central	.22	.41	.23	.42
South	.34	.47	.32	.47
West	.21	.41	.22	.41
Percent net migrants	.00	.04	.00	.04
Percent some college	.56	.07	.55	.07
Percent age 65 or over	.15	.03	.15	.03
Percent ages 16 to 24	.17	.02	.17	.02
Percent African American	.13	.09	.13	.08
Percent Hispanic	.10	.11	.10	.11
Percent Asian American	.03	.05	.03	.05
Percent Native American	.01	.01	.01	.01
Percent conservative religions	.25	.14	.25	.14
Male earnings inequality	.36	.03	.35	.03
Percent unemployed	.06	.01	.06	.01
Percent in durable manufacturing	.10	.04	.11	.05
Percent women separated or divorced	.13	.02	.13	.02
Percent women never married	.24	.04	.24	.04
Total fertility rate	2.04	.24	2.00	.25
Total fertility rate missing	.01	.08	.01	.08
Demand for female labor	.46	.01	.46	.02
Percent employed, women with no college	.38	.06	.38	.06
Percent employed, men with no college	.61	.06	.61	.06
Percent employed, women with some college	.49	.04	.48	.04
Percent employed, men with some college	.76	.04	.75	.04
Sex ratio (female/male)	1.03	.04	1.03	.04
Percent female among local officials	.20	.08	.20	.08

Bivariate Macro-Level Relationship

Figure 1 plots the simple macro-level bivariate relationship between the adjusted index of occupational segregation (D^*) and the gender difference in (ln) earnings for the 50 largest metropolitan areas. Metropolitan areas with low occuptional segregation generally have greater earnings equality (e.g., San Francisco); areas with high occupational segregation tend to have lower earnings equality (e.g., Detroit). "Sunbelt" MAs tend to have higher than expected earnings equality, while "Rustbelt" MAs tend to have lower

