WHAT DETERMINES THE VALUE OF LIFE? A META-ANALYSIS

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August 29, 2001

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*The authors would like to thank Ronald Cummings, Tom Dee, Nicholas Flores, James Hammitt, Stephen Schmidt, Carol Scotton, V. Kerry Smith, participants at the NBER Summer Policy Workshop and three anonymous referees for comments on earlier drafts of this manuscript. The authors would also like to thank Jean Cousineau, John Garen, Henry Herzog, J. Paul Leigh, and Jin-Tan Lui for providing additional data from their studies, and two anonymous referees for providing information to enhance and expand our data.

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ABSTRACT

A large literature has developed which uses labor market contracts to estimate the value of a statistical life (VSL). Reported estimates of the VSL vary substantially; from under $100,000 to over $25 million. This research uses meta-analysis to provide a quantitative assessment of the VSL literature. Results from existing studies are pooled to identify the systematic relationships between VSL estimates and each study's particular features such as the sample composition and research methods. Our meta-analysis suggests a VSL range of approximately $1.5 to $2.5 million (in 1998 dollars) is what can be reasonably inferred from past labor-market studies when "best practice" assumptions are invoked. This range is considerably below many previous qualitative reviews of this literature.

KEYWORDS: meta-analysis, value of statistical life, benefit-cost analysis

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INTRODUCTION

Many important public policy initiatives have mortality reduction as their primary goal. Evaluation of these policies commonly includes benefit-cost analyses, and at the federal level such analyses are compelled by Executive Orders 12291 and 12866 [Federal Register, 1981 and 1993, respectively]. Proper evaluation requires an estimate of the value society places on a life saved as a result of the policy. The concern is not with the value of an "identified" life, but the value society places on reducing the statistical probability that one among them dies, the so called "value of a statistical life" [Viscusi 1992, 1993]. To date, there have been over 40 studies which rely on labor market contracts to estimate the value of a statistical life (VSL). In these studies, the implicit tradeoffs workers make between incremental increases in the risk of death on the job and the additional wages required to accept these riskier jobs are estimated and converted into corresponding estimates of the VSL.

Controversy regarding the validity of using VSL estimates from labor market studies in benefit-cost analysis of mortality reduction policies is focused on three primary issues. First, even though the majority of published studies report a statistically significant relationship between the risk of death on the job and workers' wages, at least sixteen studies report some results indicating no statistically significant relationship, including Viscusi [1978], Viscusi [1980], Dillingham [1985], Moore and Viscusi [1988a], Leigh [1991 and 1995], and Dorman and Hagstrom [1998]. Indeed, Leigh [1995] argues that the significant wage/risk relationships found in this literature are spurious and due to poor risk measurement and mis-specification of the wage equations [see also Dorman and Hagstrom, 1998 and Miller, 2000].

A second issue is the wide variation in the VSL estimates reported in this literature. For instance, Moore and Viscusi [1990] and Olson [1981] report VSL estimates ranging between $15 and $25 million per life saved. On the other hand, Dillingham [1979], Marin and Psacharopolous [1982], and Kniesner and Leeth [1991] report VSL estimates that are less than $100,000 per life saved (all estimates in 1998 dollars). These extreme estimates, while not necessarily arising from each author's preferred specification, indicate the substantial variation in VSL estimates. Such variation results in considerable uncertainty regarding the choice of which, if any, of these estimates are appropriate for inclusion in benefit-cost analyses.[1]

In response to the need to determine a "best" value of statistical life estimate, several authors have qualitatively reviewed the literature and use their knowledge to make judgements about which VSL estimates are more reasonable or "more correct." For example, Fisher, et al., [1989] review studies using several different methods to estimate the VSL and suggest $2.5 to $12.5 million as being the most defensible VSL range based on the then extant literature (all estimates reported herein are converted to 1998 dollars). Viscusi [1992, 1993] summarizes 24 labor market studies, and suggests that the appropriate range is between $4 and $9 million, as this is the range where "most estimates lie" in the studies he includes. Neuman and Unsworth [1993] for the United States Environmental Protection Agency [1997] calculate a "best estimate" of the VSL from 26 studies (21 of which were labor market studies) which they deem are most reliable: those which include nonfatal risks in the compensating wage equations, and whose

[1]A third, important concern is whether or not a VSL estimate pertaining to fatal, work-place injuries is an appropriate value for policies reducing latent risks (i.e., reducing risks of cancers later in life due to prolonged current exposures). This criticism is certainly worth exploration, but is outside the scope of this paper. It is important to note that despite this criticism, estimates of the VSL for many federal agencies conducting benefit cost analyses are based on information primarily gathered from labor market studies [see for example, U.S. Environmental Protection Agency, 1997 and 1999].

baseline risks were most similar to the mortality risks arising from air pollution. A Weibull distribution was fit to the 26 estimates and a mean of $6 million was computed. Miller [1990] combines a quantitative and qualitative approach, assembling one or two VSL estimates from each of 27 studies and adjusting each estimate to reflect his judgement regarding the deficiencies of each study (and in doing so, he discarded 30 percent of the studies). With these preferred estimates, he computes a mean value of a statistical life of $3 million, with a range of 2.1 to 3.9 million.

The research presented here uses a quantitative meta-analysis framework to evaluate value of statistical life estimates. Meta-analysis involves pooling the results from the existing literature to identify systematic relationships between the outcome of interest (the VSL in this case) and underlying factors influencing that outcome. The key advantage of this approach over existing literature reviews is that the meta-analysis provides a quantitative, systematic analysis of the existing literature to inform the researcher's judgements. Over 40 labor market studies estimating the value of a statistical life are reviewed. With information from these studies, we identify the relationships between their VSL estimates and underlying factors influencing those estimates such as: the baseline level of risks faced by the sample population, demographic characteristics of the sample, the source of the risk data, and researcher judgements such as equation specifications and sample selection. Results of the meta-analysis are then used to develop "best-practice" VSL estimates that are based on the current "weight of the evidence" from this literature. Our results indicate that previous assessments of this literature, and previously applied VSL estimates in benefit/cost analyses of regulatory actions, may overstate the value that can be reasonably drawn from this literature by 50 percent or more.

METHODOLOGY

Wage-Risk Tradeoffs

We focus on research that has estimated the value of a statistical life *via* compensating wage eqeuations. The general form of the compensating wage equation estimated in these studies is:

$$wage_k = \alpha + \beta_r risk_k + \sum_{n=1}^{N} \lambda_n X_{kn} + \sum_{m=1}^{M} \gamma_m D_{km} + \epsilon_k , \qquad \textbf{(1)}$$

in which the wage of the k^{th} worker is estimated to be a function of: the risk of death on the job ($risk_k$); n variables describing human capital and demographic characteristics of the worker (X_{kn}) such as age and education; and m job characteristics (D_{km}) other than the risk of death such as whether or not supervisory activities are associated with the job. It should be noted that information on job characteristics is typically sparse, and so most compensating wage equation applications can include only dummy variables controlling for the occupation and/or industry classification of the worker's job.

