Work and Occupations

http://wox.sagepub.com

Gender Inequality Across Local Wage Hierarchies

Matt L. Huffman

Work and Occupations 2004; 31; 323
DOI: 10.1177/0730888404266384

Gender Inequality Across Local Wage Hierarchies

MATT L. HUFFMAN
University of California, Irvine

Is gender inequality more severe in higher paying jobs, where there is more at stake? Using a unique definition of jobs—local occupation-industry cells—and multilevel models, I offer the first investigation of how gender wage inequality varies as a function of a job's ranking in its specific local labor-market context. The results suggest that net of various individual- and job-level controls, (a) female-dominated jobs pay less than comparable male-dominated jobs, (b) the penalty associated with female-dominated jobs is steeper for women, and (c) wage inequality increases as one ascends the wage hierarchy of local labor markets. However, there is no evidence that the tendency for female-dominated jobs to pay less than comparable male-dominated jobs is stronger in high-ranking jobs. Taken together, the results are consistent with the exclusion of women from high-ranking jobs as well as gender segregation within local occupation-industry cells.

Keywords: *gender inequality; local labor markets*

Numerous approaches have been used to study gender wage inequality. Some researchers rely on individual-level data to document the gender wage gap net of human capital and other productivity-related factors, attributing the residual difference to discrimination (for a review, see Darity & Mason, 1998). Others focus on the demographic composition of contextual units, such as jobs and occupations, linking average pay rates to the percentage of women in the unit (Baron & Newman, 1989; Huffman & Velasco, 1997; Tomaskovic-Devey, 1993). These studies are motivated by the observation that the determination of what a job is "worth" is made in concrete organizational settings and is influenced by the gender of who performs the

Author's Note: *I thank Philip N. Cohen and two anonymous* Work and Occupations *reviewers for helpful comments and suggestions on an earlier version of this article. I am responsible for any errors or omissions.*

WORK AND OCCUPATIONS, Vol. 31 No. 3, August 2004 323-344
DOI: 10.1177/0730888404266384

work (Baron, 1991). A significant association between gender composition and reward levels, net of controls, has been cited as evidence of bias against jobs performed by women (England, 1992; England, Herbert, Kilbourne, Reid, & Megdal, 1994).

These studies highlight one possible source of inequality—inequality between jobs or occupations, as they address the association between gender composition and average wage levels. Explanations for between-job gender inequality that stress gender discrimination include a cultural "devaluation" of work done by women (England, 1992; Tam, 1997), and hiring discrimination that restricts women's access to some jobs, resulting in occupational "crowding" that drives down pay in female-dominated jobs (Bergmann, 1974). Whatever its cause, the finding that female-dominated jobs and occupations pay less than those that are similar but filled by men has fueled important labor market interventions such as comparable worth (see England, 1992; Nelson & Bridges, 1999).

Another line of work is concerned with processes that lead to unequal employment outcomes within jobs or occupations. For example, although there may be a general wage penalty associated with female representation—such that the average wage is less in female-dominated settings—that penalty may not affect women and men equally (Budig, 2002; Williams, 1992). In fact, several studies document the unique benefits that men enjoy when employed in female-dominated occupations (for a review, see Yoder, 1991). These studies typically rely on case studies of particular occupations or work settings, raising questions about inferences to other employment contexts (e.g., Floge & Merrill, 1986; Heikes, 1991; Williams, 1992). Thus, although between- and within-job inequality contribute to the overall gender wage gap, empirical research often focuses on one source at the expense of the other (e.g., Budig, 2002; Huffman & Velasco, 1997).[1]

In the current study, I used a new and unusually detailed definition of jobs—local occupation–industry cells—and a series of multilevel models to explore gender wage inequality within and between jobs. This construction of jobs allows me to offer the first analysis that examines these components of the gender wage gap as a function of jobs' relative position in the wage hierarchy of local labor markets. Thus, my models improve on those that rely on highly aggregated categories such as national occupations (England, Hermsen, & Cotter, 2000; Tam, 1997), or national occupation–industry cells (Budig, 2002), by measuring gender composition across categories that better approximate local jobs, thereby accounting for local variation in gender composition. This is important given that mechanisms producing and maintaining inequality are often local; for example, wage setting and other work rewards are largely determined at the job or workplace level, resulting from processes that play out in local labor market contexts (Jacobs & Blair-Loy, 1996; Nelson & Bridges, 1999; Tomaskovic-Devey & Skaggs, 2002). By analyzing a multilevel data set that constitutes a very large number of jobs, and information about the wages offered in those jobs rank in their local labor market context, I am able to get unusually reliable estimates of not only the wage gap within jobs but also how this gap varies up and down local wage hierarchies. Thus, I offer the first large-scale investigation of whether processes that lead to men's wage advantage are especially pronounced in jobs that pay better, overall.

IS WAGE INEQUALITY MORE SEVERE IN HIGH-PAYING JOBS?

Many studies document men's advantages in high-status jobs and occupations, including physicians, attorneys, and professional workers in high-technology fields (e.g., Floge & Merrill, 1986; Hull & Nelson, 2000; Kay & Hagan, 1995; Ranson & Reeves, 1996; Wood, Corcoran, & Courant, 1993). These studies, however, do not reveal whether women's disadvantages in high-paying occupations are larger than they are in other settings, or whether they simply reflect widespread patterns of gender discrimination endemic to all women.

Why might we suspect that gender inequality is more severe among high-paying jobs? Tilly (1998) argued that one important mechanism sustaining workplace inequality is the ability of powerful groups (such as men) to monopolize the most desirable positions in organizations; that is, those jobs with the highest skill requirements, opportunities for advancement, and/or chances to exercise authority. Conceptually, this is analogous to a social closure process—gender inequality is created and sustained through the allocation of women and men into positions that differ along key pay-related dimensions, rather than through a devaluation of female-dominated positions per se (Reskin, 1988; Tomaskovic-Devey, 1993). More important, because they function to maintain dominant group's interests by sustaining existing inequalities in workplace power and rewards, social closure processes in work settings may be especially strong in better jobs, where there is more at stake. Pfeffer (1989) argued that power differences among various groups affect the allocation of wages (as well as other resources); those differences may be especially pronounced among high-ranking jobs, which are more likely to be male dominated than other jobs.