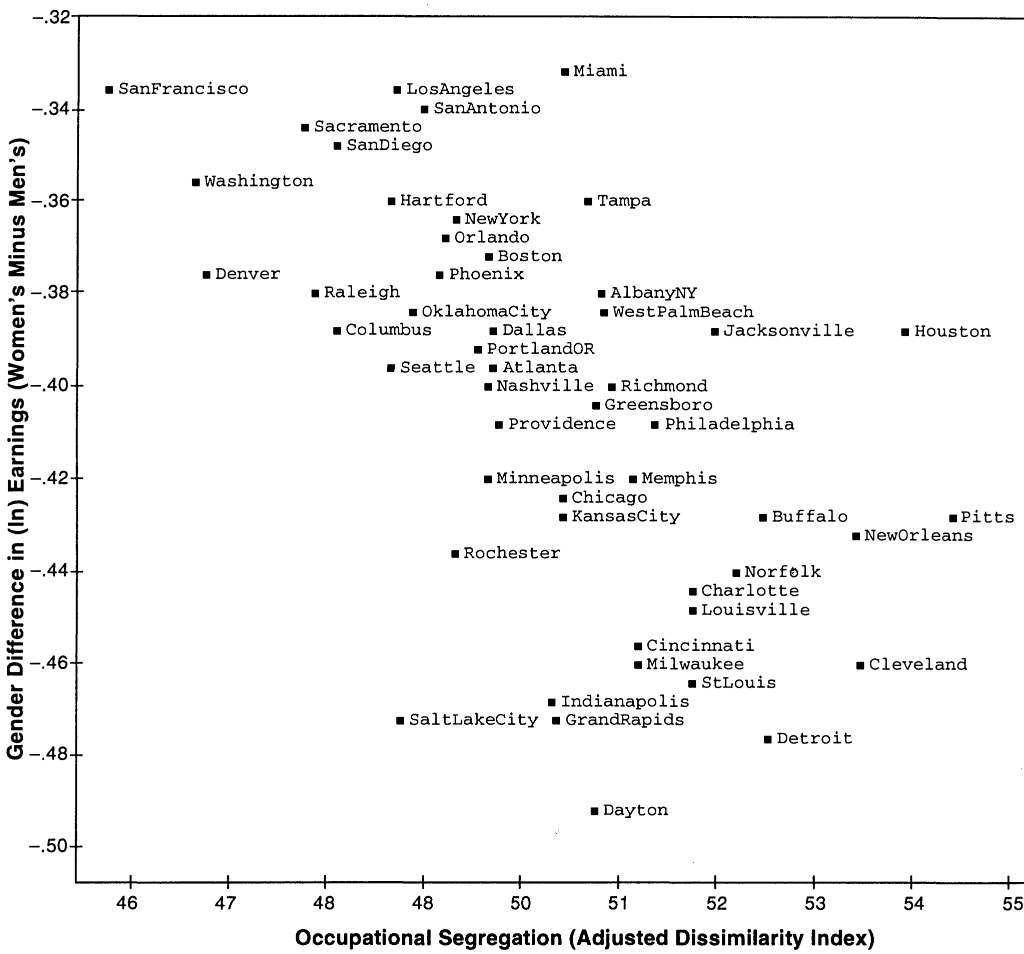

Figure 1. Scattergram Showing the Relationship between Occupational Segregation and the Gender Difference in Earnings for the 50 Largest Metropolitan Areas: United States, 1990

Sources: 1990 Census Equal Employment Opportunity File (U.S. Bureau of the Census 1992a) and 1-percent and 5-percent PUMS (U.S. Bureau of the Census 1993b).

than expected earnings equality. Across all 261 metropolitan areas, occupational segregation and the gender difference in earnings are correlated –.61.

Individual-Level Effects

Table 2 reports the stepwise micro-level analyses. For clarity, steps that include gender interaction terms (Models 3 to 5) present separate coefficients for men and women. The negative coefficient for gender in Model 2 translates into a 67 percent ratio of women's earnings to men's earnings ($\exp^{-.401} = .670$; i.e., a 33 percentage-point gap in earnings). The individual controls introduced in Model 3 increase this ratio to only 71 percent. The lack of variables for actual work experience and tenure precludes the individual-level controls from explaining much of the gender gap in earnings. Including the control for gender composition of the occupation in Model 4 reduces the coefficient for gender to –.262, implying an earnings ratio of 77 percent. Thus, the control for gender composition of the occupation, by itself, explains 6 percentage points of the 29 percentage-point earnings gap observed in Model 3 (i.e., it explains

Table 2. Coefficients from the Regression of (ln) Earnings on Individual and Occupational Characteristics: U.S. Metropolitan Areas, 1990

			Model 3		Model 4		Model 5	
Independent Variable	Model 1	Model 2	Men	Women	Men	Women	Men	Women
Variance of micro-level residuals	.465	.422	.317		.313		.297	
Intercept	10.022	10.178	10.145		10.124		10.130	
Variance of MA intercepts	.014	.013	.011		.010		.009	
Individual-Level Variables								
Gender (1 = female)	—	–.401	–.342		–.262		–.279	
Years of school completed	—	—	.092	.088	.095	.087	.070	.061
Experience (potential)	—	—	.015	.005	.016	.005	.014	.005
[Experience (potential)]^2	—	—	–.000	–.000	–.000	–.000	–.000	–.000
Hours worked (ln)	—	—	.451	.394	.446	.327	.375	.318
Formerly married	—	—	–.157	–.010	–.156	–.011	–.137	.003
Never married	—	—	–.232	–.020	–.224	–.023	–.205	–.008
Number of children	—	—	.018	–.040	.017	–.037	.017	–.032
African American	—	—	–.233	–.080	–.226	–.075	–.176	–.031
Hispanic	—	—	–.211	–.090	–.204	–.100	–.184	–.073
Asian American	—	—	–.224	–.074	–.216	–.077	–.213	–.052
Native American	—	—	–.166	–.077	–.167	–.080	–.138	–.056
Occupational Characteristics								
Percent female	—	—	—	—	–.160	–.291	–.261	–.240
Cognitive skills required	—	—	—	—	—	—	–.094	–.019
General educational development	—	—	—	—	—	—	.072	.150
Specific vocational preparation	—	—	—	—	—	—	–.030	.001
Authority	—	—	—	—	—	—	.149	.049
Nurturance	—	—	—	—	—	—	–.015	–.028
Physical skills required	—	—	—	—	—	—	–.024	–.019
Hazardous	—	—	—	—	—	—	–.043	–.025
Exposure to cold	—	—	—	—	—	—	.008	.010
Exposure to heat or humidity	—	—	—	—	—	—	.014	–.028

