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Are Estimates of the Value of a Statistical Life Exaggerated?

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Are Estimates of the Value of a Statistical Life Exaggerated?*

1. Introduction

Estimates of the value of a statistical life (VSL) are used extensively in cost-benefit analyses (CBA) of public health and safety projects worldwide.¹ Examples of such public health and safety projects include: transport safety and occupational health and safety interventions, environmental protection and rehabilitation programmes, and public health initiatives (Ashenfelter, 2006). However, CBA is often based upon VSL estimates that differ widely, even after one adjusts for regional differences, exchange rates and year. In order to make sense of this heterogeneity, researchers have turned to meta-regression analysis (Stanley, 2001). Meta-regression analysis allows researchers to account for many other dimensions of heterogeneity such as differences in average worker income, the circumstances of the risk of death, and observable variations in the econometric models and methods used to estimate VSL.

Commencing with Liu, Hammitt and Liu (1997), numerous meta-analyses of VSL estimates have been undertaken, the most recent being Bellavance, Dionne and Lebeau (2009), Lindhjem, Navrud and Braathen (2010) and US EPA (2010). Other meta-analyses of VSL estimates include Day (1999), Miller (2000), Bowland and Beghin (2001), Dionne and Michaud (2002), Mrozek and Taylor (2002), de Blaeij, Florax, Rietveld and Verhoef (2003), Viscusi and Aldy (2003), Kochi, Hubbell and Kramer (2006), Dekker, Brouwer, Hofkes and Moeltner (2008) and Kluge and Schaffner (2008). While not all of these meta-analyses provide an overall VSL estimate for policy analysis, they all attempt to make sense of the wide disparity among VSL estimates. These ‘quantitative’ and systematic reviews of VSL suggest that differences between estimates are, of course, partly due to sampling error, but also due to data differences (e.g. different countries, time periods, and groups of workers analysed) and methodological choices (e.g. the specification of the wage regression and the choice of the fatality risk variable) made by the researcher.

* We are grateful for the valuable feedback and suggestions provided by the editor and two anonymous referees.

¹ VSL is a measure of the marginal rate of substitution between income and fatality risk. It is not a measure of the value of a single *actual* life. Rather, it is the aggregation of the value of the marginal willingness to pay for infinitesimal risk reductions for different people that are aggregated to a single *statistical* life (Cameron, 2010).

To date, little consideration has been given to the possibility that the selection bias inherent in choosing which results to report may also be contributing to the observed differences found among VSL estimates. Existing meta-analyses have assumed implicitly that the reported VSL estimates are a representative sample, thereby valid and unbiased inferences can be drawn from their averages.² In particular, they assume that there is no preference to report statistically significant fatality risk coefficients and positive VSL estimates. However, if the available VSL estimates are a truncated and/or a selected sample, then any average, weighted or simple, will lead to a biased estimate of VSL.³ Typically, such truncated or skewed samples result in *inflated* averages and, hence, potentially to faulty inference (De Long and Lang, 1992; Card and Krueger, 1995; Roberts and Stanley, 2005).

In this paper, we ask whether reported VSL estimates are a reflection of publication selection and, if so, how practically important is the resulting bias. Our paper has three aims. First, we wish to make users of VSL estimates – researchers, meta-analysts and policy makers - aware of the issue of publication selection bias and its potential effects on inference. Second, we offer more accurate estimates of VSL for use in CBA. Third, we identify more fully the heterogeneity among VSL estimates and thereby provide revised estimates of key elasticities, such as the income elasticity of VSL.

Section 2 discusses how publication selection might bias estimates of VSL. Section 3 modifies the existing meta-regression model used in prior meta-analyses and uses the modified framework to detect and correct publication selection bias. Section 4 discusses the selection bias corrected meta-regression results. Policy implications are discussed in section 5. Section 6 concludes the paper. The economic theory underpinning VSL, measurement and estimation issues and limitations are not presented in this paper, as these have been discussed extensively in several other studies (e.g. Viscusi, 1978, 1993).

² Lindhjem, Navrud and Braathen (2010) raise the issue of non-random sample bias but do not formally model or correct for it. Dionne and Michaud (2002) also raise the issue and include the year of publication as an attempt to control for selection effects. Hwang, Reed and Hubbard (1992, p. 855) hypothesize that: “studies that find insignificant and wrong-signed values of compensating wage differentials have a more difficult time getting published”. The EPA (2006, p. 18) also noted the issue of the: “exclusion or failure to report models or subpopulation results that did not reach significance or did not conform to expectations ...”. However, none of these studies provide any formal tests or correction for publication bias in the VSL literature. The only exception is Day (1999), who uses an incorrect test of publication bias based on a meta-regression model of the logarithm of the reported t-value and the log of the square root of its sample size. The fit of Day’s (1999) meta-regression model is so poor that it accepts both the hypothesis that the value of a statistical life is zero and also that there is no publication selection. This logarithm meta-regression test of publication bias has been shown to be invalid (Stanley, 2005; Stanley, 2008; Doucouliagos and Stanley, 2009). More appropriate meta-regression models of publication selection are discussed in detail in Section 3.

³ This is also true for ‘fixed’ and ‘random-effects’ weighted averages. Simulations show that these conventional meta-analytic summaries are quite vulnerable to publication selection (Stanley and Doucouliagos, 2007; Stanley, Jarrell and Doucouliagos, 2010).

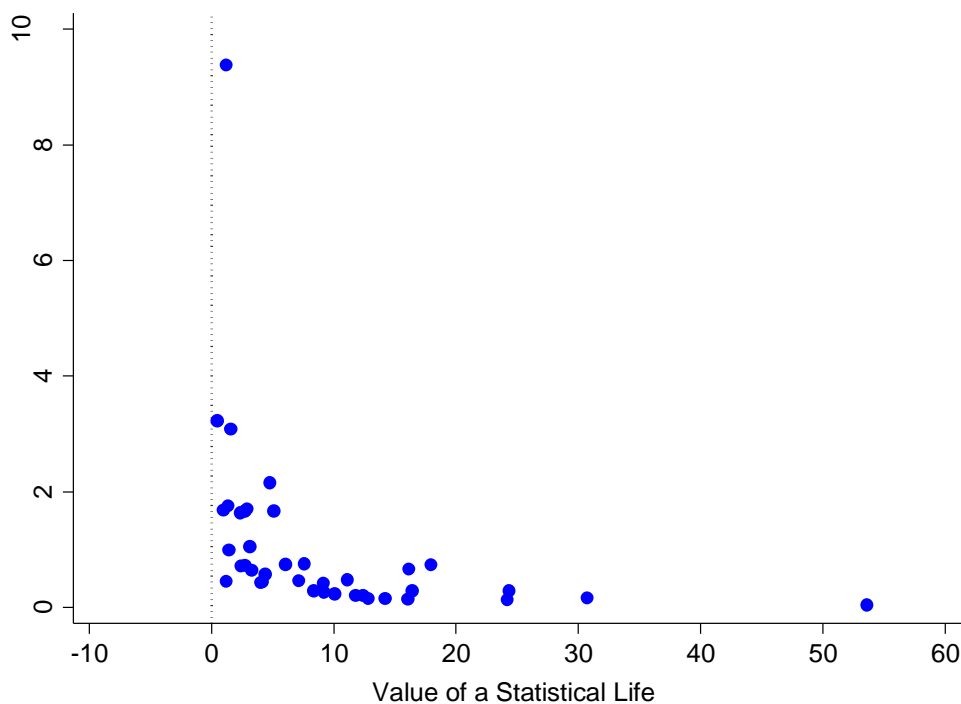
2. How Publication Selection Biases the Value of a Statistical Life

We use the data from the recent meta-analysis by Bellavance, Dionne and Lebeau (2009) to illustrate the importance of publication selection.⁴ Their comprehensive search uncovered 39 hedonic wage equation estimates of VSL from 37 studies that provided comparable estimates of VSL. The simple average value of VSL from these studies is \$9.5 million (in \$US 2000).

