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THE ROLE OF PUBLICATION SELECTION BIAS IN ESTIMATES OF THE VALUE OF A STATISTICAL LIFE

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The Role of Publication Selection Bias in Estimates of the Value of a Statistical Life W. Kip Viscusi NBER Working Paper No. 20116 May 2014 JEL No. I18,J17,J31,K32

ABSTRACT

Meta-regression estimates of the value of a statistical life (VSL) controlling for publication selection bias yield bias-corrected estimates of VSL that are higher for labor market studies using the more recent Census of Fatal Occupational Injuries (CFOI) data. These results are borne out by the findings for four meta-analysis data sets and different formulations of the variable used to capture publication bias effects. Meta-regression estimates for a large sample of VSL estimates consisting only of results of labor market studies using the CFOI fatality data indicate publication bias effects that are not statistically significant in either fixed effects or random effects models with clustered standard errors. The confidence intervals of the publication bias-corrected estimates of the value of a statistical life sometimes include the sample mean estimates and always include the values that are currently used by government agencies.

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I. INTRODUCTION

The key parameter used in policy contexts to assess the benefits of policies that reduce mortality risks is the value of a statistical life (VSL).¹ This measure of the risk-money tradeoff for small risks of death has become the standard approach used by government agencies to value reductions in mortality risks. The emphasis in the United States is on VSL estimates derived from labor market studies of VSL based on the tradeoff between wages and worker fatality rates. Countries such as the U.K. for which the labor market studies are less reliable often rely on stated preference estimates of VSL.

Typically, U.S. government agencies draw on the results of different studies in deriving their VSL estimate for policy. In some cases, this procedure has involved averaging the results across studies based on a survey of the literature or a meta-analysis, while in others the agency has used the results of a meta-regression analysis to control for different variables that may affect the estimated VSL, such as the average income of the sample. Among the meta-regression analyses that have been relied upon by U.S. government agencies in recent years are those by Mrozek and Taylor (2002), Viscusi and Aldy (2003), and Kochi, Hubbell, and Kramer (2006). Agencies also may refer to more than one meta-regression analysis as the basis for its VSL estimate. These meta-regression analyses serve to combine the results of different VSL estimates and to facilitate adjustments in the VSL to tailor the results to the particular populations whose preferences are being valued by, for example, controlling for the different countries for which the estimates have been derived.

¹ Viscusi (2014) presents an inventory of 98 government regulations and the associated VSL used to assess the policy impacts. The most frequently represented agencies are the Environmental Protection Agency, the Dept. of Transportation, and the Food and Drug Administration. Ashenfelter (2006) also stresses the broad policy applicability of the VSL estimates.

An additional factor that can be taken into account through meta-regression analyses is controlling for the effect of publication bias (Stanley and Doucouliagos 2012). Publication selection bias could result from either the selection of estimates that the researcher chooses to report or to the unwillingness of peer reviewed journals to publish results outside the conventional range of VSL estimates or which appear to be implausible. Guided by economic theory, researchers may be reluctant to report negative estimates for VSL, which are inconsistent with the basic theory of compensating differentials that jobs posing higher levels of risk will only be attractive to workers if these jobs provide additional pay. There also may be biases in the opposite direction as several early estimates of the VSL were based on labor market studies using the Society of Actuaries mortality data for people in different occupations, as opposed to the occupation-specific risk. Use of the Society of Actuaries data as a proxy for the worker's job-related risk overstated the average job-related fatality rate by an order of magnitude and led to very low estimates of VSL, which potentially induced an anchoring bias in terms of estimates that researchers viewed as being reasonable.

There have been more meta-analyses of VSL than any other economic subject, and this interest in turn has stimulated two studies of the effects of publication selection bias on VSL. These explorations of the role of publication bias with respect to VSL have indicated that such biases are statistically significant and could have a fundamental effect on the estimated VSL. Doucouliagos, Stanley, and Giles (2012) estimated the effect of publication bias on labor market estimates of the VSL and found that correction for publication selection bias reduces the estimated VSL by 70-80 percent. Making such an adjustment for policy assessments could dramatically reduce the assessed benefits of reduced mortality risks. This quite substantial estimated publication selection bias effect will be examined in my analysis below. The similar

meta-regression analysis of the effect of publication selection bias on the estimated income elasticity of VSL by Doucouliagos, Stanley, and Viscusi (2014) likewise found estimates of statistically significant publication bias. However, while the estimates of the bias-corrected income elasticity of VSL were below the mean income elasticity estimate in the literature, they were similar to the meta-regression analysis range in Viscusi and Aldy (2003) in which there was no correction for publication selection effects.

A principal theme of this article is that much of the role of the publication selection bias can be traced to studies based on earlier eras of fatality rate data. The available U.S. occupational fatality rate measures have evolved from voluntary reporting of fatalities to the U.S. Bureau of Labor Statistics (BSL), to reliance on fatality rates based on partial samples of the working population, and most recently, to the use of a comprehensive Census of Fatal Occupational Injuries (CFOI) undertaken by the BLS. The CFOI is a comprehensive census of all worker fatalities. Construction of the CFOI requires that the BLS validate every fatality as being job-related using multiple data sources such as death certificates, workers' compensation records, and coroners' reports.

