REPORT OF THE EPA WORK GROUP

ON VSL META-ANALYSES

July 25, 2006

Executive Summary

In December 2005 a work group convened by the Environmental Protection Agency met to discuss the meta-analysis of estimates of the value of statistical life (VSL) and to examine three existing meta-analyses. The following report contains an analysis of the use of meta-analytic procedures to determine an estimate of VSL. Many detailed issues are covered in this report, but several general comments are also highlighted.

Whereas meta-analysis is a reasonable analytical approach to use in obtaining information about VSL, the existing meta-analyses should not be combined in this effort. The key issues the work group uncovered include a high degree of heterogeneity (inconsistency) in the VSL estimates and dependencies (that could not be accounted for) stemming from inclusion of multiple estimates derived from the same underlying data; these issues preclude relying on these meta-analyses as a source of a final VSL estimate.

The work group recommends that in future meta-analyses results of contingent valuation and hedonic wage studies be analyzed separately. A basic consideration for the EPA is the determination of whether a single universal VSL value is applicable to all relevant subpopulations, or whether multiple VSL values should be provided for subpopulations. In particular, meta-analytic methods provide a variety of ways that could be used to characterize a population of VSL values.

1. Introduction

The U.S. Environmental Protection Agency (EPA) uses a value of statistical life (VSL) estimate to express the benefits of mortality risk reductions in monetary terms for use in benefit-cost analyses of its rules and regulations. EPA has used the same central default value (adjusted for inflation) in most of its primary analyses since 1999 when the Agency updated its *Guidelines for Preparing Economic Analyses* (USEPA, 2000).

EPA is reviewing its approach to valuing mortality risk reductions and is seeking to incorporate new information that has emerged since the 2000 release of its *Guidelines*. The literature has grown considerably since EPA's default estimate was derived and several EPA-funded reports have raised issues related to the robustness of estimates emerging from the mortality risk valuation literature. Furthermore, the economics literature now contains multiple meta-analyses of the VSL literature, providing new means of deriving central, default values for consideration.

In May 2004 EPA's Science Advisory Board-Environmental Economics Advisory Committee (SAB-EEAC) members were asked to assess the appropriateness of VSL estimates derived through meta-analytic techniques. EPA prepared a white paper (Dockins, et al. 2004) at that time summarizing three recent and widely-cited meta-analyses of the VSL literature: Mrozek and Taylor (2002), Kochi et al. (forthcoming), and Viscusi and Aldy (2003). Given the differences in study approach and scope in these meta-analyses, the SAB-EEAC expressed an interest in obtaining more information about meta-analytic techniques as well as an expert assessment of their application in the context of mortality risk valuation.

In response to this request, EPA invited two statistical experts in meta-analysis, Ingram Olkin (Stanford University) and Betsy Becker (Florida State University), to discuss the potential use of meta-analysis in estimating VSL. Both were hired as special government employees. After an initial meeting in July 2005, EPA staff and Drs. Olkin and Becker determined that a meeting of statisticians and the authors of the three VSL meta-analyses could lay the groundwork for a summary document that would provide the SAB-EEAC with a better understanding of the issues underlying the use of meta-analysis to estimate VSL. The general purpose of the meeting would be to clarify the alternative approaches used to combine estimates from VSL studies, and to engage in a discussion of the applicability of these approaches. Six statistical experts, each with significant experience with meta-analysis,[1] were identified by Dr. Olkin, Dr. Becker and EPA, and invited to participate. EPA developed a charge for the group through consultation with EPA's Economics Forum Steering Committee.

2. Charge to the Group

EPA asked the work group to address the following questions in their review of the use of meta-analysis applications to the VSL literature. EPA did not ask for a review or critique of the three existing VSL meta-analyses; however, in addressing the questions put to them, the work group had to evaluate and closely examine the three meta-analyses. Those analyses were presented to the group, and discussed to provide background and inform the broader questions below.

A. General Question:

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[1] The experts are Elaine Allen (Babson College), Jesse Berlin (Johnson & Johnson), Sally Morton (Research Triangle Institute), David Rindskopf (CUNY Graduate Center), Allan Sampson (University of Pittsburgh), and David Wilson (George Mason University). Brief biographies appear in Appendix A.

Given the nature of the economic models and data used to estimate VSL, what fundamental or novel issues arise when applying existing meta-analysis techniques in this context? How does this compare to more common applications of meta-analysis?

B. Methodological Questions:

1. Are there other methods that combine studies to generate VSL estimates for use in benefit-cost analysis? If so, what are there relative strengths and weaknesses of these methods?

2. How can multiple meta-analyses be combined when the same studies appear in different meta-analyses?

3. How can meta-analysis or other techniques be used to generate a distribution for VSL for use in benefits analysis that reflects uncertainty and variability, accounting for the representativeness of the underlying studies?

C. Modeling Issues:

1. When several different models of value of statistical life (VSL) estimates are presented in a single study, should one model (and therefore, one estimate) be selected and if so, how? Or, should multiple estimates be used from each study?

2. When several sub-samples in one study provide VSL estimates, should they be combined or entered as separate estimates into the meta-analysis?

D. Moderators:

If moderator analyses identify significantly different estimates, should those estimates be combined and if so, how should a single estimate be computed? Potential moderators include the study design (i.e., hedonic wage, stated preference), changes in preferences for risk reduction over time, and different populations.

3. The Workshop

On December 9-10, 2005 EPA convened a working meeting with the meta-analysis authors and the meta-analysis experts.[2] The purpose of this meeting was to inform the work group on the specifics of the approaches used in the literature to combine estimates from VSL studies and to invite discussion of the charge questions using the three meta-analyses as case studies. As background, EPA provided the work

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2   A full list of meeting attendees is attached as Appendix B.

group with copies of the three widely cited meta-analyses listed earlier, papers by Alberini, et al. (2004) and Viscusi (2004) that discuss analytical issues related to contingent valuation and hedonic wage studies, respectively; and background material on VSL estimation methods and practice.