2.1 Plotting publication selection

Figure 1 displays the 39 estimates of the value of a statistical life (VSL), calculated from the coefficients of a variable that represents the probability of death in hedonic wage equations.⁵ This so called ‘funnel’ plot is a graph of the precision (measured as the inverse of the standard error, SE) of these VSL estimates against their magnitudes in 2000 US dollars.

Figure 1: Funnel Plot of the Value of Statistical Life (2000 US \$m)



Source: Bellavance, Dionne, and Lebeau (2009)

⁴ In section 4.4 we look also at other meta-analyses. Our central focus is on Bellavance, Dionne and Lebeau (2009) because they offer the most recent published meta-analysis using wage-risk studies. The US EPA (2010) has recently used the Bellavance, Dionne and Lebeau (2009) database as the basis for their meta-analysis.

⁵ We use their largest dataset. Little changes if the smaller dataset of 32 observations is used. See Bellavance Dionne and Lebeau (2009) for a more complete description of the search criteria used to identify these studies, the calculation of VSL, its standard error, and the variables that were coded for each derived estimate.

In the absence of publication selection bias, a funnel plot should resemble an inverted funnel, similar to Figure 2.⁶ If each reported VSL is estimating the underlying ‘true’ value plus or minus sampling error and/or random heterogeneity, then this graph will be symmetric. Of course, known heteroscedasticity will make the distribution more widely scattered at the bottom where SE is relatively large than at the top where SE is small. Nonetheless, elementary sampling theory guarantees that the distribution will be symmetric unless, of course, there is directional selection.⁷ Figure 1 shows, however, that reported VSL estimates are clearly highly skewed, reflecting publication selection bias for positive and statistically significant fatality risk estimates.⁸

Note that there are no negative VSL values in figure 1. Like other meta-analysts Bellavance, Dionne and Lebeau (2009) include only positive VSL estimates in their dataset. Researchers tend to use a positive VSL or, equivalently, a positive coefficient on the probability of death variable in a hedonic wage regression as an additional model selection criterion.⁹ Negative values are just not intuitively or economically meaningful; hence, there is a strong theoretical reason for this selection.¹⁰ Although the selection of positive coefficients may be rational and understandable at the level of the individual researcher, it has important

⁶ Figure 1 plots VSL estimates whereas Figure 2 plots partial correlations (r). The choice of the measure of a comparable effect should not affect the distribution’s symmetry. To be sure, we have also converted all the reported VSL estimates to partial correlation coefficients and found them to be similarly highly skewed and asymmetric. These partial correlation results are available at (web address suppressed for this review).

⁷ Systematic heterogeneity could also cause asymmetry to a funnel graph, and meta-analysts always allow for this possibility. In Figure 3, below, we filter out identified systematic heterogeneity but still find considerable asymmetry and hence publication selection bias. In Section 4.2 we explicitly model potential systematic heterogeneity using a multiple meta-regression analysis (MRA). Yet, here too, there remains strong evidence of asymmetry and selection.

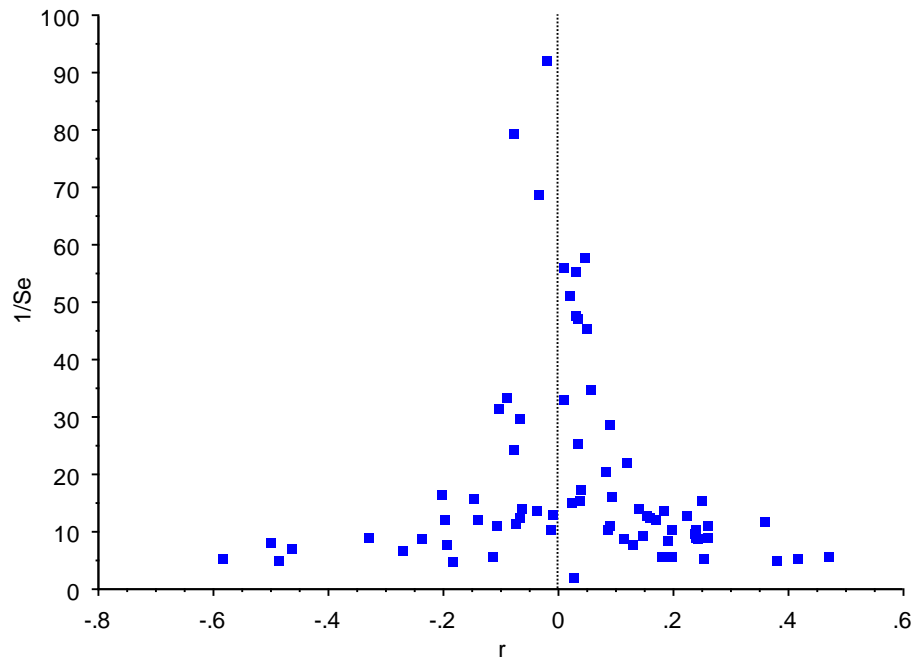
⁸ We initially considered the possibility that this extreme skewness might be due to an exception to funnel symmetry found previously among non-market environmental values (Stanley and Rosenberger, 2009). However, this previously identified exception is caused by a nonlinear transformation of estimated regression coefficients. In contrast, VSL is calculated from a simple linear transformation of the estimated coefficient on the probability of death (Bellavance, Dionne and Lebeau, 2009). Thus, the shape of VSL’s funnel graph is dictated by the shape and the selection of the estimated regression coefficients for the probability of death. Conversion to partial correlation coefficients bypasses this issue, and they have a very similar distribution. For robustness sake, we also investigate the distribution of partial correlations—see (web address suppressed for this review).

⁹ The set of all papers submitted for publication is not our universe of inquiry. Some submitted papers may simply be wrong, using inappropriate empirical methods or making other mistakes. Such methodologically poor papers are correctly filtered out by the publication process. However, even if the mean of the distribution of all possible *valid* estimates (the relevant population) is a positive value, random sampling errors alone could cause some estimates to be negative.

¹⁰ It is possible that some workers or groups of workers reveal negative VSL estimates. This could arise, for example, if taking into account the utility of their heirs means that they get more utility from death than life. This, however, is unlikely to be the behaviour of the average worker for which the value of a statistical life is constructed.

implications for the usefulness and accuracy of VSL estimates. Policies undertaken on the basis of the average value of the reported VSLs may be inappropriate or socially inefficient.