In a linear specification such as (1), the coefficient on the risk variable is the additional wages a worker would require to assume an additional increment of risk of death on the job. By normalizing over risk, the compensating wage differential is converted to the value of a statistical life. For instance, suppose risk is measured in units of deaths per 10,000 workers; wages are hourly earnings; and a simple linear compensating wage equation is estimated as illustrated in (1). To compute the value of a statistical life, the estimated coefficient for $\partial w/\partial r = \beta_r$ is multiplied by 2000 hours/year and then by 10,000. In this example, an estimate of β_r equal to 0.35 would imply a value of statistical life estimate of \$7 million.

Meta-analysis

Meta-analysis is commonly applied in the health and medical sciences literatures [see Mann, 1994] and involves pooling raw data from a variety of clinical studies to evaluate the relationships between a health outcome of interest and key variables assumed to affect that outcome. A primary benefit of these applications is the increased evidentiary weight of the larger data set, which incorporates a larger design space than any one study could provide. Our use of meta-analysis differs somewhat from the traditional use in health sciences in that the data collected and analyzed are estimates of a variable of interest (the VSL) that have been calculated in a number of studies, rather than the original raw data.[2]

In this analysis, existing estimates of the value of a statistical life from compensating wage equation studies are pooled to identify the systematic relationships between these estimates and the particular features of each study in which they are reported, such as the sample composition and research methods. While it would be possible to conduct a meta-analysis of the VSL that pools estimates from studies using methods that are very different from the compensating wage equation approach such as contingent valuation, the idiosyncracies of each of these other studies would make it difficult to assess systematic effects of research judgements on the VSL estimates. A database is constructed of 203 VSL estimates obtained from 33 studies. Multiple observations are drawn from each study if authors reported variations in model specifications or samples from which VSL estimates could be obtained. While we reviewed over 40 studies, some could not be incorporated because of missing information. An appendix is available from the authors which describes these studies and why they could not be included (see

[2]Similar examples in the economics literature include Smith and Huang [1995] and Smith and Osborne [1996] who use meta-analysis to evaluate willingness to pay estimates for improvements in air-quality.

www.gsu.edu/~ecolot/research.html).

The dependent variable in our analysis is an estimate of the value of statistical life generated by a wage equation reported in a particular study. The independent variables used to determine the source of variation in the VSL estimates are those which describe the factors assumed to influence the VSL estimate. For example, overall, one would expect that the VSL will increase with baseline risk and with baseline income [Jones-Lee, 1974; Hammitt, 2000], which therefore are independent variables in our meta-analysis regressions. Factors describing the sample composition of the workers used to estimate the VSL (e.g., blue collar versus white collar) are also included as independent variables. Lastly, factors describing the researcher's methods of estimation are included to determine what effects, if any, some basic researcher judgements might have on VSL estimates.

In our analysis, we are also able to incorporate an important and controversial aspect of the labor market literature. Leigh [1995] suggests that because the risk data most commonly used in these studies differentiates risks only by industry of the worker, and not by his or her occupation, the risk measures are correlated with inter-industry wage differentials. The essential element of Leigh's argument is that the industry wage differentials that have been long noted in the labor market literature are correlated with industry-level risk differentials, but are not due to risk differentials. Thus, to avoid mis-specification and properly assess the impact of risk on wages, compensating wage equations should at least include dummy variables indicating a worker's industry at the broadest classification level to capture the effect of inter-industry wage differentials separately from the effect of risk. Leigh finds that when he includes such dummy variables, risk measures are not significant predictors of wages [see also Dorman and Hagstrom, 1998]. He argues this indicates that risk is indeed a proxy for inter-industry wage differentials and thus the coefficient on risk does not measure compensation for variations in risk. His critique is directly incorporated in our analysis as described in the next section.

In a similar meta-analytic approach, Desvousges et al. [1995] compile 29 VSL estimates that were deemed to be the "most reliable" and regress these 29 estimates on the mean risk of the sample; no other study-specific information was included except a dummy variable indicating the source of the risk data. Their estimated model suggests a preferred VSL of $4 million (1998 dollars). Similarly, Miller, 2000 compiles sixty-eight "best estimates" from labor market, contingent valuation, and consumer behavior studies conducted in the US and abroad and estimates them to be a function of the GDP per capita of the country in which the study was conducted; a dummy variable indicating the methodology used (contingent valuation versus hedonic wage approach); and four dummy variables describing the type of risk used in the original study (e.g., perceived risks versus actual risks). While it is questionable whether a simple fixed-effect for broad methodology adequately captures the relationship between VSL estimates and the methods used to estimate them, Miller nonetheless estimates a VSL similar to Desvousges et al. of $4 million for the U.S. (1998 dollars).[3] Our analysis, by contrast, considers the entire "weight-of-the-evidence" from the literature, incorporating over 200 estimates of the value of a statistical life estimated with samples of workers from the United States and abroad. In addition, a large number of independent variables are included to determine which are the important factors leading to variations in VSL estimates reported within the same study and across studies.

[3]The validity of pooling contingent valuation and wage-risk studies is also called into question by Hammitt [2000] and Hammitt and Graham [1999]who conclude that contingent valuation surveys are not likely to be reliable sources of VSL estimates due to respondents' difficulties in understanding risk changes as they have been presented in CV surveys in the past.

DATA AND META ANALYSIS RESULTS

The Data

Forty-seven studies using compensating wage equations to estimate the value of a statistical life were reviewed. Of these, 33 provided enough information to be included in our data analysis. Summary statistics and the number of observations drawn from each study for our analysis are reported in Table 1. All VSL estimates and worker's earnings are expressed in 1998 dollars, updated using the consumer price index as reported in *The Economic Report of the President*, 1999. There is substantial variation in the data across studies. The maximum VSL estimate in our data is $30,700,000 [Olson, 1981] while the minimum is $15,863 [Marin and Psacharopoulos, 1982]. The mean VSL across all observations in our data is approximately $6 million, with approximately 50% of our observations lying between $1.5 and $8 million.

The variables we use to determine the source of variation in the VSL estimates are of three types; those which models of individual rationality would suggest influence wage/risk tradeoffs, and thus influence VSL estimates; those describing the data sources; and those describing methodological choices of the original researchers. Jones-Lee [1974] describes, in a simple expected utility framework, how rational individuals are willing to trade wealth for increases/decreases in the risk of death [see also Hammitt, 2000]. This type of model implies that for any one individual, the compensation a worker requires to take on a additional unit of risk is increasing in baseline risk and baseline income. As such, we include the mean hourly earnings of the sample used to compute the value of statistical life as well as the sample's mean risk of death as two of our regressors. Summary statistics of these variables are reported in Table 1 and 2.

The mean hourly earnings in each study varied substantially from $2.87 [Liu et al., 1997 in a study of Taiwanese workers] to $27.67 [Meng, 1989 in a study of Canadian workers]. Mean hourly earnings of studies conducted on U.S. workers varied from $10.24 [Dorsey and Walzer, 1983] to $26.17, which was the highest mean earnings for one of the subsamples reported by Herzog and Schlottman [1990]. The mean annual risk of death varied by nearly a factor of 40, ranging from 0.29 deaths per 10,000 [Liu et al., 1997] to 10.98 deaths per 10,000 [Thaler, 1976]. However, 85 percent of the mean risks reported in the studies included in our analysis were less than 2 deaths per 10,000 workers. Related to earnings, we also include in the analysis the national unemployment rate for the year in which the wage data used by a study was collected. This variable is included as one might expect that in years of high unemployment, wage premiums may be smaller.