After an initial introduction and overview by the EPA staff, presentations were made by one coauthor from each of the three meta-analyses. Each presentation was followed by a question-and-answer session with the work group participants. After the presentations had concluded, the work group met and discussed general meta-analytic issues that had been raised by the presentations. Finally the group discussed each of the charge questions in turn, and drafted initial responses to those questions.

4. The Report

Subsequent to the workshop, the work group completed this report for EPA to present to the SAB-EEAC. EPA anticipates that this report will further inform the SAB-EEAC as the Agency consults with the committee on revising its default approach to estimating VSL.

As noted above, the work group considered each question posed in the charge; responses to these questions are contained in the textual materials, rather than listed question-by-question. The remainder of the report begins with general remarks about the set of VSL meta-analyses reviewed by the work group and some observations about accepted practice in the conduct of a meta-analysis. The next section concerns the nature of the data (i.e., the results of the primary studies of VSL) summarized in the VSL meta-analyses. Here the work group raises questions about the use of different representations of wage and risk, about dependence of data points both between and within source

documents, as well as study quality. Next the group comments on the actual methods used in meta-analysis. Important issues concern analyses of subgroups of studies, weighting of individual study results, and use of regression in meta-analysis ("meta-regression"). The report concludes with a set of summary points.

5. General Remarks about the VSL Meta-analyses and the Conduct of Meta-analysis

Before remarking on the history of the use of meta-analysis, the work group wants to emphasize that meta-analysis appears to be an analytical technique appropriate to the task of estimating VSL. Meta-analysis, which provides statistical summaries of evidence from similar studies, often aims at understanding variation among studies in those effects (here, in the VSL estimates) as well as obtaining an overall (average) estimate of the size of the effect. In the context of VSL it is not clear to the work group if there is, in fact, a set of VSL values that might be of interest, each of which should be characterized, or whether a single value of VSL is always required by the EPA. The meta-analyses examined by the workgroup appear to admit to the possibility that there is a collection of VSL values. The approach taken to analyze the VSL estimates will depend on which of these views is adopted.

5.1 History of meta-analysis

Although the term "meta-analysis" was coined by a social scientist (Glass, 1976), the theoretical origins of meta-analysis date to the 1930s when the statistician R. A. Fisher, motivated by the need to combine the results of agricultural experiments, proposed a method of combining the data from different agricultural trials. Though some summaries of study results date to the early part of the 20th century, in the 1970s

researchers in several different areas of psychology sought to answer broad questions, about which much information had been gathered. The existence of large numbers of studies on such questions as "Does psychotherapy work?" (e.g., Smith, Glass & Miller, 1980) and "Can employment tests predict job performance?" (e.g., Hunter, Schmidt & Hunter, 1979) motivated researchers to want to use more than narrative summaries of study results to examine extensive literatures.

At about this same time, an explosion in the number of randomized medical trials generated a desire to combine medical study results. In 1989 the National Library of Medicine (NLM, 2004) defined meta-analysis as: "A quantitative method of combining the results of independent studies (usually drawn from the published literature) and synthesizing summaries and conclusions which may be used to evaluate therapeutic effectiveness, plan new studies, etc. with application chiefly in the areas of research and medicine." Another explanation of meta-analysis was provided in a *New York Times* article (January 7, 1994, L. K. Altman): "A meta-analysis aims at gleaning more information from existing data by pooling the results of many smaller studies and applying one or more statistical techniques. The benefits or hazards that might not be detected in small studies can be found in a meta-analysis that uses data from thousands of patients." These two quotations highlight the two purposes to which meta-analysis is often put—to arrive at an overall conclusion or summary of findings, and to examine variation in study results.

5.2 Guidelines for meta-analysis

As the number of submissions of papers using meta-analysis increased, editors of several medical journals asked for guidance in the review of such papers. This led to

three conferences relating to (1) the reporting of randomized clinical trials (Consolidated Standards of Reporting Trials, or CONSORT, Begg et al., 1996); (2) the conduct and reporting of *meta-analyses* of randomized clinical trials (Quality of Reporting of Meta-analyses or QUOROM, Moher et al., 1999); and (3) the conduct and reporting of meta-analyses of observational studies (Meta-analysis of Observational Studies in Epidemiology, or MOOSE, Stroup et al., 2000). In each case, a set of guidelines was proposed and to date those guidelines have had a clear impact on the conduct of meta-analyses, particularly in the medical realm (e.g., Moher et al, 2001).

The guidelines list several general areas that need to be addressed in the reporting of meta-analyses:

1. Background of the Problem

2. Search Strategy

3. Methods

4. Results

5. Discussion

6. Conclusions

A general principle in the reporting of results is that sufficient detail be provided to permit some degree of verification and replication. In particular, because of the wide range of VSL estimates in existing meta-analyses, the inclusion or exclusion of individual studies can have a profound effect on the summary values. These guidelines aim to provide justification for the decisions that are made in carrying out a meta-analysis.

Though they were initially proposed for use in medical meta-analyses, the points made in these guidelines have applicability to other fields, and the work group drew on

them in considering the VSL meta-analyses. The meta-analyses that the work group examined did not acknowledge or draw on the extensive literature about meta-analysis and the systematic review of evidence, including these guidelines. In general, the group found deficiencies in the reporting of the VSL meta-analyses. The guidelines cited above argue that items such as search procedures, inclusion and exclusion rules, and sample sizes of the included primary research reports should be presented. Graphical displays should be used to depict individual summary results, as well as summary results of the meta-analysis, and this was not done in any of the VSL meta-analyses. Decision rules should be made explicit about the choice of models from which VSL estimates are extracted (this could be considered an aspect of inclusion rules), and measures of uncertainty, preferably in the form of confidence intervals, should be fully reported. Providing sufficient data to permit replication is a good guiding principle for what data to include in the report of a meta-analysis. None of the VSL meta-analyses would meet the standards of reporting suggested by either the QUOROM or MOOSE guidelines.