Figure 2: Funnel Plot of Union-Productivity Partial Correlations (r)



Source: Doucouliagos and Laroche (2003)

We do not wish to suggest, in any way, that such researcher behaviour is unethical or necessarily inappropriate. However, such individually reasonable actions can lead to an interesting paradox and another economic example of the ‘fallacy of composition.’ When researchers and meta-analysts suppress or discard negative fatality risk coefficients and thus negative VSLs, the average reported VSL, however calculated, will be biased and potentially much larger than the true one. Although it is possible that each resulting wage-risk study is improved when negative VSL estimates go unreported, our collective understanding of this important phenomenon worsens.

Averages of empirical estimates will be unbiased *only* if the distribution of the reported VSL estimates is not truncated or preferentially selected but rather a representative sample from the distribution of all valid estimates. Figure 1 suggests clearly that this is not the case for reported VSL estimates from hedonic wage equations. If these VSL estimates were free of selection bias, then the funnel plot would be roughly symmetrical. It is important

to note that a symmetric distribution of VSL estimates need not include any negative observations. For example, if the mean of the relevant distribution is sufficiently large and the associated standard errors are relatively small, then no negative estimates need emerge during the estimation process to balance the distribution. When the true mean is many times larger than the typical standard errors, a symmetrical funnel plot is more likely. However, as this mean gets closer to zero, then sampling errors alone would produce more and more negative values. Researchers finding such negative VSL estimates would likely discard them, and this would produce the truncated distribution seen in Figure 1. It is further revealing that the truncation in Figure 1 seems to occur around zero, rather than at some larger positive value.

2.2 *From where do negative VSL estimates come?*

VSL estimates are derived from either revealed preference or stated preference studies. Revealed preference studies involve the use of either labor market data or data on the purchase of devices that improve safety. Labor market studies involve the estimation of a hedonic wage model where the dependent variable is the wage and one of the key explanatory variables is fatality risk. The coefficients on the fatality risk variable are then used to derive the VSL estimates. Obviously, in order to get precise and reliable VSL estimates, it is necessary to control for all factors that might explain wage differentials, other than fatality risk alone.

Selection bias in any literature occurs when certain estimates go unreported. Their absence can be detected when funnel plots of the accumulated evidence are skewed or truncated. This truncation can involve both small or large estimates, and either negative or positive estimates.¹¹ In the case of VSL, it is possible that very large positive VSL values also go unreported. Researchers might dismiss very large VSL estimates as implausible. However, Figures 1 and 3 (below) show that the main form of selection is not against large positive values. Rather, it appears that it is small positive VSL values and negative VSL values that are less likely to be reported.

Closer inspection of the VSL literature reveals a two-stage selection process, when first reporting estimates and then, secondly, when reviewing a given research literature. At the estimate reporting stage, it appears that only some negative, zero or very small positive VSL estimates are reported. The funnel plots (and the statistical analysis below) suggest that

¹¹ If both large and small positive VSL estimates go unreported, then the funnel plot would still be symmetrical but with missing observations at both tails of the distribution.

other such estimates go unreported.¹² This reduces the information available for meta-analysts and subsequently for reviewers and policy makers.

The second stage involves a selection process amongst reviewers. Meta-analysts have largely chosen not to include those few negative (or near zero) VSL estimates that have been reported. Negative VSL values are routinely dismissed. For example, Kluge and Schaffner (2008) note that some studies in their literature search found negative or statistically insignificant estimates and these were excluded from their meta-analysis. In their dataset, Bellavance, Dionne and Lebeau (2009) include studies that report both negative and positive VSL estimates, but only positive estimates are included in their meta-analysis. All of the other meta-analyses of the wage-risk literature have also excluded negative VSL estimates with one exception. Day (1999) includes two negative VSL estimates.

How is it possible to obtain a negative value of a statistical life? Obviously, misspecification of the econometric model can result in incorrectly signed regression estimates. However, data measurement errors (especially fatality risk) can produce negative VSL estimates (Black and Kniesner, 2003 and US EPA, 2010). Moreover, the ever-present sampling error can also induce negative VSL estimates, especially if the average VSL is relatively small. That is, even if a regression model is well specified, measurement and sampling errors alone should result in occasional negative VSL estimates.

Also, variation in modelling wages can result in negative VSL estimates. For example, Leigh (1995) reports negative VSL estimates in a wage-risk study.¹³ Leigh (1995) finds positive VSL estimates when industry dummies are excluded from the econometric model and negative VSL or positive but statistically insignificant regression coefficients once industry dummies are included. He speculates that the correlation between wages and fatality risk might be driven by inter-industry differentials, rather than compensating wages. Leigh (1995) also finds that the available data (at that time) could not “be relied on to produce credible estimate of the value of a statistical life” (p. 94). Viscusi and Aldi (2003) note that the VSL literature contains some ‘wrong signing’ and they list several studies (their Table 9a) that find that non-union workers “had insignificant or statistically significant *negative* compensating differentials for risk.” (p.44). Recently, the US EPA (2010) also notes that negative estimates have been excluded from existing meta-analyses.

¹² We are not saying that all authors have found negative or small positive VSL estimates and chose to discard them. We are simply saying that the evidence suggests that there are missing negative and small VSL estimates from the literature *as a whole*. It is possible that there are entire studies that have gone unreported.

¹³ Leigh (1995) lists some of the other studies that have found negative or statistically insignificant coefficients on the death risk variable.

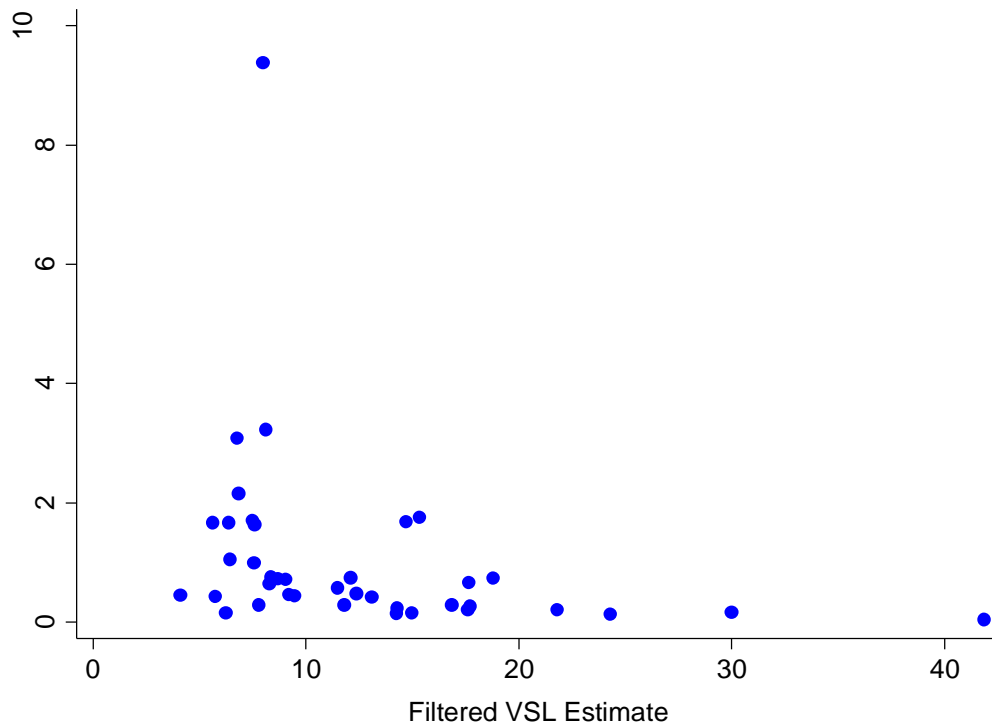
Some authors argue that the theory of compensating wage differentials is just that, a theory that is subject to empirical support or rejection. It is possible that compensating wage differentials do not occur, or not to the extent that neoclassical economics predicts. Dorman and Hagstrom (1998) find a lack of robustness in VSL estimates including the possibility of negative VSL for non-union workers. They question the validity of the compensating wage differentials theory upon which VSL estimates from wage-risk studies are derived and argue that disadvantaged workers have: “found their way into situations of high risk and low pay” and that: “they face a restricted set of options in which their preferences for safety are not given much weight” (p. 133).

