THE VALUE OF LIFE: ESTIMATES WITH RISKS BY OCCUPATION AND INDUSTRY

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The worker fatality risk variable constructed for this article uses BLS data on total worker deaths by both occupation and industry over the 1992–97 period rather than death risks by occupation or industry alone, as in past studies. The subsequent estimates using 1997 CPS data indicate a value of life of $4.7 million for the full sample, $7.0 million for blue-collar males, and $8.5 million for blue-collar females. Unlike previous estimates, these values account for the influence of clustering of the job risk variable and compensating differentials for both workers' compensation and nonfatal job risks. (*JEL* J3, I1)

I. INTRODUCTION

Economic values of a statistical life are now part of generally accepted economic methodology. The theoretical foundations dating back to Adam Smith's (1776) theory of compensating differentials are widely accepted. For roughly a quarter century, economists have developed empirical estimates of the trade-off between wages and fatality risks, which continue to dominate the value-of-life literature.

The magnitude of the value-of-life estimates is of considerable policy importance as well. For the past two decades, U.S. federal agencies have used labor market estimates of the value of statistical life to assess the benefits of health, safety, and environmental regulations. These benefit values are critical inputs to the policy because the benefits from reducing risks to life are often the dominant benefit component, and the magnitude of these benefits is consequential given the increased reliance on benefit-cost tests for policy assessment.

Notwithstanding the widespread use of value-of-life estimates, empirical estimates of the value of life remain an object of considerable controversy. A prominent area of concern stems from the nature of the job risk variable used in the wage equation. Ideally, one would want a measure of the worker's subjective assessment of the fatality risk,[1] or at the very least an objective risk measure that captures the variation in risk by both occupation and industry. Most studies in the literature use a measure of industry death risks; the remainder use a measure of occupational fatality risks. This procedure, which is employed in studies using data from the United States as well as other countries,[2] consequently never

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1. The variable for the worker's perceived exposure to dangerous conditions was used in Viscusi (1979) and elsewhere, where this measure is also interacted with objective measures of job risks. Other studies have elicited workers' subjective assessments of the probability of job injury, as in Viscusi and O'Connor (1984), leading to estimates of the implicit value of injury that paralleled those generated using objective risk data.

2. For a recent survey of U.S. value-of life studies, see Viscusi and Aldy (2003). See also the industry-based estimates of risk in Kniesner and Leeth (1991) for Australia and Japan and the analysis of occupational mortality data for the United Kingdom by Marin and Psacharopoulos (1982).

ABBREVIATIONS

BLS: Bureau of Labor Statistics
CFOI: Census of Fatal Occupational Injuries
CPS: Current Population Survey
NTOF: National Traumatic Occupational Fatality Project

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incorporates the variation in job risks by both occupation and industry.

These deficiencies in the job risk variable create four potentially serious problems. First, failure to recognize the variation in job risks by occupation and industry creates a familiar situation of errors in variables. However, there is no a priori reason to assume that the measurement error is random so that the direction of the bias in the value-of-life estimates in not known.[3]

Second, because the industry-based job risk variable is not pertinent to workers in relatively safe positions, full-sample estimates often fail to yield significant estimates of wage premiums for risk. Researchers have attempted to cope with this problem by restricting the wage equation estimates to blue-collar workers or male blue-collar workers. That approach may yield significant fatality risk coefficients, but the empirical magnitudes are biased. The job risk variable is calculated based on the total fatalities in the industry divided by total employment in the industry. If all fatalities are incurred by blue-collar workers or blue-collar male workers, use of the total employment denominator will lead to an understatement of the worker's job risk for the blue-collar subsample used for the analysis, biasing the estimated job risk coefficient upward.

A third consequence of the job risk data shortcomings has been the failure of most studies to capture the influence of nonfatal job risks and workers' compensation on worker wages. There are only two studies that have included a measure of workers' compensation benefits and nonfatal job risks in a wage equation estimating wage-fatality risk trade-offs. [See Moore and Viscusi (1990) and Kniesner and Leeth (1991).] The main practical consequence is that observed wage premiums for fatality risks may also be capturing the influence of these two omitted risk-related variables rather than being a measure of the trade-off between wages and fatality risk alone.

A fourth limitation of studies using existing job risk data stems from the construction of the risk variable. In the absence of information on the worker's own job risk, researchers have matched job risk data by occupation or industry to the worker based on the worker's reported job. All workers in the same industry or occupational group receive the same value for the job risk variable; as a consequence, the estimated residuals will be correlated and standard errors will be underestimated. This article is the first study of estimates of the value of life that explicitly accounts for this aspect of the fatality risk variable.

This analysis uses job fatality data by industry and occupation to construct a fatality risk variable that will make it possible to obtain more refined estimates of the value of life. Section II describes the mortality risk data and how the fatality frequencies were constructed for this article. After reviewing the hedonic wage model approach in section III, I report estimates based on occupation and industry risk in section IV and compare these to industry-level risk results using the same data in section V. These estimates show significant premiums for job fatality risks for a wide range of specifications and subsamples, including both male and female workers. The concluding section VI summarizes the differences arising from the aggregation of the fatality risk variable by occupation and industry, which can affect the estimates of the value of life by a factor of two.

II. FATALITY RISKS BY OCCUPATION AND INDUSTRY

The critical input to sound estimation of wage-fatality risk trade-offs is to have an accurate measure of the risk of the worker's job. The health and safety risk lottery associated with a job consists of various adverse health outcomes and their associated probabilities. Based on the constraints of available data, the analysis here focuses on the risks of fatality and injuries severe enough to lead to the loss of at least a day of work. The primary risk variable of interest will be the probability of death associated with the job. The analysis will also control for the job's probability of injury and expected workers' compensation benefits to distinguish the influence of fatality risk from other hazards on the job.

The two main approaches to establishing values for the fatality risk variable have been to use measures of occupational risk, ignoring variations by industry, and measures of industry risk, ignoring variations by occupation. Many early studies used the occupational risk approach, but the greater availability of detailed industry risk measures has contributed

3. Measurement error remains a continuing issue in the value-of-life literature. Black and Kniesner (2003) provide an in-depth analysis of measurement error for the job risk variable.

to the greater reliance on industry risk variables. Some early studies of the value of life, such as Thaler and Rosen (1976) and Brown (1980), used occupational risk measures based on data from the Society of Actuaries. These risk estimates were for overall mortality of people in different occupations, as opposed to the mortality risk specifically attributable to job exposures. The variable also did not capture differences in occupational risks across industries. Estimates generated using these data tended to yield comparatively low values of life (in year 2000 dollars) of $1.1 million for Thaler and Rosen (1976) and $2.1 million for Brown (1980). The average worker risk levels implied by these data were 0.001, so that the comparatively low values of life are consistent with workers who are more willing to bear risk self-selecting themselves into high-risk jobs.

Most studies in the literature have relied on industry-based fatality data. The first set of industry data used was that developed by the U.S. Bureau of Labor Statistics (BLS) Researchers match objective death risk measures to workers based on their broad industry group SIC code. Both the BLS and the Society of Actuaries data used in these studies are measured at the one-digit or two-digit-SIC level, so there are usually no more than 30 different values that the death risk variable has for a given sample. Two early studies using BLS data are by Smith (1976) and Viscusi (1979), who found implicit values of life of $6.6 million and $5.9 million, respectively (year 2000 $). The average risk levels for these studies of 0.0001 was an order of magnitude smaller than that using the actuarial occupational risk.