Note: All coefficients are statistically significant ($p < .001$). All models allow only the intercept to vary across MAs.

about 20 percent of the earnings gap). This figure is similar to previously cited individual-level estimates of the effect of occupational segregation on the earnings gap. The addition of all the occupational control variables in Model 5 increases the micro-level effect of an occupation's gender composition for men, but decreases it for women. Using regression decomposition techniques, these regression coefficients for Model 5 imply that at the individual level, occupational segregation accounts for 26 to 38 percent of the total gender gap in earnings, a high estimate but within the range of earlier results.

Total Effects of Occupational Segregation

We begin the macro-level analyses using the micro-level Model 3 from Table 2 (i.e., the model omitting the individual's occupational characteristics) because these characteristics are in part a function of the occupational segregation of the labor market. The coefficient for gender, when allowed to vary across MAs, has a variance of .00252. Table 3 reports the analysis of that variance in the coefficients for gender. Model 2 reports the simple regression of the MA-level gender coefficients on the MA's adjusted dissimilar-

Table 3. Coefficients from the Regression of Coefficients for Gender on Selected Characteristics of 261 Metropolitan Areas

Independent Variable	Model 1	Model 2	Model 3	Model 4
Variance of gender coefficient	.00252	.00148	.00075	.00050
Intercept	–.356***	.143***	.192**	.024
Occupational segregation (D^*)	—	–.990***	–1.090***	–.756***
MA Characteristics				
Size of labor force (ln)	—	—	.001	.003
[Size of labor force (ln)]^2	—	—	–.002	–.001
North Central	—	—	–.032***	–.030***
South	—	—	–.027**	–.020
West	—	—	–.047***	–.012
Percent net migrants	—	—	.113	.204***
Percent some college	—	—	.047	.032
Percent age 65 or over	—	—	–.048	–.132
Percent ages 16 to 24	—	—	–.204*	–.063
Percent African American	—	—	–.093**	–.136**
Percent Hispanic	—	—	.026	.001
Percent Asian American	—	—	–.108*	–.187***
Percent Native American	—	—	.045	.363
Percent conservative religions	—	—	.034	.030
Economic Characteristics of MA				
Male earnings inequality	—	—	.391**	.220*
Percent unemployed	—	—	.643**	1.189***
Percent in durable manufacturing	—	—	–.205***	–.065
Family Characteristics of MA				
Percent women separated or divorced	—	—	—	–.630**
Percent women never married	—	—	—	–.143
Total fertility rate	—	—	—	.007
Total fertility rate missing	—	—	—	.012
Gender Characteristics of MA				
Demand for female labor	—	—	—	.670***
Percent employed, women with no college	—	—	—	.128
Percent employed, men with no college	—	—	—	–.050
Percent employed, women with some college	—	—	—	.305**
Percent employed, men with some college	—	—	—	–.047
Sex ratio (female/male)	—	—	—	–.011
Percent women among local officials	—	—	—	.022

Note: The dependent variable is the coefficient for gender in the micro-level model that omits characteristics of individuals' occupations. All models allow only the intercept and the coefficient for gender to vary across MAs.

*$p < .05$ **$p < .01$ ***$p < .001$ (two-tailed tests)

