Doubling the Estimated Value of Life: Results Using New Occupational Fatality Data

Michael J. Moore
and
W. Kip Viscusi

Abstract

Using a new series of data on occupational fatalities compiled by the National Institute for Occupational Safety and Health, the authors reassess value-of-life calculations based on labor market tradeoffs between fatality risks and wages. The new data are less subject to the problems of measurement error that plague previously used measures of risk. They indicate higher risk levels than previously believed and a significantly different composition of risk levels within industries. The more comprehensive risk data yield value-of-life estimates of $5 million or more—at least twice as large as estimates obtained using the Bureau of Labor Statistics risk data employed in previous studies.

INTRODUCTION

One very prominent and controversial application of benefit assessment is the valuation of policies that reduce the risks to human life.[1] From a conceptual standpoint, the task of valuing life is no different from that of any other public policy. The appropriate benefit measure for a safety-enhancing policy is society's willingness to pay for the expected number of lives that are extended as a result of the policy.[2]

Policy analysts typically estimate the value of life from labor markets because the availability of information on risks in labor markets and the associated wage rates that workers receive enable estimation of the market-generated wage-risk tradeoff. Analysts interpret the observed market tradeoff between dollars and mortality risk as an indication of the compensation a worker would forgo for a reduction in risk. They then statistically extrapolate to generate the dollar value of life. Almost without exception, labor-market studies of the value of life utilize risk measures based on U.S. Bureau of Labor Statistics (BLS) death-risk data.[3]

The accuracy of the estimates obtained using this approach has recently been called into question by the release of a new and much more refined data series on occupational death risks. In order to provide a more reliable

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statistical basis for assessing job-related deaths, the National Institute of Occupational Safety and Health (NIOSH) initiated its own occupational death statistic system. The first set of death statistics, which was released in 1987, implied that the overall number of deaths experienced by workers was 84 percent greater than was indicated by the BLS data. More importantly, as the comparisons presented in this article indicate, the bias in reported deaths is not uniform—as most industry risks are above the BLS levels, but by differing amounts, while two major industry groups have a risk level in the NIOSH data that is below the BLS risk. Such an extensive revamping of the death-rate statistics potentially undermines the validity of the value-of-life estimates generated using BLS risk data. At the very least, there is a need for a fundamental reexamination of the value-of-life results.

The focus of this article is on exploring the implications of this new risk data series for labor market estimates of the value of life. Will statistically significant risk-dollar tradeoffs still be observed, and how will they differ from estimates obtained using BLS data? In the next section we discuss the data base used to explore these issues, and provide a detailed comparison of the NIOSH and BLS risk data that represent the pivotal components of the analysis. We then report wage equation estimates using the new occupational death data, as well as comparable equations using BLS risk data. The reassuring aspect of the results is that there is a powerful and statistically significant positive relationship between job risks and worker wages. The magnitude of this tradeoff is, however, substantially underestimated by use of the BLS data. Our estimates indicate that use of the more accurate risk measure approximately doubles the estimated value of life.

THE SAMPLE AND THE VARIABLES

The basic building block for the empirical analysis is a large set of data on worker wages and characteristics of individual workers that provides the basis for relating wages to NIOSH data for workers in different states and industries. Several employment data sets could serve this function adequately. For purposes of this study we selected the 1982 wave of the University of Michigan Panel Study of Income Dynamics (PSID). The PSID is a widely used national survey of employment patterns for which we can select a survey year that is appropriate for both the NIOSH and the BLS risk data, because the PSID survey is repeated annually. The 1982 wave of the PSID summarizes the work experiences of workers in 1981. This wave of the PSID covers the only year that is included in both of the fatality risk measures used below and is consequently most appropriate for estimation purposes.

The PSID includes a random sample of families and a nonrandom group of families who were selected because their incomes fell below a prespecified poverty line. To maintain the representativeness of our sample, this latter group is excluded from the sample we use in our estimation. Also excluded are workers for whom no death-risk data are available—principally farmers and farm managers and government employees. We also excluded nonhousehold heads and blacks because intermittent labor supply and the influence of racial discrimination may distort estimates of the wage equations for these groups. The remaining sample contains 1,349 complete observations.

Table 1. Variable definitions.

WAGE	Hourly after-tax wage.
AGE	Age in years.
EXPERIENCE	Years worked since age 16.
FEMALE	Sex indicator variable (i.v.): 1 if worker is female, 0 otherwise.
EDUCATION	Years of schooling.
HEALTH	Health limitations i.v.: 1 if worker has a physical or nervous health condition that limits the amount of work he can do, 0 otherwise.
BLUE	Occupation i.v.: 1 if worker is in a blue-collar occupation, 0 otherwise.
UNION	Union membership i.v.: 1 if worker's job is covered by a collective bargaining agreement, 0 otherwise.
NCENT	Region i.v.: 1 if worker lives in North Central United States, 0 otherwise.
SOUTH	Region i.v.: 1 if worker lives in Southeastern United States, 0 otherwise.
WEST	Region i.v.: 1 if worker lives in Western United States, 0 otherwise.
FATAL1	NTOF death-rate variable. Number of fatal accidents per 100,000 workers.
FATAL2	BLS death rate variable. Number of fatal accidents per 100,000 workers.
DEATHCOMP	Workers' compensation fatality benefits replacement rate. Predicted value from first-stage regression.