In addition to the average risk faced by workers and their earnings, other descriptive variables included in the meta-analysis control for differences in VSL estimates across studies that arise from differences in the samples or methods used to estimate the value of a statistical life. Broadly, variables are included that control for: samples with very high risks, characteristics of the sample of workers used in a study, wage data sources, risk data sources, differences in the specification of the wage equation models across studies, and differences in how studies controlled for a job's industry or occupational category.

Four studies reported mean risks that were at least two-fold larger than the mean risk of the majority of our observation, with a range between 5 and over 10 deaths per 10,000 workers.[4] These high risks are primarily due to the specialized sample used in the studies (i.e., Low and McPheters, 1983 used police officers and Liu and Hammitt, 1999 used petro-chemical workers) or the reliance on Society of Actuaries risk data [Thaler and Rosen, 1976 and Gegax, et al., 1991]. The Society of Actuaries (SOA)

[4]Eighty-eight percent of our observations had a mean risk of 2.5 or less.

data has been criticized as overstating the risk of death since it computes the risk of premature death from all causes, not just those that occur on the job, and it is limited to more risky job classifications [Viscusi, 1992]. Each of these highest-risk studies also reported value of statistical life estimates that are at, or below, the mean for all the studies. Thus, the analysis here includes a dummy variable (HIGHRISK), indicating whether or not a VSL estimate was based on a sample of workers whose mean risk is greater than 5 deaths per 10,000 workers.

Variables are constructed to control for variation in sample characteristics that arise through either the data sources or the choice of what types of workers are included in the analysis (Table 2, "Sample Variables"). Three broad categorical variables are created to describe the source of the data on worker's wages and job-characteristics, and four dummy variables are created to control for the source of the risk data. In addition, a dummy variable is created indicating whether or not the measures of job risk used in a study included a worker's self-assessment of his/her job risk. For instance, Gegax, et al. [1991] presented survey respondents with a risk ladder (whose risk levels were derived from SOA data) and ask workers to identify the risk they face on their job. Similarly, Moore and Viscusi [1988b] interact BLS risk measures with a dummy variable indicating whether or not a survey respondent considered his/her job to be risky, thus assigning a zero risk of death to those who did not consider their jobs to be risky.

To control for the specialized samples, variables are created that indicate if a sample of workers was 100 percent unionized, 100 percent white collar, or 100 percent blue collar. Other variables which we attempted to include, but could not due to missing observations, were the mean age of the sample of workers and the racial and gender composition of the sample. Omitting age, race, and gender could bias our coefficient estimates if there are important VSL variations across studies resulting from differences in the sample compositions with respect to these variables. Fortunately, the variation in these measures across studies seemed to be somewhat limited. Based on the information from studies which did report this information, 95 percent of the observations used samples of workers that were at least 75 percent white (or the majority race of the country); 80 percent of the observations had 75 percent or more male workers; and the mean age of the sample of workers varied from 32 to 44 across studies. This limited variation, combined with the controls for these factors within the original studies, may suggest the remaining bias is limited. However, we cannot measure or test for the bias.

It is possible to have several estimates of the value of a statistical life from one study even if the mean risk, mean earnings, and sample used to compute the VSL do not vary in the study. In these cases, VSL variation arises from different estimating equations used by the authors. To control for these effects in the meta-analysis, we include eight variables reflecting the specification of the compensating wage equations underlying each VSL estimate. These are described in Table 2 under "Specification Variables." For instance, for the same sample of workers, some authors may have reported both a linear and a semi-log specification for their compensating wage equations. Although identical in other respects, these two equations would result in different VSL estimates. We therefore include a variable in our analysis describing the original wage model specification to control for this effect within each study.

Lastly, we include in our analysis three variables designed to address the relationship between industry wage differentials, risk measures, and the estimated value of statistical life (Table 2, "Industry/Occupation Variables"). In compensating wage equations, it is important to control for the broad classification of a worker's occupation and industry in explaining variation in wages across workers [see, for example, Ehrenberg and Schumann, 1982]. The degree to which studies in our analysis included variables that control for broad industry and occupation classifications varied. Nine studies did not control for either effect in their wage equations (accounting for 23 percent of our observations), while fourteen studies controlled for both effects (accounting for 44 percent of our observations) and eleven studies controlled for occupational characteristics, but did not control for the industry in which the person worked (26 percent of our observations). We include in our analysis two variables which indicate whether or not the original authors controlled for at least one occupation or job characteristic in their wage equations (OCCDUM and CHARDUM, respectively). We also include variables describing whether or not the original authors included industry-specific dummy variables in their wage equations. We create two variables to control for this important effect; one is a continuous count for the number of industries controlled for by the original authors (INDUSTRIES), and one is a summary dummy variable indicating whether or not the original authors controlled for at least four industries in their wage equations (INDDUM).[5] The robustness of our results is tested with respect to which of these two variables we include in our anslysis.

Results

Table 3 reports four models used to estimate the sources of variation in the value of statistical life estimates. For each model, the natural log of the VSL is the dependent variable. With this specification, we are assuming that additional increments in our explanatory variables affect the VSL proportionally. Since studies vary in the number of estimates they report, we apply weighted least squares rather than

[5]There is a "natural break" in our data in the number of industries authors controlled for in their wage equations. Generally, authors included either zero, one, or two controls for industry, or were very detailed and controlled for 7, 8, or more industry classifications.

OLS, using a weight on each observation equal to the inverse of the number of estimates from that study which we are able to include in our analysis. Thus, in our regression, each study, rather than each observation, has equal weight in determining the regression coefficients. An appendix, available from the authors (www.gsu.edu/~ecolot/research.html), explores variation in the models, estimation methods, and other assumptions used in the meta analysis. The results of these robustness tests support the findings reported here.

An important issue that had to be taken into consideration is the relationship between studies using the same database of workers. Different authors conducting studies on U.S. national samples (91 of the 203 observations) used a few key data sources repeatedly. For instance, the Panel Study of Income Dynamics (PSID), which follows individuals over time, was used by four authors in seven studies (data years were 1974, 1976, 1981, and 1982). While identical samples did not appear to be used across studies due to the criteria each author used for inclusion or exclusion of workers from their data base, some individuals would have appeared in the samples of multiple studies. Thus, even though authors use different sub-samples, different risk measures, and different model specifications for their wage equations,[6] there may be some residual correlation between these studies resulting in inefficient parameter estimates.

To address this issue, we compute robust standard errors which allow for correlation (clustering) among observations across studies arising from data sources that were of the same year (or arising from

[6]For instance, Leigh and Folsom [1984] and Moore and Viscusi [1988b] both use the Quality of Employment Survey from 1976. However, Moore and Viscusi use only blue collar workers (resulting in a mean wage of $15.73) and Leigh and Folsom use a mix of blue and white collar workers (mean wage $20.79). Leigh and Folsom included the age of worker, marital status, and two-digit occupation dummies, while Moore and Viscusi included race, and the expected life years lost, expected annuity, and estimated discount rates of workers. Moore and Viscusi weighted their regression (dependent variable ln(wage)), while Leigh and Folsom did not, but reported both linear and semi-log wage models.

the same panel of workers if a group was followed over time, as is the case with the PSID).[7] In all other cases, we allowed observations to be correlated within a study, but assumed observations were independent across studies. Models were also estimated which included fixed effects for authors using a common sample of workers. The results of these models for the variables of interest were unchanged and are reported in the appendix available from the authors.

