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Anchoring biases in international estimates of the value of a statistical life

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Abstract U.S. labor market estimates of the value of a statistical life (VSL) were the first revealed preference estimates of the VSL in the literature and continue to constitute the majority of such market estimates. The VSL estimates in U.S. studies consequently may have established a reference point for the estimates that researchers analyzing data from other countries are willing to report and that journals are willing to publish. This article presents the first comparison of the publication selection biases in U.S. and international estimates using a sample of 68 VSL studies with over 1000 VSL estimates throughout the world. Publication selection biases vary across the VSL distribution and are greater for the larger VSL estimates. The estimates of publication selection biases distinguish between U.S. and international studies as well as between government and non-government data sources. Empirical estimates that correct for the impact of these biases reduce the VSL estimates, particularly for studies based on international data. This pattern of publication bias effects is consistent with international studies relying on U.S. estimates as an anchor for the levels of reasonable estimates. U.S. estimates based on the Census of Fatal Occupational Injuries constitute the only major set of VSL studies for which there is no evidence of statistically significant publication selection effects. Adjusting a baseline bias-adjusted U.S. VSL estimate of $9.6 million using estimates of the income elasticity of the VSL may be a sounder approach for generating international estimates of the VSL than relying on direct estimates from international studies.

Keywords Value of a statistical life · Fatality risk · Publication bias · Anchoring effect · Reference dependence · Meta-analysis · VSL

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1 Introduction

A substantial U.S. labor market literature on the value of a statistical life (VSL) has established the VSL as a critical policy parameter and has stimulated similar research used throughout the world.[1] Policymakers use estimates of the VSL to value the economic benefits of reduced mortality risks achieved by government policies. These mortality risk benefits often serve as the most important benefit component. However, the VSL estimates that are published based on both U.S. and international labor market data are potentially subject to publication selection effects. This article demonstrates the existence of such biases and that the extent of such biases is much greater for international studies, which overestimate the underlying VSL.

The medical literature first generated evidence of publication selection effects whereby substantial publication biases may affect the research findings submitted to and accepted by journals for publication (Stanley and Doucouliagos 2012; Viscusi 2015). Because neither researchers nor the drug companies that provide funding have an interest in publishing information about unproductive lines of research, the results of clinical drug trials often go unpublished. Studies that fail to yield statistically significant results are also less likely to be accepted for publication.

As in the case of medical research, the VSL estimates that are published are potentially subject to publication selection effects that could arise at different stages of the publication process.[2] Researchers may choose to report results that they believe are most credible or are most consistent with economic theory and the literature. For example, because good health is positively valued, compensating differentials for fatality risks should be positive not negative. Journals may be reluctant to publish VSLs that are inconsistent with economic theory, outside the conventional range, or statistically insignificant. Researchers and journal editors may use the early studies in the literature, which were based on U.S. labor market studies, as guideposts for what constitutes the acceptable range of empirical estimates. In much the same way that anchoring influences and reference point effects affect economic behavior generally (Tversky and Kahneman 1974; Kahneman and Tversky 1979), the U.S. evidence may establish a reference point for subsequent international studies. Such subsequent biases lead to an overestimation of the international VSL as compared to its bias-corrected value. This phenomenon is consistent with U.S. studies generating an anchoring effect that leads to disproportionate reporting of higher VSL estimates from international studies.

The concern with possible publication selection effects for the VSL is not new. Ashenfelter and Greenstone (2004) hypothesized that publication bias may be influential in the VSL literature, but they did not present an empirical assessment to document the existence or magnitude of such biases. The meta-analysis by Doucouliagos et al. (2012) found evidence of dramatic publication selection effects in the VSL literature overall, suggesting that the bias-corrected VSL estimates were 70–80% lower than the published

[1] See, for example, Viscusi and Aldy (2003), the U.S. Department of Transportation (2015), U.S. Environmental Protection Agency (2016), and Narain and Sall (2016).

[2] Stanley and Doucouliagos (2012) and Brodeur et al. (2016) analyze the effects of publication selection effects in the economics literature more generally.

values. However, Viscusi (2015) found that studies based on recent occupational fatality data are not subject to such biases. Moreover, much of the apparent bias derives from meta-analysis researchers focusing on only a sample of the single best estimates of the VSL from different studies rather than the full set of estimates in these publications. The evidence of bias is considerably less pronounced for the full set of estimates (Viscusi 2017). In this article, we consider the potential impact of publication selection effects using all estimates from a large sample of studies from the U.S. and other countries. Our empirical estimates adjust for publication selection biases, and these adjustments have especially strong impacts on VSL estimates based on data from outside the U.S.

Section 2 presents our meta-analysis dataset, which includes 1025 VSL estimates from 68 studies that we categorize based on five different governmental and non-governmental sources of the occupational fatality data used in these studies. The distribution of the estimates that are reported in Section 3 suggests that researchers are particularly reluctant to report negative or very low VSL estimates. The publication selection biases vary across the distribution of VSL estimates, with the greatest biases being evident at the upper end of the VSL distribution. The regression results in Section 4 estimate the effect of publication selection bias for each subsample to assess whether the biases vary depending on the source of the data and whether it is a U.S. or international study. Only the U.S. studies based on recent fatality rate data are free of estimated biases, and the most substantial biases occur in the international studies. As indicated in the concluding Section 5, the considerable biases in international estimates may reflect a more general economic phenomenon in which empirical evidence from the U.S. establishes a reference point that serves as an anchor for determining which economic parameter estimates from other countries are treated as publishable.

Fortunately, the presence of such biases need not result in policy paralysis. The U.S. VSL estimates based on recent fatality rate data display no evidence of statistically significant publication selection effects. In conjunction with information about income differences across countries and estimates of the income elasticity of the VSL, it is possible to generate unbiased VSL estimates for use throughout the world.

2 Sample and subsample descriptions

2.1 The hedonic labor market model

Labor market estimates of the VSL constitute the largest set of revealed preference estimates of the VSL. The wage-risk tradeoff rate used to calculate the VSL is derived from either a linear or semi-logarithmic hedonic wage equation. The linear wage equation that researchers use to estimate the VSL is given by

$$Wage_i = \beta_0 + \beta_1 Fatality\ Rate_i + X_i^{'} \beta_2 + \varepsilon_i \quad (1)$$

where the subscript i indexes individuals, *Wage* is the hourly wage, *Fatality Rate* is an individual's risk of a workplace fatality, and X is a vector that includes education, gender, race, or other relevant individual characteristics. Some studies have utilized panel data, incorporating many individual characteristics through fixed effects, leading to a slightly modified version of eq. (1). The VSL equals β_1 after appropriately adjusting the units to reflect compensating differentials per expected fatality. Most studies measuring the VSL have used the following semi-log equation of the form:

$$\ln Wage_i = \beta_0 + \beta_1 Fatality\ Rate_i + X_i^{'} \beta_2 + \varepsilon_i \tag{2}$$

The chief advantage of the semi-log equation is to reduce the influence of outliers (Kniesner et al. 2014). For studies using a semi-logarithmic equation, the VSL is:

$$VSL = \widehat{\beta_1} \times \overline{Wage} \tag{3}$$

where $\overline{Wage}$ is the average wage of the sample, adjusted to reflect annual compensation. In our sample, 9.7% of the estimated VSL figures are based on a wage equation, while the remainder estimated the VSL using a semi-log equation.