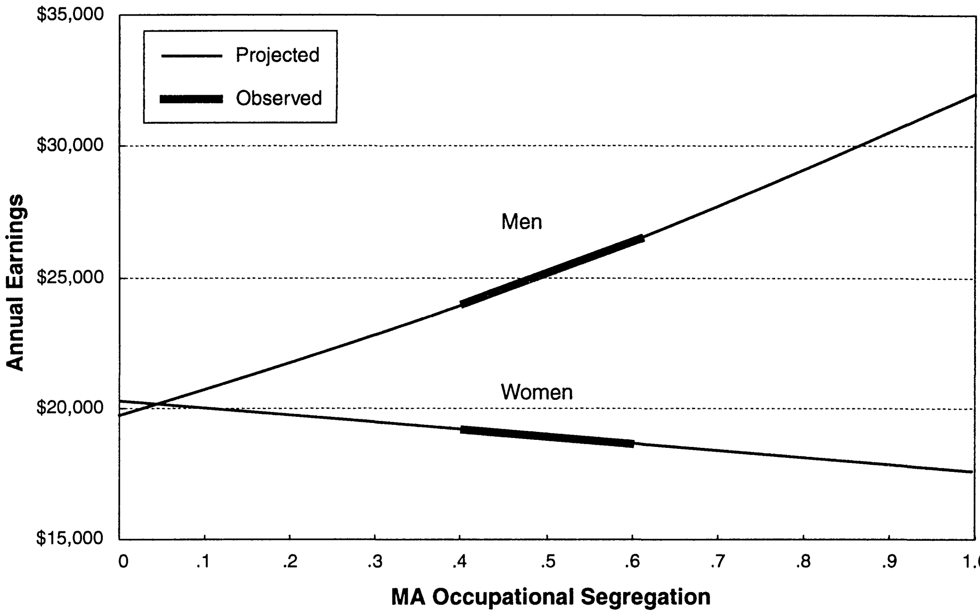

Figure 2. Estimated Earnings by Gender and Metropolitan Area Occupational Segregation: United States, 1990

Sources: 1990 Census Equal Employment Opportunity File (U.S. Bureau of the Census 1992a) and 1-percent and 5-percent PUMS (U.S. Bureau of the Census 1993b).

ity index. This bivariate result confirms the strong relationship between the gender gap in earnings and occupational segregation that was illustrated in Figure 1. For every percentage-point increase in occupational segregation, the gender difference in log earnings increases by almost a full percent. Model 3 adds controls for several background characteristics of the MA, but the segregation coefficient is changed little. Several control variables are related to earnings equality (e.g., region, percent employed in durable goods manufacturing), but they have mixed relationships with occupational segregation so there is no net change in the segregation coefficient.

Model 4 introduces controls for metropolitan area variables describing family structure and other dimensions of gender stratification. These controls reduce the occupational segregation coefficient to –.756, but an increase of one percentage point in occupational segregation still yields three-quarters of a percent decrease in earnings equality. The size of this coefficient implies a much larger effect of occupational segregation than was found in the individual-level results reported in Table 2. The intercept in Model 4 represents the estimate for the gender coefficient when the adjusted dissimilarity index is 0, and all the other MA variables are at their means (because those variables were centered). The intercept, .024, is less than twice its standard error (i.e., not significantly different from 0). This calculation should be treated cautiously because it extrapolates well beyond the range of occupational integration observed in these MAs (the most integrated labor market area, Columbia, MO, has an occupational segregation index of .404). Nevertheless, this provides an idea of the size of the macro-level effect of occupational segregation and its far greater influence at the macro level than the micro level.

Some control variables have interesting effects in this model, but they should be interpreted with caution because including so many variables in an equation based on only 261 MAs creates substantial problems of multicollinearity. We refrain from commenting on these control variables to maintain the central focus on the effects of occupational segregation.

The Effect of Segregation on Women's and Men's Earnings

Both men and women tend to earn less in segregated labor markets (results not shown), but this is partly a function of background factors. For example, small labor market size is correlated with low average earnings and low occupational segregation. Once these factors are controlled, the coefficient for occupational segregation in the men's earnings equation becomes positive, as expected. In fact, the positive effect on men's earnings is noticeably larger than the negative effect on women's earnings. This is illustrated in Figure 2, which plots predicted average annual earnings for men and women at varying levels of occupational segregation. The thick parts of the line represent predicted values over the range of occupational segregation observed in the 261 MAs; the thinner lines are projections to the full range of the adjusted dissimilarity index. Two observations are important: The slope for men's earnings is steeper than the slope for women, and the plots for men's and women's earnings converge at full occupational integration.

