Compensating Differentials for Gender-Specific Job Injury Risks

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The theory of compensating differentials holds a prominent place in the analysis of wage determination, and a large empirical literature documents substantial wage-risk trade-offs.[1] Although women comprise over 45 percent of the labor force, job risks have been viewed as primarily a male province, and studies have largely excluded female workers from the analyses. Since most of the occupational injury data are available only at the industry level, if women are in safer jobs within industries, matching industry injury rates to female workers may lead to large measurement problems and misleading estimates.

In this paper I use new national data to construct gender-specific estimates of injury and illness incidence rates by both industry and occupation. These rates are the first gender-specific injury incidence rates in the literature, as well as the first occupational incidence rates. Although women are less likely than men to be injured on their jobs, their injury experience is considerable, as one-third of all injuries and illnesses with days away from work are to women. Adjusted for gender differences in employment, women face a job risk that is 71 percent of men's. Further, the gender-specific injury rates reveal substantial and statistically significant wage-risk trade-offs for female workers. All female workers, not only those employed in blue-collar occupations, receive a significant compensating differential for job risks. Female workers at the average level of risk receive a wage premium of 2–3 percent, equal to an additional \$400–\$563 per year as compensation for nonfatal job risks.

The results using the gender-specific injury measures are in stark contrast to those obtained for women using the standard industry risk measures. Estimates based on the U.S. Department of Labor, Bureau of Labor Statistics (BLS), industry injury and illness incidence rates do not indicate a significant wage-risk trade-off. These findings suggest that assigning industry risk measures to female workers without adjusting for gender differences in injury experience may lead to biased estimates of the returns to job risk and a misleading view of who bears injury risks in the workplace.

I use these estimates of the wage-risk trade-off based on the gender-specific incidence rates to calculate the first estimates in the literature of the implicit value of an injury or illness for women workers. The values, which range from \$20,000 using the female-specific industry rate, to \$30,000 using the female-specific occupation rate, are similar to those I find for male blue-collar workers.

Similar concerns about measurement error have led to the exclusion of white-collar male workers from most studies. The industry- and occupation-specific risk measures calculated here certainly reduce this measurement error. In contrast to the findings for female workers, however, in many cases there is an inverse relation between wages and risk for white-collar males, whether the risk measure pertains to the individual's three-digit industry or three-digit occupation.

The estimating procedure used in this paper follows the standard approach in the literature of matching average risk measures to individuals by industry or occupation. Because all workers within an industry or occupation are assigned the same injury rate, the residuals in the regression for workers in a given industry or occupation group are likely to be correlated. The robust standard errors calculated in this paper are generally 2–3 times the size of those calculated without recognizing this source of correlation.

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[1] A recent survey of the literature is by W. Kip Viscusi, 1993.

I. Industry Job Risks and the Treatment of Female Workers in the Literature

Before discussing the construction of gender-specific injury incidence rates, it is useful to consider the method used by the Bureau of Labor Statistics. For each industry, the incidence rate is calculated as

$$\text{(1) BLS Industry Rate} = (N/H) \times 200{,}000,$$

where N = number of injuries and illnesses, H = total hours worked by all employees during the calendar year, and 200,000 = base for 100 full-time equivalent workers (40 hours per week, 50 weeks per year.) These values are reported annually in the *Survey of Occupational Injuries and Illnesses in the United States, 1993* (BLS, 1995a).

These incidence rates pertain to all workers within an industry, so that, for instance, secretaries and miners within the mining industry are assigned the same risk measure. Since data on occupational injuries and on the gender distribution of injury cases were not available until recently, the standard practice in the literature has been to impute these industry risk values to all individuals in the wage sample by three-digit industry code. If workers with certain characteristics are in riskier or less risky jobs within their industry, however, the estimated returns to risk may be biased.[2] In order to reduce this potential source of bias, many authors limit their sample to male blue-collar workers or to workers in manufacturing. In addition, other restrictions are typically imposed, such as restrictions to household heads, hourly workers, or to full-time employees. Even among samples which do not explicitly exclude women, such restrictions severely limit the number of women eligible for inclusion in the analyses.