2.2 Sample definition

Our sample of labor market estimates of the VSL contains all estimates included in the meta-analyses by Viscusi and Aldy (2003), Bellavance et al. (2009), and Viscusi (2015), as well as the VSL estimates from six other studies. We identified the additional studies by performing an EconLit search for studies published since 2010 containing the term "Value of Statistical Life." The whole sample in this article contains 1025 different estimates of the VSL reported in 68 studies. Thus, the sample consists of the "all-set" sample that includes all the VSL estimates in these studies rather than a "best-set" sample in which the analysis is restricted to the single "best" estimate from each of the 68 studies (Viscusi 2017). Reliance on the all-set sample eliminates the potential influence of the judgmental biases associated with selection of the best estimate from the different studies.

The principal explanatory variable of interest is the occupational fatality rate, which is generally matched to workers in employment samples based on the worker's job and personal characteristics, such as industry, occupation, and age. As indicated in Black and Kniesner (2003) and other studies, the extent of the bias in the VSL estimates is likely to be quite sensitive to the particular fatality data source that is used. This article distinguishes five different sets of fatality risk variables: U.S. Government, U.S. Non-Government, Census of Fatal Occupational Injuries (CFOI), Non-U.S. Government, and Non-U.S. Non-Government. The Appendix provides a detailed discussion of these fatality risk data groups, and the studies that comprise each group are indicated in the Online Appendix.

The first dimension by which studies were categorized was articles that relied on government and non-government data sources. These risk data differ because government agencies have consistent methods over time, have more resources to collect data, and often collect data to provide it to researchers. As a result, data that the government collects are likely to systematically differ from data that private entities collect.

We make a distinction between U.S. data and data from other countries both because of differences in data collection methods and the decades of experience that the U.S. has had in refining its fatality risk statistics. As Viscusi and Gentry (2015) noted, U.S. labor market estimates of the VSL are more stable than some international estimates. For the U.S. Government data group, we break out the CFOI data into a separate subsample. The CFOI data represent a major advance in the accuracy of the fatality risk data, as these data are based on a comprehensive census of all occupational fatalities, which are validated using multiple sources. Although the majority of the studies have relied on U.S. data, there are 22 studies in the sample using non-U.S. government data and three studies using non-U.S. non-government statistics.

Tables 1 and 2 summarize the means and standard errors of the VSLs in those international studies, indicating some notable patterns. Studies from the United Kingdom have exceptionally high VSL values and standard errors. Canada, Australia, and India have very wide ranges of VSLs with several imprecisely estimated values that cover the range of most U.S. CFOI estimates.

2.3 Subsample summary statistics

The summary statistics in Table 3 for the full sample and each fatality risk subsample highlight some of the principal differences. The VSL averages $12.0 million overall, with a range from $3.1 million for the U.S. Non-Government subsample to a high of $13.8 million for the Non-U.S. Government subsample.[3] Annual worker fatality risks average about 1/10,000, with the main exception being the 6.7/10,000 risk in the U.S. Non-Government data that confounds occupational fatality risks with non-job fatality risks of people in different occupations.

Table 3 also presents four groups of explanatory variables that reflect differences in the underlying VSL studies: sample annual income, variables indicating whether the underlying regression estimating the VSL controlled for nonfatal injury risk or workers' compensation levels, variables indicating the regression specification, the procedure for calculating standard errors, and sample characteristics. Occupations that have high fatality rates are likely to also have high nonfatal injury rates, which will command compensating differentials introducing positive omitted variables bias if not included in the equation. Overall, 38.8% of the estimates controlled for nonfatal injury risks. Individuals covered by higher workers' compensation rates will require lower compensating risk differentials. Half of the estimates included control for workers' compensation levels.

Labor market studies of the VSL match worker injury rates to multiple workers, such as all workers in an industry-occupation group. As a result, the standard errors for different worker observations will not be independent. If a researcher fails to use robust and clustered standard errors, the assignment of a common fatality rate biases standard errors downward (Cameron and Miller 2015). In the whole sample, 54% of estimates used clustered standard errors, while 87.1% of the estimates in the CFOI studies reported clustered standard errors.

In semi-log equations, the variance of the VSL is the variance of the product of two random variables: the fatality rate coefficient and the average wage. Not all studies calculate standard errors correctly; instead, the standard error that researchers report for most VSL estimates is the standard error of the risk fatality variable, multiplied by the average wage in the sample. It is impossible to correct these standard errors post hoc without a study's original sample. This issue does not arise in a wage equation estimating the VSL because the variance of the VSL is the variance of one random variable, scaled by a constant. For the whole sample, 41.4% of estimates had correct standard errors. The sample with the greatest proportion of correct standard errors was the CFOI subsample; 63.0% of VSL estimates in the CFOI sample correctly adjusted

[3] All dollar figures in this article are expressed in 2015 dollars.

Table 1 Non-U.S. Government subsample of VSL estimates

Article	Country	Data source	Mean VSL estimate
Arabsheibani and Marin (2000)	United Kingdom	Occupational Mortality Decennial Survey 1979–1983	56.705
			(49.826)
Cousineau et al. (1992)	Canada	Quebec Compensation Board Data Bank 1981–1985	6.690
			(0.630)
Giergiczny (2008)	Poland	National Labor Inspectorate of Poland 2001–2003	2.487
			(2.492)
Gunderson and Hyatt (2001)	Canada	Ontario Workers' Compensation Board 1988	15.440
			(9.503)
Kim and Fishback (1999)	South Korea	Ministry of Labor's Analysis for Industrial Accident	1.509
			(0.240)
Kniesner and Leeth (1991)	Australia	Industrial Accidents and Manufacturing Establishments 1984–1985	7.076
			(0.665)
Kniesner and Leeth (1991)	Japan	Yearbook of Labour Statistics, Ministry of Labour	−31.284
			(68.465)
Lanoie et al. (1995)	Canada	Quebec Compensation Board Data Bank 1981–1985	2.168
			(26.364)
Liu et al. (1997)	Taiwan	Taiwan Labor Insurance Agency 1982–1986	0.796
			(0.331)
Marin and Psacharopoulos (1982)	United Kingdom	Office of Population Censuses and Surveys 1978 Occupational Mortality Decennial Supplement	10.810
			(13.593)
Martinello and Meng (1992)	Canada	Occupational Safety and Health Branch of Labour Canada 1986	7.339
			(3.245)
Meng (1989)	Canada	Labour Canada and Quebec Workers' Compensation Board 1981	6.224
			(0.455)
Meng and Smith (1990)	Canada	Labour Canada and Quebec Occupational Health and Safety Board 1981–1983	9.714
			(4.837)

Table 1 (continued)

Article	Country	Data source	Mean VSL estimate
Meng and Smith (1999)	Canada	Ontario Workers' Compensation Board 1986–1987	5.075 (2.428)
Miller et al. (1997)	Australia	Worksafe Australia, National Occupation Health and Safety Commission 1992–1993	22.007 (5.857)
Miyazato (2012)	Japan	Ministry of Health, Labor, and Welfare's 2008 Population Trends Statistics	6.615 (9.459)
Parada-Contzen et al. (2013)	Chile	Chilean Safety Association 2006	10.827 (7.105)
Rafiq et al. (2010)	Pakistan	Punjab Employees Social Security Institute 2006–2007	12.271 (5.412)
Sandy and Elliot (1996)	United Kingdom	Office of Population Censuses and Surveys Occupation Mortality Tables Decennial Supplement 1979–1983	41.964 (54.036)
Shanmugam (2000)	India	Administrative Report of the Chief Inspector of Factories, Madras 1987–1990	4.917 (0.460)
Shanmugam (2001)	India	Administrative Report of the Chief Inspector of Factories, Madras 1987–1990	13.734 (7.007)
Siebert and Wei (1994)	United Kingdom	Health and Safety Executive	14.188 (4.132)
Tsai et al. (2011)	Taiwan	Bureau of Labor Insurance Labor Insurance Compensation File 1998–2002	0.126 (0.196)