Macro-Level Models Net of Occupational Characteristics

Table 4 presents an MA-level regression of the gender coefficient for Model 5 in Table 2, the model that includes characteristics of the individual's occupation. This analysis determines whether occupational segregation affects the gender difference in earnings, even when comparing men and women with similar occupations (i.e., at the mean level of 41 percent female). The effect of occupational segregation is smaller in Table 4, but in all models, occupational segregation still has a large and statistically significant impact on the coefficient for gender. After all MA-level factors are controlled in Model 4, the effect of occupational segregation (.626) is still 83 percent of the effect estimated in Table 3. Most of the macro-level relationship between occupational segregation and earnings inequality is contextual: All women are hurt by a segregated labor market, not only those in predominantly female occupations. All men benefit from a segregated labor market, not just those in predominantly male occupations.

Some women may still benefit more than others from occupational integration (and some men may benefit more than others from occupational segregation). For instance, do women in predominantly male occupations benefit more (or less) in an integrated labor market compared to women in predominantly female occupations? We can answer this question by allowing the coefficient for percent female to vary across MAs and test whether that variation is correlated with occupational segregation. In effect, this tests for an interaction between micro-level and macro-level segregation. Results (not reported here) show no statistically significant difference between the slopes for percent female in integrated labor markets compared to segregated labor markets for either men or women. Looked at another way, the benefits of MA-level occupational integration extend to women throughout the occupational distribution.

DISCUSSION

We have shown that at the macro-level, occupational segregation accounts for most gender differences in earnings. This relationship is robust: It remains statistically and substantively significant after introducing an extensive set of micro-level and macro-level control variables. In contrast, at the individual level, occupational segregation accounts for only 15 percent of earnings inequality (Cotter et al. 1995b). Moreover, other individual-level explanations account for only a modest share of the earnings gap: O'Neill and Polachek (1993) attribute about one-fourth of the decline in the earnings gap to convergence in men's and women's years of work experience. We argue that individual-level analyses miss most of the important effects of occupational segregation. In labor markets where women are segregated into a small segment of occupations, earnings for all women are hurt by the effects of this crowding. As occupations become integrated, all women benefit, including women in occupations that remain predominantly female. However, a large earnings gap and high occupational segregation continue to exist, although both are declining (Cotter et al. 1995b). At the current rate of occupational integration (6.3 points per decade), it will take *80 years* to eliminate

Table 4. Coefficients from the Regression of Coefficients for Gender on Selected Characteristics of 261 Metropolitan Areas (Micro-Level Model Includes Individual-Level Controls for Occupation)

Independent Variable	Model 1	Model 2	Model 3	Model 4
Variance of gender coefficient	.00239	.00155	.00085	.00054
Intercept	–.289***	.160***	.203**	.026
Occupational segregation (D^*)	—	–.891***	–.979***	–.627***
MA Characteristics				
Size of labor force (ln)	—	—	–.002	.001
[Size of labor force (ln)]^2	—	—	–.002	–.001
North Central	—	—	–.036***	–.031***
South	—	—	–.023*	–.015
West	—	—	–.050***	–.010
Percent net migrants	—	—	.138*	.235***
Percent with some college	—	—	.058	.045
Percent age 65 or over	—	—	–.128	–.179
Percent ages 16 to 24	—	—	–.269**	–.123
Percent African American	—	—	–.083*	–.126**
Percent Hispanic	—	—	.025	.008
Percent Asian American	—	—	–.103	–.182**
Percent Native American	—	—	–.006	.362
Percent conservative religions	—	—	.029	.027
Economic Characteristics of MA				
Male earnings inequality	—	—	.455***	.292**
Percent unemployed	—	—	.510**	1.267***
Percent in durable manufacturing	—	—	–.143**	–.000
Family Characteristics of MA				
Percent women separated or divorced	—	—	—	–.667**
Percent women never married	—	—	—	–.145
Total fertility rate	—	—	—	.003
Total fertility rate missing	—	—	—	.016
Gender Characteristics of MA				
Demand for female labor	—	—	—	.747***
Percent employed, women with no college	—	—	—	.168
Percent employed, men with no college	—	—	—	–.044
Percent employed, women with some college	—	—	—	.273**
Percent employed, men with some college	—	—	—	.010
Sex ratio (female/male)	—	—	—	–.065
Percent female among local officials	—	—	—	.005

Note: The dependent variable is the coefficient for gender in the micro-level model that includes the characteristics of individuals' occupations. All models allow only the intercept and the coefficient for gender to vary across MAs.