The four models vary by sample composition and the variables used to control for the original treatment of industry variables by the authors. Models 1, 2, and 3 only vary by sample composition. Model 1 is is the most inclusive, including the full sample, while the second model restricts the data set by excluding VSL observations based on samples with risks greater than 5 deaths per 10,000 workers (i.e., samples for which HIGHRISK=1), or based on SOA risk data, which has been severely criticized for not reflecting actual job-risks. Model 3 further restricts the data to just VSL estimates that were computed using US national data sources for worker characteristics. Variables are dropped in models 2 and 3 if the sample restriction eliminates their variation. In addition, UNION and URBAN are dropped because the sample restriction results in a high degree of collinearity between UNION, URBAN and other specification variables such as REGDUM. In addition, UNION becomes a dummy variable specific to Herzog and Schlottmann [1990] which is the only study using a U.S. national sample of workers which did not control for unionization of the worker, and is not significant when included in the model. Model 4 is the same as model 3, but includes the continuous variable representing how industry-categories were controlled for in

[7]If the data used in several studies were from the same source (such as BLS), but collected in different years, we assume independence of the error terms across these studies. We expect that any effects of the sampling methods used by the various agencies in collecting their wage data across years would be captured directly by our inclusion of dummy variables reflecting the data source.

the original regressions (INDUSTRIES), instead of the summary dummy variable (INDDUM).

All models indicate a positive and significant relationship between the mean risk faced by a sample of workers and the value of a statistical life. This relationship is concave, however. Model 1 indicates that the value of statistical life estimates begin to decline when the mean risk of a sample of workers becomes greater than approximately 1.2 deaths per 10,000.[8] Fifty-percent of the full sample has mean risks that are less than 1.2 deaths per 10,000 workers. These results may indicate that selection effects among workers with heterogenous risk-preferences may dominate over some range of risks. In other words, those with lower risk aversion may be self-selecting into higher risk jobs and require less compensation, all else equal. If this selection effect is dominant in the market, we would expect to see the risk premia begin to decline at higher levels of risk when making comparisons across samples of workers with different baseline risks (i.e., across studies).[9] Models 2, 3 and 4 also indicate a similar relationship. However, the relationship between VSL and risk is positive over a larger range of the data when excluding the observations arising from high-risk and SOA samples. For model 2, the value of statistical life estimates begin to decline when the mean risk of a sample of workers becomes greater than 1.67 deaths per 10,000. Approximately 72 percent of the sample used in model 2 have mean risks less than $1.67\text{x}10^{-4}$. For models 3 and 4, the VSL estimates begin to decline at $1.46\text{x}10^{-4}$ and $1.53\text{x}10^{-4}$, respectively, and approximately 95 percent of the

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[8]The partial derivative $\partial VSL/\partial MEANRISK$ is evaluated with UNION100 and HIGHRISK set equal to zero (i.e., the partial derivative is computed for non-specialized samples of workers).

[9]This hypothesis is also supported by the surprisingly large, negative coefficients for HIGHRISK in Model 1. This variable reflects six observations in the data set that are from Thaler and Rosen [1976], six from Gegax, et al. [1991], and two each from Marin and Psacharopoulos [1982] (data on U.K. workers) and Lui and Hammitt [2000] (data on Taiwanese workers). Each of these studies report the highest mean risks in our data, yet report relatively small VSL estimates. Twelve of these 16 VSL observations rely on risk data from the Society of Actuaries that is suggested to be biased upwards as it reports the risk of death from all sources, not just on the job risks. An upwardly biased risk measure in a compensating wage equation will result in a downwardly biased VSL estimate.

U.S. national sample used in these two models have mean risks that are less than $1.46x10^{-4}$.

Consistent with our expectations, the coefficient for earnings is positive; however, this variable is only a significant predictor of ln(VSL) in the models that include both U.S. and non-U.S. samples of workers. The elasticity of the VSL estimates with respect to mean earnings of the workers is 0.49 and 0.46 for models 1 and 2, respectively, when evaluated at the approximate mean wages for the two samples of \$13.25. The elasticity estimates using models 3 and 4 are 0.37 and 0.46 when evaluated at the sample mean wages of \$15.94, although these are based on imprecise coefficient estimates. These measures are about half the magnitude of those reported by Miller, 2000 which varied between 0.85 and 1.0. We might expect Miller's estimates to be different than ours if the important determinants of the VSL that he omitted in his study, such as the mean risks faced by the workers in each study, are correlated with income. Also, Miller uses each country's per capita GDP as a measure of income and we use hourly earnings, a crude proxy for income as it does not incorporate information on the number of hours worked per year or non-wage sources of income. More importantly, approximately 78% of our observations arose from models using a semi-log specification for their wage equation. In the case of semi-log wage models, an artificial relationship between wages and the VSL arises as the VSL is computed by: $VSL = bw_{:}X$, where b is the estimated impact of risk on wages, $w_{:}$ is the mean wage of the sample of workers, and X is an adjustment factor as described earlier. For these reasons, our elasticity measure should be interpreted with caution.

Not surprisingly, the data sources used by the original authors significantly impact their VSL estimates. Estimates arising from studies using U.S. national samples of workers and those using non-US samples resulted in higher VSL estimates than those arising from specialized US samples such as those used by Butler [1983], Gegax, et al. [1991], Low and McPheters [1983], Dillingham [1979], and Brown

[1980]. Results also indicate that use of National Institute for Occupational Safety and Health (NIOSH) risk data results in significantly larger estimates of the VSL as compared to BLS risk data (the category left out of the model).[10] Dillingham constructed a unique data set on risks and when used, it resulted in lower estimates of the VSL. The use of SOA did not significantly affect VSL estimates, once controlling for the fact that this data is associated with very high mean risks (i.e., including HIGHRISK as well). Lastly, our first two models seem to indicate that risk data which incorporates a worker's self-assessed risk of death did not have a significant affect on the VSL estimates. While this variable is significant in models 3 and 4, it should be interpreted with caution as SELF REPORT is equivalent to a dummy variable for the Moore and Viscusi [1988b] study in these models because of the sample restriction.

Restricting the sample of workers to 100 percent unionized workers resulted in larger VSL estimates, however, this result is only significant in models based on U.S. workers only. Value of statistical life estimates arising from samples of white collar workers were significantly higher than estimates arising from samples of mixed-samples of workers. Regressions were also estimated in which BLUECOL was the dummy variable left out of the regression, and WHITECOL was also significant and positive in these cases. Interestingly, VSL estimates arising from samples of all blue collar workers were also significantly larger than those arising from a mix of blue and white collar workers.

We also included eight dummy variables in our model indicating various specification choices of the original researchers. The sign and significance of these variables depended on the sample composition.