Status closure processes in work organizations could contribute to inequality in several ways. Increased inequality in jobs that pay better, overall, is consistent with a "glass ceiling" effect, which blocks women's upward mobility into the upper levels in organizational hierarchies. Such an effect is documented by Cotter, Hermsen, Ovadia, and Vanneman (2001). They argued that one characteristic of a glass ceiling effect is increasing gender inequality at higher levels of an outcome, such as earnings or authority. Although my analysis does not provide a strict test of a glass ceiling effect, a finding of more gender inequality in better-paying jobs would nevertheless fit a glass ceiling explanation.[2]

Differential returns to work-related social networks may also produce larger wage gaps at the upper end of wage hierarchies. Research has shown that women are disadvantaged by their social networks with respect to garnering employment in male-dominated jobs (Drentea, 1998; Hanson & Pratt, 1991). Moreover, work-related contacts—including coworkers (Bartlett & Miller, 1985; Brass, 1985; Ibarra, 1993; McGuire, 2000) and differences in the clientele served in various work contexts (Hagan, 1990)—may limit women's upward mobility even after they enter high-paying positions, widening the gender gap. Thus, although work-related contacts may disadvantage women's attainment across the board, their effect on the wage gap is likely to be strongest in high-paying jobs.

Grodsky and Pager (2001) invoked variation in the importance of client-based networks across occupational contexts to explain their finding that within-job racial wage gaps increase with occupational status. High-status occupations (e.g., lawyers and physicians) are more likely to be client based and rely directly on workers' social networks for success. For lower status workers, such as hotel clerks and bus drivers, wage rates are more closely linked to production rather than providing a service to a specific clientele; as a result, racial wage gaps are relatively small (Grodsky & Pager, 2001).

This finding of more wage inequality in high-status occupations may reflect a more general process of intraoccupational segregation by job and/or establishment, through which subordinate groups are channeled into lower paying positions, even in integrated occupations. It is well known that intraoccupational segregation by gender is severe (Bielby & Baron, 1984, 1986), and segregation across broad occupational categories has been shown to influence wages less than segregation across specific job titles (Huffman, Velasco, & Bielby, 1996; Tomaskovic-Devey, 1995). My construction of local jobs (described in detail below) more accurately measures inequality within detailed jobs.

RESEARCH AGENDA AND EXPECTATIONS

My analysis examined wage inequality within and between jobs and targets the relationship between each type of inequality and a job's wage rank relative to other jobs in the local wage hierarchy. Consistent with a social closure perspective (Tilly, 1998; Tomaskovic-Devey, 1993), which highlights men's ability to monopolize highly desirable jobs, I expected to find increasing within-job inequality as one moves up the occupational hierarchy. Here, I extended Grodsky and Pager's (2001) work on racial wage gaps to gender inequality—my research design, however, relied on a ranking of jobs that is labor market specific, rather than relying on highly aggregated, national estimates that are insensitive to labor market variation; that is, my local ranking allows for variation in the "best" jobs across labor markets; in contrast national measures such as occupational prestige do not vary across labor markets (Grodsky & Pager, 2001). This analysis is also important because it provides a context for interpreting increases in the proportion of women in management and other professional, high-paying positions (see Jacobs, 1992). For example, if there is gender discrimination in higher paid occupations we have less reason to be confident about the positive effects of decreasing gender segregation on inequality in wages and other work rewards.

In contrast, the inequality-rank relationship is more opaque with respect to between-job inequality. Numerous empirical studies document low pay in female-dominated jobs (England, 1992; Huffman & Velasco, 1997; Tomaskovic-Devey, 1993), with some attention paid to how this penalty varies across diverse establishment and job-level characteristics, (Baron & Newman, 1989; Huffman & Velasco, 1997), as well as broader local labor-market attributes (Cohen & Huffman, 2003b). The question of whether the gender composition penalty is stiffer among higher paying jobs has not been directly addressed in empirical research. However, the relative scarcity of female-dominated jobs at, or even near, the top of local wage hierarchies make it difficult to argue that high-ranking female-dominated jobs would suffer a stiffer gender composition penalty than other female-dominated jobs. Thus, although I expect that a job's gender composition will have a significant net effect on wages, I do not expect that this penalty will vary systematically with the rank of a job in its local wage hierarchy. In other words, to the extent that social closure processes restrict women's access to upper-rank jobs, there may be no effect of the gender composition of jobs on wages within ranks. In contrast, I expect within-job inequality to be positively related to a job's rank in its local wage hierarchy.

DATA, MEASURES, AND STATISTICAL MODELS

DATA

The main data source is the 1990 Census (5% Public Use Microdata sample [PUMS]). At the individual level, I used all workers in the PUMS who (in 1989) were (a) not self-employed, (b) between the ages of 25 and 59 years, and (c) earned between U.S.$1 and $250 per hour. This selection yields the individuals at the first level of the analysis.

My second level of the analysis was the job. My definition of jobs follows that recently developed by Cohen and Huffman (2003a). Specifically, to construct jobs, each respondent was mapped into an occupation-industry-metropolitan area cell, using the three-digit occupation and industry codes, and matching them to codes for 261 U.S. metropolitan areas. Although less desirable than a true job-level measure derived from individual work establishments (e.g., Tomaskovic-Devey, 1993), the job measure used here approximates such a measure more closely than do those derived from national classifications such as national occupations or occupation-industry cells. Grodsky and Pager (2001) use national measures of occupational characteristics but note that these aggregated measures do not adequately capture variation across local labor markets. Similarly, Haberfeld, Semyonov, and Addi (1998) examined wage inequality across national (Israeli) occupation categories, thereby treating each occupation as if it were a separate labor market. In addition, Budig (2002) and England, Reid, and Kilbourne (1996) used detailed occupation-industry cells as "jobs"; however, their job measures lack a geographic dimension. Finally, Hirsch and Schumacher (1992) construct cells from the less detailed, two-digit occupation and industry categories in conjunction with the four major Census regions, which they considered a proxy for labor markets. Although it includes a rough geographic component, that approach offers less occupation-industry detail. My measure more closely approximated local jobs, by including the detailed occupation and industry categories as well as a more detailed local labor market dimension.

Within highly aggregated national categories such as occupation-industry cells, there is substantial local variation in important variables such as gender composition. For example, nationally, 79% of social workers employed in hospitals are women. Locally, however, these workers can be found in local occupation-industry cells that are 50% women (in the Harrisburg-Lebanon-Carlisle, Pennsylvania, metropolitan area) and 100% women (in the Orlando, Florida, metropolitan area). Similarly, workers in real estate sales in the real estate industry are 57% women; however, across local labor markets, the gender composition of this occupation-industry combination ranges from 30% to 86% women.[3] Thus, is there considerable job-level segregation not only within broad occupational categories (Bielby & Baron, 1986) but also within cells defined by national occupation-industry combinations as well.