Given the small samples of female workers remaining after such restrictions have been imposed, most authors either exclude women entirely from the analysis, or include them by allowing gender to affect wages only through an intercept. While these approaches are reasonable in the absence of data on gender-specific injury experience, they do not allow tests of whether women receive a compensating differential for the job risks they face. Furthermore, since women are disproportionately employed in white-collar occupations, estimates of compensating differentials for blue-collar workers would not be representative of the population of women workers overall.

II. Gender-Specific Injury and Illness Incidence Rates

In this section, I calculate gender-specific injury and illness incidence rates for both industry and occupation. Recently, the BLS began collecting more extensive information on the worker and case characteristics of injury and illness cases involving days away from work. The restriction of the survey coverage to injuries and illnesses involving at least one day away from work provides a lower bound on the severity of the incidence, and increases the homogeneity of the definition of injury and

[2] In the hedonic wage model, an individual worker i is compensated for market beliefs about the objective riskiness R_i^* of his or her job. The wage equation for the ith individual can be written as

$$\text{(i)} \qquad y_i = \beta R_i^* + \mu_i,$$

where y_i is the log of wage and μ_i is a random error term. In general, R_i^* is not observed, but is related to the observed average industry risk R_i as

$$\text{(ii)} \qquad R_i^* = R_i + \varepsilon_i,$$

where ε_i is an unobserved risk component associated with the specific type of job held by the individual within the industry. The wage equation to be estimated is

$$\text{(iii)} \qquad y_i = \beta R_i + v_i,$$

where $v_i = \beta\varepsilon_i + \mu_i$. If ε_i and μ_i are uncorrelated with R_i, then by solving for the OLS estimator of β and taking the expected value, one can show that the OLS estimator of β is unbiased. The variance of the error term in equation (iii) is larger than in equation (i), so the estimated standard errors of the coefficients in the wage regression will tend to be larger using group means. If ε_i is correlated with R_i (for instance if women tend to be in less risky jobs within industries), then using industry average risk can lead to biased and inconsistent estimates. This is a kind of omitted variable bias and can be either positive or negative.

illness.[3] These data reveal that female workers experience a surprising number of job injuries and illnesses. Of 2.25 million BLS-reported nonfatal occupational injuries and illnesses with days away from work in 1993, one-third occurred to women. It is notable that, at least in terms of duration, men and women suffer injuries of similar severity. The median days away from work for those experiencing such an injury or illness is five days for both male and female workers (BLS, 1995b). Furthermore, the same five injury types account for 68–69 percent of the injuries for both male and female workers.[4]

Although women's share of injuries of 32.7 percent is less than their employment share of 46 percent of private industry employees, the magnitude of their injury experience is quite surprising since women are largely concentrated in the safer white-collar occupations. Taking into account the different levels of employment by gender, women face a job risk that is 71 percent of men's. Only 20.8 percent of the cases with days away from work in 1993 occurred in white-collar occupations. Among private employees, 69 percent of the women, but only 43.5 percent of the men, are employed in white-collar occupations. Within white-collar occupations, the injury rate for women is 80 percent higher than for men.

To calculate gender-specific industry job risk rates, I use data from two BLS tables. These tables provide information on the number of cases with days away from work in 1993 by gender for three-digit or four-digit SIC code or three-digit occupation. The BLS does not calculate gender-specific incidence rates for either industry or occupation. Because of differences in the information available, I use different procedures, described below, to calculate these rates.

[3] Injury and illness cases not involving days away from work are far more common. There were about 67 percent more cases without days away from work in 1993 than with days away from work.

[4] These injuries are sprains, strains and tears; bruises and contusions; fractures; cuts and lacerations; and soreness, pain, hurt, except the back.