The general approach in this study, as in the literature, is to regress the worker's wage or its natural logarithm on a series of explanatory variables including the worker's personal characteristics, job characteristics, and risk level. An accurate assessment of the wage-risk tradeoff must hold these nonrisk characteristics constant in measuring the effect of changes in death risk on the wage. The coefficient of the death-risk variable then yields the risk-dollar tradeoff that is used to calculate the implied value of life. This value represents the value of a statistical life based on the rate of tradeoff implied by the amount workers require as compensation for exposure to small risks of death.

One can view such estimates in either of two ways. First, the estimated value of life represents the total amount of compensation that a group of workers requires to face a job that is expected to kill one additional worker. Second, it represents the compensation required per unit risk that is faced, so that the rate of tradeoff that is estimated for small risks is used to provide an index of the tradeoff society should have when dealing with larger-scale risk reduction policies.

Table 1 summarizes the definitions of variables used in the empirical analysis. The dependent variable is WAGE, the worker's after-tax hourly wage, or lnWAGE, its natural logarithm. The PSID included either an hourly wage variable or information that could be used to construct an hourly wage so that it was not necessary to use annual earnings as a proxy for wages, which was necessary in some of the earlier studies in this area. A more novel aspect of our formulation is the tax adjustment of wages. This adjustment is not common in the compensating differential literature, despite the fact that it is the theoretically appropriate measure, because it is the after-tax wage that drives worker behavior. In those studies that have adjusted for taxes, such as our two earlier analyses, use of the after-tax wage led to significant changes in the results.[4]

The explanatory variables that we included as regressors to control for the wage variation that is not due to variation in risk are fairly standard in studies of this type. These include human capital variables for years worked since age 16 (EXPERIENCE), years of schooling (EDUCATION), and a dichotomous variable indicating whether the worker has a health impairment (HEALTH). Also included are job-related variables indicating whether the worker's job is covered by a collective bargaining agreement (UNION) and whether he works in a blue-collar occupation (BLUE). Finally, regional indicator variables for residence in the North Central (NCENT), Southeastern, (SOUTH), or Western (WEST) United States are included to capture regional differences in wages.

One limitation of many earlier analyses has been the failure to control for the facility insurance provided by the workers' compensation system. If compensating differentials for death risks reflect, in part, protection against financial losses and medical expenses due to injury, as seems plausible, then state-provided earnings and medical insurance for such injuries are necessarily related to these differentials. Failure to control for this *ex post* component of compensation for risk will bias regression estimates of the compensating wage increase and, therefore, of the value of life. In those studies that have incorporated these effects, the workers' compensation system has proven to play a fundamental role in altering wage-risk tradeoffs.[5]

The impact of the workers' compensation system is captured by including the variable DEATHCOMP, which is a measure of the annuity provided by workers' compensation. This variable is also intended to serve as a proxy for other forms of workers' compensation benefits, including medical coverage and earnings replacement for nonfatal injuries. The DEATHCOMP variable is similar to that used in Viscusi and Moore, where the role of insurance for nonfatal injuries is analyzed.[6] DEATHCOMP is a first-stage regression estimate of the annual replacement rate of after-tax wages by fatality insurance benefits (b): DEATHCOMP = b/WAGE.[7]

Table 2 summarizes the descriptive statistics for these variables. The sample is broadly representative of the working population. The average worker has a high-school degree, 12 years of experience, and is 37 years old. Approximately half of the sample members hold blue-collar jobs, and 30 percent are covered by union contracts. The relatively small proportion of women (FEMALE) is common in studies of this kind, and is due primarily to the restriction of the sample to household heads.

THE DEATH-RISK VARIABLES

To establish the worker's death risk, one must link workers to death-risk measures based on the worker's reported industry. The death-risk data most often used for this task, the BLS occupational facility data, are measured only at highly aggregative levels and do not allow a precise matching of risk exposure on the job to individual workers. The BLS data are estimated based on a survey of occupations, so that some sampling error is also present in the

Table 2. Selected sample characteristics. Means and standard deviations.[a]

WAGE (in dollars)	7.010 (2.416)
AGE (in years)	37.142 (11.605)
EXPERIENCE (in years)	11.906 (10.565)
FEMALE (i.v.)	0.154 (0.361)
EDUCATION (in years)	12.984 (2.504)
HEALTH (i.v.)	0.072 (0.258)
BLUE (i.v.)	0.518 (0.500)
UNION (i.v.)	0.285 (0.451)
FATAL1 (deaths/100,000 with NTOF data)	7.918 (9.737)
FATAL2 (deaths/100,000 with BLS data)	5.209 (10.178)
DEATHCOMP	0.544 (0.190)

[a] The sample size is 1349.

data. The BLS data used in this article were obtained from unpublished statistics available at the U.S. Bureau of Labor Statistics office. Industry death rates were available at the two-digit Standard Industrial Classification (SIC) code level, and we averaged these death statistics over the 1972–1982 period to remove the distortions that arise because of the effects of catastrophic accidents in any particular year.

