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THE VALUE OF STATISTICAL LIFE:
A META-ANALYSIS OF META-ANALYSES

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ABSTRACT

The Value of Statistical Life (VSL) is arguably the most important number in benefit-cost analyses of environmental, health, and transportation policies. However, agencies have used a wide range of VSL values. One reason may be the embarrassment of riches when it comes to VSL studies. While meta-analysis is a standard way to synthesize information across studies, we now have multiple competing meta-analyses and reviews. Thus, to analysts, picking one such meta-analysis may feel as hard as picking a single "best study." This paper responds by taking the meta-analysis another step, estimating a meta-analysis (or mixture distribution) of six meta-analyses. The baseline model yields a central VSL of $7.0m, with a 90% confidence interval of $2.4m to $11.2m. The provided code allows users to easily change subjective weights on the studies, add new studies, or change adjustments for income, inflation, and latency.

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The Value of Statistical Life: A Meta-analysis of Meta-analyses

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1. Introduction

The Value of Statistical Life (VSL) is arguably the single most important number used in benefit-cost analyses of environmental, health, and transportation policies. For example, the US Environmental Protection Agency found that 85% of monetized benefits from the Clean Air Act are from mortality reductions (US EPA 2011). Given the importance of this category, over-all benefit-cost evaluations and other welfare calculations involving mortality risks will be highly sensitive to the selected VSL.[1]

When choosing a VSL or range of VSLs, analysts must sift through a vast literature of hundreds of empirical studies and numerous commentaries and reviews to find estimates that are (i) up to date, (ii) based on samples representative of the relevant policy contexts, and (iii) scientifically valid. When doing so, they can arrive at different values based on different judgments, a fact highlighted by practices of US government agencies. For example, the US Department of Health and Human Services (2016) uses a central estimate of $10.4m ($2019) with low and high values of $4.9m and $15.8m, respectively.[2] These values are based on a range of estimates from three stated preference (SP) studies dated 2001-13 and six hedonic wage studies dated 2004-13 (Robinson and Hammitt 2016). The US Department of Transportation (2016) also uses a central estimate of $10.4m, but one taken from an average of nine hedonic wage studies dating from 1997 to 2003, with a range ("for illustrative purposes") of $5.8m to $14.5m representing the broader literature. The US EPA is the only one of the three agencies that uses a formal meta-analysis. It uses a value of $9.4m with a 90 percent confidence interval of $1.3m to $22.9m (US EPA 1997, 2020). However, even today, these estimates are based on very old studies published between 1974 and 1991.[3]

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[1] Important reviews and discussions of the VSL literature include Ashenfelter (2006), Kniesner and Viscusi (2019), Viscusi (2012), and Viscusi and Aldy (2003). Additionally, Banzhaf (2014) discusses the VSL in historical context.

[2] All values reported in this paper have been converted to 2019 dollars using the US CPI-U. The appendix shows values as taken from the original studies along with the necessary inflation adjustments.

[3] More recently, the US EPA (2016) attempted to update this meta-analysis using 18 studies published between 1999 and 2013 (with underlying data collected between 1993 and 2006). However, the EPA's

In short, despite the importance of the parameter, US agencies are basing their VSLs either on judgements summarizing a small number of studies or on data that are grossly out of date. This is all the more surprising given that there have been several meta-analyses published since EPA's effort, together synthesizing over 800 unique estimates from scores of studies (Mrozek and Taylor 2002, Viscusi and Aldy 2003, Kochi, Hubbell, and Kramer 2006, and Viscusi 2018). Compared to the ranges adopted by US agencies, these meta-analyses either synthesize more systematically a wider range of studies or use more recent data—or both.

Perhaps one reason for this surprising gap is that we now have an embarrassment of riches when it comes to summarizing VSL studies. With so many to choose from, the process of selecting which meta-analysis to use, and defending that choice, might feel to some analysts almost like picking a single "best study." As with choosing a single study, the choice of a meta-analysis has profound implications for resulting benefit-cost estimates, with estimated mean VSLs varying across meta-analyses from \$3.7m to \$12.3m—a factor of 3.3. This discrepancy is driven by differences in the statistical methods used in the meta-analyses, the set of original studies they synthesize, and choices about whether and how to correct for "best practices." Comparing these meta-analyses, many analysts may conclude that, as with the individual studies underlying them, each of them has a bit of something to offer, that no single one is best. Thus, the old problem of selecting a single best study has just been pushed back to the problem of selecting a single best meta-analysis.

In this paper, I suggest a novel way to break this impasse: A "meta-analysis of meta-analyses" yielding a smooth mixture distribution of VSL estimates. Essentially, I place subjective mixture weights on eight models from five recent meta-analyses and reviews of VSL estimates applicable to the United States. I then derive a mixture distribution by, first, randomly drawing one of the eight meta-analyses (the mixture component) based on the mixture weights and, second, randomly drawing one value from the distribution describing that component's VSL (e.g., a normal distribution with given mean and standard deviation), and, finally, repeating these draws until the simulated mixture distribution approximates its asymptotic distribution.

Science Advisory Board recommended substantial revisions to this work and it was not adopted. Its current proposal is to continue using the older meta-analysis (EPA 2020).