A second, more recent set of industry fatality risk data is that generated by the National Institute of Occupational Safety and Health's National Traumatic Occupational Fatality Project (NTOF). Unlike the BLS data that used a partial sample to project death risks, these data are based on a census of all occupational fatalities using information reported on death certificates. However, notwithstanding the data's designation as pertaining to "occupational" fatalities, the data used in past studies have only been by industry and state, not occupation. Using these fatality data where the industry level of aggregation is at the one-digit SIC level, Moore and Viscusi (1990) estimated an average value of life of $10.4 million (year 2000 $), where the worker's average risk level was 0.0001. To the extent that the BLS measure has more random measurement error than does the NTOF data, one would have expected that the estimated values of life would be greater with the NTOF data than with the BLS data.[4] That was in fact the case, as the value-of-life estimate using the BLS risk measure was $3.6 million (year 2000 $) based on a direct comparison of the results using the same underlying employment data.

The fatal injury data that provides the basis for the mortality risk measure used here is the U.S. BLS Census of Fatal Occupational Injuries (CFOI) (available on CD-ROM from the BLS). The BLS has gathered the CFOI mortality data since 1992, and these statistics are the most comprehensive tallies of occupational deaths available. The sources of information for the mortality data include death certificates, workers' compensation reports, medical examiner reports, and reports by the Occupational Safety and Health Administration. The agency uses source documents and follow-up questionnaires to ensure that the deaths are work-related. The number of deaths based on these data was 6238 in 1997. By way of comparison, the BLS reported only 3750 occupational fatalities in 1984, and the NTOF measure recorded 6901 average annual fatalities for 1980–84 (See Moore and Viscusi [1990], 73.). The key time period for analysis in this article will be 1997, which is the year of individual employment data that will be matched to the job risk estimates.

Though the BLS reports the total number of fatalities for different categories of workers, it does not calculate the fatality rate for occupational industry groups. The incidence rate of fatalities is the ratio of the fatalities in any occupation-industry group to that group's employment in that time period. In calculating the incidence rate for these different cells, I divided occupation-industry groups into 720 possible categories consisting of 72 two-digit SIC code industries by 10 one-digit occupational groups. The employment data are based on BLS estimates for that category.[5] Some occupation-industry cells were not viable, because there were no reported employment levels for those cells. For the 1992–97 period, there were 13 such

4. The levels of the risk values also differed, however, complicating the theoretical predictions.

5. See U.S. BLS Current Population Survey (CPS) unpublished table, Table 6, Employed persons by detailed industry and major occupation, annual average 1997 (based on the CPS).

categories, such as transportation employees in nondepository credit institutions. In addition, my analysis excludes agricultural workers and those on active duty in the armed forces.

Evidence presented in Mellow and Sider (1983) indicated that there is measurement error in the reporting of the individual's industry and occupation. These errors were greater for occupational categories than for industries. For this reason, the death risk variable is constructed based on occupational groups that are less narrowly defined than the industry breakdowns, which should diminish this problem to some extent.

Because fatalities are relatively rare events, two approaches were used to construct the fatality risk data. First, fatality risk estimates were constructed using 1997 fatality data, coupled with 1997 employment data. Focusing on only a single year leads to 290 cells out of the 720 occupation-industry categories with no reported worker deaths. To reduce this problem, I constructed a second fatality risk measure based on an average of fatalities for each group from 1992 to 1997. Using this six-year average of deaths for each occupation-industry cell leads to a more precise measure of the underlying fatality risk. This approach reduces the number of occupation-industry cells with zero fatality risk from 290 to 90. This averaging process is likely to be consistent with the overall riskiness of jobs in 1997, as there were 6217 worker fatalities in 1992, which is just below the level of 6238 in 1997.[6] Thus there were no major trends in fatality rates during this period that are likely to distort the measure of job riskiness.

The overall fatality rate implied by the CFOI data was 0.00004. By way of comparison, the fatality rate for most previous studies using industry fatality data historically has been approximately 0.0001, but some more recent studies report lower risks that nevertheless are a bit higher than these CFOI estimates.[7] A somewhat lower risk level is to be expected for the recent period covered by the CFOI data because of the decreased incidence of occupational fatalities over the past quarter century during which labor market value-of-life estimates have been generated. There are also differences in reporting and mortality attribution that may enter.

Table 1 presents a grid of the mortality risk probabilities, where panel A presents the results using 1997 fatality data and panel B is based on average fatalities from 1992 to 1997. The ten different occupational groups make up the rows of Table 1. This listing consequently reflects the complete level of occupational aggregation used in constructing the fatality risk measure. To make the industry groups a more manageable size for summarizing in this table, the 72 industry groups have been collapsed into 9 major categories. The risk estimates for panel A and panel B are reasonably similar. The most noteworthy difference is the presence of five occupation-industry categories with zero risk in panel A, whereas there are no such categories in panel B. Overall average risks by industry and occupation are of fairly comparable magnitude even though the component risks differ to a greater extent.

The importance of analyzing risk variations by both occupation and industry is apparent from the patterns in Table 1. Consider the implications of the longer-term fatality estimates in panel B. The fatality risks by industry, which have been the principal reference points for previous studies, vary from 1.36 per 100,000 workers for finance, insurance, and real estate to 25.99 per 100,000 workers for mining. In every instance, including the lower-risk industry groups, there is considerable heterogeneity in the risks by occupation. Administrative support occupations are always the lowest risk, with an annual fatality rate ranging from 0.44 per 100,000 workers for finance, insurance, and real estate to 1.41 per 100,000 workers for transportation and public utilities. However, even within the safest industry groups, such as services and public administration, there are substantial mortality risks exceeding 10 per 100,000 employees for occupational categories such as transportation and material moving occupations and handlers, equipment cleaners, helpers, and laborers. The greatest occupational variations in riskiness occur in the most dangerous industries, as the fatality risks vary by almost two orders of magnitude for different mining occupations. The empirical estimates to follow will capture the substantial variation in risk associated with workers' jobs across both occupation and industry.

6. Indeed, the only year in which the number of workplace fatalities differed by more than 100 from that for 1997 was 1994, in which there were 6632 fatalities, or 394 more than 1997, which is a 6% difference.

7. For example, Moore and Viscusi (1990), 73, report BLS risk levels of 0.00005 and NTOF death risks of 0.00008.

TABLE 1

Incidence of Fatality by Major Occupation and Industry (Fatalities per 100,000 employees)

	Industry									
Major Occupation Group	**Mining**	**Construction**	**Manufacturing**	**Transportation & Public Utilities**	**Wholesale Trade**	**Retail Trade**	**Finance, Insurance, & Real Estate**	**Services**	**Public Administration**	**Occupation Total**
A: *Estimates using fatalities, 1997*										
Executive, administrative, and managerial occupations	4.35	6.12	1.73	1.87	3.06	3.96	1.52	1.48	1.79	2.22
Professional specialty occupations	11.76	3.16	0.98	2.84	1.82	1.41	0.33	1.09	2.79	1.26
Technicians and related support occupations	8.00	11.11	2.47	17.06	4.17	0.00	1.32	2.01	5.41	3.56
Sales occupations	10.00	1.39	3.82	2.11	2.39	3.57	1.15	1.24	3.13	2.90
Administrative support occupations, including clerical	0.00	0.24	0.59	1.31	0.81	0.61	0.40	0.39	0.69	0.58
Service occupations	0.00	2.86	2.24	4.00	5.45	1.49	4.56	1.59	11.73	2.63
Precision production, craft, and repair occupations	37.55	11.24	4.27	7.80	6.44	3.58	3.98	5.06	11.05	7.69
Machine operators, assemblers, and inspectors	20.83	39.18	1.99	8.27	10.53	1.52	0.00	1.53	8.00	2.71
Transportation and material moving occupations	37.62	22.04	16.01	32.72	16.73	12.17	0.00	13.27	27.66	23.48
Handlers, equipment cleaners, helpers, and laborers	45.83	38.91	7.12	13.56	8.91	2.65	7.41	12.40	26.47	13.00
Industry total	24.64	13.62	3.01	11.51	4.83	3.00	1.19	1.66	5.40	4.00
B: *Estimates using average fatalities, 1992–97*										
Executive, administrative, and managerial occupations	5.80	4.89	1.84	2.22	3.34	4.77	1.67	1.56	2.60	2.38
Professional specialty occupations	6.86	2.64	1.20	2.72	2.88	1.80	0.71	1.13	2.72	1.30
Technicians and related support occupations	10.67	15.19	2.49	21.03	3.82	0.87	0.77	1.74	7.88	3.92
Sales occupations	5.00	4.86	3.54	2.23	3.26	3.87	1.45	2.11	2.60	3.30
Administrative support occupations, including clerical	0.51	0.98	0.56	1.41	0.63	0.59	0.44	0.47	0.97	0.66
Service occupations	22.22	4.76	5.66	6.06	5.45	1.69	5.21	1.90	11.26	2.92
Precision production, craft, and repair occupations	38.54	11.38	3.63	7.48	7.82	3.11	3.13	5.43	11.58	7.59
Machine operators, assemblers, and inspectors	24.31	30.41	2.15	6.64	9.90	1.43	4.17	2.33	14.67	2.81
Transportation and material moving occupations	42.90	20.88	15.79	28.82	14.97	11.86	10.61	12.02	25.89	21.47
Handlers, equipment cleaners, helpers, and laborers	45.83	31.41	7.57	12.93	10.09	3.60	12.35	10.40	42.65	12.02
Industry total	25.99	12.62	3.02	10.75	5.19	3.29	1.36	1.76	5.72	4.02