Because the CFOI data consist of individual records of fatalities, researchers have used it to construct much more precise measures of the fatality rate that can be matched to the worker in the employment sample. Whereas previous BLS job fatality data pertained to average fatality rates by industry, it is now possible to construct fatality rates by very refined dimensions such as industry, occupation, age, gender, race, and immigrant status.² For example, some studies have constructed a fatality rate stratified by 50 industries and by 10 occupations so that both industry and occupational variations in the fatality rate are taken into account. Using multiple years of

 $^{^{2}}$ Viscusi (2013) reviews these studies using CFOI data and the different dimensions on which the article constructed the fatality rate and matched it to the worker.

CFOI data to have an adequate sample size, it is feasible to construct risk estimates for such narrowly defined categories. Most previous labor market studies of VSL before the advent of the CFOI data relied on industry level data and, in effect, assumed all jobs within an industry were equally risky.

In recognition of the superiority of the CFOI fatality rate measure in estimates of the VSL, the U.S. Dept. of Transportation (2013) has adopted for policy evaluation purposes an average of VSL estimates from nine labor market studies based on the CFOI data rather than relying on a meta-regression analysis including studies based on less reliable risk measures. As this paper will demonstrate, VSL estimates derived using the CFOI data will exhibit a differing performance with respect to estimates of publication selection bias as well.

Section II introduces the four data sets used in the aggregate level meta-regression analysis. To maintain comparability to Doucouliagos, Stanley, and Giles (2012) and Doucouliagos, Stanley, and Viscusi (2014), I use the meta-regression sample of Bellavance, Dionne, and Lebeau (2009) as the starting point in my analysis, but I also augment this sample with different samples of additional studies. The meta-regression estimates in Section III indicate a statistically significant publication selection bias effect, but the estimated VSL after adjusting for this bias is much greater for studies using the CFOI data. In Section IV I construct a new data set based on a large sample of individual regression results using the CFOI data. The magnitude and statistical significance of publication selection bias varies across the different specifications and is not statistically significant based on models with clustered standard errors and including either fixed effects or random effects. In all specifications, the extent of the bias for the CFOI is well below the 70-80 percent publication bias estimate found by Doucouliagos, Stanley, and Giles (2012) for VSL studies. The main result is that the publication-bias corrected

estimates using the CFOI data are very similar to the estimated values that are relied on for policy purposes.

II. AGGREGATE META-ANALYSIS DATA SETS

The first set of examination of the role of publication selection bias will utilize four data sets. Each of these data sets is based on a "best-set" approach in that a best or preferred single estimate from each study is generally used. Sample 1 is the Bellavance, Dionne, and Lebeau (2009) meta-regression analysis sample used in the publication selection bias analysis of Doucouliagos, Stanley, and Giles (2012) and Doucouliagos, Stanley, and Viscusi (2014). That sample consists of 39 VSL estimates drawn from 37 different studies. Sample 2 augments Sample 1 by including estimates from 14 VSL studies using the estimates from studies using the CFOI data that were not included in Sample 1. The additional estimates incorporated in the sample are all based on the semi-logarithmic wage equation estimates using the author's preferred specification. Sample 3 adds to Sample 2 the six studies that were included in the meta-analysis of labor market estimates in Viscusi and Aldy (2003) but which are not already included in Sample 2. Finally, Sample 4 restricts Sample 3 to only those studies using U.S. data, leading to a sample size of 39.

Table 1 summarizes the sample characteristics for the variables that will play some role in the analysis. The average of the VSL estimates ranges from \$10 million for Sample 4 to \$12 million for Samples 1-3, where all estimates in this article are in \$2010 based on the CPI-U. Due to the skewed nature of the distribution, the sample mean is above the median VSL of \$8.9 million (\$2010) in the meta-analysis in Viscusi and Aldy (2003). Interestingly, the lowest observed VSL estimates among the four samples considered here are for the U.S. Sample 4 notwithstanding the positive income elasticity of VSL. This result is not too surprising in that the explanatory variables included in the U.S. analyses are often more comprehensive including, for example, a measure of workers' compensation benefits and the nonfatal injury rate, each of which may affect the estimated compensation for fatality risks.

The two variables that will be used to capture publication selection bias effects are the standard error (Std. Error) and the Variance of the VSL estimates. The average standard errors of the VSL estimates are about one-third of the size of the VSL estimates for all four samples.

Three other variables will be included in various regression analyses. The most important of these is CFOI, which is an indicator variable that takes on a value of 1 for VSL estimates based on CFOI fatality rate data, and 0 otherwise. The share of studies in the different samples relying on CFOI data ranges from a low of 8 percent for Sample 1 to a high of 44 percent for Sample 4, with Samples 2 and 3 being intermediate cases with just under one-third of the studies based on CFOI data. The Ln Income variable is the natural log of the sample's average income level. Workers' Compensation is an indicator variable that takes on a value of 1 if the wage equation included a workers' compensation variable, and 0 otherwise. About onefifth of the studies controlled for the effect of Workers' Compensation on wages.