Standard deviations of the VSL in parentheses. Refer to Online Appendix for full bibliographic information

Table 2 Non-U.S. Non-Government subsample of VSL estimates

Article	Country	Data source	Mean VSL estimate ($ millions)
Baranzini and Ferro Luzzi (2001)	Switzerland	Swiss National Accident Insurance Company 1994–1995	10.857 (3.296)
Schaffner and Spengler (2010)	Germany	Statutory Accident Insurance Corporations	2.662 (3.796)
Weiss et al. (1986)	Austria	Three Austrian insurance companies	11.563 --

Standard deviations of the VSL in parentheses. Weiss et al. (1986) has no standard deviation because this paper provided only one estimate in our sample

the standard errors to account for the variation in wage. In all other subsamples, each estimate that had correct standard errors used a wage specification.

The final category of variables in our study records whether an article used a sample limited according to union status, type of work, sex, or race. Many articles restricted their samples based on whether workers were in white-collar or blue-collar occupations because relatively few white-collar workers suffer workplace fatalities, making it difficult to calculate reliable fatality rates.

3 Subsample distributions and funnel plots

3.1 VSL distributions

The distributions of the VSLs calculated using different risk data sources are likely to differ, as the data sources themselves collect fatality rates differently. Table 4 presents the distributions of the VSL estimates in our sample. The first row presents the distribution for the whole sample, while each subsequent row corresponds to one of the five subsamples discussed above. In the absence of publication selection bias, each distribution would be symmetric around its mean VSL value. If each study suffered from the same magnitude of publication selection bias, then each distribution would be skewed but would resemble the other distributions.

The median VSL for the whole sample is $9.7 million. The medians in each subsample differ substantially. The U.S. Non-Government sample has the smallest median, $1.5 million, while the CFOI subsample has the largest median at $11.1 million. The Non-U.S. Non-Government subsample's median of $9.8 million is close to the whole sample median. The remaining two subsamples have medians below the whole sample median. The median of the U.S. Government subsample is $4.5 million, while the Non-U.S. Government subsample has a median of $6.9 million.

The right tail of the whole sample's distribution is more than twice as long as the left tail, consistent with publication selection bias favoring positive estimates of the VSL. The subsamples largely replicate this pattern. The difference between the 95th percentile and median values is more than twice as large as the difference between the median

Table 3 Summary statistics by data source

Variable	Whole sample	U.S. Gov.	CFOI	U.S. Non-Gov.	Non-U.S. Gov.	Non-U.S. Non-Gov.
VSL & fatality rates:						
VSL estimates ($ millions)	11.955 (15.970)	7.291 (10.184)	13.125 (11.861)	3.107 (6.013)	13.838 (28.084)	8.738 (4.938)
Standard error	8.011 (18.933)	7.095 (13.165)	5.992 (5.449)	3.306 (6.201)	16.593 (40.072)	3.380 (3.505)
Fatality rate (per 10,000 workers)	1.015 (1.699)	1.685 (1.564)	0.469 (0.192)	6.671 (3.469)	1.556 (2.430)	0.592 (0.304)
Income:						
Income ($ thousands)	42.436 (13.959)	44.038 (8.455)	44.931 (13.226)	57.555 (15.963)	30.921 (13.845)	41.163 (11.356)
Ln income ($ thousands)	3.675 (0.443)	3.770 (0.177)	3.761 (0.302)	4.024 (0.229)	3.268 (0.677)	3.571 (0.826)
Regression specification:						
Nonfatal injury	0.388 (0.488)	0.561 (0.498)	0.366 (0.482)	--	0.394 (0.490)	--
Workers' compensation	0.502 (0.500)	0.370 (0.484)	0.699 (0.459)	0.083 (0.282)	0.080 (0.272)	--
Wage specification	0.097 (0.296)	0.110 (0.314)	0.106 (0.308)	0.208 (0.415)	0.048 (0.214)	--
Clustered standard errors	0.540 (0.499)	--	0.871 (0.335)	--	0.069 (0.254)	--
Correct standard errors	0.414 (0.493)	0.110 (0.314)	0.630 (0.483)	0.208 (0.415)	0.048 (0.214)	--
Sample characteristics:						
Union sample	0.056 (0.229)	0.214 (0.411)	0.005 (0.069)	0.125 (0.338)	0.064 (0.245)	0.105 (0.315)
Non-union sample	0.039 (0.194)	0.156 (0.364)	0.003 (0.057)	0.125 (0.338)	0.032 (0.176)	0.105 (0.315)
Blue-collar sample	0.167 (0.373)	0.301 (0.460)	0.106 (0.308)	0.208 (0.415)	0.250 (0.434)	0.053 (0.229)
White-collar sample	0.014 (0.116)	0.017 (0.131)	0.003 (0.057)	0.125 (0.338)	0.032 (0.176)	--
Male sample	0.326 (0.469)	0.416 (0.494)	0.264 (0.441)	0.542 (0.509)	0.452 (0.499)	--
Female sample	0.062 (0.242)	--	0.103 (0.304)	--	--	--
White sample	0.038 (0.191)	0.191 (0.394)	0.010 (0.098)	--	--	--
Non-white sample	0.014 (0.116)	--	0.023 (0.149)	--	--	--
Observations	1025	173	621	24	188	19

All monetary figures have been converted to 2015 U.S. dollars

Table 4 Raw quantiles of the VSL levels by data source

	Quantile						
Sample	5%	10%	25%	50%	75%	90%	95%
Whole sample	−1.695	0.444	4.490	9.672	15.374	25.533	35.722
U.S. Government sample	−4.887	−1.732	0.638	4.471	13.162	20.822	25.322
U.S. CFOI sample	1.793	4.299	7.263	11.108	16.792	27.718	35.722
U.S. Non-Government sample	−2.412	−0.163	0.481	1.504	3.962	9.876	15.237
Non-U.S. Government sample	−1.878	0.038	1.020	6.915	15.426	28.474	68.256
Non-U.S. Non-Government sample	−0.401	0.082	7.030	9.762	11.563	14.506	18.566

and 5th percentile values in the U.S. Government, CFOI, and Non-U.S. Government subsamples. The difference is particularly pronounced in the Non-U.S. Government subsample, where the range in the upper half of the distribution is nearly an order of magnitude larger than the lower half; the difference between the 95th and 90th percentile alone is \$40 million. The Non-U.S. Non-Government and U.S. Non-Government samples exhibit narrower distributions than the other subsamples.

3.2 Funnel plots of the VSL

Figures 1a-f illustrate the distributions of the subsamples. Each figure presents a funnel plot of the whole sample or one of the five subsamples. The VSL estimate is on the horizontal axis, while the inverse of the estimate's standard error is on the vertical axis. Estimates that are more precisely measured are thus higher on the funnel plot's vertical axis. If the subsamples are not influenced by publication selection bias, the estimates of the VSL should be symmetrically distributed around the mean value and will resemble an inverted funnel. Estimates clustered just above zero suggest potential bias against publishing negative estimates.