III. THE HEDONIC WAGE EQUATIONS

The empirical framework used for estimation will be based on the standard hedonic wage framework and, as a consequence, will only be summarized briefly.[8] The outer envelope of the individual firm curves for wages as a function of job risk comprises the market opportunities curve. Workers, who would rather be healthy than not, select their most preferred wage–job risk combination from the market opportunities curve. The resulting estimates of the wage-risk locus traces out the average pattern of these market decisions but does not have a structural interpretation in terms of either demand or supply influences individually.

The hedonic wage equations that I estimate will be of the standard semi-logarithmic form:

$$(1)\quad \ln(Wage_i) = X_i\beta + \gamma_1 \text{ Death Risk}_i + \gamma_2 \text{ Injury Risk}_i + \gamma_3 \text{ Injury Risk}_i \times \text{Replacement Rate}_i + \varepsilon_i,$$

where $Wage_i$ is worker i's hourly wage rate, X_i is a vector of personal characteristics and job characteristics for worker i, the *Death* $Risk_i$ variable is matched to the worker based on worker i's occupation and industry, *Injury* $Risk_i$ is the lost workday injury and illness rate for worker i's industry,[9] and *Injury* $Risk_i \times$ *Replacement* $Rate_i$ is the worker's expected workers' compensation replacement rate. A simple linear wage equation will also be estimated.

The variables included have several distinctive features. The CFOI death risk will be included by occupation-industry group and, in separate regressions, by industry alone, making it possible to examine the effect of abstracting from occupational differences. To the extent that measurement error is random, one would expect that recognition of occupational differences would boost the estimated value of a statistical life given by $\partial Wage/\partial Death\ Risk$ (converted to an annual basis) and also shrink the standard errors. Though section V will report estimates aggregating fatality risks by industry, my efforts to derive similar estimates with the job risk variable based solely on the worker's occupation, excluding industry differences, failed to yield stable results. The fatality risk variable in these equations often yielded insignificant effects of varying sign. The weak performance of fatality risks based solely on occupation possibly arose because of the relatively high degree of aggregation by occupation type for the job risk measure.

The equation also includes a measure of workers' compensation benefits so that the results will control for these insurance payments. The particular measure used is the expected workers' compensation replacement rate. Thus the lost workday injury and illness rate is interacted with the level of workers' compensation benefits for that particular worker, divided by the worker's wage rate. Thus, if the injury risk for the worker is zero, this variable drops out of the analysis. The expected workers' compensation replacement rate is given by

$$(2)\quad \text{Expected WC Replacement Rate} = \text{Lost Workday Rate}_i \times \text{Benefit Rate}_i \times \text{Wage}_i \text{ (Adjusted for min, max)} /(1 - t_i) \text{ Wage}_i,$$

where t_i is the average state and federal tax on the worker's wages.[10]

The workers' compensation benefit amount is given by the worker's weekly earnings (or spendable weekly earnings depending on the state) multiplied by the state's benefit rate. The particular benefits category used was that for temporary total disability. This benefit category comprises about three-fourths of

8. For additional discussion, see Thaler and Rosen (1976), Viscusi (1979; 1993), Smith (1979), and Rosen (1986), among others.

9. The injury risk variable is the BLS incidence rate for nonfatal occupational injuries and illnesses, lost workday cases, by industry in 1997.

10. Wages and benefits in equation (2) are measured on a weekly basis rather than an hourly basis. Taxes were assigned as follows. Workers with a married spouse present are assigned married filing status, workers with married spouses absent are assigned married filing separately, and all others were assigned single filing. Each person received the standard deduction and exemptions, that is, married filers received three exemptions and married filing separately received two exemptions, as did single filers. Federal tax data were from the Commerce Clearing House, 1998 U.S. Master Tax Guide, 1997; state taxes were from the U.S. Census Bureau (1999), No. 522 State Governments—Revenue by State: 1997 and No. 732 Personal Income, by State: 1990 to 1998. Data for District of Columbia were from the U.S. Census Bureau Web site, www.census.gov/govs/estimate/97sl09dc.html.

workers' compensation claims. Permanent partial disability formulas are typically almost identical except for differences in benefit duration that are not captured in the measure used here. Though the benefit measure is not free of error, it should be highly positively correlated with the expected benefits from workers' compensation.

The workers' compensation variable is also distinctive from almost all previous measures used in the literature in that it is calculated on an individual worker basis using state benefit formulas coupled with information on the individual worker rather than being based on a statewide average.[11] Benefit levels were adjusted to reflect state minimum and maximum allowed benefits. Because of the favorable tax treatment accorded to workers' compensation benefits, these benefit levels were inflated to reflect the fact that there are state and federal taxes on wages but not on workers' compensation benefits, leading to the $(1 - t_i)$ adjustment in the denominator. Thus both wages and the expected workers' compensation replacement rate are in comparable tax terms.

The expected replacement rate is a function of the worker's wage rate when the benefit minimum and maximum values are binding.[12] Thus it is potentially endogenous. Tests using instrumental variable estimators for the expected replacement rate yielded statistically significant instruments. The compensating differential estimates also were very similar to those generated with ordinary least squares (OLS). Pertinent Hausman tests implied that one could not reject the hypothesis that the expected workers' compensation rate was not endogenous.[13]

The death risk variable is distinctive in that it varies by occupation and industry, but all workers in the same industry and occupation category receive the same value for the death risk. Similarly, the injury rate variable only varies by industry. The first set of reported standard errors will be the White heteroscedasticity-adjusted standard errors. This correction adjusts for the fact that the error term ε_i may have different values by industry or occupation. In addition to adjusting for this group heteroscedasticity, I also adjust for the influence of clustering as, for example, workers in the same occupation-industry group may have correlated residuals. Neglect of this clustering often leads to underestimation of the standard errors. The robust and clustered standard errors that are reported adjust for the within-group correlation for the occupation-industry cells for the results in section IV and for the correlations within the industry-based cells for the results reported in section V.[14] To date, the only studies in the hedonic wage risk literature that have made this adjustment have been analyses of the implicit value of nonfatal job injuries by Hersch (1998) and Viscusi and Hersch (2001). By failing to make this adjustment, previous studies of the value of statistical life consequently may have overstated the statistical significance of the value-of-life estimates by failing to account for this clustering.