One can obtain a general sense of the possible presence of a publication selection bias by considering a funnel plot of the VSL estimates in which the precision of the estimate (the inverse of the standard error) is on the vertical axis and the VSL (in millions of \$2010) is on the horizontal axis. Meta-regression analyses of VSL generally assume that the estimates reported are an unbiased sample. If there is no publication bias and the assumptions underlying the regression model are satisfied, the estimates should be independent of their standard error and should be symmetrically distributed around the mean estimated value. This property is best

suited to analyzing situations in which there is a single true population parameter. The funnel plot approach excludes the influence of other factors in the analysis that may influence the estimates such as the presence of substantial heterogeneity in the levels of VSL across the different samples. The shape of the distribution should be similar to that of an inverted funnel if there are no selection effects or reporting biases.

Figure 1 presents a funnel plot of VSL estimates for Sample 3. The circles indicate estimates based on the CFOI data, and the triangles indicate estimates using other fatality rate data. The funnel plot is highly skewed, with the outliers in terms of both precision and size of the VSL estimates being from studies that did not use the CFOI data. The non-CFOI studies have estimates along the vertical axis with low VSL and high precision as well as estimates along the horizontal axis with low precision and high VSL. The very low estimates of VSL are the most precisely estimated. The CFOI estimates are more tightly clustered with more moderate levels of precision and less extreme VSL estimates. Notably, the distribution of VSL estimates is truncated as none of the estimates is negative, which is consistent with the theory of compensation differentials. However, given the pattern of VSL estimates that are often clustered along the vertical axis, one would have expected similar clustering for negative values if negative values had not been selectively screened out.

Best-set sample analyses are not well-suited to analyzing the possibility of negative VSL estimates. The emphasis of the best-set sample approach is on the author's preferred specification. This approach will tend truncate the distribution and omit any negative VSL estimates, as negative VSL results are unlikely to be an economist's chosen specification. However, the all-set CFOI sample in Section IV that utilizes a comprehensive set of regression results finds that negative VSL estimates sometimes are published despite being inconsistent

with theoretical predictions. Similarly, the underlying studies that comprise the Bellavance et al. (2009) sample likewise include some negative values.

III. META-REGRESSION ESTIMATES OF PUBLICATION SELECTION BIAS

The tests for publication bias will involve a series of different regressions involving a similar methodology where these models adhere to the accepted norms for meta-regression analyses of publication selection effects (Stanley and Doucouliagos 2012). In the basic model in which the Std. Error is included in the equation to account for publication selection bias, the equation takes the form:

$$VSL_i = \alpha_0 + \alpha_1 Std. Error_i + \varepsilon_i.$$
(1)

A statistically significant estimate of α_1 is evidence of publication selection effects in that the reported VSL estimates are correlated with the estimated Std. Error as opposed to having a symmetrically distributed funnel plot. This coefficient is the regression analysis counterpart of the funnel asymmetry test. The estimated VSL after adjusting for publication selection effects is given by the constant term α_0 . Thus, as the Std. Error goes to zero, the constant term equals the expected value of VSL corrected for publication selection effects.

One can undertake a similar analysis using the Variance of the VSL estimate rather than the Std. Error. Simulation studies suggest that the inclusion of the Variance in the equation is a preferable correction for the role of publication selection effects (Stanley and Doucouliagos 2012). The Variance counterpart to equation 1 takes the form:

$$VSL_i = \beta_0 + \beta_1 Variance_i + e_i.$$
(2)

As in the case of equation 1 using the Std. Error, the coefficient β_1 reflects the influence of publication selection effects. The constant term β_0 is the estimated VSL corrected for publication selection effects.

To capture the potential effect of the CFOI fatality rate data on estimates of the VSL, I explore two additional specifications in which the CFOI variable is also included:

$$VSL_{i} = \alpha_{0}' + \alpha_{1}' Std. Error_{i} + \alpha_{2}' CFOI_{i} + \varepsilon_{i}'$$
(3)

and

$$VSL_{i} = \beta_{0}' + \beta_{1}' Variance_{i} + \beta_{2}' CFOI_{i} + e_{i}'.$$
(4)

The coefficients α_1 ' and β_1 ' reflect the influence of publication selection effects. Similarly, the constant terms α_0 ' and β_0 ' will correspond to the estimated average VSL controlling for both publication bias and the use of CFOI data. One can readily calculate this average VSL estimate and its confidence interval based on the estimated constant term and its standard error. However, my main interest here is whether the use of CFOI data affects the estimated VSL after accounting for publication bias effects. In particular, are α_2 ' and β_2 ' statistically significant, and how do they influence the average VSL? Conditional on using the much more reliable CFOI data, what is the estimated VSL? That mean value is given by α_0 ' + α_2 ' for the Std. Error formulation and by β_0 ' + β_2 ' for the variance formulation. When reporting the VSL and its confidence interval for the equations including the CFOI variable I will do so for estimates in which the CFOI variable take on a value of 1 and publication selection effects are set equal to zero.

The errors associated with the different VSL estimates are likely to exhibit substantial heterogeneity. As a result, the estimates of equations 1 - 4 will utilize a weighted least squares (WLS) model using the inverse of the variance of each of the VSL estimates as the weights.

This approach is known as the precision-effect estimate with standard error (Stanley and Doucouliagos 2012).