Like other authors and reviewers before us, we deem negative VSL estimates to be quite problematic. However, the failure to report them will, by necessity, bias all conventional summary statistics of VSL. Our point of departure is that efficient public policy requires unbiased, or at least less biased, estimates of VSL. The meta-regression methods presented below are designed to reduce this well-documented bias.

2.3 *Can heterogeneity explain asymmetry?*

Perhaps, this observed asymmetry in VSL’s funnel graph is the result of the researchers’ choices of samples, methods and variables rather than a sign of publication selection? We employ two independent strategies to ensure that what we identify as publication bias is not the fortuitous result of heterogeneity in the modelling and calculation of VSLs. First, we filter out such predictable heterogeneity from our data and present its funnel plot in Figure 3.

Figure 3: Funnel Plot of the Filtered VSL Estimates



Predictable heterogeneity is calculated from the first multiple meta-regression model reported in Bellavance, Dionne and Lebeau (2009, table 4, column 1).¹⁴ Their meta-regression model is used to predict the values of statistical life purely on the basis of observed characteristics of the workers' sample and wage equation. The resulting systematic and predictable variation from the average VSL is subtracted (or filtered) from estimated VSLs and shown in Figure 3. Figure 3 still reveals much asymmetry; hence, publication selection bias.¹⁵

Secondly, we include the full range of moderator variables coded by Bellavance, Dionne and Lebeau (2009) along with a term that captures publication bias should it be present. These multiple meta-regression models are reported in Section 4, Table 3 and also contain clear evidence of residual publication selection.

¹⁴ The meta-regression model from Bellavance, Dionne and Lebeau (2009) is chosen to minimize the potential of selection bias on our part.

¹⁵ This publication bias of the heterogeneity-filtered estimates is confirmed by the conventional Egger test (also called the 'funnel-asymmetry test', Egger *et al*, 1997; Stanley, 2008). See Table 1 below.

2.4 *Will the truth float to the top?*

The top of a funnel graph is made up of the most precise estimates and is less susceptible to selection bias (Stanley, Jarrell and Doucouliagos, 2010); therefore, it serves as a rough indicator of the true value of a statistical life untainted by selection. The top of Figure 1 is somewhat less than \$2 million, and, as we demonstrate below, this rather impressionistic assessment holds up to rigorous statistical scrutiny. The value of a statistical life as estimated by the most precise hedonic wage estimate is \$1.2 million, while the average of the four most precise values is \$2.0 million. In any case, the top is much less than the mean of all 39 estimates, which is \$9.5 million. Although the visual investigation of a funnel graph can be very informative (Stanley and Doucouliagos, 2010), we need a more objective and rigorous statistical method to identify and correct publication selection bias. Fortunately, such methods exist and have been widely adopted elsewhere. To these publication bias detection and correction methods we now turn.

3. **Meta-Regression Models of Publication Selection and Heterogeneity**

Medical researchers and economists employ meta-regression models to accommodate and filter out publication selection bias (Card and Krueger, 1995; Egger *et al.*, 1997; Stanley, 2005, 2008; Moreno *et al.*, 2009a; Moreno *et al.*, 2009b). When publication selection is present, the reported empirical effects are positively correlated with their standard errors, *ceteris paribus*; otherwise, estimates and their standard errors will be independent as required by the conventional t-test. The basic reasoning is quite simple. With publication selection, researchers who have only small samples and thereby large standard errors will be forced to search more intensely across model specifications, data, and econometric techniques to find correspondingly larger estimates. Otherwise, their results will not be statistically significant.¹⁶ In contrast, researchers with larger samples and smaller standard errors need not search quite so hard from the practically infinite model specifications to find statistical significance and will thereby be satisfied with smaller estimated empirical effects.

¹⁶ We are not suggesting that all researchers engage in specification searches and selection. However, if enough researchers do, it will be revealed visually in the data (*e.g.* Figure 1) as well as in these MRA tests.

Such considerations suggest that the magnitude of the reported estimate will depend on its standard error when there is selection for statistical significance. Or,

$$effect_i = \alpha_0 + \alpha_1 SE_i + \varepsilon_i \quad (1)$$

(Egger *et al.*, 1997; Stanley, 2005; Stanley, 2008). Here $effect_i$ is an individual estimate of VSL, and SE_i is its standard error. $\alpha_1 SE_i$ allows for publication selection bias, and estimates of α_0 serve as corrections for publication bias. Note that as $SE_i \rightarrow 0$, $E(effect_i) \rightarrow \alpha_0$. However, simulations have shown that it is somewhat better to use the variance, SE_i^2 , in equation (1) rather than the standard error to estimate the genuine effect, corrected for publication bias (Stanley and Doucouliagos, 2007; Moreno *et al.*, 2009a; Moreno *et al.*, 2009b).

$$effect_i = \gamma_0 + \gamma_1 SE_i^2 + e_i \quad (2)$$

Meta-regression models (1) and (2) are generally not estimated due to their obvious heteroscedasticity. Recall that SE_i is the standard error of the estimated effect, the dependent variable in equations (1) and (2); thus, $effect_i$ has different estimated variances. In practice, these variances differ greatly from one another. Differences among the reported VSL variances are as much as 400 times. To accommodate this heteroscedasticity, weighted least squares (WLS) are routinely employed. Most statistical software can calculate the WLS version of (1) and (2) by weighting the squared errors with the inverse of each estimates' variance (*i.e.*, $1/SE_i^2$). Equivalently, we can divide these equations through by SE_i . Meta-regression analysis (MRA) coefficients from the simple WLS models (1) can be used to test for the presence of publication selection and a genuine effect beyond publication selection bias (Stanley, 2008)—see Table 1, below. Estimates of γ_0 from MRA model (2) correct for publication selection.