The labor market data set to which the risk variables are merged for this empirical analysis is the 1997 CPS merged outgoing rotation group. The workers retained in the sample used for this study are nonagricultural workers who are not in the armed forces. All regression runs focus on full-time workers (usual hours at least 35) age 18 to 65. The hourly wage was calculated as weekly earnings divided by

11. The notable exception is the analysis in Viscusi and Moore (1987) and Moore and Viscusi (1990).

12. Moreover, the average tax rate depends on the wage rate as well.

13. The instruments used for the full sample runs and the blue-collar female runs included the state's average tax rate and the total workers' compensation benefits in the state divided by the size of the labor force. The instruments used for the blue-collar male sample runs included the total workers' compensation benefits in the state divided by the size of the labor force, the state's unemployment percentage, and a Republican governor dummy variable. These variables were all significant predictors of the workers' compensation replacement rate and were not significant predictors of the wage rate either individually or jointly. The instrument set varied for the blue-collar male workers and the blue-collar female runs as well as the full-sample runs because some variables were not valid instruments in different samples, that is, they were significant predictors of the wage rate. The instrumental variables regression estimates generated were very similar to the OLS estimates in magnitude. The Hausman test for endogeneity, however, implied that one could not reject the hypothesis that the expected workers' compensation replacement rate was not endogenous, for example, $\chi^2(1) = 0.51$, $\text{Prob} > \chi^2 = 0.48$ for the full-sample equation with the occupation-industry death risk variable, $\chi^2(1) = 2.42$, $\text{Prob} > \chi^2 = 0.12$ for the blue-collar male equation, and $\chi^2 = 0.74$, $\text{Prob} > \chi^2 = 0.39$ for the blue-collar female equation.

14. For discussion of this procedure, see Huber (1967) and Rogers (1993).

usual weekly hours.[15] Workers whose wage was below the statutory minimum wage of \$4.75 (the minimum wage until September 1997) were excluded from the sample. The principal worker background variables included in the analysis were worker age, gender, dummy variables for racial groups (black, Native American, Asian, Hispanic), being married, and education in years.[16] The job characteristic variables in addition to those related to risk were whether the worker was a union member or under a union contract, was employed in public rather than private industry, and a series of nine occupational dummy variables for the full-sample results and four such variables for the blue-collar-sample results. Each equation also included eight regional dummy variables as well as a variable for whether the respondent lived in a standard metropolitan statistical area.

Hersch's (1998) analysis of wage premiums for job injuries indicated that it was more appropriate to estimate separate wage equations for men and women. Not only does the influence of human capital variables vary by gender, but preferences with respect to job risks may differ as well. Whereas many previous studies found that only blue-collar males received significant job risk premiums, Hersch (1998) found significant positive premiums for females but not for males as a group, though she did find effects for male blue-collar workers. Pertinent F tests for the equations presented here indicate that pooling males and females and allowing only for separate intercepts by gender is not appropriate.[17] Although the discussion will report full-sample findings including a female dummy variable to provide comparability with much of the literature I will also report separate equations by gender.

IV. VALUE-OF-LIFE ESTIMATES: FATALITY RISKS BY OCCUPATION AND INDUSTRY

The empirical analysis will consider a series of different equations for five alternative samples of respondents: the full sample, males, females, blue-collar males, and blue-collar females. The variants to be considered will explore the robustness of the results with respect to different specifications, many of which have proven to be problematic in previous studies.

Table 2 reports representative ln(*Wage*) equations for the full sample, blue-collar males, and blue-collar females. Restricting the sample to blue-collar male workers has been a common practice in past studies because the industry death risk data were poor measures of the risk in white-collar jobs, leading to insignificant wage premiums for death risks in many studies. However, Hersch (1998) found that females did in fact receive significant compensating differentials for nonfatal risk measures. Whereas Hersch (1998) calculated gender-specific injury risks, this article uses the same fatality risk measure for men and women. The risk measures do, however, control for differences in occupation and industry, which should account for most gender-related variations in riskiness.

The nonrisk variable coefficients in Table 2 follow the expected patterns, as wages increase with age but at a diminishing rate, are lower for minorities and females, are higher for better educated workers, and are higher for union members. The magnitudes of the effects are also comparable to those in the literature, as one would expect from a conventional wage equation with a widely used data set.

The death risk variable has a positive effect on wages, consistent with the theory of compensating differentials. In all three samples reported in Table 2, the death risk coefficients are statistically significant at the 99% level, two-tailed test, based on the heteroscedasticity-adjusted standard errors. However, the

15. Top coded observations were excluded from the sample. Workers with wages of \$1923 per week (or \$100,000 per year) and usual weekly hours of 99 were excluded. The highest percent of the omissions was for the male subsample, for which under 4% were eliminated. For the full sample, about 2% of the observations were affected. For the key samples of male and female blue-collar workers, less than 1% of the observations were affected.

16. Respondents who reported less than a ninth-grade education were also excluded from the sample.

17. The critical F values for the test are for tests such as $F_{0.05}$ (31, 98,969), for which the critical test value is 1.46. The estimated F values for pooling the male and female subsamples as opposed to a simple female dummy variable ranged from 30.7 to 30.9 for the four different fatality risk measures (1992–97 average industry-occupation risk, 1997 industry-occupation risk, 1992–97 industry risk, and 1997 industry risk) for the wage equation, and similarly a range of F vales of 41.3 to 42.0 for the semi-logarithmic equation results. Similarly the estimated F values for pooling the blue-collar male and blue-collar female subsample, as opposed to a simple female dummy variable, ranged from 38.3 to 38.6 for the four different fatality risk measures for the wage equation results and ranged from 24.5 to 24.8 for the semi-log equation results.

TABLE 2
Regression Estimates for ln(*Wage*) Equations for Occupation-Industry Death Risk Measure

	Coefficients (Robust SE) [Robust and Clustered SE]		
	Full Sample	**Blue-Collar Male Sample**	**Blue-Collar Female Sample**
Age	0.0417	0.0384	0.0274
	(0.0007)[a]	(0.0012)[a]	(0.0018)[a]
	[0.0016][a]	[0.0017][a]	[0.0030][a]
Age squared	– 0.0432	– 0.0396	– 0.0296
	(0.0009)[a]	(0.0015)[a]	(0.0022)[a]
	[0.0020][a]	[0.0020][a]	[0.0034][a]
Black	– 0.0960	– 0.1164	– 0.0714
	(0.0040)[a]	(0.0073)[a]	(0.0092)[a]
	[0.0069][a]	[0.0078][a]	[0.0103][a]
Native American	– 0.0306	– 0.0268	0.0012
	(0.0116)[a]	(0.0193)	(0.0285)
	[0.0137][b]	[0.0197]	[0.0414]
Asian	– 0.0744	– 0.1246	– 0.0671
	(0.0064)[a]	(0.0132)[a]	(0.0169)[a]
	[0.0103][a]	[0.0169][a]	[0.0184][a]
Hispanic	– 0.1050	– 0.1373	– 0.1294
	(0.0045)[a]	(0.0072)[a]	(0.0118)[a]
	[0.0081][a]	[0.0095][a]	[0.0151][a]
Female	– 0.1453		
	(0.0026)[a]		
	[0.0110][a]		
Education	0.0469	0.0324	0.0436
	(0.0007)[a]	(0.0016)[a]	(0.0027)[a]
	[0.0024][a]	[0.0019][a]	[0.0029][a]
Married	0.0115	0.0361	– 0.0108
	(0.0025)[a]	(0.0046)[a]	(0.0071)
	[0.0045][b]	[0.0054][a]	[0.0086]
Union	0.1400	0.2022	0.1821
	(0.0032)[a]	(0.0048)[a]	(0.0103)[a]
	[0.0128][a]	[0.0102][a]	[0.0211][a]
Death risk	0.0017	0.0027	0.0047
	(0.0002)[a]	(0.0003)[a]	(0.0013)[a]
	[0.0010][c]	[0.0007][a]	[0.0015][a]
Injury and illness rate, lost workday cases	0.2702	0.2300	0.1321
	(0.0025)[a]	(0.0038)[a]	(0.0108)[a]
	[0.0157][a]	[0.0141][a]	[0.0172][a]
Expected workers' compensation	– 0.3811	– 0.3173	– 0.1584
replacement rate	(0.0034)[a]	(0.0050)[a]	(0.0142)[a]
	[0.0212][a]	[0.0202][a]	[0.0236][a]
R^2	0.49	0.44	0.23
Observations	99,033	28,060	9902

[a]Indicates statistical significance at the 99% confidence level, two-tailed test.
[b]Indicates statistical significance at the 95% confidence level, two-tailed test.
[c]Indicates statistical significance at the 90% confidence level, two-tailed test.