*$p < .05$ **$p < .01$ ***$p < .001$ (two-tailed tests)

the earnings gap between men and women (Bianchi 1995:125).

Further Concerns

Although the relationship between occupational segregation and the earnings gap is strong and remains robust after controls are introduced, there still are reasons to be cautious about a causal interpretation of this association. First, despite extensive controls for micro and macro determinants of earnings, other determinants may remain inadequately measured or even unspecified. Some of these weaknesses would be correctable with other data. For instance, we were unable to control for *actual* work experience. Better work-experience measures would permit a more complete comparison of micro-level and macro-level explanations of the decline in earnings inequality.

Second, endogeneity remains a concern—the causal direction of this relationship could easily go the other way. For example, in labor markets where occupations have more equal male/female earnings ratios, male workers may have less incentive to keep women out, so these occupations may become more integrated over time. Panel analyses might help to sort out the causal direction of this relationship.

Causal inferences based on macro-level data are inherently more difficult than those based on individual-level data. The life courses of individuals provide some guidance for cause and effect (e.g., education causes earnings) that is not available at the macro level (e.g., have women invested in education because their labor markets provide greater returns, or are labor markets more equal because women have higher human capital?). The most cautious interpretation of our results is that occupational segregation and gender differences in earnings have a macro-level association across metropolitan areas that is far stronger than that observed when comparing individuals in predominantly male occupations with those in predominantly female occupations.

Selection Effects

Macro-level relationships may arise from two processes: Selection effects that pull high-earning women into certain geographical areas (or keep them there), and contextual effects on the earnings of women already working in those areas (Hannan 1992; Achen and Shively 1995). This means either that women are better paid because, for example, they work in occupationally integrated San Francisco or they work in San Francisco because they are better paid. Blalock (1964) identified the source of the ambiguity: If people are selected into geographical areas partly *on the basis of the dependent variable* (earnings), the relationships of the macro-level variables will be inflated, which can then appear as a contextual association. This selection process surely accounts for some of the macro-level association between occupational segregation and earnings inequality. Women are drawn to the San Francisco labor market (and men to Detroit) because of the higher earnings there. And because high-earning women are found disproportionately in predominantly male occupations, San Francisco will be more integrated than Detroit. Moreover, because of the distortions introduced by aggregation bias, the MA-level association between occupational segregation and earnings inequality will be much stronger than the individual-level association (Firebaugh 1978)—precisely the relationship we have shown above.

In sum, then, several processes could explain the macro-level relationship we found. We noted three separate paths by which occupational segregation could have a contextual effect on earnings: crowding, male decision-making power, and normative expectations about women's roles. Selection effects represent another, quite different, explanation. In contrast, the more common *compositional* explanation relies on the shifts of women into male, higher paying occupations to account for women's higher earnings. That compositional explanation is the only process we have measured directly and it plays a role but a surprisingly small role. The next task is to choose from among the remaining explanations those that best account for the macro-level association between occupational segregation and gender earnings inequality.

That task will not be easy. Broad guidelines are available but no simple tests. All critics of contextual effects insist that the selection process, or in Hannan's (1992) terminology the "grouping" process, be studied directly. An examination of migration might offer some insight into the process: Fixed-effects models relating *changes* in earnings with *changes* in labor markets might control for some of the unmeasured individual-level differences between women working in San Francisco and those working in Detroit. The problem is that the types of women who move to (or stay in) San Francisco are more likely to be career-oriented women whose earnings would have improved in Detroit as well. Whether their earnings would have improved as much without relocation is the heart of the question about contextual effects. Migration studies also could clarify whether the women moving to San Francisco were already high earners (and in disproportionately male occupations) before moving.

The intervening variables in the contextual effects need to be studied as well. Do women working for female managers earn more? Are expectations about women and women's occupations different in an occupationally integrated area? Do women working for more egalitarian bosses (or women with more egalitarian views) actually earn more? Relatively little is known about the strengths of these associations, much less whether these associations represent causal effects on earnings. Also, there is no straightforward way to isolate the crowding mechanism and measure its strength.