The job-level data set was created by using the worker-level data before imposing the age restriction, thereby allowing workers outside the age range to contribute to the aggregate characteristics of jobs, such as gender composition. To increase the reliability of the estimated within-job wage gap, I included only those jobs with at least 20 incumbents. The final data set included 1,572,779 individuals employed in 28,866 jobs. The mean job size is approximately 72 workers, with a standard deviation of 71.

MEASURES

Individual-level variables. The individual-level variables constitute those used in standard wage models. The dependent variable was the respondents' hourly wage (logged to account for skewness), constructed by dividing annual earnings by the product of weeks worked and hours usually worked per week (thereby including part-time and part-year as well as full-time and full-year workers). Sex is a dummy variable coded 1 for women and 0 for men. Racial differences are controlled with dummy variables identifying White (the reference group), Black, Latino, Asian, and other race respondents (White, Black, Asian, and other race are non-Latino). Other control variables included dummy variables for marital status, foreign-born workers, and disabled workers. A set of continuous control variables comprises potential labor market experience (age – education – 6) and its square (to capture potential nonlinearity), hours usually worked per week (logged), the number of householder's own children present, and years of education.

Job-level variables. At the job level, the key independent variables are the percentage female in the job and job rank. The job rank measure, unique to the current study, was based on a ranking of each job's position in the local hierarchy of jobs, based on its average (mean) wage. Specifically, I computed the percentile rank for each job relative to all other jobs in the local labor market, defined as the metropolitan area.[4] For example, in Houston, the highest paying job is physicians working in physician's offices, whereas in Detroit it is attorneys employed in the motor vehicle and motor vehicle and repair industry.[5] Because the ranking was based on a percentile score, these jobs have the highest possible value on the job rank variable. Although some have used occupational status to vertically rank three-digit occupational categories in studies of earnings inequality across occupations (e.g., Grodsky &

Pager, 2001), using national rankings for local jobs is ill-advised because those measures neglect within-occupation heterogeneity. In my data set, there is a strong negative zero-order correlation between job rank and percentage female ($r = -.39$, $p < .001$), and a small yet significant positive correlation between job size and percent female ($r = .03$, $p < .001$), and between job size and rank ($r = .02$, $p = .005$). The zero-order correlation between job size and average wages is somewhat larger ($r = .06$, $p < .001$).

I also included three variables from the *Dictionary of Occupational Titles* data sets as controls for skill/educational requirements, following prior research on wage inequality by gender and race (e.g., England, 1992; Huffman & Cohen, 2004; Huffman & Velasco, 1997; Reid, 1998; Tam, 1997). These variables are standard vocational preparation (SVP), general educational development (GED), and a scale of physical demands.

SVP measures the typical amount of training type needed to learn the necessary information and techniques for average job performance. It includes training received in employment, school, institutional, vocational, or military settings. It excludes schooling that does not have specific vocational content (England & Kilbourne, 1988). SVP can be thought of as a measure of occupation-specific human capital, as it taps workers' investments in skills of value to particular employers, rather than more portable skills that transfer easily across various work settings (Becker, 1975; Tam, 1997; Tomaskovic-Devey & Skaggs, 2002). SVP is measured on a 9-point scale, corresponding to the length of training time (1 = *short demonstration only* and 9 = *over 10 years*).

In contrast, GED measures general human capital by tapping an occupation's educational requirements that are not vocationally specific (England et al., 2000). GED measures workers' productive capacities that would be of value to numerous employers, such as general educational skills and work habits (Tomaskovic-Devey & Skaggs, 2002). GED includes formal and informal education that augment workers' reasoning, language, and mathematical skills (England & Kilbourne, 1988). It is measured on a 6-point scale, with 6 indicating the highest level of educational development. Last, the value of the Physical Demands Scale is an average computed across five physical demand factors: climbing, reaching, stooping, talking, and seeing. High values of this variable represent a greater demand for physical work.[6]

Other aspects of jobs' demographic composition are controlled with variables measuring jobs' percentage Black, percentage Latino, percentage Asian, and percentage other race. I also controlled for percentage foreign born *each job*.[7] Finally, systematic pay differences across industries are controlled with dummy variables to represent 13 broad industrial categories (England et al., 1996). Descriptive statistics appear in Table 1.

TABLE 1: Descriptive Statistics for Variables in the Analysis

	M	SD	*Minimum*	*Maximum*
Individuals (*N* = 1,572,779)				
Wage (logged)	2.450	.65	.0004	5.52
Own children	.920	1.14	0	18
Female	.500	.5	0	1
Foreign	.140	.35	0	1
Disabled	.030	.17	0	1
Latino	.090	.29	0	1
Asian	.040	.2	0	1
White	.760	.43	0	1
Black	.100	.3	0	1
Other	.000	.07	0	1
Education	13.830	2.97	0	20
Potential experience	19.200	9.82	–1	53
Potential experience squared	466.520	431.27	0	2,809
Married	.670	.47	0	1
Weekly hours (logged)	3.650	.43	0	4.6
Jobs (*N* = 28,866)				
Job rank (percentile score)	50.750	28.79	.09	100
Proportion female	.480	.33	0	1
Percentage Black	.100	.12	0	1
Percentage Latino	.080	.15	0	1
Percentage Asian	.030	.07	0	0.95
Percentage Other	.010	.01	0	0.49
Percentage foreign	.110	.15	0	1
DOT: GED	3.790	.83	1.56	6
DOT: Hazards	13.680	24.86	0	97.81
DOT: Physical demands	1.650	.84	.01	3.93
DOT: SVP	5.360	1.51	1.71	8.51
Agriculture	.010	.12	0	1
Mining	.000	.06	0	1
Construction	.070	.25	0	1
Manufacturing	.160	.36	0	1
Transportation	.070	.26	0	1
Wholesale trade	.040	.19	0	1
Retail trade	.170	.38	0	1
Finance, insurance, and real estate	.080	.28	0	1
Business services	.040	.2	0	1
Personal services	.030	.18	0	1
Entertainment	.010	.12	0	1
Professional services	.240	.42	0	1
Public services	.050	.23	0	1

NOTE: DOT = Dictionary of Occupational Titles; GED = general educational development; SVP = standard vocational preparation.

STATISTICAL MODELS

Because of the bilevel structure of the data—individuals nested within jobs—the analysis was based on a set of hierarchical linear models (Bryk & Raudenbush, 1992; Snijders & Bosker, 1999).[8] Multilevel models allow simultaneous estimation of a microlevel model (in my case, an individual-level wage model) and a set of macrolevel (in my case, job-level) equations. The regression coefficients expressing the association between individual-level characteristics and wages become the dependent variables in the job-level model; implicitly, the microlevel model is estimated separately for each job. Thus, multilevel models are ideally suited for testing cross-level interaction effects, such as whether the individual-level effect of gender (measuring the within-job gender difference) covaries with job-level attributes, such as gender composition or a job's rank in the local wage structure.