Notes: The full-sample equation also includes variables for public employment, SMSA, nine occupational groups, eight regions, and a constant term. The blue-collar male and blue-collar female equations also include variables for public employment, SMSA, four occupational groups, eight regions, and a constant term.

estimates adjusted also for clustering have larger standard errors. Significance levels remain at the 99% level for blue-collar males and blue-collar females, but drop to the 90% level (two-tailed test) or 95% level (one-tailed test) for the full sample. Higher job risks should unambiguously raise wages, so a one-tailed test is warranted in this instance. It is also the commonly used threshold in many previous studies that included less demanding tests that never adjusted for clustering and, in most instances, did not include a nonfatal job risk variable. Moreover, as additional specifications summarized in Table 3 indicate, in instances in which the death risk variable is the only job risk variable included in the full-sample equation, as in most previous studies, the death risk coefficient is statistically significant at the 99% level even with the clustered standard errors. The lost workday injury and illness variable and the expected workers' compensation replacement rate also are strongly significant with the hypothesized sign.

The general magnitude of the premiums is plausible. Evaluated at the mean values of the variables, death risks raise worker wages by an average of \$0.095 per hour for the full sample, \$0.324 per hour for blue-collar males, and \$0.123 an hour for blue-collar females. On an annual basis, assuming 2000 hours worked per year, these levels of compensation are \$190 for the full sample, \$648 for blue-collar males, and \$246 for blue-collar females. These values are for fatality risks controlling for nonfatal job injury risk and workers' compensation benefits.

The lost workday injury and illness variable commands a significant wage premium as well, in addition to the premiums for mortality risk. At the mean risk level, the nonfatal job risk accounts for \$0.151 in higher wages per hour for the full sample, \$0.251 for the blue-collar male subsample, and \$0.534 for the blue-collar female sample. On an annual basis, this contribution is \$302 for the full sample, \$502 for the blue-collar male sample, and \$1068 for the blue-collar female sample. Total premiums for fatal and nonfatal job risks consequently are \$492 for the full sample, \$1150 for blue-collar male workers, and \$1314 for blue-collar female workers.

The final risk variable is the expected workers' compensation replacement rate, which has a significant negative effect on wages. As with the few previous studies that have included a workers' compensation variable in a wage equation estimating the value of life, there is a wage offset that workers are willing to incur in return for insurance coverage of the income loss associated with hazardous jobs.[18] This result is also consistent with the theory of compensating differentials.

As is shown in Moore and Viscusi (1990, 39), if the insurance loading parameter is h, p is the risk of job injury, w is the wage rate, and b is the benefit level, the optimal level of workers' compensation benefits satisfies

$$(3) \qquad dw/db = -ph/(1-p).$$

If there were no administrative costs, the trade-off rate would be $p/(1-p)$. Thus, with actuarially fair insurance, it is optimal to accept lower wages in response to higher benefits so that the trade-off rate is $p/(1-p)$, which is simply the odds of being injured divided by the probability of no injury. In insurance contexts this ratio often is viewed as a measure of the price of insurance, and it emerges as an implication of actuarially fair insurance pricing.[19]

On a theoretical basis the wage offset workers are willing to accept in return for an additional dollar of insurance benefits is given by (*Injury Rate*)/(1 − *Injury Rate*), which for this sample is 0.032 for the full sample, 0.043 for blue-collar males, and 0.037 for blue-collar females. With a rate of insurance loading h of approximately 1.25,[20] the wage offset for an additional dollar of benefits should be h(*Injury Rate*)/(1 − *Injury Rate*), which is 0.040 for the full sample, 0.054 for blue-collar males, and 0.046 for blue-collar females. The actual wage effect for an additional dollar of weekly workers' compensation benefits implied by the results in Table 2 is −0.032 for the full sample, −0.034 for blue-collar males, and −0.015 for blue-collar females.

18. The studies that have included a workers' compensation variable in the hedonic wage equation for fatality risks are Arnould and Nichols (1983), Butler (1983), Kniesner and Leeth (1991), and a series of works summarized in Moore and Viscusi (1990).

19. More specifically, abstracting from the influence of loading, the worker structures his or her compensation to maximize expected utility subject to the constraint that the marginal product equals $(1-p)w + pb$.

20. See Moore and Viscusi (1990), 39. This value of h is what they label "$1 + a$" in their model.

TABLE 3
Regression Results for Occupation-Industry Death Risk Measure

	Coefficients (Robust SE) [Robust and Clustered SE]				
	Death Risk	**Injury and Illness Rate**	**Expected Workers' Compensation Replacement Rate**	**Value of Life ($ millions)**	**Value of Injury or Illness ($)**
A: ln(*Wage*) *equation results*					
1992–97 death risk					
Full sample	0.0017	0.2702	– 0.3811	4.7	9570
	(0.0002)[a]	(0.0025)[a]	(0.0034)[a]		
	[0.0010][c]	[0.0157][a]	[0.0212][a]		
	0.0032			8.9	
	(0.0003)[a]	—	—		—
	[0.0009][a]				
Male sample	0.0016	0.2626	– 0.3797	4.9	13,379
	(0.0003)[a]	(0.0029)[a]	(0.0040)[a]		
	[0.0008][c]	[0.0139][a]	[0.0194][a]		
	0.0030			9.1	
	(0.0003)[a]	—	—		—
	[0.0007][a]				
Female sample	– 0.0007	0.2851	– 0.3899	– 1.7	10,921
	(0.0008)	(0.0047)[a]	(0.0064)[a]		
	[0.0029]	[0.0280][a]	[0.0367][a]		
	0.0006			1.5	
	(0.0008)	—	—		—
	[0.0031]				
Blue-collar male sample	0.0027	0.2300	– 0.3173	7.0	12,226
	(0.0003)[a]	(0.0038)[a]	(0.0050)[a]		
	[0.0007][a]	[0.0141][a]	[0.0202][a]		
	0.0037			9.6	
	(0.0003)[a]	—	—		—
	[0.0006][a]				
Blue-collar female sample	0.0047	0.1321	– 0.1584	8.5	29,642
	(0.0013)[a]	(0.0108)[a]	(0.0142)[a]		
	[0.0015][a]	[0.0172][a]	[0.0236][a]		
	0.0061			11.0	
	(0.0014)[a]	—	—		—
	[0.0016][a]				
1997 death risk					
Full sample	0.0015	0.2704	– 0.3813	4.2	9737
	(0.0002)[a]	(0.0025)[a]	(0.0034)[a]		
	[0.0008][c]	[0.0157][a]	[0.0212][a]		
	0.0026			7.3	
	(0.0002)[a]	—	—		—
	[0.0007][a]				
Male sample	0.0014	0.2627	– 0.3799	4.3	13,270
	(0.0002)[a]	(0.0029)[a]	(0.0040)[a]		
	[0.0007][b]	[0.0139][a]	[0.0194][a]		
	0.0024			7.3	
	(0.0002)[a]	—	—		—
	[0.0006][a]				