This approach has four advantages. First, it triangulates on the estimates coming from all these meta-analyses, encapsulating the idea that the truth is probably somewhere in the middle of all of them. Second, it makes explicit, in the form of the mixture weights, the inevitable judgements that experts must make when picking studies. Third, it easily allows sensitivity analysis through changing the weights. And, finally, it generates a smooth probability distribution representing, simultaneously, the variation within and between meta-analyses. This distribution can be incorporated into Monte Carlo simulations of uncertainty or provide percentiles that can be used as upper or lower bounds around a central estimate.

The paper illustrates the approach using two sets of subjective judgements about these weights. Inevitably such judgements will depend on the policy context. The hypothetical context considered here is for US policies affecting the lives of average Americans. Policies applicable to international contexts, for young children, or for the elderly might involve different judgments.

Finally, to facilitate implementation of this mixture approach and to make it applicable to a wider set of contexts, the appendix provides simple STATA code that easily can be adapted by users to reflect their own judgement or policy context or to update it with new studies.

2. Empirical Estimates of the VSL

Studies empirically estimating VSLs can be grouped into three categories. Hedonic wage studies, the largest group, use labor market data to infer people's willingness to accept on-the-job risks in return for higher wages. Hedonic wage studies have two significant advantages. First, they combine solid data on household wages with objective data about on-the-job risks. Second, they infer VSLs from people's actual tradeoffs between money and mortality risks in real-world decisions, making them especially credible.

On the other hand, transferring these labor market willingness-to-pay (WTP) estimates to public policy contexts raises at least two issues. One consideration is the difference in age between individuals affected in the two contexts. For example, individuals at risk from air pollution tend to be older and in poorer health than the labor market participants in the hedonic studies. Evidence is emerging that potentially would allow analysts to adjust for differences in age (Aldy and Smyth 2014, Aldy and Viscusi 2007, 2008). A second consideration is the nature of the risk, whether workplace risks are qualitatively similar to those in the policy context and whether people feel similarly about facing them. If one type of risk is surrounded by a greater feeling of dread or fear, in principle the WTP to avoid it would be greater. For example, Itaoka et al. (2006) find evidence that Japanese households would pay more to avoid risks from nuclear power than quantitatively equivalent risks from fossil fuels. Nevertheless, at this time evidence on these issues is too limited to allow researchers to adjust for qualitative differences in the types of risk.

The second group of studies similarly uses decisions by people in consumer markets, such as their choice for automobiles with various safety features or their willingness to tradeoff time and bother to wear seatbelts against the reduced risk, or their willingness to wear bicycle helmets or change batteries in smoke detectors (e.g. Rohlfs, Sullivan, and Kniesner 2015). Like hedonic wage studies, these studies have the advantage of being based on real-world decisions. However, one disadvantage is that important components of the data must be imputed by researchers. For example, whereas wages in a hedonic wage study are readily observed, the time taken to click a seatbelt or put on a helmet, and the value of that time, must be imputed. For this reason, such studies have generally been omitted from meta-analyses.

Third, SP studies use surveys to construct hypothetical markets for mortality risks. SP studies, in turn, generally come in one of two types. "Contingent valuation" studies describe a single scenario and elicit the WTP for that scenario. Choice experiments offer a series of scenarios varying in risk levels, costs, and potentially other factors, and ask respondents to choose which scenario they would prefer. From the patterns in how respondents trade off money for risk levels, analysis can then infer VSLs.

Because what people say they would do does not always match what they actually do, revealed preference studies are generally preferable to stated preference studies, other things equal. However, stated preference studies are a widely accepted tool for measuring values for goods and services that are not traded in markets. Moreover, they have the potential to overcome some of the limits of hedonic wage studies. In particular, they can focus on more policy-relevant risks and avoid features peculiar to labor markets, such as worker's comp and life insurance benefits offered through work. They also can focus on the elderly or other populations that may not be earning wages in formal labor markets. Accordingly, some of the meta-analyses considered here make use of stated preference studies as well as labor market studies.

3. Review of VSL Meta-analyses

In its benefit-cost analysis of the Clean Air Act, the US EPA used a meta-analysis of 26 studies (US EPA 1997), the latest being from 1991. EPA fitted a Weibull distribution to these data, finding a central estimate of $9.4m and 90% confidence interval between $1.3m and $22.9m. More recent work by EPA has continued to use this estimate without updating it except for inflation (e.g. US EPA 2015, 2019, Benmap 2018) and the agency plans to continue using it (US EPA 2020), despite the fact that the most recent study is now nearly 25 years old.

Since EPA's work, four additional meta-analyses have been conducted with US data, incorporating newer studies and/or using newer methods in their analysis.[4] First, Mrozek and Taylor (2002) conducted a meta-analysis only of the hedonic labor market studies. They use linear regression to predict the effects on VSL estimates of various features of individual studies. They then use their model to predict what each study's VSL would have been had it used generally accepted best practices, and then average those predicted values to derive a central VSL estimate under such best practices. In Mrozek and Taylor's view, the best practices for purposes of estimating US VSL values include

- Controlling for other job characteristics in addition to risk;
- Controlling for an individual's occupation;
- Flexibly modeling the effect of risk;
- Controlling for morbidity effects as well as mortality;
- Controlling for union status of the worker;
- Controlling for features of the location of the job such as region and whether it is in a city;
- Using after-tax wages;
- Using a wide range of occupations;
- Using objective rather than self-reported risk measures; and
- Using US data.