Figure 1a indicates publication selection bias in the whole sample, but also shows that many values exhibit the desired inverted funnel shape around \$10 million. Comparing the subsequent figures demonstrates that the estimates in the CFOI sample form the appropriate inverted funnel, while the other samples provide the most estimates that hew close to \$0. Figure 1c demonstrates that the CFOI distribution has a clear funnel, though the values to the right of the mean are denser than those to the left. The left tail has several negative values and does not exhibit significant clustering close to \$0. In contrast, the distributions of the other U.S. subsamples in Fig. 1b and d have a large mass of estimates close to \$0.

Figure 1e and f illustrate the distributions of the two Non-U.S. subsamples, where the larger sample is that of government sources. The Non-U.S. Government subsample demonstrates the asymmetry against the vertical axis that is characteristic of publication selection bias. There are only 16 negative estimates in the subsample, compared to 31 estimates that are positive but less than \$1 million. The Non-U.S. Government sample has several large positive outliers, including eight estimates of the VSL in excess of \$100 million based on two articles using U.K. data, Sandy and Elliot (1996) and Arabsheibani and Marin (2000). The distribution has one large negative outlier of

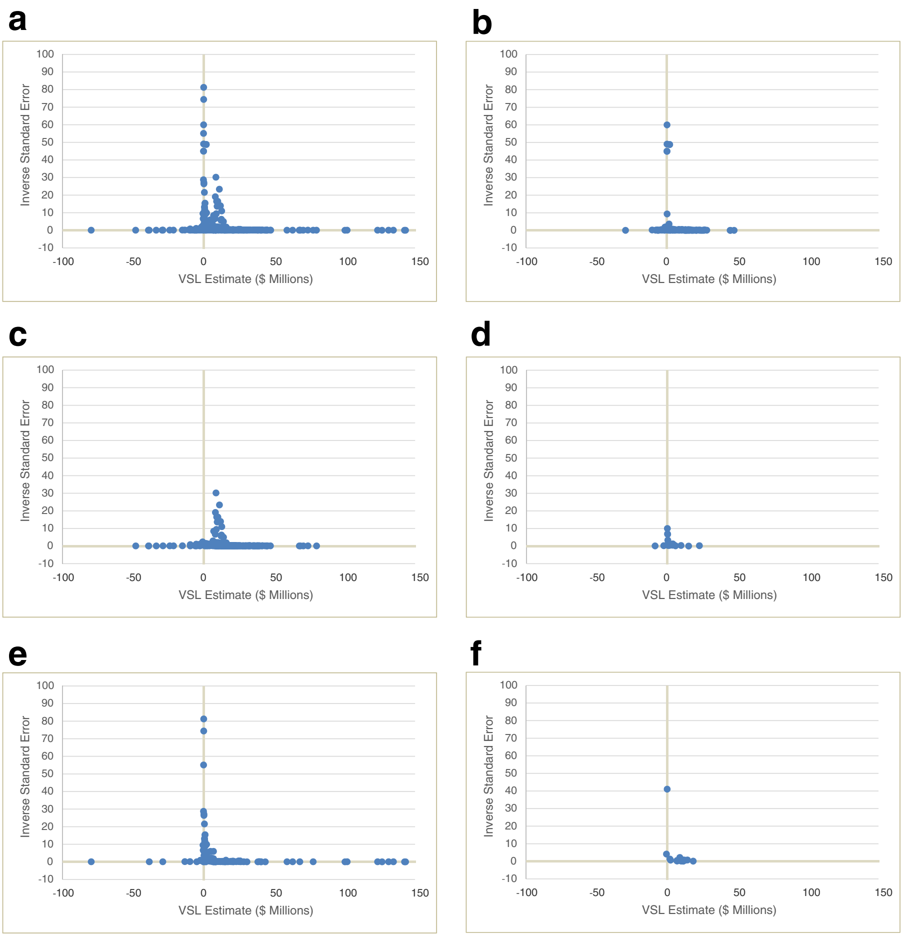

Fig. 1 **a** Funnel Plot of the VSL Estimates for the Full Sample. **b** Funnel Plot of the VSL Estimates for the U.S. Government Sample. **c** Funnel Plot of the VSL Estimates for the U.S. CFOI Sample. **d** Funnel Plot of the VSL Estimates for the U.S. Non-Government Sample. **e** Funnel Plot of the VSL Estimates for the Non-U.S. Government Sample. **f** Funnel Plot of the VSL Estimates for the Non-U.S. Non-Government Sample

–$79.6 million from Kniesner and Leeth (1991). The Non-U.S. Non-Government sample only has 19 estimates, making it difficult to deduce a pattern from its funnel plot. There are a few estimates clustered against the vertical axis, with one estimate from Schaffner and Spengler (2010) having a particularly high inverse standard error.

These funnel plots and distribution characteristics are not formal tests of differential publication selection effects between the subsamples, but they present strong evidence that the effect of publication selection bias differs among the samples. With the exception of the CFOI subsample, each subsample has an abnormal funnel plot. Very large estimates are more common than moderately negative estimates, although some of the subsamples have large negative outliers. These figures suggest that correcting for the effect of publication selection bias will reduce the estimated VSL on average.

3.3 Publication selection effects across quantiles

To formally test the effects of publication selection, we use weighted least squares (WLS) and quantile regression estimation. The base regression for the WLS model is of the VSL on its standard error for each observation j. The estimating equation takes the form:

$$VSL_j = \beta_0 + \beta_1 \times Standard\ Error_j + \varepsilon_j \tag{4}$$

The weights in the WLS estimation are the inverse variance of the VSL estimate. In the absence of publication selection bias, estimating eq. (4) would demonstrate no correlation between the VSL estimate and the estimate's standard error. However, if publication selection bias exists, the funnel plot would not be symmetrically distributed. As a result, a statistically significant estimate of the coefficient on *Standard Error* indicates that the sample of VSL estimates exhibits publication selection bias. The coefficient β_1 is the numerical equivalent of the funnel plot observations above.

For most observations in our sample, the article provided the standard error for the VSL, or it was possible to calculate the standard error of the VSL from the standard error of the fatality risk coefficient in the regression equation. However, this was not always feasible for regressions that included quadratic fatality risk terms or interactions with other explanatory variables. Calculating the standard error of the VSL in an equation that includes a quadratic term requires information on the average fatality rate in the sample, which not all studies provided. Calculating the standard error of the VSL when the regression equation includes an interaction term requires the covariance of fatality risk and the interacted term, which no study provided. For the 14% of the VSL estimates in our sample for which it was not possible to calculate standard errors, we estimated standard errors for each such VSL using the procedure outlined in Bellavance et al. (2009). Using the sample of all VSL estimates for which standard errors are available, we estimated a regression of an estimate's standard error divided by the VSL on a single variable, the estimate sample size. We then assigned standard errors to the remaining VSL estimates using the results of this regression and the estimate's VSL level and sample size.