continued

TABLE 3 continued

	Coefficients (Robust SE) [Robust and Clustered SE]				
	Death Risk	**Injury and Illness Rate**	**Expected Workers' Compensation Replacement Rate**	**Value of Life ($ millions)**	**Value of Injury or Illness ($)**
Female sample	0.0004	0.2849	– 0.3899	1.0	10,422
	(0.0007)	(0.0047)[a]	(0.0064)[a]		
	[0.0022]	[0.0279][a]	[0.0367][a]		
	0.0011			2.7	
	(0.0007)	—	—		—
	[0.0023]				
Blue-collar male sample	0.0022	0.2301	– 0.3178	5.7	11,566
	(0.0002)[a]	(0.0038)[a]	(0.0050)[a]		
	[0.0006][a]	[0.0141][a]	[0.0202][a]		
	0.0030			7.8	
	(0.0003)[a]	—	—		—
	[0.0006][a]				
Blue-collar female sample	0.0039	0.1332	– 0.1595	7.0	30,177
	(0.0010)[a]	(0.0107)[a]	(0.0142)[a]		
	[0.0012][a]	[0.0173][a]	[0.0237][a]		
	0.0049			8.8	
	(0.0011)[a]	—	—		—
	[0.0014][a]				
B: *Wage equation results*					
1992–97 death risk					
Full sample	0.0130	5.1024	– 7.2595	2.6	4150
	(0.0034)[a]	(0.0471)[a]	(0.0645)[a]		
	[0.0119]	[0.2932][a]	[0.4044][a]		
	0.0392			7.8	
	(0.0039)[a]	—	—		—
	[0.0112][a]				
Male sample	0.0150	4.9624	– 7.2360	3.0	8384
	(0.0036)[a]	(0.0550)[a]	(0.0758)[a]		
	[0.0105]	[0.2559][a]	[0.3670][a]		
	0.0396			7.9	
	(0.0042)[a]	—	—		—
	[0.0092][a]				
Female sample	– 0.0103	5.3050	– 7.3212	– 2.1	6747
	(0.0100)	(0.0885)[a]	(0.1217)[a]		
	[0.0316]	[0.5492][a]	[0.7330][a]		
	0.0095			1.9	
	(0.0108)	—	—		—
	[0.0369]				
Blue-collar male sample	0.0311	4.0809	– 5.6948	6.2	7518
	(0.0034)[a]	(0.0692)[a]	(0.0938)[a]		
	[0.0083][a]	[0.2756][a]	[0.4000][a]		
	0.0485			9.7	
	(0.0040)[a]	—	—		—
	[0.0081][a]				
Blue-collar female sample	0.0610	2.0362	– 2.5713	12.2	31,830
	(0.0147)[a]	(0.1559)[a]	(0.2087)[a]		
	[0.0162][a]	[0.2725][a]	[0.3681][a]		

continued

TABLE 3 continued

	Coefficients (Robust SE) [Robust and Clustered SE]				
	Death Risk	Injury and Illness Rate	Expected Workers' Compensation Replacement Rate	Value of Life ($ millions)	Value of Injury or Illness ($)
	0.0774 (0.0160)[a] [0.0180][a]	—	—	15.5	—
1997 death risk					
Full sample	0.0123 (0.0029)[a] [0.0097]	5.1029 (0.0471)[a] [0.2933][a]	– 7.2608 (0.0645)[a] [0.4045][a]	2.5	4068
	0.0316 (0.0033)[a] [0.0093][a]	—	—	6.3	—
Male sample	0.0134 (0.0031)[a] [0.0089]	4.9630 (0.0551)[a] [0.2560][a]	– 7.2376 (0.0758)[a] [0.3670][a]	2.7	8286
	0.0317 (0.0036)[a] [0.0082][a]	—	—	6.3	—
Female sample	0.0030 (0.0083) [0.0238]	5.3021 (0.0885)[a] [0.5489][a]	– 7.3209 (0.1217)[a] [0.7330][a]	0.6	6210
	0.0136 (0.0085) [0.0273]	—	—	2.7	—
Blue-collar male sample	0.0243 (0.0031)[a] [0.0075][a]	4.0830 (0.0693)[a] [0.2760][a]	– 5.7004 (0.0938)[a] [0.3996][a]	4.9	7143
	0.0389 (0.0036)[a] [0.0076][a]	—	—	7.8	
Blue-collar female sample	0.0488 (0.0122)[a] [0.0140][a]	2.0511 (0.1560)[a] [0.2738][a]	– 2.5862 (0.2089)[a] [0.3699][a]	9.8	32,635
	0.0613 (0.0132)[a] [0.0155][a]	—	—	12.3	—

[a]Indicates statistical significance at the 99% confidence level, two-tailed test.
[b]Indicates statistical significance at the 95% confidence level, two-tailed test.
[c]Indicates statistical significance at the 90% confidence level, two-tailed test.

The marginal wage offset falls short of the wage reduction that would imply an optimal level of benefits. Taken at face value, these estimates would imply that the level of workers' compensation benefits is above the efficient insurance amount. Moore and Viscusi (1990) found a somewhat higher rate of trade-off, implying that workers' compensation was more than self-financing.[21] However, those results reflect a different era of workers' compensation.

21. The equation estimated here also differed in other ways, such as inclusion of a fatality risk variable.

Beginning in the late 1980s, many states enacted reforms that altered the structure of benefits and also reduced workers' compensation costs from $31 billion in premiums written in 1990 to $22 billion in 1999.[22]

Table 3 summarizes the risk coefficients from a series of specifications using alternative fatality risk measures. Other variables included in the analysis are the same as in Table 2. The implicit value of life based on equation (1) is

$$(4)\ \textit{Implicit Value of Life} = \partial \textit{Wage} / \partial \textit{Death Rate} = \textit{Wage}\gamma_1.^{23}$$

The first row reports coefficients from the full sample in Table 2. The implied value of life based on these estimates is $4.7 million. The value-of-life estimates are net of the value of income support provided through workers' compensation so that the value of fatal injuries would be greater in the absence of social insurance. Similarly, the implicit value of a job injury is $9570 for the full sample and $12,226 for blue-collar males. These estimates fall near the low end of the range of estimates of the implicit value of injury in the literature.[24] However, most of these studies of nonfatal risk premiums omitted the fatality risk variable from the wage equation, thus boosting the estimated injury coefficient.

The second row of full sample estimates in panel A of Table 3 omits the two nonfatal risk variables and includes only the fatality rate. Doing so boosts the estimated value of life to $8.9 million.[25] This equation is more comparable to that used in previous studies in that the only job risk variable included pertains to fatalities.

The second set of results in panel A of Table 3 parallels those in the upper part of the table except that the fatality risk variable is based solely on fatalities that occurred in 1997. The subsequent imprecision in the risk variable will lead to lower estimated values of life if the error in the variable is random. The consequence is somewhat lower estimated coefficients for fatality risk, thus reducing the estimated value of life.

Panel B in Table 3 reports estimates for which the worker's wage is the dependent variable rather than its natural log. The value-of-life estimates for the full sample are $2.6 million with the full set of risk variables and $7.8 million when only the fatality risk is included.

For each of these sets of results, Table 3 also includes comparable estimates for various male and female subsamples. Males as a group have estimated implicit values of life ranging from $2.7 million to $4.9 million for equations including injury variables, and $6.3 million to $9.1 million for the fatality risk–only specification. However, these estimates are sometimes not statistically significant at the 95% level based on the robust and clustered standard errors.