Table 2 reports the estimates of the Standard Error versions of the model in equation 1 and equation 3 for each of the four samples. In every instance there is evidence of statistically significant publication bias effects. These biases are all positive, indicating that the effect of the bias is to boost the estimated VSL. The magnitudes of the coefficients of the Std. Error terms range from 3.2 to 3.4 in Panel A and from 2.9 to 3.1 in Panel B. The size of the publication bias effect is noteworthy since a coefficient of 2 or more in the Std. Error version of the model is generally viewed as a sign of substantial publication bias (Doucougliagos, Stanley, and Giles 2012).

The mean estimates of the VSL implied by the constant terms in the four equations in Panel A of Table 2 all indicate a VSL on the order of \$1 million, about an order of magnitude below the mean values for each sample in Table 1. The findings in Panel B of Table 2 likewise indicate publication bias effects that have somewhat smaller point estimates than in Panel A. The constant term estimates remain in a similar range around \$1 million except for Sample 4 for which the constant term is small and not statistically significant. Notably the CFOI variable is strongly significant in all instances, implying a CFOI premium above the average publication bias-adjusted VSL of \$2.5 million for Sample 1 to \$4.1 million for the U.S. sample of studies in Sample 4.

The 95 percent confidence intervals (CI) for VSL at the bottom of each panel in Table 2 do not include the average VSL for each of the samples. However, in the case of estimates based on the CFOI data in Panel B of Table 2 the upper end of the confidence intervals is higher than in

Panel A and closer to many estimates of VSL in the literature, as it is in the \$5 million to \$6 million range.

The counterpart estimates of equations 2 and 4 based on the Variance rather than the Std. Error appear in Table 3. These values, which are the empirically preferred estimates based on studies of the relative performance of Std. Error and Variance approaches to capturing publication selection effects, consistently indicate a strong publication bias effect in every equation. However, the constant terms that reflect the average VSL excluding the role of all other variables in the equation are larger in Table 3 than in Table 2. For Panel A these average VSL amounts range from \$2.1 million in Sample 1 to \$3.7 million in Sample 4. These differences in the constant terms in Panel A can be traced to the greater share of CFOI estimates in some of the samples, particularly Sample 4. The intercepts reported for the Panel B equations that include the CFOI variable are tightly clustered in the \$1.8 million - \$1.9 million range. The CFOI variables are positive and all strongly statistically significant, with the average CFOI premium ranging from \$3.9 million - \$4.7 million.

The estimated VSL levels based on the Variance versions of the models are greater than the VSL estimates for the Std. Error models in Table 2. The Panel A estimates in Table 3 imply average VSL amounts of \$2 million to \$4 million, with a high of \$6 million for the upper end of the confidence interval for Sample 4. However, after accounting for the influence of CFOI estimates in Panel B of Table 3, the mean of the VSL estimates is in the \$6 million to \$7 million range, which still reflects substantial publication bias effects, but the extent of the bias is less than in Panel A. The upper ends of the VSL confidence intervals are \$8 million to \$9 million, which remain below the sample means but are much closer to these values than the overall effects from Panel A.

The final set of regression estimates using these four samples includes several different explanatory variables. In particular, I add the Ln Income of the sample and whether the study included a Workers' Compensation variable. The Ln Income variable should have a positive effect due to the positive income elasticity of VSL, and Workers' Compensation should have a negative effect as this form of insurance coverage reduces wage premiums for risk. These equations differ from those reported in Table 3 of Doucouliagos, Stanley, and Giles (2012) in that instead of a time trend variable I include the CFOI indicator. Thus, the effect of the CFOI variable is broken out separately, and the average effects on the intercept of all previous eras of fatality rate data are reflected in the constant term.

The rationale for distinguishing CFOI apart from a temporal trend is that the role of the temporal trend is that the studies have become refined over time, particularly in terms of the fatality rate data that they use. There have been several improvements in the fatality rate data that influence the VSL. Consider, for example, the effect on the VSL of the transition from the early BLS industry fatality rate data to the National Traumatic Occupational Fatality data, which was a precursor to the CFOI data developed by the National Institute of Occupational Safety and Health. Use of this newer fatality rate variable alone led to a doubling of the estimated VSL based on estimates of otherwise identical equations, due to the reduction in the amount of measurement error in the fatality rate variable (Moore and Viscusi 1988). Indeed, the important role of measurement error in the fatality rate measure had been a prominent, long-standing theme in the VSL literature dealing with studies in the pre-CFOI era.³

The estimated VSL and the associated confidence intervals shown in the bottom rows of Panel A and Panel B of Table 4 are all constructed after setting the publication bias term equal to

³ See, for example, the discussion in Moore and Viscusi (1988), Black and Kniesner (2003), and Ashenfelter (2006). These critiques either predated the use of CFOI data in labor market estimates of VSL or were not aware of the CFOI data and did not include the CFOI-based studies in the critique.

zero, the value of CFOI equal to 1, and with all other variables evaluated at their mean values for the sample. The mean VSL estimates range from \$4 million to \$5 million for the Std. Error formulations of the model in Panel A of Table 4 to a range from \$7 million to \$8 million for the Variance version. The broadest confidence intervals for the VSL estimates are for Sample 1, for which the range is from \$2 million to \$8 million for the Std. Error formulation, and from \$5 million to \$12 million for the Variance formulation. The narrowest confidence interval range is for the U.S. Sample 4, where the range is \$3 million to \$5 million for the Std. Error formulation and \$5 million to \$8 million for the model in which the Variance is used to capture publication bias selection effects. The role of publication selection bias is statistically significant and reduces the VSL, but the VSL estimates based on CFOI data are at levels more similar to the observed distribution in the literature.