However, doesn't this leave out all of the other factors, such as income, compensation insurance, and the endogeneity of risk that might also affect the value of an estimated VSL? Like any regression analysis, it is important to control for any variable that might influence reported results to ensure that omitted-variable bias is not affecting the results. Although it is always important to be sure that the simple findings are robust relative to a more complex multivariate MRA, the simple MRA models of publication selection bias provide an excellent first approximation to the corrected underlying empirical effect. MRA model (1) can be

expanded to include moderator variables, Z_k , that explain variation in reported VSL estimates and other factors, K_j , that are correlated with the publication selection process itself.

$$effect_i = \alpha_0 + \sum \beta_k Z_{ki} + \alpha_1 SE_i + \sum \gamma_j SE_i K_{ji} + \varepsilon_i \quad (3)$$

(Stanley and Doucouliagos, 2007; Doucouliagos and Stanley, 2009). The multivariate version of equation 2 is given by:

$$effect_i = \alpha_0 + \sum \beta_k Z_{ki} + \alpha_1 SE_i^2 + \sum \gamma_k SE_i^2 K_{ji} + \varepsilon_i \quad (4)$$

Equation (3) is the more conventional and commonly-used MRA model. While equation (2) is preferable to equation (1) for the purpose of providing an estimate of empirical effect corrected for potential publication selection, it is still not clear whether using the standard error or the variance is preferable in a multivariate explanatory MRA context—*i.e.*, equations (3) or (4). Here, we present the results of both, but focus on equation (3) in our discussion because it is the conventional MRA model and also fits this particular research data better.

4. Meta-Regression Results and Discussion

4.1 The selection bias corrected VSL

Table 1 reports the WLS estimates for both MRA models (1) and (2).¹⁷ Recall that testing $H_0: \alpha_1=0$ detects whether or not there is publication selection. For this VSL literature, we find clear evidence that published values of statistical life are selected to be significantly positive (reject $H_0: \alpha_1=0$; $t=6.02$; $p<.001$).

The magnitude of $\hat{\alpha}_1$ is also a measure of the severity of publication selection. For the value of a statistical life estimates, $\hat{\alpha}_1$ is quite large, 3.20. Simulations show that values of $\hat{\alpha}_1$ that are larger than 2 are associated with severe publication selection bias (Doucouliagos and Stanley, 2008). To see this, consider the extreme case where the actual empirical effect is zero, but all estimates are selected to be significantly positive. In such a case, reported t-

¹⁷ We follow Bellavance, Dionne and Lebeau (2009) and use VSL as the dependent variable. Some prior meta-analyses use the natural logarithm of VSL.

values will average slightly more than 2, and $\hat{\alpha}_1$ will also be approximately 2 (Card and Krueger, 1995; Stanley and Doucouliagos, 2007).

Table 1: Simple Meta-Regression Analysis of Publication Selection
(Dependent Variable= VSL in Millions of US 2000 \$)

Variables	(1)	(2)
Intercept: $\hat{\alpha}_0$ or $\hat{\gamma}_0$	0.81 (2.85)	1.66 (5.50)
SE_i : $\hat{\alpha}_1$	3.20 (6.02)	-
SE_i^2 : $\hat{\gamma}_1$	-	0.33 (2.81)
Adjusted R^2	0.48	0.15
n	39	39
Standard error	1.5	1.9

Notes: t-values are reported in parentheses. Columns 1 and 2 report estimates of equations 1 and 2, respectively, using weighted least squares. The intercept is an estimate of VSL corrected for selectivity bias. SE_i and SE_i^2 estimate the degree of publication selection.

In spite of the extreme skewness that is exhibited by the funnel graph, recall Figure 1, we have clear evidence that the value of a statistical life is in fact positive (reject $H_0: \alpha_0=0$; $t = 2.85$; $p < .01$ — Table 1). Testing the MRA coefficient, $\hat{\alpha}_0$, serves as a test for a genuine effect beyond publication bias (Stanley, 2005; Stanley, 2008). This statistical test is rather powerful and is valid in most cases; however, $\hat{\alpha}_0$ is biased downward when there is a genuine effect (Stanley, 2008). To be conservative in our correction for publication selection, we focus on $\hat{\gamma}_0$; it is known to be a less biased corrected estimate of the ‘true’ effect when there is an actual effect (Stanley and Doucouliagos, 2007; Stanley 2008; Moreno *et al.*, 2009a). $\hat{\gamma}_0$ estimates the value of a statistical life to be \$1.66 million (or 18% of the mean). That is, after correcting for likely publication selection bias, we estimate the value of a statistical life to be \$1.66 million (or somewhere between \$1.05 million and \$2.28 million when a 95% confidence interval is constructed). Hence, publication selection distorts the average reported value of a statistical life by a factor of five; recall that the raw average is \$9.5m.

An obvious criticism of these findings is that they only control for publication selection. Bellavance, Dionne and Lebeau (2009) explicitly investigate several sources of the

variation observed among the reported estimates of VSL. The main weakness of their meta-analysis is that, like all the other prior meta-analyses of this literature, it does not account for publication selection. As with any conventional econometric model, the failure to include relevant explanatory variables in the MRA can bias the estimates of the remaining effects. In this case, the omitted variable is the standard error, or its square, which proxies for publication selection. But similar omitted-variable bias could be present in these simple MRA models of publication selection; thus, we conduct our own multivariate meta-regression analysis.

Table 2: Moderator Variables for Hedonic Wage Estimates of the Value of a Statistical Life

<i>MRA Variable</i>	<i>Definition</i>	<i>Mean (standard deviation)</i>
<i>VSL</i>	the estimate of VSL in 2000 US \$m	9.5 (10.3)
<i>SE</i>	the standard error of VSL in 2000 US \$m	3.02 (3.91)
<i>LnIncome</i>	the natural logarithm of average income	10.20 (.48)
<i>Death</i>	the average probability of death; times 10,000	2.08 (2.50)
<i>Year</i>	the year of publication with 2000 as the base year	-9.56 (7.92)
<i>EndoRisk</i>	=1, if the hedonic wage equation uses an endogenous measure of risk	.13 (.34)
<i>Comp</i>	=1, if the hedonic wage equation includes compensation insurance	.21 (.41)
<i>US</i>	=1, if the study used US data	.54 (.51)
<i>UK</i>	=1, if the study used UK data	.10 (.31)
<i>Canada</i>	=1, if the study used Canadian data	.18 (.39)
<i>White</i>	=1, if VSL estimate relates to white workers	.13 (.34)
<i>Union</i>	=1, if VSL estimate relates to unionized workers	.15 (.37)
<i>SOA</i>	=1, if the data comes from the Society of Actuaries	.10 (.31)

Table 2 lists the potential moderator variables coded by Bellavance, Dionne and Lebeau (2009) that can be used as either Z- or K-variables, or both. We choose the log of average income (*LnIncome*), *Year*, and *Death* to be Z-variables (*i.e.*, those that potentially explain the observed heterogeneity in VSL) but not K-variables (*i.e.*, those that potentially influence the likelihood of a VSL estimate being reported and published), because these moderator variables are study invariant and could not have been used by researchers to select which results to report. All of the other coded moderator variables are allowed to be both Z- and K-variables. Next, we employ a general-to-specific approach or backwards selection. Our general model begins by including all 20 explanatory variables. Then, the least statistically significant variable is removed, one at a time, until only statistically significant variables remain. “The strength of general to specific modelling is that model construction proceeds from a very general model in a more structured, ordered (and statistically valid) fashion, and in this way avoids the worst of data mining” (Charemza and Deadman, 1997, p. 78). Using the WLS-MRA version of equation (3), general-to-specific approach found four variables to be statistically significant. These results are shown in Table 3.