[4] In this application, I preferred US-only estimates for their applicability to US agencies and to restrict the heterogeneity of estimates. Naturally, other research questions would lead to different judgements. For example, more international meta-analyses that include developing countries are useful for cross-country comparisons or developing income elasticities (e.g. Lindhjem et al. 2011, Majumder and Madheswaran 2017, Masterman and Viscusi 2018, Robinson, Hammitt, and O'Keefe 2019, Viscusi and Masterman 2017).

Mrozek and Taylor provide estimates at different baseline levels of occupation risk. Following their recommendation, I rely on results at risks of $1.0x10^{-4}$ as representative. They also break down results under two different assumptions about what the best practice would be for sources of risk data, whether from the Bureau of Labor Statistics (BLS) or from the National Institute for Occupational Safety and Health (NIOSH). When controlling for the number of industry classifications controlled for in each study, the central estimate using the BLS data is $3.7m. Using NIOSH data, their central estimate is $6.5m.

Second, Viscusi and Aldy (2003) published an extensive literature review of VSL studies which included a meta-analysis. They used a similar approach as Mrozek and Taylor, predicting the effects of various features of study designs on the estimates. However, they did not predict average VSL under best practice conditions, instead averaging over the actual practices used in the original studies. They estimate the mean VSL to be $9.1m.[5]

Third, Kochi, Hubbell, and Kramer (2006) collected 76 hedonic wage and stated preference studies estimating VSLs in the US and other high-income countries, which they whittled down to 45 that used best practices. Specifically, they discarded studies if they used actuarial risk data (which includes risks to employees other than those on the job) and stated preference studies with very small sample sizes. Kochi et al. then synthesized these 45 studies using an empirical Bayes approach. Essentially, they model an individual study's estimates as being drawn from a study-specific distribution, with study-specific distributions in turn drawn from one overarching (or "mother") distribution. Individual studies thus provide indirect, noisy signals about the true VSL underlying the data-generating process. Studies with high within-sample variance provide noisier signals and so are less informative about the VSL mother distribution than studies with low within-sample variance.

In their base model, Kochi, Hubbell, and Kramer estimate the average VSL to be $8.0m. However, this estimate is less than ideal for our purposes, for three reasons. First, it includes some hedonic wage studies from the UK and other developed countries. In a sensitivity analysis, they find that restricting the hedonic studies to the set from the US would decrease the mean value by

[5] I use Model 4 of Table 8. This model uses robust regression, which reduces uncertainty in the estimate by putting more weight on estimates closer to the central tendency of the data. The model also does not control for practices of the original study, which adds noise and has no advantage if they are not to be controlled for by setting values at best practices.

about 7%. Combining this estimate with the estimate from the stated preference studies gives a value of $7.0m.[6] Second, they omitted some studies based on missing standard errors. In a sensitivity analysis imputing those parameters, they obtained a VSL of $7.0m, suggesting the selection on this set is important. Third, and most importantly, the central estimate excludes estimates with negative VSLs. Although it is implausible that the true VSL is negative, individual estimates should be interpreted as random variables. Viewed as extremely low draws from a distribution, such estimates are not at all implausible. Indeed, they should be treated symmetrically with very high draws, which were not excluded. In a sensitivity analysis including these estimates, the central estimate of the VSL is $6.1m.

Fourth and finally, Viscusi (2018) provides a more recent analysis of 818 estimates from 42 studies using US data. Following Doucouliagos, Stanley, and Giles (2012), he uses statistical techniques to account for publication bias. These techniques are based on the idea that, across study estimates, standard errors should not be systematically correlated with coefficients. If smaller coefficients observed in published studies tend to have lower standard errors, it suggests the observed data might be selected in favor of statistically significant estimates. Viscusi corrects for this selection by including the standard error as a regressor in his meta regression and setting the coefficient to zero when predicting an appropriate value. This meta-analysis is particularly useful as it has the most up-to-date set of studies and corrects for publication bias, but the disadvantage of excluding SP studies. In models with US data, Viscusi obtains a mean VSL of $6.7m when using the entire set of estimates. In an alternative model, he uses a single "best" estimate from each study, restricts the sample to 20 using the most reliable and recent estimates of risk from the Census of Fatal Occupational Injuries (CFOI), and further predicts values under "best practices." The estimated mean VSL in this case is $4.7m.

Additionally, Robinson and Hammitt (2016) have recently reviewed and synthesized 6 recent wage hedonic studies and 3 recent SP studies. Although they do not explicitly conduct a meta-analysis, their review has been quite influential, underlying the VSL estimates used by the US Department of Health and Human Services (US HHS 2016). Like Viscusi (2018), it has the

[6] Based on data from rows 1-3 of Table 11 of Kochi, Hubbell, and Kramer (2006), I estimate the weight on stated preference studies relative to hedonic wage studies in their base model solving for p in the equation $p*2.8 + (1-p)*9.6 = 5.4$. Keeping these weights constant, I then substituted the US-only labor-market estimates (row 4) for the international labor-market estimates (row 3).

advantage of using more up-to-date studies, but also has the advantage of including both hedonic and SP studies, to better reflect the breadth of the literature. Based on their review and synthesis, they recommend a range of \$4.6m to \$15.0m. The median of their selected studies is \$9.3m and the mean is \$8.9m.

4. A Mixture of Meta Distributions

As previously discussed, a meta-analysis can represent a large range of estimates holistically while, pragmatically, reducing the pressure on an analyst to pick a single best study. However, there are now these five meta studies to choose from, some with separate analyses under different judgements, with a range of values among them from \$3.7m to \$12.3m. Moreover, each has its characteristic advantages and disadvantages. Thus, it appears that the problem of selecting a single best study has just been pushed back to selecting a single best meta-analysis.