Predetermined protocols are basic requirements in medical syntheses, and have several benefits. Protocols set up *a priori* criteria that will apply to study selection and analysis. Protocols should, for instance, specify whether the synthesis will include unpublished studies. (In general the inclusion of unpublished studies reduces the problem of publication bias (Sterne et al., 2001).) The relevance of particular studies should be specified in the protocol (e.g., whether to include studies with participants from other countries in the estimation of VSL, or studies that are limited in particular ways, e.g., involve only blue collar workers). A rationale for any such decision should be provided in the protocol. In addition, the protocol should specify possible variables for sensitivity

analysis, and include a detailed discussion of heterogeneity of both the designs and results of the studies in the meta-analysis. None of the VSL meta-analyses reported using a protocol to guide the conduct of the meta-analysis.

In addition, the guidelines mentioned above argue for clear reporting of the methods used to synthesize results. Because VSL studies are based on regression models, follow-up discussions may be needed on how best to proceed with methods of combining results of the VSL studies. Methods for synthesizing regression results have been less well described than methods for other outcome metrics (e.g., mean differences and odds ratios) based on simpler study designs (Becker and Wu, 2006). A key issue is how to deal with regression models that do not include the same independent variables (which is typical in VSL studies).

6. The Data

In meta-analysis one of the key issues is what should be combined. When meta-analytic procedures were first developed, arguments focused on exclusion rules and what kinds of studies should be combined. As meta-analysis applications and methods progressed the issue changed to a concern over what types of data and indices of results from reasonably similar studies can legitimately be combined (e.g., Morris and Deshon, 2002).

One of the key questions in meta-analysis is whether study results agree, and the answer to this question hinges in part on similarity of the study designs and effect indices being summarized. A general rule is that one should combine studies and effect measures that are comparable. Often this means that standardized measures of effect (such as correlations or standardized mean differences) are combined, and in meta-

analysis one does not combine different measures (indices) of study outcomes – for instance one would not expect correlations and proportions to represent "the same" kind of study outcome. Similarly, results for an outcome on a linear scale may not be commensurate with results expressed on a quadratic scale (e.g., linear and quadratic terms for time). In the VSL literature variables such as wages are often transformed via the logarithmic function, which leads to similar lack of comparability of VSL values.

A second related point is that it is typical for studies using similar or identical study designs to be summarized. Many VSL studies use regression designs, but differences are seen in the numbers and kinds of variables that are included (in addition to wages and risk variables).

Finally the fact that one of the goals of most meta-analyses is to examine variation in study outcomes means that study characteristics that may relate to the size of an effect (here, the size of the VSL estimate) ought to be recorded and later analyzed. Such factors as the metric used, the additional variables included in primary-study regression models from which the VSL estimates are drawn, the time period of the study and the source of the data all should be coded for use in the meta-analysis.

6.1 Metrics

One issue that often (perhaps always) arises in meta-analyses of VSL estimates is that primary studies may report VSL results using different metrics. More specifically, one study might use a logarithmic model to relate wage (y) versus risk (x):

(1) $\log y = a_1 + b_1 x,$

and another study might use a linear model without a log transformation of wages:

(2) $y = a_2 + b_2 x.$

The slope coefficients (b_1 and b_2) from these two models are not comparable, and need to be put on a common (VSL) scale or metric.

Although tests of hypotheses and confidence intervals are intimately related, some differences need to be noted. The test of a hypothesis H: $\theta_1 = \theta_2$ is equivalent to a test of the hypothesis H: $\log \theta_1 = \log \theta_2$, but a confidence interval for $\theta_1 - \theta_2$ will not be comparable to (on the same scale as) a confidence interval for $\log \theta_1 - \log \theta_2$ so there are issues in how to combine two parameter estimates or confidence intervals, one of each type, computed from only summary data.

If VSL values are obtained from models based on different transformations similar to those described above, the metrics used in the primary research should be coded in the meta-analysis. This should be coded even if a transformation is used to place the estimates on a common scale, in part because different metrics may lead to different levels of uncertainty (i.e., different weights are used, as discussed below). Because a coefficient reported in a primary study may need to be transformed to make its scale comparable to estimates from other studies, its standard error would also require a transformation. This issue has not been studied in the context of the synthesis of slopes in meta-analysis. EPA may want to explore alternative modeling approaches in the primary studies and the consequences of those alternatives. For example, consideration might be given to modeling wage and log(wage) as a function of both risk and log(risk) and then examining the consequences of use of the different functions. There are few rules for the choice of a model. Goodness-of-fit tests may help in making the choice. Of particular concern is the determination of whether risk or log(risk) provides a more suitable metric.

A last issue related to the metric used to represent VSL concerns how the measures of VSL are to be combined. Typically, meta-analysts average effect measures by weighting large and precise effects more heavily than imprecise (or uncertain) effects. Given VSL outcome measures from several studies and possibly in several metrics, one key issue is how to weight the study results. Because a variety of weighting methods exist, an issue is the appropriate method of weighting when VSL estimates are combined.

Comparable estimates of VSL (i.e., estimates on the same scale) would be combined or averaged using weights, typically based on variances or standard errors. The form (and value) of the weight that is appropriate for each VSL estimate will depend in part on the metric or scale used to represent wages and risk within the primary study because different metrics have different levels of uncertainty. For example, if the variance of a variable X is v then the variance of log X is 1/v. Thus it is important that sufficient data be provided in individual studies to permit transformations, when appropriate.

6.2 Study design and model used

In general it seems that two study designs appear in the VSL literature – hedonic wage (HW) and contingent valuation (CV) studies. Both designs appear to rely on regression analyses but critical differences exist between the two study types.

Although regression analysis is a powerful analytical method, it is a more complex design (e.g., than a simple comparison study) that raises some theoretical issues. For example, if one study uses two independent variables u and v, and another study uses u alone, or u and w, then results from these two studies may not be comparable.

Often hedonic wage (HW) studies report several different regression models from which VSL estimates can be drawn. The choice of which model from each primary study to use in representing VSL is critical but complex. Such factors as the functional forms of the wage and risk variables, or whether industry or occupational category is controlled for within a study may lead to critical variations in VSL (e.g., by over-controlling for risk) and thus may lead to differences seen within the meta-analysis. Specifically, VSLs from studies in which certain factors are controlled may systematically differ from VSLs for which those variables are not controlled. The meta-analyst should code for whether key variables were controlled for in each primary study, and these codes should be used in a meta-regression model. EPA needs to decide what level of specificity of control (e.g., for industry or occupational category) is appropriate within primary HW studies. This may require further investigation.

