A Meta-Analysis of Wage-Risk Estimates of the Value of Statistical Life

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Abstract

This paper presents the results of a meta-analysis of estimates of the value of statistical life (VOSL). Data on the sample characteristics, data sources and analytical approach used to derive some 60 separate estimates in 17 published papers are used in the analysis. Tests lead us to reject the hypothesis that this sample shows evidence of publication bias. A meta-regression of these estimates provides evidence that VOSL is increasing in income but is invariant with respect to baseline risk. Controlling for aspects of the sample, data sources and analytical approach allows us to derive a best estimate of the VOSL of around $7 million.

Keywords: Value of a Statistical Life, Hedonic Wage-Risk, Meta-Analyis

Introduction

The economic literature abounds with estimates of the Value of Statistical Life (VOSL) derived from hedonic wage-risk studies. The diversity in these estimates has been a source of concern for policy-makers (estimates reviewed here range from US$-2.65 million to US$95.17 million). Unfortunately, no individual study is likely to provide an estimate of the VOSL that can be reliably used for policy purposes.

The inaccuracy in any one study derives from two causes; the fact that it is based on just one sample of individuals, and the fact that it is unlikely to control for all possible biases that might enter into the estimation of the VOSL. Taken as a whole, however, information from all the studies provides a means by which we can control for estimation biases and investigate the influence of sample characteristics on the estimated VOSL.

The statistical techniques used for analysing the summary findings of different pieces of original research are known as meta-analysis. Meta-analysis allows us to test various hypotheses concerning the values derived from the numerous wage-risk studies. One issue that is addressed here is that of publication bias. Specifically we investigate whether the published VOSL estimates reflect a tendency to only publish significant results. The existence of publication bias would cast doubt on the validity of using reported estimates of the VOSL for policy purposes.

Also, meta-analysis allows us to 'control' not only for the characteristics of the individual study samples but also for aspects of the study's data sources and analytical approach. A meta-regression of the VOSL estimates allows us to determine the influence of study characteristics on reported result. The results of this regression allow us to derive best 'controlled' estimates of the VOSL that summarise the findings in the literature.

Measuring the VOSL in Labour Markets

The value of statistical life (VOSL) is a measure of society's willingness to tolerate risks of mortality. Since no market exists where mortality risks are explicitly traded, different valuation techniques are relied upon to infer people's preferences for risks. In general, preferences are measured in terms of peoples' willingness to pay (WTP) to avoid risk or willingness to accept (WTA) risk of dying. The WTP/WTA for a change in risk is converted into a value of statistical life via the following relationship:

$$\mathrm{VOSL} = \frac{\sum_{i} \mathrm{WTP}_{i}}{\Delta\, \mathrm{risk} \times \mathrm{population}}$$

Hedonic wage-risk studies determine WTA by estimating the wage-premium associated with a higher risk of job fatality. It is assumed that in freely operating labour markets, workers will seek compensation through wages in order to accept greater risk of job-related death.

For example, suppose that Job A differs from Job B only in so much as for every 1,000 workers one more death is experienced per year. If workers in Job A earn $500 more than workers in Job B, it is assumed that this represents their WTA compensation for the extra risk they face; an amount often termed the compensating differential or risk premia. Given that workers in Job A are willing to accept $500 for a 1-in-1,000 increase in the risk of death, the suggested VOSL in this hypothetical workforce would be $500,000.

Of course, in the real world it is nigh on impossible to find two occupations that are identical in every aspect apart from the risk of job-related fatality. Instead researchers use multi-variate regression analysis to estimate a hedonic wage function that relates wages commanded to the characteristics of the worker, occupation, firm/industry and labour market as well as the risk of fatality in that occupation. The coefficient estimated on the risk variable gives an indication of workers' WTA compensation for a marginal reduction in occupational safety and provides the basis from which VOSL estimates can be derived.

Empirical Estimates of the VOSL from Wage-Risk Studies

Over the past three decades, a large number of hedonic wage-risk studies have appeared in the literature. The different studies have resulted in an extraordinary range of VOSL estimates (those analysed in this paper range from US$-2.65 million to US$95.17 million, see Table 1). To all intents and purposes, however, the source of this heterogeneity remains unclear. A number of good reviews of the hedonic wage-risk literature have already been undertaken including those by Violette and Chestnut (1983), Fisher, Chestnut and Violette (1989), Miller (1990) and Viscusi (1993). It is not our intention to repeat the work of these authors here. Rather we summarise the main issues that have been raised in the estimation of the VOSL and use this to frame the meta-analytical work to follow.

Sample Data:

Though some studies (e.g. Smith, 1974; Kneisner and Leeth, 1971) have attempted to estimate hedonic wage functions using aggregate industry-level data, these have tended to be unsuccessful in isolating compensating wage differentials for risk. In general, hedonic wage studies rely on micro data sets that provide details of workers' characteristics, wages and the characteristics of their occupations.

Clearly, one source of variation in estimates of the VOSL, will be variation in the characteristics of the sample of workers used in each individual study. Some of the most important sources of variation in the characteristics of worker samples include;

- *Income:* Assuming that risk is a normal good, we would expect VSOL estimates derived from generally more affluent samples to be higher than those from less wealthy groups. In general, differences in WTA compensation for risk brought about by differences in income have not been tested for in the wage-risk literature. However, this may be an important issue to policy-makers wishing to apply the values derived from one population to a target population which differs in its mean income. If the VOSL has an income elasticity different from zero then its value must be adjusted according to the population to which it is being applied.

- *Baseline Risk:* A second factor in which economic theory can provide guidance as to why estimates of the VOSL might differ is that of the mean level of risk faced by workers in the sample. Simple economic models suggest that marginal WTA compensation for risk will increase as baseline risk increases. Thus a sample of workers facing higher baseline risks will demand more in compensation for a marginal increase in risk than those at lower levels. The logic behind this is exemplified by taking the extreme example where a marginal change in risk takes the worker to a point of certain death. Clearly, we would expect WTA compensation at this point to be infinite. We might expect, therefore, that estimates of the VOSL will be higher for samples exposed to relatively high levels of risk. However, these models also suggest that marginal WTA compensation for risk will be relatively stable over a large range of low levels of risk. As such it may prove difficult to detect evidence of increasing WTA within the range of risks found within the workplace.

- *Gender:* Many wage risk studies have restricted their attention to male workers (e.g. Smith, 1976; Brown, 1980; Thaler and Rosen, 1975; Marin and Psacharopoulos, 1982; Arnold and Nichols, 1983; Dillingham, 1985; Leigh, 1995; Arabsheibani and Marin, 1999). Even if women are included in the sample this fact is usually only reflected in the wage-risk analysis through the inclusion of a dummy variable such that gender-related differences in the compensating wage differential go unaccounted. It is a source of contention as to whether the inclusion or exclusion of women results in biased estimates of the VOSL. Social convention would suggest that women are more risk averse than men. Indeed, as Leigh (1987) points out, women, in general, do not take risky jobs and even in the same risky job, men tend to be delegated the highly risky tasks and women the only moderately risky tasks.

  As we discuss below wage-risk studies are rarely able to define risks with such precision that they could distinguish between those faced by women and men in the same occupation in the same industry. More usually risk data is constructed by dividing the total number of fatalities (which will tend to be predominantly male) in a particular occupation-industry category by the total workforce (both male and female) in that category. If Leigh's argument is correct, and this author believes it to be so, then risk data used to estimate hedonic wage equations will almost certainly underestimate the true risk faced by males in the workplace. Assuming workers are compensated for the actual risk they face, then estimates of the compensating wage differential based on lower than actual measures of risk will result in upwardly biased estimates of the VOSL.

The evidence in the literature supporting this contention is limited. Leigh (1987), investigating the issue, found that the compensating wage differential differed only slightly when he excluded women from his sample.