To overcome this challenge, I first assign a subjective weight to each of the five studies reviewed in the previous section. One-fifth might be a natural choice, but I have elected to give double weight to the two most recent studies, Viscusi (2018) and Robinson and Hammitt (2016), which include a number of more recent original studies that have appeared since the earlier analyses.[7] Thus, I assign a weight of 2/7 each to those two studies and a weight of 1/7 each to Mrozek and Taylor (2002), Viscusi and Aldy (2003), and Kochi, Hubbell, and Kramer (2006).

For some of these studies, I further sub-divide these weights and assign them to separate analyses reported in the original meta-analysis. In the case of Mrozek and Taylor (2002), I give half the weight to the estimated distribution using NIOSH data on job risks and half to the distribution using BLS data. Viscusi and Aldy (2003) suggest that, for the older studies that they considered, the NIOSH data are more reliable. However, Mrozek and Taylor defend the use of the BLS data, suggesting the opposite is true because of aggregation issues. In the case of Kochi, Hubbell, and Kramer (2006), I again assign half the weight to each of two distributions, one based on a more complete set of studies including imputed standard errors, and one substituting US-only hedonic wage studies for the complete set. However, in both cases I adjust the estimates by the

[7] These include Aldy and Viscusi (2007), Cameron and DeShazo (2013), Evans and Schauer (2010), Gentry and Viscusi (2016), Hammitt and Haninger (2010), Hersch and Viscusi (2010), Kniesner et al. (2010, 2012, 2014), Kochi and Taylor (2011), Lee and Taylor (2019), Scotten (2013), Viscusi (2013), and Viscusi and Gentry (2015).

proportionate effect of including original studies with negative estimates (6.1/8.0 = 0.76). With this adjustment, the mean values for these two distributions are then $5.3m and $5.8m respectively. Lastly, in the case of Viscusi et al (2018), I divide the weight into the component using the whole sample and into the component using only the select "best" estimate for each study, for those studies using only the CFOI data, and estimates predicted under best practices. Table 1 summarizes all the components underlying the resulting mixture distribution.

For each estimate from the first four meta-analyses, I use the mean and standard deviation to characterize the distribution of VSL estimates. However, Robinson and Hammitt (2016) do not report these parameters and themselves prefer to think of their synthesis as providing a central estimate and range. In my meta-analysis of meta-analyses, I treat their study as having a triangular distribution, with their suggested range as the two endpoints. I calibrate the mode of the triangular distribution so that the mean of the resulting distribution equals the mean value of the studies in their synthesis. These resulting parameters are also summarized in Table 1.

The code supplied in the appendix shows all calculations back to the figures reported in the original meta-analyses, including all inflation adjustments. Readers consulting the original studies may find this code a useful reference. The code is user friendly, with user-defined inputs for the component weights assigned to each of the underlying components. It also allows for the introduction of any additional new component, such as a new meta-analysis, so long as it is represented by a normal, Weibull, uniform, or triangular distribution. Finally, as discussed more below, it includes parameters that users can set to allow for adjustments based on income elasticities or latency between a policy and mortality response. Thus, in future work, other analysts can easily compute the sensitivity of results to some of the subjective judgements used here.

Combining the above subjective weights given to each underlying component along with the distribution of VSLs within each component, we can derive an overall mixture distribution of VSLs. In this case, the overall distribution has a mean VSL of $7.0m in 2019 dollars. Table 2 provides additional details about the percentiles of the distribution, and Figure 1 shows the mixture density function, with the vertical line representing the mean value of the distribution. The table and the figure show the mixture distribution has little skew, with the median close to the mean. Indeed, it is close to normal in the tails, but with more density in the center and less in the shoulders. The 90% confidence interval ranges from $2.4m to $11.2m.

5. Sensitivity Analyses and Potential Adjustments

The weights used in the base model reflect one set of judgements about the reasonable models that one might use. To see the potential sensitivity of the results to these judgements, I consider an alternative set of weights, as shown in Table 1. For the alternative weights, I include the EPA (1998) meta-analysis, which used a Weibull distribution, bringing the number of underlying studies up to six. I also use a more even-handed approach, assigning a weight of 1/6 to each, rather than giving more weight to the recent studies. Finally, I include two additional sub-models presented by Viscusi (2018): In addition to the model using the whole sample and the model using the "best set" and predicted at "best practices," I also consider intermediate models using the whole sample with best practices and the best set with the original practices.

These alternative weights increase the mean VSL to $7.5m, an increase of about 7 percent from the base weights. Interestingly, although the mean remains relatively unchanged, the other moments of the mixture distribution are quite different. As seen in Figure 2, the mixture distribution is more diffuse, positively skewed, and leptokurtic. Moreover, it is now multi-modal, with different components providing some local central tendency at different points in the distribution.

Next, I consider the potential effect of increasing income over time, which will likely increase the VSL. Ideally, such adjustments would occur from the point in time of the original hedonic or SP studies, but such adjustments would have had to have been made in the underlying meta-analyses. However, we can adjust for income growth from the time of each meta-analysis to 2019. Here, I use changes in US median household income together with an income elasticity of 0.4, as suggested by US EPA (2020).[8] Given the short time horizon and little income growth in recent years, this has little effect, increasing the VSL by less than 3 percent, from $7.0 to $7.1m.