IV. PUBLICATION SELECTION BIAS ESTIMATES FOR A SAMPLES OF CFOI STUDIES

Given the difference in the publication bias-corrected estimates of the VSL for the studies based on the CFOI data, it is useful to explore the role of publication bias using a sample consisting of only studies that utilized the CFOI data. However, rather than focusing on a single preferred estimate from each study, I include a comprehensive set of regression estimates, thus avoiding any selection effects in terms of which estimates are included in the meta-regression analysis. Unlike the best-set approach, this "all-set" sample incorporates the entire range of estimates from a particular study and their heterogeneity. The resulting sample consists of 487 observations drawn from 15 different studies. The Appendix summarizes the list of the studies used in this analysis and the procedure for constructing this sample. The estimated VSL for the

CFOI sample is fairly similar to that for Samples 1-4, with a mean value of \$14.013 million and a standard error of \$6.246 million.

Figure 2 provides the funnel plot of the VSL estimates for the CFOI sample. There is some positive skewness in the distribution, as there was in Figure 1, but much of the distribution exhibits more of a reasonable funnel shape than in Figure 1. The large number of estimates in the \$5 million to \$15 million VSL range displays a funnel-shaped distribution. The estimates in this range also exhibit the greatest precision. Unlike Figure 1 in which there were no negative VSL estimates, Figure 2 includes several negative values. There is also less clustering of estimates along the vertical axis than in Figure 1, as there are fewer outliers observed in Figure 2 in terms of estimates with very low VSL and high precision. Nevertheless, the distribution of VSL estimates is positively skewed as many of the more extreme estimates in Figure 2 stem from unique aspects of the particular studies, which we will account for in the statistical analysis. The principal outliers that induce skewness in the distribution are the large positive estimates that are also coupled with relatively low levels of precision.

The CFOI sample analysis includes estimates of several different models for both the Std. Error and the Variance formulations of the model. The first equation to be estimated is the basic equation 1 for Std. Error and equation 3 for Variance, using a WLS approach. Because there are multiple observations for any particular study, in brackets we report the pertinent clustered standard errors where the errors are clustered on the particular article. The robust standard errors are reported in parentheses. All coefficient estimates and the associated confidence intervals that are reported for this sample include both the robust standard errors as well as the clustered standard errors.

The second estimation approach is a fixed effects model including fixed effects for the different articles s in the sample. This approach captures the article-specific factors that influence the average estimated VSL for the sample. These influences include differences in sample composition as well as differences in econometric specification. Thus, we report fixed effects estimates for the Std. Error model of the equation for this unbalanced panel, given by

$$VSL_{is} = \alpha_0'' + \alpha_1'' Std. Error_{is} + a_s + \varepsilon_{is}$$
(5)

and for the Variance model we estimate

$$VSL_{is} = \beta_0'' + \beta_1'' Variance_{is} + b_s + e_{is}.$$
 (6)

We also estimate each of these equations using a random effects framework where the articlespecific intercepts a_s and b_s are random effects in the model rather than fixed effects.

Although both fixed effects and random effects models are reported below, based on the Hausman test one can reject the hypothesis that the article-specific effects are uncorrelated with the other regressors in the equation. The differences between the coefficients in the models are strongly statistically significant at the 0.000 level for the Std. Error model and at the 0.002 level for the Variance model. Thus, for this sample the fixed effects model estimates are consistent, but the random effects model estimates are not.

Table 5 reports the estimation results for the Std. Error models in Panel A and the Variance models in Panel B. For both the Std. Error and Variance specifications based on WLS, the publication selection bias terms are statistically significant and positive, as in the previous estimates based on more aggregative data. The magnitudes of the publication bias effects are considerably diminished. For the estimates in Panel A the coefficients of the Std. Error term range from 0.3 to 0.7, whereas the earlier results were about one and half time the size of the coefficient level of 2 that is a sign of substantial publication bias. For the estimates utilizing

either a fixed effects or a random effects model, the publication bias terms are no longer statistically significant based on the clustered standard errors that account for the multiple observations per article.

The intercept terms, which are the estimates of the VSL after accounting for the influence of publication selection bias, are about an order of magnitude greater than the earlier results for the Std. Error model estimates in Table 2 and at least five times greater than the intercepts for the Variance model estimates in Table 3. The mean estimated VSL based on the Std. Error models ranges from \$9 million to \$12 million, and for the Variance model the estimates are from \$9 million to \$14 million. The upper ends of the confidence intervals reach a high value of \$16 million for the fixed effects Std. Error model and \$15 million for the fixed effects Variance model.

The adjustments for article-specific differences using either a fixed effects or a random effects model lead to higher estimates of VSL than the WLS results. In the case of the Variance specifications, the confidence interval for the VSL based on the WLS estimates lies below and does not overlap with the confidence intervals based on either the fixed effects or random effects model.