Quantile regression estimation indicates how publication selection bias varies at different points of the distribution of VSL estimates. Similar to WLS estimation, the base regression is of the VSL on its standard error for each observation j at the q quantile. The estimating equation takes the form:

$$VSL_j^{(q)} = \beta_0^{(q)} + \beta_1^{(q)} \times Standard\ Error_j + \varepsilon_j^{(q)} \tag{5}$$

A statistically significant estimate of $\beta_1^{(q)}$ indicates publication selection bias exists at the q quantile. The constant term $\beta_0^{(q)}$ in this model is the publication bias-corrected estimate of the quantile q of the distribution of the VSL. For both eq. (4) and eq. (5), we estimate a second version of the equation that includes subsample fixed effects to calculate a subsample-specific bias-corrected VSL estimate.

Table 5 Quantile regressions of the VSL

Panel A: Base case quantile regressions						
	WLS	10%	25%	50%	75%	90%
Standard error	4.372*** (0.482)	0.008 (0.179)	0.115 (0.075)	0.447** (0.181)	1.458*** (0.160)	1.990*** (0.298)
Constant	0.137*** (0.051)	0.410 (0.665)	4.088*** (0.529)	7.449*** (0.377)	7.641*** (0.697)	9.673*** (0.931)
R^2	0.057	0.001	0.012	0.050	0.214	0.394
Panel B: Quantile regressions with data source intercepts						
	WLS	10%	25%	50%	75%	90%
Standard error	1.007*** (0.146)	0.011 (0.186)	0.109** (0.044)	0.463** (0.202)	1.570*** (0.104)	1.925*** (0.283)
CFOI	9.006*** (0.572)	6.048*** (0.738)	6.463*** (0.472)	6.384*** (0.644)	6.647*** (0.873)	6.731*** (0.667)
U.S. Non-Government	−0.462 (0.362)	1.944 (1.905)	−0.019 (0.403)	−1.714** (0.834)	−1.482 (1.669)	−2.329* (1.358)
Non-U.S. Government	−0.568 (0.361)	1.812*** (0.546)	0.312 (0.475)	1.620** (0.780)	1.266 (1.084)	3.022 (2.613)
Non-U.S. Non-Government	−0.528 (0.363)	1.864 (2.688)	6.160* (3.502)	4.626*** (0.658)	6.751* (3.486)	4.949*** (0.736)
Constant	0.626* (0.361)	−1.782*** (0.628)	0.404 (0.409)	2.733*** (0.837)	1.620* (0.911)	4.828*** (0.538)
R^2	0.911	0.063	0.106	0.104	0.251	0.412

$N = 1025$. Robust standard errors are in parentheses. R^2 presented is Adjusted R^2 for the WLS column, and Pseudo R^2 for the quantile regressions

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

The estimation of both eqs. (4) and (5) provide evidence that statistically significant publication bias exists in the VSL distribution. The sample WLS estimates are in the first column of Table 5, and the estimates for the specific quantiles follow. Panel A of Table 5 presents the base case estimates of eqs. (4) and (5), while Panel B presents estimates that include fixed effects for each subsample, where the omitted subsample is U.S. Government. The base case estimates imply that there is no significant publication selection bias at the 25th percentile and below. Starting at the median, the bias is statistically significant and large. The publication bias monotonically increases over the distribution; the coefficient on the standard error is 0.447 at the median, and it increases to 1.990 at the 90th percentile. The bias-corrected median VSL is \$7.4 million, \$2.3 million less than the raw median value. The bias-corrected range from the 10th percentile to the 90th percentile is only \$9.3 million, less than half the size of the corresponding \$26 million from the raw VSL distribution in Table 4. The decline results almost entirely from reducing the 90th percentile, reflecting the larger effect of publication selection bias on the right tail of the VSL distribution.

The results in Panel B are very similar to those in Panel A. In addition to showing the extent of publication selection bias, Panel B also demonstrates the influence of the subsamples at various levels of the VSL distribution. Panel B provides stronger evidence of publication selection bias throughout the distribution. The coefficient on the standard error is significant in each regression except for the 10th percentile. Panel B demonstrates the same monotonic pattern as Panel A, with the publication selection bias increasing over the distribution. The standard error coefficients are nearly identical in the two sets of quantile regressions. The effect of the sample constants is fairly stable across the levels of the distribution. The strongest consistent effects are for the CFOI sample, indicating a VSL premium from \$6.0 million to \$6.7 million across the distribution. The Non-U.S. Non-Government sample premium is also positive but more variable.

Table 6 compares the raw VSLs in the whole sample and subsamples to the bias-corrected VSLs based on the Table 5 estimates. The bias-corrected VSLs are the sum of the constant from the WLS regression in Table 5, Panel B, and the sample-specific fixed effect for each subsample. We calculated the sum using Stata's non-linear combination of parameters routine. The difference between the raw mean VSLs and the bias-corrected mean VSLs demonstrates the effect of publication selection bias on the sample as a whole and on each subsample. The bias-corrected mean VSL for the whole sample is \$6.1 million, only half of the raw mean value of \$12 million. The bias-corrected mean VSL is smaller for each subsample than the raw mean VSL, and there is significant heterogeneity in the size of the effect. The VSL for the U.S. Government subsample shrinks from \$7.3 million to \$0.6 million. The bias-corrected mean VSL for the CFOI subsample is \$9.6 million, which is the same as the bias-corrected estimate reported in Viscusi (2015). This figure is \$3.5 million less than the raw VSL mean of \$13.1 million. The U.S. Non-Government, Non-U.S. Government, and Non-U.S. Non-Government subsample values each fall to values less than \$175,000. The dramatic effect for each of these subsamples demonstrates the substantial publication selection bias they exhibit.

Tables 5 and 6 demonstrate that publication selection bias is pervasive in our sample of VSL estimates. Moreover, the results in Table 6 indicate that the magnitude of publication selection bias in each sample likely differs substantially. Correcting for the bias affects the CFOI subsample less than each other sample, and the two non-U.S. subsamples are affected most of all. Less publication selection bias in the VSL estimates based on the CFOI is reasonable because papers using the CFOI are less likely to suffer

Table 6 Raw and bias-corrected mean VSLs by subsample

	Whole Sample	U.S. Gov.	CFOI	U.S. Non-Gov.	Non-U.S. Gov.	Non-U.S. Non-Gov.
Raw mean VSL	11.955 (15.970)	7.291 (10.184)	13.125 (11.861)	3.107 (6.013)	13.838 (28.084)	8.738 (4.938)
Bias corrected mean VSL	6.061 (0.302)	0.626 (0.361)	9.631 (0.448)	0.164 (0.064)	0.058 (0.005)	0.098 (0.048)

For the raw mean VSLs, standard deviations are in parentheses. For bias-corrected mean VSL, standard errors are in parentheses. Bias-corrected mean VSLs are calculated by adding the constant and subsample fixed effects in the WLS regression in Column 1 of Table 5 from attenuation bias from measurement error or selection bias and, as a result, are less likely to be biased downward and yield results that researchers are unwilling to report or journals unwilling to publish. However, selection bias and measurement error cannot completely explain the dramatic effect on the non-U.S. subsamples. Researchers' unwillingness to report values that differ substantially from U.S. values—which dominate VSL research—likely explains the portion of bias in those studies that measurement error and selection bias cannot. The next section investigates differences in publication bias for each subsample, yielding findings consistent with a pattern of researchers and journal reviewers anchoring on U.S. estimates.