Third, I consider the effect of latency. Many policies enacted at a point in time may have impacts on future mortality rates. For example, recent epidemiological evidence has stressed the importance of long-term chronic exposures to particulate pollution. Accordingly, changes in emissions *now* would show up in mortality rates over a *future* time horizon (as they are part of the lifetime exposure that households accumulate from this time forward). The best evidence suggests

[8] For international transfers, recent research has suggested an income elasticity of 1 may be more appropriate, with higher elasticities for lower-income countries (Masterman and Viscusi 2018; Robinson, Hammitt, and O'Keefe 2019; Viscusi and Masterman 2017).

the majority of these effects occur within two-to-five years, but then some lingering effects probably occur many years in the future. To account for this delay in effects, the EPA's Science Advisory Board has proposed discounting VSL values by 14%.[9] Such an adjustment would reduce the VSL from $7.0m to $6.0m. However, the appropriate adjustment will depend on the specific policy context, so I omit such considerations from the base model.

Potentially, one might also consider adjustments for age and remaining life years. A simple economic model of age-specific values for risk reduction isolates two potentially offsetting factors (Shepard and Zeckhauser 1984). First, and most simply, as people age they have fewer life-years remaining. Other things equal, people would be expected to pay more to reduce the risk of dying earlier in their life than later in their life. Second, expenditures generally increase as people enter mid life. This pattern would tend to increase the willingness to pay to avoid the risk of losing a remaining life year as people age, potentially offsetting the effect of fewer life-years remaining. While some early work imposed a constant value of a life year, thus imposing that the VSL declines by age, more recent work has empirically estimated age effects, rather than simply imposing constant WTP per life year and so automatically making the VSL decreasing in remaining life years. These empirical studies allow the WTP per life year to vary by age as incomes and expenditures vary or as attitudes toward risk change. Aldy and Viscusi (2008) estimate VSLs by age allowing both for changes in WTP per life year as well as changes in life years remaining as people age. They also allow cohorts to have different WTP at the same age. That is, today's 50 year-olds, for example, need not have the same WTP as today's 60 year-olds did 10 years ago. They find that WTP per life-year increases from age 18 up to about age 55, and only slightly decreases from 55 to 62 (the highest age in their data, which is based on labor-market risks). On the other hand, naturally the number of remaining life-years declines with age. Putting the two effects together, the VSL has an inverted-U shape. It is $4.62m at age 18, increases to $10.62m at its peak at age 46, and then declines to $6.94m at age 62. Aldy and Smyth (2014) calibrate a model allowing one to predict how these effects extrapolate out to older ages. They find that the VSL at age 80 is about

[9] Specifically, EPA assumes 30% of effects are in the 1st year after the emissions, 50% are spread out evenly in years 2-5, and 20% are spread out evenly in years 6-20. Applying a discount rate of 5% leads to the overall 14% adjustment.

one-third that at age 50. A recent stated preference study finds strikingly similar patterns (Cameron and DeShazo 2013). While such adjustments may be important, they will depend on the specific policy context, so I have omitted consideration of them for this work.

6. Conclusions

Meta-analyses can synthesize the results from numerous underlying studies estimating common parameters like the VSL. Each meta-analysis estimates a mother distribution of VSL values from the underlying studies, which are viewed as draws from the mother distribution. But like the studies underlying them, these meta-analyses themselves involve subjective judgements. Nevertheless, these judgements, while differing, are well informed by the expertise of the analysts making them. This suggests no one probability distribution (as estimated from one particular meta-analysis) is solely correct, but rather each has something to offer.

In this setting, it is reasonable to estimate a mixture distribution, or meta-analysis of meta-analyses. Each individual meta-analysis can be thought of as representing one distribution, and these distributions can be mixed into an overarching distribution. Taking this approach, and using the subjective weights described here, yields a central VSL of $7.0m, with a 90% confidence interval of $2.4m to $11.2m. The provided code allows users to easily change subjective weights on the studies, add new studies, or change adjustments for income, inflation, and latency.

Future research might consider the implicit weight being given to individual underlying studies at each point in this distribution, the trends in the underlying data, or adjustment factors that might be imposed for change economic environments and research methods.