A. *Industry Incidence Rates*

In principle one could use equation (1) to calculate gender-specific incidence rates for each industry by replacing N and H with the corresponding gender-specific values. However, while the number of injuries and illnesses by gender are provided in the new BLS survey, total hours worked by industry and gender are not available. I therefore allocate the BLS average industry rate into gender-specific shares by weighing the BLS rate by the gender-specific share of cases relative to the gender-specific hours share for each industry i as follows:

$$\text{(2)} \quad \text{Gender Industry Rate} = (N_g/N)/(H_g/H) \times \text{BLS Industry Rate},$$

where N_g = total number of cases of gender g in industry i, and H_g = total hours worked by gender g in industry i. As in equation (1), N and H represent the total number of injury and illness cases and total hours worked by all employees.

To calculate gender-specific shares of total employment hours within three-digit industries, I use data from the *Census of Population and Housing, 1990* (U.S. Department of Commerce, Bureau of the Census, [1993]) 5-percent sample. Since government and self-employed workers are excluded from the BLS survey used to estimate injury incidence rates, I restrict the Census sample to paid employees in private industry who report working positive hours in the preceding week. This yields a sample of 4,149,478 observations.

Table 1 provides a comparison of the BLS industry incidence rate and the gender-specific rates for the major industry categories. For workers in private industry overall, the adjusted female incidence rate is 2.2 injury or illness cases with days away from work per 100 workers, considerably lower than the BLS average incidence rate of 2.9. Industries with larger shares of female employees, such as finance, insurance and real estate, and services, have lower than average risk. As the female/male incidence ratio in the last column indi-

TABLE 1—INJURY AND ILLNESS INCIDENCE RATES WITH DAYS AWAY FROM WORK BY MAJOR INDUSTRY, 1993[a]

Industry	Percent female in industry[b]	BLS rate[c]	Female rate[d]	Male rate[d]	Female/male ratio
Private industry	45.9	2.9	2.2	3.4	0.65
Goods-producing					
Agriculture, forestry, and fishing	22.9	4.2	3.5	4.6	0.76
Mining	13.5	3.3	0.8	4.1	0.19
Construction	10.4	4.9	1.1	5.3	0.21
Manufacturing	33.6	3.3	2.5	3.4	0.75
Service-producing					
Transportation and public utilities	30.4	4.3	2.5	4.6	0.55
Wholesale trade	31.0	2.8	1.3	3.7	0.35
Retail trade	53.1	2.7	2.3	3.1	0.74
Finance, insurance, and real estate	63.5	1.0	0.9	1.3	0.65
Services	64.7	2.3	2.4	2.4	1.00

[a] Per 100 full-time workers.
[b] Author's calculation from *Census of Population and Housing, 1990.* Sample restricted to private, paid employees employed in industries reporting injury and illness cases by gender.
[c] *Survey of Occupational Injuries and Illnesses, 1993.*
[d] Author's calculations. See text.

cates, on average women face considerably less risk than men in the high-risk industries such as mining and construction that employ relatively few women. This indicates that there is considerable occupational sorting by gender within these industries.

The correlation between the three-digit BLS industry rate and the female-specific industry rate is 0.67. The corresponding correlation between the BLS rate and the male-specific rate is 0.96. This suggests that estimates of wage-risk trade-offs for men are likely to be similar using either the BLS industry rate or the gender-specific rate, but this is less likely to be true for women.

B. *Occupational Incidence Rates*

The BLS does not provide occupational injury and illness incidence rates, so the procedure I use to estimate industry incidence rates cannot be used. A modification of the BLS equation (1) leads to estimates of occupational risk for each occupation k:

(3) Gender Occupation Rate

$$= (O_g/H_{go}) \times 200{,}000,$$

where O_g = number of cases for gender g in occupation k, and H_{go} = total hours worked by gender g in occupation k. Since the BLS does not provide occupational employment values, I again use Census data to estimate employment within each occupation.