Another variable that is likely to be important is the time period covered by the data of a primary study. Some of the time effect is adjusted for by setting VSLs to a particular year's monetary scale (e.g., 1999 dollars), but other factors change over time, such as the levels of risk that exist for particular occupations and the economic climate. The dates of the data sources for the wages and risk values in each primary study should be coded and incorporated into the meta-regression or sensitivity analyses.

In simple meta-analyses with independent data points, the variance of each study outcome (here the VSL estimate) is used in weighting. But synthesis of regression results also may require covariances among slopes, or correlations, and these may not be reported in individual studies. Regressions from different studies will undoubtedly contain some missing ingredients, and the consequences of this may need to be

addressed. The workgroup suspects that the impact of added predictors on the VSL

estimates will be smaller, and the importance of having covariances among predictors (or

the slopes in a model) will be less critical, when the additional predictors used in

regression models are not strongly interrelated. However, to date there have been no

investigations of these influences on the synthesis of slopes (here, VSL estimates).

6.3 Origins of the data

It appears that different authors of hedonic wage primary studies draw on a

limited number of data sets (i.e., Current Population Survey (CPS) and Panel Study of

Income Dynamics (PSID)) as sources of the wage data. Different authors present models

based on the same data source, sometimes for different subpopulations and/or for

different years. Even within a primary study, an author may present several estimates,

sometimes for different individuals from the same data source, but sometimes stemming

from different model specifications fit to the same individuals.

Overlapping samples. The primary issue for meta-analysts is the degree of

overlap of the samples on which different VSL estimates are based. To the extent they

overlap, the VSL estimates will not provide independent information, which is a problem

for standard univariate meta-analytic techniques that assume independence. If the

primary studies examine non-overlapping subpopulations, the problem of dependency

would not arise, but this is often not the case. So, for instance, if a study reports one

model for a large group of workers, then also reports separate results for men and

women, and for blue-collar and non-blue-collar workers, the results for men and women,

and for blue-collar and non-blue-collar samples, will overlap with the full sample and

with each other. It would not be advisable to include, say, five VSL estimates from this

report because they would be correlated due to the overlap in samples that came from the same larger population. However one could report results for independent nonoverlapping subgroups (e.g., two results, from the separate samples of men and women).

Common data sources. Reviews should code the source of the wage data and should not include multiple estimates of VSL from the same exact populations (or subpopulations). Instead meta-analysts should attempt to obtain a single VSL estimate to represent each specific set of individuals extracted from a data source. The same primary data source may provide several independent VSLs. If these estimates are independent, i.e., based on different individuals such as men and women or non-overlapping industries or timepoints, they may all be included in a single meta-regression model. It may be difficult in some situations to discern whether two study reports or estimates refer to the same individuals in the same data source or not.

Sensitivity analysis. Another issue in meta-analysis that can be addressed, in part, via sensitivity analyses is the determination of whether a specific data point is particularly influential, thereby skewing the results in the direction of this point. A variety of procedures can be used to detect influential points or data sources, some of which might be aberrant. For example, reanalyses with the deletion of one study at a time will indicate whether there is consistency across all results. If deletion of a single study has a substantial effect on the interpretation of the summary result, then a more cautious interpretation of the overall result (including all studies) may be warranted. In any case, and as noted above, the rationale used to choose among estimates based on the same individuals should be made explicit.

Indeed, future authors of primary HW studies should be urged to be explicit about exactly how they choose their samples of wage data (i.e., the data source, how data were selected or sampled from that source), and of risk data. In addition, the meta-analyses examined by the workgroup use a fairly limited set of risk values. The source of the risk data should be coded, including any specific procedures used to finalize the set of risk data.

Another aspect of sensitivity analysis relates to consistency of interpretations with other factors. Because the beta coefficients in a regression are correlated, an examination of individual beta weights might lead to erroneous conclusions. Furthermore, the estimate of a slope carries implications that are not obvious. To illustrate this point, suppose that the shape parameter for fitting a Weibull distribution is estimated to be 1.3. A shape parameter greater than one means that the failure or hazard rate is increasing. This conclusion may or may not be reasonable across all subpopulations. In particular, it could be that for 40 year olds the failure rate should be decreasing, whereas for 60 year olds it would be increasing. Thus an overall estimate would carry an incorrect interpretation for the younger group.

Quality of studies. The issue of study quality is a contentious one and is based on the question of whether to combine the results of all studies regardless of quality (e.g., perhaps summaries should include only studies of "good" quality). Meta-analysts continue to research this issue, but one view that all group members share is that it is not appropriate to weight studies using a "quality score" based on a conglomeration of items. Many meta-analysts define particular individual aspects of quality that can be coded and used either in analyses (as moderator variables or in sensitivity analyses) or to exclude

studies from analysis. If the reviewer is explicit about defining an *a priori* criterion for quality and setting a minimum criterion for inclusion/exclusion, there is no problem with excluding studies on such a basis. For example, one might decide to exclude studies using Society of Actuaries (SOA) estimates of risk. Alternatively, one might decide to include a variable in a meta-regression (i.e., a regression analysis to explore predictors of VSL estimates) that indicates whether an SOA estimate was used, or to stratify the primary studies based on this indicator and provide separate estimates. It may be particularly important to distinguish among various aspects of quality. In particular, one may wish to consider quality and completeness of *reporting* of the original studies separately from the nature of the data source or the adequacy of the statistical models used. Reporting itself may be a poor surrogate for the underlying quality of a study's design and analysis.

Publication status is one issue that is sometimes included as a measure of quality. Two of the meta-analyses examined by the workgroup excluded unpublished studies; this practice has the potential consequence of eliminating studies that may have systematically different, nonsignificant estimates. In general it is unwise to completely exclude unpublished studies. Publication status should not be used as a proxy for study quality. Rather, the eligibility criteria should explicitly establish the quality standards for that meta-analysis and those standards should be applied to all studies independent of publication status.