To provide a sounder statistical basis for assessing death risks, NIOSH has collected data on occupational fatalities as part of its National Traumatic Occupational Fatality (NTOF) project. The NTOF data differ from the BLS data in several important ways. Most importantly, a partial sample is not used to project national death risks. Rather, the NTOF data are based on a census of all occupational fatalities recorded on death certificates during the years 1980–1985, so that no sampling error is present in the data. The mix of injuries covered is also more extensive, as the NTOF data include all work-related traumatic fatalities. The types of fatal injuries covered include industrial accidents (e.g., slips and falls), fire-related deaths, homicides, and suicides. 84 percent of the recorded deaths were due to unintentional injuries, 13 percent resulted from homicides, and 3 percent were suicides. Although it is unlikely that suicides are a component of job risks for which workers will receive compensation, they constitute a very small portion of the sample and should not affect the results significantly. The NTOF data are classified by state and by one-digit SIC industry code, yielding 450 distinct observations of the death risk faced by workers. This state-specific aspect of the data, in particular, makes possible a more precise match of the death risk with the measure of death insurance benefit (DEATHCOMP) than is possible with available BLS data.

Two striking empirical differences in the perspectives on job risks are provided by a comparison of the BLS data and the NTOF data. The first is in the overall riskiness of the job. The BLS reports 3,750 occupational fatalities in 1984, with similar magnitudes reported for adjacent years. The NTOF system, on the other hand, recorded average annual deaths of 6,901 for the period 1980–1984, which is 84 percent larger, or almost double the risk measured by the BLS.

In constructing our measures of the death risk, we assign the NTOF data to workers by reported state of residence and industry, and assign the BLS data only by industry. The mean NTOF death risk (FATAL1) is 7.9 deaths per 100,000 workers, while the average fatality rate reported in the BLS (FATAL2) is 5.2 per 100,000 workers, so that for the particular mix of workers in our sample the NTOF risk levels exceed the BLS risk by over 50 percent. There is also substantial variation in the risk, as the standard deviations of FATAL1 and FATAL2 are at least 1.5 times greater than their means.

The understatement of death risks in the BLS measure has a direct impact on the value of life calculations. Systematic understatement of death risks by a factor of about two will cause regression-based value of life estimates to roughly double in magnitude. This is due to the nature of value-of-life calculations based on regression estimates. If the death-risk measure is cut in half, its associated regression coefficient, which provides the basis of the calculation, is doubled.

This bias assumes, of course, that worker behavior is governed by the true death risks rather than the death statistics published by BLS. In particular, suppose that the true risk level is equal to the NTOF measure, so that the average of the true death risk is 7.9 deaths per 100,000 workers. Using the wage-risk tradeoff that we estimate below (i.e., a 0.4 percent increase in wages per unit increase in risk), a doubling of the true risk to 15.8 deaths per 100,000 workers would yield an increase in the hourly wage of 22 cents, evaluated at the sample mean wage of $7 per hour. If the risk level observed by the researcher is given by the BLS measure, however, it will appear that the 22-cent increase was generated by a risk increase of only 5.2 deaths, or double the mean BLS risk. This observed tradeoff would then imply an estimated wage-risk tradeoff of 0.6 percent, which is roughly 1.5 times as large as the true tradeoff, and value-of-life estimates based on the observed tradeoff are overstated by 50 percent.

This result derives from the fact that, by introducing the smaller observed risk with no change in the true underlying risk, the estimated wage-risk tradeoff must rise. If, on the other hand, worker perceptions of risks are equal to the published statistics, introduction of the new risk information will increase wages also, and there will be no change in the observed wage-risk tradeoff. This latter case does not appear likely. The BLS publishes death rates only at the one-digit level and does not publicize these figures. It is highly unlikely that worker perceptions have been distorted by the available BLS statistics.

Nevertheless, the relationship of workers' risk perceptions to the two death-risk measures is a central issue for interpreting the empirical results linking the objective risk measures and workers' wages. The available evidence suggests that workers utilize diverse forms of information in a

Table 3. Industry risk comparison. Means and standard deviations.