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[10]Moore and Viscusi [1988a] discuss two differences between the BLS and NIOSH data sources: measurement error and scale-factor bias, that lead to opposite expectations as to which data set will result in higher VSL estimates. Moore and Viscusi suggest that their empirical results demonstrate that the former factor dominates, leading to substantially higher VSL estimates when using the NIOSH risk data.

In general, these variables were not significant predictors of the value of a statistical life in the models based on only U.S. workers. The effects of controlling for occupations in a wage regression were not significant in any model. Wage equations that included at least one job characteristic dummy variable (such as whether a job is supervisory or not) did result in a significantly larger estimate of the VSL in Models 2 and 3.

Other than mean risk, the inclusion of industry dummy variables in the wage equations is the effect of greatest interest as it relates directly to Leigh's [1995] hypothesis that risk/wage tradeoffs found in this literature are spurious relationships. Our results indicate that studies which control for five or more industry classifications in their wage regressions did result in significantly lower estimates of the VSL, although this effect is not significant in the model containing VSL observations arising from high-risk samples or SOA risk data. This effect is robust to the treatment of the variable we use to describe this effect. In model 4, the coefficient estimate for INDUSTRIES indicates that adding an additional industry dummy variable in a wage equation reduces the estimated VSL by 12 percent.[11] The magnitude of this effect on the estimated value of a statistical life is substantial, and is discussed in the next section.

REVISED ESTIMATES OF THE VALUE OF A STATISTICAL LIFE

"Best-Practice" Estimates of the VSL

The models estimated in the previous section may be used to compute estimates of the value of a

[11] Models were estimated that used the same samples as model 1 and 2, but which included INDUSTRIES instead of INDDUM. They are not reported here as their results support models 1 and 2. The variable INDUSTRIES was not significant in the model based on the full sample (like model 1), but was significant and negative in the model dropping VSL estimates arising from high-risk and SOA data sources (like model 2).

statistical life in several ways. One could simply compute the mean, $\Sigma_i VSLHAT_i/N$, where i represents an observation, N is the number of observations in our data set, and $VSLHAT_i = \exp(\Sigma_j b_j \cdot X_{ji})$, where X_{ji} is the value of the j^{th} covariate for the i^{th} observation, and b_j is the estimated coefficient for the j^{th} covariate in our model.[12] Such an approach, however, would create VSL estimates whose values vary because of differences in specifications, data, and importantly, whether or not "best-practice" methods were employed. This approach implies a lack of comparability across estimates and continues to make it difficult to infer the appropriate range for the value of a statistical life from this literature.

To avoid these problems, we apply a more structured approach. Rather than simply computing a $VSLHAT_i$ using the values for each observation as contained in the "raw data," we adjust the covariate matrix for all observations to reflect "best-practice" assumptions. For instance, model 2 and 3 indicate that inclusion of variables describing job characteristics in the compensating wage equation yields higher estimates of the value of a statistical life. On theoretical grounds one can assert that such a term should be included in the specification as a preferred practice since job characteristics influence wages. However, a number of studies did not control for job characteristics in their compensating wage equations. We impose a "best-practice" specification on these observations by predicting the VSL <u>as if</u> the studies had included at least one dummy variable describing job characteristics. Specifically, for the j^{th} covariate representing whether or not the wage equations included a job characteristic dummy variable, we set $X_{ji} = 1$ for all i observations and calculate $VSLHAT_i$ as above. Thus, the fitted VSL calculated for each observation incorporates an adjustment to the VSL estimate if a study did not consider the influence non-

[12]The method of predicting lnVSL and exponentiating the result will underestimate the expected value of VSL. For the model ln(y) = xb + u, it can be shown that $E(y|x) = \alpha^* \exp(xb^*)$, where xb* is the prediction of ln(y), and α^* is a consistent estimate of E(exp(u)|x). See Manning and Mullahy [2001] and Wooldridge [2000] for a discussion.

risk job characteristics may have on wages.

Adjustments to the X_{ji} matrix reflecting best-practice methods were to set RISKSQ, MORBIDITY, UNION, WORKCOMP, URBAN, REGDUM, OCCDUM, and CHARDUM equal to 1 for all observations. This adjusts the predicted VSL from those studies in our database that did not include these effects by an amount suggested by our empirical models. In addition, we make other adjustments to the X_{ji} matrix to impose uniformity across studies in cases where we have no *a-priori* reason to prefer one specification over another. These adjustments include restricting AFTERTAX, US NATIONAL DATA, and LOGDEP equal to 1 for all observations; and to restrict SELFREPORT, NON-US NATIONAL, and DILLINGHAM equal to zero for all observations. We also restrict UNION100, WHITECOL, and BLUECOL to be equal to 0 for all observations in the data set so the results may be as consistent as possible with the general population.

After making these adjustments to the X_{ji} matrix, we compute an adjusted, predicted VSL for each observation using Models 3 and 4 in Table 3. Note that some adjustments discussed in the previous paragraph do not apply as the variables are not contained in model 3 or 4. Each predicted value is also adjusted to account for the bias introduced by Jensen's inequality (see footnote 12). These models are chosen since they contain studies that are most comparable in terms of their sample compositions and data sources. The mean of these predicted values are reported in Table 4. Because the models in Table 3 indicate a non-linear relationship between risk and the VSL, predicted VSL estimates are reported based on five different baseline risks, ranging from 0.25 to 2 deaths per 10,000 workers (98 percent of the observations in models 3 and 4 had a mean risk of less than 2 deaths per 10,000). Also, since BLS and NIOSH are two very commonly used data sources, and the choice of which data source to use leads to significantly different estimates of the VSL, we report two sets of results; one assuming all studies used BLS risk data, and one assuming that all studies used NIOSH risk data. Although we report estimates arising from both BLS and NIOSH data, it should be noted that the risk data from NIOSH are aggregated to the 1-digit industry SIC code (although they vary by state) and as such, are viewed with some skepticism [see also Fisher et al., 1989 and Dorman and Hagstrom, 1988].[13]

Lastly, to incorporate the Leigh [1995] critique of this literature, the results are distinguished according to the degree the original studies controlled for inter-industry differences in the compensating wage equations. One set of results are reported that assumes either INDDUM = 0 or INDDUM = 1 for all observations. For comparison purposes, we also report another set of results based on model 4 in which either INDUSTRIES = 0 or INDUSTRIES = 7 is assumed for all observations. There are eleven 1-digit SIC-code industries (the broadest category of industry classification). We thus consider controlling for 7 broad industry classifications as a reasonable approach in any attempt to capture inter-industry wage differentials (see Leigh [1995] for a more detailed discussion of this issue).