Table 3: General-to-Specific Multivariate MRA of the Value of a Statistical Life
(Dependent Variable= VSL in Millions of US 2000 \$)

<i>Moderator Variables</i>	(1)	Robust (2)	(3)
<i>Intercept</i>	-15.8 (-2.11)	-31.6 (-2.58)	-31.5 (-3.99)
<i>LnIncome</i>	1.86 (2.28)	3.36 (2.70)	3.63 (4.20)
<i>Year</i>	0.19 (3.36)	0.18 (3.76)	0.21 (3.18)
<i>Comp</i>	-1.88 (-2.20)	-1.52 (-2.45)	-2.71 (-2.71)
<i>SE</i>	3.07 (5.12)	2.80 (6.55)	–
<i>SE²</i>	–	–	0.28 (2.78)
<i>Adj R²</i>	.58	–	.40
<i>Standard Error</i>	1.3	–	1.6

Notes: t-values are reported in parenthesis. Columns 1 and 3 report estimates of equations 3 and 4, respectively, using weighted least squares. Column 2 reports a robust regression.

The interpretation of these MRA coefficients is both important and informative. Take first the coefficient on *SE*, 3.07, from column 1. This coefficient is in millions of US 2000 dollars and represents publication selection. If the standard error of the VSL estimate were to increase by \$1 million, we expect publication bias to increase the value of VSL by \$3.07 million, greatly inflating the reported estimate of the value of a statistical life. Not only is this effect statistically significant ($p < .001$), this estimated publication selection bias alone (as measured by *SE*) explains nearly half of the wide variation among reported VSL estimates.¹⁸ This effect alone is sufficient to inflate the average estimate of VSL by nearly \$9 million.¹⁹ Needless to say, selection of VSL estimates (or their associated hedonic wage coefficients) dominates this area of research, regardless of the control variables one uses. By ignoring selection bias, existing meta-analyses are likely to also be affected by omitted variable bias.

4.2 Heterogeneity

Three other variables, *LnIncome*, *Year*, and *Comp*, help explain the genuine heterogeneity among VSL estimates, and their coefficients are also quite important. Clearly life is a normal good. We would expect workers to place a higher value on their own lives as they become more affluent. This is confirmed by column 1 of our meta-regression analysis ($p < .01$), Table 3. The coefficient on *LnIncome*, 1.86, gives an estimated income elasticity of 0.20.²⁰ Our result is thus consistent with the findings of Viscusi and Aldy (2003) that “the income elasticity for the value of a statistical life is less than 1.0” or, in other words, that a statistical life is a necessity. However, Viscusi and Aldy (2003) report a larger income elasticity ranging between 0.50 and 0.60, and their meta-analysis has been used to guide income elasticities used by the U.S. Department of Transportation (Kniesner, Viscusi and Ziliak, 2010).

We also find that there is a trend in the reported value of a statistical life. On average, VSL estimates increase by \$190,000 per year. Note that this trend remains even after controlling for income, so it is not a function of rising incomes alone. Bellavance, Dionne and Lebeau (2009) also detect such a trend.

The MRA coefficient on *Comp* confirms the findings of Bellavance, Dionne and Lebeau (2009). Even after controlling for publication selection bias, income and a time trend,

¹⁸ The Adjusted R-squared is .48, reported in Table 1.

¹⁹ This is calculated by multiplying the estimated coefficient on *SE* by the average *SE* in this literature.

²⁰ This is calculated by dividing the estimated coefficient for *LnIncome* by the average VSL.

we find that studies which take the existence of worker's compensation insurance into account ($Comp = 1$) report VSL estimates, on average, \$1.88 million lower. Thus, we corroborate the common observation made in this research literature. Researchers that fail to account for the presence of some type of worker's compensation insurance are likely to exaggerate VSL by a practically significant amount.

These multivariate MRA results also allow the meta-analyst to estimate or 'predict' the corrected value of a statistical life, once these other relevant research dimensions are considered. Recall that our corrected estimate of VSL (from table 1) is \$1.66 million with a 95% confidence interval of \$1.05 million to \$2.28 million. However, this does not specifically account for the potential effects of including worker's compensation insurance, time trends or worker average income. To account for a more complex research reality, we first need to factor out the publication selection bias. Recall that this is captured by the SE variable. As $SE \rightarrow 0$, we approach the perfect study with 'infinite' information and no estimation error, hence no publication bias. Thus, $SE=0$ should be substituted in the estimated MRA model.

Next, we must pick a year. But year is entirely arbitrary, merely providing a baseline for comparison. We select 2000. As discussed above, it is widely argued that omitting worker's compensation insurance biases results downward; thus, it is important to recognize the presence of worker's compensation insurance and thereby to substitute 1.0 for $Comp$. Lastly, what is the appropriate value of income ($LnIncome$)? This too is somewhat arbitrary, depending on which groups of workers the meta-analyst wishes to estimate. Here, we choose the sample mean, because we wish to estimate the VSL for the typical worker in the entire research literature. Coincidentally, the sample mean of income is nearly the same as the average of the two most recent US studies included in the dataset. Thus, it will also serve to approximate what US workers regard as their value of life.

When the selected values of our moderator variables are substituted into the WLS multivariate MRA model reported in Column 1 of Table 3, the 'predicted' value of a statistical life becomes \$1.36 million and a 95% confidence interval is between \$34,000 and \$2,693,000.²¹ Roughly speaking, VSL for this reference group is something larger than zero but less than \$3 million. Note that this is quite consistent with the simple MRA estimate—Table 2, WLS-MRA (2)—that did not explicitly control for these other economic

²¹ Here, we used a 'mean' rather than an 'individual' prediction interval because we are estimating the VSL for the typical worker under these broad conditions, rather than what the next econometric study might estimate it to be. Because there is always much variation between studies, the individual prediction intervals would be larger.

considerations. Thus, even after considering more than a dozen factors thought to have a potential effect on reported VSL estimates, we estimate the value of a statistical life to be rather small, less than \$2 million (in 2000 US \$).

4.3 Robustness

In keeping with conventional practice in applied econometrics, we conducted a number of robustness checks. We report a robust regression because there is one study, Sandy and Elliot (1996), which contains a very large VSL, nearly \$54 million. Robust regression methods minimize the influence of any one or few potentially influential outliers. The overall statistical fit and significance for the robust regression results (column 2 Table 3) is the same as found by the WLS-MRA (column 1). The only noticeable difference is the marginal effect of higher incomes is considerably greater, with the income elasticity now being 0.35. Predictions or corrections based on the estimated coefficients from the robust regression are also consistent with our previous ones—\$1.15 million for a worker with the sample of average income in 2000 when workers' compensation is included.