In addition, hierarchical models circumvent problems arising from correlated error terms resulting from nested data. For example, individuals in the same job share values on all job-level measures. This clustering may produce biased significance tests because standard errors will be understated; hierarchical models avoid this problem by providing corrected standard errors (Bryk & Raudenbush, 1992; Guo & Zhao, 2000; Haberfeld et al., 1998). These properties have contributed to the increased popularity of multilevel models in studies of earnings inequality by gender and race (Cohen, 1998; Cohen & Huffman, 2003b; Cotter, Hermsen, & Vanneman, 1999; Grodsky & Pager, 2001; Kreft & De Leeuw, 1994; McCall, 2001).

Specifically, the individual-level model can be expressed as

$$Y_{ij} = \beta_{0j} + \beta_{1j}\,(\text{gender}_{ij}) + \beta_{2j}(X_{2ij} - \overline{X}..) + \ldots + \beta_{kj}\,(X_{kij} - \overline{X}\,..) + r_{ij}$$

where Y_{ij} equals the logged wages of person i in job j, and β_{0j} is the Level-1 intercept. β_{1j} is the regression coefficient associated with gender, which represents the average wage difference between men and women in job j. X_{2ij} through X_{kij} is a set of $K - 1$ worker-level control variables, each centered around its grand mean ($\overline{X}..$), and β_{2j} through β_{kj} are the associated regression coefficients (see Bryk & Raudenbush, 1992, for a discussion of variable centering). Because all the individual-level independent variables except gender are grand-mean centered, the intercept equals the predicted logged wage of a man with mean values on all the control variables. Finally, r_{ij} is an error term, assumed to be normally distributed with mean zero and variance σ^2.

To gauge the within-job gender wage gap, the individual-level gender effect (β_{1j}) is modeled as random, allowed to vary across jobs. The intercept term (β_{0j}) is also permitted to vary across jobs. These effects are modeled as random because they are the outcomes in the job-level equations below. The other Level-1 independent variables are fixed across jobs.

The complete job-level equation takes the form:

$$\beta_{0j} = \gamma_{00} + \gamma_{01}(\text{gender composition}_j) + \gamma_{02}(\text{job rank}_j) + \gamma_{03j}(W_{3j} - \overline{W}..) + \ldots + \gamma_{0sj}(W_{sj} - \overline{W}..) + u_{ij}$$

$$\beta_{1j} = \gamma_{10} + \gamma_{11}(\text{gender composition}_j) + \gamma_{12}(\text{job rank}_j) + \gamma_{13j}(W_{3j} - \overline{W}..) + \ldots + \gamma_{1sj}(W_{sj} - \overline{W}..) + u_{ij}$$

$$\beta_{kj} = \gamma_k$$

where γ_{00} is the intercept for the job-level wage model, and γ_{01} and γ_{02} are the effects of gender composition and job rank, respectively, on β_{0j}. The job-level intercept for the effect of gender on wages is denoted by γ_{10}, and γ_{11} and γ_{12} are the effect of gender composition and job rank on β_{1j}, the within-job wage gap. In equations predicting β_{0j} and β_{1j}, W_{3j} through W_{sj} are a set of S-2 job-level control variables (each centered at its grand mean, $\overline{W}..$), whereas γ_{03j} through γ_{1sj} are the Level-2 coefficients associated with those control variables. The effects of the Level-1 control variables do not vary across jobs; therefore, γ_k represents the fixed effects β_k across all jobs. Finally, u_{0j} and u_{1j} are Level-2 random effects, assumed to be uncorrelated and with means of zero. It is common to denote the variance of these Level-2 error terms as τ_{00} and τ_{11}, respectively (see Bryk & Raudenbush, 1992). Among the Level-2 predictors, only gender composition and job rank are uncentered.

In the last model presented, I altered the Level-2 specification predicting the intercept and the gender coefficient to include a Job Rank × Gender Composition interaction term. This reveals how the gender composition effect varies across jobs of different rank and how the within-job gender gaps depend on job rank and job percentage female. As my final step, I supplemented the two-level analysis by re-estimating a subset of my three-level models, with the metropolitan area as the third level. This is done to adjust for variability across metropolitan areas in gender wage inequality. The results of this model are discussed below but are not reported in the tables.

RESULTS

GENDER, JOBS, AND WAGES

The results of the multilevel analysis appear in Table 2. Because they are the only individual-level effects permitted to vary across jobs, I reported

TABLE 2: Hierarchical Linear Regression Results for Logged Earnings on Individual and Job-Level Characteristics

Variable	*Model 1* *Coeff.*	*Model 2* *Coeff.*	*Model 3* *Coeff.*	*Model 4* *Coeff.*	*Model 5* *Coeff.*	*Model 6* *Coeff.*
Intercept (β_0)						
Intercept (γ_{00})	2.353***	2.502***	2.582***	1.982***	1.921***	1.907***
Job percentage female (γ_{01})	—	—	–.194***	—	.105***	.153***
Job rank, local hierarchy (γ_{02})	—	—	—	.010***	.010***	.010***
Job Percentage Female × Job Rank	—	—	—	—	—	–.001***
Female (β_1)						
Intercept (γ_{10})	—	–.266***	–.233***	–.139***	–.141***	–.081***
Job percentage female (γ_{11})	—	—	–.027***	—	–.027***	–.135***
Job rank, local hierarchy (γ_{12})	—	—	—	–.002***	–.002***	–.003***
Job Percentage Female × Job Rank	—	—	—	—	—	.002***
Controls included	None	Level 1	All	All	All	All
Level-1 R^2	—	.208	.336	.409	.409	.409
Variance components						
Level-1 variance (σ^2)	.269	.236	.236	.236	.236	.236
Intercept (τ_{00})	.154	.099	.045	.014	.014	.014
Intraclass correlation coefficient (ρ)	.364	.296	.160	.056	.056	.056

***p < .001 (two-tailed).

coefficients only for the intercept and gender. Similarly, at the job-level (Level 2), the coefficients are reported for the intercept, job percentage female, and job rank, for their effects on the intercept and on the individual-level gender coefficient.[9]

I began with a model that includes no predictors at either the individual or job level. This model is equivalent to a one-way ANOVA, which expresses variation in the outcome variable as the sum of the estimated grand mean outcome in the population (γ_{00}), a Level-1 random effect (r_{ij}) and a Level-2 random effect (u_{0j}). This model allows the variability in the outcome variable to be decomposed into within- and between-group components and is a useful starting point for a multilevel analysis (Bryk & Raudenbush, 1992; Snijders & Bosker, 1999). Specifically, the variance of Y_{ij} is equal to $\tau_{00} + \sigma^2$, where $\tau_{00} = \text{var}(u_{0j})$, which yields the between-group variability, and $\sigma^2 = \text{var}(r_{ij})$, the within-group variability. The variance components τ_{00} and σ^2 can be used to form the intraclass correlation coefficient (ρ), which yields the proportion of the variance in the outcome variable that exists between the Level-2 units. It is computed as $\rho = \tau_{00} \div (\tau_{00} + \sigma^2)$. From Model 1, ρ suggests that approximately 36% of the total variability in wages is due to differences across jobs, while 64% is attributable to wage differences across individuals.