The reduction in the mean value of VSL from the sample mean of \$14 million to the levels shown in Table 5 produces estimated values of the VSL similar to those used by government agencies based on the most reliable estimates. The publication bias selection adjustment and the accounting for article-specific differences dampen the influence of some of the more extreme outliers. For example, the VSL estimates exploiting the panel data aspect of the Panel Study of Income Dynamics reported in Kniesner et al. (2012) are considerably smaller than the overall estimates using the Panel Study of Income Dynamics in Kniesner, Viscusi, and

Ziliak (2006) in which there is no accounting for worker-specific effects. Thus, the publicationcorrected estimates of the VSL lie in a quite reasonable range based on the characteristics of the studies.

V. CONCLUSION

These findings indicate a potentially statistically significant role of publication bias in estimates of the value of a statistical life. The bias adjustment may be quite substantial. This result holds for the best-set samples based on individual estimates from a large series of studies as well as in some specifications for the all-set sample of regression results based solely on the CFOI fatality rate data. However, the clustered standard error results for the all-set estimates using either fixed effects or random effects models based on studies relying on the CFOI data do not indicate statistically significant publication bias effects.

In assessing the implications of the meta-regression analyses for estimates of VSL, the role of different eras of fatality rate data is consequential. The estimates for four different samples of studies found that there was a CFOI premium of \$2 million - \$4 million for the Std. Error model estimates and \$4 million - \$5 million for the Variance model estimates. These higher values are consistent with the reduced measurement error associated with the CFOI data.

The estimates based solely on the individual regression results utilizing individual regression estimates and the CFOI data generate larger VSL estimates than the results of the more broadly based best-set samples. The estimated mean values are \$9 million - \$12 million for the Std. Error equations and \$9 million to \$14 million for the Variance equations, which are below the sample mean estimate of the VSL using the CFOI data of \$14 million. However, the estimated publication-bias corrected estimates of VSL are very similar to or somewhat above the

\$9.1 million level for VSL adopted for policy assessment purposes by the U.S. Dept. of Transportation (2013) based on its review of a series of VSL studies using CFOI data. An inventory by Viscusi (2014) of the VSL amounts used from 1985 to 2013 in 98 U.S. regulatory impact analyses found that agencies employed levels of VSL that ranged from \$1.2 million to \$9.6 million in \$2010. Early policy assessments of the VSL were at the low end of this range, and more recent policy values have been at or near the upper end of that range. Even these high levels that have been used for policy purposes are consistent with the mean publication-bias corrected estimates of VSL based on the CFOI data.

The confidence intervals for the estimated VSL based on the CFOI data are reasonably tight, but they sometimes include the average VSL amount for the entire sample. Nevertheless, the publication-bias corrected estimates of VSL for the CFOI sample produces estimates more in line with the average VSL levels that are generated once high estimate outliers are excluded. Accounting for publication selection effects reduces the VSL to the levels that are consistent with the studies in the literature that are generally viewed as most reliable based on their econometric approach.

Appendix. Description of the CFOI Data Set

The CFOI sample is based on the individual regression results reported in 15 articles. A detailed review of the characteristics of these CFOI studies appears in Viscusi (2013). The sample included VSL estimates from the following articles: Aldy and Viscusi (2008), Evans and Schaur (2010), Hersch and Viscusi (2010), Kniesner and Viscusi (2005), Kniesner et al. (2012), Kniesner, Viscusi, and Ziliak (2006, 2010, 2014), Scotton (2013), Scotton and Taylor (2011), Viscusi (2003, 2004 2013), Viscusi and Aldy (2007), and Viscusi and Hersch (2008). Note that the VSL estimates have been transformed to 2010 dollars using the CPI-U.

In some cases, the paper did not include information that made it possible to calculate the standard error (SE) of the VSL. In the case of Kniesner and Viscusi (2005), and estimates in Kniesner et al. (2012), the procedure used followed that of Bellavance, Dionne, and Lebeau (2009). The first stage involves an OLS regression of SE(VSL) on sample size. Based on saving the constant term (α) and the coefficient of sample size (β), the SE(VSL) is calculated based on the equation: SE(VSL) = VSLx[$\alpha + \beta$ sample size].

One estimate of \$158 million VSL (\$2010) from Scotton and Taylor (2011) was excluded because it pertained only to a specific, narrowly defined class of fatalities--homicides to transportation drivers—rather than typical job accidents affecting a broad class of workers. Two studies—Leeth and Ruser (2003) and Kochi and Taylor (2011)—were excluded because of the infeasibility of constructing standard errors for the VSL. References

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Figure 1 Funnel Plot of VSL for the Sample 3 Data Set