Table 1. Original Meta-Analyses and Parameters

Study / Model	Baseline Weights	Alternative Weights	Distribution	Parameters	Notes
EPA (1998)	0	$\frac{1}{6}$	Weibull	α = 1.509588 β = 9648168	Parameters Reported in Benmap (2018). Distribution in dollars, not millions.
Mrozek & Taylor (2002) -- NIOSH Data	$\frac{1}{7}*\frac{1}{2}$	$\frac{1}{6}*\frac{1}{2}$	Normal	Mean = 6.48 SD = 2.63	Table 4, Col. 4, R=1.0
Mrozek & Taylor (2002) -- BLS Data	$\frac{1}{7}*\frac{1}{2}$	$\frac{1}{6}*\frac{1}{2}$	Normal	Mean = 3.70 SD = 1.25	Table 4, Col. 4, R=1.0
Viscusi & Aldy (2003)	$\frac{1}{7}$	$\frac{1}{6}$	Normal	Mean = 9.06 SD = 1.36	Table 8, Col. 4, prediction for US sample
Kochi et al. (2006) -- Full set (with imputed SEs)	$\frac{1}{7}*\frac{1}{2}$	$\frac{1}{6}*\frac{1}{2}$	Normal	Mean = 5.30 SD = 2.59	Table II, Row 14. Proportionate adjustment for studies with negative values from Ratio of Row 18 to Row 1.
Kochi et al. (2006) -- Only US Hedonic Studies	$\frac{1}{7}*\frac{1}{2}$	$\frac{1}{6}*\frac{1}{2}$	Normal	Mean = 5.78 SD = 3.19	Weighted avg. of Table II Rows 2 and 4. Weights calibrated to Rows 1-3. See above adjustment for negative values.
Viscusi (2018) -- whole sample	$\frac{2}{7}*\frac{1}{2}$	$\frac{1}{6}*\frac{1}{4}$	Normal	Mean = 6.67 SD = 0.49	Table 5, Col. 3, Row 8
Viscusi (2018) -- best estimates, best practices	$\frac{2}{7}*\frac{1}{2}$	$\frac{1}{6}*\frac{1}{4}$	Normal	Mean = 4.74 SD = 1.93	Table 5, Col. 4, Row 15
Viscusi (2018) -- best estimates, original practices	0	$\frac{1}{6}*\frac{1}{4}$	Normal	Mean = 3.93 SD = 1.38	Table 5, Col. 4, Row 8
Viscusi (2018) -- whole sample, best practices	0	$\frac{1}{6}*\frac{1}{4}$	Normal	Mean = 12.27 SD = 0.31	Table 5, Col. 3, Row 15
Robinson & Hammitt (2016)	$\frac{2}{7}$	$\frac{1}{6}$	Triangular	a = 4.61 b = 15.03 c = 7.02	a, b from their suggested range. c calibrated so mean of distribution equals mean of studies synthesized.

Table 2. Summary Statistics of Resulting Mixture Distribution

Parameter	Value (millions of $2019)
Percentiles	
1^{st}	0.61
5^{th}	2.36
10^{th}	3.31
25^{th}	5.32
Median	6.91
75^{th}	8.80
90^{th}	10.55
95^{th}	11.61
99^{th}	13.42
Moments	
Mean	6.98
Standard Deviation	2.75
Skewness	-0.03
Kurtosis	3.04

Figure 1. Estimated Mixture Distribution, Baseline Weights

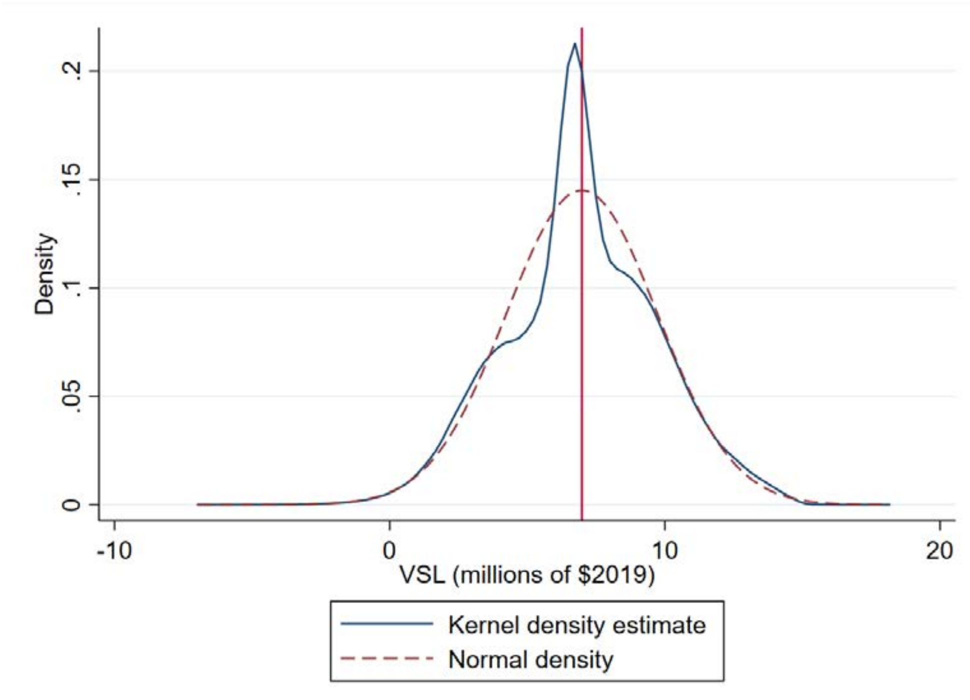
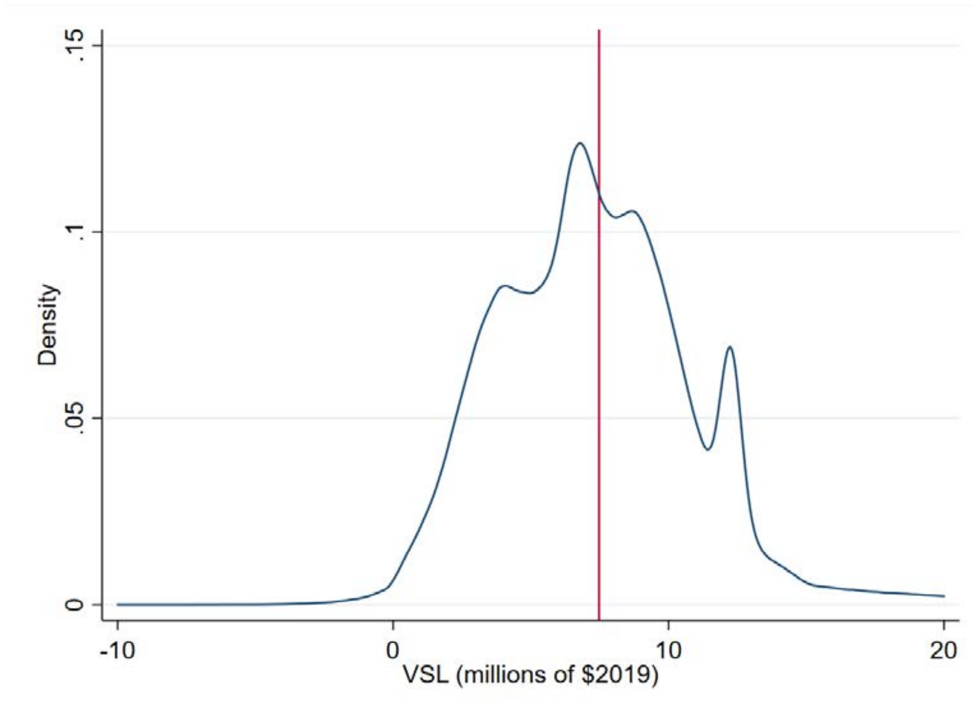