Model 2 includes only the individual-level controls.[10] Because all the individual-level variables except gender are grand-mean centered, the intercept in this model (2.502, or \$12.21) represents the predicted wage for a man with average values on the control variables. Net of the individual-level controls, women's wages are predicted to be significantly less (2.502 – 0.266 = 2.236, or \$9.36). Thus, adjusting for gender differences in the individual-level controls, women's wages are approximately 77% as large as men's.

Model 3 includes controls at Level 1 and Level 2. It also includes the effect of job gender composition on the model intercept and the individual-level gender coefficient. This model suggests that the effect of job percentage female is significant and negative for all workers; however, this effect is less pronounced among men (among men, the effect of job percentage female is –.194; among women, the effect is –.194 + –.027 = –.221). For a man with average values of the control variables, switching from an all-male to an all-female job reduces their wages by 17.5%; the analogous decrease for women is 21%. Although wages decline as female representation in a job increases, women suffer a more severe penalty than do men, which indicates that the largest gender wage gap is found in female-dominated jobs.[11] This finding is at odds with those reported by Budig (2002), who reported a constant male advantage across jobs with diverse gender mixes.[12]

Model 4 includes the main effect of job rank, but not the gender composition variable. Not surprising, the effect of job rank is positive and significant

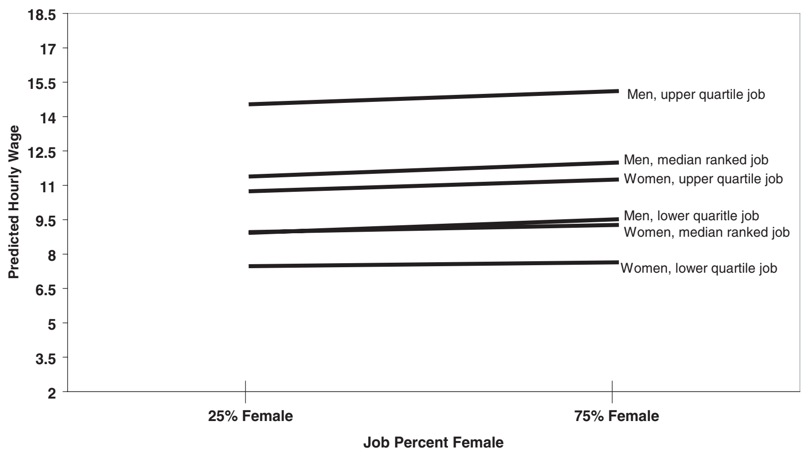

Figure 1: Effect of Job Gender Composition and Job Rank on Wages, by Gender
NOTE: Predictions are based on Model 5 of Table 2.

for all workers; however, of most interest is the effect of job rank on the within-job gender gap (the Level-1 effect of gender). The negative and significant effect of job rank on this coefficient indicates that women reap significantly smaller wage benefits from working in a high-rank job than do men. More important, this means that the within-job gender gap increases with a job's rank in the local hierarchy of jobs. This finding complements Grodsky and Pager's (2001) recent findings documenting increasing racial disadvantage as one ascends the occupational hierarchy.

The final model in Table 2 includes the Gender Composition × Job Rank interaction term to capture variation in the effect of gender composition across levels of job rank, and vice versa. In other words, this model tests whether the gender composition effect is stronger or weaker among highly ranked jobs, and similarly, whether the wage benefit of employment in a high-rank job is conditional on the gender composition of the job. Because these interaction effects in Model 5 are complex, they are plotted in Figure 1. The figure is based on predictions for individuals with average values on the control variables, in male-dominated (25% female) or female-dominated (75% women) jobs, in jobs that rank at the upper quartile, lower quartile, or median.

One prominent feature of the plot is that among jobs with average wages that rank them near the top the wage hierarchy, the within-job gender gap is substantially larger than that found in jobs ranking at the median or below. Thus, within-job wage inequality increases with job rank. Also striking is the fact that net of individual- and job-level controls, men in median-ranked jobs earn slightly more than women who are in jobs that rank at the 75th percentile of the local wage hierarchy. In addition, job gender composition has little effect on the within-job gender gap, regardless of the job rank. Within levels of job rank, the gender composition of jobs has virtually no effect on wages—a finding more consistent with the exclusion of women from high-ranking jobs than with a gender-based devaluation of women's work.

DISCUSSION

This study extends prior work on the gender wage gap by using an improved, local definition of jobs (local occupation-industry cells) and the ranking of those jobs in the local wage hierarchy of labor markets. This allowed me to engage previously unanswered questions about wage inequality in the United States, such as whether the wage gap varies as a function of where a job ranks in the local wage structure. My analysis differs from most prior research, which relied on highly aggregated measures such as the gender makeup of national occupation-industry cells or occupational prestige scores computed for broad national occupations. In this sense, my models are an improvement over those used in other studies of gender composition effects on wages (e.g., England et al., 2000; Tam, 1997), in that they are sensitive to local variation in inequality processes, therefore acknowledging that competition over jobs and wages occur in local labor-market contexts (Nelson & Bridges, 1999; Tomaskovic-Devey & Skaggs, 2002).

The multilevel analysis yielded several important empirical results. First, the results provide additional evidence that the gender composition of jobs is associated with wage levels, such that female-dominated jobs are penalized (Baron & Newman, 1989; Tomaskovic-Devey, 1993). Moreover, one strength of the present analysis is that the compositional effects documented here is estimated net of the overall low pay of women. What is attributed to a gender composition effect in studies that examine the association between average wages and percentage females in a job (e.g., Huffman & Velasco, 1997) may instead partially reflect constant levels of discrimination against individual women. The multilevel design used here circumvents this problem by distinguishing wage inequality between and within jobs. Furthermore, the research design allowed a direct test of whether the wage effect of gender composition is uniform for male and female workers—the results provide strong evidence that men's wage advantage increases as female representation in a job grows, resulting in the largest net pay gaps in female-dominated jobs.