4 Weighted least squares estimates of bias-corrected VSL

4.1 Estimating equation and results

Using weighted least squares, we estimate the magnitude of publication selection bias for each of the subsamples. The estimating equation takes the form:

$$VSL_j = \beta_0 + \beta_1 \times \text{Standard Error}_j + \beta_{2S} \times S_j + \beta_{3S} \times \text{Standard Error}_j \times S_j + X_i^{'}\beta_4 + \varepsilon_j \quad (6)$$

where S_j is a fixed effect for each of the five subsamples, *Standard Error*$_j \times S_j$ is an interaction term for each of the five subsamples, and all other variables are as above. Including an interaction between standard error and the subsample constant allows us to test whether estimates in each subsample have different magnitudes of publication selection bias. The full version of the model also includes a vector X_i of variables controlling for the specification of the equation estimating the VSL and sample characteristics. The weights in both specifications are the inverse variance of the VSL estimate. Estimates in a subsample exhibit publication selection bias if the pertinent $\beta_1 + \beta_{3S}$ is statistically significant.

Table 7 reports the results of estimating eq. (6). The heteroskedasticity-robust standard errors are in parentheses, while standard errors that are robust and clustered on article are in brackets. U.S. Government is the omitted subsample. The most consistent main effect for sample groups is the positive CFOI coefficient, indicating a \$9.1 million VSL premium in the base case and a \$6.0 million premium in the full model.

In both the base case and the full model, the subsamples exhibit different levels of publication selection bias. The standard error coefficient is positive and statistically significant. Whether there is any bias in particular samples depends on their net influence in conjunction with this main effect of the *Standard Error* term. Using robust standard errors, all three interactions other than the U.S. Non-Government interaction are significant. The CFOI subsample's coefficient is negative and, when summed with the coefficient on *Standard Error*, is statistically indistinguishable from zero. The Non-U.S. samples fare significantly worse than the omitted U.S. Government sample. The total effect of publication selection bias for the Non-U.S. Government sample is nearly three times as large as the U.S. Government sample, while the Non-U.S. Non-Government sample fares even worse with an effect four times the size of that in the U.S. Government sample. These results persist in the full model. The coefficient on CFOI remains essentially offsetting in magnitude.

Table 7 WLS regressions of the VSL

	Base case	Full model
Standard error	1.164	1.503
	(0.212)***	(0.181)***
	[0.417]***	[0.282]***
CFOI	9.110	5.977
	(0.589)***	(0.438)***
	[0.598]***	[0.857]***
U.S. Non-Government	−0.575	1.722
	(0.371)	(0.660)***
	[0.600]	[0.813]**
Non-U.S. Government	−0.577	0.678
	(0.365)	(0.377)*
	[0.593]	[0.340]*
Non-U.S. Non-Government	−0.650	0.380
	(0.366)*	(0.943)
	[0.593]	[0.734]
CFOI × Std. Error	−1.069	−1.341
	(0.283)***	(0.250)***
	[0.550]*	[0.605]**
U.S. Non-Government × Std. Error	0.472	−0.678
	(0.465)	(0.623)
	[0.700]	[0.775]
Non-U.S. Government × Std. Error	2.246	0.931
	(0.437)***	(0.333)***
	[0.953]**	[0.577]
Non-U.S. Non-Government × Std. Error	3.718	3.187
	(1.223)***	(1.204)***
	[0.503]***	[0.736]***
Ln Income ($ thousands)		0.124
		(0.277)
		[0.215]
Workers' compensation		0.416
		(0.159)***
		[0.297]
Nonfatal injury		−0.521
		(0.163)***
		[0.159]***
Wage specification		−6.735
		(1.111)***
		[2.907]**
Clustered standard errors		0.166
		(0.992)
		[2.465]
Correct standard errors		5.746
		(1.021)***
		[2.721]**

Table 7 (continued)

	Base case	Full model
Union sample		−0.047
		(0.086)
		[0.148]
Non-Union sample		−2.108
		(1.579)
		[2.628]
Blue-Collar sample		2.859
		(0.409)***
		[0.656]***
White-Collar sample		−11.539
		(4.006)***
		[5.182]**
White sample		−2.043
		(0.830)**
		[1.150]*
Non-White sample		−7.950
		(1.328)***
		[2.641]***
Male sample		−0.696
		(0.368)*
		[0.338]**
Female sample		−2.985
		(0.439)***
		[0.324]***
Constant	0.622	−0.439
	(0.365)*	(1.002)
	[0.593]	[0.776]
Adjusted R^2	0.916	0.971

$N = 1025$. Robust standard errors are in parentheses, robust and clustered standard errors are in brackets.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

The controls for sample characteristics and regression specification are generally significant and consistent with results from previous meta-analyses of the VSL literature. Estimates that included nonfatal injury risk are smaller than those that do not. Using a wage rather than log wage regression specification results in a lower estimate, while correctly calculating VSL standard errors to account for wage as a random variable results in a higher estimate. This pattern is consistent with VSL estimates getting higher over time as researchers have used log wage equations and correctly calculated standard errors more often. Estimates utilizing samples of blue-collar workers estimated VSLs that were \$2.9 million higher on average, while estimates using white-collar worker samples estimated VSLs \$11.5 million lower. Samples limited to individuals who are white or non-white both estimated VSLs that were lower on average than samples that were not limited by race. The magnitude of the effect for non-white samples was \$8.0 million, much higher than the \$2.0 million effect for white samples. Likewise, samples that were limited based on sex both estimated lower than average VSLs. Male samples estimated VSLs $0.7 million lower on average, while female samples estimated VSLs $3.0 million smaller.

To examine the net impact of the publication selection bias terms, Table 8 presents the net coefficient on standard error for each of the five subsamples. Both columns are the sum of the standard error coefficient and the sample-specific interaction and the standard error from the sum. We calculated the sum using Stata's non-linear combination of parameters routine. A larger net coefficient indicates a greater degree of positive publication selection bias, while a coefficient that is statistically indistinguishable from zero indicates that a sample does not suffer from publication selection bias. U.S. Government and U.S. Non-Government both have positive and significant publication selection bias, although the effect is insignificant for the U.S. Non-Government sample in the full model. In both models, the CFOI subsample standard error coefficient is indistinguishable from zero. These results suggest that those numbers have likely not been inflated by publication selection bias. This consistent statistical insignificance has policy relevance because the U.S. Department of Transportation and the U.S. Environmental Protection Agency now rely on CFOI studies when using labor market studies to set their VSL for policy analyses.

The results for both Non-U.S. samples are striking, as both samples exhibit large and very significant publication selection bias in both the base case and full model. The effect is largest for the Non-Government subsample. The summed standard error coefficients for both Non-U.S. samples are larger than each of the other subsamples. This result is consistent with the implication of Fig. 1e and f. Published studies using non-U.S. data overwhelmingly favor positive VSL estimates over negative VSL estimates, resulting in a highly skewed distribution. The raw mean of the Non-U.S. VSLs severely overstates the true mean value.

4.2 Income-adjusted international VSL estimates

The results in Table 8 indicate that the non-U.S. data studies suffer from more publication selection bias than the U.S. studies. As we discussed above, each subsample except for the CFOI suffers from large measurement error that contributed to publication selection bias. However, the large difference in the magnitude of publication bias

Table 8 Net standard error coefficient by data source

	Net effect (Base case)	Net effect (Full model)
U.S. Government	1.164	1.503
	[0.212]***	[0.282]***
CFOI	0.096	0.162
	[0.188]	[0.525]
U.S. Non-Government	1.636	0.825
	[0.414]***	[0.790]
Non-U.S. Government	3.410	2.435
	[0.383]***	[0.552]***
Non-U.S. Non-Government	4.882	4.690
	[1.205]***	[0.670]***

Clustered standard errors are in brackets

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

between the U.S. and non-U.S. studies indicates the non-U.S. studies are affected by publication bias attributable to factors unique to the non-U.S. studies, i.e., something other than measurement error.