- *Unions:* The influence of union membership on compensation for fatal risk is not clear. Sandy and Elliot (1996) sum up the opposing arguments. In the main, it would seem more likely that compensating wage differentials will be higher for unionised workers since unions provide their members with both greater information about occupational hazards and a mechanism for voicing their concerns over risk.

  Researchers have tended to investigate the issue by estimating a separate risk coefficient for workers who are members of a union or by running separate regressions on union and non-union sub-samples. The evidence from such work is, to say the least, inconclusive. Most of the early studies found larger compensating wage differentials paid to union workers. Thaler and Rosen (1976), for example, estimated compensating differentials that were 80% to 10 times greater for union than non-union workers. Likewise, significantly larger risk premia for union workers have been reported by Viscusi (1980), Olson (1981) and Dorsey (1983). On the other hand, Dickens (1984) and Dillingham and Smith (1984) find lower compensating wage differentials for union workers in the US. Whilst in the UK Marin and Psacharopoulos (1982), Herzog and Schlottman (1990) and Sandy and Elliot (1996) find that workers in occupations that are covered by union terms and conditions have a significantly lower compensation for exposure to fatal risk. Arabsheibani and Marin (1999) found that whether union membership was included as an exogenous or endogenous variable, there was only a small difference between the size of the coefficient on fatal risk between union and non-union members. They conclude that whilst union membership clearly impacts on overall wage, it has little impact on the compensating differential for exposure to fatal risk.

Risk Data:

Clearly, one of the key variables in a hedonic wage-risk regression is that used to measure workers' to risk of fatality. Unfortunately, in the majority of studies, it is also the variable that is possibly least well defined. In general, fatality risk has been calculated by reference to aggregate data on the fatalities in particular industries and usually (though not always) occupational categories. Measures of risk in a industry-occupation category are returned by dividing the fatalities data through by the number of workers in that category.

Though this objective measure of risk is not theoretically the one that should be considered (compensation for risk will depend on the worker's subjective belief about the risks he faces), it is the one used in the vast majority of empirical work.

The sources of data on fatalities differ widely in their accuracy and level of aggregation. In the US, particular attention has been paid to two sources of data on risk.:

- *Bureau of Labour Statistics* (BLS). The BLS have provided researchers in the US with information on occupational fatalities aggregated within two- and three-digit Standard Industry Classifications (note, one-digit SIC is the broadest categorisation of industries). Clearly, this level of aggregation presents problems to the analyst, since even within 'risky' industries there are occupations which bear little to no risk.

Assigning workers in one such occupation with the average risk levels in the industry would be inappropriate.

The BLS's data are collected as part of an annual survey of occupational injuries and illnesses. Information was collected from roughly 250,000 to 280,000 firms, depending on the year. However, it is claimed (Sandy, pers. comm.) that the BLS industry-based measures of fatal workplace risks miss about half of all workplace accidental deaths in the US. The BLS did not collect data at all from firms with less than 12 workers, plus all workers in farming, airlines and railroads. Even within the covered industries, the BLS data miss a substantial fraction of all workplace deaths. If the BLS data underestimate the risk faced by workers, it is likely that using this data will bias the coefficient on risk upwards and result in higher than average estimates of the VOSL.

- *National Institute of Occupational Safety and Health (NIOSH)*. Through their National Traumatic Occupational Fatality Survey (NTOF) the NIOSH provide industry level data on workplace fatalities for each state in the US. The NTOF provides a complete count of workplace deaths and records 84% more fatalities than the BLS (Viscusi and Moore, 1988). However, the NTOF is recorded at only the one-digit SIC industry level.

  Moore and Viscusi (1988) prefer the NIOSH fatality data to that of the BLS because the former are based on a census rather than a survey and are therefore freer of error. They also point our that the NIOSH data is recorded solely for workplace fatalities and compared to the BLS is a more accurate measure of risk in the workplace.

A number of researchers have directly compared the impact of using the BLS risk measures with those from other sources, within the same data set. Dillingham (1985) compared the BLS risk estimates with those that he derived from records of workers compensation claims in New York in 1970. Though the latter is, in itself, not a great measure of fatality risk, the BLS data return consistently higher estimates of the VOSL. Leigh (1995) compares the BLS with the NIOSH risk measures in two separate data sets. He finds that with regard to one data set the BLS data returns the higher estimates of the VOSL whilst with regard to the other, the BLS returns lower estimates. Leigh (1995) also test to see whether the aggregate nature of the BLS and NIOSH data lead to erroneous conclusions. He hypothesises that the observed relationship between wages and fatal risk may be due to the coincidental patterns of wages and death rates across broad industry divisions. He suggests that the inclusion of dummy variables distinguishing broad industry divisions should be included to account for such effects. Having carried this out, Leigh finds that the inclusion of industry dummy variables significantly reduces estimates of the VOSL. Indeed he can no longer detect a compensating wage differential in his data and uses this result to cast doubt on the use of the poor quality BLS and NIOSH data. Using the BLS data, the studies of Dickens (1984) and Dillingham and Smith (1983) support this result. Whilst Viscusi (1978) and Dillingham (1985) and Cousineau et al. (1992) still find significant differentials with their data once industry dummies have been included.

Specification of the Wage-Risk Function:

The VOSL estimates reported by researchers will not only be influenced by the data they use in their analysis but also the decisions they make about how to analyse the data. Again, this may be a source of variation in reported estimates of the VOSL.

- *Functional Form of the Dependent Variable:* A major decision faced by researchers in their analytical approach is the choice of the functional form of the hedonic wage-risk equation. In practice, functional form specification tends to be relatively simple, with researchers plumping for either a linear or semi-log form (i.e. regressing wages against regressors or the natural log of wages against regressors). Viscusi (1978a) and Leigh and Folson (1984) report details of both specifications for the same data and find that the linear form returns higher estimates of the VOSL. Conversely, Herzog and Schlottman (1990) report a slightly lower estimate of the VOSL with the linear specification.

- *Functional Form of the Risk Measure:* Along similar lines, researchers must choose how the risk variable will enter the hedonic wage-risk equation. Whilst many have opted to include risk alone and untransformed (e.g. Dillingham, 1985; Leigh, 1987; Cousineau et al., 1992, Leigh, 1995; Arabsheibani and Marin, 1999), others have reported more interesting specifications in which risk is included both linearly and as a squared term, or in which risk is interacted with characteristics of the worker, some have even included squared terms and interactions (e.g. Arnould and Nichols, 1983, include both risk, risk squared and risk interacted with workers' age, marital status and race; Olson, 1981, includes risk, risk squared and interacts both risk and risk squared with a union membership dummy; Moore and Viscusi, 1990, interact risk and risk squared with regional dummies).

  Clearly, the more complex the specification of risk in the hedonic wage function, the more complete is the characterisation of the compensating wage differential. Including, squared risk terms allows the marginal WTA compensation for risk to be a function of risk. Interacting risk with worker characteristics allows for segmentation in the labour market whereby, for example, a worker in one region can receive greater compensation for risk than an equivalent worker in another region. We would expect that studies including more complex specifications will give more accurate estimates of the VOSL of the sample.

- *Endogeneity of Risk:* In recent years another issue with specification of hedonic wage-risk equations has come to the fore, that of the endogeneity of risk. It is claimed that risk is an endogenous variable and that workers who chose risky jobs are substantially different from other workers. It is claimed that ignoring this issue biases estimates of the VOSL downward since it is likely that more dangerous jobs are chosen by those who are less averse to danger and who, therefore, require a lower compensation to induce them to face the risk.