Table 2 lists representative incidence rates for occupations with a large number of cases for female workers. For comparison, the corresponding incidence rates for men in these occupations are also included. While women generally face less risk than men within occupations, in most the gap is fairly narrow.

TABLE 2—SELECTED INJURY AND ILLNESS INCIDENCE RATES BY OCCUPATION, 1993

Occupation title	Percent female hours in occupation	Female rate	Male rate
Secretaries	98.9	0.46	1.03
Bank tellers	91.2	0.83	0.37
Cashiers	78.5	1.50	1.77
Registered nurses	94.5	2.12	3.30
Health aides, except nursing	81.2	7.80	9.04
Nursing aides, orderlies, and attendants	89.2	8.05	7.85
Miscellaneous food preparation	45.8	8.33	8.09
Truck drivers	4.3	9.63	6.62
Laborers, except construction	21.5	9.71	15.74
Public transportation attendants	80.0	11.14	7.76

Source: Author's calculations. See text.

Furthermore, within many occupations, such as truck drivers and public transportation attendants, women actually face greater risk than men.

III. Empirical Specification and Data

In order to test for the presence of compensating differentials, I estimate wage equations for both female and male workers of the following form:

$$(4)\qquad \ln(WAGE_i) = \alpha + \beta\, RISK_i + \Sigma_j \gamma_j \mathbf{X}_{ij} + \varepsilon_i,$$

where *WAGE* is the hourly wage rate; *RISK* is a measure of job risk; **X** is a vector of explanatory variables such as years of work experience, education, union status, and occupation; α, β, and γ_j are parameters to be estimated; and ε is a random error term. The prediction of hedonic wage theory is that $\beta > 0$.

Equation (4) is the standard specification used in the hedonic wage literature. Since the ε_i may have different variances in different industries or occupations, many authors correct the standard errors for group heteroskedasticity. For comparability to the literature, I present these standard errors in Table 3 in parentheses.

However, since individuals within the same industry or occupation group are assigned the same risk rate, the residuals in the regression for workers in a given industry or occupation may be correlated. Standard errors not corrected for this correlation may be too small. I therefore use a procedure for robust estimation of the standard errors, which accounts for the within-group correlation by industry or occupation.[5] I present these in brackets below the standard errors corrected for group heteroskedasticity in Table 3.

To estimate the wage equations, I use data from the 1994 *Current Population Survey*

[5] Peter J. Huber (1967) and William H. Rogers (1993). The estimations are performed using *Stata Release 5.0* (StatCorp, 1997).

(CPS), U.S. Department of Commerce, Bureau of the Census. The wage equations include workers aged 18–65 whose hourly wage rate exceeds $2, and who provide complete information on all variables used in the analysis. Further restrictions corresponding to those made by the BLS in the scope of its job injury data collection are necessary in order to assign risk measures to the individuals in the study; that is, I exclude workers in public administration, self-employed workers, and private household workers. I also exclude workers employed in the agriculture, forestry, and fisheries industries. The resulting samples consist of 6,037 female and 5,960 male workers.

Hourly wage is the reported hourly wage for 64 percent of the women and 58 percent of the men, and is calculated from weekly pay and hours usually worked on this job for the remainder. Since information on actual work history is unavailable, I use years of potential experience, measured as age − education − 6. While this approximation is adequate for the purpose of this paper, comparisons by gender might lead to misleading conclusions, since potential experience overstates actual experience by a greater magnitude for women than for men.

Other variables in the wage equation include years of completed schooling and indicators of race and union status. Differences in cost of living that may affect wages are controlled for by indicators of region and city size. Industry and occupation characteristics other than job risk also have a direct effect on wage levels. To the extent that unobserved industry and occupation characteristics are correlated with job risk, the estimated returns to job risk may be biased. To reduce the likelihood of this source of bias, I include indicators of major occupation and industry categories.