The estimates for blue-collar males are of particular interest because these are the first estimates for such a subsample in which the job risk variable has been constructed to be pertinent to blue-collar workers rather than being a measure of overall industry risk for all workers. The results for blue-collar males are consistently significant at the 99% level, and they yield higher estimated values of life. Estimates for the blue-collar male subsample reported in Table 3 range from $4.9 million to $7.0 million for equations including all risk-related variables. With only the fatality risk variable included, the implicit values of life for the blue-collar male samples range from $7.8 million to $9.7 million.

Somewhat surprisingly, the implicit value of life estimates are more evident for blue-collar males than the full sample of males even though the risk measures reflect both the worker's occupation and industry. On a theoretical basis, more affluent workers should exhibit higher wage-risk trade-offs, but empirically it may be that workers in risky white-collar jobs are less productive or have other characteristics that make it difficult to disentangle such effects. Estimates for the white-collar male subsample, which are not reported, yield negative coefficients for the fatality risk variable. Because these estimates focus on only male workers, gender differences do not account for the effect. Moreover, the implicit values of lost workday job injuries for the full male

22. See p. 82 of Insurance Information Institute (2001).

23. This equation was multiplied by 200,000,000 to annualize the wages (assuming 2000 hours worked per year) and to take into account the fact that the death risk measure is per 100,000 workers.

24. These findings for injuries are surveyed by Viscusi (1992; 1993) and Viscusi and Aldy (2003).

25. If instead, the injury variable had been retained but not the workers' compensation variable, the value of life would be $8.4 million.

sample are only marginally greater than the values for the blue-collar male subsample, whereas one might have expected greater valuations. Both the fatality risk variable and the lost workday risk variable generate results that reflect a similar departure from theoretical predictions in this regard.

Estimates for the female subsamples are remarkably similar to those for the males. The full sample females results do not yield positive and statistically significant premiums for fatality risks, but there are significant premiums for lost workday injuries, as in Hersch (1998).

Because few white-collar females are exposed to fatality risks, the blue-collar female results are more instructive. In every instance, blue-collar females exhibit positive and significant premiums for fatal and nonfatal risks of the job. Interestingly, the point estimates of the magnitudes of the wage-risk trade-offs are higher for female blue-collar workers than their male counterparts, as is evidenced by the somewhat higher implicit values of life and implicit values of injury for the blue-collar females. For the equations including all three risk-related variables, female blue-collar workers have implicit values of life ranging from \$7.0 million to \$12.2 million; with the injury-related variables excluded, the estimates range from \$8.8 million to \$15.5 million. The degree to which females exhibit a higher implicit value for lost workday injuries, as compared to their male blue-collar counterparts, is even greater than the implicit value of life disparity.

V. VALUE-OF-LIFE ESTIMATES: FATALITY RISKS BY INDUSTRY

To provide a comparable reference point for the consequences of moving from an industry level of aggregation for fatality risk data to data that are available by both occupation and industry, I will use the same CPS data set except that the fatality risk measure will not be permitted to vary by occupation. Thus the job risk measure will be comparable to the marginal values along the bottom row in the panels in Table 1 except that the level of aggregation is for 72 industries rather than only 9 industries.

The value-of-life estimates by occupation and industry provide a more precise match to the actual risk of a worker's job than if only the influence of the worker's industry was considered. Using the CFOI data taking into account only the worker's industry makes it possible to examine the incremental effect of considering occupational variations in job riskiness. If the errors-in-variables problem arising from moving to the industry level of aggregation involves random errors, the industry-based value-of-life estimates should be lower. The results do not indicate such a relationship, implying that taking into account occupational differences may have important systematic effects as well.

Table 4 summarizes empirical estimates that follow the same structure as did those in Table 3 except for the use of the industry-based fatality rate. Here the clustered standard errors reflect clustering only by industry rather than by industry and occupation. The estimated value of life for the full sample with all the risk variables included is \$10.0 million with the log wage equation and \$8.3 million with the wage equation. If the nonfatal risk and workers' compensation variables are omitted, these values rise to \$14.5 million for log wage and \$13.7 million for the wage equation. Thus these estimates are greater than those generated by fatality risks by occupation and industry.

Because the industry-based measure excludes occupational differences, one might have expected the results for the overall male and female samples to be less consistently significant. However, the fatality risk coefficients in Table 4 display higher levels of statistical significance for most of the male sample results as well as positive effects that are often significant for the female sample, where levels of significance vary depending on the type of standard error. In contrast, the statistical significance of the results in Table 4 for blue-collar females is consistently lower with the industry-based measure. Recognition of occupational differences in job risks is most pertinent to the context in which female workers are exposed to fatality risks, which is blue-collar jobs.

Estimated values of life for the full equation for blue-collar males are \$9.3 million (semi-logarithmic form) and \$8.6 million (linear wage equation). Including only the fatality risk measure of the three risk-related variables boosts the value of life to \$12.7 million and \$12.6 million, respectively. The comparable estimates for female blue-collar workers for the full equation are \$6.7 million (semi-logarithmic form) and \$11.5 million (linear

TABLE 4
Regression Results for Industry Death Risk Measure

	Coefficients (Robust SE) [Robust and Clustered SE]				
	Death Risk	**Injury and Illness Rate**	**Expected Workers' Compensation Replacement Rate**	**Value of Life ($ millions)**	**Value of Injury or Illness ($)**
A: ln*(Wage) equation results*					
1992–97 death risk					
Full sample	0.0036	0.2677	−0.3806	10.0	3571
	(0.0003)[a]	(0.0025)[a]	(0.0034)[a]		
	[0.0011][a]	[0.0265][a]	[0.0381][a]		
	0.0052			14.5	
	(0.0003)[a]	—	—		—
	[0.0014][a]				
Male sample	0.0032	0.2603	−0.3793	9.7	7218
	(0.0003)[a]	(0.0029)[a]	(0.0040)[a]		
	[0.0010][a]	[0.0255][a]	[0.0382][a]		
	0.0048			14.6	
	(0.0003)[a]	—	—		—
	[0.0012][a]				
Female sample	0.0035	0.2825	−0.3897	8.7	4786
	(0.0005)[a]	(0.0047)[a]	(0.0064)[a]		
	[0.0022]	[0.0327][a]	[0.0448][a]		
	0.0041			10.2	
	(0.0006)[a]	—	—		—
	[0.0022][c]				
Blue collar male sample	0.0036	0.2283	−0.3178	9.3	6900
	(0.0003)[a]	(0.0038)[a]	(0.0050)[a]		
	[0.0009][a]	[0.0184][a]	[0.0267][a]		
	0.0049			12.7	
	(0.0004)[a]	—	—		—
	[0.0009][a]				
Blue-collar female sample	0.0037	0.1323	−0.1599	6.7	28,031
	(0.0014)[a]	(0.0108)[a]	(0.0142)[a]		
	[0.0025]	[0.0177][a]	[0.0240][a]		
	0.0071			12.8	
	(0.0014)[a]	—	—		—
	[0.0026][a]				
1997 death risk					
Full sample	0.0035	0.2676	−0.3806	9.8	3292
	(0.0002)[a]	(0.0025)[a]	(0.0034)[a]		
	[0.0011][a]	[0.0264][a]	[0.0381][a]		
	0.0050			14.0	
	(0.0003)[a]	—	—		—
	[0.0015][a]				
Male sample	0.0032	0.2601	−0.3794	9.7	6404
	(0.0003)[a]	(0.0029)[a]	(0.0040)[a]		
	[0.0009][a]	[0.0253][a]	[0.0383][a]		
	0.0046			14.0	
	(0.0003)[a]	—	—		—
	[0.0012][a]				