  Garen (1988) was the first to address the issue and presented a specification of the hedonic wage-risk equation which accounted for the endogeneity of risk. As would be expected he found that accounting for endogeneity considerably increased his estimate of the sample's VOSL. Similar findings have been presented by Seibert and Wei (1996), Sandy and Elliott (1996) and more recently Arabsheibani and Marin (1999). Indeed, many of the estimates accounting for endogeneity are two to three times as large as those where risk is considered exogenous. Arabsheibani and Marin (1998), however, cast some doubt on the Garen procedure (pp. 41-44) and suggest the very high values returned from these models may be an idiosyncrasity of the model itself.

- *The Inclusion of Non-Fatal Risk:* Clearly, we would expect workers to demand compensation for exposure to the risk of injury at work as well as their exposure to risk of death. Frequently researchers fail to include measures of non-fatal risk in their specification of the hedonic wage-risk equation (e.g. Arnould and Nichols, 1983; Dillingham, 1985, Herzog and Schlottman, 1990; Leigh 1987 and 1995; Marin and Psacharopoulos, 1982; Sandy and Elliott, 1996). Since the risk of injury is likely to be highly correlated with the fatal risk variable, wage-risk functions which do not include a non-fatal risk variable will return an upward biased estimate of the fatal risk premium.

  This contention has been supported by Viscusi (1978) who found that the estimate of the VOSL reduced considerably when non-fatal risks were included in the specification of the hedonic wage-risk function. Evidence is less clear from the two other studies that report results including and excluding a measure of the risks of injury. Maritnello and Meng (1992) find that with some specifications the inclusion of a non-fatal risk measure reduces estimates of the VOSL whilst in others the estimate of the VOSL is increased. More recently, Arabsheibani and Marin (1999) found that the coefficient estimated on the fatal risk variable is not sensitive to the inclusion or exclusion of non-fatal risks.

It is clear from this brief review, that a number of differences in the characteristics of original studies may result in differences in the estimate of the VOSL that they report. Specifically we have identified three key areas of variation;

- *Characteristics of the sample*; including their income, baseline risk, gender and union membership status.
- *Source and quality of the risk data*.
- *Specification of the wage risk equation*; including whether the risk of non-fatal injuries are included in the equation, whether risk is treated as exogenous or endogenous, the functional form of the hedonic wage equation and the functional form of the risk variable.

In the meta-regression reported below we attempt to discern how these various sources of variation influence the reported VOSL.

Meta Analysis of Wage Risk Studies

Compilation of the Meta Data Set

To undertake a meta-analysis of the VOSL, information was collected from sixteen published hedonic wage-risk studies. This is by no means an exhaustive list and further work should be undertaken to extend this research.

All the papers reviewed contained details of more than one hedonic wage-risk regression. A regression was treated as a separate observation in the meta data set based on one of three criteria:

- First, if it was based on a unique sample of workers,
- second if, within the analysis of a unique sample, the measurement of the risk variable was changed and
- third if within the analysis of a unique sample, the authors reported specifications of the hedonic wage-risk equation that differed in the inclusion of non-fatal risk, in the treatment of risk as endogenous or exogenous, in the functional form of the dependent variable and in the functional form of the risk variable.

Details of the original papers and key characteristics of the studies are contained in Table 1.

Table 1: Data Sources, Sample Characteristics and Estimates of the VOSL

Authors	Number of Unique Estimates	Country	Worker Data Source[a]	Sample Size	Risk Data Source[b]	Mean Income (US$ 1996)	Mean Risk per '000 per year	VOSL Range (mill. US$ 1996)
Arabsheibani & Marin (1999)	4	UK	GHS	2,669 - 3,608	OPCS	24,079	-.006[c]	13.47 – 41.28
Arnould & Nichols (1983)	4	US	PUS	1,832	SA	-	-	1.03 - 11.83
Cousineau et al. (1992)	2	Canada	LCS	12,718 - 19,995	QCB	33,989	.076	2.31 - 5.1
Dillingham (1985)	6	US	NY, QES	514 - 3,714	BLS, NY	25,264 - 35,532	.008 - .14	.25 - 8.59
Garen (1988)	2	US	PSID	2,863	BLS	28,932	-	6.91 - 15.83
Herzog & Schlottman (1990)	2	US	PUS	2,954	BLS	-	-	7.75 - 9.85
Kneisner & Leeth (1991)	2	US	CPS	8,868	NIOSH	31,201	.044	.49 - 4.25
Leigh (1987)	4	US	CPS, QES	326 - 2,158	BLS	22,374 - 38,110	-	11.63 - 13.59
Leigh (1995)	10	US	CPS, PSID, QES	315 - 1,528	BLS, NIOSH	17,831 - 30,949	.011 - .013	-2.66 - 15.34
Leigh and Folson (1984)	4	US	PSID, QES	361 - 1,529	BLS	33,653 - 34,797	.126 - .142	9.49 - 12.48
Marin & Psacharopoulos (1982)	2	UK	GHS	5,464	OPCS	15,598	.004[c]	3.1 - 3.49
Martinello & Meng (1992)	4	Canada	LMAS	4,352	OSH	43,129	.25	8.31 - 14.43
Olson (1981)	2	US	CPS	5,993	BLS	32,373 - 38,529	.079 - .14	1.76 - 30.91
Sandy & Elliott (1996)	4	UK	SCELI	440	OPCS	25,062	.045	8.05 - 95.17
Siebert & Wei (1994)	4	UK	GHS	514 - 1,292	HSC	16,408 - 17,723	.033 - .061	5.92 - 14.18
Viscusi (1978a)	4	US	SWC	496.	BLS	30,122	.118	2.65 - 7.54

Notes For Table 1:

[a] Abbreviations used for Worker Micro-Data sources:

CPS	Current Population Survey, US
GHS	General Household Survey, UK
LMAS	Labour Market Activity Survey, Canada
QES	Quality of Employment Survey, US
PSID	Panel Study of Income Dynamics, University of Michigan, US
PUS	Public Use Sample of Census, US
SCELI	Social Change and Economic Life Initiative, UK
SWC	Survey of Working Conditions, University of Michigan, US

[b] Abbreviations used for Risk Data sources:

BLS	Bureau of Labour Statistics
NIOSH	National Institute of Occupational Safety and Health
NTOF	National Occupational Fatality Survey
OPCS	Office of Population Censuses and Surveys
SA	Society of Actuarials

[c] Risk data in Marin & Psacharopoulos (1982) and Arabsheibani & Marin (1999) is not based on absolute fatality risk but is the difference between fatality risk and average fatality risk

It is clear from the final column of Table 1, that the meta sample contains a wide range of estimates of the VOSL. The values for the full sample are plotted in Figure 1 and those for the North American studies and those from the UK plotted in Figures 2 and 3 respectively.

A number of observations can be made. The majority of estimates lie in the range US$0 to US$15 million. Two of the hedonic wage functions contained in the meta data set estimate a negative coefficient on the risk variable and hence translate into negative VOSLs. Though this does not concord with economic theory these estimates are retained to avoid introducing selectivity bias into the sample. The sample also shows a distribution that is skewed to the right; a small number of estimates take on relatively high values. Separating the estimates into North American (US and Canada) and UK sub-samples, reveals that the majority of these high values come from the UK. Indeed, the values over US$40 million come from two recent UK papers by Sandy and Elliott (1996) and Arabsheibani and Marin (1999), both of which estimated hedonic wage functions that treated risk as an endogenous variable.