Overall, the results in Table 4 indicate the nonlinear nature of the relationship between baseline risks and the estimated value of a statistical life. The estimated value of statistical life is approximately 75 percent to 110 percent higher at mean risks of 1.5×10^{-4} as compared to mean risks of 0.25×10^{-4}. For risks greater than approximately 1.5×10^{-4}, our models indicate that VSL estimates begin to decline, with an initial

[13]At the time when NIOSH was actively collecting this data, it was thought to be a more complete census of occupational fatalities than the BLS had been collecting. However, this turns out to not be the case. The NIOSH data collection was based on a review of death certificates, while BLS was based on a survey of employers. Because there were no standard reporting mechanisms for death certificates, it was not clear that all deaths that were job-related were recorded as such. However, the main criticism of the NIOSH data is that recording risk rates at the 1-digit industry SIC code is not likely to accurately reflect the risk rates of all the industries under each SIC code. For example, Bakery Products (SIC code 205) and Petroleum Refining (SIC code 291) are both in the major group "manufacturing industries," although it is likely the risk rates of general laborers are very different in these two industries.

decrease of approximately 10 percent between risks of $2.0x10^{-4}$ and $1.5x10^{-4}$. The results also indicate that VSL estimates arising from NIOSH data are approximately 75 percent larger than those arising from BLS data; similar to the "doubling" referred to by Moore and Viscusi [1988a]. In comparing our VSL estimates with previous assessments of this literature, we will focus on our values for risks of $1x10^{-4}$ which is both typical of the risks considered in studies based on U.S. samples and is the average risk in the workplace [Viscusi, 1993].[14]

If we assume BLS = 1 and industry wage differentials are <u>not</u> controlled for adequately (i.e., INDDUM=0 or INDUSTRIES=0), our predicted values for the VSL are approximately $3 to $6.5 million. At a risk level of $1x10^{-4}$, our VSL estimate of approximately $6 million is in the middle of the range suggested by Viscusi [1993] and Fisher, et al. [1989], and is the mean value suggested by Neumann and Unsworth [1993], and applied by the U.S. EPA in their retrospective and prospective analysis of the Clean Air Act (U.S. EPA, 1995 and 1997). The mean values suggested by the two quantitative studies most similar to ours, Desvousges et al. [1995] and Miller [2000], are also in this range. However, if we instead assume NIOSH risk data is appropriate, the predicted VSL increases to $6 to $11 million and is commensurate with the upper range of Fisher, et al.'s [1989] assessment of this literature, although Fisher, et al. "place more confidence in the lower end of the range" than they do in their upper range (p. 98).

If instead, we assume BLS = 1 and moderate industry controls are used in the compensating wage equations (INDDUM=1 or INDUSTRIES=7), the VSL estimates are decreased by 60 to 65 percent to a range of $1.3 to $2.5 million. This range is below previous qualitative assessments of this literature

[14]The median and mean for MEANRISK in our data for U.S. national studies are $1.08x10^{-4}$ and $1.1x10^{-4}$, respectively, while the 25th and 75th percentiles are $0.79x10^{-4}$ and $1.31x10^{-4}$, respectively.

[Fisher et al., 1989, Viscusi, 1993], and are half the size of what Desvousges, et al. [1998] and Miller [2000] suggest as appropriate values ($4 million). This range is also about one third the mean estimate used by the U.S. EPA [1997 and 1999], in their analysis of the Clean Air Act, and 30 to 50 percent lower than what are used by several federal agencies in their benefit/cost regulatory analyses, e.g., the Food and Drug Administration and the U.S. Department of Transportation.[15] If we assume NIOSH=1 with industry controls in place, the value of statistical life estimates again increase approximately 75 percent, and generally fall in the $2 to $4 million range. This is commensurate with the suggested range by Miller [1990], and is in the lowest range, or below, other previous assessments.[16]

CONCLUDING COMMENTS

The studies estimating the value of a statistical life with labor-market data are an example of a literature that has evolved using relatively homogeneous methods, yet has generated results that in some instances vary greatly across studies. As a result, it can be difficult to ascertain the best VSL value, or range of values, for any particular policy application. We build on previous reviews of this literature by using a quantitative, meta-analysis approach. Plausible VSL estimates are developed which use the weight

[15]The Consumer Product Safety Commission uses $5 million (unindexed for inflation), and the Food and Drug Administration uses $5 million in considering mammography policy [Office and Management and Budget (OMB), 1998]. The Federal Railroad Administration uses a value of $2.9 million in considering roadway worker protection policies [OMB, 1998]; and the U.S. Department of Transportation requires $2.9 million for use in preparing economic evaluations of their regulations [U.S. Department of Transportation General Counsel, 1995], all in 1998 dollars. Also, in preparing regulatory analyses for proposed actions imposing requirements on licensees, the Nuclear Regulatory Commission based its valuation of radiation exposure avoidance based a value of a statistical life estimate of $3 million [U.S. Nuclear Regulatory Commission, 1995a and 1995b, presumedly in 1995 dollars].

[16]An anonymous reviewer notes that our computations, which are based on individual decisions over risk, should be adjusted by approximately $200,000 to reflect “societal” WTP measures, which should include the present value of income taxes foregone and worker’s compensation payments per occupational fatality (see Arthur, 1981 and Miller et al., 1989 for a discussion of this issue).

of the evidence from the entire literature, not just a few preferred studies or preferred estimates. This approach also has an advantage over qualitative reviews of the literature since VSL estimates may be adjusted in a systematic manner to reflect "best practice" ideals and to impose uniformity. An adjustment which we find to be important involves consideration of how authors controlled for inter-industry wage differentials in their original compensating wage equations.

Our research suggests the value of a statistical life that can reasonably be inferred from past labor market studies, for populations facing risks approximately equal to the current average risk of accidental death in the workplace of $0.5x10^{-4}$ [Marsh and Layne, 2001], is approximately $2 million in 1998 dollars, a 50 percent or greater decrease over previous assessments of this literature which have tended toward values of $4 million or more [Viscusi, 1993, Neuman and Unsworth, 1993, Desvousges, et al., 1995, and Miller, 2000].[17] Indeed, our analysis suggests that value of statistical life estimates over $2 to $3 million are likely to reflect the lack of attention this literature has given to the control of unobserved determinants of wages at the industry level [Leigh, 1995]. These results are particularly important for the conduct of benefit/cost analyses involving policies that have mortality reduction as a primary goal.

[17]We further refine this VSL estimate by computing a value of statistical life for an 'average' U.S. worker based on workplace fatality data obtained from NIOSH [Marsh and Layne, 2001] for the years 1983 to 1995. Workplace fatalities for 45 occupations were used to compute 10 occupational-risk deciles. According to the NIOSH data, occupations in the lowest risk decile had an average fatality risk of $0.04x10^{-4}$ and occupations in the highest risk decile had an average fatality risk of $2x10^{-4}$. A VSL estimate is computed for each risk decile in the same manner as used to compute the estimates reported in Table 4. We did not have the mean wage corresponding with the workers in each risk decile, and so all deciles are evaluated at the mean wage of our sample. Using model 3 in Table 3 (with NIOSH and INDDUM set equal to one), we estimate the value of statistical life for the average worker to be $2,579,000, which is commensurate with the value reported in Table 4 for risks of $0.5x10^{-4}$. If instead our predictions are adjusted to reflect the upward bias in VSL estimates arising from NIOSH risk data (i.e., set BLS=1 and NIOSH=0), the estimated value of a statistical life for an average U.S. worker is $1,493,000.