For the sake of robustness, column 3 of Table 3 reports the multivariate MRA (equation 4) that uses the variance, SE^2 , rather than SE . Here too, we find very consistent statistical results. Like the robust regression, column 3 coefficients give a larger role to worker income. There is a slightly larger coefficient for worker's compensation insurance, with the effects of time being similar, and a corrected VSL based on this multivariate MRA is somewhat higher, \$2.74 million, for a worker sample of average income in 2000 that has accounted for the presence of worker's compensation insurance. But even this larger corrected VSL greatly reduces, by over 70%, the uncorrected average reported VSL in the research literature. The simple MRA corrected estimate from Table 1 is contained within this multivariate MRA's confidence interval (\$1.30; \$4.18 million US).²²

It should be recalled that we have not selected these studies. We rely purely on the comprehensive selection of studies made by a prior meta-analysis. To ensure that our results are not driven by quirks of some sub-sample of VSL estimates, we re-run the MRA (equation 3) after excluding various parts of the data. The selection bias coefficient, $\hat{\alpha}_1$, is 3.36 ($t = 6.84$) when the Society of Actuaries (SOA) studies are excluded. It is 3.11 ($t=5.87$) when the

²² The income elasticity of VSL is now 0.38.

four most precise estimates are *excluded*.²³ It is 3.35 (t=6.26) when the four most imprecise estimates are excluded. It is 2.01 (t=4.08) when any VSL estimate less than \$7m is excluded. It is 3.62 (t=5.03) when only US estimates are used and 3.48 (t=4.39) when only non-US estimates are used. We also converted all the hedonic wage-risk estimates to partial correlation coefficients, rather than VSL estimates to be sure that the evidence of publication selection is robust to how empirical effects are measured. Doing so gives $\hat{\alpha}_1 = 2.11$ (t=4.46).

In summary, regardless of how the data are partitioned or how the effects are measured, there is robust evidence of severe publication selection. The MRA models (equations 1 to 4) provide robust methods for detecting and correcting publication bias. Some reviewers argue that the problem is diminished if all studies, both published and unpublished, are included in the meta-analysis. Indeed, past meta-analyses of the VSL literature have included unpublished studies. Most of the included studies, however, have been published. de Blaej *et al.* (2003) argue that selection bias can be “partly circumvented” by including unpublished studies. This, however, is not a sufficient correction. The inclusion of unpublished studies is unlikely to alleviate the problem of publication bias if authors select their results. That is, it is quite likely that some results will go unreported even at the working paper stage and some research projects might not even make it to a working paper if only ‘unacceptable results’ emerge. These studies will remain in the file drawer.²⁴

4.4 What of other VSL meta-analyses?

Are the VSL estimates from other methods such as stated preference or hedonic pricing (safety products) studies also affected by publication selection? This is an important question because government agencies also employ VSL estimates from stated preference studies (see, for example, US EPA, 2010). We are unable to answer this critical question because, as already noted previously, meta-analyses have not formally tested or corrected for selection bias. However, given the strength of selection bias that we find in the wage-risk literature, it would be prudent to investigate whether selection is an important issue for estimates of VSL calculated by other methods. For example, authors of stated preference

²³ Deleting the most precise 10 percent of the reported research is especially ill-advised. Stanley, Jarrell, and Doucouliagos (2010) show that doing the opposite - that is, deleting the *least* precise 90% and averaging the most precise 10% - will often improve the resulting estimate when there is substantial publication selection.

²⁴ Kluge and Schaffner (2008) include a dummy variable in their meta-regression model to control for publication status. They find that papers published in journals report smaller VSL estimates in most of their regressions, though it was also positive in some others. Another name for publication selection bias is the ‘file drawer problem’ to denote the tendency for insignificant results never to be seen (Rosenthal 1979).

studies might be reluctant to report small VSL estimates and researchers using hedonic pricing (safety products) studies might also find it difficult to accept and publish a negative value of life or regression coefficients that are not statistically significant. In general, Doucouliagos and Stanley (2008) find that two-thirds of empirical economics suffers from substantial selection bias. They also show that in areas where there is agreement about the direction of the effect, such as positive values for VSL, then selection bias will tend to be larger. Hence, selection bias might be an issue for estimates of VSL derived from other valuation methods.

Of course, the degree of selection bias might differ between valuation methods. Perhaps, there is less selection within stated preference studies? In their meta-analysis, Kluge and Schaffner (2008) found that wage-risk studies report VSL estimates that are more than 200% larger than those from stated preference studies. Leggett, Neumann and Penumalli (2001) also find that VSL estimates are smaller from stated preference studies than they are from wage-risk studies. It is possible that some of these differences could be driven by publication bias. If publication bias exists in wage-risk studies but not stated preference studies, or it is more severe in the former, it can result in an artificial difference between the two groups of studies. The multiple MRA models that we advance here, equations (3) and (4), could easily accommodate such differences. Unfortunately, the required data for such a 'trans-method' MRA of VSL valuation studies do not currently exist. Nonetheless, it would be interesting for future research to explore this issue.²⁵

As already noted, Liu *et al.* (1997) provide the first meta-analysis of the hedonic wage literature. They use 17 of the studies listed in Viscusi (1993, Table 2). Thus, we can re-estimate their MRA for those studies included in their MRA. The $\hat{\alpha}_1$ coefficient is 2.19 (t= 6.47) for this subsample, which is consistent with severe publication selection bias. Using the larger Viscusi and Aldy (2003) dataset, we find that $\hat{\alpha}_1$ is 2.76 (t = 6.56), again indicating severe publication selection bias. The US EPA (2010) uses the Bellance, Dionne and Lebeau (2009) dataset as the base for their meta-analysis of wage-risk studies but discarded some and added a few more recent studies (see their paper for details). Not surprisingly, there is again evidence of severe publication bias the US EPA data; $\hat{\alpha}_1$ coefficient is 3.50 (t = 5.46). Thus,

²⁵ A key limitation of stated preference studies is the lack of reported standard errors for the derived VSL estimates. In their recent meta-analysis, the US EPA (2010) was able to collect 40 estimates of VSL drawn from stated preference studies but only eleven contained standard errors.

we find clear evidence of publication selection for all sets of VSL estimates for which there is sufficient information.

5. Implications for Policy

For the sake of consistency and clarity and compatibility, this paper focuses on wage-risk studies included in Bellance, Dionne and Lebeau (2009). This focus provides the largest set of comparable estimates of VSL that also contains the necessary associated standard errors. But with all good things, there are limitations. Our MRA of wage-risk estimates of VSL estimates may not fully reflect all types of VSL estimates. However, they are regarded sufficiently highly to serve as the core of the US EPA's (2010) assessment. With these limitations in mind, we consider what the publication bias correction procedures imply about VSL for policy purposes.

Using our most conservative adjustment for publication bias gives a corrected VSL of \$2.74m in US 2000 dollars.²⁶ This is typically less than what has been found in most other meta-analyses. For example, converting prior estimates into US 2000 dollars, Miller (2000) reports a VSL of \$3.9m, while Viscusi and Aldy (2003) use a figure of \$7m. On the other hand, Mrozek and Taylor (2002) arrive at a VSL of \$2.1m.