Figure 2. Estimated Mixture Distribution, Alternative Weights



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Appendix. STATA Code for Estimating the Mixture Distribution with User Inputs

```
capture log close

*user-defined default directory
cd "c:/defaultdirectory"

log using "mortality bootstrap.log", replace

clear

*******************************************************************************
*This STATA program simulates a mixture distribution of VSL estimates from meta-analyses of
*US studies.
*If using this code, please cite the companion paper, "The Value of Statistical Life:  A
*Meta-Analysis of Meta-Analyses," by H. Spencer Banzhaf, NBER Discussion Paper, 2021.
*The code may be cut-and-paste into STATA from this file.
*Alternatively, a do-file can be obtained from the author's webpage at
*http://hsbanzhaf.gsucreate.org/Banzhaf_Research.html or requested by contacting him at
*hsbanzhaf@gsu.edu

*******************************************************************************
*set basic parameters for simulation
set seed 123456789
set obs  500000
gen str40 VSL_study = ""
gen VSL = .
gen u = .

*******************************************************************************
*set parameters for inflation and income adjustments

*price index for desired year.  Default is 2019 using US CPI-U.
local pindex =      255.657
*pindex`i' below is for the study-year's price index

*income elasticity adjustment.
*0 implies no income adjustment; 1 proportionate adjustment.  Default is 0.
local incelasticity = 0

*income index for desired year.  Default is 2019 US median household income
*from FRED table MEHOINUSA672N (St. Louis Federal Reserve Bank).
local incindex = 63688
*incindex`i' below is for the study-year's income level

*latency adjustment for delay between policy action and lives saved
*E.g., EPA's SAB has recommended adjustments to account for the latency between
*emissions of pollution and eventual effect on later life expectancy.
*Default is 1 (i.e. no adjustment).  EPA's recommendation for particulate pollution is 0.86.
local latencyadj = 1

*******************************************************************************
*Input data for studies being used here.  These parameters can be changed by the user.
*Default assumes 11 studies.  If a different number is used, change <numstudies>
*and add study details using the format below.
*Studies may similarly be deleted or (more simply) their weight can be set to zero.
*For any study, the weights and values can be edited.
*With exception of Weibull parameters, values are in $mil
*Valid distributions are:
*  normal  (with parameters Mean, SD),
*  uniform (LB, UB),
*  triangular (a, b, c),
*  or Weibull (Shape, Scale) in dollars [not millions of dollars]
```

```
*set number of studies used
local numstudies = 11

*Study 1
local i           = 1
local study`i'    = "Mrozek & Taylor 2002 NIOSH"
local distrib`i' = "normal"
local weight`i'  = (1/7)*(1/2)
local pindex`i'  = 163.0
local incindex`i'= 60040
local Mean`i'    = 4.13
local SD`i'      = 1.68

*Study 2
local i           = 2
local study`i'    = "Mrozek & Taylor 2002 BLS"
local distrib`i' = "normal"
local weight`i'  = (1/7)*(1/2)
local pindex`i'  = 163.0
local incindex`i'= 60040
local Mean`i'    = 2.36
local SD`i'      = 0.80

*Study 3
local i           = 3
local study`i'    = "Viscusi & Aldy 2003"
local distrib`i' = "normal"
local weight`i'  = (1/7)
local pindex`i'  = 172.2
local incindex`i'= 61399
local Mean`i'    = 6.1
local SD`i'      = (8.2-4.6)/3.92   /*from reported confidence interval*/

*Study 4
local i           = 4
local study`i'    = "Kochi et al. 2006 imputed SEs"
local distrib`i' = "normal"
local weight`i'  = (1/7)*(1/2)
local pindex`i'  = 172.2
local incindex`i'= 61399
local Mean`i'    = 4.7*(4.1/5.4)
local SD`i'      = 2.3*(4.1/5.4)
*The ratio 4.1/5.4 is the adjustment for excluding studies with negative values,
*from rows 1 and 18 of Table II

*Study 5
local i           = 5
local study`i'    = "Kochi et al. 2006 US-only wage hedonics"
local distrib`i' = "normal"
local weight`i'  = (1/7)*(1/2)
local pindex`i'  = 172.2
local incindex`i'= 61399
local Mean`i'    = (0.618*2.8 + (1-0.618)*8.9)*(4.1/5.4)
local SD`i'      = (0.618*1.3 + (1-0.618)*5.3)*(4.1/5.4)
*0.618 is weight on SP vs hedonic studies.