In addition, the workgroup acknowledges the problem of reporting bias – the exclusion or failure to report models or subpopulation results that did not reach significance or did not conform to expectations from previously published literature.

This is a more difficult issue to deal with than publication bias. Many sophisticated approaches exist for detecting and dealing with publication bias (see, e.g., Rothstein, Sutton and Borenstein, 2005). Typically, adjustment methods require the meta-analyst to assume that significant results have been observed in some frequency (e.g., all significant results are reported but only half of nonsignificant results) and then the observed results are modified "as if" all results had appeared. Typically, these methods have the property of reducing the size of the estimated effect, because observed results will be reduced by the inclusion of the hypothesized (and presumably weaker) missing values.

7. Meta-analysis Methods

7.1 Goals of the meta-analyses

Ultimately, the goal of VSL meta-analyses is to provide a means of valuing mortality risks. What is not clear is what population should be represented in deriving that value, or whether in fact a single value should indeed be the goal. Because there is variability among individuals in valuing mortality risk, a single "average" value may smooth effects. For example, the effects at the 10th and 90th percentiles may be in opposite directions, so that the average may show no effect. An analysis with the 10th, 50th, and 90th (or 25th, 50th, and 75th) percentiles can illuminate whether a smoothing effect has taken place in focusing on an overall average value. It will also provide an indication of the degree of variability in VSL, especially with respect to different segments of the population. Similarly a collection of meta-analytic investigations known as random-effects analyses can be used to explore the location and spread of a distribution of population VSL values, and to acknowledge the variation in those VSL values.

Every meta-analysis should state the goal for the combined effect. For example drawing from a recent controversial medical meta-analysis, one might ask whether mammography has a beneficial screening effect for breast cancer, *among 40-49 year old women*. The consideration of age is critical because some studies have participants who are younger, and others have participants who are older. If there are many studies of older women, then this would influence the results because it is known that mammography has a positive screening effect for older women, whereas it is less clear whether the benefit extends to younger women. The point in this example is that there may not be a single answer for all women and that specifying the population of interest will influence what studies are considered relevant.

The EPA may want to estimate a single value of VSL, but there does not appear to be a universal VSL value that is applicable to all specific subpopulations. It is more likely that there is a collection (population) of VSL values corresponding to various population segments. The EPA may want to characterize the relationship between VSL estimates and population characteristics. One could provide, for instance, the range of estimated VSLs and their confidence intervals corresponding to a set of subpopulations of interest. Estimating each of these will entail certain assumptions (e.g., about the shape of the distribution of VSL values, etc.).

Measures of uncertainty in the form of standard errors or confidence intervals for the predicted values should be obtained. Indeed, measures of uncertainty are mandated for all combined estimates in any high quality meta-analysis. An estimated response surface (i.e., from a meta-regression) could provide a range of estimates for particular points or areas on the surface. If a response surface can be generated, then it provides a

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method for obtaining estimates for a particular idealized (or at least a clearly specified) population, even though that population is not exactly represented in the studies in the synthesis.

An important issue in conducting meta-analyses in this area is the impact of various analytic choices in the primary studies. Sensitivity analyses (e.g., using alternative models, omitting influential studies) might be used to outline the consequences of making a variety of meta-analytic assumptions and to obtain a set of VSL estimates.

7.2 Subgroup analyses

Analyses of subgroups of studies done separately (piecewise or one at a time) skirt the issue of confounding of study characteristics and interactions among those characteristics. A general principle is that it is preferable to incorporate subpopulations in a single model, rather than to have multiple models for different subpopulations. Then variables or characteristics common to all subpopulations strengthen the analysis in a composite model. Also, study characteristics are typically confounded in meta-analysis because the studies are not conducted in a systematic and structured way (as primary data collection in an individual experiment might be). For instance, studies of particular subpopulations may, by chance, all examine a particular form of regression model, or use a particular set of predictors. Analyses that incorporate several study characteristics together (e.g., meta-regressions) are preferable to separate analyses of individual predictors of outcomes for different subsets of studies. In this way one can examine the meta-regression for multicollinearity among predictors and thereby identify confounding, and similarity of predictive models.

The one exception for the current set of meta-analyses is the analysis of the HW and CV studies. The work group recommends these two sets of studies be analyzed separately. The overriding principle is that incommensurate measures or indicators should not be combined. Among studies with commensurate indicators of VSL, the impact of study features, such as mean risk level or inclusion of controls for industry, should be examined within the context of all such studies.

When the bulk of the evidence and the theoretical underpinnings suggest that sets of studies are estimating different aspects of VSL, the work group argued that separate analyses should be done. The theoretical justifications for, and designs of, the two types of study (HW and CV) are quite different. In addition, the HW and CV studies produce results that appear empirically quite different in magnitude and variability – thus the group believes that analyses of these two study types should be kept separate.

7.3 Weighting

The meta-analyses the group examined used a variety of weighting schemes for combining the VSL estimates. One combining method that the work group does not endorse is including several estimates (say k) from each study and weighting each one in proportion to 1/k. Although this method reduces the chance that a study will have undue influence on the overall meta-analytic mean, this approach does not account for the dependence among the results within individual studies, and thereby may overly weight the data from a single study reporting several estimates.

In typical meta-analyses, individual study results are weighted by their precision, often with weights equal to the inverse of the estimates' variances (standard error squared). In the case of VSLs, the standard errors of component parts (e.g., slopes from

regression analyses) may not be well reported. Standard errors should be obtained. When they are not reported they should be estimated from reported *t* values or other tests. One could also attempt to impute missing standard errors from the studies that do provide standard errors.

An alternative but inferior method would be to weight effects in proportion to sample size. Although sample size is an important ingredient in standard error, it is not the only ingredient. This may be evident by noting that the variances of many sample estimates (e.g., the sample proportion) depend not only on the sample size but also on the relevant population parameter (e.g., the true proportion). The impact of weighting by sample size alone on the standard errors for the meta-analytic regression results needs to be acknowledged. This could be part of a sensitivity analysis.