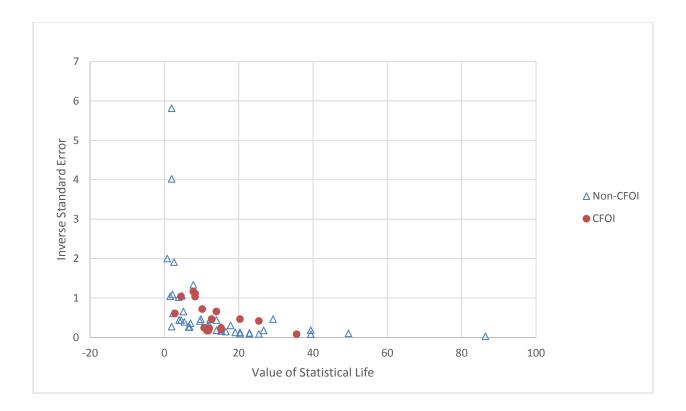
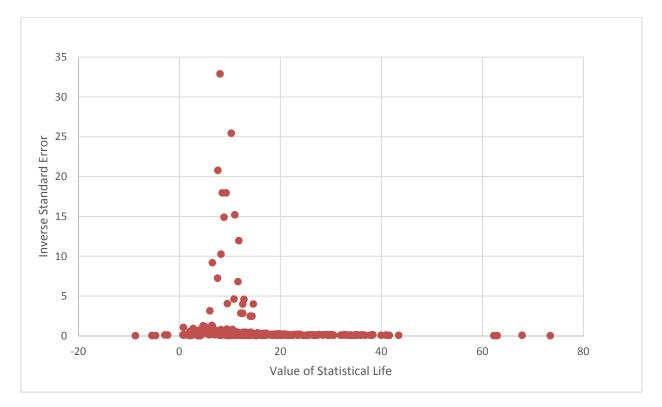


Figure 2 Funnel Plot of VSL for the CFOI Data Set



Variable	Sample 1	Sample 2	Sample 3	Sample 4
VSL (\$ millions)	12.040	11.653	11.480	9.561
	(13.098)	(11.611)	(11.127)	(6.085)
Std. Error	3.839	3.620	3.549	2.826
	(4.967)	(4.450)	(4.274)	(2.168)
Variance	38.778	32.531	30.548	12.570
	(135.925)	(117.498)	(111.537)	(19.881)
CFOI	0.077	0.321	0.288	0.436
	(0.270)	(0.471)	(0.457)	(0.502)
Ln Income	10.441	10.498	10.446	10.616
	(0.482)	(0.431)	(0.627)	(0.176)
Workers' Compensation	0.205	0.151	0.186	0.205
	(0.409)	(0.361)	(0.393)	(0.409)
Ν	39	53	59	39

Table 1 Sample Characteristics for Four Samples^a

^a Sample 1 is from Bellavance, Dionne, and Lebeau (2009); Sample 2 augments the Bellavance, Dionne, and Lebeau (2009) sample with additional U.S. studies using CFOI fatality rate data; Sample 3 augments Sample 2 with studies in Viscusi and Aldy (2003) that were not included in Sample 2; and Sample 4 restricts Sample 3 to those studies using U.S. data.

 Table 2

 Basic WLS VSL Regressions with Standard Errors for Four Samples^a

Variable	Sample 1	Sample 2	Sample 3	Sample 4
Intercept	1.026	1.162	1.087	1.257
	(0.194)***	(0.219)***	(0.165)***	(1.133)
Std. Error	3.201	3.411	3.441	3.326
	(0.463)***	(0.386)***	(0.353)***	(0.636)***
\mathbb{R}^2	0.49	0.51	0.54	0.41
VSL (\$ millions)	1.026	1.162	1.087	1.257
	(0.194)***	(0.219)***	(0.165)***	(1.133)
CI VSL	(0.633, 1.418)	(0.723, 1.600)	(0.757, 1.417)	(-1.038, 3.552)

Panel A: Basic WLS Regressions with Std. Error

Panel B: Basic WLS Regressions with Std. Error and CFOI

Variable	Sample 1	Sample 2	Sample 3	Sample 4
Intercept	0.977	1.042	1.015	-0.250
	(0.217)***	(0.195)***	(0.151)***	(0.461)
Std. Error	3.037	2.853	2.924	3.096
	(0.452)***	(0.385)***	(0.347)***	(0.390)***
CFOI	2.539	3.027	2.981	4.069
	(1.470)*	(0.760)***	(0.732)***	(0.759)***
\mathbb{R}^2	0.53	0.61	0.63	0.66
VSL (\$ millions)	3.516	4.069	3.995	3.819
	(1.449)**	(0.739)***	(0.721)***	(0.689)***
CI VSL	(0.577, 6.455)	(2.585, 5.552)	(2.550, 5.440)	(2.422, 5.216)

^a Robust standard errors are in parentheses. Statistical significance at the *0.10 level, **0.05 level, and ***0.01 level. CI is the 95 percent confidence interval.

 Table 3

 Basic WLS VSL Regressions with Variance for Four Samples^a

	υ			
Variable	Sample 1	Sample 2	Sample 3	Sample 4
Intercept	2.114	2.487	2.301	3.711
	(0.462)***	(0.652)***	(0.462)***	(1.058)***
Variance	0.256	0.282	0.300	0.465
	(0.109)**	(0.110)**	(0.113)***	(0.105)***
\mathbb{R}^2	0.18	0.17	0.18	0.22
VSL (\$ millions)	2.114	2.487	2.301	3.711
	(0.462)***	(0.652)***	(0.462)***	(1.058)***
CI VSL	(1.179, 3.050)	(1.177, 3.796)	(1.376, 3.225)	(1.568, 5.854)

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Panel A: Basic	WLS Regressions	s with variance