Figure 1: Distribution of the Estimates of the VOSL for all Countries

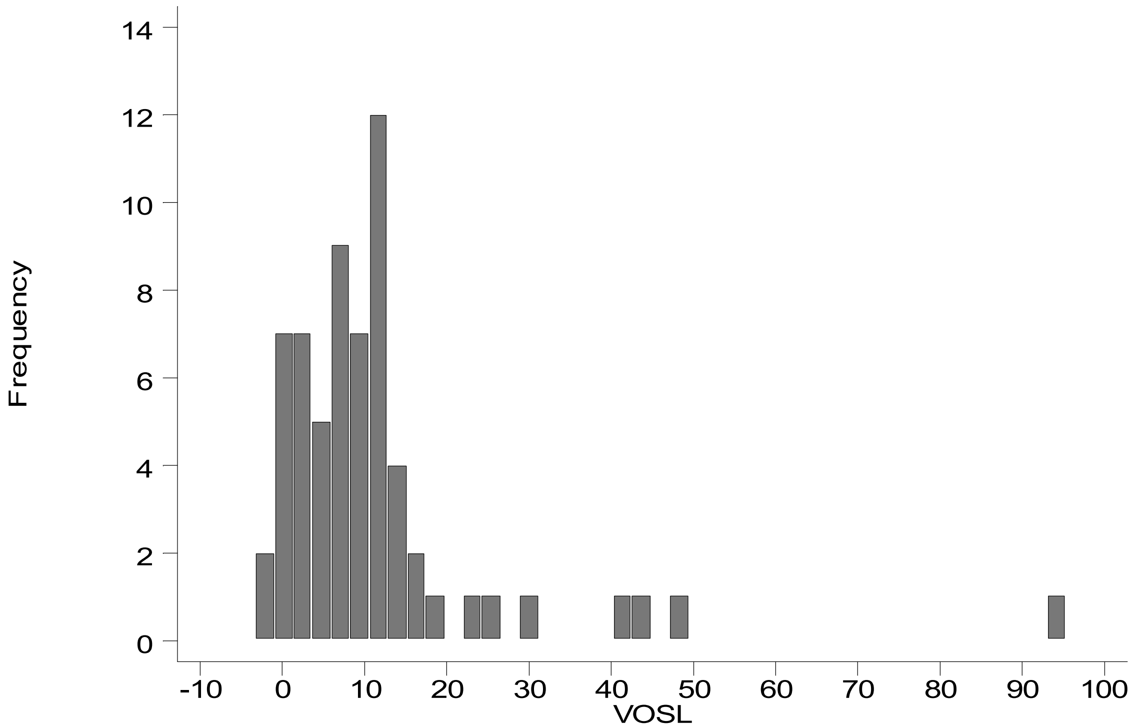


Figure 2: Distribution of the Estimates of the VOSL for North American Studies

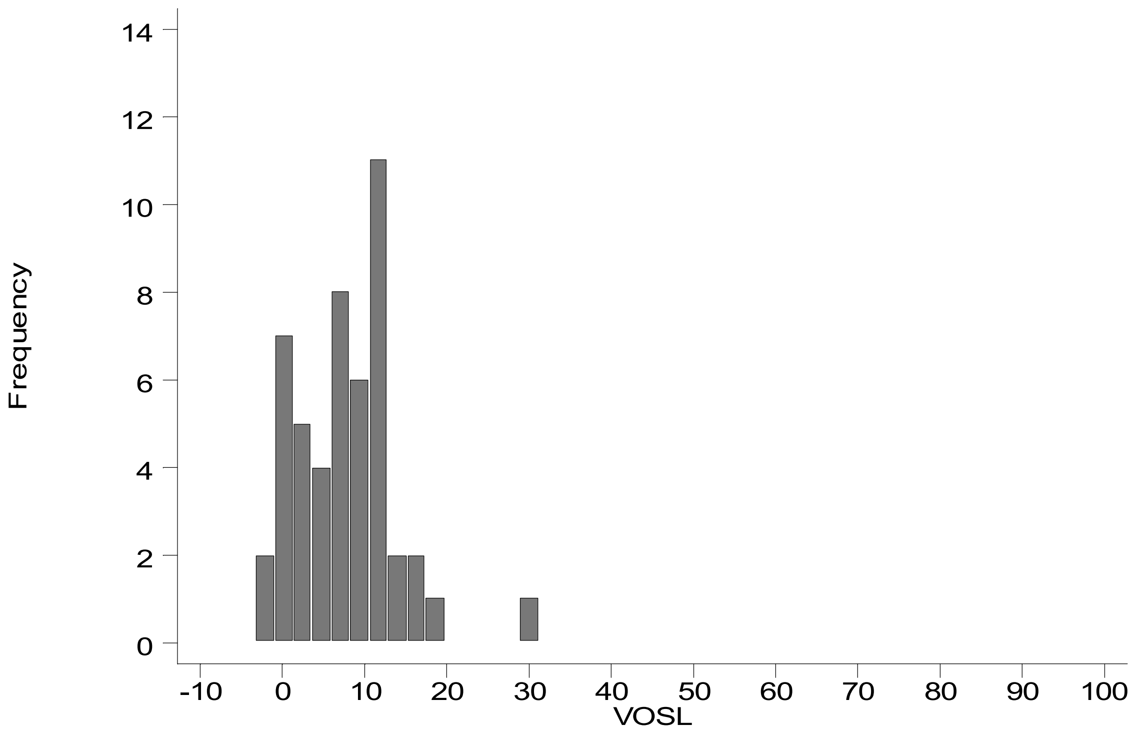
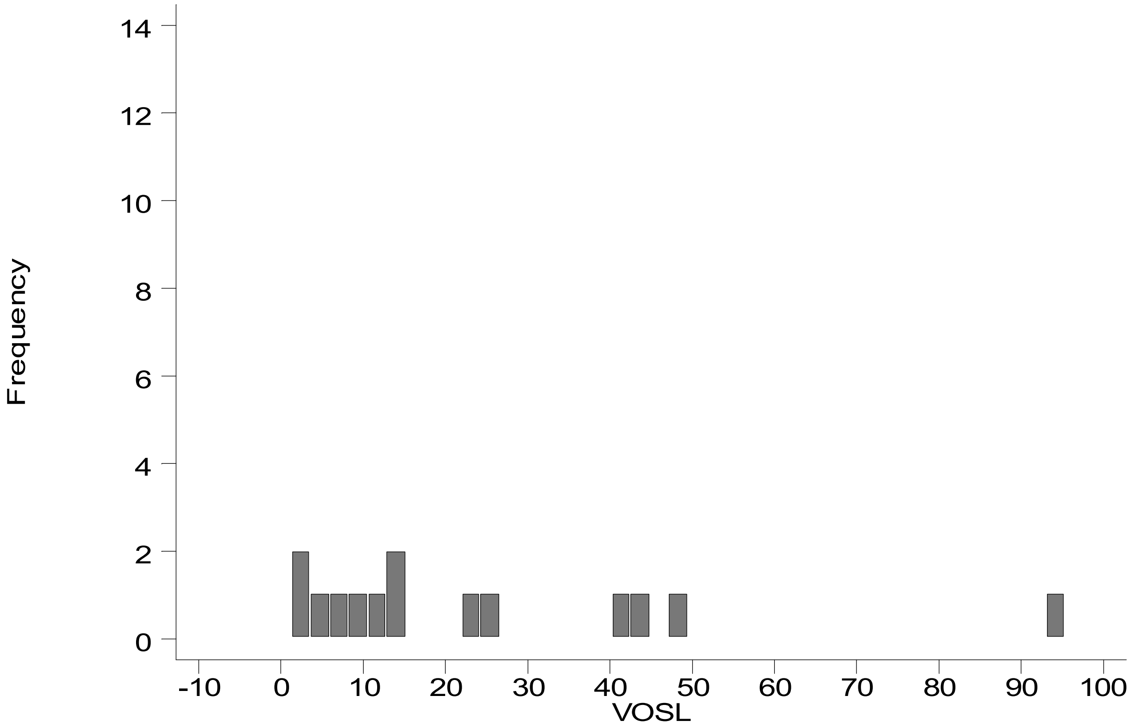