Means and standard deviations for the risk measures are provided in the first column of Table 3. The BLS industry rate faced by women is lower than for private industry overall, and reflects the fact that women sort into safer industries. That women sort into safer jobs within industries in addition to sorting into safer industries can be seen by comparing the average BLS rate for women in the sample to the average female-specific rate, which is 16 percent lower than the average BLS rate.

IV. Wage Equation Estimates

A. *Female Workers*

Table 3, Panel A, presents coefficient estimates of the risk measures in the wage equations.[6] Equation (1) uses the customary BLS industry risk measure. Based on this measure, there is no evidence of a compensating differential for job risk for women workers. However, the estimates based on the gender-specific risk measures show strong evidence of compensating differentials. The results in column (2) using the female-specific industry risk measure indicates a wage-risk trade-off which is significant at the 1-percent level based on the heteroskedasticity-corrected standard errors, although it is no longer significant using the robust standard errors allowing for within-group correlation. However, the estimates in column (3) using the female-specific occupation risk measure reveals substantial and statistically significant effects (at the 5-percent level or better in 1-sided tests) based on either standard error. The magnitude of the estimated wage-risk trade-off is larger using the occupation risk measure than using the industry risk measure (0.014 and 0.009, respectively).

The results based on gender-specific injury and illness incidence rates strongly indicate that women do receive a compensating differential for their exposure to job risk. To determine whether the source of the job risk derives from the pervading riskiness of the industry, from the riskiness of the worker's specific job, or from both industry and occupation risk characteristics, I estimate wage equations including both industry and occupation risk. For instance, although secretarial jobs are quite safe, secretaries employed in textile mills may be exposed to various job hazards, such as cotton dust, that secretaries in insurance companies do not face.

Column (4) presents the estimates including the BLS rate as well as the occupational rate, followed by the estimates based on the female-specific industry and occupation rates in column

[6] Selectivity-corrected estimates of the wage equation for female workers are virtually identical and are available upon request.

TABLE 3—WAGE EQUATION ESTIMATES[a]

	Mean (standard deviation)	Dependent variable: log of hourly wage[b] (1)	(2)	(3)	(4)	(5)
Panel A: Female Workers (sample size = 6,037)						
BLS industry rate	2.48 (1.57) —	0.443 (0.360) [0.927]	—	—	−0.025 (0.388) [0.608]	—
Female industry rate	2.14 (1.56) —	—	0.897* (0.364) [0.953]	—	—	0.463 (0.387) [0.649]
Female occupation rate	1.94 (2.22) —	—	—	1.362* (0.374) [0.740]	1.369* (0.401) [0.739]	1.232* (0.395) [0.725]
Hourly wage	10.60 (7.39)	—	—	—	—	—
Adjusted R^2	—	0.45	0.45	0.45	0.45	0.45
Panel B: Male Workers (sample size = 5,960)						
BLS industry rate	3.05 (1.67) —	−1.959* (0.395) [0.646]	—	—	−1.894* (0.397) [0.643]	—
Male industry rate	3.35 (1.80) —	—	−2.042* (0.366) [0.573]	—	—	−1.982* (0.368) [0.570]
Male occupation rate	3.23 (3.58) —	—	—	−0.550 (0.262) [0.377]	−0.465 (0.260) [0.251]	−0.446 (0.260) [0.248]
Hourly wage	13.52 (8.80)	—	—	—	—	—
Adjusted R^2	—	0.45	0.45	0.45	0.45	0.45
Panel C: Male Blue-Collar Workers (sample size = 3,197)						
BLS industry rate	3.62 (1.56) —	1.360* (0.452) [1.073]	—	—	1.319* (0.454) [0.079]	—
Male industry rate	3.93 (1.65) —	—	1.280* (0.435) [1.032]	—	—	1.236* (0.438) [1.040]
Male occupation rate	5.24 (3.78) —	—	—	0.224 (0.236) [0.297]	0.158 (0.239) [0.272]	0.144 (0.239) [0.270]
Hourly wage	10.84 (6.50)	—	—	—	—	—
Adjusted R^2	—	0.34	0.34	0.34	0.34	0.34