7.4 Regression in meta-analysis

Ordinary least squares (OLS) regression is not appropriate for the computation of meta-regressions because the estimates being combined do not meet the assumption of homogeneity of variance. Alternative methods based on weighting by precision are easily available as macros for statistical packages such as SAS, SPSS and Stata (using the "metareg" routine, which can be downloaded from the Stata website), in meta-analysis specific software such as Comprehensive Meta-analysis, and in programs such as HLM, MLWin, and HBLM (DuMouchel, 1994). Additional methods can be produced via BUGS and are described in many publications on meta-analysis (e.g., Hedges and Olkin, 1985). These procedures differ not only in the use of weights but also in the computation of standard errors and related inferential statistics. As such, using standard OLS regression procedures, even with inverse variance weights, produces incorrect results.

In addition, standard practices (such as not including too many predictors in any regression model) should be followed. Problems that may arise are that predictors of VSL based on differences among studies may be confounded, leading to regression analyses that tell essentially the same story. Also, if the set of VSL estimates were small, then one would not want to include a large number of predictors in any one model (thus having an overdetermined model). A general principle is to be wary of relying greatly on information that is based largely on differences among studies.

Because synthesis methods using regressions are based on a number of assumptions, it is important to determine whether the assumptions are violated, and if so how to resolve the problem. Regression diagnostics, including graphs, should also be routinely used (see, for example, Cook and Weisberg, 1999). In particular, meta-analyses commonly produce plots of the confidence intervals for all estimates from primary studies (here these would be VSL estimates), which allow for exploration of variation in estimate magnitude. Similarly familiar graphics such as scatter plots of VSL against predictor variables (measured at the study level) may lead to better understanding of the variation in VSL values.

EPA has the task of determining whether the existing collection of studies represents good evidence about VSL. If so, then meta-analysis via meta-regression would be an appropriate and useful tool for examining that collection of studies. Given the current approaches available for summarizing results, meta-analysis (and specifically meta-regression) is the best available approach for synthesis. However a potential alternative is for EPA to undertake a new large scale study using the most recent data and available methods, or a longitudinal study that would look across a specified time frame.

Because CV and HW methodologies yield such disparate estimates, it may be important for EPA to use both CV and HW methodologies together to better assess the differences between the results of these two approaches.

8. Discussion

The work group concluded that whereas meta-analysis is a reasonable tool for the analysis of the literature on VSL, the existing meta-analyses all suffer from weaknesses in execution that preclude relying on any of them as a source of a final VSL estimate. In addition the group members question the value of obtaining a single VSL estimate, in part because meta-analysis provides explicit methods for estimating parameters of a population of values (such as a collection of VSL values).

Should further meta-analytic work be desired, the work group described a number of key issues to be considered (e.g., proper weighting of results, publication bias, the use of graphics), and also identified guidelines for the conduct of meta-analysis that should be implemented. In addition the group identified several fundamental issues concerning the VSL studies (e.g., population overlap, metric for wage and risk) that could impact the construction, analyses, and results of any future meta-analysis.

9. Brief Summary Caveats

The following set of principles arose from the discussions of the three meta-analyses. This list is not exhaustive, and other principles are noted in the various text books on the subject.

I. General comments

I.1. The work group concluded that if the underlying collection of studies provides good evidence about VSL, then meta-analysis is an appropriate methodology for examining the results of that collection of studies.

I.2. The work group does not recommend combining the results of existing meta-analyses.

I.3. Because hedonic wage and contingent valuation methodologies yield distinctly different estimates of VSL, the work group recommends that studies using these two approaches be analyzed separately.

I.4. Multiple VSL estimates from the same study, and therefore from the same data set, should be combined cautiously or not at all. Studies that use the same data and similar analytic methods should not contribute several VSL estimates to one meta-analysis. It is often preferable to choose one best index from each study (or possibly each independent data set) for use in the meta-analysis.

I.5. Bias considerations should be addressed in the reporting of a meta-analysis. The work group does not recommend that quality scores be used, but does recommend that quality considerations be addressed in the protocol for any further meta-analysis.

I.6. Because there is variability among individuals in valuing mortality risk, an "average" value may smooth effects. Analyses focusing on percentiles or other indices of the nature

of a distribution of VSL values may prove useful and reveal variations across different segments of the population.

I.7. Risk is an elusive concept, especially when risks are very small. Risk reduction is often examined for small values, and may be difficult to estimate. Alternative metrics for risk, as well as for VSL estimates, should be investigated by EPA.

I.8. Sufficient ambiguities in procedures for estimating VSL exist, which leads the work group to strongly recommend a full-scale study wherein HW and CV methods would both be used and compared directly.

I.9. Geographic considerations (e.g., whether to include foreign studies) should be decided upon *a priori*.

II. Statistical issues

II.1. When combining estimates of VSL, each VSL estimate should be weighted by the reciprocal of its variance or squared standard error.

II.2. Confidence intervals should be provided for individual VSL estimates, and for the combined VSL value.

II.3. Explanatory, study level or VSL-estimate level variables, when used, should be included in one model and not in separate subgroup analyses.

II.4. Graphics should be included whenever a regression model is used, as for example, plots of residuals and scatter plots of the X-Y relations.

II.5. Regression methods are available as macros for SAS, SPSS and Stata, in Comprehensive Meta-Analysis (CMA) and in programs such as HLM, MLWin and HBLM (see also BUGS). For example, Stata has available a number of user-provided routines for meta-analysis. One of these, "metareg," is specifically designed to perform the sort of metaregressions being proposed.

II.6. Multiple analyses should be presented to justify the interpretation of results from meta-regressions. For instance, in fitting distributions, analyses of hazard or failure rates may enable the meta-analyst to detect inconsistencies in slope values.

II.7. EPA should study the use of Huber weights to address the problem of variable dependence. (Huber-White weights were used to obtain robust standard errors in the meta-analysis by Mrozek and Taylor.) The work group was unclear on the details of this method as it applies in this context.