It is interesting to compare our estimate of VSL with the values used in actual project evaluations. Adler and Posner (2000) and Viscusi and Aldy (2003) report VSL figures used for various projects in the US. Of the 16 projects listed in the latter's Table 12, nine use a figure greater than \$2.74m (in 2000 dollars) (Viscusi and Aldy, 2003, p. 55). This suggests that the anticipated net benefits from many US government policy interventions might be inflated. Take for example the recent study by Carpenter and Stehr (2010), who find that while U.S. bike helmet laws reduce fatalities, they also reduce cycling activity. Using a value of a statistical life of \$8 million, Carpenter and Stehr (2010) find that the benefit of reduced fatalities is about \$157 million and that the net benefit of bike helmet laws is \$800 per cyclist. However, if the selection bias corrected VSL is used, the benefit shrinks to \$39 million and the net benefit is about \$200 per cyclist. Krupnick (2002) notes that efficiency is only one criterion driving policy decisions; thus, lower VSL estimates may not actually make a difference to which policies are implemented. Nevertheless, even though it might not be sufficient, it is certainly necessary to use the most reliable estimate of VSL.

²⁶ Recall that estimates of VSL under \$2 million are also well supported by the research record.

It is tempting to think that the whole issue can be avoided by simply becoming more selective. For example, instead of using all the data illustrated in Figure 1, why not just choose only those studies that are deemed to be more methodologically sound or those that appear to be ‘about right’?²⁷ Unfortunately, what is methodologically sound or ‘about right’ is not always clear cut and choosing studies that are deemed to be ‘correct’ needs to be based on objective criteria.²⁸ Without explicitly stated, objective criteria, such methodological selection runs the risk of worsening selection bias. Indeed, the more selective the choice of studies becomes and the narrower the sub-set of studies reviewed, the more important it is to ensure that selection bias is absent or minimized. Simply taking an average of a further selected set of observations will not resolve the underlying problem.

A number of reviews of the literature have used arbitrary criteria to derive estimates for VSL in cost-benefit analyses (CBA). As a consequence, some have adopted what appear to be inflated figures. For example, using a simple average of 26 studies, the US EPA recommends a VSL of \$6.2 million (2000 US dollars) (US EPA, 2000). However, as we show here, taking a simple average of reported estimates is likely to inflate VSL. Note that our estimate of the US VSL, using sample averages from the studies included in the meta-analysis and correcting for publication selection, is \$2.74 million (2000 US dollars). Using 2009 income and the time trend identified by our MRA increases this to \$5.88 million for 2009.²⁹

Other agencies appear to have *understated* somewhat the value of a statistical life. For example, Abelson (2008) performs a qualitative (non-meta-analysis) review of the Australian and international evidence,³⁰ arriving at a subjective ‘plausible’ figure of \$3.5 million in 2007 Australian dollars. This subjective figure has now been adopted as a standard for project evaluation in Australia (Australian Government, Department of Finance and Deregulation, 2008). This recommended VSL figure for Australia is on the low side, equivalent to \$2.85 million AUD for 2000, which is lower than the AUD equivalent value of our MRA estimate (\$3.59 million AUD = \$2.74 million US, using purchasing power parity rates). Similarly, the

²⁷ Judgemental ‘best’ estimates of VSL have a long history. See, for example, Fisher, Chestnut and Violette (1989).

²⁸ If this approach is to be adopted, we recommend that precision be used as a selection criterion. More precise estimates are more reliable and are more informative. At least, precision is an objective statistical measure whose properties are well documented. Nonetheless, including all comparable estimates is preferable, as this ensures a more representative and less biased sample. Furthermore, it helps to quantify and account for sampling error and to identify genuine heterogeneity. This is exactly what our MRA selection bias correction methodology achieves.

²⁹ Annual income was constructed from Bureau of Labor Statistics and the Current Population Survey data on weekly earnings of full-time workers aged 16 years and over.

³⁰ Abelson (2008) looks at 20 studies, including both wage risk and contingent valuation studies.

UK Department of Transport (2009) recommends a figure of £1.64 million in 2007 (British pound) prices, equivalent to £1.48 million in 2000, which is less than our corrected estimate (£1.74 million = \$2.74 million US, using purchasing power parity). However, both the UK and Australian estimates are well within the confidence interval of our MRA prediction.

Different agencies within the same government use different VSL values (Krupnick, 2002). Consequently, there have been many calls for agencies to adopt a more consistent and scientific set of VSL estimates (*e.g.* US GAO, 2005). Such calls lead naturally to some form of a systematic review or meta-analysis of the evidence. Indeed, agencies such as the US EPA (see Robinson, 2007 and US EPA, 2010) and the US Department of Homeland Security (Robinson, 2008) are starting to use the results of meta-analysis to guide policy. Hence, the issue of selection bias cannot simply be avoided. Moreover, even highly respected experts, such as Viscusi, have turned to meta-analysis to make sense of the wide variation in results (Viscusi and Aldy, 2003). That is, even if the aim is only to explain heterogeneity, it is still necessary to correct for publication selection bias as, without this, the average VSL is inflated and the contribution of heterogeneity across studies is distorted.³¹

6. Conclusions

The magnitude of the value of a statistical life (VSL) is central to the evaluation of numerous public health and safety initiatives. There have been many reviews of VSL studies, ranging from those that calculate a simple average using only a portion of the available studies to comprehensive meta-analyses of the entire published research literature. Unfortunately, none of the previous reviews, including thirteen meta-analyses, have explicitly corrected or correctly modelled publication selection effects. Such neglect imparts its own omitted-variable bias to even the most comprehensive and rigorous survey.

Accommodating potential publication selection among reported empirical estimates is essential if one is to gain an accurate picture of the underlying economic phenomenon in question. This is especially true for the VSL, because it exhibits clear and robust evidence of

³¹ VSL is not a constant, varying as income and price levels change and as new data is made available (Viscusi, 2010). However, it is clear that it is much easier to revise upward the value of VSL for policy purposes, than it is to reduce it. Previous reductions in the value of VSL have created political storms (see Viscusi 2009 and Cameron 2010).

publication selection. Among the VSL estimates derived from hedonic wage-risk equations, this correction greatly reduces, by 70% to 80%, the average estimate of VSL. The failure to correct for the selection of VSL estimates makes many more projects appear to have positive net social benefits than they might otherwise deserve.

Furthermore, accounting for selection bias is required to understand the heterogeneity among the reported VSL estimates. By allowing for selection, MRA explains much of the large reported variation among VSL estimates and identifies several other key factors: average incomes, the year the study was published and the inclusion/exclusion of worker's compensation insurance.

Are estimates of VSL exaggerated? Policy makers have used various subjective approaches to choose an appropriate value of a statistical life in their cost-benefit analyses. While some of these have used exaggerated estimates of VSL, others no doubt have used more conservative estimates. Fortunately, VSL research is becoming more and more systematic and thereby less subjective. Over recent years, several meta-analyses have carried out systematic, objective and scientific reviews of the VSL literature. However, by ignoring publication selection bias, even the most scientific review will tend to report inflated measures of VSL. Corrections for this publication selection bias are rather simple but have a large practical impact on the best available assessment of the value of a statistical life.

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