Figure 3: Distribution of the Estimates of the VOSL for UK Studies



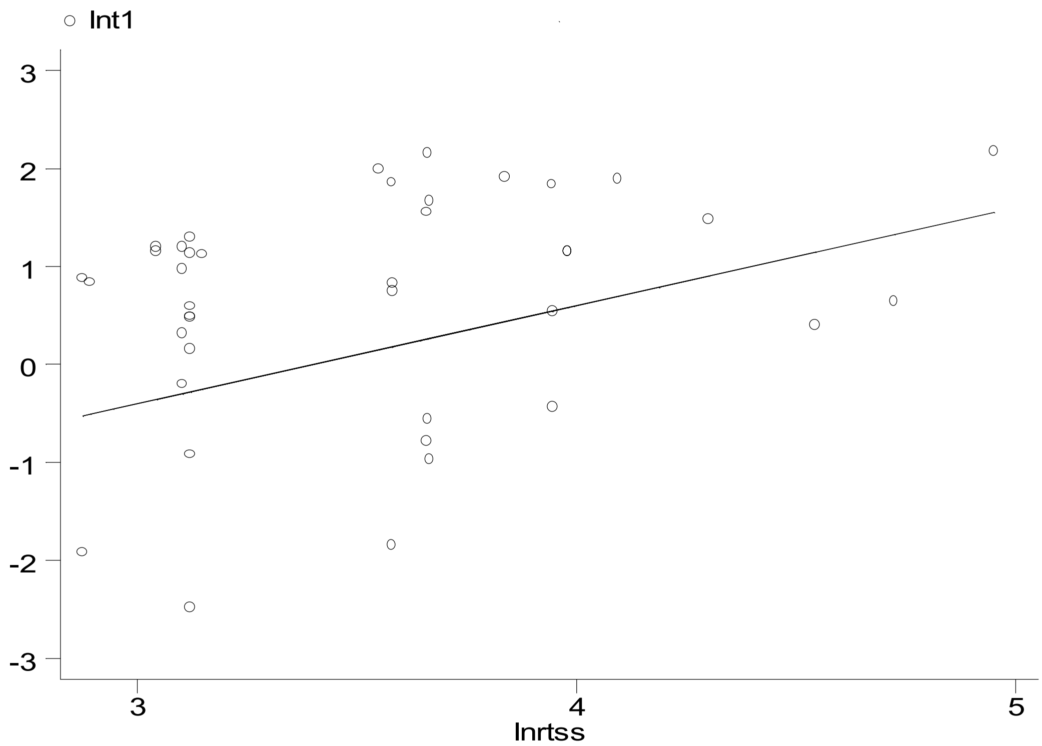
Publication bias

Meta-analysis is the statistical analysis of the summary findings of prior empirical studies for the purpose of integrating findings. One possible problem facing meta-analyses is that the studies published in the available literature may over represent that subset of all studies which produce ‘positive’ or significant results if studies yielding ‘negative’ or non-significant findings tend not to be published. However, it is possible to test whether the meta sample shows indications of publication bias.

Basic sampling theory suggests that there should be a simple “inverse-square-root” relationship between the sample size and the *t* ratio obtained in different studies. Provided we assume that the data from different studies are independent (or control for this) and that the statistical model is stable, then we would expect to see studies with larger sample sizes returning larger *t* ratios for the coefficient on the fatality risk variable. A lack of this relationship would be suggestive of publication bias. For example, if journals follow a rule of only publishing studies that report significant findings and authors manipulate their specifications (by varying functional forms, changing the set of included regressors, etc.) until they achieve a result, we might expect to find high *t* ratios even in small samples.

Figure 4 provides a plot of the log of the *t* ratio against the log of the root of the sample size. Reassuringly, the data shows a definite positive relationship; the *t* ratios on the risk coefficient tend to be larger in large sample studies and smaller in small sample studies.

Figure 4: Plot of the log of estimated t-ratio on risk coefficient against the log of the root of the sample size



Since, statistical theory predicts that the value of the *t* ratio should vary proportionally with the square root of the sample size,[1] it is possible to carry out a quantitative test for publication bias. Specifically a regression of the log of the *t* ratio on the log of the square root of the sample size should yield a coefficient of one (see line plotted on graph). The results of such a regression are presented in Table 2. The non-independence of estimates from the same author has been controlled for by accounting for within-study heteroskedasticity and robust standard errors are reported using the Huber-White adjustment to the variance-covariance matrix.

[1] More correctly number of degrees of freedom though, since most hedonic wage studies contain relatively few covariates, the difference is not considered a mjor issue.

Table 2: Regression of the log of estimated t-ratio on risk coefficient against the log of the root of the sample size

	Coefficient	**Robust Standard Error**
Log of Root Sample Size	.635	.343
Constant	-1.604	1.23

A *t* test of the hypothesis that the estimated coefficient on the log of the root of the sample size is not equal to one can be rejected with a high degree of confidence (p (coeff = 1) = .23). We conclude that the sample does not show signs of publication bias.

Meta-Regression

The main objective of this study is to obtain a 'best' VOSL estimate by summarising the information provided in the published studies. The process by which we derive this best estimate is through meta-regression; a regression of the estimates of the VOSL coming from each study.

Meta-regression recognises the inherently stochastic properties of the estimation process; that repeated identical studies will lead to different results because each study is a sample drawn from a distribution of possible studies. We can think of the estimate from each individual study as being a random realisation of this overall "mother" distribution of estimates. Figure 1 provides a pictorial depiction of the mother distribution based on the VOSL estimates reviewed in this paper. If we assume, for now, that differences in VOSL estimates are not a result of characteristics of the individual studies, Figure 1 suggests that the mother distribution is not normally distributed. As mentioned previously, the distribution is skewed to the right. Indeed using a test suggested by Royston (1991) we can reject the hypothesis that the distribution is normal with a high level of confidence (χ^2 = 53.08, Probability mother distribution is not normal = .0000). Figure 1 is more reminiscent of a log normal distribution. Indeed, when we perform the same test we can not reject the hypothesis that the mother distribution is log normal (χ^2 = 3.40, Probability mother distribution is not log normal = .1827). We shall return to this observation later when we discuss the choice of functional form for the meta-regression.

In this study we assume that estimates of the VOSL are drawn from a distribution whose mean is conditional upon a set of other variables. As discussed above, it seems reasonable to assume that the characteristics of the individual studies have had a significant effect on their estimate of the VOSL. Accordingly we control for characteristics of the individual studies that may have effects on the mean of the mother distribution. Specifically we control for characteristics of the sample in each study, characteristics of the risk data used in each study and details of the specification of the wage risk equation estimated in each study. Table 3 provides definitions and mean values for the variables used in the meta-regression.

The justification for the selection of this set of variables was provided in the last section. Note in Table 3 the inclusion of two dummy variables that indicate studies where no income data or no risk data could be extracted from the published paper. These were included to avoid loss of data through missing variables. Whilst this is a relatively minor problem for income data (only six estimates from two studies did not provide details of sample mean income) the problem was more pronounced for the baseline risk variable (eighteen estimates from six different studies did not provide details of mean baseline risk in the sample).