We do not want to be too pessimistic—data are currently available to address most of these questions. We have evaluated one possible process—the compositional effect—and obtained an estimate of its importance. Future analyses should help determine which process offers a stronger explanation, although probably no single study can definitively sort out all competing explanations. The first step is to acknowledge that it is not just women in men's occupations who are doing better in integrated labor markets (nor just the men in men's occupations who do better in segregated labor markets). For whatever reason, *all* women benefit from occupational integration.

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Appendix A. Calculation of the Adjusted Dissimilarity Index

The usual formula for the dissimilarity index is:

$$D=\frac{1}{2}\sum_{i=1}^{Nocc}\left|\frac{f_i}{F}-\frac{m_i}{M}\right|, \qquad \text{(A-1)}$$

where f_i is the number of women in occupation i; F is the number of women in the metropolitan area's labor force, m_i is the number of men in occupation i; and M is the number of men in the metropolitan area's labor force.

This equation is re-written by Cortese et al. (1976) as,

$$D=\frac{1}{B}\sum_{i=0}^{Nocc}\left|f_i-pt_i\right|, \qquad \text{(A-2)}$$

where p is the proportion of women in the metropolitan area's labor force; t_i is the number of men and women in occupation i; B is $2p(1-p)T$; and T is the size of the metropolitan area's labor force.

The quantity inside the absolute-value signs is the difference between the actual number of women in an occupation and the number expected if the occupation had the same proportion of women as the total

MA labor force (i.e., was *perfectly* integrated). If women were distributed *randomly* across occupations, the expected value of this number, e_i, would be:

$$e_i = \sum_{f_i=0}^{t_i} |f_i - pt_i| H_f, \tag{A-3}$$

where H_f is the hypergeometric probability distribution,

$$\frac{\binom{M}{m_i}\binom{F}{f_i}}{\binom{T}{t_i}}.$$

The expected value of the dissimilarity index is calculated by summing these e_i across all occupations.

An adjusted dissimilarity index, D^*, can be calculated as

$$D^* = \frac{1}{B} \sum_{i=1}^{Nocc} \max\left[\text{int}\left(|f_i - pt_i| - e_i\right), 0\right], \tag{A-4}$$

where int is the next largest whole integer. For each occupation, this calculates the number of women who would have to move into (or out of) that occupation so that the observed number of women was no larger (or smaller) than what would be expected by chance. This formulation preserves the usual interpretation of the dissimilarity index as the proportion of women who would have to change occupations in order to make the distributions equivalent, but uses a chance distribution rather than absolute equality as the standard.

Appendix B. Definitions of Variables Used in the Analysis

Variable	Data Source	Definition
Macro-Level Measures		
Occupational gender segregation	1990 EEO Census	See text and Appendix A.
Labor force size (ln)	1990 PUMS	Logarithm of the number of persons working full-time year-round in 1989.
Region	1990 STF3C (U.S. Bureau of the Census 1991)	Three dummy variables for North Central, South, and West (Northeast is the excluded category).
Percent net migrants	1990 County to County Migration (U.S. Bureau of the Census 1995)	The number of migrants into an MA from 1985–1990 minus the number of migrants out of an MA from 1985–1990 as a percent of the total 1990 MA population.
Male earnings inequality	1990 PUMS	Gini coefficient for annual earnings of 25- to 54-year-old men working full-time year-round.
Percent unemployed	1990 STF3C	The total number of unemployed persons in the MA as a percent of the total civilian labor force.
Percent some college	1990 STF3C	The number of persons age 25 or over with some college, an Associate, a Bachelor's, or professional degree, divided by the total number of persons age 25 or over.
Percent age 65 and over	1990 STF3C	Total number of persons age 65 or over divided by the total number of persons 16 or over in the MA.
Percent ages 16 to 24	1990 STF3C	Total number of persons ages 16 to 24 divided by the total number of persons age 16 or over in MA.
Percent African American	1990STF3C	Percent of population non-Hispanic African American.
Percent Hispanic	1990 STF3C	Percent of population Hispanic, any race.
Percent Asian American	1990 STF3C	Percent of population non-Hispanic Asian American.
Percent Native American	1990 STF3C	Percent of population non-Hispanic Native American.
Percent conservative religions	1990 National Survey of Religious Identification (Kosmin and Lachman 1993)	Percent of population identified as Baptist, Fundamentalist, or Mormon.