Second, the analysis provides the first test of how the magnitude of within-job gender inequality varies as a function of how well a job pays its incumbents, relative to other jobs in the local labor market. Mirroring two studies on racial wage gaps, gender inequality within jobs is magnified as one moves up the job hierarchy in a local labor market (Grodsky & Pager, 2001; Huffman, in press). This pattern could arise from gender segregation across establishments or jobs, even within my detailed local job cells. For example, if female physicians are channeled into relatively low-paying practices or medical specialties this could help explain men's wage advantage among physicians (Hinze, 2000). Relatedly, Roach (1990) documented such interfirm segregation, and its consequences for gender inequality, among lawyers (see also Hagan, 1990). If these patterns of segregation—which could result from employers practicing statistical discrimination (see Bielby & Baron, 1986; Tomaskovic-Devey & Skaggs, 1999)—are related to the overall pay of the job, this would help produce the positive gender gap–job rank relationship. Such patterns of segregation could also result from social closure processes through which dominant groups' interests are served. A better test of this would require more detailed data describing specific job titles in work establishments.[13]

To summarize, my results indicate a large and significant effect of the gender composition of jobs (local occupation-industry cells) on wage inequality, as well as substantial inequality within jobs, which increases with job rank. However, my two-level model specification does not account for regional variation in processes that sustain gender inequality. As a result, my job-level effects may reflect, at least in part, variation in gender inequality across labor markets, which has been documented by a number of empirical studies (Cohen, 1998; Cotter et al., 1997; McCall, 2001). In fact, gender inequality has been shown to vary more across U.S. metropolitan areas than it does over time, nationally (Lorence, 1992).

To address this potentially important source of variation, I supplemented the analysis by re-estimating Models 3 through 5 as three-level models, with the metropolitan area as the third level. In these models, which included no metropolitan area–level variables, the intercept and the effect of job gender composition were allowed to vary across metropolitan areas. This specification accounts for variation across metropolitan areas in gender wage inequality and highlights whether the effects I report reflect that variation. More interesting, the original estimates from the two-level models reported in Table 2 are virtually unchanged by this modification (results available from the author upon request). Thus, the effects I report in Table 2 are robust with respect to the substantial differences that exist in across metropolitan areas in average wages by gender.

CONCLUSION

In conclusion, it is worth noting that the underlying mechanism for the positive relationship between intrajob wage inequality and job rank is not directly accounted for in this analysis. Although a likely mechanism for this is the association between job rank and gender segregation—segregation either by specific job title within local occupation-industry cells or across establishments—my data preclude a direct test of this possibility. Thus, although my construction of jobs is unusually detailed, there is still room for social closure processes to operate, creating substantial segregation within them by allocating workers by sex to different establishments and/or specific job titles within local occupation-industry cells (Petersen & Morgan, 1995).

The association between the gender composition of jobs and within-job inequality also deserves more attention, given the mixed results in previous studies. For example, although Budig (2002) reported no net association between that within-job inequality the gender composition of occupation-industry cells, Tomaskovic-Devey, Kalleberg, and Marsden (1996) and De Ruijter and Huffman (2003) found the most inequality in gender-mixed jobs. In the current study, gender composition was also related to within-job inequality, with the largest inequalities in female-dominated jobs.

Both relationships—between inequality and (a) job rank and (b) job gender composition—are fertile ground for future research and data collection, as the data required to test the probable mechanisms for these patterns extend beyond what is currently available. In one sense, this takes us full circle. Although qualitative case studies of particular jobs or occupations do not tell us about general patterns of wage inequality across diverse organizational or labor market contexts, it is precisely those kinds of studies that might tell us most about the underlying processes at work. This is especially important given that the definition of jobs used is not based on workplace-level data. This points to the promise of a multimethod approach to uncovering the processes that create and maintain gender inequality in the labor market.

NOTES

1. A third component of the wage gap is the interaction of the between- and within-job sources. If levels of wage inequality within jobs is associated with variation in average wage rates across jobs, then the interaction contributes to the wage gap (Grodsky & Pager, 2001; Nelson & Bridges, 1999).

2. A more direct test would require longitudinal data on promotions as well as wages, to document whether disadvantages become worse later in a person's career (see Cotter, Hermsen, Ovadia, Vanneman, 2001).

3. Additional evidence of this variability comes from a supplementary analysis (not presented here) of data from the National Organizations Study (NOS), which includes a true job-level gender composition measure for each of the 688 work organizations in the NOS sample (further details about the NOS can be found in Spaeth & O'Rourke, 1996). I examined the correlation between the gender composition of establishment-specific jobs and the gender composition of the occupation-industry cell in which the jobs are embedded. Only one half of the variation in the NOS job-level gender composition measure was explained by the national measure, suggesting considerable variation in job-level gender segregation occurring within detailed occupation-industry cells. For example, nurses employed in hospitals are 94% women nationally; however, the NOS job-gender composition ranges from 59% to 100% women. Similar examples exist for other occupations, including some that are mixed nationally, but vary from 100% men to 100% women across jobs.

4. This study follows other research that uses metropolitan areas (included consolidated metropolitan areas, where appropriate) to define local labor markets (e.g., Cohen, 1998; Cotter, DeFiore, Hermsen, Kowalewski, & Vanneman, 1997).

5. Clearly, earnings is not the only dimension of a job's overall desirability, as it does not completely account for variation in important nonmonetary aspects of work. However, earnings do exhibit a strong positive correlation with the Index of Job Desirability, developed by Jencks, Perman, and Rainwater (1988).

6. The Dictionary of Occupational Titles (DOT) measures do not capture local variation in skill demands across jobs. So, gardeners have the same DOT values in my data set, whether they work in Los Angeles or Michigan. To the extent that some occupations have skill requirements differ across labor markets, there may be some measurement error introduced by using the DOT variables to measure the skill demands of local jobs.

7. Analyzing gender and racial inequality across local labor markets is beyond the scope of this article. Therefore, I present findings regarding Black-White inequality across local wage hierarchies elsewhere (Huffman, in press).

8. The statistical models were estimated using the Hierarchical Linear Model (HLM) software package (v.5.04).

9. Following Snijders and Bosker (1994), I also report a Level-1 R^2 measure, which is equal to the proportional reduction in the quantity $\tau_{00} + \sigma^2$ due to inclusion of predictors in the model. Thus, R^2 is computed by comparing the quantity $\tau_{00} + \sigma^2$ from the random intercept model (see Model 1 of Table 2) with the same quantity from a model that includes independent variables. Thus, $R^2 = 1 - [\tau_{00} + \sigma^2$ for model that includes predictors $\div\ \tau_{00} + \sigma^2$ for model with no predictors]. For example, for Model 2 of Table 2, $R^2 = 1 - [(0.099 + 0.236) \div (0.154 + 0.269)] = 0.208$.