Table 3: Definition of Variables in Meta-Regression

Variable	**Description**	**Mean (Weighted by root of sample size)**
VOSL	*VOSL; calculated for the mean of study if risk is specified non-linearly (mill. US$ 1996)*	*10.075*[a]
Income	*Mean income of study sample (US$ 1996)*	*29,436*[a]
Baseline Risk	*Mean risk of study sample (per '000 per year)*	*.094*
No Income	*Dummy variable; equals 1 if sample mean income not quoted in original paper, 0 otherwise.*	*.104*
No Risk	*Dummy variable; equals 1 if sample mean risk not quoted in original paper, 0 otherwise.*	*.324*
Union Workers Only	*Dummy variable; equals 1 if estimate for Union workers only, 0 otherwise*	*.172*
Male Workers Only	*Dummy variable; equals 1 if only males in sample, 0 otherwise*	*.458*
UK	*Dummy variable; equals 1 if UK study, 0 otherwise*	*.209*
BLS Risk Data	*Dummy variable; equals 1 if risk data is from the BLS, 0 otherwise*	*.364*
Risk Endogenous	*Dummy variable; equals 1 if risk is treated as an endogenous variable, 0 otherwise*	*.096*
Risk of Injury	*Dummy variable; equals 1 if risk of injury included, 0 otherwise*	*.455*
Linear Model	*Dummy Variable; equals 1 if the dependent variable is linear form, 0 if it log form*	*.122*
Non-Simple Risk	*Dummy Variable; equals 1 if the risk variable is interacted with other covariates or entered as a squared term, 0 otherwise.*	*.34*

Notes:

[a]All values translated into $US 1996 by expanding by the consumer price index to mid 1996 in the study country and converting to $US using the PPP exchange rate in 1996.

The large number of dummy variables in this list of covariats may be a cause of concern. With a relatively small data set, such as the one used here, over-specification with dummy variables may lead to coefficient estimates that merely act as proxies for dummy variables on individual studies. In such a case interpretation of the coefficients is difficult. However, no such problem exists with the dummy variables included here. As illustrated in Table 4, no dummy variable solely defined any one study and conversely, no two studies were defined by the same set of dummy variables. At the same time, as illustrated in Table 5, the choice of estimates of the VOSL taken from one study was made in such a way as to ensure that there is within-study variation in the dummy variables. It is possible that at a later date, the data could be refined such that the dummy variables describing the characteristics of the study sample are represented by continuous percentages (e.g. the percentage of females in the sample).

Table 4: Between Study Variation in Dummy Variables

Authors	Male Only	Union Only	BLS	Endog. Risk	Injury	Linear	Risk Inter.
Arabsheibani & Marin (1999)	✓			✓	✓		
Arnould & Nichols (1983)	✓					✓	✓
Cousineau et al. (1992)		✓			✓		
Dillingham (1985)			✓				
Garen (1988)	✓		✓	✓	✓		
Herzog & Schlottman (1990)	✓		✓			✓	
Kneisner & Leeth (1991)					✓		✓
Leigh (1987)			✓				
Leigh (1995)	✓		✓				
Leigh and Folson (1984)	✓		✓		✓	✓	
Marin & Psacharopoulos (1982)	✓						✓
Martinello & Meng (1992)		✓			✓		
Olson (1981)		✓	✓		✓		
Sandy & Elliott (1996)	✓	✓		✓			✓
Siebert & Wei (1994)	✓	✓		✓	✓		
Viscusi (1978a)			✓		✓	✓	

Table 5: Within Study Variation in Dummy Variables

Authors	Male Only	Union Only	BLS	Endog. Risk	Injury	Linear	Risk Inter.
Arabsheibani & Marin (1999)				✓	✓		
Arnould & Nichols (1983)							
Cousineau et al. (1992)		✓					
Dillingham (1985)			✓				
Garen (1988)				✓			
Herzog & Schlottman (1990)						✓	
Kneisner & Leeth (1991)							✓
Leigh (1987)	✓						
Leigh (1995)			✓				
Leigh and Folson (1984)						✓	
Marin & Psacharopoulos (1982)							✓
Martinello & Meng (1992)		✓			✓		
Olson (1981)		✓					
Sandy & Elliott (1996)		✓		✓			✓
Siebert & Wei (1994)		✓		✓			
Viscusi (1978a)					✓	✓	

A further cause of concern is the application of ordinary least squares (OLS) regression to this data. Two observations would suggest that this is an inappropriate estimation technique.

First, it is recognised that different studies estimate the VOSL to differing degrees of precision. This implies that the errors in the meta-regression equation are likely to be heteroscedastistic. The method employed in this paper, therefore, uses Weighted Least Squares (WLS) rather than OLS regression. The WLS technique assigns a weight to each observation which is a measure of the precision of the estimate of the VOSL. Since VOSL is calculated directly from the coefficient estimated on the risk variable in the hedonic wage-risk function, an ideal measure of precision would be the estimated standard error of the risk coefficient. Unfortunately, many authors include the risk variable interacted with workers' characteristics or as a squared term and fail to report details of the joint significance of the risk variable. In such cases no estimate of the standard error is available. As such, we adopt an alternative weight based on the relationship described in the previous section between the expected significance of the risk coefficient and the size of the sample from which it is estimated. Specifically, we weight each estimate by the root of the sample size from which it was derived. Put simply, estimates of the VOSL from large samples are assumed to be more accurate and hence are allotted greater weight in the meta-regression than estimates from small samples. For example, the highest estimate of the VOSL in the data set is some US$95 million, twice as much as the next highest value. This estimate was derived from Sandy and Elliott (1996) using a sample of only 440 workers. Since this estimate is based on a relatively small sample it is given lower weighting in estimation of the meta-regression using WLS. It can be show that the WLS procedure possesses the Best Linear Unbiased Estimator (BLUE) property.

A further cause of concern, is that the meta data set contains multiple estimates of the VOSL from each study. We might expect that results emanating from one piece of original research will be more similar than those coming from different studies. In econometric terms this will manifest itself as correlation in the error terms associated with estimates from the same study. It can be shown that not accounting for this form of heteroscedasticity will bias down the standard errors estimated on the coefficients, erroneously increasing the coefficients apparent significance. To overcome this problem we account for the clustering of estimates by study and employ the White correction to the variance-covariance matrix to return robust estimates of the standard errors.

Results and Discussion

The results from four meta-regressions are presented in Table 6. Both a linear specification and, to account for the apparent log normality of the mother distribution, a log-linear specification are presented. Further, both the linear and log specifications were estimated with and without the variables representing baseline risk. It was found that considerable and spurious collinearity existed between the risk and income variables in the data set ($\rho = 0.76$). As such, the estimates on neither parameter are likely to be stable when both are contained in the same regression.

Overall the models perform commendably. Judging by the R^2 statistics almost half of the variation in the various estimates of the VOSL is explained by the included parameters (ranging from 45% to 52%). Each of the models has a fair number of significant coefficients, though on this criteria the joint significance of the parameters in the log models far exceeds that of the equivalent linear model (for the specifications without the risk variable, $F_{10,5} = 2.68$ for the linear model compared to $F_{10,5} = 11.42$ for the log model and for the specifications with the risk variables, $F_{12,5} = 14.13$ for the linear model compare to $F_{12,5} = 25.8$ for the log model).

Interpretation of the coefficients in the models containing the baseline risk variables is problematic due to the existence of collinearity with income. For two reasons the author believes that removing the risk variable from the model provides a better specification. The first returns to the argument presented above; that economic theory would suggest that marginal WTA will vary little over the range of risks faced in the workplace. The second is based on the quality of the data used in the model. No information was available on the baseline risk associated with over a third of the estimates in the meta sample. Based on these observations, the preferred specification of the author is that presented in column 3 of Table 6; the log model excluding the baseline risk variables.