continued

TABLE 4 continued

	Coefficients (Robust SE) [Robust and Clustered SE]				
	Death Risk	Injury and Illness Rate	Expected Workers' Compensation Replacement Rate	Value of Life ($ millions)	Value of Injury or Illness ($)
Female sample	0.0034	0.2824	−0.3896	8.5	4716
	(0.0005)[a]	(0.0047)[a]	(0.0064)[a]		
	[0.0021]	[0.0328][a]	[0.0448][a]		
	0.0041			10.2	
	(0.0005)[a]	—	—		—
	[0.0022][c]				
Blue-collar male sample	0.0037	0.2282	−0.3180	9.6	6273
	(0.0003)[a]	(0.0038)[a]	(0.0050)[a]		
	[0.0008][a]	[0.0182][a]	[0.0266][a]		
	0.0048			12.4	
	(0.0004)[a]	—	—		—
	[0.0009][a]				
Blue-collar female sample	0.0042	0.1318	−0.1596	7.6	27,526
	(0.0014)[a]	(0.0108)[a]	(0.0142)[a]		
	[0.0023][c]	[0.0176]	[0.0240][a]		
	0.0075			13.5	
	(0.0014)[a]	—	—		—
	[0.0024][a]				
B: *Wage equation results*					
1992–97 death risk					
Full sample	0.0413	5.0682	−7.2501	8.3	−1374
	(0.0036)[a]	(0.0472)[a]	(0.0643)[a]		
	[0.0138][a]	[0.4992][a]	[0.7161][a]		
	0.0687			13.7	
	(0.0044)[a]	—	—		—
	[0.0206][a]				
Male sample	0.0371	4.9325	−7.2288	7.4	3383
	(0.0042)[a]	(0.0552)[a]	(0.0756)[a]		
	[0.0128][a]	[0.4774][a]	[0.7156][a]		
	0.0647			12.9	
	(0.0052)[a]	—	—		—
	[0.0189][a]				
Female sample	0.0495	5.2676	−7.3176	9.9	−214
	(0.0072)[a]	(0.0884)[a]	(0.1216)[a]		
	[0.0247][b]	[0.6456][a]	[0.8839][a]		
	0.0553			11.1	
	(0.0080)[a]	—	—		—
	[0.0279][c]				
Blue-collar male sample	0.0430	4.0599	−5.6993	8.6	2679
	(0.0046)[a]	(0.0696)[a]	(0.0939)[a]		
	[0.0110][a]	[0.3485][a]	[0.5070][a]		
	0.0632			12.6	
	(0.0056)[a]	—	—		—
	[0.0124][a]				

continued

TABLE 4 continued

	Coefficients (Robust SE) [Robust and Clustered SE]				
	Death Risk	**Injury and Illness Rate**	**Expected Workers' Compensation Replacement Rate**	**Value of Life ($ millions)**	**Value of Injury or Illness ($)**
Blue-collar female sample	0.0573 (0.0175)[a] [0.0284][b]	2.0302 (0.1563)[a] [0.2758][a]	−2.5846 (0.2089)[a] [0.3744][a]	11.5	28,688
	0.0941 (0.0180)[a] [0.0284][a]	—	—	18.8	—
1997 death risk					
Full sample	0.0399 (0.0036)[a] [0.0140][a]	5.0680 (0.0472)[a] [0.4984][a]	−7.2509 (0.0643)[a] [0.7163][a]	8.0	−1526
	0.0650 (0.0042)[a] [0.0215][a]	—	—	13.0	—
Male sample	0.0366 (0.0042)[a] [0.0129][a]	4.9315 (0.0552)[a] [0.4756][a]	−7.2295 (0.0756)[a] [0.7156][a]	7.3	3088
	0.0614 (0.0050)[a] [0.0199][a]	—	—	12.3	—
Female sample	0.0471 (0.0069)[a] [0.0242][c]	5.2677 (0.0884)[a] [0.6464][a]	−7.3172 (0.1215)[a] [0.8842][a]	9.4	−137
	0.0532 (0.0076)[a] [0.0275][c]	—	—	10.6	—
Blue-collar male sample	0.0434 (0.0046)[a] [0.0106][a]	4.0590 (0.0694)[a] [0.3461][a]	−5.7015 (0.0938)[a] [0.5068][a]	8.7	2187
	0.0607 (0.0054)[a] [0.0134][a]	—	—	12.1	—
Blue-collar female sample	0.0604 (0.0166)[a] [0.0273][b]	2.0258 (0.1563)[a] [0.2749][a]	−2.5830 (0.2090)[a] [0.3743][a]	12.1	28,042
	0.0958 (0.0169)[a] [0.0274][a]	—	—	19.2	—

[a]Indicates statistical significance at the 99% confidence level, two-tailed test.
[b]Indicates statistical significance at the 95% confidence level, two-tailed test.
[c]Indicates statistical significance at the 90% confidence level, two-tailed test.

form). Restricting the risk variable to only the fatality risk variable leads to values of $12.8 million and $18.8 million for these two sets of results.

The lower portions of panels A and B of Table 4 report the results including only fatalities from 1997 in the fatality rate variable. These estimates yield very similar estimates of the value of life compared to the results for which the risk variable is calculated using fatalities from 1992 to 1997.

VI. CONCLUSION

Estimates of the value of life vary considerably once differences in occupational risk within industry are recognized. For the full sample log wage equations, the value of life is \$4.7 million (or \$5.0 million in year 2000 dollars) based on occupation and industry risk and \$10.0 million (or \$10.7 million in year 2000 dollars) based solely on industry risk. Blue-collar males have higher values in each instance, of \$7.0 million (or \$7.5 million in year 2000 dollars) for occupation-industry risks and \$9.3 million (or \$10.0 million in year 2000 dollars) for industry risks. Blue-collar females likewise receive significant premiums for fatality risk, with a value of life of \$8.5 million (or \$9.1 million in year 2000 dollars) for occupation-industry risks and \$6.7 million (or \$7.2 million in year 2000 dollars) for industry risks.

The measurement error due to industry level aggregation does not appear to be random. The value-of-life estimates tend to be reduced by recognizing occupational variations in job riskiness. Estimating the value of life using only CFOI data by worker industry roughly doubles the estimated value of life for the full sample, implying that the errors arising from occupational aggregation are not the classical random errors.

The occupation-industry risk variable proved to be especially influential in making it possible to estimate significant fatality risk coefficients for female blue-collar workers. Previous studies have often restricted the sample to male blue-collar workers, with a notable exception being the analysis of nonfatal injuries by Hersch (1998). More refined risk measures yield significant fatality risk premiums for women as well as men, where the magnitude of the wage-risk trade-offs are comparable.

However, notwithstanding the greater refinement of the occupational-industry risk measure, estimates for the full sample of male workers and female workers did not perform as satisfactorily in two respects. First, particularly for females, the fatality risk coefficients had mixed signs and were not statistically significant. Second, even for males, the wage-risk trade-offs for the full male subsample were not higher than the implicit values for blue-collar workers, whereas in theory workers self-selecting into blue-collar jobs should have a lower value of life.

The additional refinement made possible by use of the CFOI mortality data yields job risk measures more pertinent to the worker's job and yielded more consistently significant value-of-life estimates than in the previous literature. Results remained statistically significant across different specifications of the wage equations. These equations also included statistically significant coefficients for both the nonfatal lost workday injury and illness rate and the expected workers' compensation replacement rate. Even with the inclusion of these variables, the fatality risk variable remained statistically significant even when judged using standard errors that recognize the effects of the clustering of the risk measure at the occupation and industry level. What these results suggest is that the lack of robustness of evidence of compensating differentials for job risks may have stemmed in part from deficiencies in the job risk measure rather than underlying shortcomings of the economic theory.

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