TABLE 3—*Continued.*

	Dependent variable: log of hourly wage[b]					
	Mean (standard deviation)	(1)	(2)	(3)	(4)	(5)
Panel D: Male Hourly Blue-Collar Workers (sample size = 2,578)						
BLS industry rate	3.62 (1.52) —	1.578* (0.503) [1.133]	—	—	1.470* (0.503) [1.126]	—
Male industry rate	3.92 (1.61) —	—	1.472* (0.479) [1.085]	—	—	1.349* (0.480) [1.082]
Male occupation rate	5.42 (3.89) —	—	—	0.494** (0.252) [0.279]	0.431** (0.254) [0.275]	0.418** (0.255) [0.275]
Hourly wage	10.58 (6.61)	—	—	—	—	—
Adjusted R^2	—	0.37	0.37	0.37	0.37	0.37

[a] All coefficients are multiplied by 100. Data set is March 1994 *Current Population Survey*. Additional variables in each equation are a constant, potential experience, potential experience squared, education, and indicator variables for union, nonwhite, three regions, and five city sizes. The female equations and the equations for all male workers also include indicators for nine occupations and six industries. The blue-collar male equations also include indicator variables for two occupations and for manufacturing. See text for definitions of variables.

[b] Standard errors corrected for group heteroskedasticity in parentheses; standard errors corrected for within-group correlation in brackets.

* Indicates significance at the 1-percent level, and ** indicates significance at the 5-percent level (1-sided tests).

(5). As the results show, the coefficient of occupation risk is not affected by the inclusion of the industry rate. The industry rate is not significantly different from zero after controlling for occupation risk. Thus the source of the wage-risk trade-off for the female sample is predominantly due to the riskiness of the occupation.

B. *Male Workers*

Panels B, C, and D of Table 3 summarize the risk coefficients from the corresponding equations for men. Estimates pooling white- and blue-collar men are reported in Panel B and indicate a significantly negative wage-risk relation using either the BLS industry risk measure, the gender-specific industry risk measure, or the gender-specific occupation measure. Since the occupational risk measures calculated here should circumvent the large measurement error that may result from assigning industry average risk measures to men in white-collar occupations, the negative wage-risk trade-off found for the full male sample is puzzling. It is possible that this results from pooling workers paid hourly with those on salary. For instance, salaried workers in risky jobs may be compensated by increased opportunities for promotion rather than directly for the riskiness of their jobs. However, the results restricted to hourly workers yield significantly negative effects of industry risk of about half the magnitude of that found for the full sample, while there is no significant effect of occupation risk. The results restricted to all white-collar workers are similar to those found for the full sample, with significant negative returns to both industry and occupation risk. Estimates restricted to white-collar males paid hourly indicate no significant wage-risk trade-off using any measure of risk.[7]

[7] These results are available upon request.

The results reported in Panel C, after making the customary restriction to blue-collar men, indicate the customary findings of a positive wage-risk trade-off using both measures of industry risk, which are significant based on the conventionally used standard errors. When corrected for within-group correlation, however, the large increase in the standard errors renders these coefficients insignificant. The coefficient of the BLS industry rate is slightly larger than that of the gender-specific rate (0.014 and 0.013, respectively). In contrast to the findings for women, the coefficient on the occupational risk measure, although positive, is not significantly different from zero in any specification.

Restricting the sample further to blue-collar men paid hourly, however, reveals a positive and significant effect (at the 5-percent level in 1-sided tests) of gender-specific occupational risk on wages, but the magnitude of the effect is about one-third that of industry risk for males as well as about one-third of the coefficient of occupation risk estimated for women. Based on the heteroskedasticity-corrected standard errors, the results indicate a significantly positive wage-risk trade-off for industry risk, but once again there is a large increase in the robust standard errors corrected for within-group correlation which renders these insignificant.