Table 1. Meta-analysis Studies and Summary Characteristics[a]

Study	N[b]	Mean VSL (1998 $ in millions)	VSL Range (1998 $ in millions)	Mean Annual Risk ($1x 10^{-4}$)	Mean Hourly Earnings
Berger and Gabriel, 1991	4	8.79	6.6 - 10.2	1.09	21.89
Brown, 1980	2	2.03	2.0 - 2.1	2.25	23.20
Butler, 1983	3	1.12	0.87 - 1.3	0.47	10.75
Cousineau et al., 1992	3	6.81	6.1 - 7.2	0.76	14.04
Dillingham, 1979	10	0.92	0.05 - 1.9	1.53	17.90
Dillingham, 1985	10	3.43	0.14 - 8.6	1.33	13.52
Dillingham and Smith, 1983	11	4.32	0.48 - 7.9	0.82	14.06
Dorsey and Walzer, 1983	2	11.59	11.5 - 11.7	2.25	10.24
Garen, 1988	2	11.15	6.8 - 15.5	1.08	15.08
Gegax et al., 1991	8	2.07	0.46 - 4.1	6.87	19.59
Herzog and Schlottmann, 1990	4	9.07	7.8 - 10.2	0.97	22.89
Kneiser and Leeth, 1991	2	0.24	0.05 - 0.44	4.36	16.02
Leigh, 1991	2	10.20	6.8 - 13.6	1.34	15.60
Leigh, 1995	7	7.18	1.0 - 15.8	1.14	15.50
Leigh and Folsom, 1984	8	10.44	7.7 - 12.7	1.42	20.79
Liu and Hammitt, 1999	2	1.00	0.67 - 1.33	5.13	8.75
Liu, Hammitt, and Liu, 1997	10	0.54	0.17 - 0.85	0.29	2.87
Low and McPheters, 1983	1	1.31	—	3.27	20.93
Marin and Psacharopoulos, 1982	21	6.97	0.02 - 21.5	0.93	5.03
Martinello and Meng, 1992	8	4.06	2.1 - 6.4	2.50	3.42
Meng, 1989	5	4.05	3.7 - 4.4	1.90	27.67
Meng and Smith, 1990	5	6.88	1.1 - 9.7	1.20	18.70
Moore and Viscusi, 1988a	8	5.92	2.9 - 9.8	0.66	12.57
Moore and Viscusi, 1988b	4	2.56[c]	2.3 - 3.2	0.50	15.73
Moore and Viscusi, 1990	1	16.51	—	0.78	19.09

Study	N[b]	Mean VSL (1998 $ in millions)	VSL Range (1998 $ in millions)	Mean Annual Risk (1x 10^{-4})	Mean Hourly Earnings
Olson, 1981	10	16.55	5.2 - 30.7	1.01	17.11
Smith, 1974	2	13.11	8.9 - 17.3	1.25	13.99
Smith, 1976	2	5.23	5.1 - 5.4	1.12	14.51
Thaler and Rosen, 1976	6	0.76	0.34 - 1.3	10.98	18.50
Viscusi, 1978	6	6.69	5.3 - 7.9	1.18	15.12
Viscusi, 1980	4	3.15	0.62 - 5.5	1.18	15.12
Viscusi, 1981	2	9.20	8.0 - 10.4	1.04	15.24
Vodden, et al., 1993	28	4.78	1.9 - 11.8	1.76	9.96

[a] All dollar amounts are in 1998 dollars. The mean VSL we report is the mean over the multiple observations recorded in our database for any particular study. The same is true for the mean risk and mean earnings. As a result, the variable means we report here differ from those reported in past reviews [e.g., Viscusi, 1993] because we are taking a mean over different numbers of observations as compared to these past reviews and/or past reviewers reported means associated with a specific sub-sample of workers in the original study.
[b] Number of observations drawn from each study for use in the meta analysis.
[c] The reported VSL estimates in this study were adjusted as suggested by Miller [1990] because the authors originally report a value based on an undiscounted number of life years remaining.

Table 2. Summary Statistics for the Meta-analysis Dataset

Variable Name	Definition	Summary Statistic[a]
VSL, Risk, and Earnings		
VSL ($ million)	Value of a statistical life (1998 dollars).	5.59 (0.016-30.7)
MEANRISK	Mean annual average risk of death (in deaths per 10,000 workers).	1.81 (0.04-10.98)
HIGHRISK	=1 if MEANRISK is greater than 5 x 10^{-4}.	16/203
EARNINGS	Mean hourly earnings (1998 dollars).[b]	13.44 (2.57-27.67)
UNEMP	National unemployment rate in the year in which the wage data were collected.[c]	6.1 (2.1-11.9)
Sample variables		
US NATIONAL DATA	=1 if wage data is for a national sample of U.S. workers collected by either the University of Michigan or the Census Bureau.[d]	97/203
US SPECIALIZED	=1 if wage data is for U.S. workers, but is not a national sample of workers (category not included in the models).[e]	24/203
NON-US	=1 if wage data is for a non-U.S. sample of workers. This variable also indicates risk data from a foreign source.	82/203
DILLINGHAM	=1 if Dillingham's (1979) constructed risk data for workers in New York is source of risk data.	12/203
BLS	=1 if Bureau of Labor Statistics is source of risk data (category not included in the models).	68/203
NIOSH	=1 if National Institute for Occupational Safety and Health is source of risk data.	9/203
SOA	=1 if Society of Actuaries is source of risk data.	8/203
SELF REPORT	=1 if risk variable included a worker's self-assessment of his/her job risk.	12/203
UNION100	= 1 if the sample was comprised of only unionized workers.	16/203
WHITECOL	=1 if sample is 100 percent white collar workers.	6/203
BLUECOL	=1 if sample is 100 percent blue collar workers.	102/203
MIX	=1 if sample is a mix of white and blue collar workers (category not included in models).	95/203
Specification variables		

Variable Name	Definition	Summary Statistic[a]
RISKSQ	=1 if a risk-squared term is included in the wage equation.	46/203
MORBIDITY	=1 if controlled for other risks (such as risk of injury) in the wage equation.	80/203
LOGDEP	=1 if semi-log functional form (log of the dependent variable) is used for the wage equation, = 0 if linear.	159/203
UNION	=1 if controlled for union status of a worker in the wage equation.	176/203
REGDUM	=1 if controlled for region of worker in the wage equation.	144/203
URBAN	=1 if controlled for urban versus rural in the wage equation.	77/203
WORKCOMP	=1 if controlled for workman's compensation in the wage equation.	26/203
AFTERTAX	=1 if after-tax income is used in the wage equation.	38/203
Industry/Occupation Variables		
INDUSTRIES	= the number of industry categories controlled for in the regression with dummy variables or through sample selection.[f]	3.5 (0 - 30)
INDDUM	=1 if more than four industry dummy variables were included in the wage equation.	71/203
OCCDUM	=1 if at least one occupational dummy variable was included in the wage equation.	142/203
CHARDUM	=1 if at least one dummy variable describing a characteristic of the job was included in the wage equation.	118/203

[a]For VSL, MEANRISK, EARNINGS, UNEMP, and INDUSTRIES the summary statistic reported is the mean (with the range in parentheses). For all other variables, the summary statistic is the number of observations for which the variable is equal to 1 (divided by the number of observations in the data set).