11. References

Alberini, Anna, Maureen Cropper, Alan Krupnick, and Nathalie B. Simon. 2004. Does the value of a statistical life vary with age and health status? Evidence from the US and Canada. *Journal of Environmental Economics and Management. 48:* 769-792.

Becker, Betsy J. and Meng-Jia Wu. 2006. Synthesizing regression slopes in meta-analysis. Manuscript to be submitted to *Statistical Science*.

Begg, Colin, M. Cho, S. Eastwood, R. Horton, David Moher, Ingram Olkin, et al. 1996. Improving the quality of reporting of randomized controlled trials: The CONSORT statement. *Journal of the American Medical Association, 276*(8), 637-639.

Cook, R. Dennis and Sanford Weisberg. 1999. *Applied Regression Including Computing and Graphics.* John Wiley & Sons.

Dockins, Chris; Kelly Maguire, Nathalie Simon, and Melonie Williams. 2004. *Value of Statistical Life Analysis and Environmental Policy: A White Paper.* Prepared for Science Advisory Board – Environmental Economics Advisory Committee.

DuMouchel, William. 1994. *Hierarchical Bayes Linear Models for Meta-Analysis.* NISS Technical Report Number 27. Research Triangle Park, NC: National Institute of Statistical Sciences

Glass, Gene V. 1976. Primary, secondary, and meta-analysis of research. *Educational Researcher, 5*, 3-8.

Hedges, Larry V., and Olkin, Ingram. 1985. *Statistical methods for meta-analysis*. New York, NY: Academic Press.

Hunter, John E., Schmidt, Frank L., and Hunter, Rhonda. 1979. Differential validity of employment tests by race: A comprehensive review and analysis. *Psychological Bulletin, 86*(4), 721-735.

Kochi, Ikuho, Bryan Hubbell, and Randall Kramer, An Empirical Bayes Approach to Combining and Comparing Estimates of the Value of a Statistical Life for Environmental Policy Analysis, *Environmental and Resource Economics*, May 2006, Pages 1 - 22, DOI 10.1007/s10640-006-9000-8, URL http://dx.doi.org/10.1007/s10640-006-9000-8

Moher, David, Cook, D. J., Eastwood, S., Olkin, Ingram, Rennie, Drummond, and Stroup, D. F. 1999. Improving the quality of reports of meta-analyses of randomised controlled trials: The QUOROM statement. *The Lancet, 354*(9193?), 1896-1900.

Moher, David, Jones, A., and Lepage, L., for the CONSORT Group. 2001. Use of the CONSORT Statement and quality of reports of randomized trials: A comparative before-and-after evaluation. *Journal of the American Medical Association, 285*(15), 1992-1995.

Morris, Scott B., and DeShon, Richard P. 2002. Combining effect size estimates in meta-analysis with repeated measures and independent-groups designs. *Psychological Methods, 7*(2), 105-125.

Mrozek, Janusz R. and Laura O. Taylor. 2002. What Determines the Value of Life? A Meta-Analysis. *Journal of Policy Analysis and Management* 21(2): 253-270.

National Library of Medicine (NLM). 2004. Quote obtained from http://www.nlm.nih.gov/archive/20040830/pubs/cbm/metaanal.html.

Hannah R. Rothstein, Alexander J. Sutton, and Michael Borenstein (Eds.) 2005. *Publication bias in meta-analysis: Prevention, assessment and adjustments*. Chichester, West Sussex, England: Wiley.

Smith, Mary L., Glass, Gene V., and Miller, T. I. 1980. *The benefits of psychotherapy*. Baltimore, MD: John Hopkins University Press.

Sterne, Jonathan A. C., Egger, Matthias, and Smith, George D. 2001. Investigating and dealing with publication and other biases in meta-analysis. *British Medical Journal, 323*, 101-105.

Stroup, Donna F., Berlin, Jesse A., Morton, Sally C., Olkin, Ingram, Williamson, G. D., Rennie, Drummond, et al. 2000. Meta-analysis of observational studies in epidemiology: a proposal for reporting. Meta-analysis Of Observational Studies in Epidemiology (MOOSE) group. *Journal of the American Medical Association, 283*(15), 2008-2012.

U.S. Environmental Protection Agency (USEPA). 2000. *Guidelines for Preparing Economic Analyses*. Office of the Administrator, EPA 240-R-00-003.

Viscusi, W. Kip. 2004. The Value of Life: Estimates with Risks by Occupation and Industry. *Economic Inquiry 42*(1): 29-48.

Viscusi, W. Kip and Joseph E. Aldy. 2003. The Value of a Statistical Life: A Critical Review of Market Estimates Throughout the World. *Journal of Risk and Uncertainty* 27(1): 5-76.

Appendix A

Brief Biographies of Work Group Participants

I. Elaine Allen is the Kevern R. Joyce Professor of Statistics and Entrepreneurship at Babson College, Wellesley, MA. She is also Director of Research of the Sloan Center for Online Education at Babson and Olin Colleges and Faculty Director of the Women's Leadership Program at Babson College. Her entrepreneurial activities include starting StatSystems, a medical device company, ARIAD Pharmaceuticals, a publicly held biotechnology company, and Pondview Associates, a high tech consulting company. She has published widely on evidenced-based practice, clinical trial design, meta-analysis and biostatistics. A Fellow of the American Statistical Association, Dr. Allen holds a PhD from Cornell University.

Betsy Jane Becker (work group co-chair) is a professor in the program in Measurement and Statistics in the College of Education at Florida State University, where she has been on faculty since Fall 2004. For the previous 21 years she was in the Measurement and Quantitative Methods program at Michigan State University. Becker earned her Ph.D. from The University of Chicago in 1985, and her dissertation on combined probability methods for meta-analysis won the American Educational Research Association's Outstanding Dissertation Award.

Becker has published widely in the area of meta-analysis and also on psychometric issues in education. She serves as co-convener of the Methods Training Group for the Campbell Collaboration, an organization whose goals include the promotion of evidence based analysis for policy making in the social sciences. She also is a member of the Technical Advisory Group for the "What Works Clearinghouse", an effort to produce research syntheses of studies of educational interventions, supported by a contract from the U.S. Department of Education. Becker is also a member of the National Assessment of Educational Progress (NAEP) Design and Analysis Committee, and is associate editor of the journal *Psychological Methods.* In the past she has also served on the editorial board of *Journal of Educational and Behavioral Statistics* and *JASA*'s Applications and Cases Section.