		Fatalities per 100,000 workers	
	No. of observations	NTOF	BLS
Mining	25	40.010	18.736
		(19.977)	(4.932)
Construction	108	32.738	28.698
		(6.253)	(16.450)
Manufacturing	503	4.369	1.503
		(2.852)	(1.391)
Transportation, Communications and Public Utilities	164	20.244	10.702
		(9.806)	(12.442)
Wholesale Trade	59	2.233	2.658
		(0.120)	(0.584)
Retail Trade	149	3.176	2.020
		(0.905)	(1.122)
Finance, Insurance and Real Estate	62	2.348	4.030
		(0.184)	(2.283)
Services	279	3.428	0.866
		(1.498)	(0.679)
Total	1349	7.918	5.209
		(9.737)	(10.178)

reasonable fashion to form their risk judgments.[8] Although there are no available data on workers' perception of fatality risks, overall assessments of nonfatal risk levels follow expected patterns. In particular, workers' risk perceptions are strongly correlated with BLS nonfatal injury risk measures and are influenced in the expected manner by opportunities for learning on the job. These influences include having experienced an injury oneself, hearing of injuries to other workers, seeing hazard warning signs, and observing whether the physical conditions at the workplace are pleasant.

Comparable data are not available to assess the extent to which there is a correspondence between subjective risk perceptions and actual risk levels for risks of fatality. It is, however, noteworthy that fatality risks are several orders of magnitude smaller than nonfatal risks. To the extent that there is any systematic bias in risk perceptions it is that individuals generally display a tendency to overestimate small probabilities and underestimate large probabilities. Any perceptual bias is likely to increase the validity of the NTOF risk measure as a reflection of workers' risk perceptions since these risk levels are larger than those reflected in the BLS measure. To the extent that workers have sound assessments of the risk level, which is the basic underlying assumption in the compensating differential literature, use of the more accurate NTOF risk variable should enhance the reliability of the empirical estimates.

Table 3 presents an industry-specific comparison of the two risk measures. As anticipated, the NTOF data usually yield a higher average risk level within industries. The most extreme relative difference in the risk levels is for services, where the NTOF risk level is almost four times as great as the BLS risk level. In the most representative industry–manufacturing—the NTOF-

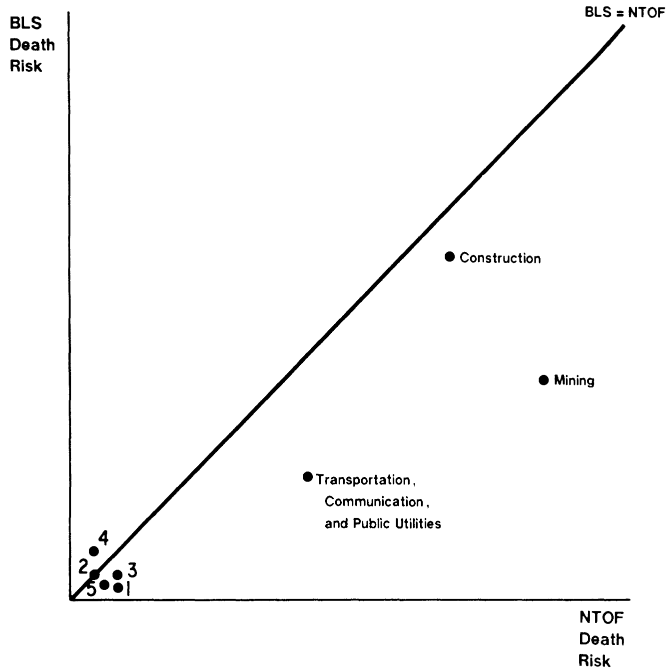

Figure 1. The relationship between BLS and NTOF measures of death risk, by one-digit SIC industry. (1) Manufacturing. (2) Wholesale trade. (3) Retail trade. (4) Finance, insurance, and real estate. (5) Services.

based fatality risk measure is almost three times as large as its BLS counterpart. The differences are narrower in the case of the construction industry, for which there is only a 14-percent discrepancy. A somewhat different pattern is in evidence in two of the white-collar industries, wholesale trade and finance, insurance, and real estate. In those instances, the BLS risk level is somewhat greater.

The statistics in Table 3 illustrate the second key difference between the two data sources. The BLS statistics do not differ from the NTOF data by a simple scale factor. Rather, the extent of the bias varies substantially across industries. Thus, in opposition to the scale factor bias documented above, there consequently is a substantial random measurement error in the BLS death risk variable that will bias past estimates of the value of life downward and also render the estimates less precise.

Figure 1 depicts the within industry risk differences graphically. If the two risk measures are identical, the BLS/NTOF industry risk pairs pictured in Figure 1 will lie on the 45° line BLS = NTOF. Likewise, if the NTOF risk is larger by a simple scale factor, the risk pairs will lie approximately on a straight line below BLS = NTOF. Because neither of these conditions hold, the presence of random measurement error in the BLS data is indicated.

One potential cause of the error portrayed in Figure 1 is the difference in the data-collection methodologies. The NTOF data are based on a census of occupational fatalities, while the BLS conducts a survey and uses the results to predict fatalities in industries. Whether the impact of the reduced measurement error on the estimated value of life offsets the scale factor bias,

Table 4. lnWAGE regression results;[a] coefficients (standard errors).