10. With no job-level variables included, this model is analogous to an ordinary least squares (OLS) model, except that the intercept and the individual-level gender effect are free to vary across jobs.

11. Tam (1997) argued that because of correlated measurement error, models that include standard vocational preparation and general educational development will overstate the negative effect of occupation percentage female on wages. Given this possibility, I re-estimated Models 3 through 5 without GED. The results were virtually unchanged. For an argument for why both SVP and GED should be included in wage models, see England, Hermsen, & Cotter (2000).

12. The result in Model 3—that there is more inequality in female-dominated jobs—is similar to that reported by Cohen and Huffman (2003b). This model, which shows the main effect of gender composition on within-job inequality, is reported here to contextualize the final model, in which the effect of gender composition is allowed to vary across levels of the job rank variable.

13. Some might argue that my finding of increasing gender inequality as one climbs the local wage hierarchy is an artifact of high wage variability at the upper end of the wage scale, relative to

the lower end. Therefore, I calculated the bivariate correlation between the mean and standard deviation of log wage in each job. I found no evidence that wage variability is positively related to the average pay in a job. Thus, the argument that wage compression could account for my findings is untenable.

REFERENCES

Baron, J. N. (1991). Organizational evidence of ascription in labor markets. In R. Cornwall & P. Wunnava (Eds.), *New approaches to economic and social analyses of discrimination* (pp. 113-143). New York: Praeger.

Baron, J. N., & Newman, A. E. (1989). Pay the man: Effects of demographic composition on prescribed pay rates in the California civil service. In R. Michael, H. Hartmann, & B. O'Farrell (Eds.), *Pay equity: Empirical inquiries* (pp. 107-130). Washington, DC: National Academy Press.

Bartlett, R. L., & Miller, T. I. (1985). Executive compensation: Female executives and networking. *American Economic Review*, *75*, 266-270.

Becker, G. S. (1975). *Human capital: A theoretical and empirical analysis with special reference to education*. Chicago: University of Chicago Press.

Bergmann, B. (1974). Occupational segregation, wages, and profits when employers discriminate. *Eastern Economic Journal*, *1*, 103-110.

Bielby, W. T., & Baron, J. N. (1984). A woman's place is with other women: Sex segregation within organizations. In B. F. Reskin (Ed.), *Sex segregation in the workplace: Trends, explanations, remedies* (pp. 27-55). Washington, DC: National Academy Press.

Bielby, W. T., & Baron, J. N. (1986). Men and women and work: Sex segregation and statistical discrimination. *American Journal of Sociology*, *91*, 759-799.

Brass, D. J. (1985). Men's and women's networks: A study of interaction patterns and influence in an organization. *Academy of Management Journal*, *28*, 327-343.

Bryk, A. S., & Raudenbush, S. W. (1992). *Hierarchical linear models: Applications and data analysis methods*. Newbury Park, CA: Sage.

Budig, M. J. (2002). Male advantage and the gender composition of jobs: Who rides the glass escalator? *Social Problems*, *49*, 258-277.

Cohen, P. N. (1998). Black concentration effects on Black-White and gender inequality: Multilevel analysis for U.S. metropolitan areas. *Social Forces*, *77*, 207-229.

Cohen, P. N., & Huffman, M. L. (2003a). Occupational segregation and the devaluation of women's work across U.S. labor markets. *Social Forces*, *81*, 881-908.

Cohen, P. N., & Huffman, M. L. (2003b). Individuals, jobs, and labor markets: The devaluation of women's work. *American Sociological Review*, *68*, 443-463.

Cotter, D. A., DeFiore, J., Hermsen, J. M., Kowalewski, B. M., & Vanneman, R. (1997). All women benefit: The macro-level effect of occupational integration on gender earnings inequality. *American Sociological Review*, *62*, 714-734.

Cotter, D. A., Hermsen, J. M., Ovadia, S. O., & Vanneman, R. (2001). The glass ceiling effect. *Social Forces*, *80*, 655-681.

Cotter, D. A., Hermsen, J. M., & Vanneman, R. (1999). Systems of gender, race, and class inequality: Multilevel analyses. *Social Forces*, *78*, 433-460.

Darity, W. A., & Mason, P. L. (1998). Evidence on discrimination in employment: Codes of color, codes of gender. *Journal of Economic Perspectives*, *12*, 63-90.

De Ruijter, J. M. P., & Huffman, M. L. (2003). Gender composition effects in the Netherlands: A multilevel analysis of occupational wage inequality. *Social Science Research*, *32*, 312-334.

Drentea, P. (1998). Consequences of women's formal and informal job search methods for employment in female-dominated jobs. *Gender and Society*, *12*, 321-338.

England, P. (1992). *Comparable worth: Theories and evidence*. New York: Aldine de Gruyter.

England, P., Herbert, M. S., Kilbourne, B. S., Reid, L. L., & Megdal, L. M. (1994). The gendered valuation of occupations and skills: Earnings in 1980 Census occupations. *Social Forces*, *73*, 65-100.

England, P., Hermsen, J. M., & Cotter, D. A. (2000). The devaluation of women's work: A comment on Tam. *American Journal of Sociology*, *105*, 1741-1751.

England, P., & Kilbourne, B. S. (1988). *Occupational measures from the Dictionary of Occupational Titles for 1980 Census detailed occupations*. Ann Arbor, MI: Interuniversity Consortium for Political and Social Research.

England, P., Reid, L. L., & Kilbourne, B. S. (1996). The effect of the sex composition of jobs on starting wages in an organization: Findings from the NLSY. *Demography*, *33*, 511-521.

Floge, L., & Merrill, D. M. (1986). Tokenism reconsidered: Male nurses and female physicians in a hospital setting. *Social Forces*, *64*, 925-947.

Grodsky, E., & Pager, D. (2001). The structure of disadvantage: Individual and occupational determinants of the Black-White wage gap. *American Sociological Review*, *66*, 542-567.

Guo, G., & Zhao, H. (2000). Multilevel modeling for binary data. *Annual Review of Sociology*, *26*, 441-462.

Haberfeld, Y., Semyonov, M., & Addi, A. (1998). A hierarchical linear model for estimating gender-based earnings differentials. *Work and Occupations*, *25*, 97-112.

Hagan, J. (1990). The gender stratification of income inequality among lawyers. *Social Forces*, *68*, 835-855.

Hanson, S., & Pratt, G. (1991). Job search and the occupational segregation of women. *Annals of the Association of American Geographers*, *81*, 229-253.