*It is p solving p*2.8 + (1-p)*9.6 = 5.4 from 1st 3 rows of Table II

*Study 6
local i           = 6
local study`i'    = "Robinson and Hammitt 2016"
local distrib`i' = "triangular"
local weight`i'  = (2/7)
```

```
local pindex`i'  = 232.957
local incindex`i'= 57856
local a`i'       = 4.2
local b`i'       = 13.7
local c`i'       = 6.4
*c is calibrated to reproduce the mean of the underlying studies, 8.1
*ie solve for c:  8.1 = (4.2 + 13.7 + c)/3 --> c = 6.4

*Study 7
local i          = 7
local study`i'   = "Viscusi 2018 wide set"
local distrib`i' = "normal"
local weight`i'  = (2/7)*(1/2)
local pindex`i'  = 237.017
local incindex`i'= 59901
local Mean`i'    = 6.187
local SD`i'      = 0.451

*Study 8
local i          = 8
local study`i'   = "Viscusi 2018 best set, best practice"
local distrib`i' = "normal"
local weight`i'  = (2/7)*(1/2)
local pindex`i'  = 237.017
local incindex`i'= 59901
local Mean`i'    = 4.396
local SD`i'      = 1.792

*Study 9
local i          = 9
local study`i'   = "Viscusi 2018 best set"
local distrib`i' = "normal"
local weight`i'  = 0
local pindex`i'  = 237.017
local incindex`i'= 59901
local Mean`i'    = 3.641
local SD`i'      = 1.283

*Study 10
local i          = 10
local study`i'   = "Viscusi 2018 wide set, best practice"
local distrib`i' = "normal"
local weight`i'  = 0
local pindex`i'  = 237.017
local incindex`i'= 59901
local Mean`i'    = 11.38
local SD`i'      = 0.288

*Study 11
local i          = 11
local study`i'   = "EPA (1998) Weibull model, from 2018 Benmap User's Manual"
local distrib`i' = "Weibull"
local weight`i'  = 0
local pindex`i'  = 237.017
local incindex`i'= 59901
local Shape`i'   = 1.509588
local Scale`i'   = 9648168

********************************************************************************
*renormalize weights so add to 1, if necessary
local double sumweight = 0
forvalues i = 1(1)`numstudies' {
local sumweight = `sumweight' + `weight`i''
```

```
}
local sumweight = round(`sumweight', .0000001)
if `sumweight' ~= 1 {
display as red "WEIGHTS SUM TO `sumweight' AND HAVE BEEN RENORMALIZED TO ADD TO ONE"
}
forvalues i = 1(1)`numstudies' {
local weight`i' = `weight`i''/`sumweight'
}

********************************************************************************
********************************************************************************
********************************************************************************
/*get VSL values*/

local cumweight = 0

forvalues i = 1(1)`numstudies' {

qui replace VSL_study = "`study`i''"          ///
            if _n > `cumweight'*_N & _n <= (`cumweight' + `weight`i'')*_N

if "`distrib`i''"=="normal" {
qui replace VSL = rnormal(`Mean`i'', `SD`i'') ///
            if _n > `cumweight'*_N & _n <= (`cumweight' + `weight`i'')*_N
}

else if "`distrib`i''"=="uniform" {
qui replace VSL = `LB`i'' + (`UB`i'' - `LB`i'')*uniform() ///
            if _n > `cumweight'*_N & _n <= (`cumweight' + `weight`i'')*_N
}

else if "`distrib`i''"=="triangular" {
qui replace u = uniform() ///
               if _n > `cumweight'*_N & _n <= (`cumweight' + `weight`i'')*_N

qui replace VSL = ( `a`i'' + sqrt(   u *(`b`i''-`a`i'')*(`c`i''-`a`i'') ) ) * ( u < (`c`i''-
`a`i'')/(`b`i''-`a`i'')) ///
                + ( `b`i'' - sqrt( (1-u)*(`b`i''-`a`i'')*(`b`i''-`c`i'') ) ) * ( u
>=(`c`i''-`a`i'')/(`b`i''-`a`i'')) ///
            if _n > `cumweight'*_N & _n <= (`cumweight' + `weight`i'')*_N
}

else if "`distrib`i''"=="Weibull" {
qui replace VSL = rweibull(`Shape`i'',`Scale`i'')/1000000 /*convert to $mil*/ ///
            if _n > `cumweight'*_N & _n <= (`cumweight' + `weight`i'')*_N
}

qui replace VSL = VSL * (`pindex'/`pindex`i'') * ( 1 + ///
                `incelasticity'*((`incindex'/`incindex`i'')-1) ) * `latencyadj' ///
            if _n > `cumweight'*_N & _n <= (`cumweight' + `weight`i'')*_N

local cumweight = `cumweight' + `weight`i''

}

sum VSL, d
local locmean = r(mean)

kdensity VSL, bw(0.20) n(500) normopts(clpatter(dash)) ///
              xtitle("VSL (millions of $2019)") ytitle(Density) ///
              xline(`locmean') graphregion(color(white)) note("") title("") ///
              name(gr1, replace)
graph save gr1 "VSL_density.gph", replace
```

```
graph export   "VSL_density.tif", as(tif) replace
capture log close
```