	Estimates using NTOF risk measures	Estimates using BLS risk measures
EXPERIENCE	0.028[b]	0.028[b]
	(0.003)	(0.003)
$EXPERIENCE^2$	−6.0E-4	−5.9E-4[b]
	(0.8E-4)	(0.8E-4)
FEMALE	−0.288[b]	−0.293[b]
	(0.024)	(0.024)
EDUCATION	0.044[b]	0.044[b]
	(0.004)	(0.004)
HEALTH	−0.079[b]	−0.082[b]
	(0.032)	(0.032)
BLUE	−0.064[b]	−0.061[b]
	(0.021)	(0.021)
UNION	0.182[b]	0.191[b]
	(0.020)	(0.020)
FATAL	7.5E-3[b]	2.7E-3
	(2.2E-3)	(2.0E-3)
FATAL × DEATHCOMP	−8.1E-3[c]	−2.8E-3
	(4.2E-3)	(3.4E-3)
$\bar{R}^2$	0.335	0.327

[a] Other variables included are the region indicator variables NEAST, NCENT, and SOUTH.
[b] Significant at the 0.01 confidence level.
[c] Significant at the 0.05 confidence level.

which operates in the opposite direction, is an empirical question that is answered below.

WAGE EQUATIONS AND THE VALUE OF LIFE

Table 4 reports selected regression results using the natural logarithm of the wage rate as the dependent variable, and Table 5 summarizes the key risk coefficients for a variety of specifications. Although most wage-equation studies in labor economics utilize lnWAGE as the dependent variable because of the nature of the theoretical relationship between wages and human capital variables, there is no comparable theory specifying the functional form linking wages and death risks. Consequently, we report both WAGE and lnWAGE regression results in Table 5. We also report estimates using the flexible functional form estimator known as the Box-Cox transformation in the appendix. These results indicate that the appropriate form of the dependent variable is closer to that of lnWAGE than WAGE, so that our discussion below will focus primarily on the lnWAGE equation results.

The overall performance of the equations reported in Table 4 accords with the wage equations in the literature, both in terms of the magnitudes and the directions of the coefficients.[9] Worker wages rise at a declining rate with experience, increase with education and union status, and are lower if the worker has a health impairment, is a blue-collar worker, or is a woman.

The main variables of interest are the fatality variables, for which the regression results are summarized across a variety of specifications in Table 5. The lnWAGE equations appear in the first two rows of Table 5, and the

Table 5. Death risk and fatality insurance summary of results; coefficients (standard errors).

	NTOF risk measure		BLS risk measure	
	(1)	(2)	(3)	(4)
lnWAGE Equations				
FATAL	0.00345[a]	0.00747[a]	0.00126	0.00272
	(0.00090)	(0.00223)	(0.00083)	(0.00196)
FATAL × DEATHCOMP	...	−0.00805[a]	...	−0.00276
		(0.00419)		(0.00336)
$\bar{R}^2$	0.334	0.335	0.327	0.327
Value of Life	$5,995,000	$5,235,000	$2,134,000	$2,064,000
WAGE Equations				
FATAL	0.027[a]	0.052[a]	0.008	0.017
	(0.006)	(0.015)	(0.006)	(0.013)
FATAL × DEATHCOMP	...	−0.050[b]	...	−0.016
		(0.028)		(0.023)
$\bar{R}^2$	0.315	0.316	0.306	0.306
Value of Life	$6,593,000	$5,916,000	$1,933,000	$2,004,000

[a] Significant at the 0.01 confidence level.
[b] Significant at the 0.05 confidence level.

WAGE equations appear in the bottom two rows. Equations (1) and (2) employ the NTOF risk measure, while Eqs. (3) and (4) utilize the BLS risk variable. In each case, results are first reported excluding the workers' compensation variable (FATAL × DEATHCOMP), because most studies in the literature have not controlled for this aspect of compensation. Equations (2) and (4) include the workers' compensation variable, which is clearly preferable from a conceptual standpoint and has been included in more recent work.[10]

The performance of the NTOF death-risk variable is consistently superior to that of the BLS risk measure. Although the BLS fatality variable coefficient is always positive, the largest *t*-ratio observed is 1.625, so that this measure at best has coefficients just shy of the level needed to achieve statistical significance at the usual 5-percent level (1.645). In contrast, the coefficients based on the NTOF variable are always positive, are several times larger than the comparable BLS coefficients, and never have *t*-ratios smaller than 3.35, thus passing even the most demanding tests for statistical significance. These results provide strong evidence of an errors-in-variables problem in the BLS data.