(Appendix B continued on next page)

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Variable	Data Source	Definition
Percent employed in durable manufacturing	1990 STF3C	Percent of 1990 labor force employed in durable goods manufacturing industry.
Percent women separated or divorced	1990 STF3C	Number of women over age 15 who are either separated or divorced divided by the total number of women over age 15.
Percent women never married	1990 STF3C	Number of women over age 15 who never married divided by the total number of women over age 15.
Total fertility rate	1989 and 1990 Vital Statistics (National Center for Health Statistics 1993, 1994) and 1990 STF3C	Calculated from age specific fertility rates derived from births in each MA divided by the number of women aged 15 to 49 in 1990.
Total fertility rate missing	1989 and 1990 Vital Statistics	Dummy variable for MAs not reported in Vital Statistics.
Demand for female labor	1990 PUMS	The extent to which the occupational structure is skewed toward female occupations. Measured as the hypothetical female share of the full-time year-round labor force if within-occupation female share is held constant at the national average, but the occupational structure varies across MAs.
Percent employed, women with no college	1990 PUMS	Percent of women ages 25 to 54 with no college education who are employed full-time year-round.
Percent employed, men with no college	1990 PUMS	Percent of men ages 25 to 54 with no college education who are employed full-time year-round.
Percent employed, women with some college	1990 PUMS	Percent of women ages 25 to 54 with at least some college education who are employed full-time year-round.
Percent employed, men with some college	1990 PUMS	Percent of men ages 25 to 54 with at least some college education who are employed full-time year-round.
Sex ratio (female/male)	1990 STF3C	The ratio of women ages 25 to 59 to men ages 25 to 59.
Individual-Level Variables		
Annual earnings (ln)	1990 PUMS	Log 1989 earnings (wage and salary income plus self-employment income).
Gender	1990 PUMS	Dummy variable: female = 1, male = 0.
Race	1990 PUMS	Four dummy variables: non-Hispanic African American, Hispanic, non-Hispanic Asian American, and non-Hispanic Native American Indian (non-Hispanic White is the excluded category).
Marital status	1990 PUMS	Two dummy variables: Formerly married (divorced, separated, widowed, and married-spouse absent) and never married. (Currently married, spouse present is the excluded category).
Number of children	1990 PUMS	Number of children in the household.

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Variable	Data Source	Definition
Years of school completed	1990 PUMS	Number of years of school completed.
Experience (potential)	1990 PUMS	(Age) – (years in school) – 6.
Hours worked (ln)	1990 PUMS	Log of the number of hours usually worked per week in 1989.
Occupational Variables		
Percent female	1990 Census EEO	Percent female of all employed in the occupation in 1990.
Cognitive skills required	1990 PUMS; England and Kilbourne (1988)	Mean of DOT scales for level of complexity of work with data, numerical aptitude, and intelligence aptitude.
General educational development	1990 PUMS; England and Kilbourne (1988)	DOT code.
Specific vocational preparation	1990 PUMS; England and Kilbourne (1988).	DOT code.
Physical skills required	1990 PUMS; England and Kilbourne (1988)	Mean of DOT scales for motor coordination, finger dexterity, manual dexterity, form perception, spatial aptitude, and demands seeing.
Hazardous	1990 PUMS; England and Kilbourne (1988)	Mean of DOT scales for hazards, atmospheric conditions, stooping, climbing, and environmental conditions.
Exposure to heat and humidity	1990 PUMS; England and Kilbourne (1988).	Mean of DOT scales for extreme heat, and wet or humid conditions.
Exposure to cold	1990 PUMS; England and Kilbourne (1988)	DOT code.
Nurturance	1990 PUMS; Kilbourne et al. (1994)	Dummy variable identifying occupations specified in Kilbourne et al. (1994:716).
Authority	1990 PUMS; Kilbourne et al. (1994)	Dummy variable identifying occupations specified by Kilbourne et al. (1994:700).

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