Panel B: Basic WLS Regressions with Variance and CFOI

Variable	Sample 1	Sample 2	Sample 3	Sample 4
Intercept	1.944	1.944	1.879	1.827
	(0.372)***	(0.368)***	(0.266)***	(0.713)**
Variance	0.253	0.252	0.270	0.461
	(0.108)***	(0.095)**	(0.099)***	(0.089)***
CFOI	3.937	4.663	4.702	4.461
	(1.667)**	(0.864)***	(0.824)***	(1.010)***
\mathbb{R}^2	0.27	0.43	0.43	0.53
VSL (\$ millions)	5.881	6.608	6.581	6.288
	(1.626)***	(0.790)***	(0.786)***	(0.752)***
CI VSL	(2.583, 9.179)	(5.020, 8.195)	(5.007, 8.155)	(4.763, 7.814)

^a Robust standard errors are in parentheses. Statistical significance at the *0.10 level, **0.05 level, and ***0.01 level. CI is the 95 percent confidence interval.

		Table 4		
Full WLS	VSL Re	gressions	for Four	Samples ^a

Variable	Sample 1	Sample 2	Sample 3	Sample 4
Intercept	-1.925	-1.590	0.193	-11.874
	(7.869)	(6.810)	(0.857)	(29.707)
Std. Error	3.027	2.798	2.948	2.927
	(0.532)***	(0.446)***	(0.345)***	(0.478)***
CFOI	3.966	3.166	3.153	4.133
	(1.477)**	(0.800)***	(0.680)***	(1.048)***
Ln Income	0.321	0.291	0.105	0.114
	(0.840)	(0.727)	(0.107)	(0.274)
Workers' Compensation	-1.881	-1.534	-1.425	-0.729
	(0.950)*	(0.816)*	(0.512)***	(0.920)
\mathbb{R}^2	0.58	0.63	0.66	0.67
VSL (\$ millions)	5.012	4.400	4.175	4.194
	(1.650)***	(0.664)***	(0.630)***	(0.582)***
CI VSL	(1.659, 8.366)	(3.066, 5.734)	(2.912, 5.438)	(3.010, 5.377)

Variable	Sample 1	Sample 2	Sample 3	Sample 4
Intercept	-19.871	-17.318	-1.707	5.764
	(7.248)**	(6.194)***	(1.789)	(33.096)
Variance	0.217	0.219	0.258	0.416
	0.093**	(0.082)**	(0.096)***	(0.084)***
CFOI	5.005	3.690	4.425	3.982
	(1.723)***	(0.933)***	(0.866)***	(1.223)***
Ln Income	2.272	2.003	0.409	-0.261
	(0.769)***	(0.657)***	(0.217)*	(0.305)
Workers' Compensation	-3.000	-2.356	-1.245	-1.929
	(1.155)**	(0.657)***	(0.813)	(1.032)*
\mathbb{R}^2	0.42	0.52	0.47	0.58
VSL (\$ millions)	8.247	7.043	6.753	6.584
	(1.810)***	(0.753)***	(0.731)***	(0.728)***
CI VSL	(4.568, 11.926)	(5.528, 8.557)	(5.288, 8.218)	(5.105, 8.063)

^aRobust standard errors are in parentheses. Statistical significance at the *0.10 level, **0.05 level, and ***0.01 level. CI is the 95 percent confidence interval.

Table 5VSL Regressions for Sample of CFOI Studies

Variable	WLS	Fixed Effects	Random Effects
Intercept	8.967	12.117	10.603
	(0.427)***	(0.080)***	(0.992)***
	[0.116]***	[1.995]***	[1.630]***
Std. Error	0.735	0.303	0.399
	(0.188)***	$(0.080)^{***}$	(0.077)***
	[0.284]**	[0.319]	[0.324]
\mathbb{R}^2	0.03	0.17	0.17
VSL (\$ millions)	8.967	12.117	10.603
	(0.427)***	(0.611)***	(0.992)***
	[0.116]	[1.995]***	[1.630]***
CI VSL	(8.127, 9.807)	(10.916, 13.319)	(8.660, 12.547)
	[8.718, 9.217]	[7.838, 16.396]	[7.409, 13.798]

Panel A: CFOI VSL Regressions for Sample of CFOI Studies with Std. Error^a

Panel B: CFOI VSL Regressions for Sample of CFOI Studies with Variance^a

Variable	WLS	Fixed Effects	Random Effects
Intercept	9.023	13.521	12.146
	(0.420)***	(0.393)***	(1.131)***
	[0.134]***	[0.708]***	[1.179]***
Variance	0.074	0.007	0.009
	(0.010)***	(0.003)***	(0.003)***
	[0.026]**	[0.011]	[0.011]
\mathbb{R}^2	0.02	0.08	0.08
VSL (\$ millions)	9.023	13.521	12.146
	(0.420)***	(0.393)***	(1.131)***
	[0.134]	[0.708]***	[1.179]
CI VSL	(8.198, 9.847)	(12.749, 14.293)	(9.929, 14.363)
	[8.735, 9.311]	[12.002, 15.040]	[9.835, 14.456]

^a Robust standard errors are reported in parentheses. All bracketed standard errors are clustered by article. Statistical significance at the *0.10 level, **0.05 level, and ***0.01 level. CI is the 95 percent interval in parentheses for the robust standard errors and in brackets for the clustered standard errors.