The associated value of life estimates, using the price level from 1986, are also reported in Table 5. These estimates range from $2 million for the BLS risk measure to $5 to $7 million for the NTOF measure. The means by which these values are calculated is straightforward. The coefficient on the death-risk variable in the wage regression equation measures the amount by which a worker's wage will increase or decrease for corresponding increases or decreases in the risk that he faces on the job. Conceptually, the wage-risk tradeoff is interpreted as the dollar amount of wages that a worker requires to face a small additional amount of risk. The risk coefficient measures the required compensation for a risk increase, so that it is a "willingness-to-accept" measure. For small changes in risk, this willingness-to-accept increased risk equals the willingness to pay for risk reductions. We extrapolate the willingness to pay of the individual worker for a small risk reduction linearly to calculate the collective willingness to pay for a statistical life.

As an example, consider a worker who works for an hourly after-tax wage that is 2.5 cents higher for every increase in the annual probability of a fatal accident of 1/100,000. On an annual basis, this worker will require $50 for a risk increase of 1/100,000. Furthermore, 100,000 similar workers will collectively accept this increase in risk in return for $5 million in wage compensation. On average, one life will be saved among this group. Hence, the workers place a collective value of $5 million on the one statistical life that is saved.

Let us analyze the implications of the estimates of the lnWAGE equation reported in column 2 of Table 5. Consider the effect of a unit increase in FATAL1, the NTOF death risk, so that the annual death risk has risen by 1/100,000. The effect on the value of the log of workers' wages equals 0.00747(0.00805 × DEATHCOMP). Evaluated at the mean levels of DEATHCOMP and WAGE of 0.544 and 7.01, respectively, this calcuation yields an estimated tradeoff of 0.021667 between the hourly wage and the risk. Multiplying this number by 2000 hours to annualize the figure and by 100,000 to reflect the scale of the risk variable yields a tradeoff in 1981 dollars of $4.34 million per statistical life. Using the GNP deflator to express this nominal value in 1986 dollars transforms the result into the current estimated value of life of $5.235 million.

In the case of the lnWAGE equations, the BLS estimates imply a value of life in the $2 million range, whereas use of NIOSH's NTOF measure yields a value of life in the $5 to $6 million range for the lnWAGE equation. Switching from the BLS to the NTOF measure more than doubles the estimated value of life.

A similar pattern occurs for the WAGE equation, except that the extent of the increase is even greater. The BLS measure yields value-of-life numbers in the $2 million range, whereas the NTOF data imply a value of life on the order of $6 million to $6.5 million. Although the upper end of the range is relatively large, it is not implausibly large, as similar estimates have appeared in the literature.[11]

Overall, the NTOF results suggest a value of life in the $5 million to $6.5 million range and, on average, the value of life is over double those obtained using the BLS risk estimates. If one is willing to select a particular functional form for the wage equation, then the variation in the value of life across different specifications is much less. Exploration of the optimal wage transformations for use as the dependent variable (see the appendix) indicates that the value-of-life estimates from the equation specifications that are most consistent with the data range between $5.38 and $5.52 million.

Because of the precision in the estimates that is made possible by the NTOF data, we can pinpoint the value of life much more accurately than previous studies. To provide a range that can be used as a frame of reference for risk-control policies, we can construct confidence intervals for the value of life, using the coefficient estimates and their standard errors. Consider the lnWAGE results, which are more consistent with the functional form exploration provided in the appendix. The coefficients on the NTOF risk variables in Table 5, column 2, indicate that the value of life will fall between \$5.17 million and \$5.52 million 95 percent of the time. The BLS-based estimates, on the other hand, yield much less precise estimates, as the asymptotic 95-percent confidence interval for the value of life includes all values between \$1.63 and \$2.50 million dollars. Thus, the upper end of the NTOF confidence interval is less than ten percent higher than the bottom end, whereas for the BLS data the variation is just over 50 percent.

CONCLUSION

The development of a new and more comprehensive occupational death-risk series by NIOSH provides a new reference point for assessing the wage-risk tradeoff that governs estimates of the value of life. Overall death risks are roughly double the rate estimated by BLS. Based solely on the average scales of the overall risk levels, the value-of-life estimates in the PSID sample were expected to fall by about 50 percent by use of this new variable. The additional influence of random measurement error in the BLS death risk measures, however, apparently exerted a substantial depressing effect on previous value-of-life estimates, so that replacing the BLS measure with NIOSH's NTOF risk variable boosts the risk coefficient by a factor of more than two. Overall, the new estimates of the value of life are therefore at least double the levels obtained using BLS risk data. It is also noteworthy that the death risk coefficients are dramatically stronger in terms of statistical significance, so that the statistical confidence one can place in the value of life estimates is greatly enhanced by the use of the new occupational risk data. The sensitivity of the results to the risk measure used indicates a need to reestimate the value of life with other employment data sets to provide a broader empirical basis for selecting a consensus value of life estimate to use in policy contexts.

MICHAEL J. MOORE is Assistant Professor of Business Administration, Duke University.