[b] If mean earnings were reported as annual wages, they were divided by 2,000 if the sample was comprised of full-time workers only, by 1900 if the sample was comprised of those working 35 or more hours a week, by 1800 if comprised of those working 30 or more hours a week, and by 1500 if comprised of both full-time and part-time workers. If mean earnings were reported as weekly wages, the weekly wage was divided by 40, 38, 35, or 30 depending on whether the sample included full-time workers only, or those working more than 35, 30, or 20 hours per week, respectively. Currencies were converted from Canadian dollars or U.K. pounds to U.S. dollars using exchange rates for the year in which the original study reported its results. Canadian and U.K exchange rates are from the U.S. Federal Reserve Board: www.stls.frb.org/fred/data/exchange/excaus.html or /exusuk.html, respectively. The U.S. dollar equivalent results were then inflated to 1998 dollars in the same manner as other estimates. Studies based on samples from other countries reported results in U.S. dollars.

[c] Unemployment rates for the US were obtained from the Economic Report of the President, 1998. Unemployment rates for the U.K. were obtained from the Organization for Economic Co-operation and Development, OECD Observer no82, July/August, 1976; rates for Canada were obtained from Labour Force Historical Review, Statistics Canada, CD ROM version, February, 1997; and rates for for Taiwan

were obtained from the Directorate-General of Budget, Accounting, and Statistics, The Republic of China (www.stat.gov.tw), at http://140.129.146.192/census~n/four/english/e44361.htm.

[d] The University of Michigan collects or has collected the "Survey of Working Conditions," "Quality of Employment Survey," and the "Panel Study of Income Dynamics." Earlier analyses were conducted controlling for the US national data sources separately (i.e., controlling for Michigan vs. Census). Results indicated no significant difference between these data sources, and so an aggregate variable was created for US national data.

[e] These sources of data were the South Carolina Department of Labor and the International City Management Association.

[f] Some authors restricted their samples to manufacturing only (a broad SIC classification). In these instances, these studies were coded as having included 7 industry categories, the most common number used to control for broad (1-digit SIC) industry classifications in labor market studies. In two instances [Lui and Hammitt, 2000 and Low and McPheters, 1983], the authors restricted their samples to very specific occupations in a particular industry (petrochemical workers and police officers). In this instance, these authors are coded as having included 15 industry classifications.

Table 3. Model Results (dependent variable is the log of the VSL reported in a study).

Variables	Model 1 all data Coef.	std. error	Model 2 less highrisk & SOA Coef.	std. error	Model 3 US national; less highrisk & SOA Coef.	std. error	Model 4 US national; less highrisk & SOA Coef.	std. error
MEANRISK	0.681**	0.295	1.628***	0.296	1.150**	0.448	1.405***	0.352
$(MEANRISK)^2$	-0.290***	0.068	-0.488***	0.063	-0.394***	0.091	-0.460***	0.077
HIGHRISK*MEANRISK	3.701***	0.776						
HIGHRISK	-16.047***	3.095						
UNION100*MEANRISK	0.041	0.070	-0.259	0.308	-0.344	0.444	-0.202	0.463
EARNINGS	0.037**	0.018	0.035**	0.015	0.023	0.030	0.029	0.033
UNEMP	-0.009	0.053	-0.068	0.044	-0.023	0.053	0.027	0.064
US NATIONAL DATA	1.843***	0.281	1.296***	0.310				
NON-US	1.363***	0.283	0.800*	0.408				
DILLINGHAM	-1.148**	0.441	-1.472***	0.428	-1.072***	0.313	-1.406***	0.385
NIOSH	0.461**	0.199	0.753***	0.160	0.546***	0.157	0.560***	0.156
SOA	0.912	0.602						
SELF REPORT	0.091	0.576	-0.136	0.390	-0.450**	0.157	-0.434**	0.149
UNION100	0.184	0.468	0.734	0.532	1.249*	0.577	1.127*	0.509
WHITECOL	1.852***	0.485	1.754**	0.776				
BLUECOL	0.613***	0.210	0.445*	0.218	-0.210	0.143	-0.035	0.178
RISKSQ	0.721***	0.202	0.718***	0.229	0.059	0.186	-0.087	0.233
MORBIDITY	0.082	0.189	-0.116	0.138	-0.104	0.240	0.017	0.214
LOGDEP	0.184**	0.079	0.325**	0.130	0.129	0.080	0.149	0.087
UNION	1.070***	0.322	1.413***	0.386				
REGDUM	-0.509*	0.253	-0.953***	0.329	0.040	0.208	-0.085	0.270
URBAN	0.394	0.259	0.385	0.281				
WORKCOMP	-0.512*	0.260	-0.231	0.169	-0.224	0.166	-0.224	0.170
AFTERTAX	0.139	0.233	0.129	0.239	-0.463*	0.260	-0.460	0.266
INDDUM	-0.181	0.179	-0.493***	0.159	-1.042***	0.198		
INDUSTRIES							-0.123***	0.026
OCCDUM	-0.204	0.304	-0.292	0.350	0.041	0.353	0.045	0.465
CHARDUM	0.005	0.211	0.340*	0.186	0.329**	0.143	0.196	0.132
CONSTANT	-1.942***	0.383	-1.718***	0.244	0.956	0.840	0.474	0.829
Number of Observations	**203**		**185**		**91**		**91**	
R^2	**0.7104**		**0.7280**		**0.7747**		**0.7711**	
sample mean-VSL [range]	5.59 [0.016 - 30.7]		6.02 [0.05 - 30.7]		7.70 [0.05 - 30.7]			
sample mean-risk [range]	1.9 [0.04 - 11]		1.27 [0.04 - 4.36]		1.11 [0.5 - 4.36]			

[a] A *, **, or *** indicate significance at the 10, 5 and 1 percent-level, respectively.

Table 4. Estimates of the Value of Statistical Life: Mean Adjusted Fitted Values [a]

Risk (x 10^{-4})	Based on Model (3), Table 3 < 5 Industries	Based on Model (3), Table 3 $ 5 Industries	Based on Model (4), Table 3 0 Industries	Based on Model (4), Table 3 7 Industries
BLS Risk Data				
P = 0.25	$3.82m (1.39)	$1.35m (0.47)	$2.99m (1.12)	$1.27m (0.40)
P = 0.5	$4.73m (1.64)	$1.67m (0.53)	$3.90m (1.44)	$1.65m (0.51)
P = 1.0	$6.25m (2.36)	$2.20m (0.73)	$5.57m (2.22)	$2.36m (0.80)
P = 1.5	$6.78m (3.02)	$2.39m (0.92)	$6.33m (2.83)	$2.68m (1.03)
P = 2.0	$6.05m (3.09)	$2.13m (0.92)	$5.72m (2.83)	$2.42m (1.03)
NIOSH Risk Data				
P = 0.25	$6.59m (2.62)	$2.32m (1.00)	$5.24m (2.08)	$2.22m (0.84)
P = 0.5	$8.16m (3.17)	$2.88m (1.20)	$6.82m (2.72)	$2.89m (1.10)
P = 1.0	$10.8m (4.57)	$3.80m (1.65)	$9.76m (4.18)	$4.13m (1.68)
P = 1.5	$11.7m (5.65)	$4.13m (1.95)	$11.1m (5.21)	$4.69m (2.07)
P = 2.0	$10.4m (5.57)	$3.68m (1.85)	$10.0m (5.06)	$4.24m (1.97)

[a] Values are expressed in millions (1998 dollars). Standard errors are in parentheses.

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