Table 6: Meta-Analytical Models of the VOSL using WLS and Clustering by Study

Variable	Linear Model		Log Model	
	No Risk[a]	Risk[a]	No Risk[b]	Risk[b]
Sample Data:				
Mean Income	*.00091* *(.00039)***	*.00122* *(.00068)**	*.00010* *(.00004)***	*.00007* *(.00005)*
No Income Available	*27.760* *(12.026)***	*37.652* *(22.950)*	*3.037* *(1.269)**	*1.837* *(1.695)*
Mean Risk		*-40.178* *(35.940)*		*4.329* *(2.758)*
No Risk Available		*-4.351* *(7.539)*		*.543* *(.465)*
Union Workers Only	*2.596* *(4.100)*	*2.164* *(5.066)*	*.738* *(.313)***	*.807* *(.344)***
Male Workers Only	*2.796* *(2.364)*	*1.780* *(2.566)*	*.767* *(.297)***	*.868* *(.325)***
UK	*19.094* *(6.740)***	*23.241* *(10.826)***	*1.784* *(.539)****	*1.267* *(.794)*
Risk Data:				
BLS Risk Data	*5.918* *(2.950)**	*6.798* *(3.469)**	*.914* *(.313)***	*.784* *(.301)*
Specification:				
Risk Endogenous	*13.611* *(7.860)*	*13.548* *(7.840)*	*.624* *(.307)**	*.634* *(.353)**
Risk of Injury	*-1.684* *(3.769)*	*-2.555* *(4.046)*	*-.095* *(.228)*	*.004* *(.245)*
Linear Model	*.364* *(1.464)*	*.815* *(1.212)*	*.161* *(.175)*	*.125* *(.145)*
Risk Variable Interacted	*-1.484* *(2.362)*	*-.431* *(2.378)*	*-.424* *(.353)*	*-.525* *(.332)*
Constant	*-24.892* *(12.053)**	*-30.765* *(17.807)*	*-2.411* *(1.326)**	*-1.714* *(1.407)*
N	*60*	*60*	*58*	*58*
R^2	*0.449*	*0.466*	*0.495*	*0.520*
Root Mean Square Error	*9.954*	*10.006*	*0.898*	*0.895*

Notes:
[a] Dependent variable is VOSL; Coefficients presented with robust s.e.'s errors in brackets
b Dependent variable is natural log of VOSL; Coefficients presented with robust s.e.'s errors in brackets
*significant at the 10% level
**significant at the 5% level
***significant at the 1% level

Before we begin discussion of the model parameters, it is worth noting some possible interpretations of the VOSL. For decision-makers the VOSL is a value that can be placed on fatalities in the analysis of policy decisions which involve changes in the incidence of deaths in the population when those deaths manifest themselves as small changes in each individual's exposure to risk. Alternatively, we can view the VOSL estimated from a study as the sample's total WTA in compensaton per year in order to accept one more fatality in their number per year (again when the actual change in risk to each individual is small). In the discussion of the parameters that follows, both these interpretations will be called upon. When considering the variables included to control for aspects of the research itself, it seems more sensible to talk about how these factors have influenced the estimate of the VOSL. On the other hand, it is more natural to discuss the variables that describe the characteristics of the sample population in each study, in terms of how these factors influence the samples WTA in compensation.

Let us deal with the sample characteristics first. Reassuringly, the coefficient on income is consistently positive coefficient. All else being equal, samples with higher incomes require higher levels of compensation to accept increases in risk than do those on lower incomes. In three of the four models presented here the income coefficient is also statistically significant. However, due to the problem of collinearity with risk, the significance of the income variable declines markedly when risk is included in the model specification. Since risk and income are positively correlated in this data set, the possibility that the coefficient on income in the preferred specifications (i.e. those excluding risk) may also reflect the impact of base line risk must be bourne in mind.

The coefficients on income presented in Table 6 can be used to calculate the income elasticity of the VOSL. These are pesented in Table 7.

Table 7: Implied Income Elasticity of the VOSL

	Linear Model		**Log Model**	
	No Risk	**Risk**	**No Risk**	**Risk**
Income Elasticity of the VOSL:	2.65	3.56	.55	.36

Clearly, the estimate of the income elasticity of the VOSL is highly dependent on the specification of the model. Using the linear form the calculated elasticity is much greater than unity, implying that the VOSL has the characteritics of a luxury good. Alternatively, in the log specifications, the calculated elasticity is less than unity. These findings add little to the debate over the transfer of the VOSL across populations. In previous transfer exercises it has frequently been assumed that the VOSL has an income elasticity of unity. From our models this assumption would appear to be incorrect. Since the majority of values for the VOSL have been estimated in relatively rich countries (usually North America or Western Europe) and applied to relatively poor countries, previous transfer exercises are likely to have considerably over- or under-stated the VOSL in the target country. Unfortunately, the disparity in the estimates between the linear and log specifications make it difficult for us to suggest which.

The coefficients estimated on the risk variable are not significant in either specification. Further, the coefficient is negative in the linear model and positive in the log model. Interpretation of these coefficients is problematic due to the presence of collinearity.

As would be expected, the dummy variables included for those studies in which the sample income (or exposure to risk of death) were not available, tend to be significant when the coefficient on income (risk) is significant. Naturally, the samples with missing observations do not behave as if they have a mean income (exposure to risk of death) of zero. Indeed, we can use the ratio of the coefficients (adjusted for functional form) to calculate the income (baseline risk) with which these observations are consistent.

The coefficients on the ‘union only sample’ dummy always takes a positive coefficient and is significant with a 10% confidence level in both the log models. In line with prior expectations, the meta-analysis suggests that unionised workers are able to demand higher compensating differentials for exposrue to fatal risk than non-unionised workers.

The coefficients estimated for the ‘male only sample’ follow a similar pattern; they are always positive and significant at the 10% level of confidence for the log specified models. This fact supports the contention above that estimates from male only samples will be biased upwards since data on risks fails to regcognise that men will tend to take on riskier tasks than women within the same broad occupation-industry division. The inclusion of women in the sample can be thought of as counterbalancing this bias. By the same argument, women alotted the occupation/industry average risk in the analysis, will in actuality face lower risk than their male counterparts and consequently receive a lower compensating differential. If the estimate of risk used for women exceeds the actual risk for which they are compensated then the estimated of the VOSL will be biased downwards. Strictly speaking, we would expect that in a random sample of male and female workers these two biases will cancel each other out.

The dummy variable distinguishing UK studies from North American studies is highly significant in three of the four models and always positively signed. It would seem that, all else equal, the minimum WTA compensation for risk in the UK is higher than that in North America. It may, however, be a little premature to declare that UK populations place a higher value on a statistical life than their North American counterparts. Collinearity in the dummy variables may be influencing this result. In particular, 8 of the 14 UK estimates were derived from studies that employed Garen’s (1988) procedure to account for the endogenous nature of risk. In contrast, only 1 of the 47 North American studies employed this procedure. Since, accounting for endogenous risk invariably returns higher estimates of the VOSL, it is possble that some of this impact is picked up in the coefficient estimated on the UK dummy variable. That said, the weighted mean value of VOSL estimates from the UK that did not account for the endogeneity of risk is still almost twice that for equivalent US studies (US$13.26 million (n = 8) for UK studies, compared to US$7.4 million (n = 46) for North American studies).

As discussed previously, much debate has centred around the quality of the risk data used in VOSL studies. The BLS data on fatal risks has been employed by a number of researchers but criticised for its lack of detail and quality. The BLS dummy was included to test whether the use of this data introduced a discernible bias into the estimates of VOSL. The parameter estimated on the BLS dummy in all four models is positive. This supports the observation described previously that the BLS data consitently underestimates the risk exposure of workers. If workers compensating differentials are being explained by a lower than actual risk variable, the resultant estimates of the VOSL will be biased upwards. Studies using BLS risk data will tend to return higher values for the VOSL than those using other sources.

The variable included to single out those studies that had made the choice of risk endogenous in their estimation of the VOSL is, as expected positively signed. In the log models, the parameter is also significant at the 10% level of confidence. It would seem that accounting for the enodgeneity of risk is important. If we base our estimates of VOSL on the compensating differentials paid to workers in risky jobs but fail to account for the fact that this group may have selected themselves into these jobs simply because they are not as risk-averse as the rest of the population, we risk seriously underestimating the VOSL of the population. However, a word of caution is in order. The estimation procedure used by all the authors who have investigated the issue of endogeneity is that proposed by Garen (1988). As mentioned above, Arabsheibani and Marin (1998) suggest that there are problems with this procedure that may explain the considerably higher estimates of the VOSL returned from these models. Pending further investigation of these problems, little can be concluded about the size of the bias in estimates of the VOSL resulting from failure to recognise the endogenous nature of risk in the hedonic equation.