W. KIP VISCUSI is Professor of Economics, Northwestern University.

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APPENDIX: ESTIMATION OF THE VALUE OF LIFE USING FLEXIBLE FUNCTIONAL FORMS

An unresolved problem in estimating the value of life is the selection of a functional form of the dependent variable in the compensating differential model.[12] Typically, empirical studies present results for wage equations that enter the wage or its natural logarithm as the dependent variable. Neither one of these measures is theoretically superior to the other, however; so there is a degree of uncertainty introduced into the estimates of the value of life that are derived from these regressions.

In this appendix, we embed the wage and lnWAGE models in the flexible functional form given by the Box-Cox transformation. This formulation will enable us to ascertain which transformation of the WAGE variable has the highest explanatory power. This technique has been applied in the job-risk context previously using different data.[13] It is shown there and below that neither the linear nor the semilogarithmic model is ideal. Evidence does indicate that the lnWAGE regression is more compatible with the functional form that best fits the data.

The Box-Cox transformation assumes that there is a value of λ such that the regression model

$$\frac{\text{WAGE}^{\lambda} - 1}{\lambda} = \beta' X + \varepsilon \tag{A.1}$$

is normally distributed, homoskedastic, and linear in β.[14] Various functional forms are special cases of this model. For instance,

$$\lim_{\lambda \to 0} \frac{\text{WAGE}^{\lambda} - 1}{\lambda} = \ln\text{WAGE},$$

while $\lambda = 1$ implies the linear WAGE regression, $\lambda = 0.5$ the regression of the square root of the WAGE on X, and so forth. It is therefore possible to test the restrictions implied by the linear, semilogarithmic, and square-root transformations as special cases of the model given by Eq. (A.1).

The curvature coefficient λ and the vector β that includes the risk and insurance coefficients necessary to estimate the value of life are estimated using the maximum-likelihood method. The concentrated likelihood function is

$$L(\lambda) = \frac{-N}{2} \ln\hat{\sigma}^2(\lambda) + (\lambda - 1) \sum_{i=1}^{N} \ln\text{WAGE}_i, \tag{A.2}$$

where

$$\hat{\sigma}^2(\lambda) = \frac{1}{N} \left[\frac{\text{WAGE}^{\lambda} - 1}{\lambda} - X\hat{\beta}(\lambda)\right]' \left[\frac{\text{WAGE}^{\lambda} - 1}{\lambda} - X\hat{\beta}(\lambda)\right],$$

and X includes all of the variables listed in the Table 4 regressions.

Choosing λ and β to maximize Eq. (A.2) yields a value of λ that equals approximately 0.3. The test statistic for the restriction $\lambda_R = 1.0$, which implies that the WAGE is the appropriate dependent variable, and $\lambda_R = 0.0$, which implies the use of lnWAGE, against the unrestricted value $\lambda_U = 0.3$ is

$$\Omega = -2[L(\lambda_R) - L(\lambda_U)], \tag{A.3}$$

which has an asymptotic chi-square distribution with degrees of freedom equal to the number of restrictions tested (in this case, one). The values of $L(\lambda)$ corresponding to λ_U, $\lambda = 0$, and $\lambda = 1$ are 887.0, 904.2, and 932.7. Substituting these values into Eq. (A.3) yields values of the test statistic equal to 34.4 for the test of $\lambda_R = 0$, and 91.4 for the test of $\lambda_R = 1$. Since the value of χ^2 (0.05, 1) is 3.84, we reject both the linear and semilog models as admissible specifications.

The 90% confidence interval for λ contains those values of λ for which

$$[L(\lambda) > L(\lambda_U) - \chi^2(0.10,1)],$$

or all values of λ such that

$$L(\lambda) > -888.36.$$

This interval includes values of λ that fall approximately between 0.25 and 0.45. It is noteworthy that this result exactly replicates earlier results by Moore that used a different data set and a different measure of risk.[15]

We can compute the value of life based on the Box-Cox regressions as follows. Rewrite the regression model of Eq. (A.1) as

$$\frac{\text{WAGE}^{\lambda} - 1}{\lambda} = \beta_0' \text{X}_0 + \gamma\text{FATAL1} + \delta\text{FATAL1} \times \text{DEATHCOMP} + \varepsilon, \quad \text{(A.4)}$$

where β_0 and X_0 are the coefficients and individual characteristics listed in Table 3, and FATAL1 is the NIOSH death-risk variable. The wage-risk tradeoff is found by totally differentiating Eq. (A.4) with respect to WAGE and FATAL1:

$$\text{WAGE}^{\lambda-1} d\text{WAGE} = (\gamma - \delta\text{DEATHCOMP}) d\text{FATAL1},$$

which upon rearrangement of terms simplifies to

$$\frac{d\text{WAGE}}{d\text{FATAL1}} = (\gamma - \delta\text{DEATHCOMP})/\text{WAGE}^{\lambda-1}.$$

Thus, computation of the wage-risk tradeoff requires estimates of γ, δ, and λ. The maximum-likelihood estimates of these parameters are $\hat{\gamma} = 0.016$, $\hat{\delta} = 0.017$, and $\hat{\lambda} = 0.4$. Evaluated at the sample mean values of WAGE (\$7.01) and DEATHCOMP (0.544), the wage-risk tradeoff is 0.0225. Using the technique described above, this yields a value of life of \$5.438 million, which is bounded from below by the lnWAGE equation estimate, and from above by the WAGE equation estimate. The 90-percent confidence interval for the value of life lies approximately between \$5.3 and \$5.5 million. Thus, the lnWAGE equation estimates, although different from the unrestricted estimates in a statistical sense, yield a comparable estimate of the value of life.