One possibility to obtain meaningful international VSL estimates would be to rely on the bias-corrected values in Table 6. However, these values are implausibly small. The results in Table 7 also facilitate projecting international VSLs by evaluating each variable in the regression at its sample mean, setting the standard error equal to 0, and setting the appropriate sample constant equal to 1. The projected international estimates of the VSL based on the full model are positive, with values of $2.1 million for the government sample and $1.8 million for the non-government sample. The standard errors for the projections are 0.7 and 0.9, respectively.

An alternative approach that we favor is to use the bias-corrected U.S. estimates coupled with an income elasticity adjustment for that country's income relative to that in the United States. For illustrative purposes, we present calculations based on the most common estimates of the income elasticity of the VSL in the literature, which usually fall between 0.6 and 1.0. Meta-analyses that have estimated such income elasticities of the VSL include Viscusi and Aldy (2003), Doucouliagos et al. (2012), and Viscusi (2015). Kniesner et al. (2010) report a somewhat higher mean income elasticity estimate of 1.44 across the quantiles of the wage distribution. Using a range of income elasticities between 0.6 and 1.0, the projected VSL for the United Kingdom is between $6.3 million and $7.6 million, which is dramatically smaller than the values found in studies of the U.K. labor force.[4] Our proposed income elasticity adjusted value for the VSL nevertheless would lead to higher VSL levels than currently adopted in the United Kingdom, which are based on a conservative interpretation of the estimates from stated preference studies, leading to a VSL of about $2.4 million for transport regulations (Narain and Sall 2016). Our projected VSL in Canada is between $7.1 million and $8.1 million, while the VSL we estimate for Australia is between $7.8 million and $8.5 million. Some Canadian and Australian estimates in our sample were close to this range, while others differed greatly. As a final pair of examples, our projected VSL in South Korea is between $4.5 million and $6.6 million, and in Japan it is between $6.4 million and $7.7 million.

Utilization of non-U.S. studies to set policy will tend to lead to a VSL that exceeds the appropriate value after adjusting for publication selection biases. Until non-U.S. countries develop fatality risk data that are comparable in quality to the CFOI, a preferable approach for international VSL levels is to use the U.S. estimates as a baseline and make adjustments based on income level differences.

5 Conclusion

Publication selection bias significantly influences the distribution of VSL estimates, particularly for international VSL studies. Both the quantile regression results and the WLS estimates generated evidence of statistically significant publication selection bias. The magnitude of publication selection bias is highly heterogeneous across studies using

[4] For this example and the following examples, income levels for each country (including the United States) are average household net adjusted disposable income per capita from the OECD's Better Life Index. The baseline U.S. VSL is $9.6 million.

different fatality rate sources. The VSL estimates based on the CFOI data exhibited no statistically significant publication selection bias, while studies using fatality information from outside the United States suffer from dramatic publication selection bias.

Differential bias based on data source should prompt policy makers to carefully evaluate the values they use to measure the benefits of reducing fatality risks. This article demonstrates that U.S. agencies restricting their analysis to the whole sample of CFOI studies need not further adjust the VSL values to account for publication selection bias. But policy makers outside of the United States face significant perils. The massive publication selection bias in the Non-U.S. Government and Non-Government subsamples indicate that an average of values in the literature or a meta-analysis that fails to adjust for the bias will dramatically overstate the benefits of reducing fatality risks.

Based on income differences across countries, one would expect international estimates of the VSL to be lower than the values in the United States. The evidence of publication selection effects that generate upward biases in international VSL estimates are consistent with international studies relying on higher U.S. values as an anchor for what level of VSL is appropriate. Such biases could arise because of the efforts by researchers to report estimates in line with the previous literature, much of which is based on U.S. evidence. Journal editors and reviewers likewise may be more likely to favor publication of results in the usual range. Until better data sources exist for non-U.S. studies, the best course of action for international governments will be to set their VSL levels by adjusting the U.S. VSL estimates based on CFOI studies using income elasticity estimates and international income differences.

Policy analyses outside the U.S. generally use VSL levels substantially below those implied by U.S. estimates even after making pertinent income difference adjustments.[5] These analyses do not rely on labor market estimates of the VSL in those countries, for which the results here showed an upward bias in the VSL. Instead, the emphasis is on the very low VSL estimates implied by stated preference studies involving hypothetical risks. Consequently, reliance on U.S. evidence will lead to a higher VSL than current policy practices and a lower VSL than if those countries relied on pertinent labor market evidence.

While the focus of this article was on estimates of the VSL, the underlying phenomenon may be more general. The first studies in the literature on empirical phenomena are likely to establish an anchoring effect with respect to future studies that are regarded as publishable. In contexts in which U.S. evidence is published first, there will be a subsequent bias in international estimates, as they will be slanted in the direction of U.S. findings. While the prospect of such biases should provide a reason for caution, it is nevertheless feasible to test for the presence of publication selection effects and to obtain bias-corrected estimates. The best case scenario is one represented by the U.S. evidence using the CFOI data, as there is no evidence of statistically significant publication biases. These estimates in turn can serve as a suitable reference point for other countries after making pertinent adjustments for considerations such as income differences across countries.

[5] Examples of international VSL studies are provided by the World Bank report by Narain and Sall (2016) and the report by the OECD (2012). Both the World Bank and the OECD rely principally on stated preference survey studies of the VSL rather than revealed preference evidence from market decisions. The U.K. likewise relies on stated preference evidence.

Appendix: Description of fatality risk data

U.S. Government fatality rate data

The U.S. Government subsample contains all studies using fatality data published by the U.S. federal government, other than studies that used the Census of Fatal Occupational Injuries (CFOI). Nearly all studies in the subsample used fatality rates from either the Bureau of Labor Statistics (BLS) or the National Institute of Occupational Safety and Health National Traumatic Occupational Fatality (NTOF) data. The only exception is Low and McPheters (1983), which constructed police officer death risks using the U.S. Department of Justice's statistics on police officer deaths.

The earlier BLS data extrapolated fatality rates from a sample of compliance surveys administered under the Occupational Safety and Health Act of 1970. All survey responses were voluntary. The BLS indexed fatal injury rates by three-digit SIC industry code. In the early years of the data, it included limited information about the workers involved and the circumstances of the injury, but even these details were available only in a limited number of states and were not generally used in VSL studies. In 1992, the BLS stopped gathering information on fatal injuries through the Survey of Occupational Injuries and began the CFOI.

The BLS fatality rates suffered from multiple shortcomings. Because BLS fatality rates were extrapolated from a partial sample of firms, there existed sampling error in the fatality rates calculated from BLS data. The sample likely also exhibited selection bias because all responses to the survey were voluntary. Further, BLS indexed the data only by industry, limiting researchers' ability to accurately match workers with fatality rates. The BLS data were the most common fatality rates in the early VSL literature.