Heikes, J. (1991). When men are the minority: The case of men in nursing. *Sociological Quarterly*, *32*, 389-401.

Hinze, S. W. (2000). Inside medical marriages: The effect of gender on income. *Work and Occupations*, *27*, 464-499.

Hirsch, B. T., & Schumacher, E. J. (1992). Labor earnings, discrimination, and the racial composition of jobs. *Journal of Human Resources*, *27*, 602-628.

Huffman, M. L. (in press). More pay, more inequality? The influence of average wage levels and the racial composition of jobs on the Black-White wage gap. *Social Science Research*.

Huffman, M. L., & Cohen, P. N. (2004). Racial wage inequality: Job segregation and devaluation across U.S. labor markets. *American Journal of Sociology*, *109*, 902-936.

Huffman, M. L., & Velasco, S. C. (1997). When more is less: Sex composition, organizations, and earnings in U.S. firms. *Work and Occupations*, *24*, 214-244.

Huffman, M. L., Velasco, S. C., & Bielby, W. T. (1996). Where sex composition matters most: Comparing the effect of job versus occupational sex composition on earnings. *Sociological Focus*, *29*, 189-207.

Hull, K. E., & Nelson, R. L. (2000). Assimilation, choice, or constraint? Testing theories of gender differences in the careers of lawyers. *Social Forces*, *79*, 229-264.

Ibarra, H. (1993). Personal networks of women and minorities in management: A conceptual framework. *Academy of Management Review*, *18*, 56-87.

Jacobs, J. A. (1992). Women's entry into management: Trends in earnings, authority and values among salaried managers. *Administrative Science Quarterly*, *37*, 282-301.

Jacobs, J. A., & Blair-Loy, M. (1996). Race, gender, local labor markets and occupational devaluation. *Sociological Focus*, *29*, 209-230.

Jencks, C., Perman, L., & Rainwater, L. (1988). What is a good job? A new measure of labor market success. *American Journal of Sociology*, *93*, 1322-1357.

Kay, F. M., & Hagan, J. (1995). The persistent glass ceiling: Gendered inequalities in the earnings of lawyers. *British Journal of Sociology*, *46*, 279-310.

Kreft, I., & De Leeuw, J. (1994). The gender gap in earnings: A two-way nested multiple regression analysis with random effects. *Sociological Methods and Research*, *22*, 319-341.

Lorence, J. (1992). Service sector growth and metropolitan occupational sex segregation. *Work and Occupations*, *19*, 128-156.

McCall, L. (2001). *Complex inequality: Gender, class and race in the new economy.* New York: Routledge.

McGuire, G. M. (2000). Gender, race, ethnicity, and networks: The factors affecting the status of employees' network members. *Work and Occupations*, *27*, 500-523.

Nelson, R. L., & Bridges, W. P. (1999). *Legalizing gender inequality: Courts, markets, and unequal pay for women in America.* New York: Cambridge University Press.

Petersen, T., & Morgan, L. A. (1995). Separate and unequal: Occupation-establishment sex segregation and the gender wage gap. *American Journal of Sociology*, *101*, 329-365.

Pfeffer, J. (1989). A political perspective on careers: Interests, networks, and environments. In M. B. Authur, D. T. Hall, & B. S. Lawrence (Eds.), *Handbook of career theory* (pp. 380-396). Cambridge, UK: Cambridge University Press.

Ranson, G., & Reeves, W. J. (1996). Gender, earnings, and proportions of women: Lessons from a high-tech occupation. *Gender and Society*, *10*, 168-184.

Reid, L. L. (1998). Devaluing women and minorities: The effects of race/ethnic and sex composition of occupations on wage levels. *Work and Occupations*, *25*, 511-536.

Reskin, B. F. (1988). Bringing the men back in: Sex differentiation and the devaluation of women's work. *Gender and Society*, *2*, 58-81.

Roach, S. L. (1990). Men and women lawyers in in-house legal departments: Recruitment and career patterns. *Gender and Society 4*, 207-219.

Snijders, T., & Bosker, R. L. (1994). Modeled variance in two-level models. *Sociological Methods and Research*, *22*, 342-363.

Snijders, T., & Bosker, R. L. (1999). *Multilevel analysis: An introduction to basic and advanced multilevel modeling*. Thousand Oaks, CA: Sage.

Spaeth, J. L., & O'Rourke, D. P. (1996). Design of the National Organizations Study. In A. L. Kalleberg, D. Knoke, P. V. Marsden, & J. L. Spaeth (Eds.), *Organizations in America: Analyzing their structures and human resource practices* (pp. 23-44). Thousand Oaks, CA: Sage.

Tam, T. (1997). Sex segregation and occupational gender inequality in the United States: Devaluation or specialized training? *American Journal of Sociology*, *102*, 1652-1692.

Tilly, C. (1998). *Durable inequality.* Berkeley: University of California Press.

Tomaskovic-Devey, D. (1993). *Gender and racial inequality at work: The sources and consequences of job segregation*. Ithaca, NY: ILR.

Tomaskovic-Devey, D. (1995). Sex composition and gendered earnings inequality: A comparison of job and occupational models. In J. A. Jacobs (Ed.), *Gender inequality at work* (pp. 23-56). Thousand Oaks, CA: Sage.

Tomaskovic-Devey, D., Kalleberg, A. L., & Marsden, P. V. (1996). Organizational patterns of gender segregation. In A. L. Kalleberg, D. Knoke, P. V. Marsden, & J. L. Spaeth (Eds.), *Organizations in America: Analyzing their structures and human resource practices* (pp. 276-301). Thousand Oaks, CA: Sage.

Tomaskovic-Devey, D., & Skaggs, S. (1999). An establishment-level test of the statistical discrimination hypothesis. *Work and Occupations*, *26*, 422-445.

Tomaskovic-Devey, D., & Skaggs, S. (2002). Sex segregation, labor process organization, and gender earnings inequality. *American Journal of Sociology*, *108*, 102-128.

Williams, C. (1992). The glass escalator: Hidden advantages for men in the "female" professions. *Social Problems*, *39*, 253-267.

Wood, R. G., Corcoran, M. E., & Courant, P. N. (1993). Pay differences among the highly paid: The male-female earnings gap in lawyers' salaries. *Journal of Labor Economics*, *11*, 417-441.

Yoder, J. D. (1991). Rethinking tokenism: Looking beyond numbers. *Gender & Society*, *5*, 178-192.

Matt L. Huffman is an assistant professor at the University of California, Irvine. His current research examines organizational patterns of gender and racial inequality and how they vary across labor market contexts. His other recent work investigates the role of job seekers' social contacts in creating and sustaining gender inequality.