NOTES

1. See W. Kip Viscusi, "The Valuation of Risks to Life and Health: Guidelines for Policy Analysis," in J. D. Bentkover et al., Eds., *Benefits Assessment: The State of the Art* (Dordrecht, Holland: D. Reidel, 1986), pp. 193–210, for a review of the literature and discussion of policy applications. Also see Robert S. Smith, "Compensating Wage Differentials and Public Policy: A Review," *Industrial and Labor Relations Review*, (3) (1979): 339–352.
2. A discussion of the willingness-to-pay principle can be found in any standard policy analysis text, such as the widely used text by Edith Stokey and Richard Zeckhauser, *A Primer for Policy Analysis* (New York: W. W. Norton, 1978).
3. The main notable exception is a study using Society of Actuaries data for very hazardous occupations by Richard Thaler and Sherwin Rosen, "The Value of Saving a Life: Evidence from the Labor Market," in N. Terleckyj, Ed., *Household Production and Consumption* (New York: Columbia University Press, 1976), pp. 265–298.
4. See W. Kip Viscusi and Michael J. Moore, "Rates of Time Preference and Valuations of the Duration of Life," Center for the Study of Business Regulation

Working Paper No. 87-1 (1987a); Michael J. Moore and W. Kip Viscusi, "The Quantity Adjusted Value of Life," *Economic Inquiry* to be published.

5. See Viscusi and Moore, *op. cit.*, Moore and Viscusi, *op. cit.*, W. Kip Viscusi and Michael J. Moore, "Workers' Compensation: Wage Effects, Benefit Inadequacies, and the Value of Health Losses," *The Review of Economics and Statistics*, 69(2) (1987b): 249–261; Michael J. Moore and W. Kip Viscusi, "Have Increases in Workers' Compensation Benefits Paid for Themselves?" in David Appel, Ed., *Proceedings of the Sixth Annual Conference on Economic Issues in Workers' Compensation*, in press.
6. See Note 5, *supra*.
7. To control for the endogeneity of this measure, DEATHCOMP is regressed on a vector of state indicator variables in a first-stage regression. The predicted value of DEATHCOMP is then interacted with the death risk term to reflect the fact, proven in Viscusi and Moore, *op. cit.*, 1987b, that insurance benefits will only affect wages at positive risk levels. Because benefits are only paid to decedents with surviving dependents, DEATHCOMP is set equal to zero if the worker is single.
8. For an analysis of workers' risk perceptions, see W. Kip Viscusi, *Employment Hazards: An Investigation of Market Performance* (Cambridge: Harvard University Press, 1979); W. Kip Viscusi and Charles O'Connor, "Adaptive Responses to Chemical Labeling: Are Workers Bayesian Decision Makers?" *American Economic Review*, 74(5) (1984): 942–956.
9. A nonfatal risk variable was not included since it was not statistically significant and did not substantially alter the death-risk coefficients. Excluding the nonfatal-risk variable is a common practice in the literature. In addition, mixing the NTOF fatality variable with a BLS nonfatal risk variable creates comparability problems.
10. See Notes 4 and 5, *supra*.
11. Indeed, using the BLS data on the 1976 PSID, the estimated value of life estimate is \$8–\$12 million in 1986 dollars (the year for which our nominal life-values are calculated). See W. Kip Viscusi, *op. cit.*
12. This problem was first noted in the seminal article in the literature by Sherwin Rosen, "Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition," *Journal of Political Economy*, 82 (1974), and in the review by Smith, *op. cit.*
13. See Michael J. Moore, "Estimation and Tests of the Equilibrium Relationship Between Earnings and Job Hazards," in *Three Essays in Labor Economics*, Ph.D. dissertation, The University of Michigan, Ann Arbor, Michigan, 1984.
14. It has been shown elsewhere that Box-Cox estimates are sensitive to the problem of heteroskedasticity when cross-section data such as ours are used. See also Takeshi Amemiya and James L. Powell, "A Comparison of the Box-Cox Maximum Likelihood Estimator and the Non-Linear Two-Stage Least Squares Estimator," *Journal of Econometrics*, 17 (1981): 351–381, who analyze the sensitivity of Box-Cox estimates to the normality assumption, which only holds when $\lambda = 0$. In our earlier runs with the 1982 PSID data, these problems were not apparent.
15. See Note 13, *supra*.