In 1987, the National Institute of Occupational Safety and Health created the NTOF data series. The NTOF data differed from the BLS data in a few important ways. Fatality rates were calculated with a census of all occupational fatalities recorded on death certificates, reducing the sampling error present in BLS data. The NTOF data were indexed by state and one digit SIC industry code. The finer NTOF indexing allowed researchers to assign fatality rates to workers with less measurement error. Moore and Viscusi (1988), the first article to use the NTOF data to estimate the VSL, found that use of the NTOF data generated an average fatality rate 84% higher than the BLS data and doubled the VSL relative to BLS data.

Together, 18 studies containing 173 VSL estimates utilized the BLS, NTOF, and FBI fatality rates to estimate a VSL. The mean VSL in these estimates was \$7.3 million, \$4.7 million less than the whole sample mean of \$12.0 million. The mean fatality rate for these studies was 1.685 fatalities per 10,000 full-time equivalent workers, more than the sample mean and more than three times higher than the mean fatality rate in the CFOI studies.

CFOI Subsample

The CFOI subsample contains all studies whose fatality data is from the CFOI's restricted access microdata file. While the Bureau of Labor statistics provides summary figures from the CFOI on its website, the microdata file provides much more detailed information. In 1992, the BLS launched the CFOI data series as a cooperative program between the federal and state governments to accurately catalogue fatal workplace injuries. The CFOI uses multiple data sources, such as accident reports, coroners' records, and workers' compensation records to identify fatal injuries. Each injury is substantiated with two or more independent source documents. For each injury in the data, the CFOI provides diverse personal characteristic data, the type of injury, and details regarding the circumstances of the accident. An average of four source documents supports each fatality that the CFOI records (Wiatrowski 2014).

Initially, the CFOI utilized Standard Industry Classification and U.S. Census Bureau Occupation codes to classify workers according to industry and occupation. In 2003, the CFOI adopted the North American Industrial Classification codes for industries and the Standard Occupational Classification Codes for occupations. Since 2003, the CFOI has been the dominant source of fatality data for studies calculating the VSL in the United States. When using labor market studies to define a VSL for policy, the U.S. government exclusively uses studies using the CFOI fatality rates. For example, the United States Department of Transportation (2015) Revised Departmental Guidance on the VSL lists nine CFOI studies that it uses to reach the agency's preferred VSL of $9.4 million. Likewise, the Environmental Protection Agency (2016) report on calculating the VSL using meta-analytic methods restricted its analysis to stated preference studies and studies utilizing CFOI data to calculate a VSL of $10.5 million.

The CFOI data provide a greater level of detail, dramatically reducing the amount of measurement error inherent in the construction of a worker's fatality rate. The CFOI allows researchers to construct fatality rates by industry, occupation, demographic variables, and any combination thereof, limited only by the imprecision introduced by defining fatality rates by a very large set of categories. The dimensions that studies in the CFOI literature have utilized include occupation, industry, sex, race, age, and immigrant status (Viscusi 2013).

The CFOI subsample is the largest subsample in this study, containing 20 studies and 621 VSL estimates. The mean VSL estimate in the CFOI subsample is $13.1 million, which exceeds the mean in the whole sample. This pattern is consistent with the finding that studies using CFOI fatality rates have less classical measurement error. The mean fatality rate in the CFOI studies is 0.469 per 10,000 workers, with a small standard deviation of 0.192. The CFOI subsample has the lowest fatality rate; the lower rate likely results because of a combination of increased workplace safety in the modern era and reduced sampling error in the data collection.

U.S. Non-Government

The U.S. Non-Government subsample contains all studies whose fatality data was based on the United States labor force, but that a United States federal government agency did not compile. The most common source of data in the U.S. Non-Government subsample was the 1967 Occupation Study from the Society of Actuaries (SOA). The SOA data measured occupational risks using a sample of insurance company records from 1955 to 1964. The SOA indexed the data by industry and occupation, possibly reducing the measurement error relative to the early BLS data. However, the critical deficiency in the SOA data was the measure of death risk it utilized. Rather than tabulating the probability of a fatal accident due to occupational risks, the data calculated mean mortality rates. The SOA fatality rates were thus probabilities of death from *any* cause, rather than a workplace fatality. Actors, for example, had very high mortality rates.

The remaining fatality rate sources in the U.S. Non-Government subsample were unique to the studies that used them. Leigh (1991) constructed fatality rates from workers' compensation files from 11 state governments. Gegax et al. (1991) constructed fatality rates using a survey instrument to directly elicit workers' perception of workplace fatality risks.

Together, six studies comprise the U.S. Non-Government subsample, containing 24 VSL estimates. The mean VSL estimate in the U.S. Non-Government subsample is \$3.10 million, which is smaller than the other U.S. subsamples and less than one-third of the whole sample mean. The mean fatality rate in the U.S. Non-Government subsample is 6.671, dwarfing the fatality rate in the other samples. The SOA studies, by calculating total mortality rather than workplace fatality rates, drive this exceptionally high rate.

Non-U.S. Government

The Non-U.S. Government subsample contains all studies measuring the VSL using non-U.S. workers with fatality data from a government source. The countries in this subsample include the United Kingdom, Canada, Australia, South Korea, India, Poland, Pakistan, Japan, Taiwan, and Chile. The type of government agencies providing fatality rates varied significantly among studies. Siebert and Wei (1994), whose data was from the U.K. Health and Safety Executive, and Kim and Fishback (1999), whose data was from the Korean Ministry of Labor, both used data from labor ministries that are analogous to the U.S. Bureau of Labor Statistics or National Institute of Occupational Safety and Health. Shanmugam (2000; 2001) used the Administrative Report of the Chief Inspector of Factories in Madras. Other studies used data from national government agencies that resemble workers' compensation boards. For example, Meng (1989) and Meng and Smith (1990) both used data from Canadian Workmen Compensation and Liu et al. (1997) utilized fatality data from the Taiwanese Labor Insurance Agency.

The Non-U.S. Government subsample includes 21 studies containing 188 VSL estimates. The mean VSL estimate in the subsample is \$13.8 million, the largest of any of the subsamples. The estimates in the Non-U.S. Government subsample were the least precisely measured, with an average standard error greater than the average VSL and more than twice as large as the average standard error in the whole sample. The average fatality rate per 10,000 workers in the Non-U.S. Government sample was 1.556, comparable to the average fatality rate in the U.S. Government subsample. However, the standard deviation of the fatality rate in the Non-U.S. Government subsample is quite large at 2.430. The heterogeneity of the fatality rates is unsurprising, given that they measure risks in ten different countries with very different labor conditions.

Non-U.S. Non-Government

The final subsample is the Non-U.S. Non-Government sample, which contains all studies that estimate a VSL for non-U.S. workers using fatality data that was not released from an agency in a foreign government. The countries in this subsample include Austria, Switzerland, and Germany. Weiss et al. (1986) constructed fatality rates using data from Austrian insurance companies. Baranzini and Ferro Luzzi (2001) collected fatality rates by industry from the Swiss National Accident Insurance

Company, an independent, non-profit company established under Swiss Law to manage Switzerland's public worker insurance. Schaffner and Spengler (2010) collected risk information from German statutorily created independent accident insurance corporations. These three studies comprise the entire Non-U.S. Non-Government subsample and contain 19 VSL estimates. The mean VSL estimate in these studies was $8.7 million, which is substantially lower than the other non-U.S. subsample. The mean fatality rate for these studies was 0.592 per 10,000 workers.

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