V. Implicit Value of an Injury or Illness

The preceding results demonstrate that women and blue-collar men receive a significant compensating differential for job risk. Table 4 provides estimates of the wage premia for bearing risk and the implicit value of an injury or illness based on the estimates presented in Table 3. The wage premium per unit of risk is $\partial w / \partial q$, where w is the hourly wage used in the estimation of the wage equations, and q represents the risk measure used. Evaluated at the sample means of risk and hourly wages, the compensation for female workers for average risk is 1.9–2.6 percent of hourly wages. Assuming 2,000 hours worked per year, female workers at the average risk level earn a wage premium of $408–$563 annually.

Since the injury and illness incidence rates are per 100 full-time workers, the implicit annual value of an injury or illness is calculated as

$$\partial w / \partial q \times 100 \times 2{,}000, \tag{5}$$

again assuming 2,000 hours worked per year for full-time employment. Based on the female-specific industry rate, the implicit value of an injury or illness is around $20,000, while the estimated value based on the occupation risk measure yields an implicit value around $30,000.

For comparison, Table 4 also presents corresponding values for blue-collar men. The values based on industry risk indicate that men's higher average risk level results in a larger annual compensation for risk. The values based on the occupational risk measures reveal similar values of annual compensation for female workers and for male hourly blue-collar workers. The implicit annual value of an injury or illness of about $30,000 is close to that obtained for women based on the occupational risk measure.

VI. Conclusion

Women have largely been excluded from analyses of compensating differentials for job risk since they are predominantly employed in safer, white-collar occupations. New data reveal that their injury experience is considerable. One-third of the total injury and illness cases with days away from work accrue to female workers. Adjusted for employment, women are 71 percent as likely as men to experience an injury or illness.

As one would predict on theoretical grounds, these risks generate compensating differentials. Based on gender-specific injury incidence rates for both industry and occupation, I find strong evidence of compensating wage differentials for the job risk faced by female workers. Furthermore, all women—not only women in the riskier blue-collar jobs—receive a substantial and statistically significant premium for bearing job risk. Occupational risk has a larger impact on the wage rate than industry risk, and when both risk measures are included in the wage equation, only occupational risk is significant. In contrast, there is a negative relation between risk and

TABLE 4—ANNUAL VALUES OF RISK COMPENSATION[a]

	All female		Male blue-collar		Male hourly blue-collar	
Risk measure:	Female industry rate	Female occupation rate	BLS industry rate	Male industry rate	Male industry rate	Male occupation rate
Annual compensation for average risk[b]	\$408	\$563	\$1,067	\$1,091	\$1,221	\$567
Risk differential as a percentage of average wage[c]	1.93	2.66	4.92	5.03	5.77	2.68
Implicit annual value of an injury or illness[d]	\$19,631	\$29,023	\$29,485	\$27,750	\$31,148	\$10,453

[a] Based on coefficient estimates in Table 3.
[b] Calculated as $q \times \partial w/\partial q \times 2{,}000$, where q denotes the risk measure.
[c] Calculated as $(q \times \partial w/\partial q)/w$.
[d] Calculated as $\partial w/\partial q \times 100 \times 2{,}000$.

earnings for white-collar men. This is a puzzling finding, since the use of occupation-specific incidence rates reduces the measurement error that may result from imputing industry risk averages to men in safer white-collar occupations.

In contrast to the estimates based on gender-specific risk measures, estimates based on the BLS industry rate fail to reveal evidence of a compensating differential for job risk faced by women. Imputing this measure of overall industry risk to female workers apparently results in measurement error too great to yield reliable estimates of the wage-risk trade-off for female workers.

The wage-risk trade-off and the implicit value of an injury or illness are of a magnitude similar to that found in this study for male blue-collar workers. Since women comprise over 45 percent of the labor force, it is comforting to discover that, at least with regard to job risk, women and blue-collar men face a wage-determination process yielding similar compensation for job risk.

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