Non-fatal accidents in the workplace are likely to be correlated with fatal accidents. As such, estimates of the coefficient on fatal risk in specifications ignoring the incidence of risk of injury, will in part reflect workers WTA compensation for exposure to non-fatal risk. Consequently, we would expect the estimate of the VOSL coming from such studies to biased upwards. The meta regression provides qualified support for this contention. In three of the four models the dummy variable distinguishing estimates that accounted for the risk of injury has a negative sign. In none of the models, however, is this parameter significant.

The final two variables in the model are included to reflect the functional form of the hedonic wage-risk equation adopted by the resarcher. All four models return similar conclusions. Models using the linear form (as opposed to the log transformation of the dependent variable) tend to return higher estimates of the VOSL, whilst models in which the risk variable is interacted with workers' characteristics or introduced non-linearly tend to provide lower estimates of the VOSL. In none of the models, however, are these parameters significant.

Deriving the 'Best' Estimate of the VOSL

The meta-regression of VOSL estimates has proved generally successful. The coefficients estimated in the preferred specification of the model (assuming a log distribution of VOSL estimates and excluding baseline risk as a covariate), are all correctly signed, and several are significant at normally accepted levels of confidence.

It is possible to use the models presented here to derive a 'best' estimate of the VOSL which accounts for biases in the estimation procedure and summarises the findings in the literature.

In effect our model provides an estimate of the "mother" distribution of VOSL estimates. Denoting the mother distribution F_M we can write;

$$F_M \sim LogNormal\left(X\beta, \tilde{\sigma}^2\right), \qquad (1)$$

where X is the vector of values taken by the covariates in the meta -regression

β is the vector of parameter estimates on these covariates

and $\tilde{\sigma}^2 = \frac{\sum_i^N e_i^2}{N}$, is our estimate of the variance of the mother distribution given by the mean of the squared residuals (e_i) from the regression.

Notice that the mother distribution is defined as following a log normal distribution since the preferred model uses the log of the VOSL estimates as the dependent variable. The location parameter of this distribution is given by $X\beta$ and hence, the distribution will shift according to the values taken by the covariates. We can calculate the mean of the mother distribution according to;

$$E(VOSL) = \exp(X\beta)\exp\left(\tilde{\sigma}^2/2\right) \qquad (2)$$

which is the standard formula for calculating the mean of a log normal distribution.

One possible summary measure of the meta data set, therefore, would be to calculate (2) with the X vector evaluated at the sample means. This reveals that the mean VOSL in the meta-sample is US$9.12 million.[2]

Of course, setting the covaraites to their sample means ignores the fact that some of these variable represent biases in the underlying study. For example, the dummy variable included for studies that accounted for non-fatal injuries in the work place has a negative sign. We contend that the coefficient estimated by the meta analysis on this dummy variable indicates the downward bias in estimates of the VOSL that results from ignoring non-fatal injuries in the specification of the hedonic wage-risk equation. Our calculation of the 'best' estimate of the VOSL coming from the studies should control for these biases.

[2] As would be expected, this figure is relatively close to the weighted arithmetic mean of the VOSL estimates presented in Table 3 (US$10.75 million).

Table 8 details the assumptions made in defining the values of the covariates included in estimation of the best estimate of the VOSL.

Table 8: Values Chosen for the Best Estimate of the VOSL

Variable	**Reason**	**Value used to Derive Best Estimate**
Sample Data:		
Mean Income	*Sample Mean*	*US$29,436*
No Income Available	*Excluded; Income accounted for by use of sample mean income above*	*0*
Union Workers Only	*Excluded; Best estimate will provide the value for general population samples*	*0*
Male Workers Only	*Excluded; Best estimate will account for the overestimate of the VOSL in male only samples*	*0*
UK	*Sample Mean; Best estimate will provide the value for the general population represented in the meta-sample*	*.209*
Risk Data:		
BLS Risk Data	*Excluded; Best estimate removes bias from the use of poor quality of BLS Risk Data*	*0*
Specification:		
Risk Endogenous	*Included; Best estimate corrects for the downward bias in VOSL estimates that do not account for the endogeneity of risk*	*1*
Risk of Injury	*Included; Best estimate removes the upward bias introduced by the failure to account for non-fatal risk.*	*1*
Linear Model	*Sample Mean; no clear reason why the linear specification should be preferred to the log specification, or vice-versa*	*.122*
Risk Variable Interacted	*Included; Under the assumption that more complex specifications of the risk variable provide better estimates of the VOSL*	*1*

Evaluating the covariates at the values suggested in Table 8 provides our best 'controlled' estimate of the VOSL; US$5.63 million. Clearly this value is somewhat lower than that derived at the means of the data. (US$9.12 million) it would appear that the net effect of the various biases identified in the estimation of wage-risk equations is to increase the estimates of the VOSL contained in this sample.

Conclusions

The main results of the research reported in this paper can be summarised as follows:

1. By means of a review of published literature, 60 estimates of the VOSL derived from 16 separate studies were collected. Each estimate differed either in the sample of workers from which it was derived or by the data that had been used to measure risks of fatality or by the specification of the hedonic wage-risk equation used by the researcher.
2. Sampling theory suggests that the significance of estimates in regression analysis should increase as the size of the sample on which a regression is based increases. Indeed, in the absence of publication bias we would expect to see a straight line relationship between the log of the root of the sample size and the log of the *t* statistic estimated on the fatal risk variable in wage-risk regressions. For studies in which the *t* statistic estimated on the risk coefficient were available, a test of this hypothesis could not be rejected. We conclude that there is little cause to worry about the existence of publication bias in the sample of estimates used in this work.
3. A meta-regression of VOSL estimates on characteristics of the data and analytical technique performs reasonably well, explaining almost half of the variation evident in the data and returning a number of statistically significant coefficients. The meta regression provides some interesting finding:
    i. As expected, VOSL is increasing in income. Our estimates of the income elasticity of the VOSL are unstable and highly influenced by the functional form of the meta-regression. With our preferred specification, the income elasticity of the VOSL is estimated to be .55.
    ii. Estimates based on union only samples return consistently higher estimates of the VOSL as do those base on male only samples. Estimates from the UK also appear to be larger than estimates from North America. However, this may, in part, be due to the large number of UK estimates which have employed a correction for the endogeneity of risk which invariably increases the estimate of the VOSL.
    iii. The use of the poor quality BLS data in US studies would appear to consistently bias up estimates of the VOSL.
    iv. Researchers who have employed an estimation procedure that accounts for the endogenous nature of risk in wage-risk regressions derive larger estimates for the VOSL. This is consistent with the supposition that those who choose risky jobs are less risk averse than the general public and their relatively low WTA compensation for exposure to risk biases down estimates of the VOSL.
    v. Specifications of the wage-risk equation that include the risk of non-fatal injury, as well as that for the risk of death, tend to return higher estimates of the VOSL. Risk of death and risk of injury in the workplace are likely to be highly correlated. The coefficient estimated on the fatal risk variable in specifications that ignore the risk of injury, would therefore appear to be picking up, at least in part, workers WTA compensation for exposure to non-fatal risk.

vi. Linear models tend to result in higher estimates of the VOSL whilst more complex specifications of the risk variable (e.g. interacting risk with workers' characteristics or including risk squared terms) tends to reduce the estimate of the VOSL.

4. The results of the meta regression can be used to present a best estimate of the VOSL. At the sample means the mean VOSL for the sample of estimates is US$9.12 million. However, controlling for the biases introduced by sample data and analytical approach derives a best estimate of the VOSL of US$5.63 million.

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