Jesse A. Berlin, Sc.D., received his doctorate in Biostatistics from the Harvard School of Public Health in 1988. In 1989 he joined the faculty at the University of Pennsylvania, in a unit that became the Center for Clinical Epidemiology and Biostatistics, under the direction of Dr. Brian Strom.

Dr. Berlin spent several years as Director of Biostatistics for the University of Pennsylvania Cancer Center, followed by assuming the role of Faculty Director of the Biostatistics and Epidemiology Consulting Center. At the end of the summer of 2004, Dr. Berlin left Penn to join Johnson and Johnson Pharmaceutical Research and

Development as a Senior Director of Statistical Science, where he serves in an internal consulting role and is creating a group in Pharmacoepidemiology.

He has authored or coauthored over 200 publications in a wide variety of clinical and methodological areas. Dr. Berlin has a great deal of experience in both the application of meta-analysis and the study of meta-analytic methods as applied to both randomized trials and epidemiology. He has served as a consultant on meta-analysis for the Australian government, and has served on two Institute of Medicine Committees examining the association between exposure to chemicals contained in Agent Orange and risk of a wide variety of diseases.   He is currently a member of the Technical Advisory Group for the What Works Clearinghouse, a project sponsored by the U.S. Department of Education intended to provide educators and the public with useful summaries of methodologically valid evaluations of what works in education.

Sally C. Morton is Vice President for Statistics and Epidemiology at RTI International. Dr. Morton leads a department of 230 staff that consolidates statistics, epidemiology and medical studies programs. She previously held the RAND Chair in Statistics, was head of the RAND Statistics Group, and was Co-Director of the Southern California Evidence-Based Practice Center. Her work focuses on evidence-based medicine, specifically the use of meta-analysis in systematic reviews of clinical and health policy topics. She is also interested in the sampling of vulnerable populations, and has been involved in the design, implementation and analysis of primary data collection surveys of the homeless, seriously mentally ill, and those with HIV/AIDS. Dr. Morton is a Fellow of the American Statistical Association (ASA) and of the American Association for the Advancement of Science (AAAS). She is an Editor of *Statistical Science*, and served previously on the editorial boards of the *Journal of the American Statistical Association (JASA),* and the *Journal of Computational and Graphical Statistics (JCGS).* She received a Ph.D. in statistics from Stanford University.

Ingram Olkin (work group co-chair) is professor of statistics and education at Stanford University. Before moving to Stanford he was on the faculties of Michigan State University and the University of Minnesota, where he served as chair of the newly formed Department of Statistics. His academic background consists of a bachelor's degree in mathematics from The City College of New York, a master's degree from Columbia University, and a doctorate from the University of North Carolina. He has coauthored and coedited over fifteen books, and has published over 200 papers. He served as editor of the Annals of Mathematical Statistics and Annals of Statistics, and an associate editor of Psychometrika, the Journal of Educational Statistics and the Journal of the American Statistical Association, as well as on several mathematical journals. He served as chair of the National Research Council 's Committee on Applied and Theoretical Statistics, as president of the Institute of Mathematical Statistics, and has been a member of many governmental panels. Among his honors are a Lifetime Contribution Award from the American Psychological Association, a Wilks Medal and Founders Award from the American Statistical Association, a Guggenheim Fellowship, a

Fulbright Fellowship, a Lady Davis Fellowship, an honorary D.Sci. from DeMontfort University. He was elected to the National Academy of Education. His current research relates to combining the results of independent studies (meta-analysis) and models for survival analysis and reliability.

David Rindskopf is Distinguished Professor of Educational Psychology and Psychology at the City University of New York Graduate Center. He is a Fellow of the American Statistical Association, past President of the Society for Multivariate Experimental Psychology, and past President of the New York Chapter of the American Statistical Association. His areas of research and teaching interest are mainly in applied statististics, and include structural equation models, categorical data, latent class models,missing data, and Bayesian statistics.

Allan R. Sampson is Professor in the Department of Statistics at the University of Pittsburgh, with a secondary appointment in the University's Department of Biostatistics. He has extensive publications and experience in the application of statistical methodology to a variety of scientific areas, including public policy, clinical trials, neurobiology, disability studies, psychiatry and anesthesiology. His areas of statistical expertise include multivariate analysis, meta-analysis, clinical trials design and order-restricted inference. He is the author of more than 100 papers in statistics and related areas, is the co-editor of two books, and is a Fellow of both the American Statistical Association and the Institute of Mathematical Statistics. He has served as a member of number of national committees, including the Technical Advisory Panel for the Social Security Administration's Disability Evaluation Study, the FDA Endocrinologic and Metabolic Drugs Advisory Committee, and the FDA Anesthetic and Life Support Drugs Advisory Committee, as well as participating in a number of focused meta-analysis workshops. He has served on the editorial boards of various journals, including *Journal of the American Statistical Association, Journal of Multivariate Analysis, Statistical Decision Theory* and *Methodology and Computing in Applied Probability*. Previous to joining the University of Pittsburgh, Dr. Sampson was Manager of PPD Biostatistics at Abbott Labs and was on the faculty at Florida State University.

David B. Wilson, Ph.D., is an Associate Professor in the Administration of Justice Program in the Department of Public and International Affairs at George Mason University. His research interests address the effectiveness of offender rehabilitation and crime prevention efforts, program evaluation methodology, and meta-analysis. His researched has focused on the application of meta-analysis to a broad range of topics within the field of criminal justice, including the effectiveness of juvenile delinquency interventions, school-based prevention programs, correctional boot-camps, court-mandated batterer intervention programs, and drug-courts. He is co-author (with Mark Lipsey) of the book, *Practical Meta-analysis*. He is an associate editor of the *Journal of Experimental Criminology* and was awarded the Marcia Guttentag Award for Early Promise as an Evaluator by the American Evaluation Association.

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